



Faculty of Sciences
Geography Department
SPHERES Research Unit
Earth Observation and Ecosystem Modelling Laboratory

Improving Representation of Land-Atmosphere Interactions Using Remote Sensing and Climate Models : Insights from Model Coupling and Satellite Data Integration

Thesis submitted in fulfilment of the requirements
for the academic degree of Doctor in Sciences
at the University of Liège (College of Geography)
by

Thomas Dethinne

Academic year 2025-2026

Jury Members:

Louis François	President	Professor, ULiège, Belgium
François Jonard	Supervisor	Professor, ULiège, Belgium
Xavier Fettweis	Co-Supervisor	Professor, ULiège, Belgium
Nicolas Ghilain	Secretary	Senior Researcher, ULiège/IRM, Belgium
Kwinten van Weverberg	Professor, UGent/IRM, Belgium	
Christine Delire		Senior Researcher, Univ. Toulouse/CNRM, France

Abstract

The Earth’s climate depends on the interactions among multiple interconnected components of the Earth system, including the atmosphere, hydrosphere, cryosphere, biosphere, and anthroposphere. Each of these components exerts varying degrees of influence on the others, which can either amplify or dampen one system responses. These complex interactions and feedbacks make it challenging to monitor, study, and model the climate and ecosystems, as their effects can occur locally or globally and operate over short to long timescales. For instance, drought can locally accelerate leaf shedding in forests, whereas rising global temperatures can gradually increase tree mortality and induce species migration.

The land-atmosphere interface represents one of the key hotspots of these interactions. Yet, regional studies often rely on models that simulate only one side of the land-atmosphere boundary while prescribing the other, thereby limiting the representation of coupled feedback.

This thesis investigates how remote sensing data and process-based modelling can improve the representation of land-atmosphere interactions in regional models. Specifically, we integrate satellite observations into the regional climate model MAR and couple it with the dynamic vegetation model CARAIB to provide more dynamic and physically consistent surface conditions.

First, we assessed the sensitivity of MAR to vegetation cover density by replacing its standard leaf area index input derived from a fixed MERRA2 monthly climatology at 50 km resolution with satellite leaf area index data from MODIS. This replacement enhanced both spatial resolution (500 m) and temporal frequency (8-day). Despite not explicitly modelling vegetation dynamics, MAR’s internal modules responded to changes in vegetation density, showing increased maximum daily temperatures during droughts and reduced extreme precipitation, although effects over longer periods upon the present climate remained less clear.

Building on these findings, we developed a two-way coupling between MAR and CARAIB using file exchange, enabling each model to use the outputs of the other

as inputs. This coupling enables a more comprehensive representation of feedbacks between the land surface and the atmosphere. The coupled system exhibited stable behaviour over Western Europe, showing no climate drift and exhibiting good agreement with observations. Compared to the uncoupled configuration, it produced denser vegetation, enhanced day-to-day vegetation variability, and a stronger response to drought events.

Finally, we integrated satellite microwave observations into MAR to estimate the occurrence of wet snow over Antarctic ice shelves. As remote sensing remains one of the only viable means to monitor surface-melt extent across Antarctica, we applied a temperature nudging approach to align MAR’s simulated wet snowpack with satellite-derived observations over the Antarctic Peninsula. The results revealed that MAR systematically underestimates wet-snow extent, particularly during the early and late melt seasons. Substantial increase in the snowpack temperature was required to match satellite observations, suggesting possible underestimation of surface melt quantity or excessive refreezing and percolation processes. Despite the strong increase in surface melt induced by the integration of the satellite data, the simulated surface mass balance remained largely unchanged due to MAR’s snowpack absorption capacity.

In summary, both the coupling and integration experiments improved the representation of land-atmosphere interactions in MAR by providing it with dynamical data and more representative observed surface conditions. These developments are essential steps toward a better understanding of surface processes and reducing uncertainties in long-term regional climate projections.

Résumé

Le climat Terrestre dépend des interactions entre de multiples composantes interconnectées du système terrestre, telles que l’atmosphère, l’hydrosphère, la cryosphère, la biosphère ou l’anthroposphère. Chacune exerce sur les autres, à des degrés variables, des forçages qui peuvent amplifier ou compenser les forçages venant d’autres systèmes. Ces interactions et rétroactions complexes rendent difficile l’étude et la modélisation du climat et des écosystèmes naturels, puisque leurs effets peuvent se manifester à la fois localement et globalement, mais aussi sur des échelles de temps longues ou courtes. Par exemple, une sécheresse peut localement accélérer la chute des feuilles dans une forêt, tandis que l’augmentation globale des températures peut accroître la mortalité des arbres ainsi qu’induire la migration de différents espèces.

L’interface entre la surface de la Terre et l’atmosphère constitue l’un des lieux principaux de ces interactions. Cependant, les études régionales reposent souvent sur des modèles ne simulant qu’un seul côté de cette interface, tout en prescrivant l’autre, ce qui limite la représentation des rétroactions.

Cette thèse explore comment l’utilisation de données de télédétection et de modélisation pourrait améliorer la représentation des interactions entre la surface et l’atmosphère dans les modèles régionaux. Plus précisément, nous intégrons des observations satellitaires dans le modèle climatique régional MAR et le couplons ensuite avec le modèle dynamique de végétation CARAIB afin d’offrir à MAR des conditions de surface plus dynamiques et physiquement cohérentes.

Dans un premier temps, nous avons évalué la sensibilité de MAR à la densité de la couverture végétale. Pour cela, nous avons remplacé l’indice de surface foliaire (LAI) qu’il utilise comme entrée du modèle, et dérivé d’une climatologie mensuelle fixe de MERRA2 à 50 km de résolution spatiale, par des données de LAI dérivées d’observation satellitaires de MODIS. Ce changement a permis d’améliorer à la fois la résolution spatiale (à 500 m) ainsi que la fréquence temporelle (à 8 jours) du jeu de données utilisé. Bien que MAR ne simule pas explicitement toute la dynamique de la végétation, ses variables internes ont bien été influencées par la variation de densité du couvert végétal. Les résultats montrent une augmentation des températures maximales journalière durant les sécheresses et une réduction des précipitations extrêmes. Cependant, les effets observés sur le climat actuel et pour des périodes plus longues demeurent moins nets.

En se basant sur ces résultats, nous avons ensuite développé un couplage bidirectionnel entre MAR et CARAIB, via un échange de fichiers, pour permettre à chaque modèle d’utiliser les sorties de l’autre comme entrées. Ce couplage permet de modéliser une meilleure représentation des rétroactions entre la surface terrestre et

l'atmosphère. Le système couplé s'est montré stable sur l'Europe de l'Ouest, sans dérive climatique et présente une bonne concordance avec les observations. Par rapport à la configuration non couplée, les résultats simulés montrent une végétation plus dense, une variabilité quotidienne de la végétation accrue ainsi qu'une réponse aux épisodes de sécheresse plus marquée.

Enfin, nous avons intégré des observations satellitaires micro-ondes dans MAR afin d'estimer l'occurrence de neige humide sur les plateformes glaciaires en Antarctique. La télédétection demeure aujourd'hui l'un des rares moyens d'observer l'étendue de la fonte en surface à l'échelle du continent. Afin d'aligner l'extension de neige humide simulée par MAR sur celle observée par les satellite en péninsule Antarctique, nous avons appliqué une approche de nudging pour ajuster la température du manteau neigeux et le faire fondre. Les résultats révèlent que MAR sous-estime systématiquement l'étendue de neige humide, notamment en début et fin de saison de fonte. Une augmentation fréquente de la température du manteau neigeux a été nécessaire pour reproduire les extensions de fonte observées. Cela suggère une sous-estimation des processus de fonte en surface ou, à l'inverse, une surestimation du regel et de la percolation. Malgré cette augmentation de fonte de surface causée par l'augmentation de température du manteau neigeux, le bilan de masse en surface simulé reste globalement inchangé grâce à la capacité d'absorption du manteau neigeux des plateformes glaciaires en Antarctique de MAR.

Les expériences de couplage et d'intégration ont donc permis d'améliorer la représentation des interactions surface-atmosphère dans MAR en introduisant des conditions de surface plus réalistes et dynamiques. Ces développements constituent une étape essentielle pour mieux comprendre les processus de surface et réduire les incertitudes dans les projections climatiques régionales.

Remerciements

La thèse, c'est comme un voyage en bateau au XVIIe siècle. Durant sa thèse, on peut tout autant faire des découvertes extraordinaires et redéfinir (à son échelle) la Science, que faire naufrage à peine sorti du port. Moi, ma thèse, c'était un voyage sur la Radja River : j'ai été secoué, j'ai pris l'eau, mais au final, je me suis quand même amusé.

Tout d'abord, même si la communication a parfois été difficile, je tiens à remercier mon promoteur, *François Jonard*, qui m'a permis de mener ma recherche même si j'étais parfois en dehors du sujet de son labo, qui m'a fait confiance aussi bien au niveau de la recherche que de l'enseignement, et qui m'a toujours aiguillé vers ce que je voulais vraiment.

Je tiens aussi à remercier mon co-promoteur, *Xavier Fettweis*, qui, même s'il m'a retiré de la mailing list de climato environ trois minutes après que je sois parti en géomatique, n'a jamais cessé de répondre à mes mille questions sur MAR, m'a toujours accueilli la porte ouverte et m'a laissé travailler sur ses serveurs.

Merci à mes deux co-promoteurs officiels, *Quentin et Nicolas*. Sans l'un, ma thèse n'aurait jamais commencé ; sans l'autre, elle n'aurait jamais fini. Même si vous avez été à mes côtés à des moments différents, vous avez été présents tout au long de mon voyage.

Bien sûr, je remercie aussi *Louis François* pour son aide et son expertise de CA-RAIB, ainsi que *Ghislain Picard* pour son soutien lors de ma période antarctique.

Durant ma thèse, j'ai pu travailler dans trois bâtiments différents : le CSL, le B11 et le B5a, et je tiens à remercier toutes les personnes que j'y ai croisées et qui m'ont soutenu. La liste est longue, et je suis certain d'en oublier certains, mais merci à *Anne, Christian, Romy, Quintia, Ali, Chris, Clara, Damien, Josip, JF, Brice, Benoît, Anna, Roland, JPK, Imane, Charline, Zouhair, Anass, Abder, Caneren, Benjamin et Cadwal*. Si je pense à vous, c'est que vous m'avez soit aidé dans ma recherche, égayé mes temps de midi ou mangé des cacahuètes avec moi.

À *ma famille et mes amis*, je vous dis aussi merci. Merci de m'avoir écouté parler d'un sujet parfois un peu rébarbatif, de m'avoir demandé la météo du lendemain, et d'avoir peut-être même essayé de comprendre ce que j'ai fait de ma vie ces dernières années en lisant ce document.

Evelyne, merci aussi à toi de m'avoir compris, d'avoir parfois laissé le travail empiéter sur le privé. Ton aide et ta curiosité naturelle m'ont permis de terminer ce

travail, en me remettant toujours en question et sans jamais me reposer sur mes acquis.

Enfin, je remercie toutes les personnes avec qui j'ai pu travailler et publier, celles qui ont reviewé mon travail, ainsi que toutes celles qui ont pris ou prendront le temps de le lire.

Contents

1	Introduction	1
1.1	General Context	2
1.1.1	Climate change and the Earth system	2
1.1.2	Land-atmosphere interactions	4
1.1.3	Modelling	9
1.1.4	Remote sensing of the Earth	11
1.2	Thesis Objectives	15
1.3	Thesis Outline	16
2	RCM Sensitivity to Satellite-derived LAI	19
2.1	Introduction	20
2.2	Model and Experiments	23
2.2.1	Regional climate model	23
2.2.2	Study region	24
2.2.3	LAI data	26
2.2.4	Model experiments	28
2.3	Results	31
2.3.1	Model assessment	31
2.3.2	Impact of replacing MERRA2-derived dataset by MODIS LAI dataset	32
2.3.3	Sensitivity of the model to noise in LAI	36
2.3.4	Sensitivity to the integration method of the LAI	39
2.3.5	Sensitivity to the temporal evolution of the LAI	40
2.4	Discussion	43
2.5	Conclusions	46
3	RAVEL Atmosphere-Vegetation Coupled Model	49
3.1	Introduction	50
3.2	Material and Methods	53
3.2.1	Description of the models	53
3.2.2	Settings for a study case	57
3.2.3	Simulation experiment	60
3.2.4	Statistical analyses	62
3.3	Results	64
3.3.1	Model assessment	64
3.3.2	Impact of the coupling	65
3.4	Discussion	74
3.5	Conclusions and Future Works	75

4	Assimilation Wet-Snow Occurrence Into MAR	79
4.1	Introduction	80
4.2	Methods and Data	83
4.2.1	Satellite data	83
4.2.2	Regional climate model	87
4.2.3	Data assimilation	88
4.3	Evaluation	92
4.4	Results	94
4.4.1	MAR sensitivity	98
4.5	Discussion and Conclusions	105
5	Discussion and Conclusions	109
5.1	Modelling Strategies: From remote sensing data integration, to model coupling and data assimilation	110
5.2	Land-Atmosphere Interactions in MAR	111
5.3	Structural Limitations of the Model	111
5.4	Key Scientific Contributions	112
5.4.1	Improving the input dataset	112
5.4.2	RAVEL 1.0 coupled model	114
5.4.3	Integrating wet-snow occurrence	115
5.5	Implications for Regional Climate Modelling	116
6	Perspectives and Future Developments	119
	Bibliography	123
	Appendix	160
A	Additional elements for Chapter 2	160
B	Additional elements for Chapter 4	164
	List of Publications and Conferences	172

List of Abbreviations

α	Water Content Threshold
Δ_z	Assimilation Depth Threshold
ψ_c	Leaf Water Potential at Stomatal Closure
ψ_v	Leaf Water Potential
ρ	Snowpack Density
ρ_a	SBL Top Air Density
σ_0	Backscattering Coefficient
An	Net CO_2 Assimilation Rate
ASW	Relative Soil Water
CO_2	Carbon Dioxide
E_{tr}	Transpiration Vapour Flux
g_0	Minimum Stomatal Conductance
g_1	Slope for the Stomatal Conductance
g_s	Stomatal Conductance
h_s	Relative Humidity at the Leaf Surface
LAI_e	Effective Leaf Area Index
q_a	SBL Top Specific Humidity
q_{sat}	Saturation Specific Humidity at T_v
r_0	Minimal Stomatal Resistance
r_{av}	Aerodynamic Resistances for Heat

r_s	Stomatal Resistance
S	Water Stress Factor
SW_{mins}	Soil Water Mortality Threshold
T_v	Vegetation Temperature
$WATSUP$	Water Stress Factor
AIS	Antarctic Ice Sheet
AMSR2	Advanced Microwave Scanning Radiometer 2
AP	Antarctic Peninsula
ASCAT	Advanced Scatterometer
AWS	Automatic Weather Stations
BAG	Bioclimatic Affinity Group
BIM	Biomass
C3S	Copernicus Climate Change Service
CARAIB	CARbon Assimilation in the Biosphere
CMIP6	Coupled Model Intercomparison Project phase 6
CRMSE	Centered Root Mean Square Error
DJF	December-January-February
DV(G)M	Dynamic Vegetation (Global) Model
ECV	Essential Climate Variables
EO	Earth Observation
ESA	European Space Agency
ESM	Earth System Model
ET	Evapotranspiration
EVI	Enhanced Vegetation Index
GC	Green Carbon
GCM	Global Climate Model
GCOS	Global Climate Observing System
GEE	Google Earth Engine
GHG	Greenhouse Gases

GPP	Gross Primary Productivity
IBM	Improved Bucket Model
IGBP	International Geosphere Biosphere Programme
IPCC	Intergovernmental Panel on Climate Change
JAXA	Japan Aerospace Exploration Agency
JJA	June-July-August
L-A	Land-Atmosphere
LAI	Leaf Area Index
LHF	Latent Heat Flux
LSASAF	Satellite Application Facility on Land Surface Analysis
LSM	Land Surface Model
LWC	Liquid Water Content
LWU	Longwave Upward Flux
MAR	Modèle Atmosphérique Régional
MB	Mean Bias
ME	Surface Melt
MODIS	Moderate-Resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
NEE	Net Ecosystem Exchanges
PBL	Planetary Boundary Layer
PFT	Plant Functional Type
r	Pearson Correlation Coefficient
RAVEL	Regional Atmosphere-VEgetation uLiège model
RC	Remaining Carbon
RCM	Regional Climate Model
RESM	Regional Earth System Model
RH	Relative Humidity
RMSE	Root-mean-square Error
RS	Remote Sensing

RU	Runoff
RZ	Refreezing
S1	Sentinel-1
SAR	Synthetic Aperture Radar
SBL	Surface Boundary Layer
SHF	Sensible Heat Flux
SISVAT	Soil Ice Snow Vegetation Atmospheric Transfer module
SMB	Surface Mass Balance
SPEI	Standardized Precipitation Evapotranspiration Index
SW	Soil Water Content
SWU	Shortwave Upward Flux
TT	Surface Air Temperature

CHAPTER 1

Introduction

1.1 General Context

1.1.1 Climate change and the Earth system

Climate is a key determinant of species distributions and ecosystem functioning. Long-term climatic regimes, including patterns of temperature, water availability, and wind, play a fundamental role in determining which plants can grow and which animals will be able to survive (Woodward and Williams, 1987; Guisan and Thuiller, 2005; Parmesan, 2006). Building a resilient and balanced ecosystem takes time (De Leo and Levin, 1997). Yet, since the industrial revolution, humans have unintentionally altered the climate by increasingly releasing greenhouse gases (GHGs) in the atmosphere, mainly from the combustion of fossil fuels such as coal, oil, and natural gas. These emissions are driving unprecedented changes in the Earth’s climate system (Meinshausen et al., 2011; Taylor et al., 2012; Eyring et al., 2016; Meinshausen et al., 2020).

The primary consequence of rising GHG concentrations is a global temperature increase, which is projected to continue throughout the century if no significant mitigation efforts are undertaken (Fig. 1.1; IPCC, 2023b). As a result, both the Earth’s atmosphere and oceans are warming (Held and Soden, 2006; Moss et al., 2010), polar ice caps are melting (Rignot et al., 2019; Glaude et al., 2024), sea levels are rising (Fairbanks, 1989), and forest fires are becoming more frequent and intense (Carnicer et al., 2011; Dai, 2011; Allen et al., 2015).

These events are intensifying over time and have direct consequences for human societies (IPCC, 2023b). Populations are being forced to migrate due to crop failures, increasing flood or fire risks, and other climate-induced stresses, which in turn can lead to armed conflicts over territory and basic resources (McMichael, 2015).

In this undeniable context, studying the climate has become an urgent scientific and societal priority (Biella et al., 2024). This growing need to better understand the Earth system has prompted the scientific community to mobilize collectively to investigate ongoing changes, mitigate human impacts on the climate, and guide the implementation of adaptation strategies that can help ensure more liveable conditions worldwide. These efforts have led to the establishment of major international scientific bodies, most notably the Intergovernmental Panel on Climate Change (IPCC). Created to provide regular assessments of the scientific basis of climate change, its impacts and future risks, as well as options for adaptation and mitigation, the IPCC plays a central role in synthesizing current knowledge. Its core mission is to evaluate the state of climate science by drawing on the global scientific literature and expert consensus (IPCC, 2024).

To guide both the scientific community and the policymakers in this complex system, the Global Climate Observing System (GCOS) program developed the concept of Essential Climate Variables (ECVs). The ECVs are physical, biological, or chemical variables (or groups of variables) that critically characterise the Earth’s climate (Bojinski et al., 2014). The concept of ECVs should not be understood as a set of isolated variables; rather, it forms part of a broader framework that provides guide-

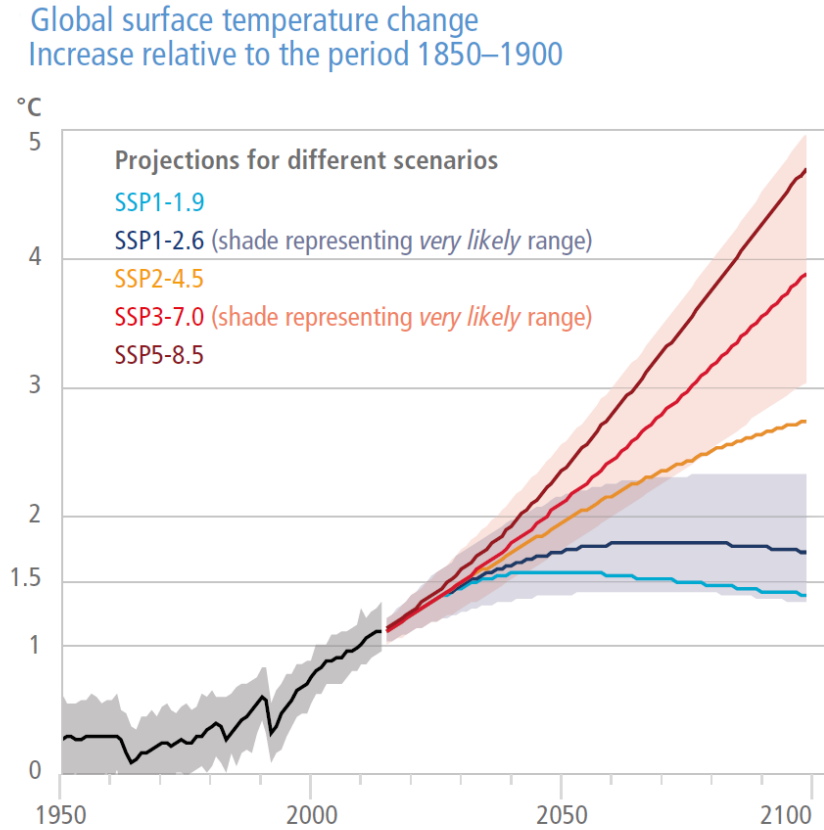


Figure 1.1: Projected increase in temperature compared to 1850-1900 given different shared socio-economic pathways (IPCC, 2023b, adapted).

line on the observation of ECVs, their relevance, and prioritization. In this way, the ECVs framework helps translate a complex observational landscape into a more structured and manageable set of actions (Bojinski et al., 2014).

While ECVs provide a structured framework to observe and monitor the climate system, they do not act independently. Earth’s climate variability and change emerge from the interactions among several interconnected spheres: the biosphere, hydrosphere, atmosphere, lithosphere, cryosphere, and, more recently, the anthroposphere (Seneviratne et al., 2010; Vogel et al., 2017; IPCC, 2023b; Bevacqua et al., 2024). Each component of this system can actively influence the others through dynamic interactions (Seneviratne et al., 2006, 2010; Strengers et al., 2010; Zhang et al., 2018). For instance, drought periods can influence vegetation health (Jonard et al., 2011; Kolb et al., 2019), while large-scale infrastructure, such as dam construction, can significantly modify regional hydrological cycles and contribute to the drying of downstream ecosystems (Swanson et al., 2021).

In some cases, interactions between components of the Earth system can trigger loops that either dampen or amplify the initial perturbation. These processes are known as climate feedbacks (Dirmeyer et al., 2006; Liu et al., 2006; Chen et al., 2022a). Although difficult to study, they are essential for understanding current functioning of the climate system, as such feedbacks are pervasive throughout the

Earth system (Zhang et al., 2014; Ho-Hagemann et al., 2017; Santanello et al., 2018; Chen et al., 2022a; Delhasse et al., 2024).

An example of positive feedback is the amplification of warming in polar regions: an increase in temperature leads to snow and ice melt, as well as greening of the region, which reduces surface albedo. This results in less solar radiation being reflected back into space and more energy being absorbed by the surface, thereby further increasing temperatures (Vogel et al., 2017; Stuecker et al., 2018; Zhang et al., 2018). Another example is that forest fires can dry out soils, increase atmospheric greenhouse gas concentrations, and generate substantial amounts of dead biomass, thereby increasing the probability of subsequent fire events (Certini, 2005; Westerling et al., 2006; Gonzalez et al., 2010; Abatzoglou and Williams, 2016). Conversely, negative feedback can occur when rising land surface temperatures enhance convective activity, leading to increased cloud formation. These clouds can promote precipitation, increase albedo, and in turn, cool down the land surface (Ho-Hagemann et al., 2017; Gröger et al., 2021).

The land-atmosphere (L-A) boundary, in particular, is a hotspot for these interactions. Many land and atmospheric ECVs, such as surface air temperature, soil moisture, above-ground biomass, and evaporation from land, are tightly coupled through physical and biological processes occurring at the L-A interface. Understanding how these variables interact, rather than considering them in isolation, is therefore essential to interpret observations consistently and to improve climate prediction. This makes L-A interactions a central element in the Earth system feedbacks.

1.1.2 Land-atmosphere interactions

At the L-A interface, interactions involve numerous components of the Earth system (Fig. 1.2; Santanello et al., 2018) and play a crucial role in shaping weather and climate (Dirmeyer et al., 2006; Santanello et al., 2018). These interactions can be understood through the exchange of energy, water, and momentum between the surface and the atmosphere, which governs the behaviour of the lower atmosphere.

The energy available at the surface consists of the balance between incoming solar radiation (modulated by the surface albedo), the longwave radiation emitted by the overlying atmosphere, and the longwave radiation emitted by the surface. This net radiation is partitioned into soil heat flux, sensible heat flux (which warms the air column above the surface), latent heat flux (associated with evapotranspiration), and snowmelt (Bonan, 2015). Unlike sensible heat flux, latent heat flux can have non-local effects on the atmosphere, as evaporated water is transported upward through convection, where it condenses, releases latent heat, contributes to cloud formation, and ultimately leads to precipitation (Sellers et al., 1997). This partitioning is strongly controlled by soil moisture availability. When soils are moist, a larger fraction of energy is used for evapotranspiration, atmospheric humidity and moderated surface temperatures. Conversely, under dry conditions, evapotranspiration is limited, and more energy can be converted into sensible heat, enhancing surface warming. These processes directly influence the development of the plane-

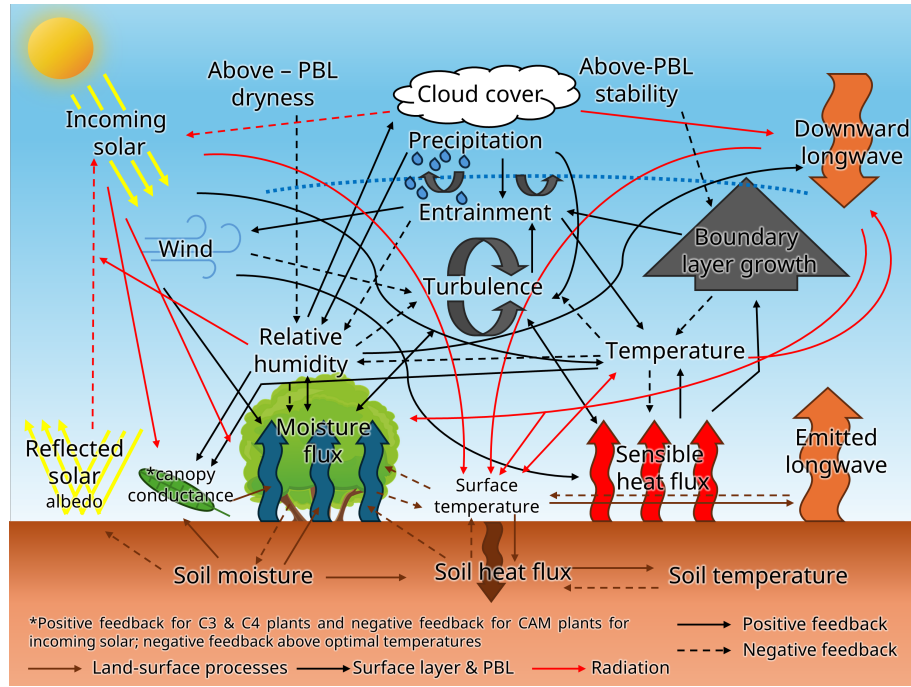


Figure 1.2: Schematic representation of local land-atmosphere interactions in a stable synoptic pattern, including soil moisture-precipitation feedback. Solid arrows indicate positive feedback, while dashed arrows represent negative feedback. The red arrows indicate radiative processes, black arrows indicate surface layer and Planetary Boundary Layer (PBL) processes, brown arrows indicate land surface processes. The dotted blue line represents the top of PBL (Santanello et al., 2018, adapted). From an original image of Ek and Mahrt (1994) and Ek and Holtslag (2004).

tary boundary layer and can affect cloud formation and precipitation (Seneviratne et al., 2010; Santanello et al., 2018).

Vegetation plays a central and active role in these exchanges by regulating both water and energy fluxes through a combination of biophysical and biogeochemical processes (Meir et al., 2006). It directly influences surface albedo and thus the amount of energy absorbed at the surface. Forests typically have lower albedo than non-forested areas, leading to greater absorption of solar radiation and potential localized surface warming. However, this additional energy can also enhance evapotranspiration, generating a cooling effect. This cooling effect is further reinforced by vegetation through multiple mechanisms. Plants can access deeper soil water, increasing the availability of water for transpiration, while increased surface roughness enhances turbulent exchanges and promotes evaporation (Meir et al., 2006). The transfer of water from soil to atmosphere is regulated by plant transpiration, which is tightly linked to photosynthesis. During photosynthesis, photosynthetically active radiation is used by plants to transform atmospheric CO_2 and water into sugar and organic compounds. During that process, an open path is required for the atmospheric CO_2 to enter the plant tissues. To assimilate it, plants open stomata, allowing gas exchange but also causing water loss (Jarvis, 1976; Sellers et al., 1997). This stomatal conductance responds dynamically to environmental conditions such as radiation, temperature, and water stress (Jarvis, 1976; Bonan, 2015). For example, plants will respond to environmental stress, such as drought, by closing their

stomata to conserve water and prevent desiccation. This regulation directly influences evapotranspiration rates and thus the partitioning of available energy at the surface. Therefore, stomatal closure or leaf shedding can further amplify L-A feedbacks by reducing evapotranspiration and increasing sensible heat flux, thereby enhancing near-surface warming (Teuling et al., 2010; Seneviratne et al., 2010).

Building on these processes, numerous studies have investigated L-A interactions in their various forms using multitude of techniques like remote sensing, field observations, or numerical modelling. Relatively intuitive processes, such as the link between soil moisture and atmospheric variables like temperature or precipitation, have been thoroughly explored (Seneviratne et al., 2010; Miralles et al., 2012; Hsu et al., 2017; Vogel et al., 2017), highlighting differences in both the strength and the mechanisms of L-A coupling depending on time and location. Additional studies, including those based on observational data and coordinates initiatives, have further identified so-called “hotspots” of L-A coupling (Dirmeyer et al., 2006; Lorenz et al., 2015).

Using correlation-based metrics (e.g., the correlation between latent and sensible heat fluxes, or between evaporative fraction and soil moisture), Knist et al. (2017), with EURO-CORDEX simulations (Jacob et al., 2014), identified clear regional contrasts across Europe. Northern Europe was found to be a zone of weak L-A coupling, where land surface temperature primarily controls near-surface atmospheric humidity. This results in relatively similar near-surface gradients of temperature and humidity, producing a modelled positive correlation between sensible and latent heat fluxes. In contrast, Southern Europe was identified as a region of strong L-A coupling, where soil moisture strongly constrains evapotranspiration, and thus near-surface humidity, while temperature gradients and sensible heat fluxes can still increase due to solar radiation. Because latent heat fluxes further deplete soil moisture, correlations between fluxes tend to weaken or even become negative. Central Europe acts as a transition zone, where models diverge in their classification: some simulations describe it as strongly coupled, while others indicate weak coupling. This North/South behaviour had already been reported in earlier studies using similar approaches (Dirmeyer et al., 2006; Dirmeyer, 2011). Studying this transition zone is therefore also important as the coupling strength could and will probably change in the future due to climate change (Seneviratne et al., 2006).

Because of the critical role of vegetation in shaping climate (Gloege et al., 2022; Roebroek et al., 2025), studies have increasingly focused on testing different vegetation scenarios in climate models, both at the global scale (Chase et al., 1996; Delire et al., 2011; Chen et al., 2022a; King et al., 2024) and at regional scales (Heck et al., 2001; Davin et al., 2020; Anwar and Diallo, 2021; Jiménez-Gutiérrez et al., 2021), sometimes hinting toward the non-local effects of vegetation on climate (Hua et al., 2023).

Recent research has also investigated whether afforestation scenarios could contribute to climate change mitigation (King et al., 2024; Bright et al., 2025; Engel et al., 2025). These studies highlight effects that are not always intuitive. For instance, Bright et al. (2025) showed that biogeophysical radiative forcings in Europe are highly localized and largely dominated by surface albedo. Engel et al. (2025)

found that reforestation non-forested regions could both mitigate effects of climate change but also decrease soil water availability in some areas and consequently increase the drying trend induced by climate change. Similarly, King et al. (2024) also reported local decreases in soil water availability and temperature increases, consistent with the findings of Engel et al. (2025). King et al. (2024) also observed limited large-scale impacts on precipitation and atmospheric circulation, contrasting with earlier studies such as Portmann et al. (2022) or De Hertog et al. (2024).

However, because land surface properties such as land cover, vegetation type, and soil texture are highly heterogeneous in space and time, generalizing measurements and studies from one location to another is challenging. Moreover, the scarcity of observations hampers the study of these interactions (Santanello et al., 2018).

Recognizing the need to better understand system feedbacks and the interactions between land and atmosphere, the scientific community initiated several major international efforts. For example, the Global Land-Atmosphere Coupling Experiment (GLACE; Koster et al., 2004; Guo et al., 2006; Koster et al., 2006) and the Global Energy and Water Exchanges Local Land-Atmosphere Coupling (Santanello et al., 2018) initiative (GEWEX LoCo) were established to address these challenges. These programs take advantage of the advances of major field campaigns designed to capture comprehensive observations across the soil-vegetation-atmosphere continuum, such as the First International Satellite Land Surface Climatology Project (ISLSCP) Field Experiment (FIFE; Hall and Sellers, 1995), the Cooperative Atmosphere-Surface Exchange Study (CASES; Yates et al., 2001; Moeng et al., 2003), and more recently, the Land-Atmosphere Feedback Experiment (LAFE; Wulfmeyer et al., 2018). In parallel, global modelling initiatives such as the Coupled Model Intercomparison Project phase 6 (CMIP6; Eyring et al., 2016) provided a framework to evaluate L-A feedbacks across climate models.

Another important form of L-A interaction occurs through surface melt of the polar ice caps (Trusel et al., 2013; Gilbert and Kittel, 2021). Unlike soil moisture or vegetation feedbacks, which directly influence local atmospheric conditions, polar surface snow melt is largely a response to atmospheric forcing, with surface temperature acting as the dominant driver (van den Broeke et al., 2016; Tedesco and Fettweis, 2020). Therefore, the polar ice sheets are highly sensitive to climate change, and their destabilization could ultimately contribute more than 60 m to global sea-level rise (Church et al., 2013; Fretwell et al., 2013). In such manner, their impacts extend well beyond the regional scale, making them a critical component of the Earth system.

In Antarctica, surface melt generally accounts for a smaller fraction of mass loss compared to basal melting or iceberg calving (Trusel et al., 2015; Bell et al., 2018; Rignot et al., 2019; Gilbert and Kittel, 2021). In contrast, Greenland has experienced a marked increase in surface melt since the late 1990s (Noël et al., 2017). Combined with relatively stable precipitation and refreezing rates, this has led to enhanced runoff and a sustained decline in surface mass balance, the net effect of accumulation (snowfall and rainfall) and ablation (runoff, evaporation, sublimation, and snow drift) (Fig. 1.3; Noël et al., 2017).

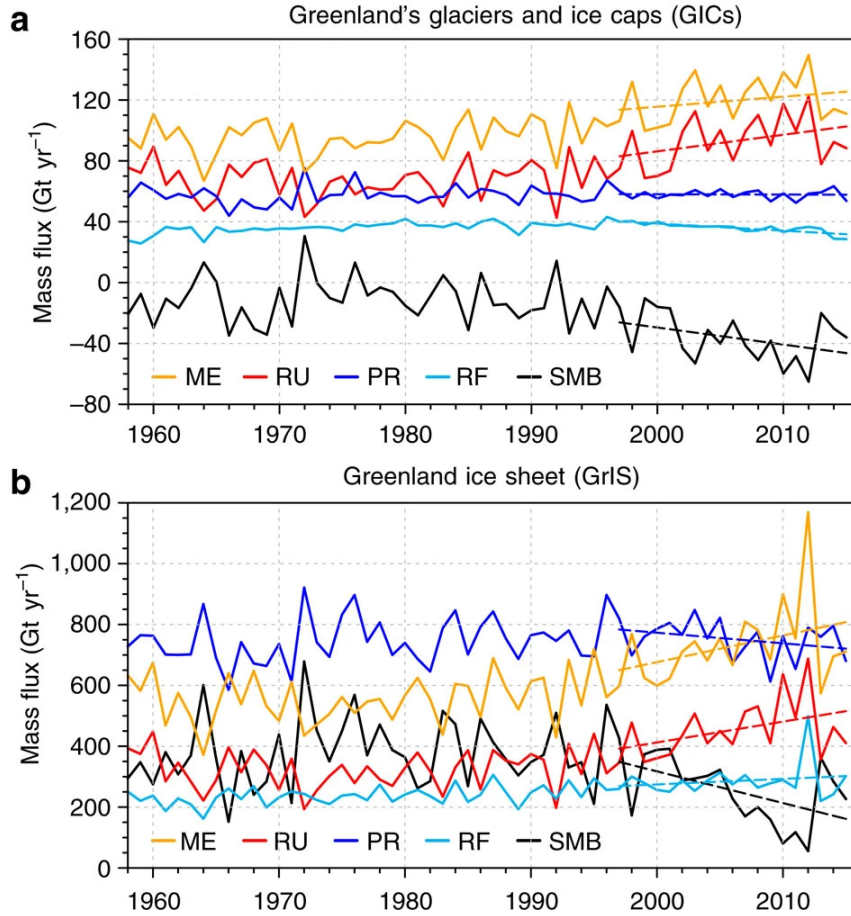


Figure 1.3: Evolution of the annual cumulative components of the surface mass balance (SMB), i.e., surface melt (ME), runoff (RU), total precipitation (PR), and rainfall (RF) for the period 1958-2015 of (a) Greenland’s glaciers and ice caps, and (b) the Greenland ice sheet. Total sublimation and snow drift erosion are not included in the graphic. Dashed lines represent the 1997-2015 trends (Noël et al., 2017, adapted).

Beyond direct mass loss through runoff, an increase in surface melt, mostly triggered by a temperature increase, also initiates feedback processes with important climatic implications like a reduction in snow/ice albedo (Curry et al., 1995; Zeitz et al., 2021), or a weakening or disintegration of ice shelves (Scambos et al., 2003; Lai et al., 2020). The ice shelves, the floating extensions of the Antarctic ice sheet, provide a buttressing effect (Fürst et al., 2016) that slows inland ice flow and consequently limits basal melt by reducing exposure to ocean waters (Favier and Pattyn, 2015; Paolo et al., 2015). Their thinning or collapse therefore generates a “double loss”: first from the disappearance of the shelves themselves, and second from the acceleration of grounded ice discharge into the ocean (Rott et al., 1996; Banwell et al., 2013; Corti et al., 2014).

Overall, existing studies show that L-A interactions remain subject to significant uncertainty (Seneviratne et al., 2010; Santanello et al., 2018). Land-surface parametrisations and the representation of key processes in individual models strongly influence the estimated coupling strength and pathways of interactions (Knist et al.,

2017; Crowhurst et al., 2020). Multi-model studies often highlight not only differences in magnitude but, in some specific cases, even in the sign of the studied metrics, underscoring the extent of structural uncertainty across models (Dirmeyer et al., 2006; Davin et al., 2020; Glaude et al., 2024). These uncertainties are further amplified by observational limitations, since key land-surface states and fluxes such as soil moisture, surface fluxes, and vegetation dynamics, remain difficult to measure routinely and at the spatial and temporal resolutions required (Koster et al., 2009).

Such limitations have direct consequences for both weather and climate predictions. Misrepresentation of L-A feedbacks can, for instance, lead to significant biases in the simulation of temperature and precipitation extremes, including droughts and heatwaves (Seneviratne et al., 2010; Santanello et al., 2018). Addressing these uncertainties requires a combination of observation (e.g., satellite missions and flux tower networks), model intercomparisons, and novel approaches such as data assimilation. Together, these efforts represent essential steps toward reducing uncertainty in L-A interactions, while improving both the predictive capacity of climate models, and the representation of ecosystem processes.

In this thesis, we use two of these key approaches to study the climate system and L-A interactions: numerical modelling and satellite-based remote sensing. These two approaches are now central to climate science, providing ways to simulate climate processes and to observe the Earth system at large spatial and temporal scales. The next sections introduce these two techniques.

1.1.3 Modelling

Since the advent of computers, scientists have developed numerical models for a wide range of applications, from predicting stock market trends (Nabipour et al., 2020), to modelling geothermal fields (O’Sullivan et al., 2009), and simulating the Earth’s climate (Beniston et al., 2007; Kjellström et al., 2018; Balcha et al., 2023). These models enable researchers to represent complex physical, biological, and economic systems using mathematical formulations that can be solved computationally. As computational power and data availability have increased, numerical modelling has become an essential tool for understanding system dynamics, testing hypotheses, and forecasting future scenarios under varying conditions.

The first attempt to simulate the atmospheric circulation numerically was made by Phillips (1956), who developed a simplified two-layer atmospheric model. This pioneering work laid the foundation for subsequent advances, notably by Manabe and Wetherald (1967), and ultimately evolved into modern Global Climate Models (GCMs). These comprehensive tools are capable of simulating the Earth’s climate system and its response to external forcings, such as increased GHG concentrations (IPCC, 2023a). GCMs reproduce the large-scale dynamics of the atmosphere across the entire planet, albeit at coarse spatial resolution, making them essential for understanding global circulation patterns.

In the late 1980, Dickinson et al. (1989) and Giorgi and Bates (1989) introduced a new class of tools to climatology, the Regional Climate Models (RCMs). RCMs

were designed to dynamically downscale the output from coarser-resolution GCMs by incorporating region-specific parametrisations and detailed topography, providing finer spatial and temporal detail (Fig. 1.4; Giorgi, 2019), and enabling a more accurate representation of climate processes at local to regional scales (Giorgi, 2019).

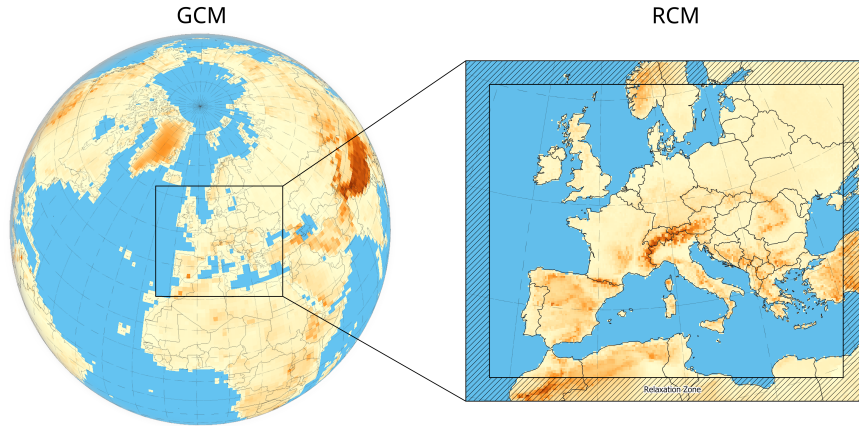


Figure 1.4: Schematic representation of the link between regional climate models (RCMs) and Global Climate Models (GCMs) (Giorgi, 2019, adapted).

Climate models are often developed to simulate a specific component of the Earth system, such as the atmosphere, ocean, ice sheets, or vegetation. Examples include atmospheric models like ALADIN (Radnóti et al., 1995), ocean models such as NEMO (Madec et al., 2024), ice sheet models like PISM (Bueler and Brown, 2009) and Dynamic (Global) Vegetation Models (DVGs) such as LPJmL4 (Schaphoff et al., 2018). In such cases, models typically rely on prescribed boundary conditions derived from observations or other models to represent the influence of the remaining Earth system components (Giorgi and Gao, 2018).

For atmospheric models like RCMs and GCMs, an accurate representation of surface conditions is particularly critical. The requirement to close the surface energy and water budgets led to the development of the first land surface models (LSMs; e.g., Manabe, 1969). However, as highlighted by Koster et al. (2009), many key LSM parameters and state variables, such as soil moisture, are either difficult to observe routinely or cannot be measured directly in ways that match model representations. As a result, the early development of LSMs and climate models was often carried out in standalone mode, due to the limited possibilities to evaluate model performance or identify biases in the coupled system (Santanello et al., 2018).

These limitations, together with the need to represent feedback between Earth system components, motivated the development of more integrated modelling approaches. This led to the coupling of individual component models to explicitly represent interactions between the atmosphere, land surface, ocean, cryosphere, and biosphere. Most modern GCMs are now embedded within Earth System Models (ESMs) (Gutjahr et al., 2019; Sellar et al., 2019; Boucher et al., 2020). In such frameworks, model outputs are used as inputs for other components or exchanged dynamically to resolve feedback at component interfaces.

The integration of RCMs into fully coupled Regional Earth System Models (RESMs) remains less common than at the global scale, but recent efforts have increasingly explored regional model coupling (Zhang et al., 2014; Knist et al., 2017; Anwar and Diallo, 2022; Huot et al., 2022). Such coupled models are essential to improve the representation of feedback between the Earth’s systems like the land-atmosphere, or the ocean-atmosphere, at the regional scale, where they can be stronger than at a global scale (Vogel et al., 2017; Giorgi and Gao, 2018; Stuecker et al., 2018).

These coupled models are widely used in coordinated experiments such as CMIP6 (Eyring et al., 2016; IPCC, 2022; King et al., 2024) for the GCMs or CORDEX (Giorgi and Bates, 1989) and its European branch EURO-CORDEX (Jacob et al., 2014) for RCMs to assess global climate responses under different greenhouse gas scenarios and to account for internal model uncertainty.

Numerical modelling is therefore a powerful tool, as it enables the study of past, present, and future climates over long time series with fine temporal resolution. However, climate models inevitably rely on empirical parametrisations and simplified representations of complex processes, making their evaluation a critical step to ensure the robustness and credibility of their outputs (Giorgi and Gutowski, 2015; Balcha et al., 2023; Grailet et al., 2025). To support this evaluation and constrain model uncertainties, independent observational information is required. In this context, satellite observations provide a unique and often indispensable source of spatially and temporally consistent observation-based datasets. These data not only allow systematic model evaluation but also offer new opportunities to improve the representation and parametrisation of key surface and atmospheric processes in climate models.

1.1.4 Remote sensing of the Earth

Since the advent of the space age, satellite-based Earth Observation (EO) has revolutionised the way we monitor the Earth’s surface and atmosphere, especially with the Global Monitoring for Environment and Security European Earth monitoring programme (GMES; Aschbacher and Milagro-Pérez, 2012), later renamed to "Copernicus". Particularly thanks to the variety in the Sentinel constellation from the Copernicus program (ESA, 2015), Remote Sensing (RS) offers high temporal and/or spatial resolution, enabling global and repeated observations of numerous geophysical and biophysical variables relevant to climate science (Myneni et al., 2002; Ghilain et al., 2011; Meier et al., 2021), including ECVs (Wan and Dozier, 1996; Entekhabi et al., 2010).

A wide variety of satellite constellations now operate using electromagnetic wave across different wavelengths range (e.g., visible, infrared, microwave) and acquisition methods (e.g., radar, multispectral, hyperspectral, LiDAR), offering complementary data (Figure 1.5 (ESA, 2019)). Depending on the wavelength and the sensing principle, different properties of the Earth’s surface or atmosphere can be observed (Picard and Fily, 2006; Buchelt et al., 2022; Chaparro et al., 2024; De Cannière et al., 2024), making RS a powerful tool to study the multiple components of the Earth system. RS also offers the ability to observe the entire Earth with high revisit times, in-



Figure 1.5: Exhaustive representation of the satellite missions coordinated by the European Space Agency (ESA, 2019).

cluding regions that are difficult to access by ground-based methods. Some satellite missions provide near-daily global coverage across multiple spectral bands (Justice et al., 2002b; Aschbacher and Milagro-Pérez, 2012). However, with the growing volume and variety of satellite data, challenges associated with big data have become increasingly prominent in the remote sensing community. To address these challenges, cloud-based platforms have emerged to support efficient data access and analysis (Gomes et al., 2020). Prominent examples include Google Earth Engine (Gorelick et al., 2017) developed by the private sector, and the EO Browser platform (<https://apps.sentinel-hub.com/eo-browser/>) developed by the European Space Agency. These platforms allow users to process and analyse large datasets without the need for local storage or high-performance computing infrastructure. While these platforms offer considerable advantages in terms of accessibility and computational resources, they may also introduce limitations related to transparency, reproducibility, and control over processing steps, sometimes functioning as "black boxes" where users rely on pre-defined algorithms or hidden proprietary data handling procedures (Gomes et al., 2020).

The diversity of these RS systems and the derived products is vast; here, we briefly describe the main principles relevant to this work.

Passive remote sensing

Passive remote sensing refers to systems that detect naturally occurring radiation, typically originating from the Sun (Elachi and van Zyl, 2006). Instruments on-board satellites measure reflected solar radiation (in the visible and near-infrared spectrum) or emitted terrestrial radiation (in the thermal infrared and microwave spectrum) to detect surface and atmospheric features (Elachi and van Zyl, 2021).

Over the years, multiple missions have collected images of the Earth's surface with increasing spatial, spectral, radiometric, and temporal resolution. Some of the most widely used datasets in RS are derived from passive sensors, including MODIS (Run-

ning et al., 1994; Justice et al., 1998), Landsat (Engle and Weinstein, 1983), and, more recently, Sentinel-2 (Drusch et al., 2012). Each of these missions has its own strengths: for instance, Sentinel-2 provides higher spatial resolution (up to 10 meters), whereas MODIS offers superior temporal resolution, with near-daily global coverage. The choice of dataset, therefore, depends on the specific requirements of the application.

Multispectral and hyperspectral instruments observe the reflectance over multiple narrow bands of different frequencies. By combining the observations in multiple bands, it is possible to derive various biophysical indices. Some of the most commonly used indices are :

- **Normalized Difference Vegetation Index (NDVI)** (Rouse et al., 1974). NDVI is calculated as the normalized difference between the reflectance in the red and near-infrared bands. It serves as a proxy for vegetation greenness and is widely used to assess plant health and vegetation cover.
- **Enhanced Vegetation Index (EVI)** (Huete et al., 2002). As NDVI, EVI has been developed to study the Earth’s vegetation health. EVI has been designed to optimize the vegetation signal by improving the sensitivity in high biomass regions by decoupling the canopy background signal and by reducing the atmosphere influence.
- **Albedo** (Liang, 2001). Albedo represents the fraction of incoming solar radiation reflected by a surface. It can be estimated from remote sensing by integrating reflectance across relevant spectral bands and is important in radiative balance and climate studies.

Active remote sensing

Unlike passive sensors, active remote sensing systems emit their own signal and measure its return after it interacts with the Earth’s surface. This capability allows them to operate independently of solar illumination and enables controlled illumination of the target, providing measurements that depend on sensor-defined wavelengths and geometry. Common active remote sensing instruments and techniques include Synthetic Aperture Radar (SAR), scatterometers, and LiDAR (Lillesand et al., 2014).

SAR systems, such as those used by Sentinel-1 (Torres et al., 2012), operate in microwave wavelengths (typically X-, C-, or L-band). They can provide high-resolution imagery and can penetrate vegetation, snow, or even shallow soil layers, depending on the frequency used and the dielectric permittivity of the medium. SAR is widely used for monitoring the Earth’s surface. Their capacity to collect reliable data under nearly all weather conditions makes them essential in many EO applications like glacier dynamics (Samsonov et al., 2021), soil moisture (Santi et al., 2018), and forest structure (Zhou et al., 2022).

Although active sensors often require more complex processing and can be sensitive to surface roughness or material properties, they provide unique and complementary information to passive systems. For example, combining SAR data with optical data

allows for better image classification, particularly in cloudy regions or during polar nights (Manakos et al., 2020; de Roda Husman et al., 2022; Zhang et al., 2022).

Observing the Earth

Remote sensing provides observations of the Earth system that can be used to derive both state variables and surface fluxes, although the level of processing required may differ between them. State variables, which describe the instantaneous condition of the surface, can often be retrieved relatively directly from satellite measurements. For example, vegetation properties such as Leaf Area Index (LAI) are commonly estimated from vegetation indices like the NDVI through empirical relationships or radiative transfer models (Myneni et al., 2002; Hu et al., 2020). Similarly, surface characteristics such as wet-snow occurrence can be inferred from brightness temperature time series using a K-means classification approach (Johnson et al., 2020). In contrast, surface fluxes, such as evapotranspiration, cannot be directly observed by satellite sensors. These variables represent exchanges of energy or mass over time and therefore require the use of models driven by satellite observations. For instance, evapotranspiration is typically estimated using surface energy balance models that integrate variables such as land surface temperature, vegetation indices, and meteorological data (Ghilain et al., 2011; Fluhrer et al., 2025).

Satellite missions such as MODIS provide a wide range of products, including vegetation properties (Myneni et al., 2002), productivity estimates (Turner et al., 2006), fire occurrence (Justice et al., 2002a), and modelled fluxes such as evapotranspiration (Faisol et al., 2020). These datasets offer near-daily global coverage, often distributed as composite products over periods of 8 to 16 days (Myneni et al., 2021), enabling continuous monitoring of both ecosystem states and processes.

Using remote sensing in modelling

The ability of remote sensing to derive a wide range of variables and indices makes it an ideal complement to modelling efforts. RS datasets can be used to evaluate model outputs (O'Neill et al., 2001; Picard et al., 2009; Puggaard et al., 2025) or even serve as input data for certain models (Dethinne et al., 2025). However, remote sensing also comes with limitations. Optical passive sensors require clear skies and sunlight, which can limit data availability in cloudy or polar regions, and active microwave sensors, generally insensitive to weather and illumination conditions, can have more complex processing and interpretation. Moreover, both observed and derived variables carry inherent uncertainties. Another key challenge lies in ensuring the comparability between satellite observations and model inputs/outputs, due to differences in signal wavelength, surface penetration depth, and spatial or temporal resolution of the sensors (Koster et al., 2009; Latifi and Galos, 2010). Addressing these discrepancies is essential to ensure the interoperability of remote sensing data with model simulations.

Currently, reanalyses such as ERA5 (Hersbach et al., 2020) and NCEP2 (Kanamitsu et al., 2002) provide concrete examples of the integration of remote sensing and modelling. Reanalysis products combine past and present observations, including satellite-based measurements, with numerical weather and climate models through

data assimilation techniques, producing physically consistent time series across multiple variables. These datasets deliver gridded reconstructions of past and present climate at global or regional scales and are widely used as boundary and forcing data for RCMs.

1.2 Thesis Objectives

Models can greatly benefit from the integration of RS data. Both approaches should be used together to advance our understanding of climate and land surface processes. Traditionally, RS datasets are employed by the modelling community mainly for evaluation and calibration by comparing model outputs against RS observations. While this step is essential, it only harnesses part of the potential of remote sensing. Direct integration or assimilation of RS datasets into climate and vegetation models can provide new insights into uncertainties from both models and RS products, while also supplying models with dynamic and realistic input data.

This thesis aims to enhance regional climate and vegetation modelling by leveraging EO and land surface modelling to improve understanding of surface processes through the integration of remote sensing with climate and vegetation modelling frameworks. The work is centred on the RCM *Modèle Atmosphérique Régional* (MAR; Gallée and Schayes, 1994), which will be described in the following sections. MODIS (Myneni et al., 2021) and Sentinel-1 (Torres et al., 2012) RS datasets will be integrated into MAR, and the DVM CARAIB (Warnant et al., 1994) will be coupled with MAR to improve its representation of land-surface processes. Two domains of application were identified where RS can provide substantial added value to modelling.

The first one is the vegetation density. The land-atmosphere interface is a critical boundary that plays a key role in regulating both climate and ecosystem dynamics. In MAR, vegetation, and hence land-surface conditions, are currently based on a prescribed, fixed LAI climatology. RS can provide temporally consistent LAI time series that improve the representation of vegetation dynamics in the model. Moreover, this work initiates the next step of coupling MAR with a DVM, enabling simulations of vegetation-climate interactions over climate projections that cannot be captured by RS.

The second one is polar-snowpack water content. RS enables the detection of liquid water within the snowpack over large areas, a task that is otherwise impossible given the scarcity of field observations in polar regions. These observations provide essential inputs to calibrate MAR's representation of surface melt and reduce uncertainties in simulated wet-snow occurrence.

In summary, this thesis focuses on improving MAR's representation of land-surface and ecosystem dynamics and tries to answer the questions: "*How can modelling approaches and remote sensing observations be combined to better quantify and represent land-atmosphere exchange and processes in regional climate modelling ?*". By combining modelling and remote sensing, we want to :

- **Improve the representation of vegetation in MAR** by implementing a new remote sensing-based input leaf area index dataset, with the hypothesis that this will enhance the model performance during extreme events and enable sensitivity analyses to leaf area index perturbations using MODIS products.
- **Enhance regional land-atmosphere interactions representations** by coupling MAR with a dynamic vegetation model, under the hypothesis that this coupling improves present-day simulations and enable more robust long-term climate projections.
- **Reduce uncertainties in MAR’s wet-snow occurrence** through the assimilation of remote sensing data, with the hypothesis that this will improve the representation of surface melt processes and reduce biases in meltwater production.

1.3 Thesis Outline

The thesis is structured into 6 chapters (Fig. 1.6). In Chapter 2, we focus on improving the representation of vegetation in MAR by replacing its standard fixed $50 \text{ km} \times 50 \text{ km}$ LAI climatology derived from MERRA2 (Global Modeling and Assimilation Office (GMAO), 2015; Gelaro et al., 2017; Wyard et al., 2021) with alternative datasets from MODIS (Myneni et al., 2021). These alternative datasets include a mean annual cycle (multi-year mean) LAI, an 8-day composite LAI, and LAIs perturbed with Gaussian noise used to perform synthetic experiments. This allows us to quantify the sensitivity of MAR to vegetation variability and to evaluate the uncertainties in its current representation of atmosphere-vegetation interactions.

Building on this analysis, Chapter 3 addresses the need to represent dynamically evolving vegetation, which cannot be achieved with remote sensing datasets in climate projection. To this end, we present the development of a coupling between the MAR RCM with the DVM CARAIB. The two-way coupling is performed through file exchange, using a dedicated setup for CARAIB. Although applied in mid-latitude regions under the present-day climate, this development opens the way toward improved representation of atmosphere-vegetation interactions in MAR, and allows CARAIB to actively respond to and influence atmospheric conditions, rather than being prescribed.

The region of interest of the thesis then shifts in Chapter 4 to the Antarctic Peninsula, where we address the uncertainties related to snow surface processes. Here, wet-snow occurrences derived from both active and passive remote sensing datasets (Johnson et al., 2020; Liang et al., 2021) are assimilated into MAR. By applying a nudging scheme on snowpack temperature (Kittel et al., 2022b) and testing different thresholds of liquid water content and depth, we evaluate the ability of data assimilation to bring MAR simulations closer to satellite observations and to reduce uncertainties in simulated surface melt.

Chapter 5 synthesizes the main findings of the thesis. The discussion frames our results within the broader context of climate modelling and Earth observation, and

highlights their scientific contributions. Finally, Chapter 6 outlines futures avenues for improving the representation of land-atmosphere interactions through the combination of remote sensing, regional climate modelling, and vegetation modelling.

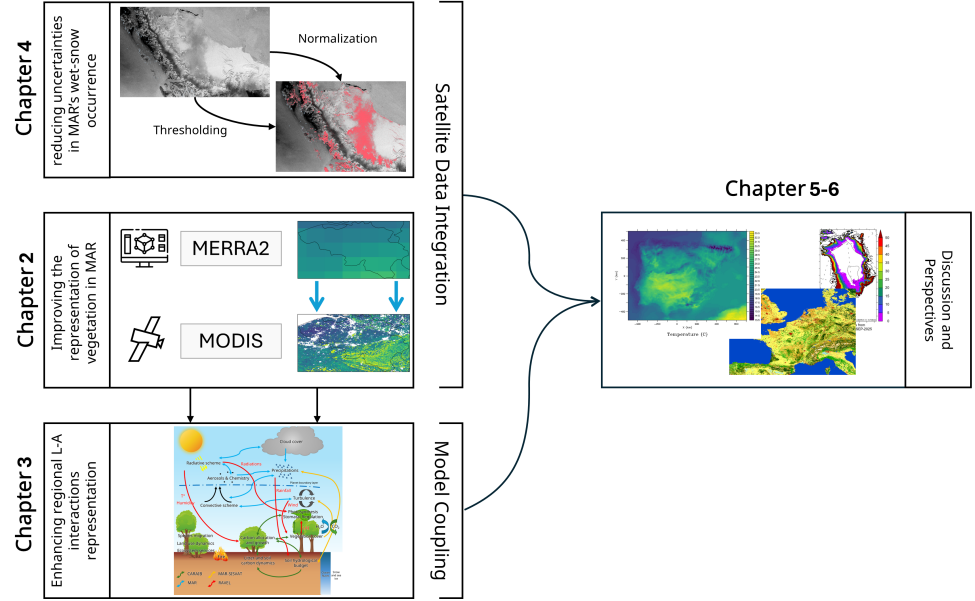


Figure 1.6: Overall structure of the thesis. Chapter 2 focuses on improving the representation of vegetation in MAR using remote sensing data; Chapter 3 addresses the enhancement of land-atmosphere interactions through model coupling; Chapter 4 investigates uncertainties in the occurrence of wet snow in MAR with remote sensing data integration; and Chapters 5 and 6 discuss the main results of the thesis and the perspectives it opens.

CHAPTER 2

Regional Climate Model Sensitivity to Satellite-derived Leaf Area Index

This chapter is adapted from : Dethinne, T., Ghilain, N., Kittel, C., Lecart, B., Fettweis, X., & Jonard, F. (2025). Assessing Regional Climate Model Sensitivity to Vegetation Dynamics Informed by Remote Sensing. *EGUsphere*, 1-43. doi:10.5194/egusphere-2025-3907. [In Review]

Abstract

Climate change significantly impacts vegetation ecosystems, and their modification may create feedback loops, exacerbating regional effects of global warming. Accurately simulating vegetation dynamics and their interactions with the atmosphere is crucial for understanding and mitigating these impacts. Regional earth system models offer the possibility to study the retroaction between the atmosphere and the vegetation at regional to continental scale by incorporating vegetation dynamics in climate models. In this chapter, we quantify the sensitivity of the *Modèle Atmosphérique Régional* (MAR) to vegetation representation at daily to annual scales over a temperate region of Europe, by means of both synthetic experiments and realistic studies. In total, we performed 10 simulations, one with the standard MAR configuration, 3 using a new Leaf Area Index (LAI) dataset, and 6 using the new dataset perturbed using a systematic bias and Gaussian noise. Our analysis of model sensitivity to LAI dynamics reveals non-linear responses of meteorological variables, with asymmetric effects relative to the direction of the change. For example, a 92 % reduction in LAI led to an 83.4 % decrease in evapotranspiration and an 88.9 % drop in evaporation. Conversely, a 178.4 % increase in LAI resulted in smaller, yet significant, increases of 29.8 % and 27.4 %, respectively. At the seasonal-time scale, evapotranspiration and albedo have the strongest response in summer and winter, while relative humidity and rainfall respond more prominently in spring. Furthermore, we assessed the model performance in simulating daily evapotranspiration and daily maximum temperature during extreme events by comparing simulations incorporating 8-day MODIS LAI data with those based on climatological LAI. Although the improvements compared to using the climatological LAI were subtle, the 8-day observation-based LAI enhanced the model's capacity to capture shorter events compared to the static LAI. This refinement also helped understanding how various vegetation types respond to extreme events by looking at their evolution during drought. The findings highlight the need to integrate dynamic vegetation into regional climate models to enhance their representation of land-atmosphere interactions and provide more accurate tools to assess the impacts of climate change on natural ecosystems.

2.1 Introduction

Vegetation plays a crucial role in regulating Earth's climate by influencing the carbon cycle, water cycle, and surface energy balance (Liu et al., 2006). Forests, in particular, act as significant carbon sinks, sequestering carbon dioxide from the atmosphere and mitigating the greenhouse effect (Heinrich et al., 2023). However, as regional effects of climate change intensify, these ecosystems are becoming increasingly vulnerable to disturbances (Gonzalez et al., 2010; Knutzen et al., 2025) and are likely to experience changes in their spatial distribution in the future (Roebroek et al., 2025). Extreme events such as droughts, wildfires, and floods can severely affect ecosystem health (Guion et al., 2022). During droughts, warmer temperatures and reduced water availability increase vegetation stress (McDowell et al., 2008), both directly through physiological impacts (e.g., Jonard et al., 2011) and indirectly through pest outbreaks such as bark beetle infestations (e.g., Kolb et al., 2019). These stresses

can lead to defoliation (Carnicer et al., 2011), elevated mortality rates (Allen et al., 2015), and large-scale die-off events (Huang et al., 2019). In response, plants may close their stomata to limit water loss and draw water from deeper soil layers, altering transpiration and soil evaporation rates (He et al., 2022). Such conditions also change surface albedo and modify land-atmosphere exchanges of energy and latent heat at regional scales (Dirmeyer et al., 2006). The resulting ecosystem degradation can amplify global warming, creating positive feedback loops that accelerate decline (Strengers et al., 2010). Consequently, monitoring natural ecosystems and simulating their future conditions are essential for supporting sustainable management and contributing to effective climate change mitigation (Verma et al., 2025). Research on surface processes advances our understanding of vegetation-climate feedbacks and informs policymakers and land managers about the potential consequences of land-use changes.

Climate evolution has been studied using climate models to simulate past, present, and future states over the Earth (Church et al., 2013; Vogel et al., 2017; IPCC, 2023a; Balcha et al., 2023). These models range from standalone systems that address individual Earth system components (e.g., atmosphere, hydrosphere, biosphere) to more complex Earth System Models (ESMs) that interactively couple multiple components at global scale, leaning on Global Climate Models (GCMs). State-of-the-art ESMs are widely used in global climate assessments (Gutjahr et al., 2019; Boucher et al., 2020; EC-Earth Consortium, 2020; IPCC, 2023a), particularly in standardized simulations like the Coupled Model Intercomparison Project phase 6 (CMIP6; Eyring et al., 2016). ESMs are used in regional studies (Cabos et al., 2020; Sein et al., 2020; Soto-Navarro et al., 2020), but, because climate change often manifests more strongly at local than global scales (Vogel et al., 2017; Stuecker et al., 2018), Regional Climate Models (RCMs) and ensembles such as EURO-CORDEX (Kjellström et al., 2018) are widely used for high-resolution regional climate assessments (e.g., Gallée and Schayes, 1994; Giorgi et al., 2012; Powers et al., 2017; Termonia et al., 2018; Giorgi, 2019; Yang et al., 2020; Haberlie et al., 2022; Zittis et al., 2022). Although often designed to simulate a single component of the Earth system, most RCMs incorporate schemes for others. These schemes can either involve model coupling, similar to what is done in ESMs (Mikolajewicz et al., 2005; Zhang et al., 2014; Anwar and Diallo, 2022), creating Regional Earth System Models, or rely on static datasets that serve as forcing for specific modules of the model (Heck et al., 2001; Tedesco et al., 2023). This enables RCMs to simulate interactions between different components of the Earth system using input forcing data, while modelling the interactions with the primary compartment of the model.

Among these components, the land surface plays a crucial role, acting as an interactive boundary that governs land-atmosphere interactions. These interactions can either occur between the soil and the atmosphere directly or between the vegetation and the atmosphere. Changes in the biosphere can impact surface albedo, evapotranspiration (ET), and modify the partitioning of surface energy fluxes. All of which are key factors in the climate system (Strengers et al., 2010), and have a direct impact on the atmosphere (Insua-Costa et al., 2022). Understanding feedback between climate and vegetation is critical for predicting future climate scenarios and developing effective mitigation and adaptation strategies (Heck et al., 2001; Beniston

et al., 2007). While land-atmosphere interactions have been studied in RCMs, their treatment varies (Giorgi and Gao, 2018). Some have addressed this interaction by incorporating land surface changes (Giorgi and Gutowski, 2015), improving existing land surface modules (Oleson et al., 2008), or through model coupling (Heck et al., 2001; Anwar and Diallo, 2022; Gröger et al., 2021; Bright et al., 2025). These efforts underscore the critical role of vegetation dynamics in regional climate modelling, enhancing our ability to predict and mitigate the impacts of climate change (Giorgi and Gao, 2018; Gröger et al., 2021).

Remote sensing has become a key tool in climate modelling due to its ability to capture long-term, consistent observation time series of ecosystem state at broad spatial scales (Latifi and Galos, 2010; Jonard et al., 2022). With short revisit times and high spatial resolution, satellite datasets offer valuable information on essential climate variables such as vegetation cover, albedo, soil moisture, and land surface temperature (Wan and Dozier, 1996; Myneni et al., 2002; Liang, 2001; Entekhabi et al., 2010; Jonard et al., 2022). They have been widely used in global and regional climate models, including in reanalyses like ERA-5 (Hersbach et al., 2020), for model evaluation (e.g., Noël et al., 2025), and as direct inputs to drive model simulations. In addition, remote sensing-based datasets can also be especially useful for assessing model performance during extreme events (Fluhrer et al., 2025).

Numerous studies have investigated the sensitivity of land surface models (either standalone or coupled to GCMs) to vegetation properties, due to their central role in regulating surface fluxes, such as evapotranspiration, and surface characteristics, such as albedo and roughness length (Chase et al., 1996; Schwinger et al., 2010; Chang et al., 2018). These sensitivities are often explored through prescribed changes in vegetation type or structure. However, despite initiatives like the LUCAS flagship pilot study (e.g., Davin et al., 2020), the sensitivity of RCMs to vegetation properties remains poorly quantified, particularly when vegetation is represented using dynamic, observation-based datasets rather than static climatologies.

In this chapter, we assess the sensitivity of the RCM MAR to vegetation variability by integrating high-resolution satellite-derived LAI observations that better capture vegetation dynamics than the static datasets currently used. While MAR is primarily an atmospheric model, it has already been coupled to ice sheet models (Delhasse et al., 2024), ocean models (Jourdain et al., 2011; Huot et al., 2022), and has been used to drive dynamic vegetation models (DVM), and its land surface scheme, the Soil Ice Snow Vegetation Atmospheric Transfer module (SISVAT; De Ridder and Gallée, 1998), allows for the representation of land-atmosphere interactions. This makes MAR an ideal framework to evaluate how realistic vegetation dynamics influence the land-atmosphere surface exchanges at regional scales.

The major highlights of this chapter are threefold : (1) We quantify the sensitivity of MAR key meteorological indicators used in climate services to vegetation changes. (2) We evaluate how using an observation-based vegetation index can improve the model performance, with a particular focus on drought and pluvial events. (3) We discuss the implications of these results for future coupling of MAR with a DVM, highlighting limitations of climatological vegetation forcing in regional climate sim-

ulations.

The study region, the model and its vegetation inputs, and the different sensitivity experiments of this chapter are presented in Sect. 2.2. The assessment of the model and the sensitivity analyses are discussed in Sect. 2.3. Sect. 2.4 provides a discussion on the model, its sensitivities, and the perspectives of coupling the MAR model with a DVM. Finally, a general conclusion for this chapter is presented in Sect. 2.5.

2.2 Model and Experiments

2.2.1 Regional climate model

The RCM used in this chapter is MARv3.13, an atmospheric model based on a hydrostatic approximation of the primitive equations of the atmosphere as described by Gallée and Schayes (1994). Its radiative transfer scheme is derived from Morcrette (2002). Originally developed to model polar climates, MAR has primarily been used for research on Greenland (Fettweis et al., 2011; Maure et al., 2023; Glaude et al., 2024) and Antarctic Ice Sheets (Agosta et al., 2019; Kittel et al., 2021; Dethinne et al., 2023), but has also been applied to climate studies in Europe (Doutreloup et al., 2022; Brajkovic et al., 2025; Grailet et al., 2025). It should be noted that a slightly upgraded version of MARv3.13 (MARv3.14.0) was used for simulations covering the years 2023-2024.

Among the different modules of MAR, SISVAT simulates the transfer of mass and energy between the atmosphere and the soil. Within the model, three sub-pixels (called sectors) are defined to represent the two predominant vegetation types as well as grass in each pixel. MAR is configured to resolve the first 7 meters of soil, divided into 7 layers (the layers have a decreasing vertical resolution from top to bottom, with the near-surface layers of a few millimetres and the deepest layers a few meters thick). Within SISVAT, the plant water flow is dictated by the water potential difference between the soil and the plant leaves, and the turbulent transfer is computed by considering canopy-air and ground-air exchanges separately, without an explicit parametrisation of environmental stress (De Ridder and Schayes, 1997). The annual vegetation cycle is generated by linearly interpolating leaf area index (LAI) values, which are provided daily from MERRA or weekly from MODIS (see section 2.2.3) to six-hourly time steps. The LAI input is used to derive an effective LAI, defined as the LAI of the leaves that receive sufficient radiation and have adequate soil water for their stomata to open (De Ridder and Schayes, 1997). From this effective LAI is derived the vegetation albedo, the precipitation interception following De Ridder (1997), and the stomatal resistance, which is used to simulate the vegetation transpiration, following De Ridder and Schayes (1997). Minimal stomatal resistance and root density are derived from values proposed in Taylor et al. (1997) and Jackson et al. (1996), respectively. Other vegetation-dependent variables like the roughness length for momentum are based on equations described in De Ridder and Schayes (1997).

The non-dynamic vegetation cover classification and its fraction are derived from the International Geosphere Biosphere Programme (IGBP) surface land classifica-

tion (Loveland and Belward, 1997). It has been resampled into 13 categories: barren soil, low-medium-high crops, low-medium-high grass, low-medium-high broadleaf, and low-medium-high needleleaf. The meteorological inputs for SISVAT include near-surface wind speed, temperature and humidity as well as downward shortwave and longwave radiations and precipitation.

For this chapter, MAR was run using the same setup as Grailet et al. (2025) over a longer time period, i.e., using a 5 km pixel size over Belgium, with 24 pressure layers from surface to low stratosphere, with a 25-second time step and hourly outputs from September 2010 to December 2024. MAR was forced every 6 hours by the ERA5-reanalysis data (Hersbach et al., 2020) at its lateral boundaries, over the ocean and in altitude (in the stratosphere) where nudging is applied over 3 layers. To minimize the influence of the model initial conditions, the first four years of each simulation and uncompleted years are excluded from the analysis, resulting in a study period of 2015-2024.

The modelled area extends slightly beyond Belgium, encompassing the southern Netherlands, northern France, western Germany, and the North Sea to the north, south, east, and west of the domain, respectively, as in Wyard et al. (2017). A relaxation zone of 5 pixels is removed from each lateral boundary of the domain, resulting in the domain presented in Fig. 2.1. In the end, only pixels intersecting the Belgian territory are used in this chapter. In urban areas, no vegetation is defined except hypothetical grass. Therefore, pixels classified as urban by MAR were excluded from this analysis.

2.2.2 Study region

The study area encompasses Belgium, a Western European country with an area of approximately 3,068,000 hectares. According to the National Institute of Statistics, in 2023, the land cover of Belgium was composed of 44 % agricultural land (crops and pastures), 20 % forests, and 22 % built-up areas. However, this distribution varies across the country's two main administrative regions (Statbel, 2025) :

In the North, Flanders, which accounts for 45 % of Belgium's territory, is more densely urbanized with only 8 % forest cover and nearly 30 % built-up land. In contrast, Wallonia, in the South, contains the majority of Belgium's forests, which cover around 30 % of its territory, mainly concentrated in the south, in the Ardenne region (Statbel, 2025). The land cover used in this chapter (Fig. 2.1) do not match these numbers as MAR uses only the main two land cover within pixels of 25 km², with a slight overestimation of agricultural land in spite of built-up area. For illustration purposes, the land cover in Fig. 2.1 has been smoothed using a 3x3 mode filter.

The Belgium's current climate is classified as Cfb in the Köppen-Geiger climate classification (Beck et al., 2018), which corresponds to a temperate oceanic climate with mild summers and relatively wet, cool winters. The mean annual temperature reaches around 10 °C and the main factor for the temperature spatial variability is caused by the change in altitude. Also, the proximity to the sea has a role in the change in temperature in the northwest of Belgium (Ercicum et al., 2018). With an

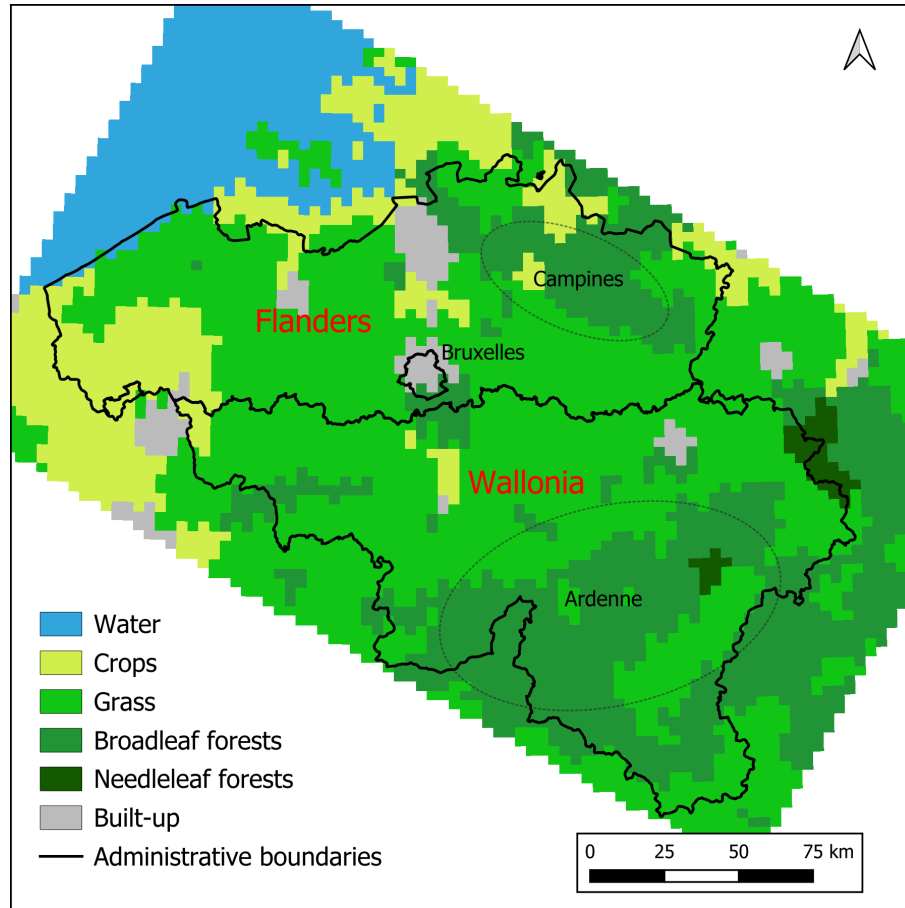


Figure 2.1: Extension of the studied domain. The names of regions of interest and those used during the study are included on the map. Forested (or partially forested) regions of Ardenne and Campines are indicated with grey dashed outlines. The background map shows the dominant land cover used by the MAR model. For clarity purposes, the land cover has been smoothed using a 3x3 mode filter.

average annual rainfall ranging from approximately 700 mm to 1300 mm, depending on the location, precipitation is fairly evenly distributed throughout the year. Though seasonal variations occur with a minimum monthly rainfall observed during the winter-spring transition (Erpicum et al., 2018).

Under this climate, Belgium’s characteristic forests consist mainly of deciduous broadleaved and coniferous species. In Wallonia, the dominant species include oak, beech, and spruce, the latter being widely planted in the Ardenne for forestry purposes (Latte et al., 2020). Low vegetation is primarily composed of agricultural land (Statbel, 2025).

Belgium’s spatial variability in land cover, diversity of vegetation types, and relatively uniform topography make it an ideal region for assessing the MAR model’s sensitivity to vegetation inputs.

During the study period, Belgium underwent multiple events of drought and pluvial periods. These periods can be identified through the Standardized Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al., 2010), a multiscale index using both precipitation and evapotranspiration for determining drought durations

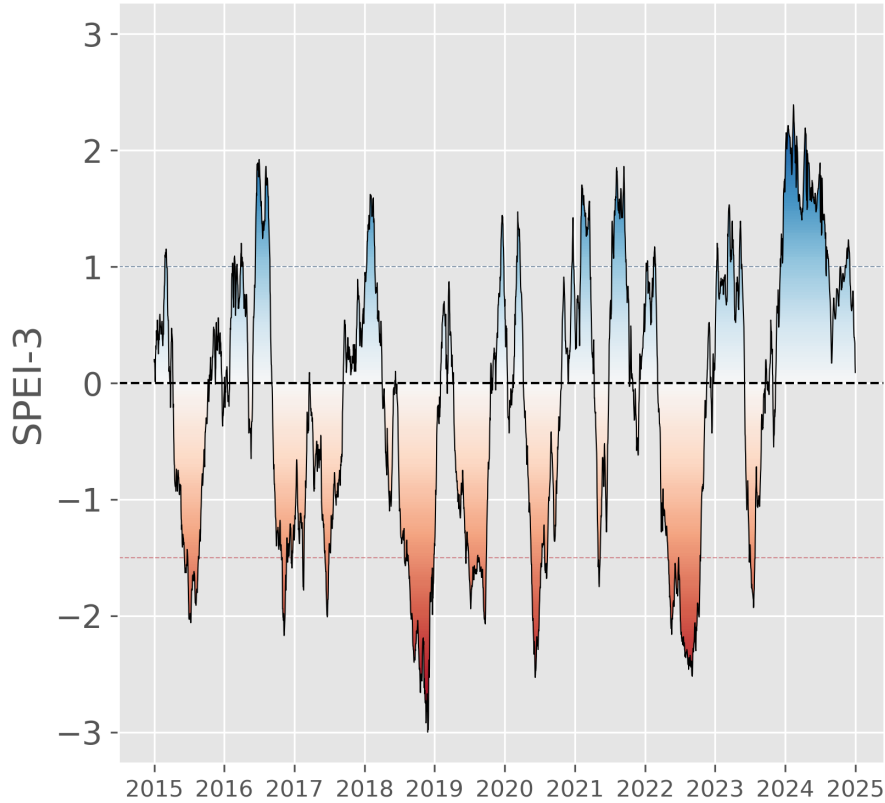


Figure 2.2: Evolution of the average SPEI-3 over Belgium for the study period. Strong events of drought are easily identified in summer 2018-2019-2022, while 2024 stands out as a relatively wetter year.

and magnitudes. Three periods of relative drought and three periods of relatively moist conditions were selected to study the behaviour of the model during stronger events. The events were selected based on the mean daily SPEI-3 index (SPEI computed over a 90-day timescale to reflect short-term moisture conditions) averaged over Belgium during summer (JJA). Drought events (summer-mean SPEI-3 < -1.5) occurred in 2018, 2019, and 2022, while pluvial periods (summer-mean SPEI-3 > 1) were observed in 2021, 2023, and 2024 (Fig. 2.2).

2.2.3 LAI data

As explained in Section 2.2.1, the vegetation cycle in MAR is externally prescribed. In this case, MAR uses as primary information the leaf area index, which represents the one-sided green leaf area of a canopy per unit ground area, influencing processes like photosynthesis and energy exchange at the vegetation-atmosphere interface (Chen and Black, 1992). Because carbon and water exchanges between vegetation and the atmosphere occur at the leaf scale, LAI is closely linked to land-atmosphere fluxes and is therefore a key variable in climate modelling (Rogers et al., 2021). In addition, LAI is strongly associated with major phenological stages such as leaf expansion, maturity, and senescence, making it a direct indicator of seasonal vegetation dynamics (Richardson et al., 2013).

In its standard configuration, MAR uses a climatological mean LAI, derived from

the MERRA2 reanalysis (Global Modeling and Assimilation Office (GMAO), 2015; Gelaro et al., 2017) for the 1961-1990 period at 50 km spatial resolution (Wyant et al., 2021). We refer to this LAI dataset as "MERRA2 LAI" in the text hereafter. The climatology is computed as monthly LAI values, which are later linearly interpolated to a 6-hour time step to create a continuous time series to force the vegetation model of MAR. MERRA2 LAI is integrated into MAR by linearly interpolating the values to the MAR grid using a weight proportional to the distance between the pixel centres. Then, for the first two sub-pixels, a correction coefficient is applied to the LAI values, depending on the vegetation considered by MAR for that sub-pixel (Fig. 2.3(a)). The correction coefficient value is determined to maintain consistency in the results with the previous version of the model, not using MERRA2 LAI.

For this chapter, we replaced the MERRA2 LAI with the 8-day LAI composite from the MCD15A2H Version 6.1 MODIS Level-4 product (Myneni et al., 2021), which provides higher spatial (500 m) and temporal resolution. The product selects the best available pixel from NASA's Terra and Aqua satellite acquisitions within each 8-day period. This already long series of vegetation indices is convenient because it fulfils the requirements of our study: the possibility to explore spatial and temporal sensitivities over climate-compatible horizons. To minimize boundary effects in the model, the MODIS data were extracted over a region extending beyond the MAR domain. From the 8-day MODIS, we also computed a 10-year daily mean cycle by averaging values for each calendar day across the 2012-2022 period. While this period differs from the studied period (2015-2024) and may introduce potential bias, the resulting LAI values are very similar to those obtained using a mean annual cycle computed over 2015-2024 (see appendix A). Only MODIS pixels with quality flags indicating confidence scores of 0 (best results) and 1 (good results) were used from the images. However, artefacts of relatively high LAI appear at the end of December, as already observed in Satellite Application Facility on Land Surface Analysis LAI time series (LSA SAF; Ghilain et al., 2012b). To further refine the mean annual cycle, we applied a moving average with a 32-day window (2 images before and two images after) to smooth the LAI time series for each pixel. This mean annual cycle and the 8-day product were linearly interpolated at 6-hour intervals to match MAR forcing time step requirements. This MODIS mean annual cycle is hereafter referred to as "MODIS LAI". Since MODIS does not provide LAI values for urban pixels, we decided to set LAI to zero in these areas, given that MAR does not compute vegetation-related processes in cities.

MODIS LAI values are resampled to match the MAR 5 km grid by computing the weighted average of all MODIS pixels partially or totally included within each MAR pixel, with weights decreasing linearly with distance from the MAR pixel. In case no MODIS pixel was available for a given MAR pixel, the closest MODIS pixel available was then used. During the resampling, more than 90 % of MAR LAI values are computed using more than 80 MODIS pixels. The few MAR grid cells with a lower number of contributing MODIS pixels correspond mainly to pixels classified as urban by MODIS but not by MAR, for which no LAI value is provided in the MODIS product. The resampling for the MODIS LAI is similar to the one used for MERRA2, but without any correction coefficient, as we do not need to keep the consistency in the vegetation indices with the MERRA2 version (Fig. 2.3(b)).

Table 2.1: Summary of the names of the simulation, the LAI datasets used in the simulation, and the type of noise applied to the LAI dataset for all the simulations performed.

Simulation name	LAI dataset	Noise
MAR_{ref}	MERRA2 climatology	-
MAR_{MODIS}	MODIS 8-day	-
$MAR_{MODIS_{cyc}}$	MODIS mean annual cycle	-
MAR_{sector}	MODIS mean annual cycle per sector	-
$MAR_{\pm 2\mu}$	MODIS mean annual cycle	$\pm$ Gaussian ($2\mu, \sigma$)
$MAR_{\pm \mu}$	MODIS mean annual cycle	$\pm$ Gaussian (μ, σ)
$MAR_{\pm 0}$	MODIS mean annual cycle	$\pm$ Gaussian ($0, \sigma$)

The experiments use the same LAI values in the first two sub-pixels and a value of 0.75 for the third one, except for one of the simulations where the values from the MODIS LAI are adjusted given the vegetation considered in the MAR sub-pixel. The adjustment is performed during the resampling from the 500 m MODIS pixel size to the 5 km MAR resolution by creating a mask of LAI values derived from the vegetation cover given in the IGBP surface land classification and by only using the MODIS pixel having the same vegetation than the one given by the MAR sub-pixel (Fig. 2.3(c)).

2.2.4 Model experiments

In total, we conducted 10 different simulations to assess the sensitivity of MAR to variations in its vegetation input (see Table 2.1). The first simulation, referred to as MAR_{ref} , was performed using the standard MAR configuration with MERRA2 LAI described above. This simulation serves as the reference scenario to assess the model results. The nine other simulations use MODIS LAI data. One of these simulations, MAR_{MODIS} , employed the 8-day MODIS LAI, while the other used the mean annual cycle described above. The statistical significance of the differences between the simulations was assessed using a block bootstrapping approach with a 10-day block length.

First, the $MAR_{MODIS_{cyc}}$ simulation used the MODIS mean annual cycle process as explained in the previous section. Replacing MERRA2 LAI, with MODIS LAI allows us to evaluate the impact of using another dataset that has different calibration and that provides higher spatial resolution (from 50 km to 500 m) and finer temporal resolution (from monthly to 8-day intervals). Given that LAI is the only input used by MAR to represent vegetation, these changes are expected to have a substantial impact on the model outputs.

Six simulations ($MAR_{+2\mu}$ to $MAR_{-2\mu}$) were designed to explore the impact of perturbations in the MODIS LAI mean annual cycle. These perturbations were generated by adding either positive or negative Gaussian noise to the LAI values. The LAI perturbation experiments do not represent pure stochastic noise but rather a systematic bias applied on the daily LAI cycle, combined with random Gaussian variability. The addition of the noise allows for an increase in the spatial variability

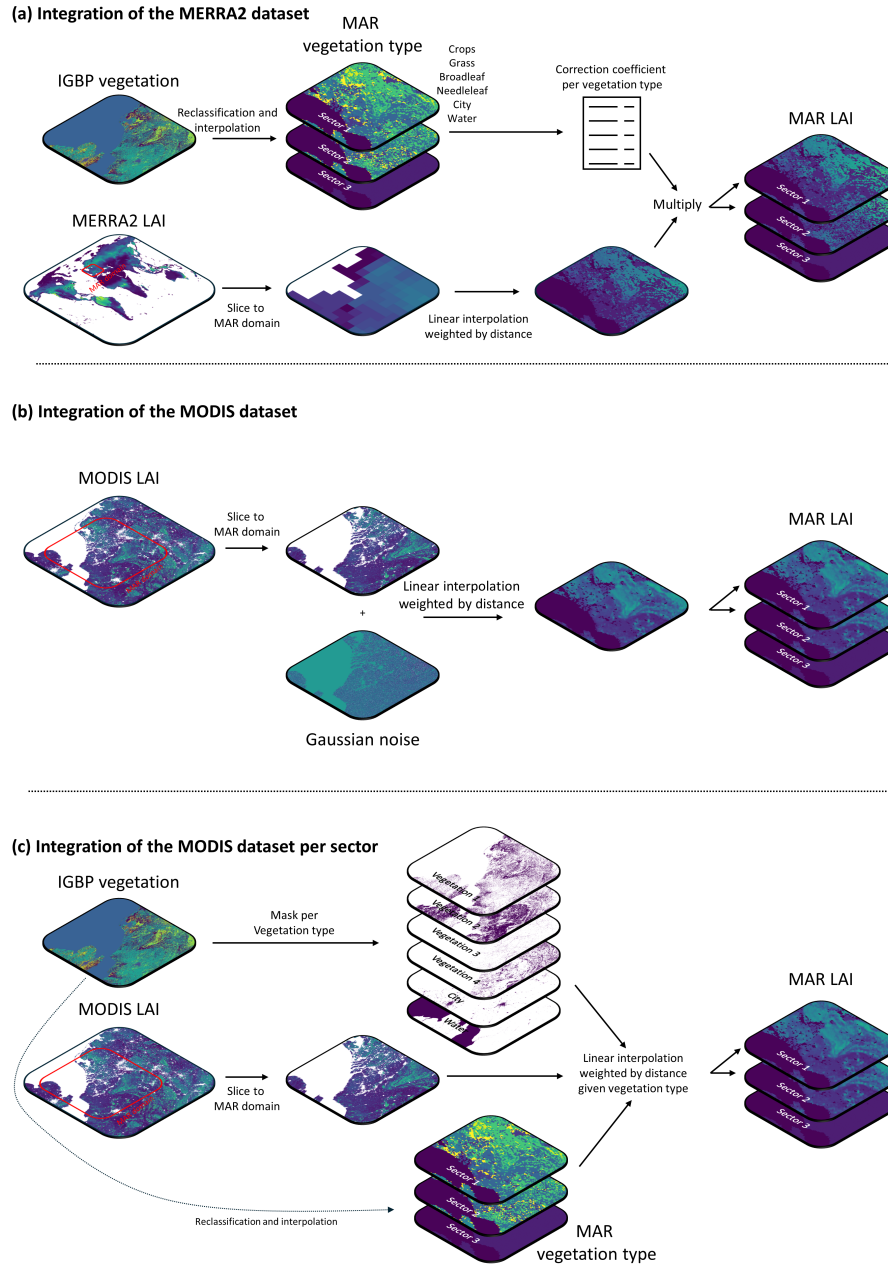


Figure 2.3: Integration of the LAI dataset into MAR. (a) Integration of the MERRA2 dataset. The global dataset is sliced to the domain and then interpolated to the finer MAR grid. Then the value is provided to the first two sectors of MAR by applying a correction coefficient depending on the vegetation type in the given pixel and sector of MAR. (b) Integration of the MODIS dataset. The dataset is sliced to the domain, and Gaussian noise can be applied to the dataset. After, the values are interpolated to the coarser MAR grid. Then, the values of LAI are provided for the first two sectors of MAR. (c) Integration of the MODIS dataset per sector of MAR. The dataset is sliced to the MAR domain and a mask of the different vegetation types is created. Then, the values are interpolated to the coarser MAR grid by only using the mask of the vegetation type in the given pixel and sector of MAR.

of the LAI change. For each day, the perturbation is defined as follows (Eq. 2.1):

$$LAI_{pert}(x, t) = LAI_{cyc}(x, t) + \mu(t) + \epsilon(x, t) \quad (2.1)$$

where $LAI_{cyc}(x, t)$ is the value of the MODIS LAI mean annual cycle for a given pixel x and day t , $\mu(t)$ is a deterministic bias equal to either 0, $\pm$ the average LAI value of the entire MODIS image of day t , or ± 2 times that average LAI value, and $\epsilon(x, t)$ is a Gaussian random noise with a mean value equal to zero and a standard deviation equal to the standard deviation of the LAI of the entire MODIS image of day t . These values are designed to maximize the potential to increase or decrease LAI when vegetation is at its peak (i.e., when LAI values are high), while exerting a smaller influence when LAI values are already low. The probability density function of ϵ , used to add noise to the bias, is given by Eq. 2.2.

$$p(x) = \frac{1}{\sqrt{2\pi\sigma(t)^2}} e^{-\frac{(x-0)^2}{2\sigma(t)^2}} \quad (2.2)$$

where $\sigma(t)$ is the standard deviation observed over the entire MODIS LAI image for day t . In this way, this variation in vegetation density across simulations is expected to have a significant impact on the modelled climate variables. Negative LAI values resulting from the application of the noise were clipped to zero, and no upper bound was imposed. The clipping happens the most in the simulation using $\mu(t)$ equal to minus two times the average value of LAI ($MAR_{-2\mu}$), with on average 30 % of the MODIS pixels were clipped to zero. When resampled to the MAR grid, only 2 % of MAR pixels were equal to zero. The noise with $\mu(t)$ equal to zero is computed twice to obtain two comparable distributions centred around zero.

The $MAR_{-2\mu}$ simulation was stopped in 2019 as the model began to drift away from observations due to numerical instability emerging in 2020 and affecting the hydrological budget (see section 2.3.3).

The MAR_{sector} simulation was generated by using the MODIS LAI mean annual cycle decomposed for each sub-pixel of MAR (Fig. 2.3(c)). This experiment allows us to study how the integration of the LAI dataset can potentially impact the results of the model by comparing it to $MAR_{MODIS_{cyc}}$. By incorporating sub-pixel variations, MAR_{sector} provides a more detailed representation of vegetation heterogeneity, which may influence key processes in MAR, especially ET.

Finally, the MAR_{MODIS} simulation is driven by 8-day MODIS LAI data, allowing the model to capture short-term vegetation dynamics. This observation-based LAI allows MAR_{MODIS} to more accurately reflect vegetation conditions during shorter meteorological events, such as droughts, compared to the mean-cycle LAI used in simulations like $MAR_{MODIS_{cyc}}$. As a results, MAR_{MODIS} should be better suited to represent real-time vegetation responses to environmental stressors, which is particularly relevant for studying feedback mechanisms.

2.3 Results

2.3.1 Model assessment

Given the inherent uncertainties in the integrated physics of RCMs, it is essential to evaluate their outputs against in situ measurements to accurately assess how well the model represents real-world conditions and reproduces observed weather patterns (Brajkovic et al., 2025; Graillet et al., 2025). In this chapter, our main focus is on evaluating the sensitivity of the MAR model to variations in vegetation input. It is important to recognize that any deviations between model outputs and observations in such studies could be more reflective of the noise applied to the input data rather than the model core physics. In this manner, only MAR_{ref} and $MAR_{MODIS_{cyc}}$ are evaluated.

To evaluate the simulations, we compared the daily averaged model outputs against observation-based data, i.e., datasets directly derived from observations but that have undergone post-processing prior to their use in the analysis. Specifically, we used data of several key meteorological variables: sea-level pressure, surface air temperature, wind speed, relative humidity, rainfall, collected from weather stations and gridded over Belgium using a statistical post-processing (Journée et al., 2023), and actual evapotranspiration estimates from LSA SAF (Ghilain et al., 2011, 2012a) to perform a statistical comparison between the model and observation-based data. The statistical metrics used for this evaluation include the mean bias (MB), root-mean-square error (RMSE), and Pearson correlation coefficient (r) (Table 2.2). A negative MB implies an underestimation by the model. These metrics were calculated for the period from 2015 to 2020. For vegetation-related variables, if a specific vegetation type is indicated, the variable value refers only to the corresponding MAR subpixel, weighted by the fractional coverage for that vegetation type. If no vegetation type is specified, values represent grid-cell averages weighted by the fractional coverage of the different vegetation types. For soil-related variables, values are integrated over the top 7 m of soil.

Overall, both simulations exhibit strong performance in capturing surface air temperature and sea-level pressure, as indicated by the high correlation coefficients ($r > 0.9$) and relatively low RMSE values. In addition, the model tends to better represent winter than summer, as already been documented for the precipitation (Doutreloup et al., 2019b).

Rainfall is the only variable showing a correlation coefficient lower than 0.8 annually, despite relatively low mean bias and RMSE. The major problem in the rainfall simulation concerns the strong rain events. Simulating their exact spatial and temporal extent can be challenging and may lead to a strong reduction of correlation values. de Vyver et al. (2021) and Brajkovic et al. (2025) already highlighted that MAR tends to underestimate the extreme precipitation events. However, the daily mean bias being lower than the daily variation of the observation still suggests a good representation of rainfalls.

For air temperature, $MAR_{MODIS_{cyc}}$ shows a slight improvement over MAR_{ref} , with

Table 2.2: Mean Bias (MB), Root Mean Square Error (RMSE), and Pearson-correlation coefficient (r) between two MAR simulations (MAR_{ref} , and $MAR_{MODIS_{cyc}}$) and daily observations over Belgium. A negative value implies a lower MAR estimate compared to the observation. Statistics are given for the sea-level pressure, surface air temperature, wind speed, relative humidity, rainfall, and actual evapotranspiration, for the summer (JJA) and winter (DJF) seasons, and annually for the 2015-2020 period. MB marked with an asterisk (*) indicates that the mean daily MB is smaller than the daily standard deviation of the observations. A dash (-) in the MB column signifies that there is no significant difference (p -value > 0.05) between the model mean daily values and the observations using a block bootstrapping approach with 10-day blocks length. Refer to Table 2.1 for the simulation names.

		Annual			Winter			Summer		
		MB	RMSE	Correlation	MB	RMSE	Correlation	MB	RMSE	Correlation
MAR_{ref}	Sea-Level Pressure (hPa)	-	1.64	0.99	-	2.12	0.99	-	1.08	0.98
	Temperature ($^{\circ}\text{C}$)	-	1.18	0.99	-	1.1	0.96	-	1.35	0.94
	Wind speed (ms^{-1})	-0.52*	0.6	0.97	-0.56*	0.63	0.98	-0.44*	0.53	0.95
	Relative humidity (%)	5.89*	7.86	0.92	8.32	9.37	0.89	-	5.57	0.92
	Rainfall (mmd^{-1})	-1.12*	2.85	0.78	-1.61*	3.14	0.78	-	2.96	0.75
	Evapotranspiration (mmd^{-1})	-1.1*	1.41	0.91	-0.29	0.36	0.83	-2.01	2.15	0.8
$MAR_{MODIS_{cyc}}$	Sea-Level Pressure (hPa)	-	1.64	0.99	-	2.13	0.99	-	1.09	0.98
	Temperature ($^{\circ}\text{C}$)	-	1.08	0.99	-	1.09	0.96	-	1.14	0.94
	Wind speed (ms^{-1})	-0.54*	0.61	0.97	-0.56*	0.62	0.98	-0.49*	0.57	0.95
	Relative humidity (%)	6.94*	8.24	0.93	8.26	9.29	0.89	5.04*	6.57	0.92
	Rainfall (mmd^{-1})	-1.12*	2.85	0.78	-1.61*	3.14	0.78	-	2.96	0.75
	Evapotranspiration (mmd^{-1})	-1.01*	1.27	0.92	-0.29	0.37	0.83	-1.79	1.92	0.81

a reduction in RMSE. This suggests that the MODIS LAI input potentially enhances the model’s ability to simulate the surface energy balance more accurately during warmer months by having a better representation of the vegetation. The higher RMSE and mean bias observed in summer and winter than on an annual basis indicate that the model underestimates extreme air temperatures, possibly due to limitations in the representation of soil moisture and vegetation feedback.

Evapotranspiration (defined as the combination of evaporation and plant transpiration whereas the evaporation is the sum of the evaporation from soil, open water, and water intercepted by the leaves) shows a consistent negative mean bias for both MAR_{ref} and $MAR_{MODIS_{cyc}}$ simulations. The lower annual RMSE in $MAR_{MODIS_{cyc}}$ suggests an improvement in the model representation of vegetation dynamics when using higher-resolution LAI data. However, the persistent underestimation could indicate a need for further refinement in the land-atmosphere transfer processes within MAR. The non-significant change may be related to the use of a mean annual cycle of LAI instead of using observed LAI, and will be assessed in section 2.3.5.

While there is still room for improvement, the model demonstrates a strong ability to accurately represent the climate of Belgium during the period 2015-2020. Overall, the two experiments show similar results when compared over a long period, with a slight improvement in the results for $MAR_{MODIS_{cyc}}$.

2.3.2 Impact of replacing MERRA2-derived dataset by MODIS LAI dataset

As a first step, the impact of replacing the LAI dataset is assessed by comparing the results of MAR_{ref} with those of the other simulations using a LAI mean an-

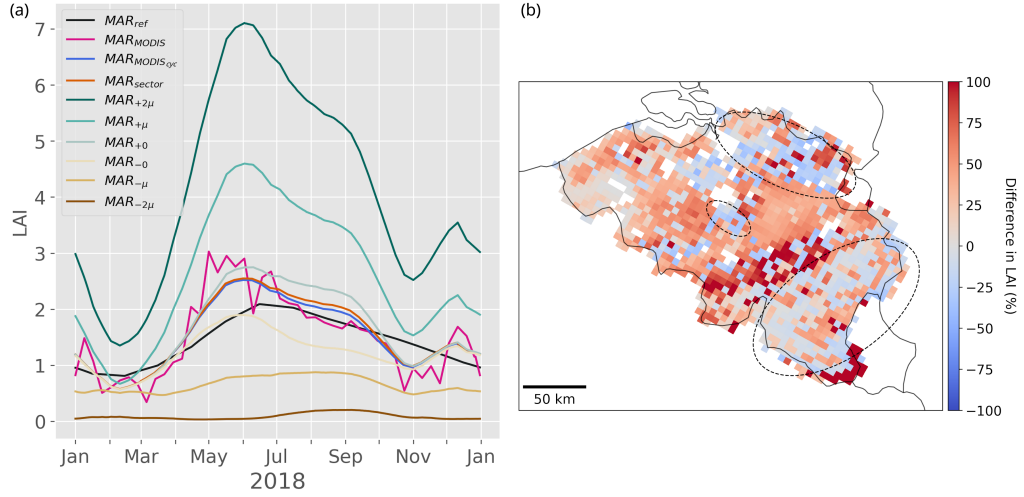


Figure 2.4: (a) Mean Leaf Area Index (LAI) over Belgium in 2018 for the different simulations. The names of the LAI curves refer to the name of the simulation in which they are considered (refer to Table 2.1 for the description of the simulations). (b) Average daily difference in LAI in percent between the MERRA2 LAI climatology and the MODIS LAI mean annual cycle used in this chapter. Forest regions are indicated with black-dashed outlines.

nual cycle. Comparing MAR_{ref} with $MAR_{MODIS_{cyc}}$ gives an indication on how the model reacts to a change in the input dataset using different periods of record, calibration, and spatial resolution. Derived from a higher spatial resolution dataset (500 m vs 50 km), the MODIS mean annual cycle captures vegetation heterogeneity more accurately than the MERRA2 climatology. In this case, the MODIS LAI generally exhibits higher LAI values compared to the MERRA2 LAI, suggesting that the current MAR configuration may be underestimating vegetation cover over Belgium (Fig 2.4(a)).

As shown in Fig. 2.4(b), LAI is doubled in certain places just north of the Ardenne while there is a decrease in forested land. Northern Belgium experiences the same evolution with an increase in LAI for agricultural land and a decrease in forested regions, such as the Campine and areas south of Brussels of approximately 75 % and 25 % respectively.

Given that the vegetation input has been modified, it is anticipated that variables directly related to vegetation, such as ET, will reflect these changes. $MAR_{MODIS_{cyc}}$ exhibits higher ET over the study period compared to MAR_{ref} , with an increase of from 120 mm of ET to 156 mm per pixel on average in summer (Table 2.3). This increase is explained by the higher LAI in $MAR_{MODIS_{cyc}}$ relative to MAR_{ref} , which leads to higher transpiration from leaves. An increase in evaporation is also observed, partly as a result of its physical formulation of MAR. In MAR, evaporation includes contributions from open water surfaces, moisture in the upper soil layers, and water intercepted by the vegetation canopy. Because MAR tends to drain soil moisture below the modelled soil depth, water reaching the ground is less available for evaporation than water intercepted by the foliage. Consequently, an increase in LAI enhances canopy interception, leading to greater evaporation. These changes

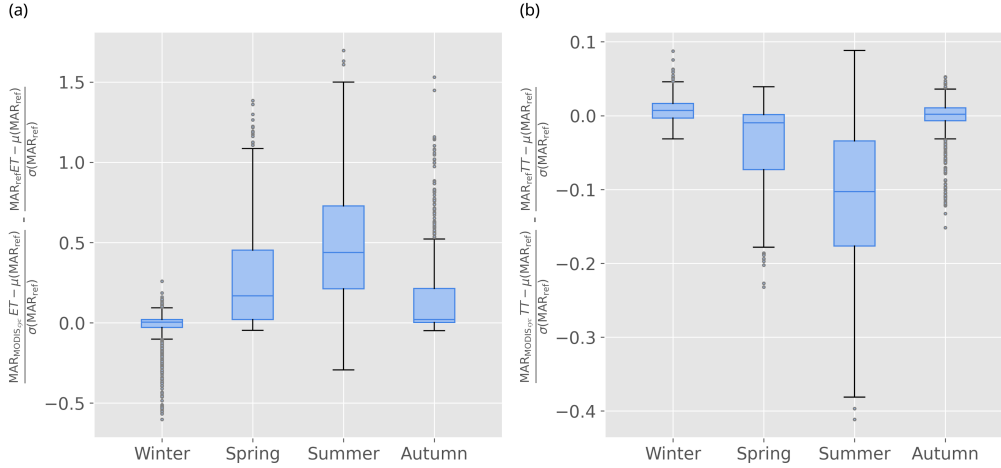


Figure 2.5: (a) Boxplot of the differences in simulated normalized daily evapotranspiration (ET) between MAR_{ref} and $MAR_{MODIS_{cyc}}$ over the 2015-2021 period. (b) Boxplot of the differences in simulated normalized daily mean surface air temperature (TT) over the same period. Normalization was performed seasonally, using MAR_{ref} as the reference. Boxes represent the interquartile range (25th-75th percentiles), the central line of the boxes indicates the median, and whiskers extend to 1.5 times the interquartile range. Outliers are shown as individual points.

are most pronounced during summer and spring when vegetation is most active, than in winter and autumn where no significant changes (p-values > 0.05) are observed (Fig. 2.5(a)).

Impact on surface air temperature also varies between seasons (Fig. 2.5(b)) and remains quite small. During the summer, $MAR_{MODIS_{cyc}}$ generally show air temperatures that are slightly more than half a degree Celsius cooler as expected with denser vegetation. On the opposite, during winter, these experiments tend to be warmer by about 0.2 °C (p-values > 0.05).

However, surprisingly, the increase in ET does not translate to a change in rainfall intensity (Table 2.3) but in the spatial patterns with a dependence on the season. The pattern of rainfall differences is neither directly correlated to the patterns observed in LAI changes nor in the vegetation cover, implying that rainfall patterns are indirectly affected (Guillod et al., 2014; Hsu et al., 2017; Santanello et al., 2018).

In terms of soil water content, defined as the ratio between the total soil water content and the soil water saturation integrated over the first 7 m of soil, MAR_{ref} shows a statistically significant steady decline throughout the simulated period of 0.5 % per year that can be attributed to the inability of the model to correctly represent the soil hydrology cycle and tend to dry over the years. The highest average soil water content in Belgium was 0.72 during spring 2015, which dropped to a minimum of 0.56 in fall 2019. This decline also occurs in $MAR_{MODIS_{cyc}}$ and is faster (0.8 % per year). Although $MAR_{MODIS_{cyc}}$ has lower soil water content than MAR_{ref} for the whole studied period (Table 2.3), a seasonal cycle emerges in the soil moisture differences between the two simulations, with smaller differences in

Table 2.3: Seasonal daily domain average values of surface air temperature, soil moisture content, and albedo, along with domain mean seasonal total rainfall and evapotranspiration, for summer (JJA) and winter (DJF) during 2015-2024, as simulated by MAR_{ref} (using the MERRA2 LAI climatology) and $MAR_{MODIS_{cyc}}$ (using the MODIS LAI mean annual cycle).

	Temperature (°C)		Soil moisture		Albedo		Rainfall (mm)		ET (mm)	
	DJF	JJA	DJF	JJA	DJF	JJA	DJF	JJA	DJF	JJA
MAR_{ref}	3.8	18.7	0.68	0.65	26.2	22.7	194	230	6	120
$MAR_{MODIS_{cyc}}$	3.8	18.4	0.66	0.63	26.3	23.8	194	232	6	156

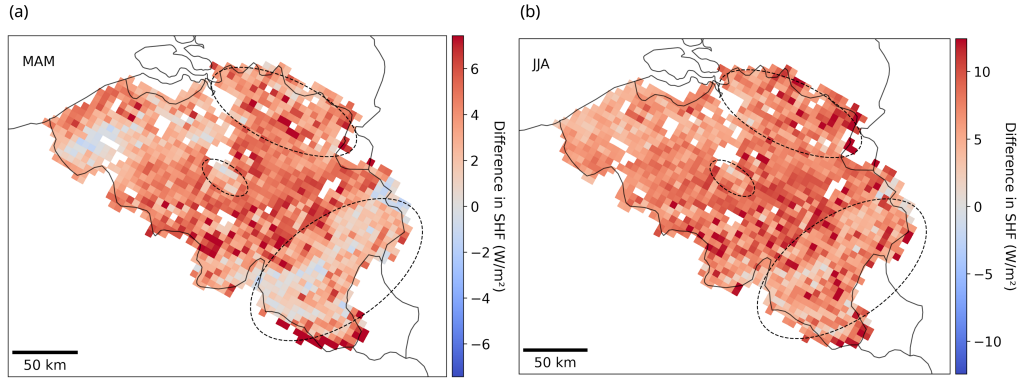


Figure 2.6: Average daily difference in sensible heat flux in Belgium between $MAR_{MODIS_{cyc}}$ (using the MODIS LAI mean annual cycle) and MAR_{ref} (using the MERRA2 LAI climatology) (a) Difference in sensible heat flux in spring (b) Difference in sensible heat flux in summer. Positive difference means an increase in $MAR_{MODIS_{cyc}}$. Forest regions are indicated with black-dashed outlines.

spring and more pronounced differences by late summer. This fluctuation in soil moisture is primarily driven by root water uptake, greater in simulations with more dense vegetation and reduced in those with sparser vegetation, and is directly linked with the increase/decrease in ET.

Finally, the comparison is concluded by examining the components of the energy budget, including longwave upward (LWU), shortwave upward (SWU), and sensible heat (SHF) fluxes. For sensible and latent heat flux, unlike other fluxes, in MAR, a positive value indicates a flux directed toward the Earth's surface. To simplify the analysis, we omit latent heat flux in the comparison as the analysis is closely linked to ET.

For SHF, we observe a generally smaller flux (flux is less negative) by about 10 to 20 % on average per year. Summer and spring seasons exhibit different behaviours (Fig. 2.6(a,b)). Summer is affected by a generally smaller flux, whereas in spring, a non-significant ($p\text{-value} > 0.05$) more greater flux is observed in forested regions, while the remaining land has a smaller flux. In winter and autumn, no significant changes are happening.

The changes in LWU and SWU are notably different, despite having similar variations in absolute values. LWU is less affected compared to SWU because the long-

wave upwelling radiation is driven primarily by surface temperature, which remains mostly unchanged in this study (often less than 1 °C). In contrast, SWU is more influenced as the alterations in albedo and surface reflectivity are more pronounced in these simulations. However, depending on the vegetation type, denser vegetation could lead to a darker region and higher emissivity.

LWU changes are not significant in both winter and autumn (p-values > 0.05) over Belgium, with differences mainly occurring in the form of small spatial pattern changes between the simulations. During spring, forested areas experience almost no changes, while the rest of the country shows a decrease in the flux. In summer, a decrease in LWU is observed across the entire country, except for coastal regions. The difference in behaviour near the coastline is explained by the higher concentration of sand in the soil composition, with higher soil water retention capabilities.

For SWU, an increase of 5 to 10 % is observed on average, with the greater changes occurring in summer and spring. As for LWU, in winter, only changes in spatial patterns are happening. These changes have no effect on the overall quantity of energy. Unlike LWU, the difference between forested regions and the other part of the study zone is less clear.

Overall, the results agree with those reported by Heck et al. (2001), whose sensitivity experiments increasing vegetation density across Europe demonstrated similar outcomes.

2.3.3 Sensitivity of the model to noise in LAI

Multiple simulations were then performed using the same baseline (the MODIS LAI mean annual cycle), but perturbed with Gaussian noise to analyse the effect of LAI perturbations on the various climate variables used previously. The changes induced by the noise are presented in Fig. 2.7. A more detailed table of the changes can be found in table 2.4. As LAI is the only input that MAR takes to represent the seasonal variability of vegetation, the sensitivity to LAI can be generalized to the sensitivity of the model to a change in vegetation.

At first, we observed that the relationship between LAI and the variables is complex, though most variables consistently respond either directly or inversely to changes in LAI. For example, as expected, some variables increase when LAI increases and decrease when LAI decreases, while others exhibit the opposite pattern. However, these sensitivity tests reveal that the response to perturbing LAI is non-linear for most variables, and the magnitude of the response is strongly asymmetric. Rainfall remains an exception, displaying a more indirect relationship with LAI, as discussed earlier.

The largest changes were observed in the $MAR_{-2\mu}$ simulation, which may explain the subsequent numerical instability of the model. This scenario, where LAI was reduced by an average of 92 % daily, resulted in significant drops in both evaporation and evapotranspiration (by 88.9 % and 83.4 %, respectively), alongside a notable 17.12 % increase in soil moisture content. On the contrary, despite an average daily

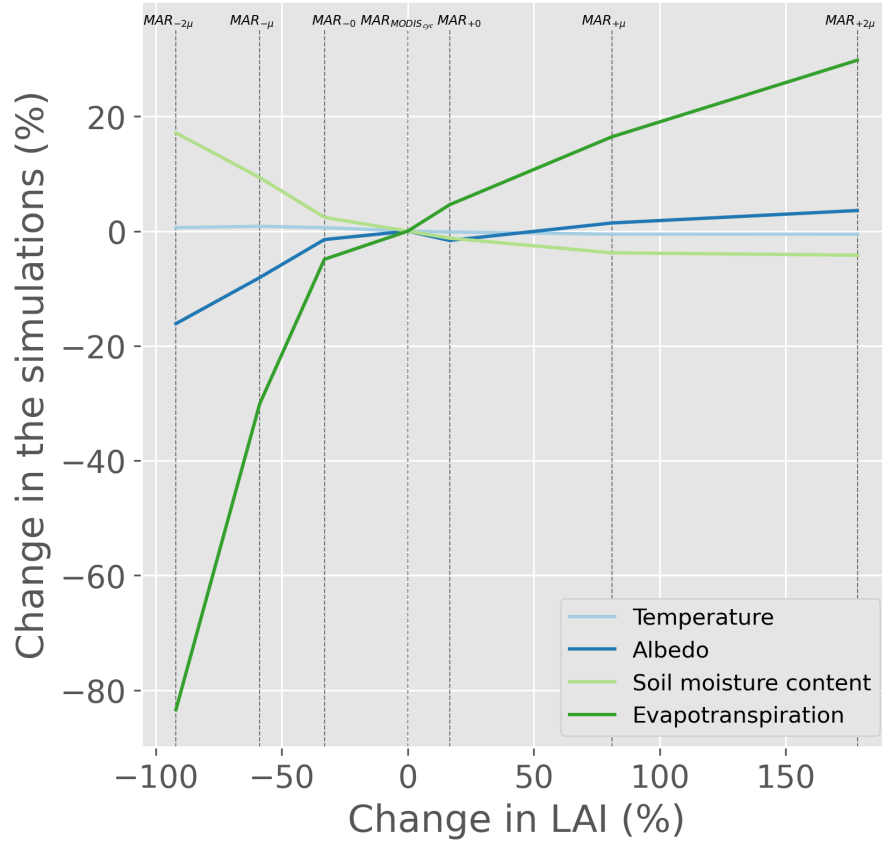


Figure 2.7: Average daily change (%) in surface air temperature, albedo, soil moisture content, and evapotranspiration given the average change in LAI (%). None of the variables experience a linear change given the LAI when the change is statistically significant. A more detailed table of the change in variables given the change in LAI can be found table 2.4.

Table 2.4: Mean daily difference (%) between $MAR_{MODIS_{cyc}}$ (using the MODIS LAI mean annual cycle) and the simulations with Gaussian noise applied to their LAI from 2015 to 2021 (excepted for $MAR_{-2\mu}$ 2015-2019). Refer to Table 1 for the description and name of the simulations. An asterisk (*) signifies that there is no significant difference (p-value > 0.05) between $MAR_{MODIS_{cyc}}$ daily values and the perturbed experiments.

Variable	$MAR_{+2\mu}$	$MAR_{+\mu}$	MAR_{+0}	MAR_{-0}	$MAR_{-\mu}$	$MAR_{-2\mu}$
Noise	Gaus. ($2\mu, \sigma$)	Gaus. (μ, σ)	Gaus. ($0, \sigma$)	-Gaus. ($0, \sigma$)	-Gaus. (μ, σ)	-Gaus. ($2\mu, \sigma$)
Leaf Area Index	178.4	81.0	16.6	-33.1	-58.8	-92.0
Temperature	-0.54*	-0.53*	-0.15*	0.61*	0.84*	0.61*
Albedo	3.59	1.42	-1.63	-1.47	-8.1	-16.13
Relative humidity	2.23	1.56	0.35*	-0.88*	-2.95	-4.97
Soil moisture content	-4.19	-3.78	-1.23	2.41	9.35	17.12
Rainfall	8.62*	5.71*	1.33*	-1.63*	4.74*	9.72*
Evapotranspiration	29.79	16.44	4.6*	-4.91*	-30.14	-83.4
Evaporation	27.36	14.99	-0.27*	-14	-35.24	-88.9
Latent Heat Flux	4.98	5.46	1.83*	-2.97	-14.04	-30.5
Sensible Heat Flux	-14.09	-11.2	-1.75*	8.16	7.83	8.5

increase in LAI of 178.4 %, the $MAR_{+2\mu}$ simulation did not exhibit similarly extreme shifts; its changes were more comparable to those seen in the $MAR_{-\mu}$ simulation.

It is also important to note that Fig. 2.7 does not fully reflect the seasonal sensitivity of these variables. As highlighted in Section 2.3.2, the evolution of certain variables varies between seasons. For example, although the overall changes in air temperature or albedo may appear small or are not significant, these variables show stronger seasonal changes, often with contrasting trends (positive or negative) depending on the season. Thus, if the trend is positive for half of the year and negative for the remaining seasons, the yearly average is lowered. Additionally, the maximum changes do not always align with peak vegetation growth (March to June, according to MODIS LAI), but can occur before or after. For instance, the largest changes in relative humidity, air temperature, and rainfall occur in spring, while the largest changes in evapotranspiration and albedo are observed in summer and winter.

As shown in Fig. 2.7, simulations with higher LAI also exhibit higher albedo and vice versa. This is the case for all the season and mostly all land-cover because in SISVAT, increasing LAI reduces the contribution of the underlying soil reflectance and increases the dominance of canopy optical properties. In our study domain, the vegetation is dominated by low vegetation and broadleaved forest types. For both classes in SISVAT, canopy albedo is higher than the underlying soil albedo, so increasing LAI leads to a net increase in grid-cell albedo. Interestingly, this relationship appears to be non-linear; simulations with reduced vegetation experience a greater decrease in albedo than the increase observed in simulations with more vegetation.

Simulations with higher LAI tend to reduce soil moisture, while those with lower vegetation cover show an increase in soil moisture. For instance, increases of up to 21 % were observed in $MAR_{-2\mu}$, whereas $MAR_{2\mu}$ exhibited decreases of less than 5 % at most. This variation is also dictated by the root water uptake, the more vegetation, the more the soil water is absorbed by the plant.

Ultimately, the overall response of each variable to changes in LAI is highly variable and is not generalized over such long period of analysis. The intricate and sometimes contrasting seasonal patterns highlight the complexity of the interactions between vegetation and climate variables in these simulations. Therefore, a closer examination of extreme events could provide valuable insights, and will be assessed in section 2.3.5.

Examining the frequency of rainfall events based on their hourly intensity across the different experiments ($MAR_{\pm x\mu}$, MAR_{ref} , and $MAR_{MODIS_{cyc}}$) reveals that changes in LAI influence only the magnitude of some high-intensity rainfall events (Fig. 2.8(a)). While lower-intensity rainfall events show little to no variation, some of the most intense rainfall events observed in $MAR_{MODIS_{cyc}}$ are absent or appear as weaker events in $MAR_{-\mu}$.

Notable changes in surface air temperature distribution are also happening. While the maximum daily air temperature remains largely unaffected, the most signifi-

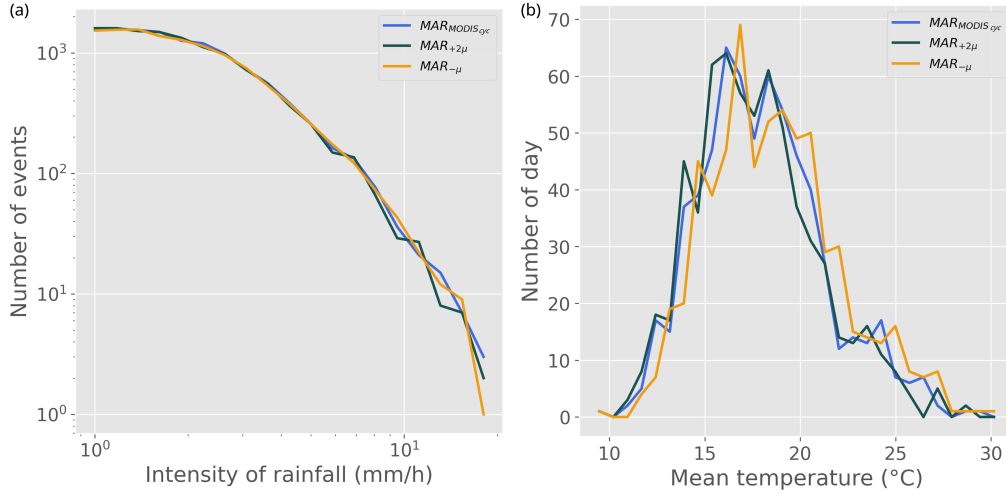


Figure 2.8: (a) Distribution of summer rainfall events by hourly intensity for the different simulations between 2015 and 2021. Simulations with lower LAI tend to exhibit fewer extreme rainfall events, as these events generally occur with reduced intensity. (b) Distribution of mean daily summer surface air temperatures for the same simulations. Lower LAI simulations show a shift toward warmer conditions, with fewer days below $20^{\circ}C$ and more days in the $20-28^{\circ}C$ range, although the frequency of very hot days ($>28^{\circ}C$) remains relatively unchanged.

cant impact is observed in the distribution of mean daily air temperatures during summer. Simulations with higher LAI tend to experience more days with lower air temperatures ($<20^{\circ}C$) and fewer days within the moderate air temperature range ($20-28^{\circ}C$). However, the occurrence of high air temperature days ($>28^{\circ}C$) does not necessarily decrease (Fig. 2.8(b)).

It may suggest that while an increase in LAI leads to overall cooling effects, it does not completely mitigate extreme heat events. The additional vegetation cover enhances evapotranspiration, which contributes to local cooling, particularly during moderate air temperature days. However, during extreme heat conditions, other factors such as the soil moisture availability may override the cooling influence of vegetation (Seneviratne et al., 2010; Vogel et al., 2017).

2.3.4 Sensitivity to the integration method of the LAI

The sensitivity of MAR to the integration method of the LAI is tested through a comparison of MAR_{sector} and $MAR_{MODIS_{cyc}}$. This comparison allows us to test for the addition of the sub-pixels of MAR in terms of vegetation. By computing the vegetation-related variable given the vegetation type and the fraction of the pixel covered by this vegetation, MAR_{sector} should have a more detailed representation of the vegetation.

For almost all the studied periods, there are almost no significant changes between MAR_{sector} and $MAR_{MODIS_{cyc}}$ (Table 2.5). However, during specific periods, there is a divergence: the only significant differences (p-values < 0.05) are happening in summer when MAR_{sector} has a higher LAI than $MAR_{MODIS_{cyc}}$. The drawn conclusions are similar to those in the previous section, as MAR_{sector} has similar

behaviour as MAR_{+0} in summer. The spatial patterns in the difference are arguably noticeable as the differences occur in places where the vegetation is not homogeneous, given MAR pixel size and varies over Belgium.

Table 2.5: Seasonal daily domain average values of surface air temperature, soil moisture content, and albedo, along with domain mean seasonal total rainfall and evapotranspiration, for summer (JJA) and winter (DJF) during 2015-2024, as simulated by $MAR_{MODIS_{cyc}}$ (using the MODIS mean annual cycle) and by MAR_{sector} (using the MODIS mean annual cycle corrected for MAR subpixels).

	Temperature (°C)		Soil moisture		Albedo		Rainfall (mm)		ET (mm)	
	DJF	JJA	DJF	JJA	DJF	JJA	DJF	JJA	DJF	JJA
$MAR_{MODIS_{cyc}}$	3.8	18.4	0.65	0.63	26.3	23.8	194	232	6	156
MAR_{sector}	3.8	18.6	0.65	0.63	26.2	23.5	190	227	6	158

2.3.5 Sensitivity to the temporal evolution of the LAI

In addition to the sensitivity analysis presented above, it is also crucial to assess how effectively the model represents extreme events when using a dynamic LAI over the years. Due to drought, vegetation may decrease its green material, leading to a noticeable decrease in LAI. We need to assess if the climate model is capable of exhibiting significant shifts in its behaviour due to short-term changes in LAI. To better capture localized effects within the model, rather than comparing daily averaged or cumulative values across the entire study area, statistics were computed on a pixel-by-pixel basis, considering different vegetation types represented in the model. For this analysis, we specifically focus on July and August of 2018, 2019, and 2022 periods characterized by severe droughts in Belgium and Europe (Schuldt et al., 2020; Chen et al., 2022b; Toreti et al., 2023; Bevacqua et al., 2024) as well as July and August 2021, 2023, and 2024, which have been relatively mild and wet (Insua-Costa et al., 2022; Toreti et al., 2024).

During the droughts, the decrease in green vegetation is captured by the 8-day LAI product but, as expected, not in the LAI mean annual cycle (e.g., in 2018 Fig. 2.9(b)). In response, MAR_{MODIS} is expected to reflect this reduction in LAI across Belgium during July and August in the simulated fluxes. However, the extent of this decrease varies across different vegetation types and the years (Table 2.6). The difference in LAI is variable on the country as the different vegetation types do not have the same response to climatic events (Chaves et al., 2003; Ji and Peters, 2003; Schuldt et al., 2020). The forests tend to be more resilient to drought due to their root growing deeper in the soil, and their health is less correlated to rainfall than low vegetation like pastures (Wang et al., 2003). Therefore, the difference between $MAR_{MODIS_{cyc}}$ and MAR_{MODIS} varies depending on the regional landscape.

As shown in Fig. 2.9(a), in the summer 2018, forests in southern Belgium exhibited higher LAI values in MAR_{MODIS} compared to $MAR_{MODIS_{cyc}}$. However, this trend is not consistent throughout the drought, as demonstrated in Fig. 2.9(c). LAI for forests initially remains higher than the mean annual cycle but drops below by the end of July. This decline is also clearly observed for low vegetation types, such as

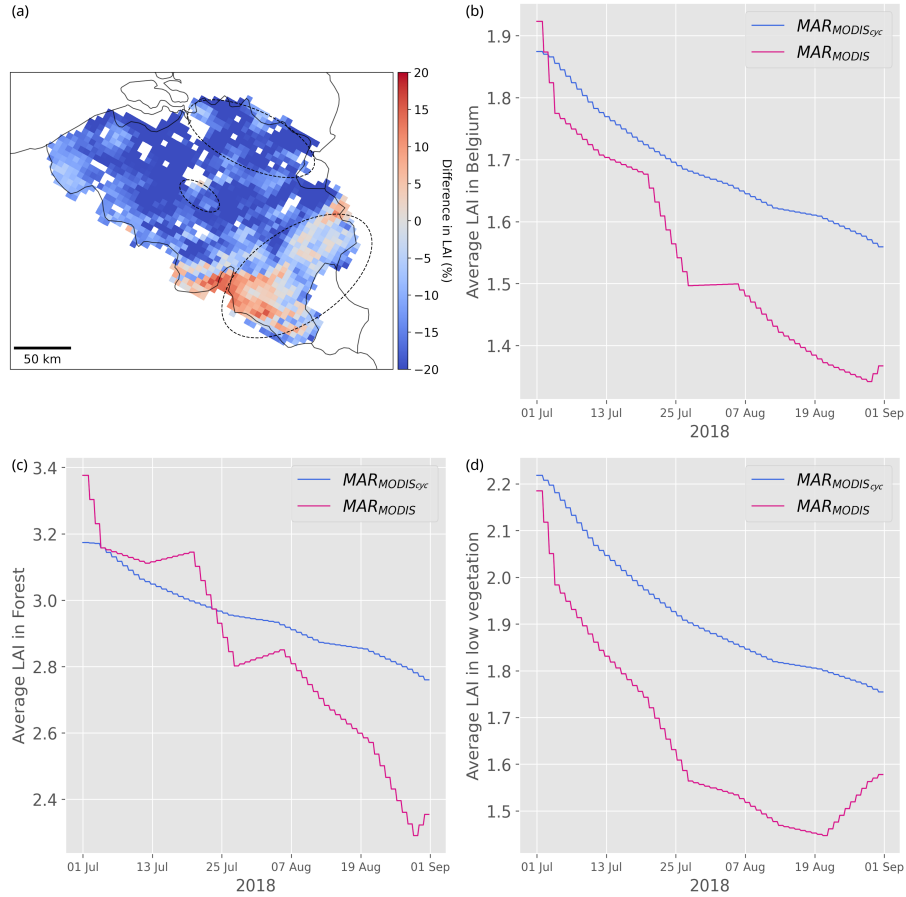


Figure 2.9: Difference in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2018. (a) Map of the average difference (in %) in Belgium. Forest regions are indicated with the black-dashed lines. (b) Average difference over Belgium. (c) Average difference for the forests. (d) Average difference for low grass. The pink line represents the 8-day MODIS LAI data, and the blue line represents the MODIS LAI mean annual cycle.

grasslands, and can be observed more broadly across Belgium (Fig. 2.9(d)). This evolution is also observed during the 2019 and 2022 summer as shown in appendix A. Roughly the opposite scenario is happening during 2021, 2023, and 2024. However, for the 6 events, the average change in LAI is not statistically significant in forests and is not significant in any of the vegetation in 2023 (Table 2.6).

During extreme events such as those studied, the use of the 8-day LAI instead of the mean annual cycle brought roughly the same evolutions as the one in the previous sections. When the LAI in MAR_{MODIS} is higher (lower) than the one of $MAR_{MODIS_{cyc}}$ (i.e., during the pluvial (drier) periods) the first simulation simulates more (less) evapotranspiration (Fig. 2.10 (a)), directly linked with the vegetation quantity. However, the difference in LAI is too small for a too short period to induce a statistically significant impact on the daily mean surface air temperature. The impact on the air temperature has to be found in the maximum surface air temperature for the day. During the pluvial periods, the larger quantity of vegetation will cool down the higher air temperature and the lower quantity of vegetation during droughts will increase it. This effect is stronger for the dryer period and

Table 2.6: Difference (%) in average LAI between $MAR_{MODIS_{cyc}}$ LAI values and MAR_{MODIS} in July - August for multiple years. Differences are given over the whole region of interest and considering the vegetation type (forests and low vegetation). An asterisk (*) signifies that there is no significant difference (p-value > 0.05) between the two datasets.

$\Delta\%$ LAI	2018	2019	2021	2022	2023	2024
Belgium	-13.2	-5.3	7.6	-10.8	2.2*	6.3
Forests	-2.2*	-0.8*	1*	-1.3*	0.6*	2.1*
Low vegetation	-9.1	-3.4	5.2	-7.9	1.3*	3.7

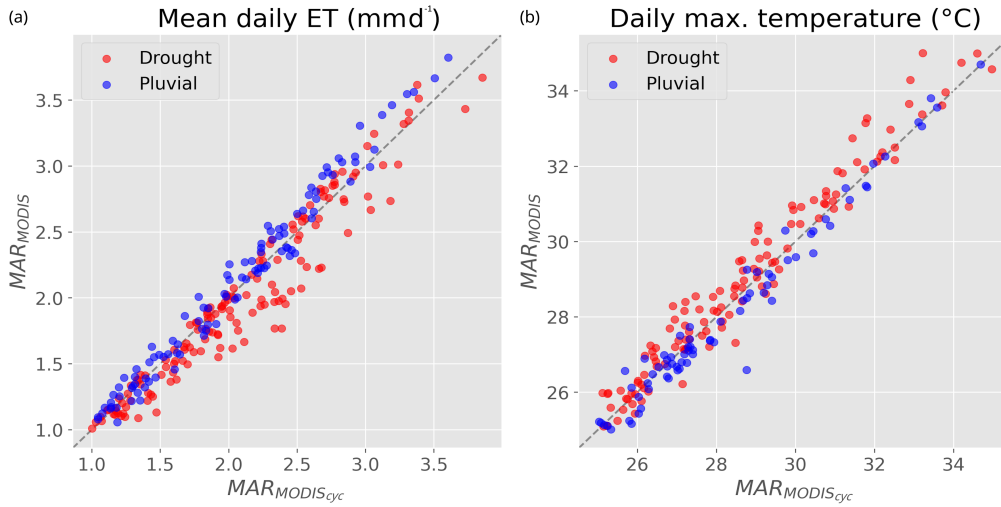


Figure 2.10: Daily difference between MAR_{MODIS} and $MAR_{MODIS_{cyc}}$ over Belgium during summer 2018, 2019, 2021, 2022, 2023, and 2024. (a) Mean daily evapotranspiration for the two models. The scatter plot has been cut between 1 and 4 mm. (b) Maximum daily surface air temperature for the two models. The scatter plot has been cut between 25 and 35 °C.

for the days where the maximum air temperature is moderately high (around 20 to 30 °C), as already observed in the sensitivity tests (Fig. 2.10 (b)). However, even though differences are visible between the two models, none of them are statistically significant, neither in forests nor in low vegetation, when comparing both July and August. Differences became statistically significant when using smaller time windows of 3 to 5 days. However, it is important to note that while a 0.5 to 1 degree of difference in the daily maximum air temperature may not be statistically significant, having 0.5 °C of difference on average over the whole summer could have a significant impact on ecosystems (Kaufmann et al., 2003; Li and Convertino, 2021).

In addition, the timing of maximum differences in ET does not consistently occur during the same period of summer across the six years studied, nor does it align between vegetation types. For instance, the highest 7-day average differences were observed in early August for both forest and low vegetation in 2018 and 2019. In 2021, the peak occurred in mid-June for low vegetation and mid-July for forest. In contrast, it appeared in late March 2022, early September 2023, and late July 2024.

2.4 Discussion

The sensitivity of MAR meteorological variables to its LAI input is non-linear and requires an in-depth analysis of the results to fully understand the impact of altering the vegetation parameters. In particular, the asymmetric nature of these responses must be examined in light of the physical formulations within MAR and the potential saturation of vegetation-related processes at higher LAI values.

Replacing the MERRA2-based LAI with the MODIS LAI led to significant changes in the model outputs and generally improved the overall performance because of the higher spatial and temporal resolution. In contrast, incorporating the 8-day MODIS LAI dataset, while offering a dynamic LAI compared to a static one, resulted in comparatively minor changes, even during extreme events. Focusing on the summer periods (July-August) of 2018, 2019, 2021, 2022, and 2023, the use of MODIS LAI instead of MERRA2 LAI improved the simulation of both daily average evapotranspiration (Fig. 2.11(a)) and maximum daily air temperature (Fig. 2.11(b)). In most cases, the correlation coefficient between the model outputs and observations increased, and the model’s standard deviation approached that of the observed values. Although significant differences were observed for both variables, the improvement was more pronounced for ET. However, the improvement of using the 8-day LAI is less pronounced, as in some cases, the model gets further from the observations. Similar conclusions are reached when focusing only on low vegetation during the 15 days with the highest or lowest mean SPEI-3 for each summer: events are generally better represented when using MODIS-derived LAI rather than MERRA2-derived LAI, with the notable exceptions of the 2019 drought and the 2021 pluvial event.

With a shorter time window and in the most impacted vegetation type (low vegetation), differences between MAR_{MODIS} and $MAR_{MODIS_{cyc}}$ become more pronounced, although they remain smaller than those relative to MAR_{ref} . In this case, $MAR_{MODIS_{cyc}}$ shows a clearer improvement in the simulation of evapotranspiration (Fig. 2.11(c)) than MAR_{MODIS} during both drought and pluvial events, which is somewhat counterintuitive. For daily maximum temperature (Fig. 2.11(d)), however, it is less clear which configuration provides the most accurate representation.

These findings suggest that MAR is sensitive to its LAI inputs; however, the atmosphere-land surface coupling may appear overly resilient compared to that observed in these regions (Knist et al., 2017).

The results are consistent with previous studies investigating scenarios with increased vegetation at regional or global scales, particularly regarding changes in soil moisture, evaporation, ET, surface air temperature, and albedo (e.g., Jiménez-Gutiérrez et al. (2021); King et al. (2024); Engel et al. (2025)). However, unlike some of those studies, the current experiments did not reproduce the associated changes in rainfall. Specifically, the observed increase in ET did not result in a corresponding increase in total or convective rainfall, contrary to expectations based on typical regional feedback mechanisms (Eltahir and Bras, 1996; van der Ent et al., 2010).

This weak sensitivity of precipitation to variations in LAI should be interpreted in light of the model configuration used in this chapter. The simulations were per-

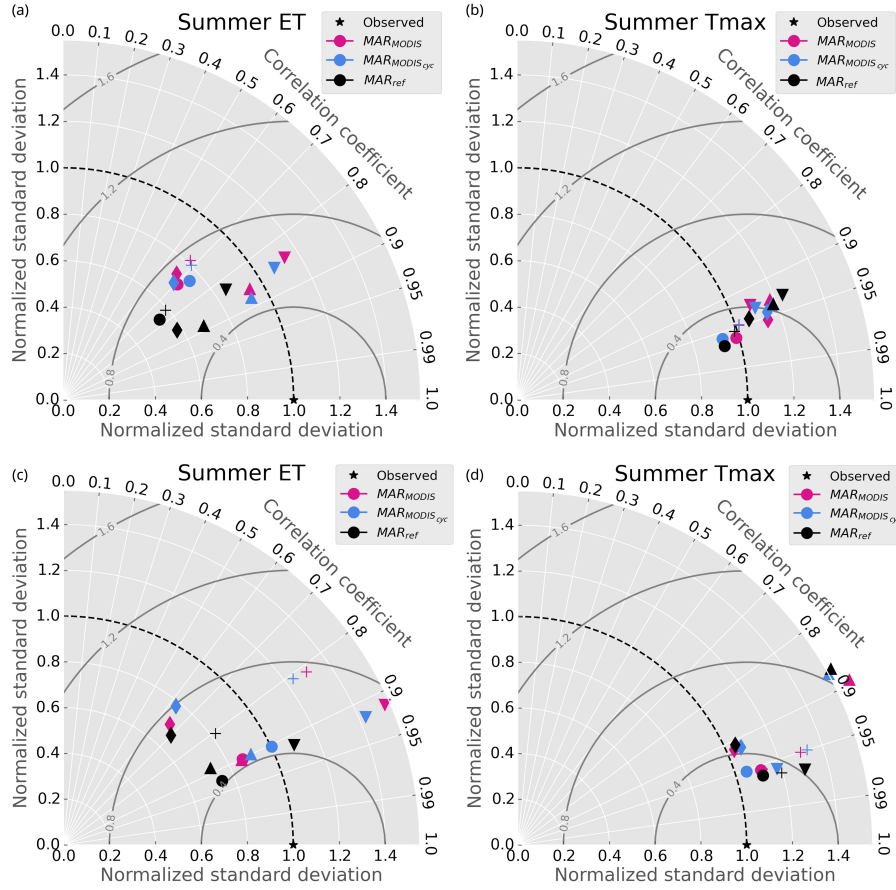


Figure 2.11: Taylor diagram showing the performance of MAR_{ref} , MAR_{MODIS} , and $MAR_{MODIS_{gcc}}$ compared to daily observations for July and August in drought (2018 (●), 2019 (+), and 2022 (◆)), and pluvial years (2021 (▼), and 2023 (▲)). (a) Taylor diagram for average daily evapotranspiration (ET). (b) Taylor diagram for daily maximum surface air temperature. (c) Same as (a) but for the 15 days with the higher/lower mean SPEI-3 in July and August, and only in low vegetation. (d) Same as (b) but for the 15 days with the higher/lower mean SPEI-3 in July and August, and only in low vegetation. Points of the same colour correspond to values from the same model, while points with the same marker shape represent the same summer. The horizontal and vertical axes show the models standard deviations, normalized by the observed standard deviation. The bold dashed line indicates the reference value corresponding to the observed standard deviation. The correlation between the model and the observations is represented by the angle with respect to the x-axis, while the root mean square error is shown by the light grey curved lines.

formed over a relatively small domain and were strongly constrained by ERA5 lateral boundary conditions updated every 6 hours, together with upper-level nudging. Under such conditions, synoptic-scale forcing can dominate atmospheric variability, thereby limiting the ability of local land-surface perturbations to influence precipitation development. Previous work has already shown that MAR exhibits limited sensitivity to convection, particularly for small domains (Doutreloup et al., 2022). Consistently, convective precipitation represents only a minor fraction of total precipitation in our simulations and shows very small to negligible changes across the experiments.

A more comprehensive assessment of precipitation sensitivity would require additional diagnostics. However, low-level moisture convergence, planetary boundary-layer height, lifting condensation level, or convective available potential energy are not available in the present experimental setup. We therefore hypothesize that the lack of precipitation response may primarily reflect moisture and energy constraints imposed by synoptic forcing, rather than a complete absence of land-atmosphere coupling at the surface.

The use of near-real-time LAI observations did not always lead to statistically significant improvements in the model performance, even during extreme events that visibly impacted vegetation cover. This limited sensitivity may reflect the resilience of the ecosystems within the study region, where the effects of climate change and extreme events tend to emerge over longer timescales, such as through increased forest mortality (Schuldt et al., 2020; Knutzen et al., 2025), or a too conservative model. Nonetheless, the decrease in extreme rainfall in the simulations with less vegetation (Fig. 2.8) is extremely interesting. It may be a sign that the model may not correctly represent extreme events in the future as they may be linked to the model representation of the vegetation.

These outcomes underscore the importance of integrating a more detailed and dynamic representation of vegetation, particularly given the uncertainties surrounding future vegetation states. As tree cover and land use are expected to evolve significantly in the coming decades (Roebroek et al., 2025), relying on a fixed climatological LAI is likely insufficient to fully capture future land-atmosphere interactions.

However, the use of remote sensing data in these experiments comes with limitations. While the 8-day MODIS LAI product is valuable for analysing past events and seasonal variability, it does not support future climate projections. A promising pathway to address these limitations lies in dynamic model coupling (Giorgi and Gao, 2018). Coupling MAR with a dynamic vegetation model such as the CARbon Assimilation in the Biosphere (CARAIB; Dury et al., 2011) model would provide temporally evolving and more physiologically realistic vegetation inputs for both present and future simulations. In addition to LAI, this approach would allow the incorporation of a broader range of vegetation-related variables, enhancing the representation of land-atmosphere interactions and potentially helping to reduce model uncertainties (Krinner et al., 2005).

2.5 Conclusions

In this work, we investigated the representation of land-atmosphere interactions in the MAR model and quantified the sensitivity of some of its key meteorological variables by using a remote sensing-based LAI dataset.

Overall, the comparison between the model’s current configuration (MAR_{ref}) and the version using MODIS LAI mean annual cycle ($MAR_{MODIS_{cyc}}$) highlights the critical importance of accurate vegetation representation in climate modelling. The results suggest that the current MAR configuration, which relies on MERRA2 LAI, may underestimate the vegetation spatial and temporal variability, and density in Belgium. In the standard MAR configuration and under current climate conditions, a model-induced drying trend of the soil is present. This trend is mitigated by the current underestimation of the vegetation density. However, by keeping the same LAI input to represent the vegetation in a potentially drier climate (IPCC, 2022; Brajkovic et al., 2025), the vegetation density could be overestimated. Therefore, the drying trend could be exacerbated by maintaining unrealistically high vegetation, affecting the reliability of long-term climate projections.

The results from our sensitivity analyses demonstrate that changes in vegetation inputs can significantly impact the estimations of the MAR model. One of the most pronounced impacts of altering LAI was on ET, with $MAR_{MODIS_{cyc}}$ consistently producing higher cumulative ET than the reference MAR run. This result aligns with the generally higher LAI values in $MAR_{MODIS_{cyc}}$ compared to the reference, which led to more vegetation activity and consequently greater water uptake and release through transpiration. This effect was particularly pronounced during the spring/summer months, as expected.

Surface air temperature responses to LAI changes also varied seasonally. In summer, simulations with higher LAI resulted in cooler temperatures thanks to the cooling and shading effect of a denser vegetation cover. In contrast, during winter, these simulations exhibited slightly warmer air temperatures, a phenomenon that may be attributed to the insulating effect of vegetation and reduced heat loss. The opposite conclusion can be drawn for simulation with lower LAI.

The comparison between the unperturbed simulations and the simulations with added noise highlighted that some variables were almost not impacted by the change in LAI input. Despite significant changes in LAI, rainfall only exhibits minor variations, suggesting that the link between vegetation and rainfall may be highly indirect or constrained by synoptic forcing.

Another key finding is the non-symmetrical effect of the LAI change (possibly linked to the physical formulations within MAR and the potential saturation of vegetation-related processes at low/high LAI values). The different experiments highlighted that there can be no linear link between the change in LAI and the studied variables. For example, while the simulation using the MODIS mean annual cycle showed a moderate decrease in soil moisture (up to 3 % in summer) compared to MAR_{ref} , simulations with even denser vegetation experienced only a slightly bigger decrease.

Conversely, simulations with lower vegetation cover showed a substantial increase in soil moisture, up to 11 % in summer on average. This variation is primarily driven by changes in root water uptake, which intensifies with denser vegetation and reduces as vegetation becomes sparser. The same effect is occurring in surface air temperature, where doubling the LAI does not result in a linear response; instead, it can lead to nearly a threefold increase. This air temperature response highlights the complex interplay between vegetation, surface albedo, and energy fluxes, demonstrating the retro-action of vegetation to the atmosphere.

The sensitivity experiment further revealed a pronounced seasonal effect in the response of modelled surface air temperature and relative humidity to changes in LAI, with the greatest changes occurring in spring during the vegetation peak. In contrast, changes in evapotranspiration were most pronounced in summer and winter.

Compared to observations, the model accurately captures the long-term climate variability but struggles to reproduce specific short-term events. The use of an observation-based 8-day LAI dataset improves the representation of some of these events, such as the 2018 drought. By avoiding the use of a climatological LAI during drought periods, vegetation responses differ according to land-cover type. The 8-day LAI dataset indicates that areas dominated by low vegetation are more strongly affected by drought than forests, reflecting both their lower resilience and the relatively short duration of these events. This results in a more pronounced decrease in LAI for low vegetation compared to forests, which in turn impacts the simulated variables both spatially and temporally. However, the use of the 8-day LAI does not systematically improve the results compared to $MAR_{MODIS_{cyc}}$, pointing toward limitations in the model representation of the land-atmosphere interactions.

Under present-day climate conditions, these results emphasize the need to better represent vegetation types that are highly sensitive to water stress, particularly low vegetation, in regional climate models. Nevertheless, forests should not be neglected. As extreme events are projected to become more frequent and intense (IPCC, 2023a), forests are expected to experience increasing stress (Knutzen et al., 2025), leading to longer-term impacts compared to the more immediate responses of low vegetation. Accurately representing forest processes and long-term vegetation dynamics will therefore be essential for improving future climate projections.

These findings underscore the crucial role that vegetation plays in RCMs. While the MAR model can currently be adjusted or forced with observational data to better reflect the existing climate, relying on a static LAI climatology to represent vegetation could lead to inaccurate representations of the future climate and extreme events or even the impossibility to represent them. The importance of this issue becomes even more pronounced when considering future climate scenarios, where uncertainties regarding vegetation states may increase.

Further investigation of the role of synoptic forcing on land-atmosphere interactions would benefit from simulations performed over larger domains with weaker large-scale constraints, together with the output of additional diagnostic variables, allowing a more detailed assessment of vegetation influences on convection in MAR.

In addition, multiplicative bounded perturbations represent an alternative approach that future work could investigate to strengthen the sensitivity analysis of MAR to its vegetation inputs. Future research should also focus on refining vegetation inputs in MAR and other regional climate models. This refining can be performed through the coupling of DVMs with RCMs. Incorporating dynamic vegetation represents a critical advancement in climate modelling (Giorgi and Gao, 2018; Gröger et al., 2021). While such integration has already been implemented in some RCMs (Zhang et al., 2014) and explored through sensitivity experiments (Heck et al., 2001; Jiménez-Gutiérrez et al., 2021), it remains far from standard practice. Given that our findings show vegetation changes already have a significant impact on the present climate, this step is essential for reducing uncertainties and to ensure data continuity in future climate projections.

CHAPTER 3

RAVEL 1.0: A Regional Atmosphere-Vegetation Coupled Model

This chapter is adapted from : Dethinne, T., Ghilain, N., François, L., Lecart, B., Fettweis, X., & Jonard, F. (2026). RAVEL 1.0: A Regional Atmosphere-Vegetation Model Based on the Coupling of the Regional Climate Model MAR and the Dynamic Vegetation Model CARAIB. *Geoscientific Model Development*. [In Preparation]

Abstract

Interactions and feedback between the atmosphere and the land surface are essential to understand and model the Earth’s climate. Their representation is essential to better study the evolution of ecosystems under climate change. Yet few climate models dynamically represent these interactions. In this chapter, we introduce RAVEL, a new coupled regional model combining the regional climate model MAR with the dynamic vegetation model CARAIB. The coupling is implemented by sequentially exchanging at each coupling time step the forcing variables required by the other model. MAR supplies daily weather variables to CARAIB, while CARAIB provides MAR with dynamic leaf area index. In the current framework, the two models share an identical spatial grid. The model is applied over Belgium, a region with a temperate European climate, for the 2015-2024 period to assess its ability to represent the present-day land-atmosphere interactions. In this configuration, the coupling leads to an increase in leaf area index input of the atmospheric model compared to a standalone configuration. The assessment of RAVEL over Belgium against observations and standalone model estimates shows that it successfully reproduces the main characteristics of the present-day climate. Although the atmospheric response to the increased leaf area index remains limited at the present scale with no significant differences in mean daily temperature or precipitation estimates, the coupling leads to a decrease in average vegetation productivity, particularly during summer. RAVEL further improves the net ecosystem productivity daily variability and simulates a lower maximum daily surface air temperature during drought events, highlighting the role of dynamic vegetation feedbacks under extreme conditions. This work highlights the added value of coupling regional climate models and vegetation models to better capture land-atmosphere interactions and ecosystem responses at regional scales, providing a more robust framework for assessing the impacts of climate change on natural ecosystems.

3.1 Introduction

Earth’s climate results from complex interactions between its major environmental components: the biosphere, hydrosphere, atmosphere, lithosphere, cryosphere, and, more recently, the anthroposphere (Seneviratne et al., 2010; Vogel et al., 2017; IPCC, 2023b; Bevacqua et al., 2024). These components continuously exchange momentum, energy, water, carbon and other chemical compounds, with each interaction potentially amplifying or dampening changes in the system. Such processes, where a change in one component affects others in ways that either reinforce (positive) or counteract (negative) the initial perturbation, are collectively referred to as climate feedbacks (Seneviratne et al., 2006, 2010; Strengers et al., 2010; Zhang et al., 2018).

These interactions are particularly evident at the land-atmosphere (L-A) boundary layer. Vegetation influences the atmospheric system through various processes, including evapotranspiration (ET) and changes in surface albedo (King et al., 2024), especially following disturbances such as mortality events or deforestation (Gonzalez et al., 2010; Hua et al., 2023; Knutzen et al., 2025). An increase in ET can enhance local or regional precipitation (Duveiller et al., 2021; Insua-Costa et al.,

2022), which in turn may increase water availability, thereby reinforcing the initial change through a positive feedback. Accurately capturing the interactions between these processes is essential for predicting how future climate changes may impact land ecosystems, particularly given the inherent uncertainties in climate projections. (Heck et al., 2001; Beniston et al., 2007; Koch et al., 2021; Engel et al., 2025; Verma et al., 2025).

Climate research frequently relies on numerical models that specialise in representing a single component of the Earth system, such as atmospheric dynamics or vegetation processes (Heck et al., 2001; Jacquemin et al., 2020; Tedesco et al., 2023). In such models, the boundary conditions between different Earth system components are typically prescribed rather than dynamically simulated, which limits their ability to capture coupled feedback processes (Giorgi and Gao, 2018; Gröger et al., 2021).

Quantification of the L-A coupling strength, i.e., the atmospheric response to anomalies in land surface conditions and vice versa, has been investigated using different techniques and tools such as remote sensing, climate models, and land surface models (Seneviratne et al., 2006, 2010; Miralles et al., 2012; Decker et al., 2015). These studies have demonstrated strong links between soil moisture and both precipitation and temperature, at global and regional scales. However, they also emphasise the need for an increased use of coupled models to better represent and understand L-A interactions (Lorenz et al., 2015; Knist et al., 2017). Moreover, the demand for models capable of capturing such interactions is growing, as reflected by the CMIP7 data request to accurately represent near-surface temperature variability and change (Dingley et al., 2025).

At the global scale, General Circulation Models (GCMs) are widely used to project future climate conditions under various greenhouse gas emission scenarios, frequently using groups of models, like the Coupled Model Intercomparison Project Phase 6 (CMIP6, Eyring et al., 2016; IPCC, 2023b; King et al., 2024). GCMs are often integrated into comprehensive Earth System Models (ESMs) that include dynamic coupling between multiple components such as the atmosphere, land surface, and ocean (Giorgetta et al., 2013; Gutjahr et al., 2019; Sellar et al., 2019; Boucher et al., 2020). This coupling exists under different strategies, ranging from offline approaches, where outputs from one model serve as inputs for another, to fully interactive online coupling where models exchange information at every coupling time step (Gröger et al., 2021). However, GCMs often struggle to represent regional and local climate features with sufficient spatial resolution, making them less suitable for studies requiring detailed regional climate information (Vogel et al., 2017; Giorgi and Gao, 2018; Stuecker et al., 2018).

To address this limitation, Regional Climate Models (RCMs) are commonly used to provide higher-resolution simulations of atmospheric processes at the regional scale (Soto-Navarro et al., 2020; de Vyver et al., 2021; Balcha et al., 2023; Brajkovic et al., 2025). In recent years, regional model coupling has become increasingly common, especially in efforts to better represent L-A or ocean-atmosphere feedbacks at regional scales (Knist et al., 2017; Giorgi and Gao, 2018; Giorgi, 2019; Huot et al., 2022). However, fully coupled Regional Earth System Models (RESMs) are less

common than ESMs.

While RCMs and GCMs are used to simulate the atmospheric processes, Dynamic Vegetation (Global) Models (DV(G)Ms) are employed to represent vegetation dynamics and biogeophysical interactions across both global and regional scales (Foley et al., 2000; Krinner et al., 2005; Hickler et al., 2012; Snell et al., 2014). They are commonly used to estimate future ecosystem productivity (Matsushita et al., 2004; He et al., 2023), or to assess the impacts of land-use changes such as afforestation and deforestation (Roebroek et al., 2025). Because vegetation responses depend strongly on climatic conditions, DVMs and other ecosystem models are typically driven by climate inputs from RCMs or GCMs (Matsushita et al., 2004; Morales et al., 2007; Engel et al., 2025).

Coupling these models offers the advantage of explicitly representing physical processes on both sides of the boundary between the coupled components and, consequently, their feedbacks (Sein et al., 2020). However, it also introduces additional sources of uncertainty compared to approaches in which some components are prescribed. One key challenge in coupled configurations is that boundary conditions between components are no longer prescribed from observations but are instead dynamically simulated. As a result, the coupled system lacks the observational nudging typically used to constrain individual models, which can lead to larger deviations from observed datasets (Gröger et al., 2021). If both model components drift in the same direction, the resulting biases may amplify over time. Achieving a stable and physically consistent coupled simulation therefore often requires careful calibration and tuning of interface variables and exchange processes. Coupling also increases computational demands, making the choice of simulation domain and spatial resolution especially important to balance physical realism and computational feasibility (Giorgi and Gao, 2018; Gröger et al., 2021).

In this chapter, we present and evaluate the Regional Atmosphere-VEgetation uLiège model (RAVEL), which interactively couples a regional climate model with a dynamic vegetation model. This atmosphere-biosphere coupling enables the simulation of two-way feedback between the land surface and the atmosphere at the regional scale. The coupled framework provides enhanced insight into vegetation responses during extreme events and their feedback on atmospheric conditions, as well as an improved representation of short-term and/or localised processes that may be overlooked when the models are used separately.

The models, the case study and the experiment set-up of this chapter are described in Sect. 3.2. The model evaluation and the simulated effects on atmosphere and land surface processes under the present climate and during extreme events are discussed in Sect. 3.3. A discussion about the model results is presented in Sect. 3.4. Sect. 3.5 provides a discussion of the model and outlines future work.

3.2 Material and Methods

The Regional Atmosphere-VEgetation uLiège model (RAVEL) results from the coupling of the Modèle Atmosphérique Régional (MAR) regional climate model (Gallée and Schayes, 1994; Grailet et al., 2025) with the CARbon Assimilation in the Biosphere (CARAIB) dynamic vegetation model (Warnant et al., 1994; Verma et al., 2025). To facilitate understanding of the RAVEL framework, we first introduce MAR and CARAIB individually, before describing the conceptual and technical aspects of their coupling.

3.2.1 Description of the models

Regional climate model

In this chapter, we use MARv3.14 (Grailet et al., 2025), an atmospheric model based on the hydrostatic approximation of the primitive equations of the atmosphere, as originally described by Gallée and Schayes (1994). MAR is primarily used to study Greenland (Glaude et al., 2024) and Antarctic ice sheets (Kittel et al., 2022a), but it has also been applied in European climate studies (Brajkovic et al., 2025; Grailet et al., 2025).

MAR includes several physical modules, one of which is its radiative transfer scheme, derived from the ecRad radiation scheme (Hogan and Bozzo, 2018). Another important physical module is SISVAT (Soil Ice Snow Vegetation Atmosphere Transfer), which governs the surface-atmosphere mass and energy exchanges. Within this module, the plant water flow is driven by soil-to-leaf water potential gradients, while turbulent fluxes are computed separately for canopy-air and ground-air interfaces following the approach of De Ridder and Schayes (1997). Vegetation seasonality follows a prescribed annual cycle defined by externally provided Leaf Area Index (LAI) input data. As described in Dethinne et al. (2025), in its standard configuration, MAR uses a climatology (1961-1990) of LAI at 50 km derived from MERRA2 (Global Modeling and Assimilation Office (GMAO), 2015; Gelaro et al., 2017; Wyard et al., 2021). Firstly computed at a monthly time step, the climatology is eventually re-interpolated at a 6-hour interval. Then, during the resampling to the MAR grid, a corrective coefficient depending on the vegetation type is applied in order to maintain consistency in the LAI range per vegetation class with previous model versions that did not use MERRA2 LAI. This LAI climatology is the only vegetation-related index used by MAR to derive both the annual vegetation dynamics and its daily variations.

From the LAI input, vegetation-related variables, like aerodynamic roughness length or stomatal resistance, are handled according to De Ridder and Schayes (1997). An effective LAI (LAI_e), defined as the LAI associated with leaves receiving sufficient radiation to allow stomatal opening (De Ridder and Schayes, 1997), is derived. LAI_e is used to compute the stomatal resistance (Eq.3.1):

$$r_s = \frac{r_0}{LAI_e} \frac{\psi_c}{\psi_c - \psi_v} \quad (3.1)$$

where r_0 is the minimal stomatal resistance, ψ_v the leaf water potential, and ψ_c the leaf water potential at which total stomatal closure occurs. This stomatal resistance is then used to compute the transpiration vapour flux (E_{tr} , Eq.3.2):

$$E_{tr} = (\rho_a \cdot cv)(1 - \delta) \frac{q_{sat}(T_v) - q_a}{r_{av} + (r_s \cdot cv)} \quad (3.2)$$

with ρ_a the surface boundary layer (SBL) top air density, δ the fraction of water intercepted by the canopy relative to the maximum amount of water intercepted by the canopy, $q_{sat}(T_v)$ the saturation specific humidity at the vegetation temperature, q_a the SBL top specific humidity, r_{av} aerodynamic resistances for heat, and cv the ventilation factor of the canopy defined as:

$$cv = 1 - e^{-0.5LAI} \quad (3.3)$$

The radiative transfer between the land surface and the atmosphere follows the methodology proposed in De Ridder (1997), where the reflectivity and transmissivity of the vegetation are proportional to the fraction of green leaves. The LAI, corrected for the snow cover, is used to derive the scattering of downward and upward fluxes, as well as surface absorption and reflectivity.

Parameters such as minimum stomatal resistance and root distribution follow the formulations of Taylor et al. (1997) and Jackson et al. (1996), respectively. The atmospheric forcing variables provided to SISVAT include near-surface wind speed, air temperature, and humidity at the lowest available level above the ground, as well as downward shortwave and longwave radiation and precipitation. Land cover is static and is based on the International Geosphere-Biosphere Programme (IGBP) classification (Loveland and Belward, 1997) aggregated into 13 categories: bare soil, low/medium/high crops, low/medium/high grass, low/medium/high broadleaf, and low/medium/high needleleaf. The diversity in vegetation is represented by simulating three sub-pixels (called sectors) representing the two most common types of vegetation in the pixel, as well as grass. In this chapter, MAR is configured to resolve the first 5m of soil with 7 layers of decreasing vertical resolution. The first layer is a few millimetres thick, while the deeper layers are a few meters thick.

Dynamic vegetation model

CARAIB is a mechanistic model that simulates ecosystem primary productivity and respiration by explicitly integrating the ecophysiological processes governing carbon exchanges between vegetation, soil, and the atmosphere (Warnant et al., 1994). CARAIB estimates the evolution of five carbon pools resulting from these atmosphere-biosphere fluxes. The five pools are (1) the leaves ("green carbon (GC)"), (2) the other part of the plant, i.e. root, branches, and stems ("remaining carbon (RC)"), (3) litter from GC, (4) litter from RC, and (5) the product of litter decomposition, the humus (Otto et al., 2002).

Initially, CARAIB included eight Plant Functional Types (PFTs). Over time, various improvements have been made, including the addition of new PFTs (François

et al., 2011; Henrot et al., 2017). A major advancement was the introduction of species groups sharing similar bioclimatic characteristics, known as bioclimatic affinity groups (BAGs; Laurent et al., 2004). In its latest version, the model can simulate individual plant species. The consideration of PFTs/BAGs/species allows for estimating the daily carbon fluxes and pools of individual PFTs/BAGs/species on every pixel of the grid.

In CARAIB, a module handles carbon allocation and biomass growth, which is critical for accurately estimating the carbon content in the plants (Loudiyi et al., 2024). The carbon flux captured by the plant during photosynthesis is allocated between two reservoirs, the first and second pools, GC and RC. The carbon is either used for metabolic growth (leaves) or for structural growth (roots and wood) (Otto et al., 2002). Then, the soil and litter carbon dynamics module allows for the transfer of carbon between the soil and the atmosphere, especially through processes such as litter decomposition.

To compute the carbon fluxes, the model includes a module dedicated to photosynthesis and stomatal regulation, following Farquhar et al. (1980) for C3 and Collatz et al. (1992) for C4 plants, which are fundamental to plant growth and the conversion of atmospheric CO_2 into organic compounds. The stomatal conductance (g_s) is derived from Ball et al. (1987), adapted to include a dependency on soil water content (eq. 3.4) by multiplying the slope of the stomatal conductance by a soil water scaling factor following Van Wijk et al. (2000) (eq. 3.6):

$$g_s = g_0(ip) + g_1(ip) \cdot f_s(t, ip) \cdot \frac{An(t, h, ip) \cdot h_s(t, h)}{C_a} \quad (3.4)$$

with $g_0(ip)$ the minimum stomatal conductance for a given PFT/BAG/species ip , $g_1(ip)$ the slope for the stomatal conductance for the same PFT/BAG/species, $An(t, h, ip)$ the net CO_2 assimilation rate for the same PFT/BAG/species for a given hour h of a day t , $h_s(t, h)$ the relative humidity at the leaf surface for a given hour h of a day t , C_a the atmospheric partial pressure of CO_2 and $f_s(t, ip)$ the scaling factor defined as:

$$S(t, ip) = \max(0, \frac{ASW(t) - 0.5 \cdot SW_{mins}(ip)}{WATSUP(ip) - 0.5 \cdot SW_{mins}(ip)}) \quad (3.5)$$

$$f_s = 1. - 0.016572 \cdot \exp(4.1 \cdot (1 - S(t, ip))) \quad (3.6)$$

Where $S(t, ip)$ is a stress factor depending on available soil water of day t for a given PFT/BAG/species ip , with $ASW(t)$ is the relative soil water of day t , $SW_{mins}(ip)$ is the soil water mortality threshold for PFT/BAG/species ip (Henrot et al., 2017), and $WATSUP(ip)$ is equal to 1 for purely isohydric plant types and decreases to values lower than 1 (e.g., towards 0.5) for plant types tending towards anisohydricity.

In the carbon module, leaves are represented as a carbon reservoir for each PFTs / BAGs / species (the GC pool). The content of this reservoir evolves from the balance

between carbon allocation to leaves, derived from net primary productivity (the difference between the gross primary productivity and the autotrophic respiration) and leaf mortality. For deciduous species, leaf mortality mainly occurs through seasonal leaf shedding, whereas for evergreen species, a baseline turnover rate is prescribed. In both cases, mortality increases under environmental stress conditions such as low temperatures or drought. Then, for each PFTs/BAGs/species, LAI is computed from its specific leaf area (SLA; eq. 3.7):

$$LAI(ip) = SLA(ip) \cdot C_{leaf}(ip) \quad (3.7)$$

With $SLA(ip)$ the specific leaf area (m^2gC^{-1}) for a given PFT/BAG/species ip , and C_{leaf} the quantity of carbon (gCm^{-2}) in the GC pool of that PFT/BAG/species ip .

Another core module of the model focuses on soil hydrology (Hubert et al., 1998). The module works as an Improved Bucket Model (IBM), which estimates the water content of a soil layer on a daily time step (Otto et al., 2002). The water budget is estimated as the difference between water inputs (precipitation) and outputs (surface runoff, actual evapotranspiration, and drainage). Currently, CARAIB does not simulate lateral hydrological fluxes between adjacent pixels, so the budget is computed independently for each pixel. Daily precipitations are provided either by external forcing or by a weather generator if only monthly data are available as input (Hubert et al., 1998). Surface runoff occurs when the precipitation rate exceeds the soil's maximum infiltration capacity. Drainage is estimated based on soil hydraulic conductivity, which is modelled as a function of soil texture and moisture following the parametrisation of Saxton et al. (1986). Actual evapotranspiration is calculated as a fraction of potential evapotranspiration, which is itself computed using Penman's equation (Mintz and Walker, 1993), with the fraction depending on soil water availability.

Other modules simulate the dispersion of seeds, fire events (Dury et al., 2011), plant mortality, and competition between the plants. Combined with the vegetation dynamics module they are key to simulate how vegetation distribution and biomass evolve (Loudiyi et al., 2024; Verma et al., 2025; Loudiyi et al., 2026). Lastly, a two-stage phenology module for crops is included to estimate yield (Jacquemin et al., 2020).

CARAIB has already been applied and evaluated for various purposes, including the reconstruction of past vegetation at the global scale (Otto et al., 2002; François et al., 2006) or in Europe (François et al., 2011), the estimation of crop yields in Belgium and Morocco (Jacquemin et al., 2020; Loudiyi et al., 2024), and the projection of future ecosystem dynamics in Wallonia (Verma et al., 2025).

RAVEL coupled model

The RAVEL model couples the regional atmospheric model MAR with the dynamic vegetation model CARAIB to represent two-way interactions between the land and the atmosphere at the regional scale. In this framework, MAR represents the atmospheric component of the system, while CARAIB simulates land surface processes

and vegetation dynamics. The two models remain independent in their internal formulations and exchange only a limited set of key variables required to represent land-atmosphere feedbacks (Fig. 3.1).

Although MAR includes a land surface scheme (SISVAT) with a representation of vegetation, its standard configuration relies on a prescribed climatology of LAI. As shown by Dethinne et al. (2025), such representation can overlook short-term vegetation responses to extreme events such as drought and pluvial events. By coupling MAR with CARAIB, the coupled system allows SISVAT to use time-varying LAI, enabling a more realistic representation of vegetation impacts on surface energy, water, and carbon exchanges.

The coupling is intentionally kept lightweight: SISVAT and CARAIB do not share internal vegetation state variables beyond LAI, nor do they exchange information on soil hydrological processes or stomatal regulation, despite both models simulating these processes. (Fig. 3.1). This design choice limits the propagation of uncertainties between the two models, reduces the risk of climate drift, and preserves the physical consistency of the parametrizations of each model.

The coupling strategy relies on sequentially exchanging variables between the two models (Fig. 3.1). CARAIB provides MAR with the daily LAI used by SISVAT to compute land-atmosphere fluxes of energy and moisture. In return, MAR provides CARAIB with daily meteorological forcing, including near-surface air temperature, diurnal temperature range, precipitation, shortwave and longwave downward radiation, relative humidity, and wind speed. This two-way exchange enables vegetation-atmosphere feedbacks, particularly during extreme events, by allowing vegetation to respond to atmospheric variability and, in turn, enables vegetation changes to influence atmospheric conditions.

3.2.2 Settings for a study case

Thanks to the extensive prior application and validation of MAR and CARAIB over a wide range of climatic regions, RAVEL can be applied to most parts of the globe. In this study, we take advantage of an established MAR domain to define a case study aimed at evaluating the performance of RAVEL against observations and at quantifying the impact of vegetation-atmosphere coupling through comparisons with standalone MAR and CARAIB simulations. This subsection presents the study region, the offline model configurations, and the coupling setup used for the RAVEL experiments.

Study region

The model evaluation is performed over Belgium (Fig. 3.2), which exhibits substantial landscape heterogeneity, with more densely urbanized northern region and a predominantly forested southern region (Statbel, 2025). This diversity allows to simulate a region of dense forest and a more urbanised region at the same time.

The climate is typical of a temperate oceanic climate (Cfb in the Köppen-Geiger climate classification (Beck et al., 2018)) that calls for mild summers and relatively

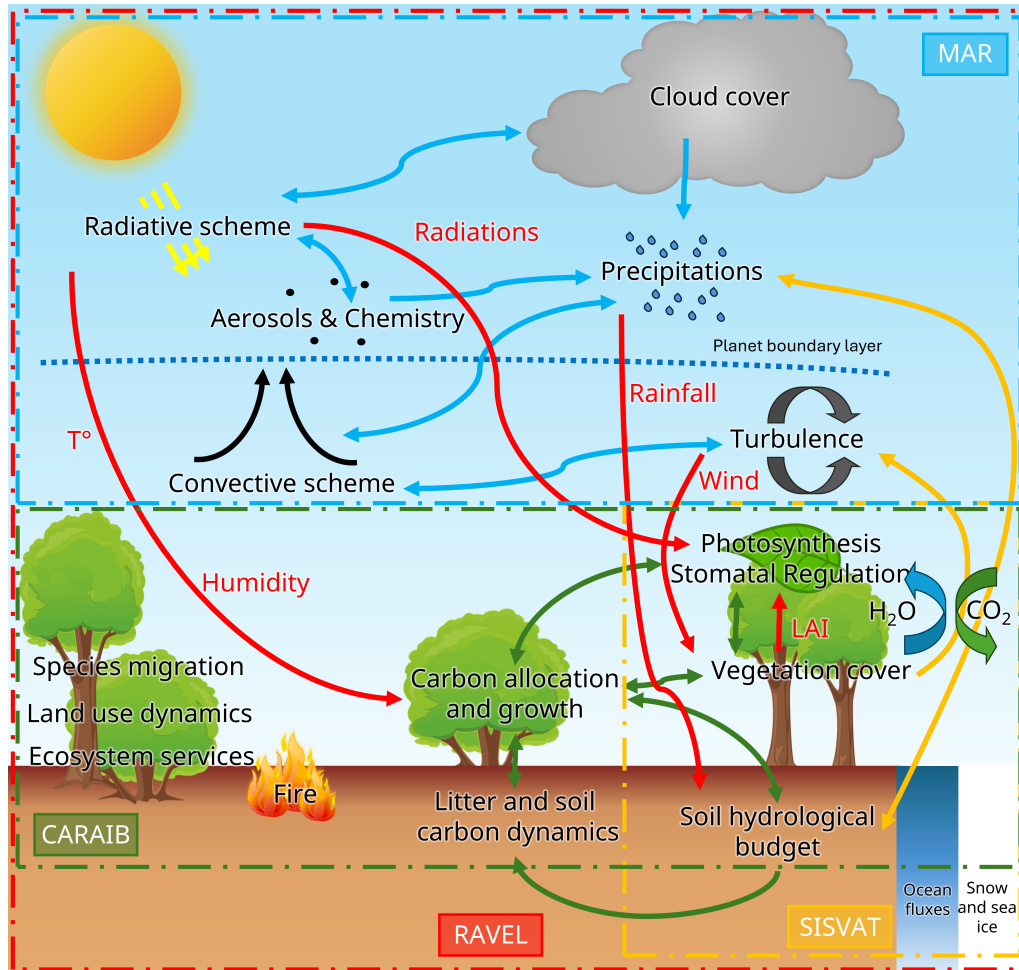


Figure 3.1: Schematic representation of the structure of the model components composing RAVEL and exchanges between the modules. While internal exchanges within MAR-SISVAT and CARAIB are preserved, RAVEL introduces additional interactions between MAR and CARAIB to explicitly couple the atmosphere and the biosphere.

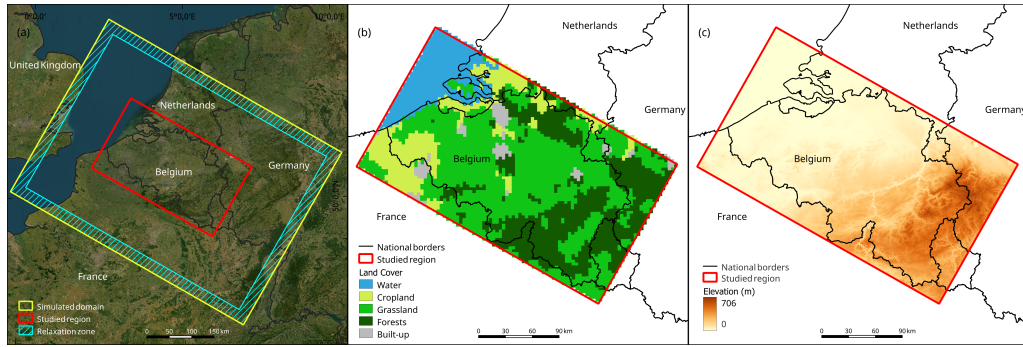


Figure 3.2: (a) Region of interest. The modelled domain is highlighted by the yellow rectangle, the studied region by the red one, and the relaxation zone is hatched in cyan. Basemap: Earthstar Geographics (TerraColor NextGen) imagery (Esri and Maxar and Earthstar Geographics and the GIS User Community, 2025). (b) Dominant land cover considered by the MAR model in the studied region. For visualization purposes, the land cover has been filtered using a 3x3 mode window. (c) Elevation in the studied region.

wet, cool winters. Under these conditions, the region experiences a mean annual temperature of about 10 °C, which mainly varies inside the region given the local topography (Erpicum et al., 2018). Annual precipitation varies also with topography, averaging between 700 mm and 1300 mm across the country, and is relatively evenly distributed throughout the year.

During the last decades, the region suffered from multiple droughts like in 2003, 2011, 2018, 2019, 2020 and 2022 (Jonard et al., 2011; Chen et al., 2022b; Toreti et al., 2023; Bevacqua et al., 2024; Neimry et al., 2025), but also episodes of extreme rainfalls (in intensity and in quantity), like in July 2021 and summer 2024 (Insua-Costa et al., 2022; Toreti et al., 2024; IRM, 2025). The combination of dry and rainy periods enables us to study vegetation behaviour during periods of water stress and strong growth (no water limitations), and its impact on the atmosphere during these periods.

Belgium is also part of the transition zone identified by Knist et al. (2017), situated between the strongly coupled land-atmosphere systems of southern Europe and the weakly coupled systems of northern Europe. This makes it a particularly interesting region for studying land-atmosphere feedbacks following the RCM and DVM coupling.

Offline models setup

To accelerate the coupled simulation and ensure a physically consistent initialisation, prior standalone simulations of both MAR and CARAIB are required (Fig. 3.3). Two main constraints motivate this approach. First, CARAIB reads a full year of climate forcing at once, whereas during the coupled simulation, it receives meteorological inputs from MAR one day at a time. To address this mismatch, the remaining days of each year are temporarily filled with climatological values derived from a previous MAR simulation, providing realistic placeholders until dynamically simulated data become available. Second, dynamic vegetation models typically require

a much longer spin-up period than regional climate models. CARAIB is therefore spun up offline before the coupled simulation, using meteorological outputs from MAR.

For the offline MAR simulation, a configuration similar to Grailet et al. (2025) and Dethinne et al. (2025) is used. MAR is run from September 1939 to December 2024 at a horizontal resolution of 5 km over Belgium, with 24 pressure levels from the surface to the lower stratosphere and a time step of 25 s. The model is forced every 6 hours by ERA5 reanalysis data (Hersbach et al., 2020) at the lateral boundaries, over the ocean, and in the stratosphere, where nudging is applied over three vertical layers. Independence from initial conditions is ensured by excluding the first years of simulation from the analysis.

The CARAIB offline simulation spans a longer period (1800-2024) to allow sufficient equilibration of vegetation and carbon pools. The model is initialised with bare soil, and the fractional coverage of each vegetation species is recomputed annually at each grid cell. The simulation includes one herbaceous, one shrub, one pasture, fourteen trees, and twelve crop species (Table 3.1) as described in Verma et al. (2025), and is forced with daily meteorological data from the offline MAR simulation. For the period 1800-1939, forcing data from 1940-1969 are replicated.

To ensure consistency between the two models, most CARAIB inputs are derived from the same sources as MAR. The land-sea mask and land use/land cover are based on the classification used by MAR (Fig. 3.2(b)), constraining vegetation types consistently across the models. Climate forcing is provided by MAR, while atmospheric CO₂ concentrations and soil properties are also taken from the MAR inputs. In this setup, to simplify the model run, the fire and migration modules of CARAIB are disabled, and the harvest and sowing dates are set to default dates.

The modelled domain (Fig. 3.2(a)) follows Wyard et al. (2017) and Dethinne et al. (2025) and encompasses southern Netherlands, northern France, western Germany, and the North Sea. To exclude the relaxation zone of MAR, a buffer of five grid cells is removed along each lateral boundary.

For this study, both models operate on the same spatial grid, so no interpolation is required for variable exchange, although an interpolation functionality has been implemented to ensure future flexibility.

3.2.3 Simulation experiment

The coupled RAVEL simulations build directly upon the offline configurations described in the previous section. RAVEL uses the same spatial domain, grid resolution, parametrisations, land-sea mask, and land-cover classification as in the standalone experiments. Consequently, the coupling does not introduce structural changes to the individual model configurations, but rather adds an interactive exchange of key variables between the atmospheric and vegetation components.

The main difference between the standalone offline simulations and the coupled ex-

Table 3.1: Vegetation species and genus considered by CARAIB for the simulations over the studied domain.

Species	Vegetation Type
<i>Anemone, Gypsophila, Helleborus, etc</i>	Herbaceous
<i>Sambucus, Frangula alnus, Prunus, Sorbus, Vaccinium</i>	Shrub
<i>Asteraceae asteroideae, Poaceae, etc</i>	Pasture
<i>Abies alba</i>	Tree
<i>Alnus glutinosa</i>	"
<i>Betula pendula</i>	"
<i>Carpinus betulus</i>	"
<i>Corylus avellana</i>	"
<i>Fagus sylvatica</i>	"
<i>Fraxinus excelsior</i>	"
<i>Larix decidua</i>	"
<i>Picea abies</i>	"
<i>Pinus sylvestris</i>	"
<i>Populus nigra</i>	"
<i>Pseudotsuga menziesii</i>	"
<i>Quercus petraea</i>	"
<i>Quercus robur</i>	"
Winter barley (early-maturing variety)	Crop
Winter barley (late-maturing variety)	"
Winter wheat (early-maturing variety)	"
Winter wheat (late-maturing variety)	"
Potatoes (early-maturing variety)	"
Potatoes (late-maturing variety)	"
Beets (early-maturing variety)	"
Beets (late-maturing variety)	"
Corn (early-maturing variety)	"
Corn (late-maturing variety)	"
Rapeseed (early-maturing variety)	"
Rapeseed (late-maturing variety)	"

periment lies in the simulated time range. As described in the previous section, the coupled model relies on the offline simulations to accelerate the spin-up phase. The RAVEL simulation therefore starts in September 2010, using the CARAIB offline simulation before that date as vegetation spin-up. From that point onward, the vegetation distribution and species fractions at each grid point are kept fixed to their 2010 values for the remainder of the run. In contrast, the atmospheric spin-up phase is performed within the coupled framework, as it is shorter (5 years in this case), so it already benefits from the dynamic vegetation. As a result, the initial few years of the RAVEL simulation are discarded, resulting in an analysed study period spanning 2015-2024.

In this experiment, the coupling time step is set to one day. At each coupling cycle, MAR first simulates one day and outputs the required atmospheric variables. These

outputs are then used as inputs by CARAIB, which is subsequently called to simulate vegetation dynamics for the same calendar day. Each model is executed only after the other has completed the update of the coupled variables. As MAR starts the simulation, it uses its standard MERRA2-based LAI climatology for the first day, while CARAIB is immediately forced by MAR meteorological outputs. From the second day onward, MAR vegetation state depends exclusively on LAI simulated by CARAIB (Fig. 3.3).

The coupling is file-based, meaning that all exchanged variables are written and read by the other model. This approach simplifies the coupling and ensures modularity but introduces a technical constraint due to differences in the temporal structure of the two models. MAR operates with a short internal time step (between 15 and 50 seconds), whereas CARAIB is fundamentally structured around a yearly time step. Although some CARAIB subroutines operate at daily or sub-daily resolution, the reading of daily input and writing of daily output are typically performed once per year. As a consequence, for each day simulated by MAR, CARAIB simulates an entire year using updated daily forcing, and only the outputs corresponding to the current day are retained (Fig. 3.3). The same calendar year is therefore simulated multiple times by CARAIB, each time with different daily meteorological conditions provided by MAR. Despite this repetition, CARAIB is computationally efficient, and the additional computational cost does not significantly affect the overall runtime of the coupled system.

This coupling methodology presents certain limitations, particularly regarding the coupling of variables that are not read as external inputs by either model. Currently, key variables like LAI or climate forcing are exchanged through file reading, but other potentially useful variables remain unused in the coupling process as they are not written or read but are computed internally by both models (e.g., stomatal conductance, surface roughness, cloud cover, spectral flux fractions).

3.2.4 Statistical analyses

Model performance relative to observations is quantified using standard statistical indicators: mean bias (MB), root-mean-square error (RMSE), and Pearson correlation coefficient (r). A negative MB indicates underestimation by the coupled model. These metrics are computed for the 2015-2024 period, both annually and seasonally, with winter defined as December-January-February (DJF) and summer as June-July-August (JJA).

Statistical significance of the difference between the model simulations and observations or the simulations by the other models is computed using block-bootstrapping with 10-day blocs.

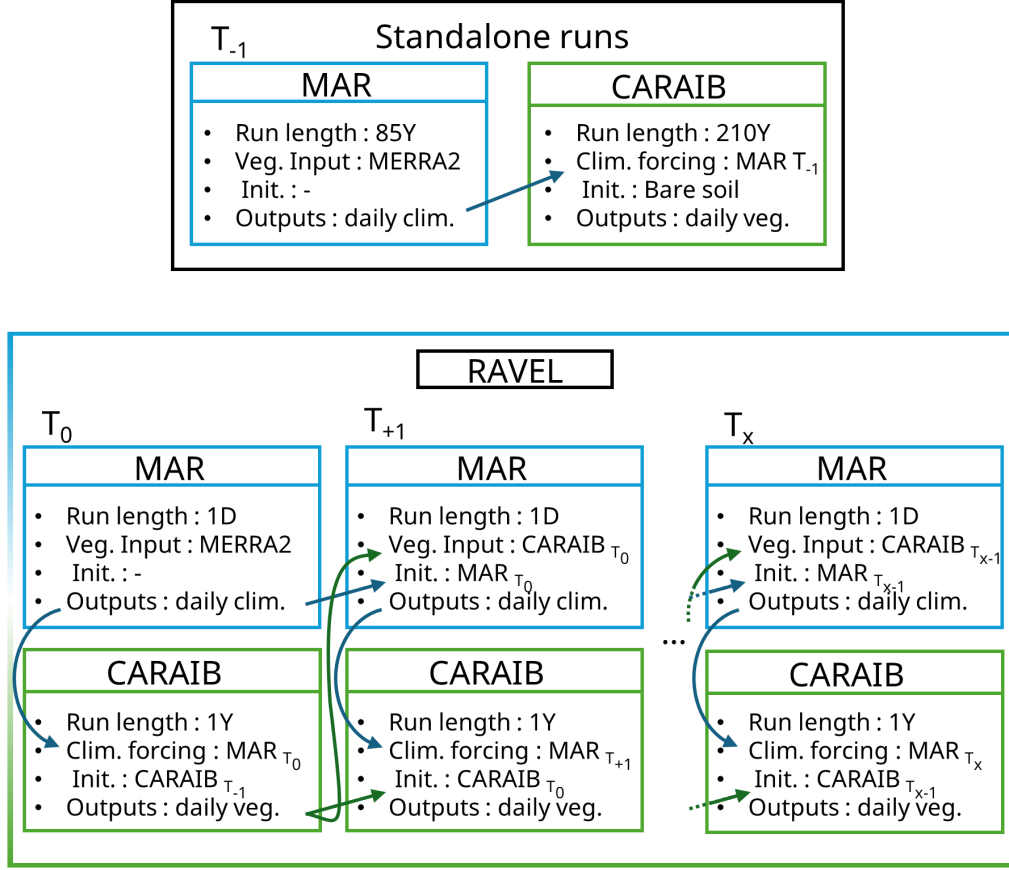


Figure 3.3: Coupling framework of RAVEL between the Regional Climate Model MAR and the Dynamic Vegetation Model CARAIB. Before the coupled run, both models are run in standalone mode (T_{-1}). MAR uses its standard MERRA2-based climatological LAI to simulate 80 years of data, which is then used as forcing for a 210-year CARAIB run. The CARAIB standalone run ensures the CARAIB spin-up in the coupled configuration. At the first coupling time step (T_0), MAR runs for one day using standard climatological LAI input (MERRA2), and CARAIB runs for one year using the daily MAR outputs as climate forcing. The remaining forcing of the year is filled with a MAR-based climatology computed from the T_{-1} MAR simulation. CARAIB is initialised using the standalone run. From the second coupling step onward (T_1 to T_x), the coupling becomes fully two-way: MAR uses daily LAI provided by CARAIB, while CARAIB receives daily meteorological inputs simulated by MAR. At each step, MAR simulates one day, and CARAIB simulates one year, using updated climate forcing and restarts from the vegetation states of the previous year.

Table 3.2: Average daily Mean Bias (MB), Root Mean Square Error (RMSE), and Pearson correlation coefficient (r) between RAVEL simulations and mean daily observations over Belgium. A negative MB value implies an underestimation of RAVEL compared to the observation. Statistics are given for the sea-level pressure, surface air temperature, wind speed, relative humidity, rainfall, actual evapotranspiration from LSA SAF and FLUXNET (ET_{LSA} and ET_{ICOS}), gross primary productivity (GPP), and net ecosystem exchanges (NEE) annually, and for the summer (JJA) and winter (DJF) seasons for the 2015-2022 period. MB marked with an asterisk (*) indicates that the mean daily MB is smaller than the daily standard deviation of the observations. A dash (-) in the MB column indicates no significant difference ($p\text{-value} > 0.05$) between the model mean daily values and the observations using block-bootstrapping with 10-day blocs.

Variable	Annual			Winter			Summer		
	MB	RMSE	Correlation	MB	RMSE	Correlation	MB	RMSE	Correlation
Sea-Level Pressure (hPa)	-	1.52	0.99	-	1.97	0.99	-	1.01	0.98
Temperature ($^{\circ}\text{C}$)	-	1.11	0.99	-	0.99	0.96	-	1.31	0.93
Wind speed (ms^{-1})	-0.46*	0.55	0.97	-0.47*	0.56	0.98	-0.41*	0.51	0.93
Relative humidity (%)	7.87*	9.21	0.92	7.84	9.14	0.88	6.94*	8.63	0.92
Rainfall (mm)	-1.19*	3.09	0.72	-1.86*	3.6	0.72	-0.76*	3.04	0.73
ET_{LSA} (mm)	-1.54	1.89	0.88	-0.51	0.58	0.73	-2.83	2.97	0.78
ET_{ICOS} (mm)	0.33*	0.72	0.82	0.19*	0.38	0.24	0.29*	0.95	0.5
GPP (gC/m^2)	-1.11*	2.41	0.85	-0.48*	0.86	0.38	-0.67*	3.15	0.32
NEE (gC/m^2)	1.19*	2.01	0.74	0.43*	1.11	0.3	1.61*	2.57	0.43

3.3 Results

3.3.1 Model assessment

In this section, we evaluate the performance of RAVEL by comparing its simulated climate and vegetation variables with observation-based datasets (Table 3.2). While both the MAR and CARAIB models have previously been evaluated over the Belgian study region (Jacquemin et al., 2020; Brajkovic et al., 2025; Dethinne et al., 2025; Grailet et al., 2025; Verma et al., 2025), it remains essential to verify that the coupled model RAVEL maintains consistency with observations and does not introduce systematic deviations or climate drift.

Daily spatially averaged model outputs are compared against observation-based datasets from multiple sources. Key meteorological variables, including sea-level pressure, surface air temperature, wind speed, relative humidity, and precipitation, are obtained from weather stations distributed across Belgium and statistically interpolated onto a 5 km grid (Journée et al., 2023). Actual evapotranspiration (ET_{LSA}) estimates are obtained from the LSA SAF product (Ghilain et al., 2011, 2012a), while ecosystem productivity is evaluated using actual evapotranspiration (ET_{ICOS}), gross primary productivity (GPP) and net ecosystem exchanges (NEE) from FLUXNET measurements at the Vielsalm ICOS station (Vincke et al., 2026). For the latter data source, the model is compared to the observations using the average value of the four closest grid cells surrounding the station. The ecosystem productivity is evaluated against FLUXNET observations from an ICOS station rather than against gridded products, in order to enable a comparison that is consistent with the local vegetation composition.

As expected, the RAVEL model reproduces the current climate over the study area

reasonably well. No statistically significant differences ($p\text{-value} > 0.05$) are observed between the model and the observations for daily sea-level pressure and surface air temperature. Sea-level pressure shows very high correlations with observations ($r \geq 0.98$) in winter, summer, and on an annual basis. Surface air temperature and wind speed also exhibit strong correlations ($r \geq 0.96$), although a slight reduction in correlation is found during summer. For relative humidity (RH), the daily mean bias in summer and annually remains lower than the daily standard deviation of the observations, but correlations are somewhat lower (though still close to 0.9), and the RMSE is relatively large ($\approx 9\%$). As previously reported for MAR (e.g., Doutreloup et al., 2019a; Brajkovic et al., 2025) and for other RCM (Danan-deh Mehr and Kahya, 2017; Hosseinzadehtalaei et al., 2018), precipitation is more challenging to simulate. While RAVEL exhibits a mean bias smaller than the daily standard deviation of the observations and a relatively low RMSE of about 3 mm, the correlation drops to around $r \approx 0.7$ seasonally and annually. This decrease can be attributed to underestimated rainfall extremes in summer and overestimations in winter (de Vyver et al., 2021) as well as underestimation of convective precipitation (Doutreloup et al., 2019b).

For the land-surface-related variables, the results are more mixed. When compared to LSA SAF ET estimates, the model shows relatively good correlations, both annually ($r = 0.88$) and seasonally ($r > 0.7$). However, when evaluated against ICOS station data on a seasonal basis, the correlations drop to lower values ($r \approx 0.2\text{--}0.5$). This discrepancy can be explained by the model’s design, which focuses on representing vegetation dynamics over long timescales and larger spatial domains rather than capturing fine-scale, day-to-day variability at a single site. This interpretation is further supported by the very low MB and RMSE and the higher annual than seasonal correlations for ET, GPP and NEE compared to ICOS. The same conclusion can be applied to both the GPP and NEE. Overall, the model provides a satisfactory representation of the general conditions but tends to underestimate the local and daily variations.

3.3.2 Impact of the coupling

Land surface variables

The overall effect of the model coupling on vegetation cover when comparing RAVEL to offline CARAIB (see Sect. 3.2.2) is a slight decrease in vegetation density and productivity by a few percent (Table 3.3). This reduction is evident in most variables but varies with season and process. For NEE (defined as positive toward the atmosphere), an increase in carbon release is observed in forested regions during winter and autumn, coinciding with higher autotrophic respiration and gross primary production during those seasons in RAVEL. However, this increase is not sufficient to offset the stronger summer decline, when fluxes are larger. The net effect is a sustained reduction in vegetation productivity, which is also reflected in total biomass, showing an overall annual decrease of 17.6 %.

Similarly, the LAI simulations from the coupled model are consistently lower than those obtained from CARAIB (Table 3.3). However, the magnitude and direction of the change depend on vegetation type and season (Fig. 3.4). In autumn, central and

Table 3.3: Seasonal (winter and summer) and annual mean daily values of CARAIB/MAR and RAVEL, together with their mean daily difference for net ecosystem exchange (NEE), biomass (BIM), soil water content (SW), evapotranspiration (ET), albedo, and leaf area index (LAI) for the 2015-2024 period. An index "M" denotes that the variable is taken from MAR, while "C" stands for CARAIB.

Variable	Annual			Winter			Summer		
	CARAIB/MAR	RAVEL	Difference (%)	CARAIB/MAR	RAVEL	Difference (%)	CARAIB/MAR	RAVEL	Difference (%)
NEE _C (gC/m ²)	-0.32	-0.14	-28.5	0.66	0.86	38.29	-1.56	-1.33	-9.8
BIM _C (gC/m ²)	2855.19	2349.73	-17.61	2770.67	2273.93	-17.81	2981.32	2472.42	-16.98
SW _M	0.63	0.57	-9.62	0.66	0.6	-8.25	0.61	0.55	-10.98
ET _C (mm)	1.38	1.56	22.35	0.43	0.6	36.05	2.25	2.45	12.41
Albedo _M	0.25	0.25	1.15	0.26	0.26	-0.33	0.23	0.24	2.64
LAI _C	2.75	2.71	-1.47	1.76	1.73	-1.59	4.31	4.17	-3.16

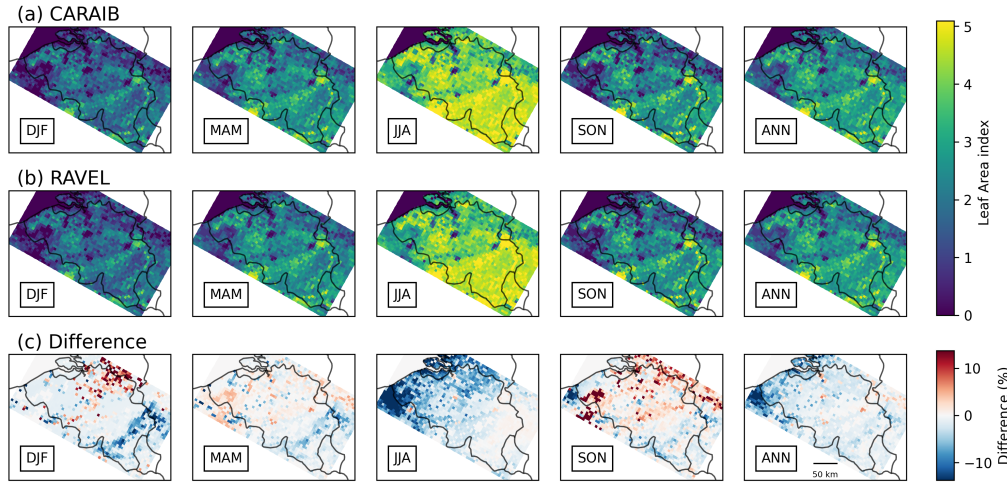


Figure 3.4: Seasonal (DJF, MAM, JJA, SON) and annual mean daily leaf area index simulated by (a) CARAIB, (b) RAVEL, and (c) their difference, for the period 2015-2024 over Belgium.

northern Belgium exhibit an increase in LAI, mainly over croplands, while the rest of the domain shows either little change or a slight decrease. In summer, croplands and the forested regions of southern Belgium experience a smaller decrease in LAI compared to the rest of the study area. Interestingly, a cropland-dominated zone in the north, which showed an increase in autumn, displays the largest decrease in summer, highlighting contrasting seasonal responses even within similar land-cover types. Conversely, RAVEL simulates higher daily ET despite the overall decline in vegetation. The increase in ET is spatially homogeneous across most of the domain, except in winter, when a stronger increase is observed in the northern half of Belgium.

While differences in LAI between CARAIB and RAVEL provide valuable information, comparing the MAR input LAI to the LAI used in the coupled configuration provides deeper insight into how and why the atmosphere is impacted, as it is this difference that drives the change between MAR and RAVEL. With the coupling, the MAR LAI input is impacted in two main ways: the spatial resolution and the temporal variability. As described in the RCM description (Sect. 3.2.1), in its standard configuration, MAR uses a 50 km LAI-climatology derived from MERRA2. When CARAIB supplies the LAI in the coupled model, the spatial resolution of the LAI input increases by a factor of ten (from 50 km to 5 km) and the daily LAI reflects

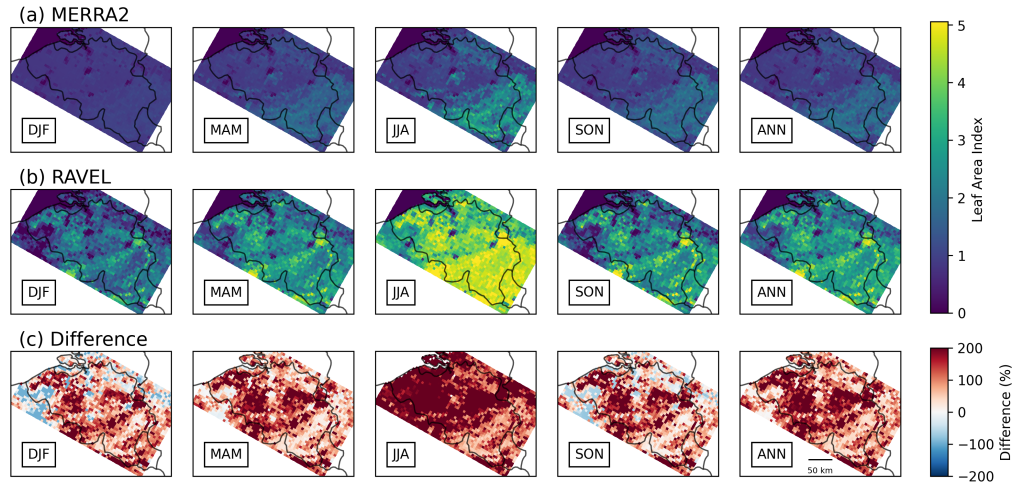


Figure 3.5: Seasonal (DJF, MAM, JJA, SON) and annual mean daily leaf area index (a) derived from MERRA2 and resampled to MAR grid, (b) simulated by RAVEL, and (c) their difference, for the period 2015-2024 over Belgium.

concurrent climate conditions as it is no longer a climatology. Consequently, the LAI used to represent vegetation in the atmospheric model is substantially altered when transitioning from the MAR offline configuration to the RAVEL coupled configuration.

A general increase in LAI is observed in RAVEL compared to the MERRA2-derived climatological LAI (Fig. 3.5). The most pronounced differences occur over low-vegetation areas, such as pastures and croplands, where LAI increases by up to 200 % across all seasons, particularly during summer. Forested regions in the south and north-east of the domain exhibit smaller increases, on the order of 50 %. In contrast, a localised decrease in LAI is found in the western part of the domain during winter and autumn, reflecting the crop cycle representation in CARAIB, where crops are harvested at the end of summer or early autumn, leading to lower LAI in autumn and winter.

With the strong increase in LAI prescribed to MAR, the coupled model simulates strong changes in surface characteristics, most notably relative soil water content, defined as the ratio to the value at saturation, and surface albedo (Table 3.3). Higher vegetation density enhances root water uptake, leading to a decrease in soil water content of about 10 % annually, slightly stronger in summer (11 %) and weaker in winter (8 %), in line with the difference observed in LAI. This reduction is spatially consistent across most of the domain, except in coastal areas and in the forested regions of southern Belgium, where changes in soil water are smaller. In coastal areas, this limited response is linked to the sandy soils represented in the model, which have higher water infiltration capacity, whereas in the southern forests, the minimal change is explained by the relatively small differences in LAI.

The differences in surface albedo are more subtle than those of soil water content and are strongly influenced by spatial heterogeneity and seasonal timing (Fig. 3.6). In summer, a relatively uniform increase of about 2 % compared to MAR is ob-

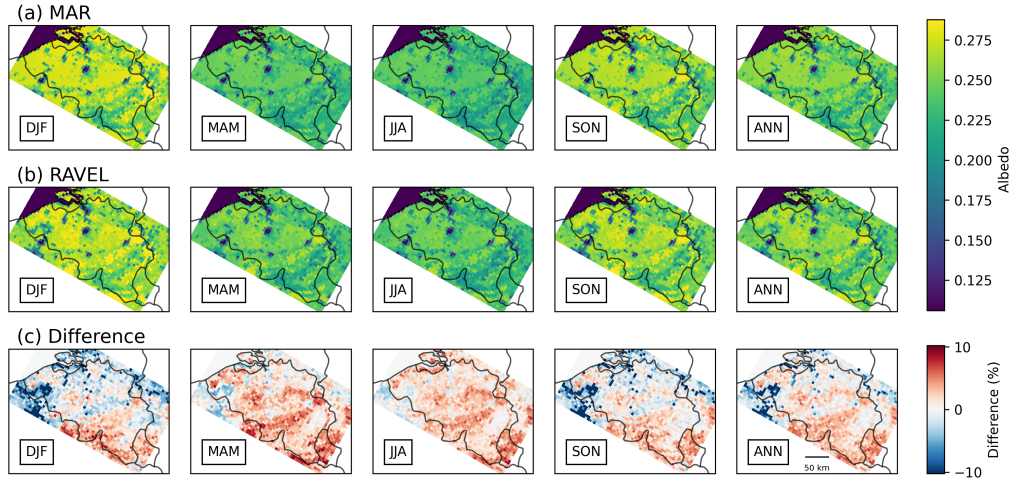


Figure 3.6: Seasonal (DJF, MAM, JJA, SON) and annual mean daily albedo simulated by (a) MAR, (b) RAVEL, and (c) their difference, for the period 2015-2024 over Belgium.

served across the study region. In winter, however, two contrasting regimes emerge: albedo decreases in the North and the East, particularly over agricultural areas, while the South shows an increase. This seasonal pattern reflects land cover dynamics, as croplands are bare in late autumn and early winter, leading to lower albedo in RAVEL, but regrow more rapidly toward late winter, ultimately producing higher albedo than MAR on an annual basis. A similar north-south contrast is observed in autumn, which also contributes to the annual differences (Fig. 3.6).

Atmospheric variables

In this section, we investigate the effect of the coupling on some atmosphere-related variables by comparing the results of MAR in a standalone configuration to those obtained with the coupled model (Table 3.4).

Table 3.4: Seasonal (winter and summer) and annual mean daily values of MAR and RAVEL together with their mean daily difference for rainfall, surface air temperature, cloud cover, relative humidity, sensible heat flux, and short and long wave upward for the 2015-2024 period. A dash (-) in the "Difference (%)" column denotes that there is no statistically significant difference between MAR and RAVEL mean daily value for the considered period and variable.

Variable	Annual			Winter			Summer		
	MAR	RAVEL	Difference (%)	MAR	RAVEL	Difference (%)	MAR	RAVEL	Difference (%)
Rainfall (mm)	2.16	2.15	-	2.02	2.01	-	2.7	2.71	-
Temperature (°C)	11.12	11.05	-	4.19	4.34	-	18.79	18.5	-
Cloud cover (%)	0.71	0.71	-	0.87	0.86	-	0.58	0.59	-
Relative humidity (%)	86.19	86.98	-	95.22	94.93	-0.3	77.12	79.22	2.94
Sensible heat flux (W/m ²)	-9.59	-8.18	-	-14.05	13.11	-	-35.7	-31.2	-12.7
Short wave upward (W/m ²)	22.87	23.77	-	6.97	7.2	-	38.88	40.58	4.62
Long wave upward (W/m ²)	369.52	368.78	-	331.46	332.17	-	413.94	411.8	-0.52

For rainfall, surface air temperature, and cloud cover, no statistically significant differences are found between the daily values simulated by the standalone and coupled

models, either in summer, winter, or annually (Table 3.4). In contrast, significant differences emerge mainly in summer for RH, latent heat flux (LHF), and the upward shortwave and longwave radiative fluxes (SWU, LWU).

Despite the increase in ET and RH, the denser vegetation cover does not lead to an increase in cloud cover, sometimes reported in other studies (Duveiller et al., 2021; King et al., 2024). Nevertheless, the increase in ET is associated with a rise of a few percentage points in relative humidity during summer. Contrary to expectations based on the moisture recycling concept (van der Ent et al., 2010; Insua-Costa et al., 2022), this additional humidity also does not translate into more precipitation.

Although surface air temperature differences between MAR and RAVEL are not statistically significant, the coupled model exhibits daily mean values about 0.3 °C cooler than MAR during summer. This small decrease can be attributed to combined changes in surface albedo and surface flux partitioning. Higher albedo increases soil reflectivity, enhancing SWU, while higher ET increases latent heat flux (positive toward the surface in this study), thereby reducing the energy available for sensible heating. Consistently, the simulations show a decrease in sensible heat flux (SHF) exceeding 10 % on average per day during summer.

These changes, directly linked to land-surface processes, are not spatially homogeneous as they follow the underlying vegetation patterns. For winter, spring, and summer, RAVEL simulates a generally smaller flux of SHF (positive toward the surface in this study) by a few percent across most of the study area, except for some forested regions in central and southern Belgium, which show a larger negative flux during spring compared to MAR (Fig. 3.7). The largest differences occur in autumn, when coastal areas in the north of the domain and cropland areas exhibit increases (more positive flux) in SHF of up to 75 %. However, these increases have a limited climatic impact as SHF values are generally low during that season. On the annual scale, RAVEL simulates a domain-wide decrease of the negative SHF flux of about 10 %, with localised small increase in the flux over forested regions and larger decrease flux in the tri-border region east of the study area, encompassing Belgium, Germany, and the Netherlands (Fig. 3.7).

The spatial differences in SWU (Fig. 3.8) closely follow those in land surface albedo (Fig. 3.6), with the same regions being affected in similar ways. On the annual scale, RAVEL simulates a general increase in SWU of about 5-10 % compared to MAR, particularly over forested and natural areas. In contrast, a decrease in SWU is observed in northwestern Belgium in predominantly cropland regions, where the surface albedo is decreasing. This reduction is more pronounced during seasons with generally lower SWU, i.e., winter and autumn. Otherwise, the increase in SWU occurs in the same regions and with similar magnitude across seasons, with the largest increases located at forest edges where the simulated LAI rises most strongly.

Extreme events

A key advantage of the coupled model is its theoretical capability to resolve short-term variability and L-A feedback, including during extreme events, which are inad-

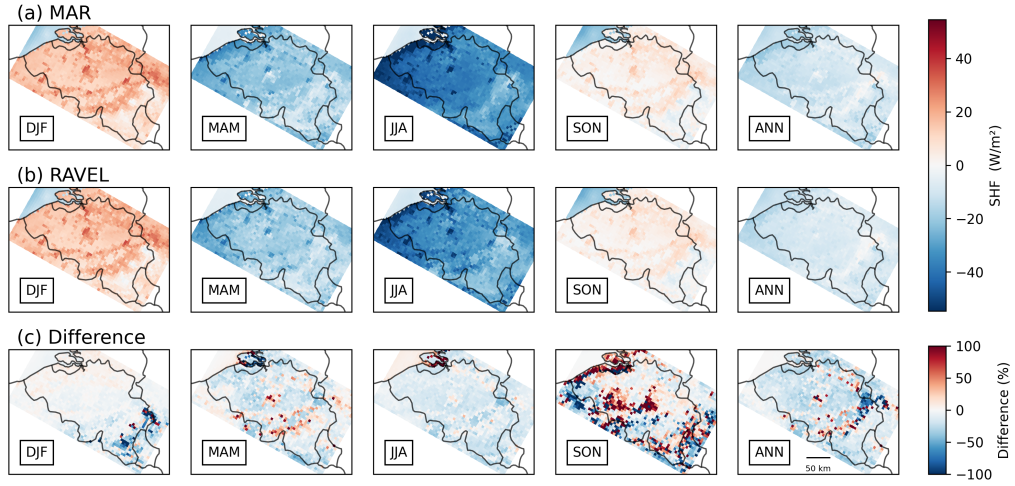


Figure 3.7: Seasonal (DJF, MAM, JJA, SON) and annual mean daily sensible heat flux simulated by (a) MAR, (b) RAVEL, and (c) their difference, for the period 2015-2024 over Belgium.

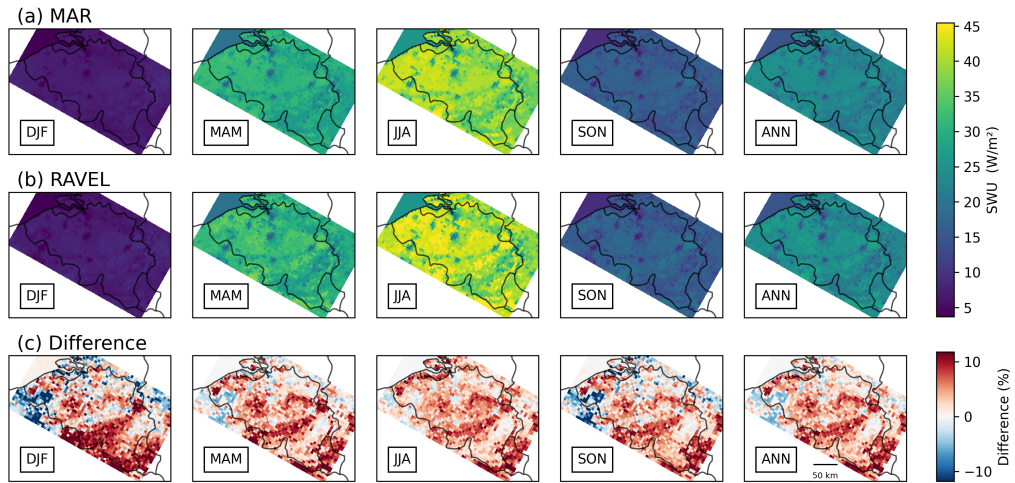


Figure 3.8: Seasonal (DJF, MAM, JJA, SON) and annual mean daily short wave upward simulated by (a) MAR, (b) RAVEL, and (c) their difference, for the period 2015-2024 over Belgium.

equately represented when using climatological means or static datasets as forcing. For RAVEL, this capability is particularly relevant for the atmospheric component. While CARAIB in standalone mode can be forced with year-to-year varying daily weather or a weather generator, MAR in its standard configuration relies on a fixed climatological LAI. As a result, the coupling not only enables long-term feedback between the land surface and the atmosphere but also allows short-term differences to emerge between the coupled and uncoupled configurations during droughts and pluvial events.

Accurate representation of L-A interaction under present-day conditions is essential for quantifying uncertainties in climate projections, particularly as the frequency and intensity of extreme events are projected to increase in the coming decades (IPCC, 2023b). In the following, we evaluate RAVEL against both the reference observations described in Sect. 3.3.1 and the standalone model runs during drought and pluvial episodes identified within the study period (Schuldt et al., 2020; Chen et al., 2022b; Insua-Costa et al., 2022; Toreti et al., 2023; Bevacqua et al., 2024; Toreti et al., 2024). Specifically, we selected summer droughts in 2018, 2020, and 2022, and winter droughts in 2017 and 2019, as well as pluvial events in summer 2016 and 2021 and in winter 2023 based on SPEI3 (Vicente-Serrano et al., 2010) values computed for the study period.

The impact of the coupling strongly depends on the variable considered and is not always straightforward. For NEE (Fig. 3.9a), the effect varies considerably across events. During the 2018 and 2020 summer droughts, the coupled model shows a further decrease in standard deviation, whereas the standalone model configuration already underestimates day-to-day variability compared to reference observations. In contrast, during the 2022 drought, the standard deviation increases. In winter, for both pluvial and drought events, RAVEL generally provides a better representation of variability. Mostly the same conclusion can be taken for the correlation with the observations. In some cases, like in 2017, 2019, and 2022, RAVEL show a smaller correlation with the observations than the offline model. In other cases like in 2018 and 2020, the opposed situation is observed, with a better correlation for the coupled model. Overall, the benefits of coupling for NEE during summer extremes remain unclear, despite its role in vegetation dynamics.

For ET (Fig. 3.9b), the results are more consistent. With the exception of the 2019 winter drought, RAVEL exhibits standard deviations closer to the observations across all events. However, this improvement in variability is sometimes accompanied by a reduction in correlation with the observations, particularly during the 2018 and 2020 summer droughts. Regardless of the variable, vegetation-related outputs from both coupled and standalone model simulations consistently exhibit lower variability than observations.

For daily maximum surface air temperature (Fig. 3.10a), the overall increase in vegetation induced by the coupling (see section 3.3.2) has a clear effect. During both drought and pluvial periods, RAVEL generally simulates lower maximum temperatures, directly linked to enhanced vegetation cover. Even during droughts, when a stronger reduction in LAI is observed in the coupled model (Fig. 3.11), the coupled

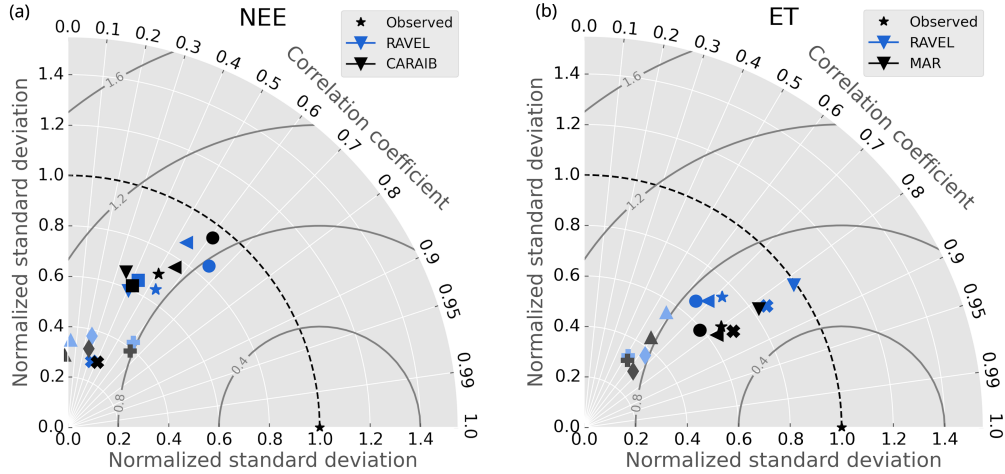


Figure 3.9: Taylor diagram for (a) net ecosystem exchange (NEE) simulated by CARAIB and RAVEL compared against FLUXNET data at the Vielsalm ICOS station, and (b) evapotranspiration (ET) simulated by MAR and RAVEL compared against LSA-SAF ET data over Belgium. Symbols indicate individual extreme events. Light grey and light blue denote winter events (droughts in 2017 (◆) and 2019 (+), pluvial in 2023 (▲)), while dark blue and black denote summer events (pluvial in 2016 (▼) and 2021 (×), droughts in 2018 (●), 2020 (★), and 2022 (◄)). Points of the same colour correspond to values from the same model, while points with the same marker shape represent the same period. The horizontal and vertical axes show the model’s standard deviations, normalised by the observed standard deviation. The bold dashed line indicates the reference value corresponding to the observed standard deviation. The correlation between the model and the observations is represented by the angle with respect to the x-axis, while the root mean square error is shown by the light grey curved lines.

model still maintains higher vegetation levels than MAR LAI climatology, leading to a cooling effect. This effect is more apparent during pluvial periods, while for drought events, the temperature differences are not always statistically significant. In cases of very strong heat-waves (daily maximum temperature $> 35^{\circ}\text{C}$), RAVEL instead simulates higher maximum temperatures than MAR. Under such extreme heat, soil moisture exerts a stronger control than vegetation (Seneviratne et al., 2010; Vogel et al., 2017), and since soil moisture is generally lower in RAVEL (Table 3.3), the resulting temperatures are higher.

Compared to CARAIB, LAI in RAVEL is generally lower (Fig. 3.10b), and consistently so during pluvial events, although these differences are often not statistically significant. During droughts, however, the impact is stronger: LAI peaks are lower and decline more rapidly in RAVEL than in CARAIB, as observed in 2018 and 2022 (Fig. 3.11).

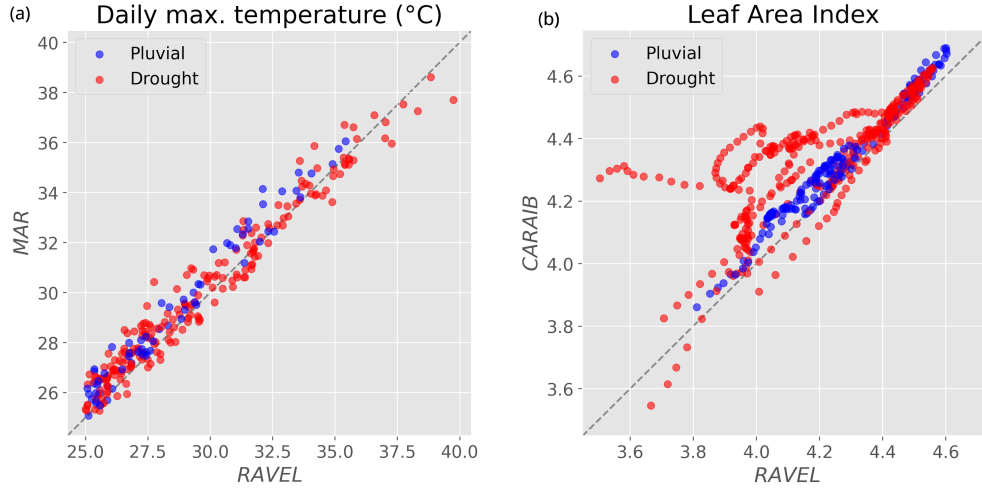


Figure 3.10: Daily differences during extreme events (winter droughts (2017, 2019) and pluvial (2023), summer pluvials (2016, 2021) and droughts (2018, 2020, 2022)) over Belgium between (a) MAR and RAVEL maximum daily surface air temperature (scatter plot truncated between 25 and 40 °C) and (b) CARAIB and RAVEL leaf area index (scatter plot truncated between 3.5 and 4.8).

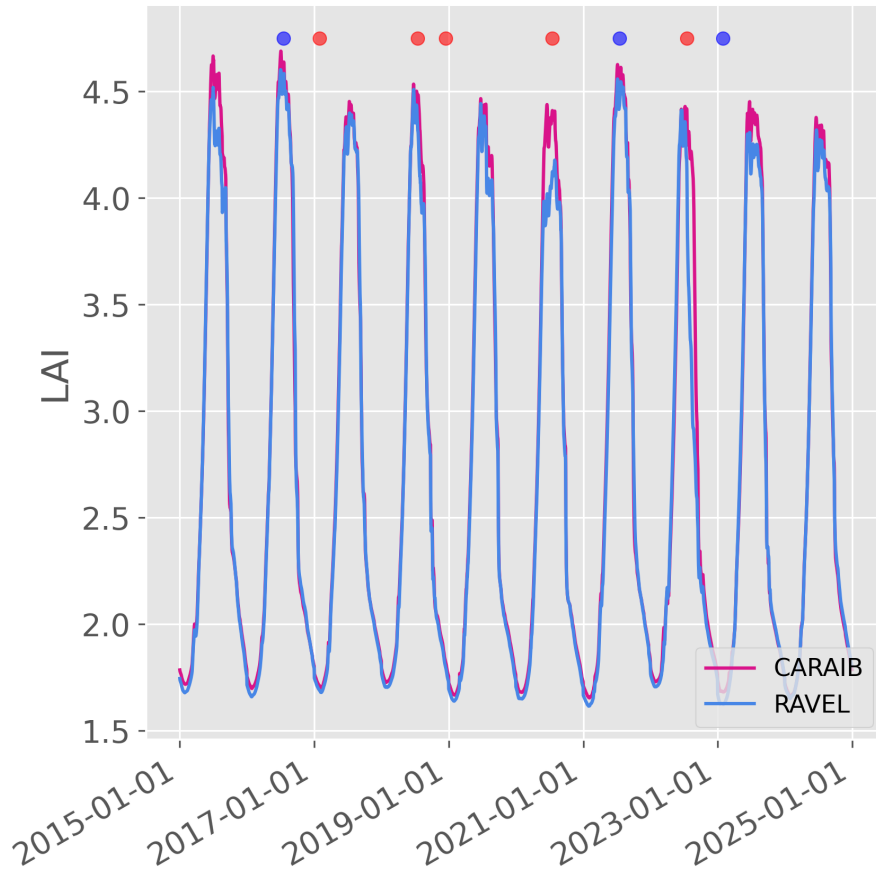


Figure 3.11: Evolution of LAI simulated by CARAIB and RAVEL over Belgium for the 2015-2024 study period. Drought events are indicated by red dots above the time series, and pluvial events by blue dots.

3.4 Discussion

By coupling the RCM MAR and the DVM CARAIB, RAVEL opens new possibilities to study the land-atmosphere interactions. However, some considerations have to be taken into account at the sight of the results. Some technical and methodological choices can orient the results and influence RAVEL performances.

First of all, the coupling is performed over a reference period rather than a long-term projection, so its impact may be moderate and can yield similar results to using observation-based forcing with a standalone model. As discussed in Sect. 3.2.1, the coupling between the land surface and the atmosphere in this study primarily consists of passing the CARAIB-simulated LAI to MAR. As shown in Sect. 3.3.2, the LAI from the coupled model is generally higher in areas of low vegetation (e.g., agricultural and grassland regions) and broadly similar in areas of dense vegetation (e.g., forests), compared to the MERRA2-derived LAI used in standalone MAR (Fig. 3.5). We therefore expected results similar to those of Dethinne et al. (2025), where MAR was provided with MODIS satellite LAI observations (Myneni et al., 2021), which were likewise consistently higher in low-vegetation regions than MAR’s standard inputs.

In addition, the limited domain size and the boundary forcing may contribute to the relatively weak atmospheric sensitivity. Synoptic control can surpass the land-atmosphere feedback occurring in RAVEL. For example, when the increase in ET in RAVEL compared to MAR was expected to increase the convective precipitation, the relatively small change in precipitation may have been driven by synoptic control. This may reflect MAR’s known tendency to underestimate of convective rainfall and extreme events (de Vyver et al., 2021; Brajkovic et al., 2025), or the limited size of the domain. Under strong synoptic control, local evapotranspiration anomalies may be exported through advection or precipitate outside the domain (Eltahir and Bras, 1996; Tuinenburg et al., 2020). Similarly, King et al. (2024) reported that simulations with the Community Earth System Model version 2 showed little to no change in precipitation across Northern Hemisphere mid-latitudes when comparing afforestation and baseline land-use scenarios over long-term projections, and attributed it to the lower influence of convective precipitation compared to large-scale processes. Therefore, the relatively weak atmospheric response to vegetation-induced surface flux changes in RAVEL is likely constrained by the domain choice.

Other changes can be attributed to the vegetation classification and land cover used by RAVEL and the static representation of vegetation fraction. The overall increase in albedo observed in this study contrasts with the findings of studies such as Portmann et al. (2022) or King et al. (2024) and may be attributed to SISVAT surface albedo computation. In the other studies, the increase in vegetation is simulated with afforestation or a land cover transition scenario. In contrast, in our setup, vegetation fractions are fixed, meaning that grasslands are not replaced by forests and most forested regions are represented as broadleaf rather than darker needleleaf forests. As discussed in Sect. 3.3.2, some of the variations in albedo and surface fluxes may be attributed to the relatively rapid dynamics of agricultural land, especially cropland, which are not represented in MAR.

However, if the results indicate that changes occurred predominantly in lower vegetation compared to forests, special attention should nonetheless be given to the forests. While under the current climate and because of the vegetation types defined in RAVEL, low vegetation is more prone to experience a decrease in LAI due to water stress (e.g., because of shallower root depth) and thus is more highlighted in this study than forests, the frequency and intensity of extreme events are predicted to increase (IPCC, 2023a). Under such conditions, forests could experience substantial reductions in productivity, delayed recovery, and increased mortality (Knutzen et al., 2025). These events are linked with important consequences for regional carbon budgets, surface energy fluxes, and land-atmosphere feedback. Forest will therefore play a very important role in climate system in the long term (Engel et al., 2025).

Despite all these limitations, RAVEL demonstrates a strong ability to simulate land-atmosphere interactions during short-term and extreme events, especially during droughts. In these periods, RAVEL exhibits a stronger LAI response than standalone CARAIB, despite the comparatively limited atmospheric response. The impact is most pronounced in the vegetation component, where RAVEL simulates vegetation dynamics that are, on average, closer to observations than those obtained with the standalone models. Nevertheless, atmospheric variables are also affected during these events, with daily maximum surface air temperature exhibiting clear changes that are closely linked to the evolution of LAI. This increased response to drought was expected, even if the events were represented in the weather forcing of CARAIB in the standalone run. With a coupled framework, land-atmosphere feedbacks become more pronounced, particularly during drought events compared to pluvial periods. During droughts, increasing water stress induces stomatal closure and leaf senescence, leading to a reduction in LAI. This reduction in vegetation cover decreases latent heat flux and canopy cooling, contributing to higher surface temperatures, which in turn further reinforces plant water stress and vegetation decline. In contrast, during pluvial conditions, soil water is non-limiting and key vegetation and surface parameters such as stomatal resistance or surface albedo tend to reach a plateau. As a result, additional moisture does not translate into stronger land-atmosphere feedbacks, and the coupled response remains weaker than during drought conditions.

Overall, RAVEL reproduced the present-day climate and vegetation with comparable or better accuracy than the model in their standalone configurations. The comparison to observations supports its suitability for investigating long-term land-atmosphere interactions at the regional scale.

3.5 Conclusions and Future Works

In this chapter, we present the new regional model RAVEL that couples the regional climate model MAR with the dynamic vegetation model CARAIB. Although the coupling is still under active development, the results are promising and highlight the potential of such a framework. The coupling is achieved through file exchanges between the two models: CARAIB provides MAR with simulated LAI, while MAR

supplies CARAIB with the relevant meteorological variables. Both models run for one time step, one after the other, exchanging information on a daily basis.

The coupled model run is performed over Belgium for a 15-year simulation from 2010 to the end of 2024, from which the 2015-2024 study period is extracted. As CARAIB generally simulates higher LAI values than the MERRA2-based climatological LAI prescribed in the standard MAR configuration, the main effect of the coupling compared to the standalone models is a strong increase in vegetation cover used by MAR as vegetation input. Consequently, the coupling behaves similarly to an increased vegetation density scenario, with a vegetation that dynamically responds to meteorological variability.

Under present-day climate conditions, the simulated impacts are broadly consistent with findings from studies investigating afforestation scenarios (King et al., 2024; Bright et al., 2025; Engel et al., 2025), except for the reported decrease in albedo and the associated slight increase in temperature. This difference can be explained by the vegetation composition in the study domain, which is dominated by broadleaf forests rather than darker needleleaf forests, by the absence of grassland-to-forest transitions that would decrease RAVEL albedo, and by SISVAT surface albedo computation.

Interestingly, the atmospheric response to the coupling is less pronounced than the vegetation response. This asymmetry may reflect a higher sensitivity of the vegetation model compared to the atmospheric model, or a strong synoptic control over the small domain. These results are consistent with Dethinne et al. (2025), who also reported a relatively weak atmospheric sensitivity to vegetation changes in MAR.

Overall, the coupling leads to an increase in vegetation in MAR, but when comparing CARAIB to RAVEL, a decrease in vegetation is observed in RAVEL. This overall decrease is primarily linked to spatial differences in LAI and to stronger effects during drought periods, especially in summer. Nevertheless, the differences in daily maximum surface air temperature, LAI, and vegetation productivity between coupled and uncoupled configurations during pluvial and drought events highlight the value of including vegetation-climate feedbacks compared to offline models.

The coupled RAVEL system provides a more realistic and coherent representation of present-day climate and vegetation interactions, particularly during extreme events. As the recurrence and intensity of such events are projected to increase in the coming decades, improving their simulation is crucial for more reliable climate projections and for supporting sustainable adaptation and mitigation strategies.

While the current configuration involves a limited number of exchanged variables, by using the same memory space and running the model sequentially, we open the possibility for future extensions of the coupling framework to include additional variables without relying on file-based exchange. For instance, surface roughness and stomatal resistance computed by CARAIB could be passed directly to MAR, while MAR calculation of the fraction of photosynthetically active radiation could be used as input for photosynthesis processes in CARAIB. Integrating such variables

via shared memory would not only enhance the biophysical interactions of the coupled system but also reduce redundant file I/O operations, improving computational efficiency. These enhancements should be considered in future developments of the RAVEL framework.

Beyond evaluating the model performance under present-day conditions, the RAVEL coupling framework also provides a basis for a wide range of future developments and applications. Key perspectives include performing long-term simulations to assess the joint evolution of climate and vegetation under different climate change scenarios, and transposing the study to a region with known strong L-A coupling, like the Mediterranean region. Such experiments would allow the assessment of cumulative land-atmosphere feedbacks under water-limited conditions.

In these climate projections, particular emphasis should be placed on forest ecosystems, given their dominant contribution to carbon storage and their strong influence on surface energy and water fluxes. Improving the representation of long-term forest dynamics, including their response to increasing drought frequency and intensity, will be essential to enhance the coherence of regional climate projections. Ultimately, these developments, along with other model inter-comparison projects, will strengthen the ability of coupled regional models to quantify uncertainties on climate, support impact assessments, and inform policymakers about adaptation and mitigation strategies under ongoing climate change.

CHAPTER 4

Assimilation of Wet-Snow Occurrence Observed by Remote Sensing Into a Regional Climate Model

This chapter is adapted from : Dethinne, T., Glaude, Q., Picard, G., Kittel, C., Alexander, P., Orban, A., & Fettweis, X. (2023). Sensitivity of the mar regional climate model snowpack to the parameterization of the assimilation of satellite-derived wet-snow masks on the Antarctic peninsula. *The Cryosphere*, 17 (10), 4267-4288. doi:10.5194/tc-17-4267-2023.

Abstract

Both regional climate models (RCMs) and remote sensing (RS) data are essential tools in understanding the response of polar regions to climate change. RCMs can simulate how certain climate variables, such as surface melt, runoff, and snowfall, are likely to change in response to different climate scenarios, but are subject to biases and errors. RS data can assist in reducing and quantifying model uncertainties by providing indirect observations of the modelled variables on the present climate. In this chapter, we improve on an existing scheme to assimilate RS wet snow occurrence data into the "Modèle Atmosphérique Régional" (MAR) RCM and investigate the sensitivity of the RCM to the parameters of the scheme. The assimilation is performed by nudging the MAR snowpack temperature to match the presence of liquid water observed by satellites. The sensitivity of the assimilation method is tested by modifying parameters such as the depth to which the MAR snowpack is warmed or cooled, the quantity of water required to qualify a MAR pixel as "wet" (0.1 or 0.2 % of the snowpack mass being water), and assimilating different RS datasets. Data assimilation is carried out on the Antarctic Peninsula for the 2019-2021 period. The results show an increase in meltwater production (+66.7 % on average, or +95 Gt), along with a small decrease in surface mass balance (SMB) (-4.5 % on average, or -20 Gt) for the 2019-2020 melt season after assimilation. The model is sensitive to the tested parameters, albeit with varying orders of magnitude. The prescribed warming depth has a larger impact on the resulting surface melt production than the liquid water content (LWC) threshold due to strong refreezing occurring within the top layers of the snowpack. The values tested for the LWC threshold are lower than the LWC for typical melt days (approximately 1.2 %) and impact results mainly at the beginning and end of the melting period. The assimilation method will allow for the estimation of uncertainty in MAR meltwater production and will enable the identification of potential issues in modelling near-surface snowpack processes, paving the way for more accurate simulations of snow processes in model projections.

4.1 Introduction

More than two-thirds of Earth's freshwater is held in the polar ice sheets (Church et al., 2013), with the majority of it trapped as land ice at the south pole, forming the Antarctic Ice Sheet (AIS). According to Fretwell et al. (2013), if all AIS ice were to melt, the global mean sea level would rise by 56 meters. Currently, the AIS is primarily losing mass due to grounded ice flowing into the ocean. There, the ice is lost mainly through a combination of basal melting and calving (The IMBIE Team, 2018; Rignot et al., 2019; Adusumilli et al., 2020).

However, the surface melt production on the ice sheet is also important for several reasons. Even moderate surface melt over the ice shelves, the floating boundaries of the ice sheet, is thought to weaken the shelf structure and to cause ponding and hydrofracturing, leading to substantial mass loss (Scambos et al., 2003; Lai et al., 2020). Additionally, surface melting is becoming a growing concern as it may increase greatly with climate change (Trusel et al., 2015; Bell et al., 2018; Gilbert and Kittel, 2021). Ice shelves exert a buttressing effect on the upstream ice flow,

regulating the amount of ice that reaches the surrounding ocean. As they thin or collapse, this buttressing effect is reduced (Favier and Pattyn, 2015; Paolo et al., 2015), and AIS ice flow velocity and mass loss are increased.

Climate models are currently one of the most useful tools in studying polar climate evolution. Some of them also include the possibility to model the evolution of the snowpack. A notable example is MAR (for “Modèle Atmosphérique Régional” in French), a Regional Climate Model (RCM) specially developed to monitor the polar climate and the surface mass balance of both ice sheets.

Proper surface melt modelling is required to study conditions leading to ice shelf destabilization, as hydrofracturing is impacted by the melting/snowfall ratio as well as the capacity of the snowpack to retain and refreeze meltwater (Donat-Magnin et al., 2021; Gilbert and Kittel, 2021). Additionally, accurate modelling of surface melt is necessary to study the evolution of the snowpack during strong melt events. Studying the ability of the snowpack to retain liquid water is crucial because, under higher melt conditions, the Antarctic snowpack could saturate and stop absorbing surface meltwater in the future, as has been modelled to occur over the Greenland Ice Sheet (Noël et al., 2017).

Despite their ability to capture snowpack melt in a high level of detail, RCMs still have some limitations. Because of uncertainty in forcing, or limitations in physical assumptions, the models may contain significant uncertainties. These uncertainties can be mitigated by employing external data, which are not already incorporated into the model, to improve its accuracy at specific points in space and/or time. This technique is known as “data assimilation” and is commonly applied in numerous fields where observations can be integrated into a model (Evensen, 2009; Navari et al., 2018).

The assimilation of data into the model is a crucial step in quantifying the uncertainties associated with the model output without assimilation. The assimilation process helps to identify areas and periods where the simulations are not consistent with the observations. This can help us to better understand the underlying physical processes and their interactions. Accordingly, data assimilation provides a powerful tool for improving the reliability of models. In our case, it is an essential step in the process of model refinement, leading to improved predictions from future scenarios.

The highly uneven topography of a region is challenging for RCMs, which typically operate at a resolution on the order of 10 kilometres. Phenomena depending on very local conditions, such as melt induced by the Foehn effect, can occur at smaller spatial scales than the spatial resolution of RCMs and thus may not be captured by the model (Datta et al., 2019; Chuter et al., 2022; Wille et al., 2022). However, high-resolution satellites can document localized or extreme events that may be missed by RCM simulations.

In this chapter, we assimilate satellite-derived binary wet-snow masks (wet/non-wet) over the Antarctic Peninsula (AP) in West Antarctica into the MAR model for two melt seasons (2019-2020 and 2020-2021). Three major ice shelves are located on the

AP: Larsen C, George VI, and Wilkins (Fig. 4.1). The ice shelves experience the highest amount of surface melt compared to the other part of the AIS, and their surface hydrological processes are also complex and poorly understood (Barrand et al., 2013; Datta et al., 2018; Johnson et al., 2020). Presently, assimilating remotely sensed products in RCMs is a promising method of quantifying surface meltwater production in Antarctica. The scarcity of field observations and the complexity of surface hydrology (Bell et al., 2018) make it difficult to evaluate and constrain models otherwise.

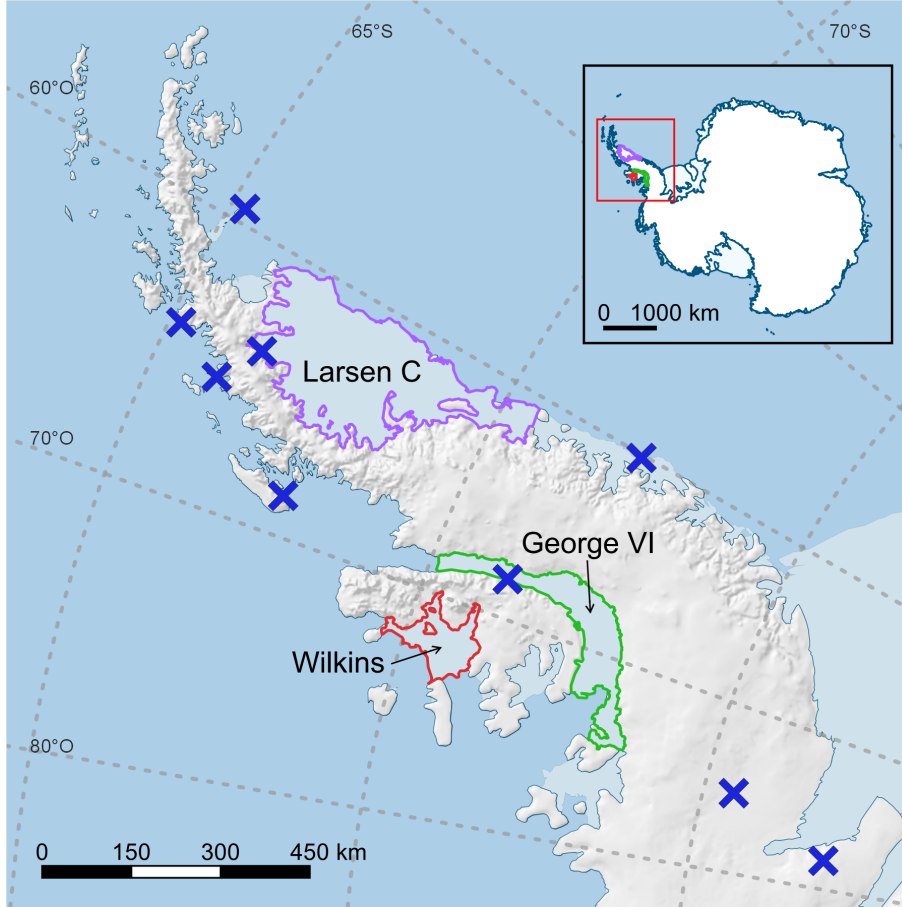


Figure 4.1: The Antarctic Peninsula and three ice shelves examined in this chapter. The ice shelves are denoted by colour outlines. Larsen C is outlined in purple, George VI in green, and Wilkins in red. Blue crosses indicate the position of the weather stations used for the model’s evaluation (Sect. 4.3). The red square around the Antarctic Peninsula corresponds to the MAR spatial extent.

The assimilation algorithm performed in this chapter is derived from the framework described in Kittel et al. (2022b) where the MAR near-surface snowpack is warmed or cooled to best match satellite-derived wet-snow masks. In this chapter, sensitivity experiments have been performed by varying the depth to which the snowpack temperature is changed (called the assimilation depth hereafter), the minimum liquid water content (LWC) threshold used to classify the modelled snowpack state as “wet”, and the wet-snow satellite product to test the sensitivity of the model to the assimilation.

The satellite data, the model, and the assimilation method are presented in Sect. 4.2. The evaluation of the model is described in Sect. 4.3. The results of the data assimilation sensitivity tests are discussed in Sect. 4.4. Finally, general conclusions and discussion on assimilation of remote sensing data into the MAR model are included in Sect. 4.5.

4.2 Methods and Data

4.2.1 Satellite data

Depending on the region of interest, the length of the simulation, or the spatial resolution, the use of one specific satellite dataset over another for assimilation can be useful. However, depending on the sensor type and acquisition times, the derived wet-snow occurrence can differ between satellites and sensors (de Roda Husman et al., 2022). Some sensors operate at a coarser resolution and provide information with higher uncertainty in areas with complex topography, but can provide long time series of daily images using wet snow detection algorithms that have proven to be efficient (Zwally and Fiegles, 1994; Colosio et al., 2021). Other sensors have a better spatial resolution but may have a lower revisit time. The choice of the satellite dataset can thus influence the results of the assimilated model.

We employed three satellite datasets (Table 4.1) to create the binary (dry/wet) snow masks to be assimilated. The three datasets are derived from sensors operating in the microwave spectrum (at GHz frequencies). Among them, AMSR2 is a "passive sensor", which records Earth's natural radiation, while the other two are classified as "active" since they actively emit electromagnetic pulses to illuminate the area covered by the satellite. Microwave sensors are commonly used to map snow cover, sea ice, or wet snow extent over ice sheets (Parkinson, 2001; Colosio et al., 2021). The presence of liquid water in the snowpack induces a change in its emissivity and absorptivity. This change leads to a change in the satellite measurements: the backscattering coefficient σ_0 for active sensors and the brightness temperature for passive sensors (Zwally and Fiegles, 1994; Johnson et al., 2022; Picard et al., 2022). In this chapter, the presence of wet snow detected by satellites is interpreted as the presence of liquid water underneath or at the surface of the snowpack. Using microwave data also brings other advantages such as atmospheric transparency and acquisitions during both day and night. However, the lower spatial resolution of passive microwave sensors (generally 10 to 50 km) compared with active sensors (10m-5km) is problematic in identifying small-scale melting (Datta et al., 2018). Finally, with pixels of $\sim 100 \text{ km}^2$ (e.g., for AMSR2 - See Table 4.1), a majority of the pixels cover regions with sub-pixel variations in land cover or surface height (Johnson et al., 2020).

Advanced Microwave Scanning Radiometer 2 (AMSR2)

The first dataset employed in this chapter is from the Advanced Microwave Scanning Radiometer 2 (AMSR2) aboard the Global Change Observation Mission - Water "SHIZUKU" (GCOM-W1) retrieved from the Japan Aerospace Exploration Agency

Table 4.1: Technical specifications of the remote sensing datasets employed for the assimilation. Datasets are referred to by the name in bold characters in the paper

Platform	Sensor	Sensor type	Pixel size	Frequency (GHz)	Revisit time (days)	Reference
Sentinel-1 (S1)	C-SAR	Active	10-40m	5.405	6	ESA (2023)
Metop	ASCAT	Active	4.45km	5.255	1	EUMETSAT (2023)
GCOM-W1	AMSR2	Passive	10km	18.7	2	JAXA (2021)

(JAXA) G-Portal (JAXA, 2021). Thanks to a sun-synchronous orbit at an altitude of 700 km and a large swath, AMSR2 obtains low-resolution daily observations of the polar regions. We used the level-3 products containing the daily mean brightness temperature at a horizontal polarization in the 18.7 GHz channel, resampled at a 10 km resolution. The 18.7 GHz channel is used as it is slightly more sensitive to liquid water content than the other frequencies (Picard et al., 2022). Ascending (south to north) and descending (north to south) satellite paths were processed separately, as they respectively happen in the morning and in the evening. The separate processing allows for the creation of two daily wet-snow masks from one instrument. Wet-snow detection with AMSR2 is based on a change in the snowpack physical properties (Zwally and Fiegles, 1994). A dry snowpack has a lower emissivity (ϵ) than a wet snowpack (Mätzler, 1987). For the passive microwave sensors, this increased emissivity is observed through augmentation of brightness temperature (Johnson et al., 2020).

The wet-snow retrieval technique applied for this study is a statistical approach developed by Fahnestock et al. (2002) and modified by Johnson et al. (2020). The wet-snow detection is performed through a K-means clustering algorithm. The algorithm is applied to the annual time series of brightness temperature. Wet snow is assumed when the time series shows a binomial distribution, using the criteria and thresholds defined in Johnson et al. (2020) (Fig. 4.2).

To ensure coherency between remote sensing products and our climate model, the wet-snow masks are interpolated onto the MAR grid. This involves overlaying the grids and assigning the wet/dry state for each MAR pixel based on the most prevalent surface condition observed in the satellite pixels encompassed within the MAR pixel. This interpolation is made with the assumption that deformation and variations in the area caused by the spatial projection are negligible between a pixel and its neighbours.

Sentinel-1 (S1)

One of the active sensor datasets is retrieved from the Sentinel-1 (S1) satellite constellation from the European Space Agency’s (ESA) Copernicus space program. Starting with the launch of S1-A in 2014, the Sentinel-1 constellation gives access to data combining high spatial resolution and low revisit time covering most of the globe. With the Synthetic Aperture Radar (SAR) technology, S1 products reach a spatial resolution on the order of tens of meters with a repeat pass of 6 days. By combining different orbital paths, it is possible to reduce the time between two observations of the same location to 2-3 days over the Antarctic Peninsula. Working in the C-band (5.405 GHz), it is possible to detect the presence of liquid water

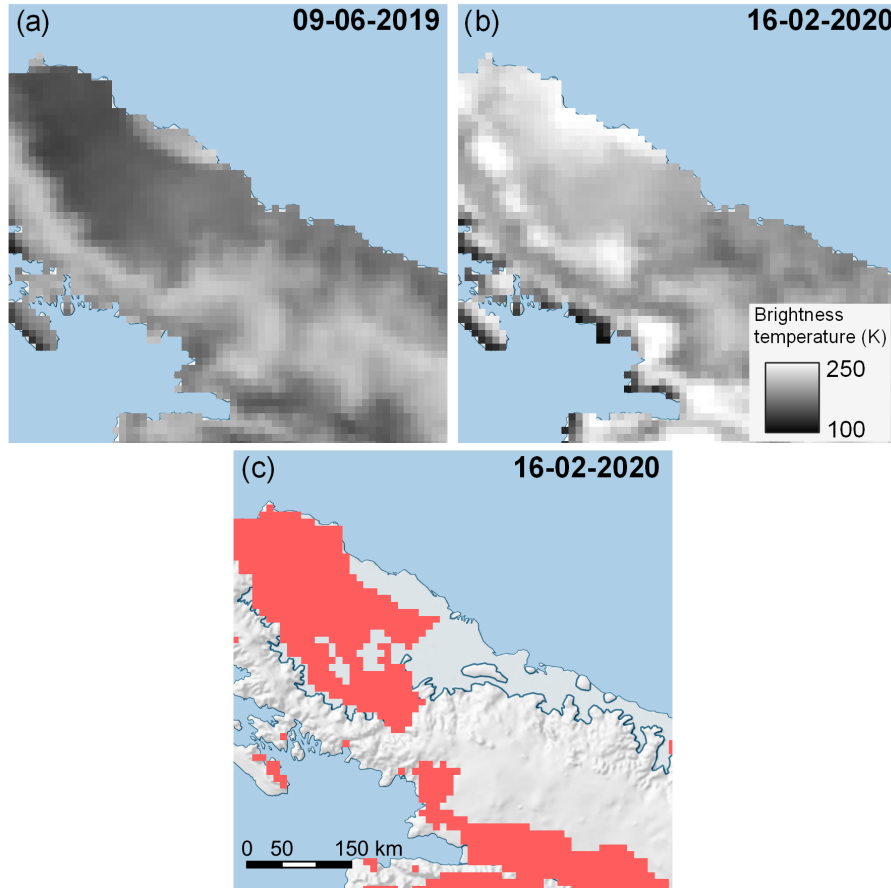


Figure 4.2: Detection of wet snow in an AMSR2 image over the Antarctic Peninsula. (a) Brightness temperature (K) on June 9th, 2019. (b) Brightness temperature (K) on February 16th, 2020. (c) Pixels considered to contain wet snow after applying the wet-snow detection algorithm. The increase in brightness temperature between (a) and (b) is attributed to the presence of liquid water in the snowpack.

in the snowpack in Sentinel-1 images by identifying changes in the backscattering coefficient σ_0 through time (Johnson et al., 2020). With the increase in liquid water in the snowpack, comes a change in absorptivity and scattering mechanism (Nagler and Rott, 2000). These phenomena both lead to a decrease in σ_0 (Moreira et al., 2013). As this coefficient changes little in Antarctica as long as the snowpack is dry, it is assumed that a significant change in backscattering is likely caused by the presence of water in the snowpack.

As for the passive sensors, several algorithms have been proposed to detect water in the snow with SAR and active sensors in general. Depending on the polarization, the frequency, and the nature of the snowpack, the threshold applied to the backscattering values is variable (Koskinen et al., 1997; Nagler et al., 2016). For a C-band radar, a 3-dB decrease in σ_0 has been employed as a threshold by Nagler and Rott (2000) and Johnson et al. (2020). In the present article, we used a -2.66 dB threshold after normalization of the images to their winter mean as the threshold to classify the snowpack as dry or wet. This threshold has been proposed by Liang et al. (2021) and was found to be effective for the Antarctic ice sheet.

To minimize the time between two Sentinel-1 acquisitions, all available images overlapping the study region were processed. To handle the large amount of data, image processing was carried out on Google Earth Engine (GEE, Gorelick et al., 2017). The S1 dataset available on GEE is already preprocessed following the implementation of the Sentinel-1 Toolbox from ESA (GEE, 2022; ESA, 2022). These processing operations include an update of the orbit metadata, removal of the low-intensity noise on the scene edges, a reduction of the discontinuities between sub-swaths, a radiometric calibration, and a terrain correction using the ASTER digital elevation model. The choice has been made to resample S1 images from the original 10-40 m resolution to a 1 km resolution using mean values before detecting wet snow as data is ultimately interpolated onto the 7.5 km MAR grid. Before resampling, a 3x3 refined Lee speckle low-pass filter developed by Mullissa et al. (2021) was applied to the images in addition to a radiometric terrain flattening using the 1 arc-minute global ETOPO1 DEM (Amante and Eakins, 2009). Pixels with values lower than -28 dB were removed from the dataset.

After resampling, the images are normalized to their austral winter mean. The winter mean is the average value of σ_0 for each pixel, calculated using observations from June to October. To deal with changes in volumetric scattering related to the acquisition geometry, only the acquisitions from the same orbit overlapping by more than 95 % are taken into account to calculate the winter mean. Consequently, differences between the acquisitions are independent of the topography and the local context. The liquid water in the snowpack is then detected in the image by applying a -2.66 dB threshold (Fig. 4.3), following Liang et al. (2021).

To create daily wet-snow masks, Sentinel-1 images collected on the same day were combined. In the case where three or more images overlap, the snow state is selected by a majority filter, and the acquisition time is defined as the mean time between the selected acquisitions. In the case where there are only two images that contradict each other, a non-wet status is assumed. The acquisition time selected is the acquisition time of the non-wet image.

Advanced Scatterometer (ASCAT)

The third sensor we are using for this chapter is the C-band “Advanced Scatterometer” (ASCAT) aboard the MetOp satellites from the space segment of the EUMETSAT Polar System. ASCAT data are retrieved from the EUMETSAT data service portal (EUMETSAT, 2023). After resolution enhancement (Lindsley and Long, 2016), the product provides a backscattering coefficient σ_0 at 4.45-km resolution by accumulating images over ~ 2 day periods. In Antarctica, only morning passes are selected for this study. The detection of wet snow is performed using a simple thresholding technique (Ashcraft and Long, 2006), similar to the one used for Sentinel-1 images. The winter-mean backscattering coefficient is first calculated for each pixel and year from the observations from June-August. Then every measurement lower than this mean by 3 dB is considered wet snow. Similarly to AMSR2 daily products, the Sentinel-1 and ASCAT daily wet/dry images are interpolated onto the MAR grid.

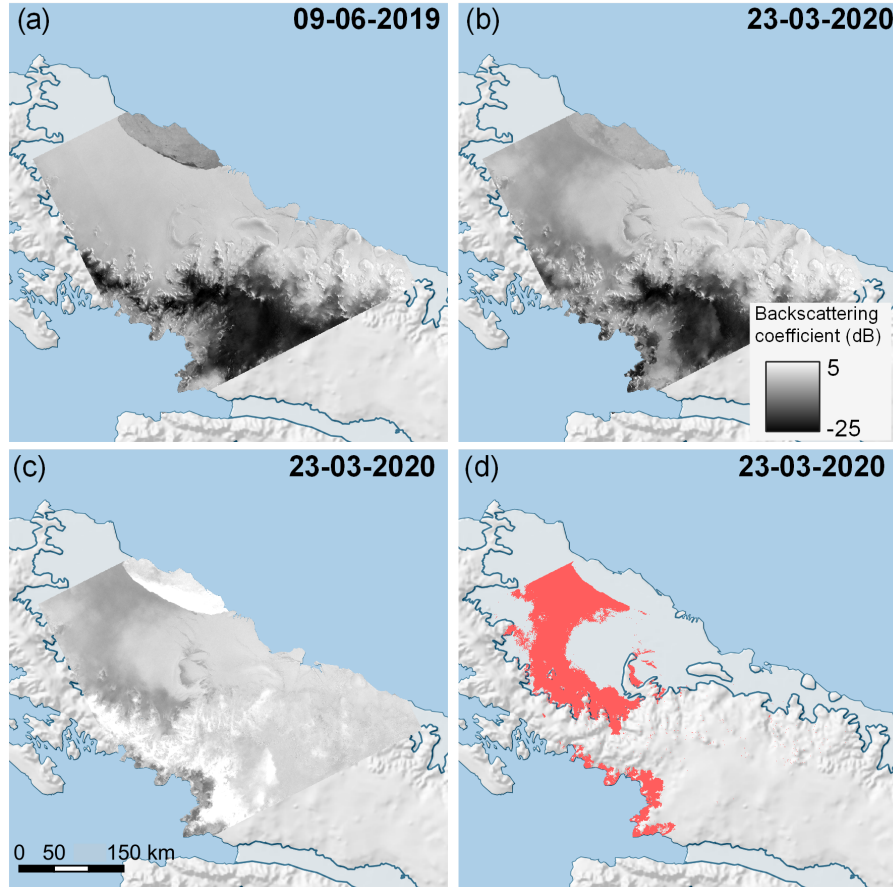


Figure 4.3: Detection of wet snow in a Sentinel-1 image over the Antarctic Peninsula. (a) Backscattering coefficient σ_0 (dB) on June 9th, 2019. (b) Backscattering coefficient σ_0 (dB) on 23rd March, 2020. (c) Normalized backscattering coefficient of 23rd March, 2020, relative to the winter mean. (d) Pixels considered to be wet snow after thresholding the normalized image. The decrease in backscatter between (a) and (b) is attributed to the presence of liquid water in the snowpack.

In the end, from the three satellite datasets, four binary masks have been created. One from Sentinel-1, one from ASCAT, and two from AMSR2, obtained by separating the ascending (evening) and the descending (morning) passes.

4.2.2 Regional climate model

For this chapter, we employed the MAR v3.12 RCM. MAR is a polar-oriented regional climate model mostly used to study both the Greenland (Delhasse et al., 2020; Fettweis et al., 2021) and Antarctic ice sheets (Glaude et al., 2020; Kittel et al., 2021). Its atmospheric dynamics are based on a hydrostatic approximation of primitive equations originally described in Gallée and Schayes (1994) and the radiative transfer scheme is adapted from Morcrette (2002). The transfer of mass and energy between the atmospheric part of the model and the soil is handled by the Soil Ice Snow Vegetation Atmospheric Transfer module (SISVAT; De Ridder and Gallée, 1998), from which snow and snow/ice albedo sub-modules are based on the CROCUS snow model (Brun et al., 1992). The model has been parametrized to resolve the top 20 meters of the snowpack, divided into 30 layers of time-varying

thickness. MAR is configured with a decreasing vertical resolution of the snow layers from the top to the bottom. The maximum thickness of near-surface layers is on the centimetre scale, while below the first meter, the maximum thickness is on the order of 1 m. The maximum layer thicknesses for the top four snow layers are for example respectively 2, 5, 10, and 30 cm. Each layer has a maximum liquid water content (LWC) of 5 % of its air content beyond which the water freely percolates to deeper layers or runs off above impermeable layers (bare ice or ice lenses) (Coléou and Lesaffre, 1998).

Version 3.12 of MAR includes recent improvements in the snowpack temperature and the water mass conservation in the soil as described in Lambin et al. (2022). MAR was run at a 7.5 km resolution over the Antarctic Peninsula, with a 40-second time step, with the spatial extent of the simulations corresponding to the extent of Figure 4.1. It was forced at its lateral boundaries and over the ocean (sea surface temperature and sea ice cover) by the 6-hourly ERA5 reanalysis (Hersbach et al., 2020) between March 2017 and May 2021. The snowpack was initialized in March 2017 with a previous MAR simulation (Kittel et al., 2021). The blowing snow module of MAR is not used in this study, and snow drift is therefore not represented in the simulation.

4.2.3 Data assimilation

The satellite sensors are sensitive to the presence of liquid water into the snowpack rather than the physical process of melt. The aim of the data assimilation is therefore to guide or constrain the snowpack LWC of the model by nudging its temperature to induce melt or refreeze to match the observed surface state (Fig. 4.4).

The assimilation routine involves comparing, pixel by pixel, the modelled and the satellite wet-snow masks. The satellite wet-snow mask pixel is used for the assimilation if the indicated acquisition time is separated by less than 1.5 hours from the time in MAR (1.5 hours before and after the MAR time). The three-hour window enables the model to adapt its behaviour, but with limited short-term impact. As up to three satellite products are assimilated at the same time, three separate cases have been developed depending on the number of assimilated masks. Each case is called according to the number of acquisitions that are taken into account. However, a daily cycle in brightness temperature and thus in wet snow can exist over Antarctica (Picard and Fily, 2006). To take this into account, if there are 3 satellite observations available for a pixel for a single day, an observation of dry snow between two wet-snow observations is considered as a false negative. Consequently, the corresponding dry-snow pixel is excluded for the day. For computational reasons, the assimilation routine is called at each MAR time step only during the melting season, between October and April. Outside of this timeframe, no assimilation is performed for computational constraints and the likely prevalence of shorter-duration melting events during winter. These events are commonly related to Foehn effects near the grounding line (Kuipers Munneke et al., 2018) where the effectiveness of passive sensors decreases.

The first case of assimilation represents the situation where a single acquisition is

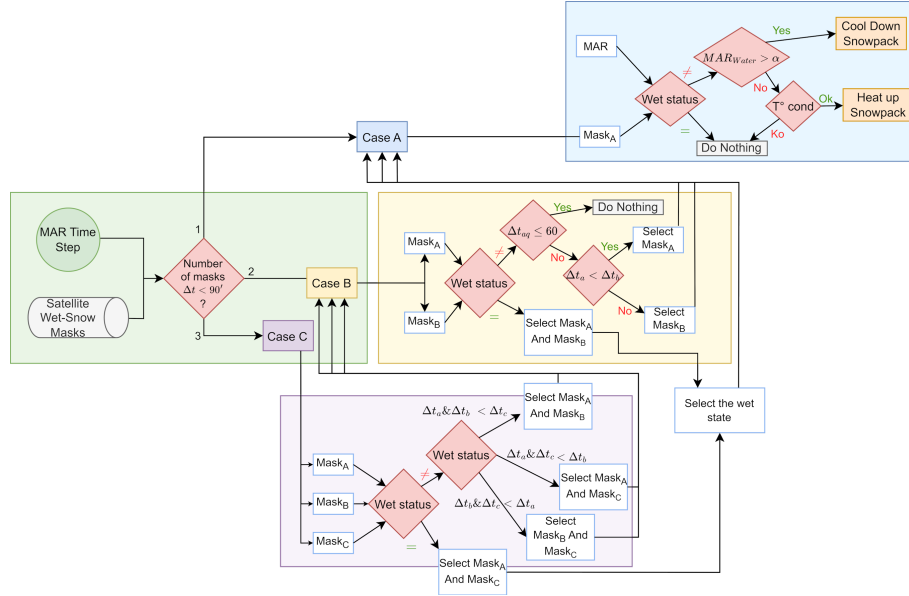


Figure 4.4: Flowchart of the assimilation algorithm. The number of satellite images available around the MAR time step determines the subprocess that is called in the routine. Three subprocesses are defined: case A, case B, and case C. They respectively represent the availability of 1, 2, and 3 wet-snow masks for assimilation. Cases B and C are funnelled to case A so that no contradictory information is passed into MAR.

available for a timestep (case "A" in Fig. 4.4). It is the most frequent case applied (between 90 and 95 % of the occurrence depending on the year). This case is inspired by the assimilation performed in Kittel et al. (2022b). For the 3 hours centred on the observation, at each MAR time step, the quantity of liquid water modelled within the pixel is compared to the satellite-based wet/snow condition for the same pixel. If the modelled LWC of the snowpack is under a certain threshold (α) while the satellite mask indicates wet snow, the snow layers up to a certain depth (Δ_z) are heated by 0.15°C if the snow layers are colder than 0°C . In the opposite case, if the LWC is above the threshold α but no wet snow is observed by satellites, the snowpack is cooled by the same amount of 0.15°C . The process is applied at each MAR time step for which the conditions apply. However, two conditions prevent changes in the MAR snowpack temperature. The first is that if the snow density is above 830 kg m^{-3} , the layer is considered to be ice and the model does not permit liquid water to accumulate within ice. The temperature in this case remains unchanged as the LWC threshold should never be reached. The second condition is the temperature of the snow layers above the depth Δ_z . If their mean temperature is below -7.5°C , the MAR snowpack is too cold to be able to produce meltwater through warming, and the satellite observation is ignored. This operation is repeated at each timestep for which MAR and observations disagree until the α threshold is reached or the observation is out of the time range. The choices for thresholds α and Δ_z are discussed in the two following sections.

The second assimilation case (case "B" in Fig. 4.4) occurs when there are only two satellite observations within the 3-hour window centred on the MAR time. If the two satellite-derived observations agree, MAR is adjusted according to the observed snow state as in case "A" but with a depth Δ_z equivalent to the mean values of the

thresholds that would have been used for the individual satellite-derived masks. If the two observations indicate different snow states, a different processing is applied if the acquisitions are close to each other in time (within an hour) or not. For two inconsistent observations spread by more than one hour, the assimilated snow state is the snow state from the closest image to the MAR time, following the first case (Case "A"). For two close contradictory observations, nothing is assimilated as they are considered both equally likely to be correct or incorrect. Valuable information may be lost in this case. For instance, the difference in penetration depth can cause a deeper penetrating signal to observe liquid water (Fig. 4.5). However, as we have no additional information on the depth at which the water may be present, in this case the model is run as if there was no observation available.

The third case is when all three observations are available within the same 3-hour time window (case "C" in Fig. 4.4). As for the second case, if the three observations agree with the same wet/non-wet snow status, they are considered as one and Case "A" is called. Again, the depth Δ_z used is equivalent to the mean values of the thresholds that would have been used separately. If a single observation is different from the other two, the two closest observations to the MAR time are analysed, applying Case "B" described above. For our configuration of sensors, this third case is only encountered a couple of times (less than 1 % of all occurrences) while assimilating wet-snow masks of AMSR2 (ascending orbit), ASCAT, and Sentinel-1.

Choice of water content threshold (α)

Estimating the quantity of liquid water in the snowpack with a single satellite acquisition is challenging. Despite numerous research studies, knowledge on the subject remains limited (Trusel et al., 2013; Fricker et al., 2021). However, as described in Picard et al. (2022), it is possible to find a typical LWC for which the satellite signal significantly changes and can be detected as melting/wet snow. Picard et al. (2022) demonstrates the capability of detecting small amounts of water using the radio frequencies employed in this study. Only 0.11 and 0.05 kg m⁻² of liquid water is necessary at respectively 6 GHz and 19 GHz if the water is uniformly spread over the pixel. This quantity can be higher for heterogeneous pixels containing dry/wet patches. For this study, the choice has been made to use the same threshold regardless of the sensor frequency. AMSR2 acquires data at higher frequencies and is theoretically more sensitive, but it has a coarser resolution than the two active sensors. Its pixels tend to be more heterogeneous, suggesting a compensation with regard to liquid water quantity. Two different thresholds are tested to study the sensitivity of the model. Both have been shown to significantly change the snowpack brightness temperature in the literature. Tedesco et al. (2007) proposed a LWC threshold of 0.2 % while Picard et al. (2022) proposed a threshold of 0.1 % of the snowpack mass. They have both been tested in Kittel et al. (2022b) where the choice between the two was found not to significantly influence the melt quantity produced by the MAR model. The sensitivity of the microwave sensors is high enough that the quantities of liquid water that can be detected are much smaller than that produced during a typical melting day ($1.2 \pm 0.6\%$ as modelled by MAR over the studied zone in the top meter of snow). Currently, there is no means of identifying the best-fitting threshold for this study.

Choice of assimilation depth threshold (Δ_z)

Microwaves have penetration capabilities directly related to their wavelength (Elachi and van Zyl, 2006). As a consequence, the C-band from Sentinel-1 and ASCAT has a different penetration depth than Ku-band from AMSR2. In addition, the water content strongly influences the penetration depth, as water at the top of the snowpack can prevent deeper penetration (Fig. 4.5). In this experiment, we set different penetration depths for each remote-sensing product to test its influence. Using AMSR2 (Ku-band), we consider an assimilation depth $\Delta_z = 0.1, 0.2$, and 0.4 m successively below the surface. Below this depth, the electromagnetic wave should not have a noticeable influence (Picard et al., 2022). For Sentinel-1 and ASCAT (C-band), the depth thresholds Δ_z are set to $0.5, 1$, and 1.5 m, as the signal is expected to penetrate deeper in the snowpack.

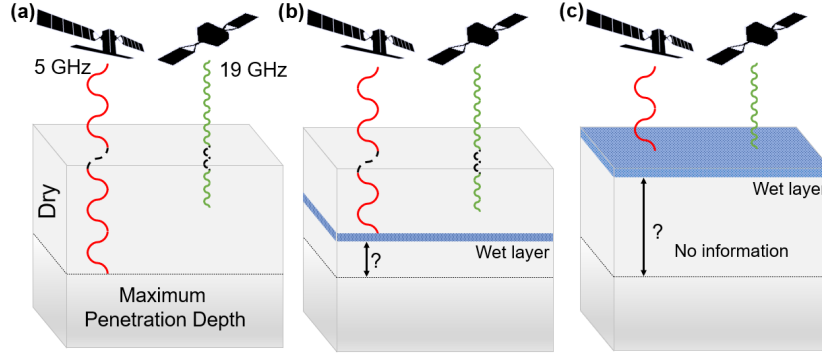


Figure 4.5: Illustration of the penetration depth of the microwave sensor according to their wavelength and the depth of the wet snow layer. (a) Penetration depth in a dry snowpack. The signal of the sensor with the lower frequency (5 GHz, in red) penetrates deeper than the signal of the higher frequency sensor (19 GHz, in green). (b) Penetration depth with a layer of liquid water deep in the snowpack. The microwave sensor with deeper penetration can detect water presence but the other cannot. (c) Penetration depth with liquid water at the top of the snowpack. Both satellites can observe the presence of liquid water.

Experiments conducted

An ensemble of 24 MAR simulations is presented here. Only the reference MAR simulation, MAR_{ref} , is performed without assimilation. The others are referred to as “assimilations” hereafter. Their naming convention is “ As ” followed by A and the value of the α threshold in the subscript (in %), the RS datasets assimilated, and their corresponding Δ_z threshold value in the subscript (in m). “ $S1$ ” refers to the S1 dataset, “ AMA ” to AMSR2 ascending, “ AMD ” to AMSR2 descending, and “ AS ” to ASCAT. The assimilations were started in January 2019, and have been initialized from the simulation without assimilation (which begins in 2017). For each assimilation, the satellite wet-snow masks are assimilated into the model, with different parameters for the α threshold and C-band and Ku-band Δ_z thresholds (Table 4.2). The reference assimilation ($Assim_{ref}$) is performed using Sentinel-1

Table 4.2: The different simulations performed in this chapter, including data assimilation parameters. When not specified, both ascending and descending paths of AMSR2 are assimilated. Simulations marked with an asterisk, and those with assimilation of only one sensor are not taken into account in the calculation of the ensemble average.

Name	α (%)	Ku-band Δ_z (m)	C-band Δ_z (m)	Sensors
<i>Assim_{ref}</i>	0.1	0.2	1	AMSR2 + S1
<i>AsA₀₁S1₀₅AMA₀₂AMD₀₂</i>	0.1	0.2	0.5	AMSR2 + S1
<i>AsA₀₁S1₁₅AMA₀₂AMD₀₂</i>	0.1	0.2	1.5	AMSR2 + S1
<i>AsA₀₂S1₁₀AMA₀₂AMD₀₂</i>	0.2	0.2	1	AMSR2 + S1
<i>AsA₀₂S1₀₅AMA₀₂AMD₀₂</i>	0.2	0.2	0.5	AMSR2 + S1
<i>AsA₀₂S1₁₅AMA₀₂AMD₀₂</i>	0.2	0.2	1.5	AMSR2 + S1
<i>AsA₀₁S1₁₀AMA₀₁AMD₀₁</i>	0.1	0.1	1	AMSR2 + S1
<i>AsA₀₁S1₀₅AMA₀₁AMD₀₁</i>	0.1	0.1	0.5	AMSR2 + S1
<i>AsA₀₁S1₁₅AMA₀₁AMD₀₁</i>	0.1	0.1	1.5	AMSR2 + S1
<i>AsA₀₂S1₁₀AMA₀₁AMD₀₁*</i>	0.2	0.1	1	AMSR2 + S1
<i>AsA₀₂S1₀₅AMA₀₁AMD₀₁*</i>	0.2	0.1	0.5	AMSR2 + S1
<i>AsA₀₂S1₁₅AMA₀₁AMD₀₁*</i>	0.2	0.1	1.5	AMSR2 + S1
<i>AsA₀₁S1₁₀AMA₀₄AMD₀₄</i>	0.1	0.4	1	AMSR2 + S1
<i>AsA₀₁S1₀₅AMA₀₄AMD₀₄</i>	0.1	0.4	0.5	AMSR2 + S1
<i>AsA₀₁S1₁₅AMA₀₄AMD₀₄</i>	0.1	0.4	1.5	AMSR2 + S1
<i>AsA₀₂S1₁₀AMA₀₄AMD₀₄</i>	0.2	0.4	1	AMSR2 + S1
<i>AsA₀₂S1₀₅AMA₀₄AMD₀₄</i>	0.2	0.4	0.5	AMSR2 + S1
<i>AsA₀₂S1₁₅AMA₀₄AMD₀₄</i>	0.2	0.4	1.5	AMSR2 + S1
<i>AsA₀₁S1₁₀AMA₀₂AS₀₂</i>	0.1	0.2	1	AMSR2 (asc.) + S1 + ASCAT
<i>AsA₀₁AMA₀₂</i>	0.1	0.2	/	AMSR2 (asc.)
<i>AsA₀₁AMD₀₂</i>	0.1	0.2	/	AMSR2 (desc.)
<i>AsA₀₁S1₁₀</i>	0.1	/	1	S1
<i>AsA₀₁AS₁₀</i>	0.1	/	1	ASCAT
<i>MAR_{ref}</i>	/	/	/	None

and AMSR2, with both their ascending and descending orbits, and with assimilation depth thresholds $\Delta_z = 1$ m and 0.2 m respectively. Also, the liquid water content threshold α is set at 0.1 %. The thresholds used to perform *Assim_{ref}* correspond to values given in the literature (Elachi and van Zyl, 2006; Picard et al., 2022). The other assimilated simulations have been performed with a combination of 3 satellite products chosen between Sentinel-1, AMSR2 ascending, AMSR2 descending, and ASCAT, and with a combination of the assimilation parameters. The assimilations have been performed for the period June 2019 to May 2020, and June 2020 to May 2021. The present document focuses on the 2019-2020 melt season, while figures for the 2020-2021 season are available in the appendix B.

4.3 Evaluation

Because the integrated physics within RCMs is either partially resolved or contains uncertainties, it is first required to evaluate model outputs against in situ measurements. The evaluation is performed in order to quantify how close the model is to reality and to determine if the model is inclined to reproduce the observations. Since our focus is on assessing the model sensitivity through assimilation, we exclusively evaluate MAR without assimilation. It is worth noting that the values derived from the assimilations may diverge from the observations due to the assimilation algorithm sensitivity rather than the model physics.

The outputs of the model simulation without assimilation are evaluated by comparing with in situ observations. The daily observations are provided by Automatic Weather Stations (AWS) spread across the AIS. Here, 9 AWS datasets available in the study area (blue crosses displayed in Fig. 4.1) have been gathered to calculate statistics for the model vs. the observations as done in Kittel (2021) and Mottram et al. (2021). The statistics employed for the evaluation are the Mean Bias (MB), Root Mean Square Error (RMSE), Centered Root Mean Square Error (CRMSE), and correlation coefficient (r) (Table 4.3). The statistics are listed for the 2016-2021 period for the near-surface pressure, temperature, wind speed, relative humidity, and modelled energy-balance components, including shortwave downward radiation (SWD), shortwave upward radiation (SWU), longwave downward radiation (LWD), and longwave upward radiation (LWU).

Small biases can occur in the comparison as a result of the elevation difference between the in situ observations and the model. The AWS observations are point measurements, whereas the model provides information over a $7.5 \times 7.5 \text{ km}^2$ pixel. Thus the mean elevation of the MAR pixel in which the AWS falls is not the same as the AWS true elevation. This difference is particularly noticeable for the near-surface pressure, which is directly linked to the elevation. Nonetheless, a high correlation ($r > 0.98$) reflects the ability of MAR to simulate the observed temporal variability.

In general, the winter season is slightly better represented by MAR with higher correlations and lower mean bias than the summer season. A weaker correlation is observed in summer for longwave downward radiation ($r = 0.65$). This difference is compensated for by an overestimation of shortwave downward solar radiation in summer. MAR does not assimilate observed temperature profiles or coastal temperatures but is forced at its lateral boundaries and at the sea surface every 6h with specific humidity, wind, sea surface temperature and temperature. Thus, modelled clouds are strongly influenced by the internal model climate and microphysics (Delhasse et al., 2020). Moreover, the radiative scheme implemented in MAR is the scheme employed by the ERA-40 reanalysis. This scheme has been updated in the ERA-5 reanalysis (Hersbach et al., 2020) but not in MAR. MAR also tends to underestimate the liquid water path during summer when compared to Cloudsat-CALISPO estimates described in (Van Tricht et al., 2016). This underestimation is partially responsible for the LWD bias in summer.

In addition, Jakobs et al. (2020) provide melt estimates from the AWS which can be compared to the surface melt production of the four closest MAR pixels to the AWS (Figure 4.6). MAR tends to overestimate some extremes in meltwater production, but also tends to underestimate melt during low-melt seasons. There are also differences in the length of the melt season, with MAR sometimes overestimating and sometimes underestimating the duration of the season. Although the difference in altitude between the AWS and MAR pixels may explain some of the differences between the two datasets, these discrepancies also highlight the importance of nudging MAR to better reproduce the remote sensing observations of the snowpack state.

Table 4.3: Mean Bias (MB), Root Mean Square Error (RMSE), Centered Root Mean Square Error (CRMSE), and correlation between MAR and daily observations over the Antarctic Peninsula. A negative value implies a lower MAR estimate compared to the observation. Statistics are given for the near-surface pressure, temperature, wind speed, relative humidity, shortwave downward (SWD), shortwave upward (SWU), longwave downward (LWD), and longwave upward (LWU) radiation annually, for the summer (DJF) and winter (JJA) seasons, and are calculated for the 2016- 2021 period. During winter, incoming solar radiation is absent, and therefore shortwave solar radiation estimates (SWD and SWU) are not provided. Locations of the weather stations used for the daily observations are marked by blue crosses in Fig. 4.1.

	Annual				Summer				Winter			
	MB	RMSE	CRMSE	Correlation	MB	RMSE	CRMSE	Correlation	MB	RMSE	CRMSE	Correlation
Near Surface Pressure (hPa)	-5.44	14.57	1.25	0.99	-5.69	13.18	0.87	0.99	-6.13	16.09	1.42	0.99
Temperature ($^{\circ}\text{C}$)	-0.32	3.32	2.81	0.93	-1.13	2.36	1.68	0.76	0.3	3.63	3.11	0.92
Wind speed (m s^{-1})	-0.39	2.58	2.28	0.79	-0.43	2.22	1.85	0.7	-0.35	2.92	2.57	0.78
Relative humidity (%)	3.2	8.73	8.13	0.72	6.88	9.32	6.29	0.75	2.87	9.1	8.64	0.79
SWD (W m^{-2})	13.87	36.23	33.46	0.97	41.58	59.21	42.15	0.79	/	/	/	/
SWU (W m^{-2})	-0.2	24.04	24.04	0.97	14.38	35.81	32.8	0.78	/	/	/	/
LWD (W m^{-2})	-14.75	26.15	21.59	0.76	-26.56	32.51	18.75	0.65	-7.12	21.08	19.85	0.81
LWU (W m^{-2})	3.4	14.2	13.79	0.93	-0.52	9.2	9.19	0.76	2.83	17.12	16.88	0.9

4.4 Results

Table 4.4 provides a comprehensive summary of the results obtained from the 24 MAR simulations. The summary includes the number of melt days (i.e., the number of days where melt is occurring over at least 10 % of the ice sheet and ice shelves of the study area), surface melt (ME), runoff (RU), refreezing (RZ), and the surface mass balance (SMB). This table offers a concise overview of the simulation results. We analyzed the evolution of several variables in order to assess the sensitivity of the MAR model to the assimilation, including ME, RU, SMB, snowpack density (ρ), and liquid water content (LWC) (Table 4.5). The first 3 variables (ME, RU, and SMB) are provided for the entire snowpack profile while ρ and LWC are provided for the first meter. The average value of the variables across all assimilations, $\overline{Assim}$, is compared to the model simulation without assimilation (MAR_{ref}). Although $\overline{Assim}$ differs from the reference assimilation, $Assim_{ref}$ is the closest simulation to $\overline{Assim}$. Three simulations have been discarded to calculate $\overline{Assim}$ because of an unrealistic freeze/thaw cycle induced by the assimilation. These simulations are marked with an asterisk in Table 4.2 and 4.4. So as not to incorporate bias from a single wet-snow mask, simulations assimilating only one wet-snow mask are also omitted in the calculation of $\overline{Assim}$.

On average, the wet-snow extent provided by the wet-snow masks is larger than the extent modelled by MAR_{ref} on the Antarctic Peninsula. This difference impacts the meltwater production in the model. Regardless of the parametrisation used for the assimilation, the surface meltwater production is increased compared to MAR_{ref} (Table 4.5), leading to a cumulative meltwater production increase of 66.7 % for $\overline{Assim}$ over the year.

Meltwater that is produced within the snowpack will eventually either refreeze or run off, depending on the saturation level and thermal condition of the snowpack. The snowpack can saturate, either from excess meltwater production or from densification. If the MAR snowpack LWC exceeds 5 % of the firn air content (the

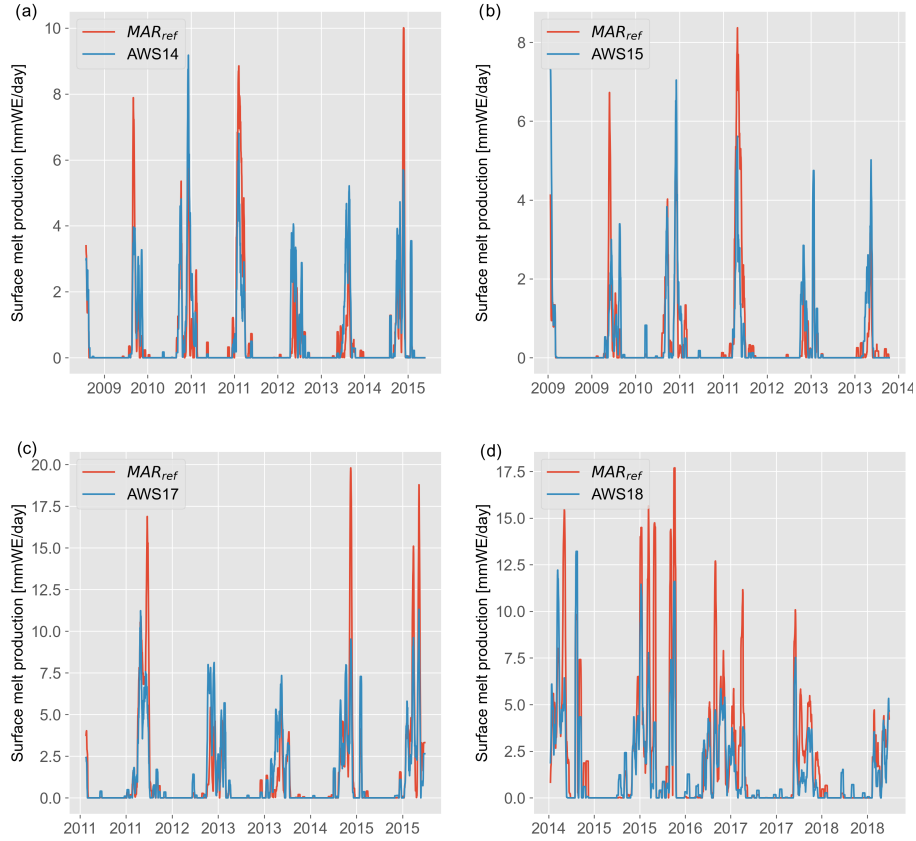


Figure 4.6: Comparison of surface meltwater production (mmWE day^{-1}) as modelled by MAR_{ref} (in red) and estimated surface meltwater production from AWS stations (a) 14, (b) 15, (c) 17, and (d) 18 (in blue), described in Jakobs et al. (2020).

irreducible water saturation), the excess water starts to percolate to deeper layers and run off. The evolution of runoff is thus directly related to the evolution of melt and the snowpack saturation level (Fig. 4.7). Therefore, the relative increase in surface melt for $Assim$ relative to MAR_{ref} (67.7%) is similar to the relative increase in runoff (63.8%), but their absolute increase in Gt yr^{-1} is different ($+95 \text{ Gt yr}^{-1}$ and $+21 \text{ Gt yr}^{-1}$, respectively).

The difference between the increase in meltwater production and the increase in runoff corresponds to an increase in refreezing, with a similar percentage change over the entire domain. This suggests that the snowpack can still absorb liquid water and convert it into refrozen ice in our simulations unless it reaches its maximum LWC. However, as discussed further below, the strongest increase in runoff occurs together with firn air content depletion over the ice shelves. In this case refreezing is large enough to substantially deplete the firn air content leaving less storage space for liquid water in the perennial snowpack (Banwell et al., 2021).

As can be seen in Fig. 4.8, the data assimilation only has a slight effect on the overall SMB. The SMB expression is defined as the sum of the ablation terms (runoff, evaporation, and sublimation) and accumulation terms (snowfall and rainfall). The cumulative SMB for the 2019-2020 melt season is only decreased by 4.5 % compared to the model without assimilation. The general trend in SMB remains positive

Table 4.4: Summary of the results of the different experiments conducted for the study. The number of melt days, cumulated surface meltwater, runoff, refreeze, and surface mass balance over the 2019-2020 melt season are provided for each experiment for the entire MAR spatial extent, excluding ocean areas.

Simulation	# melt days	ME (Gt yr ⁻¹)	RU (Gt yr ⁻¹)	RZ (Gt yr ⁻¹)	SMB (Gt yr ⁻¹)
<i>Assim_{ref}</i>	121	214	56	182	427
<i>AsA₀₁S₁₀₅AMA₀₂AMD₀₂</i>	123	214	55	181	429
<i>AsA₀₁S₁₁₅AMA₀₂AMD₀₂</i>	121	213	55	180	429
<i>AsA₀₂S₁₁₀AMA₀₂AMD₀₂</i>	129	297	59	256	425
<i>AsA₀₂S₁₀₅AMA₀₂AMD₀₂</i>	129	299	58	258	426
<i>AsA₀₂S₁₁₅AMA₀₂AMD₀₂</i>	126	298	60	256	424
<i>AsA₀₁S₁₁₀AMA₀₁AMD₀₁</i>	122	293	56	257	428
<i>AsA₀₁S₁₀₅AMA₀₁AMD₀₁</i>	123	289	48	258	436
<i>AsA₀₁S₁₁₅AMA₀₁AMD₀₁</i>	121	288	51	255	432
<i>AsA₀₂S₁₁₀AMA₀₁AMD₀₁*</i>	130	604	186	430	298
<i>AsA₀₂S₁₀₅AMA₀₁AMD₀₁*</i>	131	626	203	433	280
<i>AsA₀₂S₁₁₅AMA₀₁AMD₀₁*</i>	126	581	177	418	307
<i>AsA₀₁S₁₁₀AMA₀₄AMD₀₄</i>	120	184	45	161	438
<i>AsA₀₁S₁₀₅AMA₀₄AMD₀₄</i>	123	186	47	163	437
<i>AsA₀₁S₁₁₅AMA₀₄AMD₀₄</i>	120	183	45	161	439
<i>AsA₀₂S₁₁₀AMA₀₄AMD₀₄</i>	127	214	53	184	431
<i>AsA₀₂S₁₀₅AMA₀₄AMD₀₄</i>	129	221	56	187	427
<i>AsA₀₂S₁₁₅AMA₀₄AMD₀₄</i>	126	213	52	183	431
<i>AsA₀₁S₁₁₀AMA₀₂AS₀₂</i>	122	191	47	167	436
<i>AsA₀₁AMA₀₂</i>	121	177	48	153	436
<i>AsA₀₁AMD₀₂</i>	120	143	39	128	445
<i>AsA₀₁S₁₁₀</i>	119	148	39	131	444
<i>AsA₀₁AS₁₀</i>	121	155	41	137	442
<i>MAR_{ref}</i>	123	142	32	132	451

within the study area. Only the ice shelves show negative SMB during austral summer (Fig. 4.9).

The density and LWC of the snowpack are also impacted by the assimilation. As can be seen in Table 4.6, on the ice shelves, where most of the surface melt and refreezing occurs, densification affects the LWC. With a denser snowpack, firn air content is reduced and there is less space for liquid water to be absorbed. Therefore, despite the increase in surface melt production, the assimilation process eventually leads to a decrease in the amount of liquid water retained in the snowpack. This reduction occurs due to the assimilations' impact on water retention capabilities of the snowpack through increased refreezing.

All three highlighted ice shelves (Larsen C, Wilkins, and George VI) experience an increase in surface melt, refreeze, and runoff as a result of the assimilation (Table 4.6). On Larsen C and Wilkins ice shelves, the percentage increase in runoff strongly outweighs the percentage increase in surface melt production. For Larsen C, the ice shelf experiences increase of melt in absolute and relative terms (+21 Gt yr⁻¹, or +85.7 %), and runoff triples (+6 Gt yr⁻¹, or +311.2 %). However, over the year, its liquid water content only slightly increases (+1 %). It therefore appears that on ice shelves, the increase in refreezing is not strong enough to compensate for the increase in melting. The depletion of firn air content leads to a swift saturation of the snowpack, producing a surplus of meltwater that results in a more pronounced decrease in SMB compared to other regions of the Antarctic Peninsula.

Table 4.5: Difference (in Gt yr^{-1} and %) in surface meltwater production (ME), runoff (RU), refreezing (RZ), surface mass balance (SMB), snowpack liquid water content (LWC), and snowpack density (ρ) between MAR_{ref} and the mean value of the assimilations ($\overline{Assim}$) for 2019-2020 for the entire MAR spatial extent (including grounded ice and ice shelves). Variables are accumulated annually and over summer (November through April) except for snowpack density and the liquid water content which are averaged over the periods. LWC and ρ are the average within the first meter of the snowpack while the other variables are the total for the entire snowpack.

	Annual					Summer				
	MAR_{ref}	$Assim_{ref}$	$\overline{Assim}$	Range	% Difference	MAR_{ref}	$Assim_{ref}$	$\overline{Assim}$	Range	% Difference
ME (Gt yr^{-1})	142	214	237	183 - 299	66.7	140	212	235	180 - 296	67.1
RU (Gt yr^{-1})	32	56	53	45 - 60	63.8	32	56	53	45 - 60	64.5
RZ (Gt yr^{-1})	132	182	206	161 - 258	55.7	128	176	201	157 - 253	56.5
SMB (Gt yr^{-1})	451	427	431	424 - 439	-4.5	253	229	233	226 - 240	-8.2
LWC_{1m} (g kg^{-1})	19	17	18	14 - 24	-6.4	33	29	31	24 - 40	-6
ρ_{1m} (kg m^{-3})	407	422	421	418 - 424	3.6	425	445	445	440 - 449	4.6

Table 4.6: Difference (in Gt yr^{-1} and %) in surface melt production (ME), runoff (RU), refreezing (RZ), surface mass balance (SMB), snowpack liquid water content (LWC), and snowpack density (ρ) between MAR_{ref} and the mean value of the assimilations ($\overline{Assim}$) over the three highlighted ice shelves in 2019-2020 using the regions shown in Fig. 4.1. Variables are accumulated annually and over summer (November through April) except for snowpack density and the liquid water content, which are averages over the specified periods. LWC and ρ are given as the average of the snowpack first meter while the other variables are totals for the entire modelled snowpack.

Larsen C	Annual					Summer				
	MAR_{ref}	$Assim_{ref}$	$\overline{Assim}$	Range	% Difference	MAR_{ref}	$Assim_{ref}$	$\overline{Assim}$	Range	% Difference
ME (Gt yr^{-1})	23	38	44	31 - 58	85.7	23	38	43	30 - 57	87.6
RU (Gt yr^{-1})	2	7	8	4 - 10	311.2	2	7	8	4 - 10	311.6
RZ (Gt yr^{-1})	22	32	36	28 - 50	62.2	22	31	36	27 - 49	63.6
SMB (Gt yr^{-1})	24	19	18	15 - 21	-25.1	15	10	9	6 - 13	-38.9
LWC_{1m} (g kg^{-1})	3.6	3.5	3.6	3.1 - 4.6	1.5	6.1	6.0	6.2	5.2 - 7.8	1.1
ρ_{1m} (kg m^{-3})	463	508	509	495 - 519	9.8	500	549	552	536 - 564	10.3
Wilkins										
ME (Gt yr^{-1})	9	13	14	10 - 19	48.4	9	12	14	10 - 19	48.2
RU (Gt yr^{-1})	2	5	4	2 - 7	185.6	2	5	4	2 - 7	185.6
RZ (Gt yr^{-1})	9	9	11	9 - 15	22.2	9	8	10	8 - 15	21
SMB (Gt yr^{-1})	6	2	3	0 - 5	-51.3	2	-2	-1	-4 - 1	-141.4
LWC_{1m} (g kg^{-1})	1.3	1.0	1.0	1.0 - 1.21	-21	2.2	1.7	1.7	1.6 - 2.0	-21.2
ρ_{1m} (kg m^{-3})	529	591	578	564 - 597	9.3	599	657	646	626 - 659	7.8
Georges VI										
ME (Gt yr^{-1})	15	20	22	16 - 30	53.2	15	20	22	16 - 30	53.1
RU (Gt yr^{-1})	2	3	3	3 - 4	56.9	2	3	3	3 - 4	56.9
RZ (Gt yr^{-1})	14	18	20	15 - 27	45.8	14	18	20	15 - 27	45.2
SMB (Gt yr^{-1})	11	10	10	9 - 11	-10.3	5	3	3	2 - 4	-25
LWC_{1m} (g kg^{-1})	2.1	1.8	2.0	1.7 - 2.4	-4.1	3.6	3.2	3.5	2.9 - 4.1	-4.1
ρ_{1m} (kg m^{-3})	493	537	526	521 - 537	6.8	544	595	584	577 - 595	7.3

Except for the LWC, which remains relatively small and stable as it has been averaged over the season, the analyzed variables (ME, RU, RZ, SMB, and snowpack density) have undergone noticeable variations as a result of the assimilation, causing MAR_{ref} variables to always be outside of range of the assimilated simulations. The amplified surface melt production leads to concurrent effects, including increased runoff, reduced surface mass balance, and an increased occurrence of refreezing. This increase in runoff is attributed to the increase in melt combined with the densification of the upper layers of the snowpack, reducing its capacity to absorb meltwater.

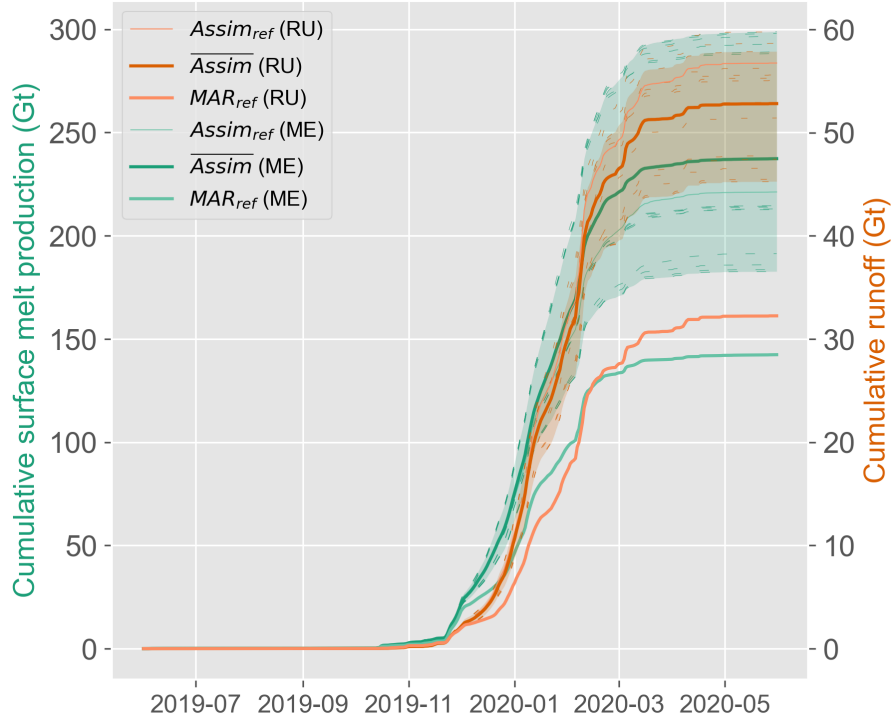


Figure 4.7: Comparison between the cumulative surface meltwater production (Gt) in green and the cumulative runoff (Gt) in orange over the whole MAR domain (excluding ocean areas) for the 2019-2020 melt season as modelled by MAR without assimilation and with data assimilation. Shaded areas represent the range of the assimilations. While the increase in Gt is larger for meltwater production, the relative increase is similar for meltwater production and runoff.

In the end, the results illustrate that, on average, $Assim_{ref}$ is the assimilation that gives the closest results to $\overline{Assim}$ and makes it an appropriate candidate in the case of limited computational resources (allowing for one simulation instead of 24). The parameters used in $Assim_{ref}$ seem to be an appropriate option given the results presented below regarding sensitivity to the assimilation parameters.

4.4.1 MAR sensitivity

Sensitivity to the assimilation depth threshold

The assimilation depth used for low penetrating sensors influences MAR meltwater production by inducing firn air content depletion. Due to refreezing, the uppermost portion of the snowpack becomes denser. The refreezing is accentuated when using a shallow-depth threshold (for example 10 centimetres with AMSR2) as the top layers of the snowpack will contain the majority of the liquid water. Consequently, the increase in meltwater production needed to reach the α threshold (0.1 % or 0.2 %) will be greater (because of the denser snowpack) than for a deeper assimilation depth where less densification occurs. Also, with firn air content depletion, two other phenomena enhance melt production. First, the available energy in the system is consumed by the melting process, preventing layers below 1 m from heating up and reducing the release of latent heat from the refreezing process. Therefore,

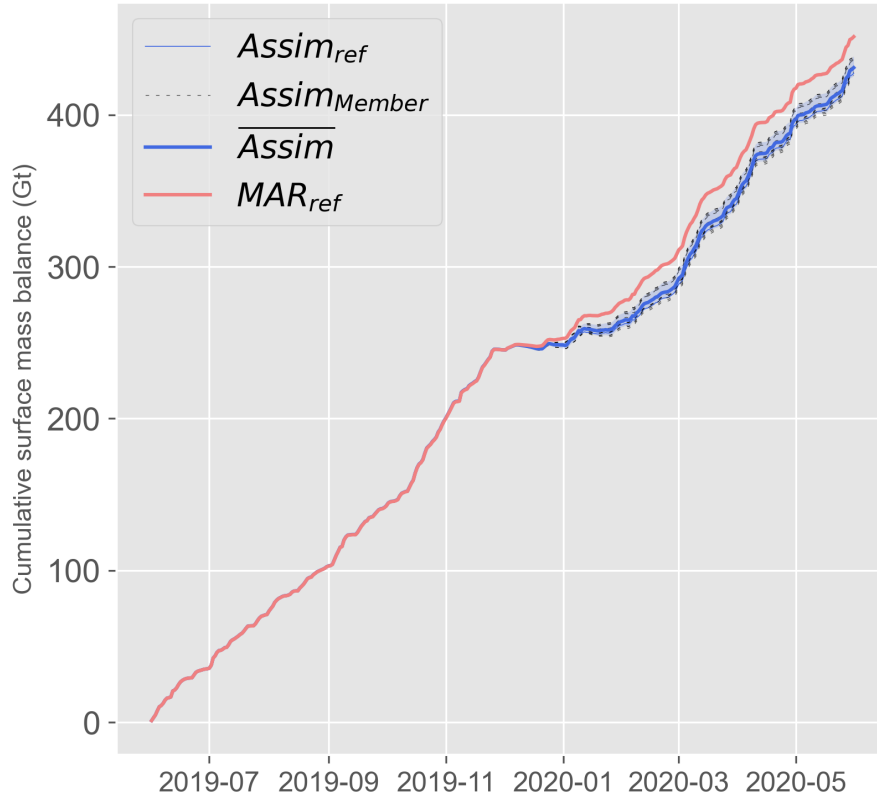


Figure 4.8: Cumulative surface mass balance (Gt) over the entire MAR domain (excluding ocean areas) for the 2019-2020 melt season as modelled by MAR without assimilation (MAR_{ref} in red), with data assimilation ($Assim_{member}$ in dashed lines), and their averaged value ($\overline{Assim}$ in blue). Shaded areas represent the range of the assimilations. Despite the increase in surface melt production, the surface mass balance does not significantly decrease.

the deeper layers will tend to cool the snowpack, necessitating more nudging. The second phenomena is that during melt events the upper layers saturate with less water due to the densification. The saturation results in increased runoff and faster percolation of the water into deeper layers outside of the assimilation depth range. If the model were to retain liquid water in its top snow layers for a longer duration, it would require less nudging to match the RS datasets. This effect could be achieved by increasing the maximum liquid water content of the snow layers. However, enhancing water retention in the near-surface snowpack layers might lead to increased refreezing and consequently, densification, depending on the snowpack temperature (Fettweis et al., 2011).

This phenomenon is illustrated in Fig. 4.10, where using a 10 cm assimilation depth threshold for AMSR2 produces more melt than the 20 cm and 40 cm thresholds, for water content thresholds of both 0.1 % and 0.2 %. The effect ends up being so important that using a 10 cm assimilation depth and 0.2 % α threshold for AMSR2 can result in an intense refreezing and firn air content depletion that leads to a strong increase in runoff, reducing SMB for the Antarctic Peninsula. This decrease in SMB is contrary to the generally observed trend (Rignot et al., 2019; Chuter et al., 2022). Consequently, the three simulations that use these parameters for the

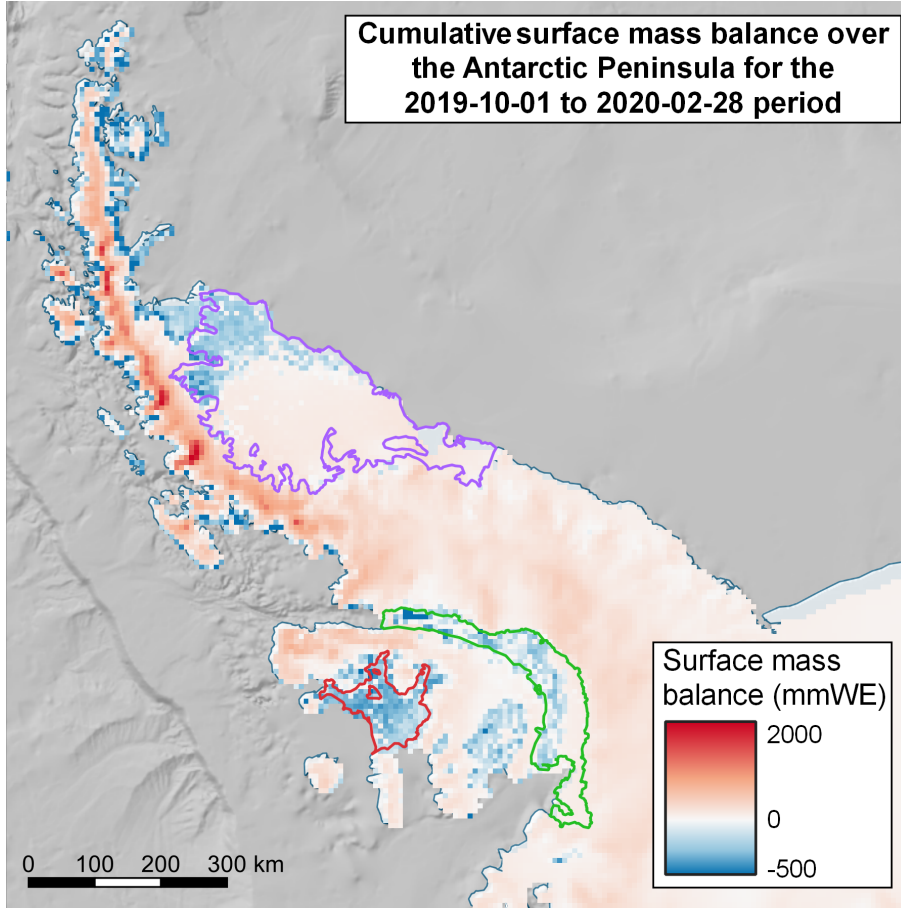


Figure 4.9: Cumulative SMB (mmWE) from 2019-10-01 to 2020-02-28 over the AP as modelled by *Assim_{ref}*. Larsen C is outlined in purple, George VI in green, and Wilkins in red. The southern ice shelves and the northernmost coastlines are experiencing a negative SMB in contrast with the rest of the AP. Larsen C is divided in two regimes. Its northern part is experiencing a negative SMB while the southern part is positive.

Ku-band sensors have been discarded in computation of the average melt for the assimilations.

In contrast, with Sentinel-1, the effect of choosing different Δ_z thresholds is less pronounced. As shown in Table 4.4, assimilations that have all parameters in common except the S1 assimilation depth threshold only vary by a few Gt yr^{-1} for all variables. Multiple reasons can explain this comparatively lighter effect. S1 has a larger revisit time compared to AMSR2 (a 6-day revisit time vs daily images). With fewer images, the assimilation depth for S1 is used less frequently in the melt assimilation process within MAR. In addition, as explained previously, the liquid water is kept longer in these slightly deeper layers due to a higher retention capacity, and thus less melt is required to reach the water content threshold. Overall, these results indicate that MAR is more sensitive to a shallower assimilation depth threshold. Most of the sensitivity is linked to refreeze and densification, more likely to occur in the first centimetre of the snowpack. The penetration depth for the C-band sensors is larger than for Ku-band sensors, and using sensors with higher frequencies increases the sensitivity to the choice of the thresholds.

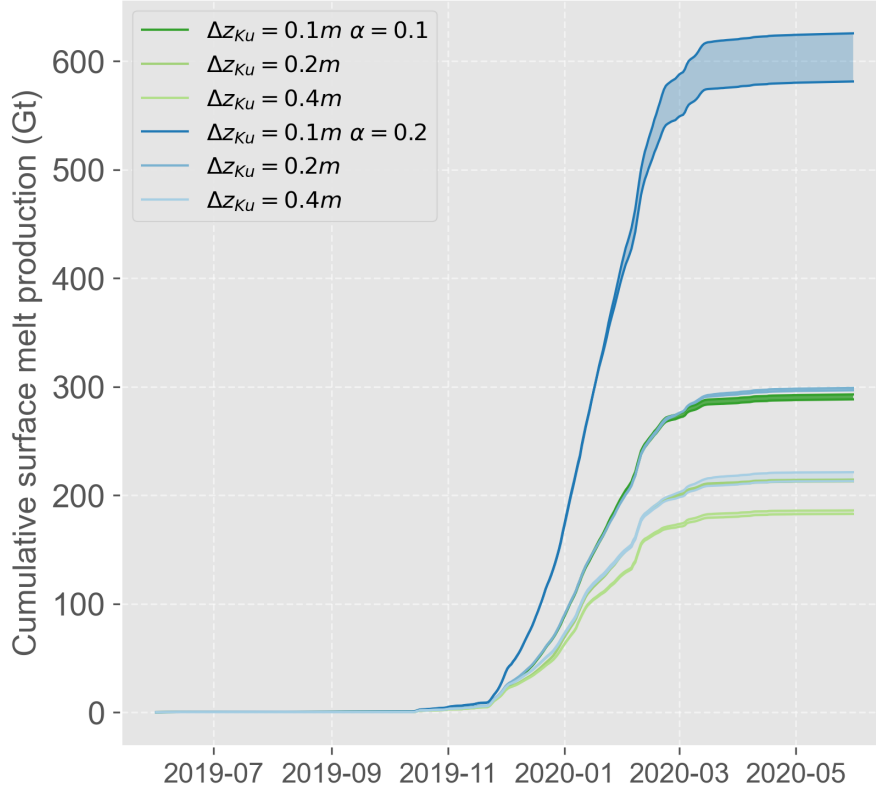


Figure 4.10: Cumulative surface melt production (Gt) over the entire MAR domain for the 2019-2020 melt season as modelled by the different assimilation experiments. The assimilations are grouped by their α and Ku-band Δ_z thresholds. Shaded areas represent the range of the assimilation of the groups. Groups of assimilations with Ku-band $\Delta_z = 0.1$ m produce more melt than the group of assimilations with the same α but different Δ_z .

Sensitivity to the water content threshold

Experiments with varying the liquid water content threshold have a smaller impact compared to the assimilation depth experiments. Varying liquid water content influences the number of melt days modelled, thus expanding the melt season duration (Table 4.7) rather than the quantity of liquid water produced by melting. The amount of liquid water required to reach the water content thresholds α is small compared to the modelled LWC of a typical melt day. In MAR_{ref} , for the 2019-2020 melt season, the value reaches 1.2 % for a melt day on average, above the 0.2 % threshold.

For this chapter, the number of melt days is defined as the number of days of the melt season where 10 % of the ice shelf experiences melt, while the melt season length corresponds to the number of days between the first melt day after the first of June and the last melt day before the last day of May in the subsequent year. Thus, the melt season length also encompasses possible colder periods where no melting occurs.

The choice of liquid water content threshold also influences the average number of melt days on the studied ice shelves (Fig. 4.11). A pixel is considered as melting for the day if the daily-averaged mass of liquid water within the first meter of snow is greater than 0.1 % of the snowpack mass. Therefore, using the 0.2 % threshold

Table 4.7: The melt season length (first to last melt day) and number of melt days modelled for MAR_{ref} and the average for assimilation simulations grouped by α -value over the three highlighted ice shelves in Fig. 4.1 for 2019-2020. A melt day over an ice shelf is a day where more than 10 % of the ice shelf is experiencing melt.

Larsen C	Melt season length (days)	Number of melt days modelled
MAR_{ref}	143	90
$\alpha = 0.1 \%$	147	110
$\alpha = 0.2 \%$	152	119
Wilkins	Melt season length (days)	Number of melt days modelled
MAR_{ref}	292	127
$\alpha = 0.1 \%$	294	125
$\alpha = 0.2 \%$	298	129
GeorgeVI	Melt season length (days)	Number of melt days modelled
MAR_{ref}	120	120
$\alpha = 0.1 \%$	123	122
$\alpha = 0.2 \%$	157	134

over 0.1 % will increase the number of melt days.

By computing the mean value of the number of melt days for each ice shelf pixel, it was found that Larsen C is the most sensitive to the threshold chosen, with an increase of 15 melt days compared to MAR_{ref} . The other two ice shelves exhibit comparatively smaller differences, with Wilkins and George VI experiencing an increase of 8 and 9 melt days, respectively (Fig. 4.11).

Examining assimilation simulations individually leads to a similar conclusion. It is important to note that the simulations that were discarded from the computation of *Assim* are assimilations that had 0.2 % as the value for the threshold. With a densified snowpack, reaching $\alpha = 0.2 \%$ required more intense melting producing unrealistic surface conditions.

Sensitivity to the RS dataset

In another set of sensitivity experiments, each of the four wet-snow masks (AMSR2 desc., AMSR2 asc., ASCAT, S1) has been assimilated individually into MAR to study its influence. Assimilating multiple datasets tends to smooth the sensor characteristics as they are only processed to be used where they provide consistent information. In this chapter, several characteristics of the remote sensing data are examined, including the acquisition time, the spatial resolution, and the revisit time, and their impact is discussed below. First, an earlier acquisition time can artificially lower the number of melt days. Because of the daily cycle of the water quantity in the snowpack, images taken earlier in the morning are less likely to observe wet snow (Picard and Fily, 2006). Over the Antarctic Peninsula, the descending orbit of AMSR2 therefore observes less wet snow than the ascending one. Using satellites whose acquisition times are well distributed during the day allows for observation of the daily melt-refreezing cycle and reduces the possibility of excluding melt days.

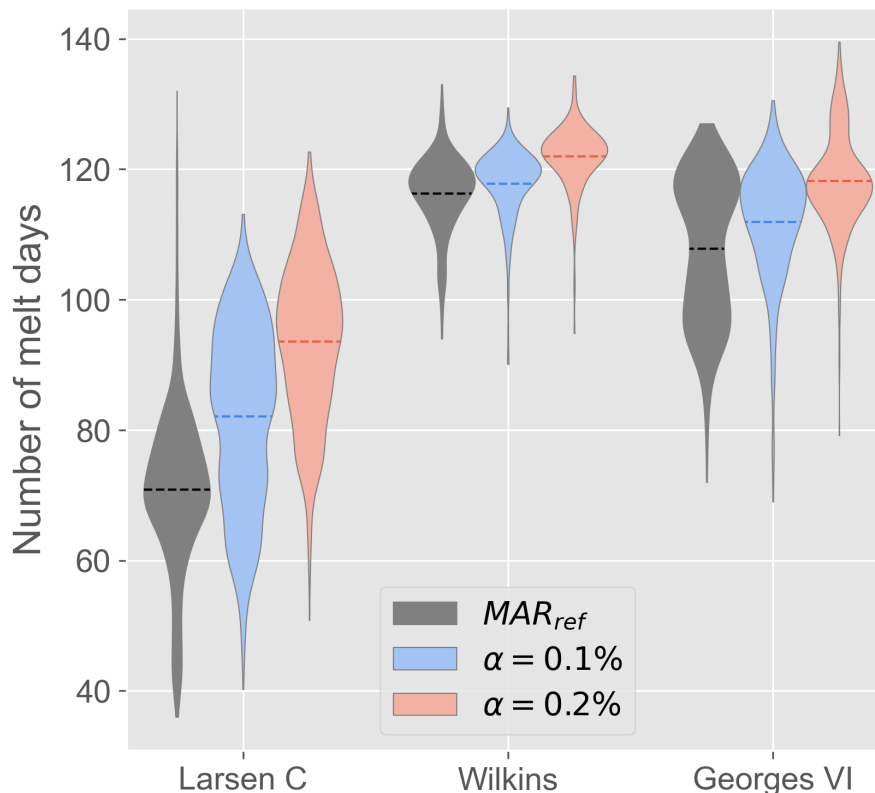


Figure 4.11: Distribution of the number of melt days for the 2019-2020 melt season as modelled by MAR_{ref} and the assimilations grouped by the specified α threshold values for the three studied ice shelves. Dashed lines represent the mean value of the distribution. On the three ice shelves, assimilations with $\alpha = 0.2\%$ produce more melt days than MAR_{ref} and the other assimilations. Assimilations with $\alpha = 0.2\%$ exhibit an increase in the mean number of melt days relative to MAR_{ref} over the Larsen C ice shelf of 15 days, 8 days on the Wilkins ice shelf, and 9 days on the Georges VI ice shelf.

Second, the spatial resolution influences the results of the assimilation because of pixel heterogeneity. Sensors that have a coarser resolution hide highly heterogeneous surface dynamics and it is possible that while only a fraction of the region covered by one pixel is experiencing melting or enough water is present in the snowpack, the entire pixel is characterized as wet snow Picard et al. (2022). In steep regions (e.g., near the grounding line), this phenomenon can lead to the detection of wet snow in places where it is unlikely to occur. In this study, the passive microwave sensor AMSR2 has a coarser resolution than MAR and can trigger the assimilation process in locations where it should not be applied.

To study the influence of the spatial resolution, we have performed a simulation assimilating ASCAT data ($AsA_{01}S1_{10}AM_{02}AS_{02}$ in Table 4.2) instead of AMSR2 in the descending orbit. The assimilation with ASCAT produces a smaller number of melt days and surface melt production on the Antarctic Peninsula for the studied period (191 Gt yr^{-1} for $AsA_{01}S1_{10}AM_{02}AS_{02}$ and 214 Gt yr^{-1} for $Assim_{ref}$). While the assimilation depth is different between AMSR2 and ASCAT, the major influence comes from the spatial resolution of the sensor (with ASCAT having a higher spatial resolution). The difference can be seen in the wet-snow masks (Fig.

4.12). AMSR2 detects melt on Alexander Island, between George VI and Wilkins ice shelves whereas ASCAT, with a finer resolution and a different frequency does not. Even if wet snow is observed for one of the AMSR masks, the duration of the increased MAR snowpack temperature is too short to produce the water quantities necessary to be detected as melt. This preservation of a cold snowpack persists throughout the day.

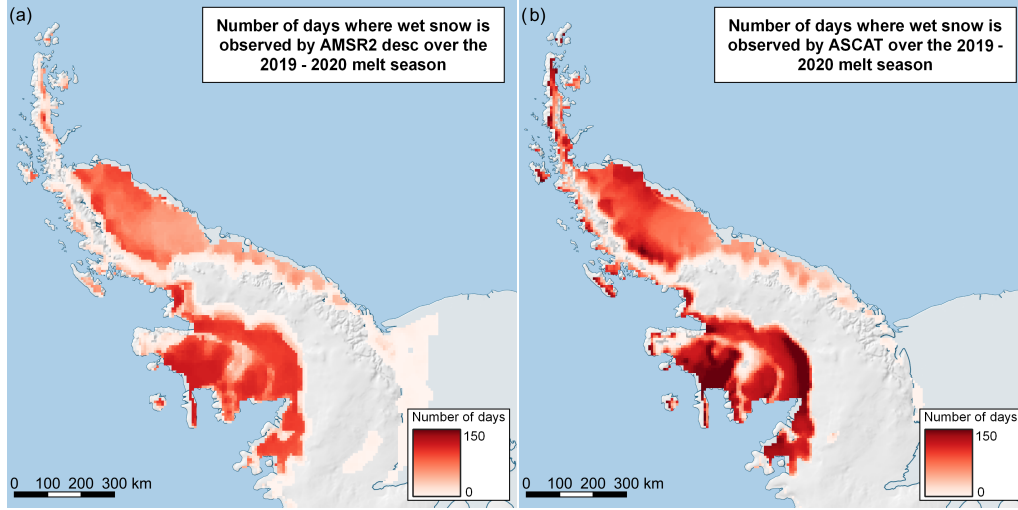


Figure 4.12: (a) Number of days with wet snow observed by AMSR2 ascending on the AP for the 2019-2020 melt season. (b) Number of days with wet snow observed by ASCAT on the Antarctic Peninsula for the 2019-2020 melt season. ASCAT observes more wet snow than AMSR2 over the ice shelves but less melt on average at higher altitudes and in areas of steep terrain.

Finally, the impact of revisit time is highlighted by studying the wet-snow extent resulting from the assimilation of only one sensor at a time (Fig. 4.13). The assimilated S1 wet-snow mask does not cover the entire AP every day and thus shows a smaller wet-snow extent than the other masks. As a consequence, there are fewer instances in which the model and the mask exhibit discrepancies regarding the snow status, resulting in reduced application of the nudging technique. Ultimately, the S1-only assimilation ($AsA_{01}S1_{10}$ in Table 4.2) has the closest wet-snow extent to MAR_{ref} , despite the bias in the raw data. The resilience of the model snowpack is such that relying solely on a non-daily dataset with intermittent nudging allows it to freely evolve with minimal external forcing. Consequently, while the high spatial resolution of Sentinel-1 provides valuable information, this advantage is not sufficient enough to be used as the only dataset assimilated. The S1 dataset needs to be used in conjunction with other datasets to combine high spatial resolution with low revisit time.

The resilience of the snowpack simulation also decreases the feasibility of assimilating only one dataset using the algorithm described in this chapter. While ASCAT-only assimilation ($AsA_{01}AS_{10}$ in Table 4.2) tends to be closest to its wet-snow mask during peaks of melt (end of November 2019, beginning of 2020) or strong refreeze (mid-March 2020), the effects of nudging do not persist over long time periods and necessitate changes in the model to match the observed wet-snow mask.

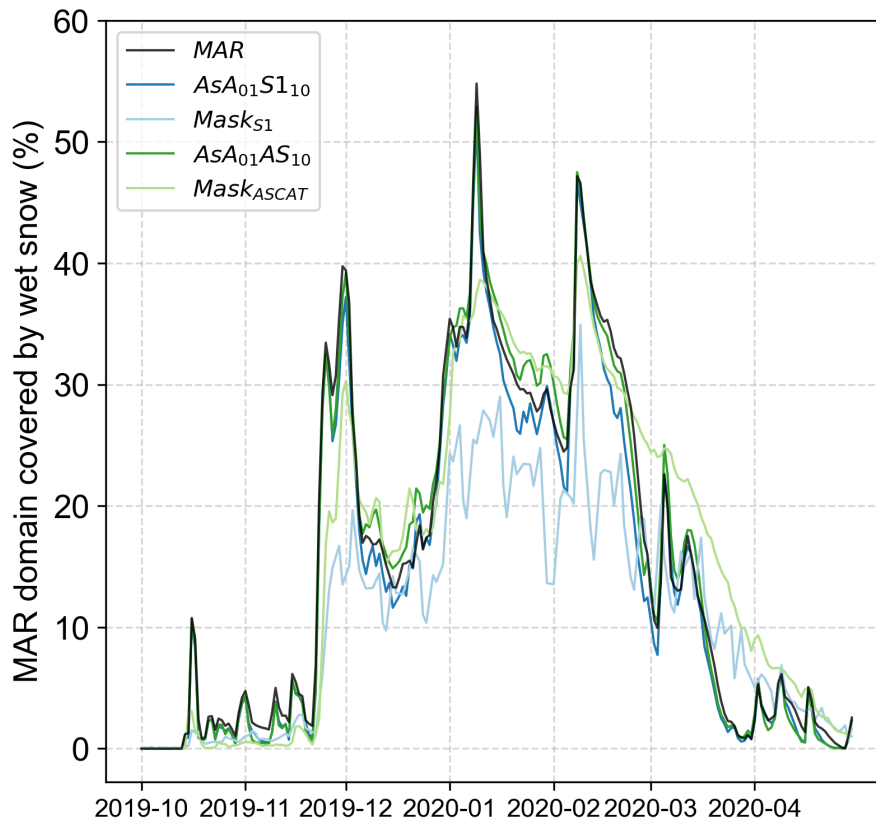


Figure 4.13: Evolution of the wet-snow extent over the entire MAR domain (including grounded ice and ice shelves) during the 2019-2020 melt season as modelled by MAR_{ref} , the assimilation of S1 alone ($AsA_{01}S1_{10}$), the assimilation of ASCAT alone ($AsA_{01}AS1_{10}$), and the wet-snow masks from S1, and ASCAT. The S1 wet-snow mask has a lower extent as the AP is not covered entirely every day by S1 images.

Assimilating two datasets that entirely cover the study area as well as a dataset that has a finer spatial resolution compared to MAR serves as a means of mitigating the sensitivity of the model to the chosen datasets. The constraints on the period in which the model snowpack temperature can be changed and the possibility of not assimilating data in case of a discrepancy between the sensors also regulates the dependence of the model on the observations. Future developments in the technique should allow for the possibility of assimilating additional datasets and weighting wet-snow masks according to the relevance of their wet/dry snow status.

4.5 Discussion and Conclusions

In this chapter, we presented results regarding the assimilation of wet-snow occurrence data estimated by spaceborne microwave sensors into the regional climate model MAR through adjustments in MAR near-surface temperature to best match the satellite data. Sensitivity tests have been performed to evaluate the effect of the data assimilation parameters on the model results.

We identified the assimilation depth (Δ_z) to be the most influential parameter when applied for shallow-penetration sensors. The influence on the quantity of water pro-

duced in the snowpack partially comes from the liquid water content threshold (α) calculation. The uppermost layer of the snowpack is considerably denser than the underlying layers, owing to the increase in refreezing caused by the exceeding liquid meltwater produced as a result of the assimilation. Heavier and denser layers require more liquid water to be present to reach the required α threshold. Also, the densification causes firn air content depletion, leaving less space for liquid water. The densified layer saturates faster, and more runoff occurs. A threshold of 0.2 m for the Ku-band sensors causes no extreme refreezing or melt and may be considered a good candidate for assimilation depth thresholds. For the C-band sensors, the three thresholds tested yield similar results to one another, and the implementation of a varying threshold should be considered to take into account the depth at which the wet snow is observed. In contrast to assimilation depth (Δ_z), the maximum LWC threshold (α) has a smaller impact on the model surface melt production (in Gt). The choice of $\alpha = 0.2 \%$ over $\alpha = 0.1 \%$ mostly increases the duration of the melting season, rather than the amount of meltwater produced.

With constant snowfall (480 Gt yr^{-1}) and an increase in surface meltwater production ($+95 \text{ Gt yr}^{-1}$ or $+66.7 \%$), the increase in runoff ($+21 \text{ Gt yr}^{-1}$ or $+63.8 \%$) associated with assimilation translates into a decrease in SMB (-4.5%), for the 2019-2020 melt season. Nonetheless, runoff values are relatively small compared to the surface mass balance, explaining the small impact of assimilation on the SMB. The general tendency of SMB remains positive in the study area. Only the ice shelves show negative SMB during periods of intense melting.

The choice of the dataset to be assimilated was also found to influence the results of the model after data assimilation. Each sensor has its particularities and wet-snow masks may differ between sensors. Several of these characteristics have been pinpointed previously. The most important ones are the signal frequency, the revisit time, and the spatial resolution.

The frequency of the sensor impacts estimated meltwater production due to differences in sensitivity to liquid water and the depth to which the signal penetrates. Because it is difficult to provide accurate surface water depth estimates (Fricker et al., 2021) and because microwave signals can be intercepted by the water in the snowpack, the vertical limit necessary for the assimilation is not always clear. If there is enough water in the near-surface layers, additional liquid water within deeper layers cannot be observed. In the same way, a thin layer of surface water can be interpreted as the presence of water in the first meter of the snowpack when the underneath layers are dry (Figure 4.5). The assimilation depth threshold Δ_z has been set to different values depending on sensor wavelengths, but remains constant regardless of the snowpack state. Introducing a density-varying LWC threshold could decrease meltwater production in the assimilation simulations. However, we encourage field observations of the evolution of the LWC vertical profile; a required step needed in introducing and validating the assimilation algorithm.

The revisit time of the satellites is influential as the model freely evolves if the forcing is not performed every day. The assimilation of only Sentinel-1 satellites (with a revisit time of 6 days, translating into one image every 2-3 days over the study area)

produces results close to those of the model simulation without data assimilation. Multiple datasets need to be assimilated on the same day for the model to consistently change its behaviour. The resilience of the model results from the refreezing of the snowpack during nights and in winter months. When taking into account a few melt seasons, at the beginning of the melt season, the model snowpack is more or less similar to its state in the previous year.

Assimilating multiple datasets into MAR also brings challenges and considerations alongside the advantages. If some missing information is fulfilled by another dataset, it adds another layer of complexity to the algorithm or additional uncertainties linked to the assimilation method used and its thresholds. Datasets may not carry the same information and may not be compatible for all the time steps. Here, none of the datasets is considered to have better wet-snow detection than the other. A possible enhancement of the technique would be to add weight to the masks in case of contradictions between them. The weight could be constructed using the confidence level of the wet-snow detection technique employed, the satellite spatial resolution, the topographic gradient from higher resolution satellite pixels interpolated to the MAR grid or the sensor sensitivity to liquid water.

The results highlight the importance and impact of utilizing data assimilation. While the assimilation does not induce a complete change in the behaviour of the model as surface melt remains marginal to snowfall, the snowpack properties tend to deviate from the model simulation performed without assimilation, impacting the ability of the snowpack to retain meltwater in the future. Here, satellite data have only been assimilated for two melt seasons over a small area. The study can be expanded in the future to cover a longer period, a larger spatial extent, or the Greenland ice sheet, where surface melt is the main driver of SMB variability (Slater et al., 2021). Further attention should be given to ice shelves as they are the most sensitive region of Antarctica and important to the Antarctic ice sheet stability (Favier and Pattyn, 2015; Paolo et al., 2015; Sun et al., 2020).

Finally, The results obtained in this chapter pinpoint the uncertainties of the regional climate model over the Antarctic Peninsula, where, without significant increases in simulated melt area, the surface melt production significantly increased. The assimilation of remotely sensed data into RCMs is a promising way of reducing the biases and errors inherent to climate models, given that there are currently no direct large-scale measurement of meltwater content within the Antarctic snowpack. This is also an easy way to provide robust uncertainties in model outputs for present climate. Using multiple RS datasets with spatial resolutions higher than the model resolution would also allow for improved model corrections through better assessment of the snowpack water content.

CHAPTER 5

Discussion and Conclusions

5.1 Modelling Strategies: From remote sensing data integration, to model coupling and data assimilation

This thesis highlights both the potential and the current limitations of regional climate models in representing land-atmosphere interactions. While these interactions play a key role in modulating regional climate, their effective representation remains challenging due to the complexity of the underlying processes and their scale dependency.

To address this challenge, we explored three complementary research axes, using different techniques:

1. **Sensitivity analyses** of the MAR regional climate model to vegetation input using MODIS satellite-derived vegetation Leaf Area Index (LAI).
2. Development of a **coupled regional atmosphere-vegetation model**, the RAVEL model, to represent two-way feedback between atmosphere and vegetation ecosystems.
3. **Assimilation of remote-sensing observations** into MAR to constrain the modelled wet-snow occurrence and reduce associated uncertainties over the Antarctic Peninsula.

The approaches explored in this thesis, integrating remote sensing data and introducing dynamic vegetation through model coupling, represent complementary strategies to address the challenge of land-atmosphere interactions representation. They illustrate a progression from prescribed surface conditions to enabling dynamic feedbacks.

First, the use of high-resolution, satellite-derived leaf area index data demonstrated that low-resolution static climatologies can limit the representation of fine-scale spatial heterogeneity and transient events, which are crucial for accurately representing surface fluxes and feedback processes. Incorporating MODIS-based LAI in MAR provided a more representative view of vegetation, improved its daily dynamics, and enhanced the simulation of surface fluxes, notably during extreme events such as droughts.

Second, the development of a two-way coupling between MAR and the dynamic vegetation model CARAIB, resulting in the Regional Atmosphere-VEgetation uLiège model (RAVEL) enabled the representation of two-way interactions between the atmosphere and vegetation. This dynamic coupling allows vegetation to evolve consistently with climatic conditions, providing a more realistic framework for long-term simulations. The results show that coupling leads to a denser and more dynamic vegetation cover, enhanced evapotranspiration, and improved representation of extreme events.

Third, the assimilation of remote sensing observations introduces a complementary approach by directly constraining model states. The assimilation of wet-snow occurrence demonstrated that even simple nudging techniques can significantly modify surface processes such as meltwater production and snowpack dynamics.

Taken together, these approaches form a coherent methodological framework in which prescribed data from remote sensing, dynamic coupling, and observational constraints contribute to improving model robustness. These approaches should not be viewed as independent solutions, but rather as interconnected elements of a broader modelling strategy aimed at reducing uncertainties in climate simulations and projections.

5.2 Land-Atmosphere Interactions in MAR

In this thesis, we aimed to improve the representation of land-atmosphere interactions in regional climate models. Improving their representation is essential for understanding present-day climate dynamics and for increasing confidence in climate projections and simulated ecosystems evolution.

A central outcome of this work is that, in MAR, vegetation exerts a strong control on surface fluxes, particularly evapotranspiration, yet the atmospheric response remains relatively weak under present-day conditions. This contrast suggests that the model’s land-surface processes are sensitive to vegetation variability, but that their influence on the atmosphere is dampened, either by model parametrisations or by the simulation setup. Nevertheless, several studies classify central Europe as a transition zone between strongly coupled regions in the Mediterranean and weakly coupled regions in northern Europe (Seneviratne et al., 2006; Miralles et al., 2012; Knist et al., 2017; Santanello et al., 2018). Therefore, the limited atmospheric sensitivity observed here may also reflect an intrinsically moderate coupling regime between surface fluxes and the atmosphere.

However, as with climate change temperatures are projected to increase (IPCC, 2023b), climate regimes in Europe are expected to shift northward (Seneviratne et al., 2006). Central Europe may evolve toward a region of stronger land-atmosphere coupling in the future. As a result, if land-atmosphere interactions are currently underestimated in MAR, this bias may be amplified in future projections, particularly as coupling strength is expected to increase, thereby reducing the reliability of projected climate responses. Further investigation of MAR land-atmosphere interactions will therefore still be required.

5.3 Structural Limitations of the Model

Beyond the individual experiments, this work also reveals several structural limitations in the representation of land-atmosphere interactions within MAR. The results showed that improving inputs alone is insufficient to significantly influence atmospheric conditions. With dynamic coupling or weekly observations, there was only a

moderate atmospheric response under temperate conditions, even during more extreme conditions.

In the first two approaches, despite the strong evolution of surface fluxes like the evapotranspiration, the response of the atmosphere was lower in comparison. The weak sensitivity of the atmosphere to surface perturbations while surface fluxes respond strongly to vegetation changes appears to be largely controlled by large-scale forcing, which can typically occur over small simulated domains, or be caused by SISVAT parametrisation. Other studies like (Engel et al., 2025) also point out that the effect of increased evapotranspiration on precipitation may occur at regional or larger scales since only a few percent of the recycled moisture precipitates locally (Theeuwens et al., 2023). The size of the simulated domain is therefore important, as in addition to larger synoptic forcing on small domains, the precipitation recycling may occur outside the domain. This imbalance suggests that the MAR coupling strength between the land surface and the atmosphere may be underestimated under current climate over small domains.

Another important limitation is the model’s tendency to revert to its internal equilibrium after external perturbations, as observed in the satellite data integration experiments over Antarctica. This behaviour indicates that the model is internally consistent but also resistant to sustained corrections, pointing to a potential over-calibration in the underlying parametrisations. In polar environments, results further indicate shortcomings in the representation of snow hydrological processes, particularly those governing meltwater refreezing and retention within the snow-pack. These processes play a critical role in determining surface mass balance and therefore require improved physical representation.

Overall, these findings emphasise that advancing regional climate modelling requires not only better input data and coupling strategies, but also targeted improvements in model physics and parametrisation to enhance the sensitivity and representation of land-atmosphere interactions.

5.4 Key Scientific Contributions

5.4.1 Improving the input dataset

The first part of this thesis investigated the sensitivity of the MAR regional climate model to vegetation cover density by improving its vegetation input dataset. The default MAR configuration derives its LAI input from the MERRA2 reanalysis to prescribe a fixed, monthly climatology of LAI at 50 km resolution. This coarse and fix climatology limit the representation of fine-scale spatial heterogeneity and transient events, which are crucial for accurately representing surface fluxes and feedback processes. To overcome this limitation, the standard input was replaced by the MCD15A2H Version 6.1 MODIS Level-4 satellite-derived LAI product (Myneni et al., 2021), which provides data at much finer spatial (500 m) and temporal (8-day) resolutions. The new dataset offers a more representative view of the vegetation dynamics and heterogeneity.

A series of sensitivity experiments was performed to assess MAR's response to vegetation variability. Results revealed that MAR's meteorological outputs are indeed sensitive to changes in vegetation cover, but this sensitivity is not uniform across variables or seasons.

With the improved vegetation input dataset, MAR showed promising agreement with observations and modest improvements relative to the standard configuration. This comparison also highlighted the importance of the LAI input dataset. The current LAI used in the standard configuration seems to underestimate the vegetation cover, especially in the lower vegetation like pasture or croplands. In consequence, surface-related variables, such as evapotranspiration and soil water content, exhibited the strongest responses to the LAI changes introduced by the improved dataset. In particular, higher vegetation density systematically increased evapotranspiration, reflecting enhanced transpiration and canopy interception. In contrast, atmospheric variables such as surface air temperature and precipitation were less affected. Nonetheless, local effects were detected, especially during summer, where increased LAI tends to reduce daily maximum temperatures through shading, evaporative cooling, and in this specific case, an increased albedo.

Changing the integration method only had a few impacts on the meteorological variables, with mostly no statistically significant changes. However, a more detailed examination of the integration technique revealed that the partitioning of vegetation across MAR sub-pixels was not functioning as intended, which in turn enabled us to identify and resolve the issue

Changing the climatology for an 8-day LAI did not substantially modify the general climate simulated by MAR as compared to using a MODIS mean annual cycle. Mean surface air temperature and precipitation patterns remained largely unchanged, suggesting that the large-scale atmospheric state is relatively insensitive to short-term vegetation variability. However, the finer temporal resolution revealed effects that the climatological representation could not capture. The 8-day LAI simulations showed clearer responses during extreme events, especially droughts. During these periods, declines in LAI corresponded to a reduction in evapotranspiration and a rise of up to 1-2°C in daily maximum temperature, reflecting the reduced evaporative cooling associated with vegetation stress. However, no change in temperature was observed during very hot days (temperature max. > 35 °C) as in such conditions temperature is driven by soil moisture. Nonetheless, these effects were spatially heterogeneous: forested areas showed little change compared to low-vegetation regions, as forests tend to be more resilient to short-term drought under present-day climatic conditions.

MAR's response to vegetation perturbations was found to be non-linear and asymmetric: depending on the variable, decreasing vegetation density can produced stronger changes than increasing it. However, the direction of the change was always consistent; if decreasing the vegetation density led to an increase in the variable, increasing the vegetation will decrease the variable. This finding highlights structural characteristics of MAR's land-atmosphere interaction and response to vegetation change. This asymmetry has implications and should be considered for future sim-

ulation interpretation.

These results emphasize the crucial role of vegetation in regional climate simulations and demonstrate that static vegetation inputs can limit the capacity of models like MAR to reproduce short-term climate variability and extreme events.

5.4.2 RAVEL 1.0 coupled model

To address climate projections, the second part of the thesis focused on the development of a two-way coupling between the regional climate model MAR and the dynamic vegetation model CARAIB, resulting in the Regional Atmosphere-VEgetation uLiège model, RAVEL. By coupling MAR and CARAIB, this work extends the capability of MAR beyond observation-driven simulations, providing a framework for climate projections in which vegetation feedbacks evolve dynamically, a key step toward long-term climate simulations with consistent land-atmosphere interactions.

In this system, the two models exchange information on a daily basis: CARAIB provides MAR with simulated LAI, while MAR supplies CARAIB with meteorological forcing such as air temperature, radiation, and precipitation. The coupling ensures temporal consistency while maintaining modularity. Although only a limited number of variables were exchanged in this first version, the framework successfully demonstrated the feasibility and stability of such coupling with no climate drift occurring.

The results showed that coupling substantially modifies vegetation representation in MAR, as CARAIB typically simulates higher LAI values than the MERRA2-based climatology used in MAR standalone configuration. This effectively acts as a denser vegetation scenario, particularly upon lower vegetations. Our results are in line with other studies like Heck et al. (2001), King et al. (2024), or Engel et al. (2025) that compared reference simulations with scenarios using denser vegetation. However, some of the results are not consistent with these studies, particularly regarding the increase in albedo observed in our works. The main differences between our results and the other studies are caused by the vegetation type considered by MAR in our studied domain and the computation of surface albedo in SISVAT. In this study, most of the forest are broadleaved composed, which is different from other studies, and, in SISVAT, an densification of broadleaved tree or grass can lead to an increase in albedo.

Under present-day conditions, the coupled system exhibits good agreement with observations over Belgium. Notably, the model simulated a denser and more dynamic vegetation cover, enhanced evapotranspiration, and a moderate cooling of the surface during summer compared to the standalone models. However, as anticipated, the atmospheric response was generally weaker than the vegetation response, reflecting differences in model sensitivities. This difference is possibly due to the limited number of exchanged variables or the reduced sensitivity of the land-atmosphere interactions modelled in MAR.

The coupling particularly improved the representation of extreme events compared

to the changes it brings to the general climate. During drought periods, feedbacks led to stronger reductions in LAI, which in turn reduced evapotranspiration and vegetation productivity, increased daily variability in vegetation dynamics, and occasionally resulted in locally warmer surface conditions, thereby amplifying water stress. During pluvial events, the coupled model also showed some feedback with relatively lower surface air temperature and increased daily variability. The coupled model thus captures important biophysical feedbacks that cannot be resolved in standalone simulations.

In line with the results obtained from the sensitivity experiments, the changes induced by the coupling were found to be strongly dependent on both spatial and seasonal factors. The most pronounced differences between the coupled and standalone configurations occurred in non-forested regions and during the spring and summer seasons, when vegetation activity reaches its annual peak. Spatially, the largest variations across most variables were concentrated in the northern part of the study domain, predominantly covered by croplands and pastures, as well as in the centre of the region, corresponding to the transitional zone between the agricultural north and the more densely forested southern part of Belgium.

Importantly, the RAVEL coupled model remained numerically stable and physically consistent throughout multi-year runs over western European climate, indicating that such two-way coupling is a viable approach for regional-scale climate-biosphere studies. This opens the way for longer simulations and future applications under different climate-change scenarios.

5.4.3 Integrating wet-snow occurrence

In the final part of this thesis, we assimilated satellite-derived wet-snow occurrence, estimated from spaceborne microwave sensors, into MAR over the Antarctic Peninsula. This step marked a shift from improving model inputs to actively constraining model states with observations, offering a complementary approach to the coupling experiment conducted in the previous research axis.

The assimilation experiments demonstrated that satellite observations can effectively influence the simulated surface energy and mass balance when carefully integrated. The method, based on a simple but robust temperature-nudging of the snowpack introduced by Kittel et al. (2022b), led to a substantial increase in meltwater production and runoff, resulting in a small decrease in surface mass balance (SMB). Although the impact on the overall SMB remained limited, the internal snowpack structure and melt-refreezing dynamics were modified. These changes indicate that even small near-surface temperature corrections can propagate through the snow and firn layers.

The uncertainties around the remote sensing wet-snow product, inherent to the sensor characteristics and the detection methods (i.e., the water depth and the liquid water content cannot be retrieved easily), lead to performing sensitivity tests. The sensitivity tests performed on the assimilation parameters further revealed how critical the physical assumptions are. In particular, the assimilation depth (Δ_z) was

identified as the most influential parameter, especially for shorter-wavelength sensors such as those operating in the Ku-band. The liquid water content threshold (α), while less influential on total melt quantity, affected the timing and persistence of surface melting events by influencing the beginning and the end of the melt season. As highlighted in other studies (e.g., Picard et al., 2022; de Roda Husman et al., 2022), these findings underscore that the link between the satellite signal and the actual water content within the snowpack remains indirect and sensor-dependent, requiring cautious interpretation when used for model correction and comparison.

Another major outcome concerns the role of sensor characteristics in determining assimilation efficiency. Frequency, spatial resolution, and revisit time all strongly influence the capacity of the model to adjust to observations as well as the number of melt day observed. In particular, despite its higher spatial resolution, the assimilation of Sentinel-1 data alone was insufficient to generate persistent model adjustments, due to its relatively long revisit time. The experiments highlighted the potential advantage of multi-sensor assimilation, combining complementary observations from C- and Ku-band active and passive sensors to better constrain both shallow and deeper wet layers in the snowpack. However, this approach also increases the complexity of the algorithm and the risk of inconsistencies between datasets.

Beyond the direct numerical results, these experiments provided valuable insight into the strengths and limitations of MAR in representing the Antarctic surface processes. The model proved to be resilient and internally consistent, meaning that once the external forcing from satellite data was removed, it tended to revert to its equilibrium state. While this is an encouraging sign of model stability, it also implies that strong or frequent observational constraints are needed to achieve a sustained improvement in simulation accuracy. Furthermore, since the largest discrepancies between MAR and the satellite-derived wet-snow occurrence were observed at the beginning and end of the melt season, the assimilation framework points to a potential overestimation of meltwater refreezing or percolation processes, or an underestimation of the snowpack's capacity to retain liquid water rather than an underestimation of surface melt production.

5.5 Implications for Regional Climate Modelling

The results obtained in this thesis have broader implications for regional climate modelling. Given the results in the previous sections, they suggest that accurately representing land-atmosphere interactions in regional climate models requires moving beyond static and prescribed surface conditions toward dynamically coupled and observation-informed modelling systems.

The relatively weak atmospheric response compared to the vegetation response observed under present-day temperate conditions suggests that the strength of land-atmosphere coupling may vary depending not only on the region and climate regime, but also on the model structure and its parametrisations. As highlighted by numerous other studies (e.g., Knist et al., 2017; Crowhurst et al., 2020; Anwar and Diallo, 2021; Jiménez-Gutiérrez et al., 2021), this underscores the importance of applying such modelling approaches across different models, parametrisations, and study re-

gions. Multi-model studies will therefore be necessary to draw robust conclusions for climate projections.

Furthermore, the integration of remote sensing data emerges as a critical component for both model evaluation and model uncertainties quantifications, particularly in data-sparse regions such as Antarctica. However, as already highlighted by Latifi and Galos (2010), Picard et al. (2022), or Leduc-Leballeur et al. (2026), effectively integrating remote sensing data into models requires careful consideration because of observational uncertainties and their relationship to the model's variables.

CHAPTER 6

Perspectives and Future Developments

Although the results of this study are promising, they also reveal several areas where further development is needed to consolidate and extend our findings.

The first research axis provided valuable groundwork for understanding land-atmosphere interactions. While it did not lead to definitive conclusions, it played a crucial preparatory role, laying the foundation for the more advanced investigations carried out in the second axis of this work. In particular, it provided valuable insights into the behaviour of the MAR model itself. The relatively weak atmospheric response to vegetation changes in MAR, contrary to some other models (Yang et al., 2020; Chen et al., 2022a), suggests that its surface-atmosphere coupling could be improved. Future work should re-examine the parametrisation controlling land-atmosphere exchanges, particularly within the SISVAT module, as well as the synoptic control over small domains. A new parametrisation scheme using MODIS-based datasets could increase MAR’s sensitivity to vegetation dynamics and improve the simulation of heatwaves and droughts. Using the MODIS mean annual cycle as the default input could reduce the need for empirical corrections such as the adjustment coefficients currently applied to MERRA2 data. Furthermore, the distribution of vegetation across MAR sub-pixels should be refined, as it currently appears to exhibit unintended behaviour.

A revised version of the sub-pixel vegetation distribution, along with a new vegetation-class input dataset, has already been initiated and is currently being tested. The new vegetation cover is based on the gridded land cover classification maps from 1992 to present, derived from satellite observations provided by the Copernicus Climate Change Service (C3S; Copernicus Climate Change Service, 2019). This dataset is resampled onto the MAR grid using a conversion table that maps C3S vegetation classes to the corresponding MAR vegetation classes, potentially splitting a single C3S class into multiple MAR classes when required. In addition to the new input dataset, the three sub-pixels of MAR now represent the three dominant vegetation types and their respective fractional coverage within each pixel, instead of the previous configuration (two vegetation types plus a hypothetical grass field). Repeating the sensitivity experiments using an updated transfer scheme and improved vegetation dataset could provide a better understanding of the land-atmosphere interactions over central Europe and further enhance MAR’s representation of surface processes.

The coupling between MAR and CARAIB also opened multiple avenues for further development. In this version of the coupled model, only a limited set of variables is exchanged, leading to redundant calculations and missing feedback. Expanding the coupling to include memory sharing of key variables such as stomatal resistance, surface roughness, spectral fluxes, and soil moisture would strengthen the representation of vegetation-climate feedbacks. Additionally, while MAR and CARAIB currently operate on the same spatial grid, future implementations could use a higher-resolution CARAIB configuration. Similarly to what is done in other coupled model, like in Ho-Hagemann et al. (2024) that coupled the regional climate model ICON-CLM to the Earth system model GCOAST-AHOI, a dedicated coupling software such as OASIS3 (Craig et al., 2017) could support the coupling framework. OASIS3 could manage the interpolation and exchange of variables between the models on

different grids. From a technical standpoint, CARAIB should also be modified to read (write) input (output) file on a daily basis rather than once a year, which would significantly improve computational efficiency.

The current results, although satisfactory, do not reveal strong land-atmosphere interactions under present-day Belgian climate conditions. Applying the coupled model to regions with a stronger coupling regime identified by Knist et al. (2017), such as southern Europe, could reveal more pronounced feedbacks. In this manner, a domain over Spain has been designed for a new RAVEL experiment and is currently being tested, with promising results.

The observed spatial patterns in the difference for most of the variables between the standalone and the coupled simulations emphasize the crucial role of vegetation type and density in modulating the strength of land-atmosphere feedbacks. In regions dominated by low vegetation, such as grasslands and croplands, the coupling between the biosphere and the atmosphere is stronger and sensitive to soil moisture variability, leading to larger impacts on surface temperature and humidity. Conversely, forests act as stabilizing buffers by attenuating short-term atmospheric responses. These findings highlight the importance of accounting for vegetation heterogeneity to improve the representation of regional climate-vegetation interactions. However, the situation may evolve in the future: while forests appeared less sensitive under current conditions, they could be increasingly affected by climate change or could disappear on longer timescales (Roebroek et al., 2025). With different vegetation distribution, coupling regimes may differ under future climatic conditions and green house gases forcing (Seneviratne et al., 2006). Therefore as also pointed by Jiménez-Gutiérrez et al. (2021) and Anwar and Diallo (2022), extending simulations to multi-decadal horizons under different global warming scenarios will be crucial to assess how projected vegetations could impact regional climate model’s long-term simulated climate as vegetation dynamics can enhance its variability (Delire et al., 2011).

Similarly to what is concluded by Puggaard et al. (2025), the third research axis, focused on data assimilation, revealed that MAR is inconsistent in terms of surface wet-snow occurrence compared to remote-sensing observations. While part of this discrepancy may arise from ambiguities in the satellite definition of wet snow (Picard et al., 2022; Nagler et al., 2024; Leduc-Leballeur et al., 2026), model biases could also stem from overestimated meltwater refreezing or underestimated snow water retention. Improving the parametrisation of snow hydrology is therefore essential, particularly over ice shelves, where the liquid-water content influences stability and mass balance. Enhancing this representation will be critical for reliable climate projections over Antarctica.

The deployment of additional SAR satellites through the densification of existing constellations (e.g., Sentinel-1C and Sentinel-1D), as well as new missions such as NISAR (launched in 2025) and ROSE-L (planned for 2028), will enable the integration of high spatial-resolution data with improved revisit times for active microwave observations. In addition, emerging techniques for refining wet-snow detection (de Roda Husman et al., 2024) and estimating melt rates (Di Biase et al., 2026) could

further enhance data assimilation by enabling the direct use of snowpack liquid water content, rather than relying solely on binary wet-snow occurrence.

Given the key role of land-atmosphere interactions in modulating regional climate, their accurate representation is essential to better assess future scenarios and support adaptation strategies. This work has paved the way toward improving their simulation through remote sensing data integration, assimilation and model coupling within regional climate modelling, but it represents only the beginning of a long and demanding effort in continuous model development.

Bibliography

- Abatzoglou, J. T. and Williams, A. P.: Impact of anthropogenic climate change on wildfire across western US forests, *Proceedings of the National Academy of Sciences*, 113, 11 770–11 775, <https://doi.org/10.1073/pnas.1607171113>, 2016.
- Adusumilli, S., Fricker, H. A., Medley, B., Padman, L., and Siegfried, M. R.: Interannual variations in meltwater input to the Southern Ocean from Antarctic ice shelves, *Nature Geoscience*, 13, 616–620, <https://doi.org/10.1038/s41561-020-0616-z>, 2020.
- Agosta, C., Amory, C., Kittel, C., Orsi, A., Favier, V., Gallée, H., van den Broeke, M. R., Lenaerts, J. T. M., van Wessem, J. M., van de Berg, W. J., and Fettweis, X.: Estimation of the Antarctic surface mass balance using the regional climate model MAR (1979–2015) and identification of dominant processes, *The Cryosphere*, 13, 281–296, <https://doi.org/10.5194/tc-13-281-2019>, 2019.
- Allen, C. D., Breshears, D. D., and McDowell, N. G.: On underestimation of global vulnerability to tree mortality and forest die-off from hotter drought in the Anthropocene, *Ecosphere*, 6, art129, <https://doi.org/10.1890/ES15-00203.1>, 2015.
- Amante, C. and Eakins, B. W.: ETOPO1 arc-minute global relief model : procedures, data sources and analysis. NOAA technical memorandum NESDIS NGDC-24, <https://repository.library.noaa.gov/view/noaa/1163>, visited on 2022-10-20, 2009.
- Anwar, S. A. and Diallo, I.: A RCM investigation of the influence of vegetation status and runoff scheme on the summer gross primary production of Tropical Africa, *Theoretical and Applied Climatology*, 145, 1407–1420, <https://doi.org/10.1007/s00704-021-03667-0>, 2021.
- Anwar, S. A. and Diallo, I.: Modelling the Tropical African Climate using a state-of-the-art coupled regional climate-vegetation model, *Climate Dynamics*, 58, 97–113, <https://doi.org/10.1007/s00382-021-05892-9>, 2022.
- Aschbacher, J. and Milagro-Pérez, M. P.: The European Earth monitoring (GMES) programme: Status and perspectives, *Remote Sensing of Environment*, 120, 3–8, <https://doi.org/10.1016/j.rse.2011.08.028>, 2012.
- Ashcraft, I. S. and Long, D. G.: Comparison of methods for melt detection over Greenland using active and passive microwave measurements, *International Journal of Remote Sensing*, 27, 2469–2488, <https://doi.org/10.1080/01431160500534465>, 2006.
- Balcha, S. K., Hulluka, T. A., Awass, A. A., and Bantider, A.: Performance evaluation of multiple regional climate models to simulate rainfall in the Central Rift Valley Lakes Basin of Ethiopia and their selection criteria for the best climate model, *Environmental Monitoring and Assessment*, 195, 888, <https://doi.org/10.1007/s10661-023-11437-w>, 2023.
- Ball, J. T., Woodrow, I. E., and Berry, J. A.: A Model Predicting Stomatal Conductance and its Contribution to the Control of Photosynthesis under Different Environmental Conditions, pp. 221–224, Springer Netherlands, Dordrecht, ISBN 978-94-017-0519-6, https://doi.org/10.1007/978-94-017-0519-6_48, 1987.

- Banwell, A. F., MacAyeal, D. R., and Sergienko, O. V.: Breakup of the Larsen B Ice Shelf triggered by chain reaction drainage of supraglacial lakes, *Geophysical Research Letters*, 40, 5872–5876, <https://doi.org/10.1002/2013GL057694>, 2013.
- Banwell, A. F., Datta, R. T., Dell, R. L., Moussavi, M., Brucker, L., Picard, G., Shuman, C. A., and Stevens, L. A.: The 32-year record-high surface melt in 2019/2020 on the northern George VI Ice Shelf, Antarctic Peninsula, *The Cryosphere*, 15, 909–925, <https://doi.org/10.5194/tc-15-909-2021>, 2021.
- Barrand, N. E., Vaughan, D. G., Steiner, N., Tedesco, M., Kuipers Munneke, P., van den Broeke, M. R., and Hosking, J. S.: Trends in Antarctic Peninsula surface melting conditions from observations and regional climate modeling, *Journal of Geophysical Research: Earth Surface*, 118, 315–330, <https://doi.org/10.1029/2012JF002559>, 2013.
- Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., and Wood, E. F.: Present and future Köppen-Geiger climate classification maps at 1-km resolution, *Scientific Data*, 5, 180 214, <https://doi.org/10.1038/sdata.2018.214>, 2018.
- Bell, R. E., Banwell, A. F., Trusel, L. D., and Kingslake, J.: Antarctic surface hydrology and impacts on ice-sheet mass balance, *Nature Climate Change*, 8, 1044–1052, <https://doi.org/10.1038/s41558-018-0326-3>, 2018.
- Beniston, M., Stephenson, D. B., Christensen, O. B., Ferro, C. A. T., Frei, C., Goyette, S., Halsnaes, K., Holt, T., Jylhä, K., Koffi, B., Palutikof, J., Schöll, R., Semmler, T., and Woth, K.: Future extreme events in European climate: an exploration of regional climate model projections, *Climatic Change*, 81, 71–95, <https://doi.org/10.1007/s10584-006-9226-z>, 2007.
- Bevacqua, E., Rakovec, O., Schumacher, D. L., Kumar, R., Thober, S., Samaniego, L., Seneviratne, S. I., and Zscheischler, J.: Direct and lagged climate change effects intensified the 2022 European drought, *Nature Geoscience*, 17, 1100–1107, <https://doi.org/10.1038/s41561-024-01559-2>, 2024.
- Biella, R., Shyrokaya, A., Pechlivanidis, I., Cid, D., Llasat, M. C., Wens, M., Lam, M., Stenfors, E., Sutanto, S., Ridolfi, E., Ceola, S., Alencar, P., Di Baldassarre, G., Ionita, M., de Brito, M. M., McGrane, S. J., Moccia, B., Nagavciuc, V., Russo, F., Krakovska, S., Todorovic, A., Tootoonchi, F., Trambauer, P., Vignola, R., and Teutschbein, C.: The 2022 Drought Shows the Importance of Preparedness in European Drought Risk Management, *EGUsphere*, 2024, 1–40, <https://doi.org/10.5194/egusphere-2024-2073>, 2024.
- Bojinski, S., Verstraete, M., Peterson, T. C., Richter, C., Simmons, A., and Zemp, M.: The Concept of Essential Climate Variables in Support of Climate Research, Applications, and Policy, *Bulletin of the American Meteorological Society*, 95, 1431 – 1443, <https://doi.org/10.1175/BAMS-D-13-00047.1>, 2014.
- Bonan, G.: *Ecological Climatology: Concepts and Applications*, Cambridge University Press, 3 edn., 2015.

- Boucher, O., Servonnat, J., Albright, A. L., Aumont, O., Balkanski, Y., Bastrikov, V., Bekki, S., Bonnet, R., Bony, S., Bopp, L., Braconnot, P., Brockmann, P., Cadule, P., Caubel, A., Cheruy, F., Codron, F., Cozic, A., Cugnet, D., D'Andrea, F., Davini, P., de Lavergne, C., Denvil, S., Deshayes, J., Devilliers, M., Ducharne, A., Dufresne, J.-L., Dupont, E., Éthé, C., Fairhead, L., Falletti, L., Flavoni, S., Foujols, M.-A., Gardoll, S., Gastineau, G., Ghattas, J., Grandpeix, J.-Y., Guenet, B., Guez, Lionel, E., Guilyardi, E., Guimberteau, M., Hauglustaine, D., Hourdin, F., Idelkadi, A., Joussaume, S., Kageyama, M., Khodri, M., Krinner, G., Lebas, N., Levavasseur, G., Lévy, C., Li, L., Lott, F., Lurton, T., Luyssaert, S., Madec, G., Madeleine, J.-B., Maignan, F., Marchand, M., Marti, O., Mellul, L., Meurdesoif, Y., Mignot, J., Musat, I., Ottlé, C., Peylin, P., Planton, Y., Polcher, J., Rio, C., Rochetin, N., Rousset, C., Sepulchre, P., Sima, A., Swingedouw, D., Thiéblemont, R., Traore, A. K., Vancoppenolle, M., Vial, J., Vialard, J., Viovy, N., and Vuichard, N.: Presentation and Evaluation of the IPSL-CM6A-LR Climate Model, *Journal of Advances in Modeling Earth Systems*, 12, e2019MS002010, <https://doi.org/10.1029/2019MS002010>, 2020.
- Brajkovic, J., Fettweis, X., Noël, B., Vyver, H. V. D., Ghilain, N., Archambeau, P., Piroton, M., and Doutreloup, S.: Increased intensity and frequency of extreme precipitation events in Belgium as simulated by the regional climate model MAR, *Journal of Hydrology: Regional Studies*, 59, 102399, <https://doi.org/10.1016/j.ejrh.2025.102399>, 2025.
- Bright, R. M., Caporaso, L., Duveiller, G., Piccardo, M., and Cescatti, A.: Biogeophysical Radiative Forcings of Large-Scale Afforestation in Europe Are Highly Localized and Dominated by Surface Albedo Change, *Geophysical Research Letters*, 52, e2024GL112739, <https://doi.org/10.1029/2024GL112739>, 2025.
- Brun, E., David, P., Sudul, M., and Brunot, G.: A numerical model to simulate snow-cover stratigraphy for operational avalanche forecasting, *Journal of Glaciology*, 38, 13–22, <https://doi.org/10.3189/s0022143000009552>, 1992.
- Buchelt, S., Skov, K., Rasmussen, K. K., and Ullmann, T.: Sentinel-1 time series for mapping snow cover depletion and timing of snowmelt in Arctic periglacial environments: Case study from Zackenberg and Kobbefjord, Greenland, *The Cryosphere*, 16, 625–646, <https://doi.org/10.5194/tc-16-625-2022>, 2022.
- Bueler, E. and Brown, J.: Shallow shelf approximation as a “sliding law” in a thermomechanically coupled ice sheet model, *Journal of Geophysical Research: Earth Surface*, 114, <https://doi.org/10.1029/2008JF001179>, 2009.
- Cabos, W., de la Vara, A., Álvarez-García, F. J., Sánchez, E., Sieck, K., Pérez-Sanz, J.-I., Limareva, N., and Sein, D. V.: Impact of ocean-atmosphere coupling on regional climate: the Iberian Peninsula case, *Climate Dynamics*, 54, 4441–4467, <https://doi.org/10.1007/s00382-020-05238-x>, 2020.
- Carnicer, J., Coll, M., Ninyerola, M., Pons, X., Sánchez, G., and Peñuelas, J.: Widespread crown condition decline, food web disruption, and amplified tree mortality with increased climate change-type drought, *Proceedings of the National Academy of Sciences*, 108, 1474–1478, <https://doi.org/10.1073/pnas.1010070108>, 2011.

- Certini, G.: Effects of fire on properties of forest soils: a review, *Oecologia*, 143, 1–10, <https://doi.org/10.1007/s00442-004-1788-8>, 2005.
- Chang, K.-Y., Paw U, K. T., and Chen, S.-H.: Canopy profile sensitivity on surface layer simulations evaluated by a multiple canopy layer higher order closure land surface model, *Agricultural and Forest Meteorology*, 252, 192–207, <https://doi.org/10.1016/j.agrformet.2018.01.027>, 2018.
- Chaparro, D., Jagdhuber, T., Piles, M., Jonard, F., Fluhrer, A., Vall-llossera, M., Camps, A., López-Martínez, C., Fernández-Morán, R., Baur, M., Feldman, A. F., Fink, A., and Entekhabi, D.: Vegetation moisture estimation in the Western United States using radiometer-radar-lidar synergy, *Remote Sensing of Environment*, 303, 113 993, <https://doi.org/10.1016/j.rse.2024.113993>, 2024.
- Chase, T. N., Pielke, R. A., Kittel, T. G. F., Nemani, R., and Running, S. W.: Sensitivity of a general circulation model to global changes in leaf area index, *Journal of Geophysical Research: Atmospheres*, 101, 7393–7408, <https://doi.org/10.1029/95JD02417>, 1996.
- Chaves, M. M., Maroco, J. P., and Pereira, J. S.: Understanding plant responses to drought - from genes to the whole plant, *Functional plant biology : FPB*, 30, 239–264, <https://doi.org/10.1071/FP02076>, 2003.
- Chen, J., Zhang, Q., Kjellström, E., Lu, Z., and Chen, F.: The Contribution of Vegetation-Climate Feedback and Resultant Sea Ice Loss to Amplified Arctic Warming During the Mid-Holocene, *Geophysical Research Letters*, 49, e2022GL098 816, <https://doi.org/10.1029/2022GL098816>, 2022a.
- Chen, J. M. and Black, T. A.: Defining leaf area index for non-flat leaves, *Plant, Cell & Environment*, 15, 421–429, <https://doi.org/10.1111/j.1365-3040.1992.tb00992.x>, 1992.
- Chen, Q., Timmermans, J., Wen, W., and van Bodegom, P. M.: A multi-metric assessment of drought vulnerability across different vegetation types using high resolution remote sensing, *Science of The Total Environment*, 832, 154 970, <https://doi.org/10.1016/j.scitotenv.2022.154970>, 2022b.
- Church, J., Clark, P., Cazenave, A., Gregory, J., Jevrejeva, S., Levermann, A., Merrifield, M., Milne, G., Nerem, R., Nunn, P., Payne, A., Pfeffer, W., Stammer, D., and Unnikrishnan, A.: Sea Level Change, in: *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Stocker, T., Qin, D., Plattner, G.-K., Tignor, M., Allen, S., Boschung, J., Nauels, A., Xia, Y., Bex, V., and Midgley, P., Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA., 2013.
- Chuter, S. J., Zammit-Mangion, A., Rougier, J., Dawson, G., and Bamber, J. L.: Mass evolution of the Antarctic Peninsula over the last 2 decades from a joint Bayesian inversion, *The Cryosphere*, 16, 1349–1367, <https://doi.org/10.5194/tc-16-1349-2022>, 2022.

- Collatz, G., Ribas-Carbo, M., and Berry, J.: Coupled Photosynthesis-Stomatal Conductance Model for Leaves of C4 Plants, *Functional Plant Biology*, 19, 519, <https://doi.org/10.1071/PP9920519>, 1992.
- Colosio, P., Tedesco, M., Ranzi, R., and Fettweis, X.: Surface melting over the Greenland ice sheet derived from enhanced resolution passive microwave brightness temperatures (1979–2019), *The Cryosphere*, 15, 2623–2646, <https://doi.org/10.5194/tc-15-2623-2021>, 2021.
- Coléou, C. and Lesaffre, B.: Irreducible water saturation in snow: Experimental results in a cold laboratory, *Annals of Glaciology*, 26, <https://doi.org/10.1017/S0260305500014579>, 1998.
- Copernicus Climate Change Service: Land cover classification gridded maps from 1992 to present derived from satellite observations, <https://doi.org/10.24381/cds.006f2c9a>, visited on 2025-11-12, 2019.
- Corti, G., Zeoli, A., and Iandelli, I.: Small-scale modeling of ice flow perturbations induced by sudden ice shelf breakup, *Global and Planetary Change*, 119, 51–55, <https://doi.org/10.1016/j.gloplacha.2014.05.002>, 2014.
- Craig, A., Valcke, S., and Coquart, L.: Development and performance of a new version of the OASIS coupler, OASIS3-MCT_3.0, *Geoscientific Model Development*, 10, 3297–3308, <https://doi.org/10.5194/gmd-10-3297-2017>, 2017.
- Crowhurst, D. M., Dadson, S. J., and Washington, R.: Evaluation of Evaporation Climatology for the Congo Basin Wet Seasons in 11 Global Climate Models, *Journal of Geophysical Research: Atmospheres*, 125, e2019JD030619, <https://doi.org/10.1029/2019JD030619>, e2019JD030619 2019JD030619, 2020.
- Curry, J. A., Schramm, J. L., and Ebert, E. E.: Sea Ice-Albedo Climate Feedback Mechanism, *Journal of Climate*, 8, 240 – 247, [https://doi.org/10.1175/1520-0442\(1995\)008<0240:SIACFM>2.0.CO;2](https://doi.org/10.1175/1520-0442(1995)008<0240:SIACFM>2.0.CO;2), 1995.
- Dai, A.: Drought under global warming: a review, *WIREs Climate Change*, 2, 45–65, <https://doi.org/10.1002/wcc.81>, 2011.
- Danandeh Mehr, A. and Kahya, E.: Grid-based performance evaluation of GCM-RCM combinations for rainfall reproduction, *Theoretical and Applied Climatology*, 129, 47–57, <https://doi.org/10.1007/s00704-016-1758-1>, 2017.
- Datta, R. T., Tedesco, M., Agosta, C., Fettweis, X., Kuipers Munneke, P., and van den Broeke, M. R.: Melting over the northeast Antarctic Peninsula (1999–2009): evaluation of a high-resolution regional climate model, *The Cryosphere*, 12, 2901–2922, <https://doi.org/10.5194/tc-12-2901-2018>, 2018.
- Datta, R. T., Tedesco, M., Fettweis, X., Agosta, C., Lhermitte, S., Lenaerts, J. T. M., and Wever, N.: The Effect of Foehn-Induced Surface Melt on Firn Evolution Over the Northeast Antarctic Peninsula, *Geophysical Research Letters*, 46, 3822–3831, <https://doi.org/10.1029/2018GL080845>, 2019.

- Davin, E. L., Rechid, D., Breil, M., Cardoso, R. M., Coppola, E., Hoffmann, P., Jach, L. L., Katragkou, E., de Noblet-Ducoudré, N., Radtke, K., Raffa, M., Soares, P. M. M., Sofiadis, G., Strada, S., Strandberg, G., Tölle, M. H., Warrach-Sagi, K., and Wulfmeyer, V.: Biogeophysical impacts of forestation in Europe: first results from the LUCAS (Land Use and Climate Across Scales) regional climate model intercomparison, *Earth System Dynamics*, 11, 183–200, <https://doi.org/10.5194/esd-11-183-2020>, 2020.
- De Cannière, S., Baur, M., Chaparro, D., Jagdhuber, T., and Jonard, F.: Water availability and atmospheric dryness controls on spaceborne sun-induced chlorophyll fluorescence yield, *Remote Sensing of Environment*, 301, 113 922, <https://doi.org/10.1016/j.rse.2023.113922>, 2024.
- De Hertog, S. J., Lopez-Fabara, C. E., van der Ent, R., Keune, J., Miralles, D. G., Portmann, R., Schemm, S., Havermann, F., Guo, S., Luo, F., Manola, I., Lejeune, Q., Pongratz, J., Schleussner, C.-F., Seneviratne, S. I., and Thiery, W.: Effects of idealized land cover and land management changes on the atmospheric water cycle, *Earth System Dynamics*, 15, 265–291, <https://doi.org/10.5194/esd-15-265-2024>, 2024.
- De Leo, G. A. and Levin, S.: The Multifaceted Aspects of Ecosystem Integrity, *Conservation Ecology*, 1, <http://www.jstor.org/stable/26271649>, 1997.
- De Ridder, K.: Radiative Transfer in the IAGL Land Surface Model, *Journal of Applied Meteorology*, 36, 12 – 21, [https://doi.org/10.1175/1520-0450\(1997\)036<0012:RTITIL>2.0.CO;2](https://doi.org/10.1175/1520-0450(1997)036<0012:RTITIL>2.0.CO;2), 1997.
- De Ridder, K. and Gallée, H.: Land Surface–Induced Regional Climate Change in Southern Israel, *Journal of Applied Meteorology*, 37, 1470 – 1485, [https://doi.org/10.1175/1520-0450\(1998\)037<1470:LSIRCC>2.0.CO;2](https://doi.org/10.1175/1520-0450(1998)037<1470:LSIRCC>2.0.CO;2), 1998.
- De Ridder, K. and Schayes, G.: The IAGL Land Surface Model, *Journal of Applied Meteorology*, 36, 167 – 182, [https://doi.org/10.1175/1520-0450\(1997\)036<0167:TILSM>2.0.CO;2](https://doi.org/10.1175/1520-0450(1997)036<0167:TILSM>2.0.CO;2), 1997.
- de Roda Husman, S., Zhongyang, H., Wouters, B., Munneke, P. K., Veldhuijsen, S., and Lhermitte, S.: Remote Sensing of Surface Melt on Antarctica: Opportunities and Challenges, *Journal of selected topics in applied earth observations and remote sensing*, <https://doi.org/10.1109/JSTARS.2022.3216953>, 2022.
- de Roda Husman, S., Lhermitte, S., Bolibar, J., Izeboud, M., Hu, Z., Shukla, S., van der Meer, M., Long, D., and Wouters, B.: A high-resolution record of surface melt on Antarctic ice shelves using multi-source remote sensing data and deep learning, *Remote Sensing of Environment*, 301, 113 950, <https://doi.org/10.1016/j.rse.2023.113950>, 2024.
- de Vyver, H. V., Schaeybroeck, B. V., Troch, R. D., Cruz, L. D., Hamdi, R., Villanueva-Birriel, C., Marbaix, P., van Ypersele, J.-P., Wouters, H., Broucke, S. V., van Lipzig, N. P. M., Doutreloup, S., Wyard, C., Scholzen, C., Fettweis, X., Caluwaerts, S., and Termonia, P.: Evaluation Framework for Subdaily Rainfall Extremes Simulated by Regional Climate Models, *Journal of Applied Meteorology*

- and Climatology, 60, 1423 – 1442, <https://doi.org/10.1175/JAMC-D-21-0004.1>, 2021.
- Decker, M., Pitman, A., and Evans, J.: Diagnosing the seasonal land–atmosphere correspondence over northern Australia: dependence on soil moisture state and correspondence strength definition, *Hydrology and Earth System Sciences*, 19, 3433–3447, <https://doi.org/10.5194/hess-19-3433-2015>, 2015.
- Delhasse, A., Kittel, C., Amory, C., Hofer, S., van As, D., S. Fausto, R., and Fettweis, X.: Brief communication: Evaluation of the near-surface climate in ERA5 over the Greenland Ice Sheet, *The Cryosphere*, 14, 957–965, <https://doi.org/10.5194/tc-14-957-2020>, 2020.
- Delhasse, A., Beckmann, J., Kittel, C., and Fettweis, X.: Coupling MAR (Modèle Atmosphérique Régional) with PISM (Parallel Ice Sheet Model) mitigates the positive melt–elevation feedback, *The Cryosphere*, 18, 633–651, <https://doi.org/10.5194/tc-18-633-2024>, 2024.
- Delire, C., de Noblet-Ducoudré, N., Sima, A., and Gouirand, I.: Vegetation Dynamics Enhancing Long-Term Climate Variability Confirmed by Two Models, *Journal of Climate*, 24, 2238 – 2257, <https://doi.org/10.1175/2010JCLI3664.1>, 2011.
- Dethinne, T., Glaude, Q., Picard, G., Kittel, C., Alexander, P., Orban, A., and Fettweis, X.: Sensitivity of the MAR regional climate model snowpack to the parameterization of the assimilation of satellite-derived wet-snow masks on the Antarctic Peninsula, *The Cryosphere*, 17, 4267–4288, <https://doi.org/10.5194/tc-17-4267-2023>, 2023.
- Dethinne, T., Ghilain, N., Kittel, C., Lecart, B., Fettweis, X., and Jonard, F.: Assessing Regional Climate Model Sensitivity to Vegetation Dynamics Informed by Remote Sensing, *EGUsphere*, 2025, 1–43, <https://doi.org/10.5194/egusphere-2025-3907>, [Preprint], 2025.
- Di Biase, V., Kuipers Munneke, P., Wouters, B., van den Broeke, M. R., and van Tiggelen, M.: Estimating Antarctic surface melt rates using passive microwave data calibrated with weather station observations, *The Cryosphere*, 20, 87–96, <https://doi.org/10.5194/tc-20-87-2026>, 2026.
- Dickinson, R. E., Errico, R. M., Giorgi, F., and Bates, G. T.: A regional climate model for the western United States, *Climatic Change*, 15, 383–422, <https://doi.org/10.1007/BF00240465>, 1989.
- Dingley, B., Anstey, J. A., Abalos, M., Abraham, C., Bergman, T., Bock, L., Fiddes, S., Hassler, B., Kramer, R. J., Luo, F., O’Connor, F. M., Šácha, P., Simpson, I. R., Wilcox, L. J., and Zelinka, M. D.: CMIP7 Data Request: Atmosphere Priorities and Opportunities, *EGUsphere*, 2025, 1–54, <https://doi.org/10.5194/egusphere-2025-3189>, 2025.
- Dirmeyer, P. A.: The terrestrial segment of soil moisture–climate coupling, *Geophysical Research Letters*, 38, <https://doi.org/10.1029/2011GL048268>, 2011.

- Dirmeyer, P. A., Koster, R. D., and Guo, Z.: Do Global Models Properly Represent the Feedback between Land and Atmosphere?, *Journal of Hydrometeorology*, 7, 1177 – 1198, <https://doi.org/10.1175/JHM532.1>, 2006.
- Donat-Magnin, M., Jourdain, N. C., Kittel, C., Agosta, C., Amory, C., Gallée, H., Krinner, G., and Chekki, M.: Future surface mass balance and surface melt in the Amundsen sector of the West Antarctic Ice Sheet, *The Cryosphere*, 15, 571–593, <https://doi.org/10.5194/tc-15-571-2021>, 2021.
- Doutreloup, S., Kittel, C., Wyard, C., Belleflamme, A., Amory, C., Erpicum, M., and Fettweis, X.: Precipitation Evolution over Belgium by 2100 and Sensitivity to Convective Schemes Using the Regional Climate Model MAR, *Atmosphere*, 10, <https://doi.org/10.3390/atmos10060321>, 2019a.
- Doutreloup, S., Wyard, C., Amory, C., Kittel, C., Erpicum, M., and Fettweis, X.: Sensitivity to Convective Schemes on Precipitation Simulated by the Regional Climate Model MAR over Belgium (1987–2017), *Atmosphere*, 10, <https://doi.org/10.3390/atmos10010034>, 2019b.
- Doutreloup, S., Fettweis, X., Rahif, R., Elnagar, E., Pourkiaei, M. S., Amaripadath, D., and Attia, S.: Historical and future weather data for dynamic building simulations in Belgium using the regional climate model MAR: typical and extreme meteorological year and heatwaves, *Earth System Science Data*, 14, 3039–3051, <https://doi.org/10.5194/essd-14-3039-2022>, 2022.
- Drusch, M., Del Bello, U., Carlier, S., Colin, O., Fernandez, V., Gascon, F., Hoersch, B., Isola, C., Laberinti, P., Martimort, P., Meygret, A., Spoto, F., Sy, O., Marchese, F., and Bargellini, P.: Sentinel-2: ESA’s Optical High-Resolution Mission for GMES Operational Services, *Remote Sensing of Environment*, 120, 25–36, <https://doi.org/10.1016/j.rse.2011.11.026>, 2012.
- Dury, M., Hambuckers, A., Warnant, P., Henrot, A., Favre, E., Ouberdous, M., and Francois, L.: Responses of European forest ecosystems to 21st century climate: assessing changes in interannual variability and fire intensity, *iForest - Biogeosciences and Forestry*, pp. 82–99, <https://doi.org/10.3832/ifer0572-004>, 2011.
- Duveiller, G., Filipponi, F., Ceglar, A., Bojanowski, J., Alkama, R., and Cescatti, A.: Revealing the widespread potential of forests to increase low level cloud cover, *Nature Communications*, 12, 4337, <https://doi.org/10.1038/s41467-021-24551-5>, 2021.
- EC-Earth Consortium: EC-Earth-Consortium EC-Earth3-Veg-LR model output prepared for CMIP6 CMIP historical, <https://doi.org/10.22033/ESGF/CMIP6.4707>, 2020.
- Ek, M. and Mahrt, L.: Daytime Evolution of Relative Humidity at the Boundary Layer Top, *Monthly Weather Review*, 122, 2709 – 2721, [https://doi.org/10.1175/1520-0493\(1994\)122<2709:DEORHA>2.0.CO;2](https://doi.org/10.1175/1520-0493(1994)122<2709:DEORHA>2.0.CO;2), 1994.
- Ek, M. B. and Holtslag, A. A. M.: Influence of Soil Moisture on Boundary Layer Cloud Development, *Journal of Hydrometeorology*, 5, 86 – 99, [https://doi.org/10.1175/1525-7541\(2004\)005<0086:IOSMOB>2.0.CO;2](https://doi.org/10.1175/1525-7541(2004)005<0086:IOSMOB>2.0.CO;2), 2004.

- Elachi, C. and van Zyl, J.: Nature and Properties of Electromagnetic Waves, in: Introduction to the Physics and Techniques of Remote Sensing, chap. 2, pp. 23–50, John Wiley and Sons, Ltd, ISBN 9780471783398, <https://doi.org/10.1002/0471783390.ch2>, 2006.
- Elachi, C. and van Zyl, J.: Introduction to the Physics and Techniques of Remote Sensing, John Wiley & Sons, Hoboken, NJ, ISBN 9781119523017, <https://doi.org/10.1002/9781119523048>, 2021.
- Eltahir, E. A. B. and Bras, R. L.: Precipitation recycling, Reviews of Geophysics, 34, 367–378, <https://doi.org/10.1029/96RG01927>, 1996.
- Engel, F., Hoek van Dijke, A. J., Roebroek, C. T. J., and Benedict, I.: Can large-scale tree cover change negate climate change impacts on future water availability?, Hydrology and Earth System Sciences, 29, 1895–1918, <https://doi.org/10.5194/hess-29-1895-2025>, 2025.
- Engle, J. L. and Weinstein, O.: The Thematic Mapper—An Overview, IEEE Transactions on Geoscience and Remote Sensing, GE-21, 258–265, <https://doi.org/10.1109/TGRS.1983.350551>, 1983.
- Entekhabi, D., Njoku, E. G., O’Neill, P. E., Kellogg, K. H., Crow, W. T., Edelstein, W. N., Entin, J. K., Goodman, S. D., Jackson, T. J., Johnson, J., Kimball, J., Piepmeier, J. R., Koster, R. D., Martin, N., McDonald, K. C., Moghaddam, M., Moran, S., Reichle, R., Shi, J. C., Spencer, M. W., Thurman, S. W., Tsang, L., and Van Zyl, J.: The Soil Moisture Active Passive (SMAP) Mission, Proceedings of the IEEE, 98, 704–716, <https://doi.org/10.1109/JPROC.2010.2043918>, 2010.
- Erpicum, M., Nouri, M., and Demoulin, A.: The Climate of Belgium and Luxembourg, pp. 35–41, Springer International Publishing, Cham, ISBN 978-3-319-58239-9, https://doi.org/10.1007/978-3-319-58239-9_3, 2018.
- ESA: The Copernicus Space Component: Sentinels Data Products List, <https://sentinels.copernicus.eu/documents/247904/685154/Sentinel+Products+List-Issue1-Rev1.pdf>, issue 1, Revision 1, 2015.
- ESA: ESA-developed Earth observation missions, https://www.esa.int/ESA_Multimedia/Images/2019/05/ESA-developed_Earth_observation_missions, visited on 2025-09-10, 2019.
- ESA: The Sentinel-1 Toolbox, <https://sentinel.esa.int/web/sentinel/toolboxes/sentinel-1>, visited on 2022-10-19, 2022.
- ESA: Sentinel-1 , <https://sentinel.esa.int/web/sentinel/missions/sentinel-1>, visited on 2023-05-24, 2023.
- Esri and Maxar and Earthstar Geographics and the GIS User Community: World Imagery [Basemap], <https://www.arcgis.com/home/item.html?id=10df2279f9684e4a9f6a7f08febac2a9>, accessed via QGIS QuickMapServices plugin, 2025.

- EUMETSAT: ASCAT Level 1 Sigma0 Full Resolution - Metop - Global, <https://navigator.eumetsat.int/product/E0:EUM:DAT:METOP:ASCSZF1B>, visited on 2023-05-24, 2023.
- Evensen, G.: Data assimilation: The ensemble kalman filter, Springer Berlin, Heidelberg, ISBN 978-3-642-03711-5, <https://doi.org/10.1007/978-3-642-03711-5>, 2009.
- Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E.: Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6) experimental design and organization, Geoscientific Model Development, 9, 1937–1958, <https://doi.org/10.5194/gmd-9-1937-2016>, 2016.
- Fahnestock, M. A., Abdalati, W., and Shuman, C. A.: Long melt seasons on ice shelves of the Antarctic Peninsula: an analysis using satellite-based microwave emission measurements, Annals of Glaciology, 34, 127–133, <https://doi.org/10.3189/172756402781817798>, 2002.
- Fairbanks, R. G.: A 17,000-year glacio-eustatic sea level record: influence of glacial melting rates on the Younger Dryas event and deep-ocean circulation, Nature, 342, 637–642, <https://doi.org/10.1038/342637a0>, 1989.
- Faisol, A., Indarto, Novita, E., and Budiyo: An evaluation of MODIS global evapotranspiration product (MOD16A2) as terrestrial evapotranspiration in East Java - Indonesia, IOP Conference Series: Earth and Environmental Science, 485, 012002, <https://doi.org/10.1088/1755-1315/485/1/012002>, 2020.
- Farquhar, G. D., von Caemmerer, S., and Berry, J. A.: A biochemical model of photosynthetic CO₂ assimilation in leaves of C₃ species, Planta, 149, 78–90, <https://doi.org/10.1007/BF00386231>, 1980.
- Favier, L. and Pattyn, F.: Antarctic ice rise formation, evolution, and stability, Geophysical Research Letters, 42, 4456–4463, <https://doi.org/10.1002/2015GL064195>, 2015.
- Fettweis, X., Tedesco, M., van den Broeke, M., and Ettema, J.: Melting trends over the Greenland ice sheet (1958–2009) from spaceborne microwave data and regional climate models, The Cryosphere, 5, 359–375, <https://doi.org/10.5194/tc-5-359-2011>, 2011.
- Fettweis, X., Hofer, S., Séférian, R., Amory, C., Delhasse, A., Doutreloup, S., Kittel, C., Lang, C., Van Bever, J., Veillon, F., and Irvine, P.: Brief communication: Reduction in the future Greenland ice sheet surface melt with the help of solar geoengineering, The Cryosphere, 15, 3013–3019, <https://doi.org/10.5194/tc-15-3013-2021>, 2021.
- Fluhrer, A., Baur, M. J., Piles, M., Bayat, B., Rahmati, M., Chaparro, D., Dubois, C., Hellwig, F. M., Montzka, C., Kübert, A., Mueller, M. M., Augscheller, I., Jonard, F., Schellenberg, K., and Jagdhuber, T.: Assessing evapotranspiration dynamics across central Europe in the context of land–atmosphere drivers, Biogeosciences, 22, 3721–3746, <https://doi.org/10.5194/bg-22-3721-2025>, 2025.

- Foley, J. A., Levis, S., Costa, M. H., Cramer, W., and Pollard, D.: INCORPORATING DYNAMIC VEGETATION COVER WITHIN GLOBAL CLIMATE MODELS, *Ecological Applications*, 10, 1620–1632, [https://doi.org/10.1890/1051-0761\(2000\)010\[1620:IDVCWG\]2.0.CO;2](https://doi.org/10.1890/1051-0761(2000)010[1620:IDVCWG]2.0.CO;2), 2000.
- François, L., Ghislain, M., Otto, D., and Micheels, A.: Late Miocene vegetation reconstruction with the CARAIB model, *Palaeogeography, Palaeoclimatology, Palaeoecology*, 238, 302–320, <https://doi.org/10.1016/j.palaeo.2006.03.034>, late Miocene to Early Pliocene Environment and Climate Change in the Mediterranean Area, 2006.
- François, L., Utescher, T., Favre, E., Henrot, A.-J., Warnant, P., Micheels, A., Erdei, B., Suc, J.-P., Cheddadi, R., and Mosbrugger, V.: Modelling Late Miocene vegetation in Europe: Results of the CARAIB model and comparison with palaeovegetation data, *Palaeogeography, Palaeoclimatology, Palaeoecology*, 304, 359–378, <https://doi.org/10.1016/j.palaeo.2011.01.012>, 2011.
- Fretwell, P., Pritchard, H. D., Vaughan, D. G., Bamber, J. L., Barrand, N. E., Bell, R., Bianchi, C., Bingham, R. G., Blankenship, D. D., Casassa, G., Catania, G., Callens, D., Conway, H., Cook, A. J., Corr, H. F. J., Damaske, D., Damm, V., Ferraccioli, F., Forsberg, R., Fujita, S., Gim, Y., Gogineni, P., Griggs, J. A., Hindmarsh, R. C. A., Holmlund, P., Holt, J. W., Jacobel, R. W., Jenkins, A., Jokat, W., Jordan, T., King, E. C., Kohler, J., Krabill, W., Riger-Kusk, M., Langley, K. A., Leitchenkov, G., Leuschen, C., Luyendyk, B. P., Matsuoka, K., Mouginot, J., Nitsche, F. O., Nogi, Y., Nost, O. A., Popov, S. V., Rignot, E., Rippin, D. M., Rivera, A., Roberts, J., Ross, N., Siegert, M. J., Smith, A. M., Steinhage, D., Studinger, M., Sun, B., Tinto, B. K., Welch, B. C., Wilson, D., Young, D. A., Xiangbin, C., and Zirizzotti, A.: Bedmap2: improved ice bed, surface and thickness datasets for Antarctica, *The Cryosphere*, 7, 375–393, <https://doi.org/10.5194/tc-7-375-2013>, 2013.
- Fricker, H. A., Arndt, P., Brunt, K. M., Datta, R. T., Fair, Z., Jasinski, M. F., Kingslake, J., Magruder, L. A., Moussavi, M., Pope, A., Spergel, J. J., Stoll, J. D., and Wouters, B.: ICESat-2 Meltwater Depth Estimates: Application to Surface Melt on Amery Ice Shelf, East Antarctica, *Geophysical Research Letters*, 48, e2020GL090550, <https://doi.org/10.1029/2020GL090550>, 2021.
- Fürst, J. J., Durand, G., Gillet-Chaulet, F., Tavard, L., Rankl, M., Braun, M., and Gagliardini, O.: The safety band of Antarctic ice shelves, *Nature Climate Change*, 6, 479–482, <https://doi.org/10.1038/nclimate2912>, 2016.
- Gallée, H. and Schayes, G.: Development of a Three-Dimensional Meso- γ Primitive Equation Model: Katabatic Winds Simulation in the Area of Terra Nova Bay, Antarctica, *Monthly Weather Review*, 122, 671 – 685, [https://doi.org/10.1175/1520-0493\(1994\)122<0671:DOATDM>2.0.CO;2](https://doi.org/10.1175/1520-0493(1994)122<0671:DOATDM>2.0.CO;2), 1994.
- GEE: Sentinel-1 Algorithms, <https://developers.google.com/earth-engine/guides/sentinel1>, visited on 2022-10-19, 2022.
- Gelaro, R., McCarty, W., Suárez, M. J., Todling, R., Molod, A., Takacs, L., Randles, C. A., Darmenov, A., Bosilovich, M. G., Reichle, R., Wargan, K., Coy, L., Cullather, R., Draper, C., Akella, S., Buchard, V., Conaty, A., da Silva, A. M., Gu,

- W., Kim, G.-K., Koster, R., Lucchesi, R., Merkova, D., Nielsen, J. E., Partyka, G., Pawson, S., Putman, W., Rienecker, M., Schubert, S. D., Sienkiewicz, M., and Zhao, B.: The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), *Journal of Climate*, 30, 5419 – 5454, <https://doi.org/10.1175/JCLI-D-16-0758.1>, 2017.
- Ghilain, N., Arboleda, A., and Gellens-Meulenberghs, F.: Evapotranspiration modelling at large scale using near-real time MSG SEVIRI derived data, *Hydrology and Earth System Sciences*, 15, 771–786, <https://doi.org/10.5194/hess-15-771-2011>, 2011.
- Ghilain, N., Arboleda, A., Sepulcre-Cantò, G., Batelaan, O., Ardö, J., and Gellens-Meulenberghs, F.: Improving evapotranspiration in a land surface model using biophysical variables derived from MSG/SEVIRI satellite, *Hydrology and Earth System Sciences*, 16, 2567–2583, <https://doi.org/10.5194/hess-16-2567-2012>, 2012a.
- Ghilain, N., Arboleda, A., Sepulcre-Cantò, G., Batelaan, O., Ardö, J., and Gellens-Meulenberghs, F.: Improving evapotranspiration in a land surface model using biophysical variables derived from MSG/SEVIRI satellite, *Hydrology and Earth System Sciences*, 16, 2567–2583, <https://doi.org/10.5194/hess-16-2567-2012>, 2012b.
- Gilbert, E. and Kittel, C.: Surface Melt and Runoff on Antarctic Ice Shelves at 1.5°C, 2°C, and 4°C of Future Warming, *Geophysical Research Letters*, 48, 9, <https://doi.org/10.1029/2020GL091733>, 2021.
- Giorgetta, M. A., Jungclaus, J., Reick, C. H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Ilyina, T., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., Mikolajewicz, U., Mueller, W., Notz, D., Pithan, F., Raddatz, T., Rast, S., Redler, R., Roeckner, E., Schmidt, H., Schnur, R., Segschneider, J., Six, K. D., Stockhause, M., Timmreck, C., Wegner, J., Widmann, H., Wieners, K.-H., Claussen, M., Marotzke, J., and Stevens, B.: Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the Coupled Model Intercomparison Project phase 5, *Journal of Advances in Modeling Earth Systems*, 5, 572–597, <https://doi.org/10.1002/jame.20038>, 2013.
- Giorgi, F.: Thirty Years of Regional Climate Modeling: Where Are We and Where Are We Going next?, *Journal of Geophysical Research: Atmospheres*, 124, 5696–5723, <https://doi.org/10.1029/2018JD030094>, 2019.
- Giorgi, F. and Bates, G. T.: The Climatological Skill of a Regional Model over Complex Terrain, *Monthly Weather Review*, 117, 2325 – 2347, [https://doi.org/10.1175/1520-0493\(1989\)117<2325:TCSOAR>2.0.CO;2](https://doi.org/10.1175/1520-0493(1989)117<2325:TCSOAR>2.0.CO;2), 1989.
- Giorgi, F. and Gao, X.-J.: Regional earth system modeling: review and future directions, *Atmospheric and Oceanic Science Letters*, 11, 189–197, <https://doi.org/10.1080/16742834.2018.1452520>, 2018.

- Giorgi, F. and Gutowski, W. J.: Regional Dynamical Downscaling and the CORDEX Initiative, *Annual Review of Environment and Resources*, 40, 467–490, <https://doi.org/10.1146/annurev-environ-102014-021217>, 2015.
- Giorgi, F., Coppola, E., Solmon, F., Mariotti, L., Sylla, M., Bi, X., Elguindi, N., Diro, G., Nair, V., Giuliani, G., Turuncoglu, U., Cozzini, S., Güttler, I., O’Brien, T., Tawfik, A., Shalaby, A., Zakey, A., Steiner, A., Stordal, F., Sloan, L., and Brankovic, C.: RegCM4: model description and preliminary tests over multiple CORDEX domains, *Climate Research*, 52, 7–29, <https://doi.org/10.3354/cr01018>, 2012.
- Glaude, Q., Amory, C., Berger, S., Derauw, D., Pattyn, F., Barbier, C., and Orban, A.: Empirical Removal of Tides and Inverse Barometer Effect on DInSAR From Double DInSAR and a Regional Climate Model, *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 13, 4085–4094, <https://doi.org/10.1109/JSTARS.2020.3008497>, 2020.
- Glaude, Q., Noel, B., Olesen, M., Van den Broeke, M., van de Berg, W. J., Mottram, R., Hansen, N., Delhasse, A., Amory, C., Kittel, C., Goelzer, H., and Fettweis, X.: A Factor Two Difference in 21st-Century Greenland Ice Sheet Surface Mass Balance Projections From Three Regional Climate Models Under a Strong Warming Scenario (SSP5-8.5), *Geophysical Research Letters*, 51, e2024GL111902, <https://doi.org/10.1029/2024GL111902>, 2024.
- Global Modeling and Assimilation Office (GMAO): MERRA-2 tavgM_2d_lnd_Nx: 2d, Monthly mean, Time-Averaged, Single-Level, Assimilation, Land Surface Diagnostics V5.12.4, 10.5067/8S35XF81C28F, visited on 2024-08-26, 2015.
- Gloege, L., Kornhuber, K., Skulovich, O., Pal, I., Zhou, S., Ciais, P., and Gentine, P.: Land-Atmosphere Cascade Fueled the 2020 Siberian Heatwave, *AGU Advances*, 3, e2021AV000619, <https://doi.org/10.1029/2021AV000619>, 2022.
- Gomes, V. C. F., Queiroz, G. R., and Ferreira, K. R.: An Overview of Platforms for Big Earth Observation Data Management and Analysis, *Remote Sensing*, 12, <https://doi.org/10.3390/rs12081253>, 2020.
- Gonzalez, P., Neilson, R. P., Lenihan, J. M., and Drapek, R. J.: Global patterns in the vulnerability of ecosystems to vegetation shifts due to climate change, *Global Ecology and Biogeography*, 19, 755–768, <https://doi.org/10.1111/j.1466-8238.2010.00558.x>, 2010.
- Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., and Moore, R.: Google Earth Engine: Planetary-scale geospatial analysis for everyone, *Remote Sensing of Environment*, 202, 18–27, <https://doi.org/10.1016/j.rse.2017.06.031>, 2017.
- Grailet, J.-F., Hogan, R. J., Ghilain, N., Bolsée, D., Fettweis, X., and Grégoire, M.: Inclusion of the ECMWF ecRad radiation scheme (v1.5.0) in the MAR (v3.14), regional evaluation for Belgium, and assessment of surface shortwave spectral fluxes at Uccle, *Geoscientific Model Development*, 18, 1965–1988, <https://doi.org/10.5194/gmd-18-1965-2025>, 2025.

- Gröger, M., Dieterich, C., Haapala, J., Ho-Hagemann, H. T. M., Hagemann, S., Jakacki, J., May, W., Meier, H. E. M., Miller, P. A., Rutgersson, A., and Wu, L.: Coupled regional Earth system modeling in the Baltic Sea region, *Earth System Dynamics*, 12, 939–973, <https://doi.org/10.5194/esd-12-939-2021>, 2021.
- Guilod, B. P., Orlowsky, B., Miralles, D., Teuling, A. J., Blanken, P. D., Buchmann, N., Ciais, P., Ek, M., Findell, K. L., Gentine, P., Lintner, B. R., Scott, R. L., Van den Hurk, B., and I. Seneviratne, S.: Land-surface controls on afternoon precipitation diagnosed from observational data: uncertainties and confounding factors, *Atmospheric Chemistry and Physics*, 14, 8343–8367, <https://doi.org/10.5194/acp-14-8343-2014>, 2014.
- Guion, A., Turquety, S., Polcher, J., Pennel, R., Bastin, S., and Arsouze, T.: Droughts and heatwaves in the Western Mediterranean: impact on vegetation and wildfires using the coupled WRF-ORCHIDEE regional model (RegIPSL), *Climate Dynamics*, 58, 2881–2903, <https://doi.org/10.1007/s00382-021-05938-y>, 2022.
- Guisan, A. and Thuiller, W.: Predicting species distribution: offering more than simple habitat models, *Ecology Letters*, 8, 993–1009, <https://doi.org/10.1111/j.1461-0248.2005.00792.x>, 2005.
- Guo, Z., Dirmeyer, P. A., Koster, R. D., Sud, Y. C., Bonan, G., Oleson, K. W., Chan, E., Verseghy, D., Cox, P., Gordon, C. T., McGregor, J. L., Kanae, S., Kowalczyk, E., Lawrence, D., Liu, P., Mocko, D., Lu, C.-H., Mitchell, K., Malyshev, S., McAvaney, B., Oki, T., Yamada, T., Pitman, A., Taylor, C. M., Vasic, R., and Xue, Y.: GLACE: The Global Land–Atmosphere Coupling Experiment. Part II: Analysis, *Journal of Hydrometeorology*, 7, 611 – 625, <https://doi.org/10.1175/JHM511.1>, 2006.
- Gutjahr, O., Putrasahan, D., Lohmann, K., Jungclaus, J. H., von Storch, J.-S., Brüggemann, N., Haak, H., and Stössel, A.: Max Planck Institute Earth System Model (MPI-ESM1.2) for the High-Resolution Model Intercomparison Project (HighResMIP), *Geoscientific Model Development*, 12, 3241–3281, <https://doi.org/10.5194/gmd-12-3241-2019>, 2019.
- Haberlie, A. M., Ashley, W. S., Battisto, C. M., and Gensini, V. A.: Thunderstorm Activity Under Intermediate and Extreme Climate Change Scenarios, *Geophysical Research Letters*, 49, e2022GL098779, <https://doi.org/10.1029/2022GL098779>, 2022.
- Hall, F. G. and Sellers, P. J.: First International Satellite Land Surface Climatology Project (ISLSCP) Field Experiment (FIFE) in 1995, *Journal of Geophysical Research: Atmospheres*, 100, 25 383–25 395, <https://doi.org/10.1029/95JD03300>, 1995.
- He, N., Yan, P., Liu, C., Xu, L., Li, M., Van Meerbeek, K., Zhou, G., Zhou, G., Liu, S., Zhou, X., Li, S., Niu, S., Han, X., Buckley, T. N., Sack, L., and Yu, G.: Predicting ecosystem productivity based on plant community traits, *Trends in Plant Science*, 28, 43–53, <https://doi.org/10.1016/j.tplants.2022.08.015>, 2023.

- He, Q.-L., Xiao, J.-L., and Shi, W.-Y.: Responses of Terrestrial Evapotranspiration to Extreme Drought: A Review, *Water*, 14, <https://doi.org/10.3390/w14233847>, 2022.
- Heck, P., Lüthi, D., Wernli, H., and Schär, C.: Climate impacts of European-scale anthropogenic vegetation changes: A sensitivity study using a regional climate model, *Journal of Geophysical Research: Atmospheres*, 106, 7817–7835, <https://doi.org/10.1029/2000JD900673>, 2001.
- Heinrich, V. H. A., Vancutsem, C., Dalagnol, R., Rosan, T. M., Fawcett, D., Silva-Junior, C. H. L., Cassol, H. L. G., Achard, F., Jucker, T., Silva, C. A., House, J., Sitch, S., Hales, T. C., and Aragão, L. E. O. C.: The carbon sink of secondary and degraded humid tropical forests, *Nature*, 615, 436–442, <https://doi.org/10.1038/s41586-022-05679-w>, 2023.
- Held, I. M. and Soden, B. J.: Robust Responses of the Hydrological Cycle to Global Warming, *Journal of Climate*, 19, 5686 – 5699, <https://doi.org/10.1175/JCLI3990.1>, 2006.
- Henrot, A.-J., Utescher, T., Erdei, B., Dury, M., Hamon, N., Ramstein, G., Krapp, M., Herold, N., Goldner, A., Favre, E., Munhoven, G., and François, L.: Middle Miocene climate and vegetation models and their validation with proxy data, *Palaeogeography, Palaeoclimatology, Palaeoecology*, 467, 95–119, <https://doi.org/10.1016/j.palaeo.2016.05.026>, reconstructing Cenozoic vegetation from proxy data and models – a NECLIME synthesis, 2017.
- Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, *Quarterly Journal of the Royal Meteorological Society*, 146, 1999–2049, <https://doi.org/10.1002/qj.3803>, 2020.
- Hickler, T., Vohland, K., Feehan, J., Miller, P. A., Smith, B., Costa, L., Giesecke, T., Fronzek, S., Carter, T. R., Cramer, W., Kühn, I., and Sykes, M. T.: Projecting the future distribution of European potential natural vegetation zones with a generalized, tree species-based dynamic vegetation model, *Global Ecology and Biogeography*, 21, 50–63, <https://doi.org/10.1111/j.1466-8238.2010.00613.x>, 2012.
- Ho-Hagemann, H. T. M., Gröger, M., Rockel, B., Zahn, M., Geyer, B., and Meier, H. E. M.: Effects of air-sea coupling over the North Sea and the Baltic Sea on simulated summer precipitation over Central Europe, *Climate Dynamics*, 49, 3851–3876, <https://doi.org/10.1007/s00382-017-3546-8>, 2017.
- Ho-Hagemann, H. T. M., Maurer, V., Poll, S., and Fast, I.: Coupling the regional climate model ICON-CLM v2.6.6 to the Earth system model GCOAST-AHOI v2.0 using OASIS3-MCT v4.0, *Geoscientific Model Development*, 17, 7815–7834, <https://doi.org/10.5194/gmd-17-7815-2024>, 2024.

- Hogan, R. J. and Bozzo, A.: A flexible and efficient radiation scheme for the ECMWF model, *Journal of Advances in Modeling Earth Systems*, 10, 1990–2008, <https://doi.org/10.1029/2018MS001364>, 2018.
- Hosseinizadehtalaei, P., Tabari, H., and Willems, P.: Precipitation intensity–duration–frequency curves for central Belgium with an ensemble of EURO-CORDEX simulations, and associated uncertainties, *Atmospheric Research*, 200, 1–12, <https://doi.org/10.1016/j.atmosres.2017.09.015>, 2018.
- Hsu, H., Lo, M.-H., Guillod, B. P., Miralles, D. G., and Kumar, S.: Relation between precipitation location and antecedent/subsequent soil moisture spatial patterns, *Journal of Geophysical Research: Atmospheres*, 122, 6319–6328, <https://doi.org/10.1002/2016JD026042>, 2017.
- Hu, Q., Yang, J., Xu, B., Huang, J., Memon, M. S., Yin, G., Zeng, Y., Zhao, J., and Liu, K.: Evaluation of Global Decametric-Resolution LAI, FAPAR and FVC Estimates Derived from Sentinel-2 Imagery, *Remote Sensing*, 12, <https://doi.org/10.3390/rs12060912>, 2020.
- Hua, W., Zhou, L., Dai, A., Chen, H., and Liu, Y.: Important non-local effects of deforestation on cloud cover changes in CMIP6 models, *Environmental Research Letters*, 18, 094 047, <https://doi.org/10.1088/1748-9326/acf232>, 2023.
- Huang, C., Anderegg, W. R., and Asner, G. P.: Remote sensing of forest die-off in the Anthropocene: From plant ecophysiology to canopy structure, *Remote Sensing of Environment*, 231, 111 233, <https://doi.org/10.1016/j.rse.2019.111233>, 2019.
- Hubert, B., Francois, L., Warnant, P., and Strivay, D.: Stochastic generation of meteorological variables and effects on global models of water and carbon cycles in vegetation and soils, *Journal of Hydrology*, 212–213, 318–334, [https://doi.org/10.1016/S0022-1694\(98\)00214-5](https://doi.org/10.1016/S0022-1694(98)00214-5), 1998.
- Huete, A., Didan, K., Miura, T., Rodriguez, E., Gao, X., and Ferreira, L.: Overview of the radiometric and biophysical performance of the MODIS vegetation indices, *Remote Sensing of Environment*, 83, 195–213, [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2), the Moderate Resolution Imaging Spectroradiometer (MODIS): a new generation of Land Surface Monitoring, 2002.
- Huot, P.-V., Kittel, C., Fichet, T., Jourdain, N. C., and Fettweis, X.: Effects of ocean mesoscale eddies on atmosphere–sea ice–ocean interactions off Adélie Land, East Antarctica, *Climate Dynamics*, 59, 41–60, <https://doi.org/10.1007/s00382-021-06115-x>, 2022.
- Insua-Costa, D., Senande-Rivera, M., Llasat, M. C., and Miguez-Macho, G.: The central role of forests in the 2021 European floods, *Environmental Research Letters*, 17, 064 053, <https://doi.org/10.1088/1748-9326/ac6f6b>, 2022.
- IPCC: Summary for Policymakers, in: *Climate Change 2022: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, edited by Pörtner, H.-O., Roberts, D., Poloczanska, E., Mintenbeck, K., Tignor, M., Alegría, A., Craig,

- M., Langsdorf, S., Löschke, S., Möller, V., and Okem, A., pp. 3–33, Cambridge University Press, Cambridge, UK and New York, NY, USA, <https://doi.org/10.1017/9781009325844.001>, 2022.
- IPCC: Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, 2023a.
- IPCC: Climate Change 2022 – Impacts, Adaptation and Vulnerability: Working Group II Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change, Cambridge University Press, 2023b.
- IPCC: About the IPCC, <https://www.ipcc.ch/about/>, visited on 2025-07-29, 2024.
- IRM: Bilan climatique annuel, Année 2024, https://www.meteo.be/resources/climatology/pdf/bilan_climatique_annuel_2024.pdf, visited on 2026-02-19, 2025.
- Jackson, R. B., Canadell, J., Ehleringer, J. R., Mooney, H. A., Sala, O. E., and Schulze, E. D.: A global analysis of root distributions for terrestrial biomes, *Oecologia*, 108, 389–411, <https://doi.org/10.1007/BF00333714>, 1996.
- Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O. B., Bouwer, L. M., Braun, A., Colette, A., Déqué, M., Georgievski, G., Georgopoulou, E., Gobiet, A., Menut, L., Nikulin, G., Haensler, A., Hempelmann, N., Jones, C., Keuler, K., Kovats, S., Kröner, N., Kotlarski, S., Kriegsmann, A., Martin, E., van Meijgaard, E., Moseley, C., Pfeifer, S., Preuschmann, S., Radermacher, C., Radtke, K., Rechid, D., Rounsevell, M., Samuelsson, P., Somot, S., Soussana, J.-F., Teichmann, C., Valentini, R., Vautard, R., Weber, B., and Yiou, P.: EURO-CORDEX: new high-resolution climate change projections for European impact research, *Regional Environmental Change*, 14, 563–578, <https://doi.org/10.1007/s10113-013-0499-2>, 2014.
- Jacquemin, I., Berckmans, J., Henrot, A.-J., Dury, M., Tychon, B., Hambuckers, A., Hamdi, R., and François, L.: Using the CARAIB dynamic vegetation model to simulate crop yields in Belgium: validation and projections for the 2035 horizon, *Geo-Eco-Trop: Revue Internationale de Géologie, de Géographie et d'Écologie Tropicales*, 44, 2020.
- Jakobs, C. L., Reijmer, C. H., Smeets, C. J., Trusel, L. D., Berg, W. J. V. D., Broeke, M. R. V. D., and Wessem, J. M. V.: A benchmark dataset of in situ Antarctic surface melt rates and energy balance, *Journal of Glaciology*, 66, 291–302, <https://doi.org/10.1017/jog.2020.6>, dataset, 2020.
- Jarvis, P. G.: The interpretation of the variations in leaf water potential and stomatal conductance found in canopies in the field, *Philosophical Transactions of the Royal Society of London. B, Biological Sciences*, 273, 593–610, <https://doi.org/10.1098/rstb.1976.0035>, 1976.
- JAXA: Globe portal system, <https://gportal.jaxa.jp/gpr/>, visited on 2022-01-10, 2021.

- Ji, L. and Peters, A. J.: Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices, *Remote Sensing of Environment*, 87, 85–98, [https://doi.org/10.1016/S0034-4257\(03\)00174-3](https://doi.org/10.1016/S0034-4257(03)00174-3), 2003.
- Jiménez-Gutiérrez, J. M., Valero, F., Ruiz-Martínez, J., and Montávez, J. P.: Temperature Response to Changes in Vegetation Fraction Cover in a Regional Climate Model, *Atmosphere*, 12, <https://doi.org/10.3390/atmos12050599>, 2021.
- Johnson, A., Fahnestock, M., and Hock, R.: Evaluation of passive microwave melt detection methods on Antarctic Peninsula ice shelves using time series of Sentinel-1 SAR, *Remote Sensing of Environment*, 250, <https://doi.org/10.1016/j.rse.2020.112044>, 2020.
- Johnson, A., Hock, R., and Fahnestock, M.: Spatial variability and regional trends of Antarctic ice shelf surface melt duration over 1979–2020 derived from passive microwave data, *Journal of Glaciology*, 68, 533–546, <https://doi.org/10.1017/jog.2021.112>, 2022.
- Jonard, F., André, F., Ponette, Q., Vincke, C., and Jonard, M.: Sap flux density and stomatal conductance of European beech and common oak trees in pure and mixed stands during the summer drought of 2003, *Journal of Hydrology*, 409, 371–381, <https://doi.org/10.1016/j.jhydrol.2011.08.032>, 2011.
- Jonard, F., Feldman, A. F., Short Gianotti, D. J., and Entekhabi, D.: Observed water and light limitation across global ecosystems, *Biogeosciences*, 19, 5575–5590, <https://doi.org/10.5194/bg-19-5575-2022>, 2022.
- Jourdain, N. C., Mathiot, P., Gallée, H., and Barnier, B.: Influence of coupling on atmosphere, sea ice and ocean regional models in the Ross Sea sector, Antarctica, *Climate Dynamics*, 36, 1523–1543, <https://doi.org/10.1007/s00382-010-0889-9>, 2011.
- Journée, M., Goudenhoofdt, E., Vannitsem, S., and Delobbe, L.: Quantitative rainfall analysis of the 2021 mid-July flood event in Belgium, *Hydrology and Earth System Sciences*, 27, 3169–3189, <https://doi.org/10.5194/hess-27-3169-2023>, 2023.
- Justice, C., Vermote, E., Townshend, J., Defries, R., Roy, D., Hall, D., Salomonson, V., Privette, J., Riggs, G., Strahler, A., Lucht, W., Myneni, R., Knyazikhin, Y., Running, S., Nemani, R., Wan, Z., Huete, A., van Leeuwen, W., Wolfe, R., Giglio, L., Muller, J., Lewis, P., and Barnsley, M.: The Moderate Resolution Imaging Spectroradiometer (MODIS): land remote sensing for global change research, *IEEE Transactions on Geoscience and Remote Sensing*, 36, 1228–1249, <https://doi.org/10.1109/36.701075>, 1998.
- Justice, C., Giglio, L., Korontzi, S., Owens, J., Morisette, J., Roy, D., Descloitres, J., Alleaume, S., Petitcolin, F., and Kaufman, Y.: The MODIS fire products, *Remote Sensing of Environment*, 83, 244–262, [https://doi.org/10.1016/S0034-4257\(02\)00076-7](https://doi.org/10.1016/S0034-4257(02)00076-7), the Moderate Resolution Imaging Spectroradiometer (MODIS): a new generation of Land Surface Monitoring, 2002a.

- Justice, C., Townshend, J., Vermote, E., Masuoka, E., Wolfe, R., Saleous, N., Roy, D., and Morisette, J.: An overview of MODIS Land data processing and product status, *Remote Sensing of Environment*, 83, 3–15, [https://doi.org/10.1016/S0034-4257\(02\)00084-6](https://doi.org/10.1016/S0034-4257(02)00084-6), 2002b.
- Kanamitsu, M., Ebisuzaki, W., Woollen, J., Yang, S.-K., Hnilo, J. J., Fiorino, M., and Potter, G. L.: NCEP–DOE AMIP-II Reanalysis (R-2), *Bulletin of the American Meteorological Society*, 83, 1631 – 1644, <https://doi.org/10.1175/BAMS-83-11-1631>, 2002.
- Kaufmann, R., Zhou, L., Myneni, R., Tucker, C., Slayback, D., Shabanov, N., and Pinzon, J.: The effect of vegetation on surface temperature: A statistical analysis of NDVI and climate data, *Geophysical Research Letters*, 30, 1–4, <https://doi.org/10.1029/2003GL018251>, 2003.
- King, J. A., Weber, J., Lawrence, P., Roe, S., Swann, A. L. S., and Val Martin, M.: Global and regional hydrological impacts of global forest expansion, *Biogeosciences*, 21, 3883–3902, <https://doi.org/10.5194/bg-21-3883-2024>, 2024.
- Kittel, C.: Present and future sensitivity of the Antarctic surface mass balance to oceanic and atmospheric forcings: insights with the regional climate model MAR, Ph.D. thesis, ULiège - Université de Liège, <https://hdl.handle.net/2268/258491>, 2021.
- Kittel, C., Amory, C., Agosta, C., Jourdain, N. C., Hofer, S., Delhasse, A., Doutreloup, S., Huot, P.-V., Lang, C., Fichet, T., and Fettweis, X.: Diverging future surface mass balance between the Antarctic ice shelves and grounded ice sheet, *The Cryosphere*, 15, 1215–1236, <https://doi.org/10.5194/tc-15-1215-2021>, 2021.
- Kittel, C., Amory, C., Hofer, S., Agosta, C., Jourdain, N. C., Gilbert, E., Le Toumelin, L., Vignon, E., Gallée, H., and Fettweis, X.: Clouds drive differences in future surface melt over the Antarctic ice shelves, *The Cryosphere*, 16, 2655–2669, <https://doi.org/10.5194/tc-16-2655-2022>, 2022a.
- Kittel, C., Fettweis, X., Picard, G., and Gourmelen, N.: Assimilation of satellite-derived melt extent increases melt simulated by MAR over the Amundsen sector (West Antarctica), *Bulletin de la Société Géographique de Liège*, 78, 87–99, <https://doi.org/10.25518/0770-7576.6616>, 2022b.
- Kjellström, E., Nikulin, G., Strandberg, G., Christensen, O. B., Jacob, D., Keuler, K., Lenderink, G., van Meijgaard, E., Schär, C., Somot, S., Sørland, S. L., Teichmann, C., and Vautard, R.: European climate change at global mean temperature increases of 1.5 and 2°C above pre-industrial conditions as simulated by the EURO-CORDEX regional climate models, *Earth System Dynamics*, 9, 459–478, <https://doi.org/10.5194/esd-9-459-2018>, 2018.
- Knist, S., Goergen, K., Buonomo, E., Christensen, O. B., Colette, A., Cardoso, R. M., Fealy, R., Fernández, J., García-Díez, M., Jacob, D., Kartsios, S., Katsargkou, E., Keuler, K., Mayer, S., van Meijgaard, E., Nikulin, G., Soares,

- P. M. M., Sobolowski, S., Szepszo, G., Teichmann, C., Vautard, R., Warrach-Sagi, K., Wulfmeyer, V., and Simmer, C.: Land-atmosphere coupling in EURO-CORDEX evaluation experiments, *Journal of Geophysical Research: Atmospheres*, 122, 79–103, <https://doi.org/10.1002/2016JD025476>, 2017.
- Knutzen, F., Auerbeck, P., Barrasso, C., Bouwer, L. M., Gardiner, B., Grünzweig, J. M., Hänel, S., Haustein, K., Johannessen, M. R., Kollet, S., Müller, M. M., Pietikäinen, J.-P., Pietras-Couffignal, K., Pinto, J. G., Rechid, D., Rousi, E., Russo, A., Suarez-Gutierrez, L., Veit, S., Wendler, J., Xoplaki, E., and Gliksman, D.: Impacts on and damage to European forests from the 2018–2022 heat and drought events, *Natural Hazards and Earth System Sciences*, 25, 77–117, <https://doi.org/10.5194/nhess-25-77-2025>, 2025.
- Koch, A., Hubau, W., and Lewis, S. L.: Earth System Models Are Not Capturing Present-Day Tropical Forest Carbon Dynamics, *Earth’s Future*, 9, e2020EF001874, <https://doi.org/10.1029/2020EF001874>, 2021.
- Kolb, T., Keefover-Ring, K., Burr, S. J., Hofstetter, R., Gaylord, M., and Raffa, K. F.: Drought-Mediated Changes in Tree Physiological Processes Weaken Tree Defenses to Bark Beetle Attack, *Journal of Chemical Ecology*, 45, 888–900, <https://doi.org/10.1007/s10886-019-01105-0>, 2019.
- Koskinen, J., Pulliainen, J., and Hallikainen, M.: The use of ERS-1 SAR data in snow melt monitoring, *IEEE Transactions on Geoscience and Remote Sensing*, 35, 601–610, <https://doi.org/10.1109/36.581975>, 1997.
- Koster, R. D., Dirmeyer, P. A., Guo, Z., Bonan, G., Chan, E., Cox, P., Gordon, C. T., Kanae, S., Kowalczyk, E., Lawrence, D., Liu, P., Lu, C.-H., Malyshev, S., McAvaney, B., Mitchell, K., Mocko, D., Oki, T., Oleson, K., Pitman, A., Sud, Y. C., Taylor, C. M., Verseghy, D., Vasic, R., Xue, Y., and Yamada, T.: Regions of Strong Coupling Between Soil Moisture and Precipitation, *Science*, 305, 1138–1140, <https://doi.org/10.1126/science.1100217>, 2004.
- Koster, R. D., Sud, Y. C., Guo, Z., Dirmeyer, P. A., Bonan, G., Oleson, K. W., Chan, E., Verseghy, D., Cox, P., Davies, H., Kowalczyk, E., Gordon, C. T., Kanae, S., Lawrence, D., Liu, P., Mocko, D., Lu, C.-H., Mitchell, K., Malyshev, S., McAvaney, B., Oki, T., Yamada, T., Pitman, A., Taylor, C. M., Vasic, R., and Xue, Y.: GLACE: The Global Land–Atmosphere Coupling Experiment. Part I: Overview, *Journal of Hydrometeorology*, 7, 590 – 610, <https://doi.org/10.1175/JHM510.1>, 2006.
- Koster, R. D., Guo, Z., Yang, R., Dirmeyer, P. A., Mitchell, K., and Puma, M. J.: On the Nature of Soil Moisture in Land Surface Models, *Journal of Climate*, 22, 4322 – 4335, <https://doi.org/10.1175/2009JCLI2832.1>, 2009.
- Krinner, G., Viovy, N., de Noblet-Ducoudré, N., Ogée, J., Polcher, J., Friedlingstein, P., Ciais, P., Sitch, S., and Prentice, I. C.: A dynamic global vegetation model for studies of the coupled atmosphere-biosphere system, *Global Biogeochemical Cycles*, 19, <https://doi.org/10.1029/2003GB002199>, 2005.

- Kuipers Munneke, P., Luckman, A. J., Bevan, S. L., Smeets, C. J. P. P., Gilbert, E., van den Broeke, M. R., Wang, W., Zender, C., Hubbard, B., Ashmore, D., Orr, A., King, J. C., and Kulessa, B.: Intense Winter Surface Melt on an Antarctic Ice Shelf, *Geophysical Research Letters*, 45, 7615–7623, <https://doi.org/10.1029/2018GL077899>, 2018.
- Lai, C.-Y., Kingslake, J., Wearing, M. G., Chen, P.-H. C., Gentine, P., Li, H., Spergel, J. J., and van Wessem, J. M.: Vulnerability of Antarctica’s ice shelves to meltwater-driven fracture, *Nature*, 584, 574–578, <https://doi.org/10.1038/s41586-020-2627-8>, 2020.
- Lambin, C., Fettweis, X., Kittel, C., Fonder, M., and Ernst, D.: Assessment of future wind speed and wind power changes over South Greenland using the Modèle Atmosphérique Régional regional climate model, *International Journal of Climatology*, pp. 1–17, <https://doi.org/10.1002/joc.7795>, 2022.
- Latifi, H. and Galos, B.: Remote sensing-supported vegetation parameters for regional climate models: a brief review, *iForest - Biogeosciences and Forestry*, pp. 98–101, <https://doi.org/10.3832/ifer0543-003>, 2010.
- Latte, N., Taverniers, P., de Jaegere, T., and Claessens, H.: Dendroecological assessment of climate resilience of the rare and scattered forest tree species *Tilia cordata* Mill. in northwestern Europe, *Forestry: An International Journal of Forest Research*, 93, 675–684, <https://doi.org/10.1093/forestry/cpaa011>, 2020.
- Laurent, J.-M., Bar-Hen, A., François, L., Ghislain, M., and Cheddadi, R.: Refining vegetation simulation models: From plant functional types to bioclimatic affinity groups of plants, *Journal of Vegetation Science*, 15, 739–746, <https://doi.org/10.1111/j.1654-1103.2004.tb02316.x>, 2004.
- Leduc-Leballeur, M., Picard, G., Zeiger, P., and Macelloni, G.: Empirical classification of dry-wet snow status in Antarctica using multi-frequency passive microwave observations, *The Cryosphere*, 20, 1199–1216, <https://doi.org/10.5194/tc-20-1199-2026>, 2026.
- Li, J. and Convertino, M.: Temperature increase drives critical slowing down of fish ecosystems, *PLOS ONE*, 16, 1–43, <https://doi.org/10.1371/journal.pone.0246222>, 2021.
- Liang, D., Guo, H., Zhang, L., Cheng, Y., Zhu, Q., and Liu, X.: Time-series snowmelt detection over the Antarctic using Sentinel-1 SAR images on Google Earth Engine, *Remote Sensing of Environment*, 256, 112318, <https://doi.org/10.1016/j.rse.2021.112318>, 2021.
- Liang, S.: Narrowband to broadband conversions of land surface albedo I: Algorithms, *Remote Sensing of Environment*, 76, 213–238, [https://doi.org/10.1016/S0034-4257\(00\)00205-4](https://doi.org/10.1016/S0034-4257(00)00205-4), 2001.
- Lillesand, T. M., Kiefer, R. W., and Chipman, J. W.: Chapter 6: Microwave and Lidar Sensing, in: *Remote Sensing and Image Interpretation*, pp. 385–484, John Wiley & Sons, 7th edn., ISBN 9781118343289, 2014.

- Lindsley, R. D. and Long, D. G.: Enhanced-Resolution Reconstruction of ASCAT Backscatter Measurements, *IEEE Transactions on Geoscience and Remote Sensing*, 54, 2589–2601, <https://doi.org/10.1109/TGRS.2015.2503762>, 2016.
- Liu, Z., Notaro, M., Kutzbach, J., and Liu, N.: Assessing Global Vegetation–Climate Feedbacks from Observations, *Journal of Climate*, 19, 787 – 814, <https://doi.org/10.1175/JCLI3658.1>, 2006.
- Lorenz, R., Pitman, A. J., Hirsch, A. L., and Srbinovsky, J.: Intraseasonal versus Interannual Measures of Land–Atmosphere Coupling Strength in a Global Climate Model: GLACE-1 versus GLACE-CMIP5 Experiments in ACCESS1.3b, *Journal of Hydrometeorology*, 16, 2276 – 2295, <https://doi.org/10.1175/JHM-D-14-0206.1>, 2015.
- Loudiyi, I., Jacquemin, I., Lahlou, M., Balaghi, R., Tychon, B., and François, L.: Atmospheric CO₂ fertilization effect on cereal yields in Morocco using the CARAIB dynamic vegetation model, *European Journal of Agronomy*, 161, 127 374, <https://doi.org/10.1016/j.eja.2024.127374>, 2024.
- Loudiyi, I., Balaghi, R., Jacquemin, I., Lahlou, M., and François, L.: Optimizing cereal yields in Morocco’s Favorable agro-ecological zone: Integrating dynamic vegetation modeling, machine learning, and climate projections for adaptive agricultural strategies, *Next Sustainability*, 7, 100 298, <https://doi.org/10.1016/j.nxsust.2026.100298>, 2026.
- Loveland, T. and Belward, A.: The International Geosphere Biosphere Programme Data and Information System global land cover data set (DISCover), *Acta Astronautica*, 41, 681–689, [https://doi.org/10.1016/S0094-5765\(98\)00050-2](https://doi.org/10.1016/S0094-5765(98)00050-2), 1997.
- Madec, G., Bell, M., Benshila, R., Blaker, A., Boudrallé-Badie, R., Bricaud, C., Bruciaferri, D., Carneiro, D., Castrillo, M., Calvert, D., Chanut, J., Clementi, E., Coward, A., de Lavergne, C., Dobricic, S., Epicoco, I., Éthé, C., Fiedler, E., Ford, D., Furner, R., Ganderton, J., Graham, T., Harle, J., Hutchinson, K., Iovino, D., King, R., Lea, D., Levy, C., Lovato, T., Maisonnave, E., Mak, J., Sanchez, J. M. C., Martin, M., Martin, N., Martins, D., Masson, S., Mathiot, P., Mele, F., Mocavero, S., Moulin, A., Müller, S., Nurser, G., Oddo, P., Paronuzzi, S., Paul, J., Peltier, M., Person, R., Rousset, C., Rynders, S., Samson, G., Schroeder, D., Storkey, D., Storto, A., Téchené, S., Vancoppenolle, M., and Wilson, C.: NEMO Ocean Engine Reference Manual, <https://doi.org/10.5281/zenodo.14515373>, 2024.
- Manabe, S.: Climate and the ocean circulation: I. The atmospheric circulation and the hydrology of the Earth’s surface, *Monthly Weather Review*, 97, 739 – 774, [https://doi.org/10.1175/1520-0493\(1969\)097<0739:CATOC>2.3.CO;2](https://doi.org/10.1175/1520-0493(1969)097<0739:CATOC>2.3.CO;2), 1969.
- Manabe, S. and Wetherald, R. T.: Thermal Equilibrium of the Atmosphere with a Given Distribution of Relative Humidity, *Journal of Atmospheric Sciences*, 24, 241 – 259, [https://doi.org/10.1175/1520-0469\(1967\)024<0241:TEOTAW>2.0.CO;2](https://doi.org/10.1175/1520-0469(1967)024<0241:TEOTAW>2.0.CO;2), 1967.
- Manakos, I., Kordelas, G. A., and Marini, K.: Fusion of Sentinel-1 data with Sentinel-2 products to overcome non-favourable atmospheric conditions for the

- delineation of inundation maps, *European Journal of Remote Sensing*, 53, 53–66, <https://doi.org/10.1080/22797254.2019.1596757>, 2020.
- Matsushita, B., Xu, M., Chen, J., Kameyama, S., and Tamura, M.: Estimation of regional net primary productivity (NPP) using a process-based ecosystem model: How important is the accuracy of climate data?, *Ecological Modelling*, 178, 371–388, <https://doi.org/10.1016/j.ecolmodel.2004.03.012>, 2004.
- Maure, D., Kittel, C., Lambin, C., Delhasse, A., and Fettweis, X.: Spatially heterogeneous effect of climate warming on the Arctic land ice, *The Cryosphere*, 17, 4645–4659, <https://doi.org/10.5194/tc-17-4645-2023>, 2023.
- McDowell, N., Pockman, W. T., Allen, C. D., Breshears, D. D., Cobb, N., Kolb, T., Plaut, J., Sperry, J., West, A., Williams, D. G., and Yezpez, E. A.: Mechanisms of plant survival and mortality during drought: why do some plants survive while others succumb to drought?, *New Phytologist*, 178, 719–739, <https://doi.org/10.1111/j.1469-8137.2008.02436.x>, 2008.
- McMichael, C.: Climate change-related migration and infectious disease, *Virulence*, 6, 548–553, <https://doi.org/10.1080/21505594.2015.1021539>, 2015.
- Meier, W. N., J. S. Stewart, H. W., Scott, D. J., and Hardman, M. A.: DMSP SSM/I-SSMIS Daily Polar Gridded Brightness Temperatures, Version 6. 2019–2020, Antarctica., <https://doi.org/10.5067/MXJL42WSXTS1>, 2021.
- Meinshausen, M., Smith, S. J., Calvin, K., Daniel, J. S., Kainuma, M. L. T., Lamarque, J.-F., Matsumoto, K., Montzka, S. A., Raper, S. C. B., Riahi, K., Thomson, A., Velders, G. J. M., and van Vuuren, D. P.: The RCP greenhouse gas concentrations and their extensions from 1765 to 2300, *Climatic Change*, 109, 213, <https://doi.org/10.1007/s10584-011-0156-z>, 2011.
- Meinshausen, M., Nicholls, Z. R. J., Lewis, J., Gidden, M. J., Vogel, E., Freund, M., Beyerle, U., Gessner, C., Nauels, A., Bauer, N., Canadell, J. G., Daniel, J. S., John, A., Krummel, P. B., Luderer, G., Meinshausen, N., Montzka, S. A., Rayner, P. J., Reimann, S., Smith, S. J., van den Berg, M., Velders, G. J. M., Vollmer, M. K., and Wang, R. H. J.: The shared socio-economic pathway (SSP) greenhouse gas concentrations and their extensions to 2500, *Geoscientific Model Development*, 13, 3571–3605, <https://doi.org/10.5194/gmd-13-3571-2020>, 2020.
- Meir, P., Cox, P., and Grace, J.: The influence of terrestrial ecosystems on climate, *Trends in Ecology & Evolution*, 21, 254–260, <https://doi.org/10.1016/j.tree.2006.03.005>, 2006.
- Mikolajewicz, U., Sein, D. V., Jacob, D., König, T., Podzun, R., and Semmler, T.: Simulating Arctic sea ice variability with a coupled regional atmosphere-ocean-sea ice model, *Meteorologische Zeitschrift*, 14, 793–800, <https://doi.org/10.1127/0941-2948/2005/0083>, 2005.
- Mintz, Y. and Walker, G. K.: Global Fields of Soil Moisture and Land Surface Evapotranspiration Derived from Observed Precipitation and Surface Air Temperature, *Journal of Applied Meteorology and Climatology*, 32, 1305 – 1334, [https://doi.org/10.1175/1520-0450\(1993\)032<1305:GFOSMA>2.0.CO;2](https://doi.org/10.1175/1520-0450(1993)032<1305:GFOSMA>2.0.CO;2), 1993.

- Miralles, D. G., van den Berg, M. J., Teuling, A. J., and de Jeu, R. A. M.: Soil moisture-temperature coupling: A multiscale observational analysis, *Geophysical Research Letters*, 39, <https://doi.org/10.1029/2012GL053703>, 2012.
- Moeng, C.-H., Poulos, G. S., and LeMone, M. A.: Cooperative Atmosphere–Surface Exchange Study-1999, *Journal of the Atmospheric Sciences*, 60, 2429 – 2429, [https://doi.org/10.1175/1520-0469\(2003\)060<2429:PCAES>2.0.CO;2](https://doi.org/10.1175/1520-0469(2003)060<2429:PCAES>2.0.CO;2), 2003.
- Morales, P., Hickler, T., Rowell, D. P., Smith, B., and Sykes, M. T.: Changes in European ecosystem productivity and carbon balance driven by regional climate model output, *Global Change Biology*, 13, 108–122, <https://doi.org/10.1111/j.1365-2486.2006.01289.x>, 2007.
- Morcrette, J.-J.: Assessment of the ECMWF Model Cloudiness and Surface Radiation Fields at the ARM SGP Site, *Monthly Weather Review*, 130, 257 – 277, [https://doi.org/10.1175/1520-0493\(2002\)130<0257:AOTEMC>2.0.CO;2](https://doi.org/10.1175/1520-0493(2002)130<0257:AOTEMC>2.0.CO;2), 2002.
- Moreira, A., Prats-Iraola, P., Younis, M., Krieger, G., Hajnsek, I., and Papathanassiou, K. P.: A tutorial on synthetic aperture radar, *IEEE Geoscience and Remote Sensing Magazine*, 1, 6–43, <https://doi.org/10.1109/MGRS.2013.2248301>, 2013.
- Moss, R. H., Edmonds, J. A., Hibbard, K. A., Manning, M. R., Rose, S. K., van Vuuren, D. P., Carter, T. R., Emori, S., Kainuma, M., Kram, T., Meehl, G. A., Mitchell, J. F. B., Nakicenovic, N., Riahi, K., Smith, S. J., Stouffer, R. J., Thomson, A. M., Weyant, J. P., and Wilbanks, T. J.: The next generation of scenarios for climate change research and assessment, *Nature*, 463, 747–756, <https://doi.org/10.1038/nature08823>, 2010.
- Mottram, R., Hansen, N., Kittel, C., van Wessem, J. M., Agosta, C., Amory, C., Boberg, F., van de Berg, W. J., Fettweis, X., Gossart, A., van Lipzig, N. P. M., van Meijgaard, E., Orr, A., Phillips, T., Webster, S., Simonsen, S. B., and Souverijns, N.: What is the surface mass balance of Antarctica? An intercomparison of regional climate model estimates, *The Cryosphere*, 15, 3751–3784, <https://doi.org/10.5194/tc-15-3751-2021>, 2021.
- Mullissa, A., Vollrath, A., Odongo-Braun, C., Slagter, B., Balling, J., Gou, Y., Gorelick, N., and Reiche, J.: Sentinel-1 SAR Backscatter Analysis Ready Data Preparation in Google Earth Engine, *Remote Sensing*, 13, <https://doi.org/10.3390/rs13101954>, 2021.
- Myneni, R., Hoffman, S., Knyazikhin, Y., Privette, J., Glassy, J., Tian, Y., Wang, Y., Song, X., Zhang, Y., Smith, G., Lotsch, A., Friedl, M., Morisette, J., Votava, P., Nemani, R., and Running, S.: Global products of vegetation leaf area and fraction absorbed PAR from year one of MODIS data, *Remote Sensing of Environment*, 83, 214–231, [https://doi.org/10.1016/S0034-4257\(02\)00074-3](https://doi.org/10.1016/S0034-4257(02)00074-3), 2002.
- Myneni, R., Knyazikhin, Y., and Park, T.: MODIS/Terra+Aqua Leaf Area Index/FPAR 8-Day L4 Global 500m SIN Grid V061, NASA EOSDIS Land Processes Distributed Active Archive Center, <https://doi.org/10.5067/MODIS/MCD15A2H.061>, visited on 2024-08-26, 2021.

- Mätzler, C.: Applications of the interaction of microwaves with the natural snow cover, *Remote Sensing Reviews*, 2, 259–387, <https://doi.org/10.1080/02757258709532086>, 1987.
- Nabipour, M., Nayyeri, P., Jabani, H., S., S., and Mosavi, A.: Predicting Stock Market Trends Using Machine Learning and Deep Learning Algorithms Via Continuous and Binary Data; a Comparative Analysis, *IEEE Access*, 8, 150 199–150 212, <https://doi.org/10.1109/ACCESS.2020.3015966>, 2020.
- Nagler, T. and Rott, H.: Retrieval of wet snow by means of multitemporal SAR data, *IEEE Transactions on Geoscience and Remote Sensing*, 38, 754–765, <https://doi.org/10.1109/36.842004>, 2000.
- Nagler, T., Rott, H., Ripper, E., Bippus, G., and Hetzenecker, M.: Advancements for Snowmelt Monitoring by Means of Sentinel-1 SAR, *Remote Sensing*, 8, <https://doi.org/10.3390/rs8040348>, 2016.
- Nagler, T., Wuite, J., Rott, H., Scheiblauer, S., Puggaard, A., and Prieto, D. F.: Monitoring Ice Sheet Melt and Refreeze Using Active Microwave Measurements, in: *IGARSS 2024 - 2024 IEEE International Geoscience and Remote Sensing Symposium*, pp. 49–52, <https://doi.org/10.1109/IGARSS53475.2024.10640970>, 2024.
- Navari, M., Margulis, S. A., Tedesco, M., Fettweis, X., and Alexander, P. M.: Improving Greenland Surface Mass Balance Estimates Through the Assimilation of MODIS Albedo: A Case Study Along the K-Transect, *Geophysical Research Letters*, 45, 6549–6556, <https://doi.org/10.1029/2018GL078448>, 2018.
- Neimry, E., Goosse, H., and Jonard, M.: Droughts in western Central Europe and associated atmospheric circulation patterns since 1844, *EGUsphere*, 2025, 1–45, <https://doi.org/10.5194/egusphere-2025-5490>, 2025.
- Noël, B., Lhermitte, S., Wouters, B., and Fettweis, X.: Poleward shift of subtropical highs drives Patagonian glacier mass loss, *Nature Communications*, 16, 3795, <https://doi.org/10.1038/s41467-025-58974-1>, 2025.
- Noël, B., van de Berg, W. J., Lhermitte, S., Wouters, B., Machguth, H., Howat, I., Citterio, M., Moholdt, G., Lenaerts, J. T. M., and van den Broeke, M. R.: A tipping point in refreezing accelerates mass loss of Greenland’s glaciers and ice caps, *Nature Communications*, 8, 14 730, <https://doi.org/10.1038/ncomms14730>, 2017.
- Oleson, K. W., Niu, G.-Y., Yang, Z.-L., Lawrence, D. M., Thornton, P. E., Lawrence, P. J., Stöckli, R., Dickinson, R. E., Bonan, G. B., Levis, S., Dai, A., and Qian, T.: Improvements to the Community Land Model and their impact on the hydrological cycle, *Journal of Geophysical Research: Biogeosciences*, 113, <https://doi.org/10.1029/2007JG000563>, 2008.
- O’Neill, P., Hsu, A., Kim, E., Peters-Lidard, C., and England, A.: Performance comparison of a point-scale LSP model and the NOAH distributed SVAT model for soil moisture estimation using microwave remote sensing, in: *IGARSS 2001*.

- Scanning the Present and Resolving the Future. Proceedings. IEEE 2001 International Geoscience and Remote Sensing Symposium (Cat. No.01CH37217), vol. 1, pp. 34–36 vol.1, <https://doi.org/10.1109/IGARSS.2001.976049>, 2001.
- O’Sullivan, M. J., Yeh, A., and Mannington, W. I.: A history of numerical modelling of the Wairakei geothermal field, *Geothermics*, 38, 155–168, <https://doi.org/10.1016/j.geothermics.2008.12.001>, 2009.
- Otto, D., Rasse, D., Kaplan, J., Warnant, P., and François, L.: Biospheric carbon stocks reconstructed at the Last Glacial Maximum: comparison between general circulation models using prescribed and computed sea surface temperatures, *Global and Planetary Change*, 33, 117–138, [https://doi.org/10.1016/S0921-8181\(02\)00066-8](https://doi.org/10.1016/S0921-8181(02)00066-8), 2002.
- Paolo, F. S., Fricker, H. A., and Padman, L.: Volume loss from Antarctic ice shelves is accelerating, *Science*, 348, 327–331, <https://doi.org/10.1126/science.aaa0940>, 2015.
- Parkinson, C.: Satellite Passive Microwave Measurements of Sea Ice, in: *Encyclopedia of Ocean Sciences*, edited by Steele, J. H., pp. 2531–2539, Academic Press, Oxford, ISBN 978-0-12-227430-5, <https://doi.org/10.1006/rwos.2001.0336>, 2001.
- Parmesan, C.: Ecological and Evolutionary Responses to Recent Climate Change, *Annual Review of Ecology, Evolution, and Systematics*, 37, 637–669, <https://doi.org/10.1146/annurev.ecolsys.37.091305.110100>, 2006.
- Phillips, N. A.: The general circulation of the atmosphere: A numerical experiment, *Quarterly Journal of the Royal Meteorological Society*, 82, 123–164, <https://doi.org/10.1002/qj.49708235202>, 1956.
- Picard, G. and Fily, M.: Surface melting observations in Antarctica by microwave radiometers: Correcting 26-year time series from changes in acquisition hours, *Remote Sensing of Environment*, 104, 325–336, <https://doi.org/10.1016/j.rse.2006.05.010>, 2006.
- Picard, G., Brucker, L., Fily, M., Gallée, H., and Krinner, G.: Modeling time series of microwave brightness temperature in Antarctica, *Journal of Glaciology*, 55, 537–551, <https://doi.org/10.3189/002214309788816678>, 2009.
- Picard, G., Leduc-Leballeur, M., Banwell, A. F., Brucker, L., and Macelloni, G.: The sensitivity of satellite microwave observations to liquid water in the Antarctic snowpack, *The Cryosphere Discussions*, 2022, 1–34, <https://doi.org/10.5194/tc-2022-85>, 2022.
- Portmann, R., Beyerle, U., Davin, E., Fischer, E. M., De Hertog, S., and Schemm, S.: Global forestation and deforestation affect remote climate via adjusted atmosphere and ocean circulation, *Nature Communications*, 13, 5569, <https://doi.org/10.1038/s41467-022-33279-9>, 2022.
- Powers, J. G., Klemp, J. B., Skamarock, W. C., Davis, C. A., Dudhia, J., Gill, D. O., Coen, J. L., Gochis, D. J., Ahmadov, R., Peckham, S. E., Grell, G. A., Michalakes, J., Trahan, S., Benjamin, S. G., Alexander, C. R., Dimego, G. J., Wang, W.,

- Schwartz, C. S., Romine, G. S., Liu, Z., Snyder, C., Chen, F., Barlage, M. J., Yu, W., and Duda, M. G.: The Weather Research and Forecasting Model: Overview, System Efforts, and Future Directions, *Bulletin of the American Meteorological Society*, 98, 1717 – 1737, <https://doi.org/10.1175/BAMS-D-15-00308.1>, 2017.
- Puggaard, A., Hansen, N., Mottram, R., Nagler, T., Scheiblauer, S., Simonsen, S. B., Sørensen, L. S., Wuite, J., and Solgaard, A. M.: Bias in modeled Greenland Ice Sheet melt revealed by ASCAT, *The Cryosphere*, 19, 2963–2981, <https://doi.org/10.5194/tc-19-2963-2025>, 2025.
- Radnóti, G., Ajjaji, R., Bubnová, R., Caian, M., Cordoneanu, E., Von Der Emde, K., Gril, J., Hoffman, J., Horanyi, A., Issara, S., et al.: The spectral limited area model ARPEGE/ALADIN, PWPR report series, 7, 111–117, 1995.
- Richardson, A. D., Keenan, T. F., Migliavacca, M., Ryu, Y., Sonnentag, O., and Toomey, M.: Climate change, phenology, and phenological control of vegetation feedbacks to the climate system, *Agricultural and Forest Meteorology*, 169, 156–173, <https://doi.org/10.1016/j.agrformet.2012.09.012>, 2013.
- Rignot, E., Mouginot, J., Scheuchl, B., van den Broeke, M., van Wessem, M. J., and Morlighem, M.: Four decades of Antarctic Ice Sheet mass balance from 1979–2017, *Proceedings of the National Academy of Sciences*, 116, 1095–1103, <https://doi.org/10.1073/pnas.1812883116>, 2019.
- Roebroek, C. T. J., Caporaso, L., Duveiller, G., Davin, E. L., Seneviratne, S. I., and Cescatti, A.: Potential tree cover under current and future climate scenarios, *Scientific Data*, 12, 564, <https://doi.org/10.1038/s41597-025-04408-y>, 2025.
- Rogers, C., Chen, J. M., Croft, H., Gonsamo, A., Luo, X., Bartlett, P., and Staebler, R. M.: Daily leaf area index from photosynthetically active radiation for long term records of canopy structure and leaf phenology, *Agricultural and Forest Meteorology*, 304-305, 108 407, <https://doi.org/10.1016/j.agrformet.2021.108407>, 2021.
- Rott, H., Skvarca, P., and Nagler, T.: Rapid Collapse of Northern Larsen Ice Shelf, Antarctica, *Science*, 271, 788–792, <https://doi.org/10.1126/science.271.5250.788>, 1996.
- Rouse, J. W. J., Haas, R. H., Schell, J. A., and Deering, D. W.: Monitoring Vegetation Systems in the Great Plains with ERTS, in: *Third Earth Resources Technology Satellite-1 Symposium*, vol. 1, pp. 309–317, NASA, Washington, DC, NASA SP-351, 1974.
- Running, S. W., Justice, C. O., Salomonson, V., Hall, D., Barker, J., Kaufmann, Y. J., Strahler, A. H., Huete, A. R., Muller, J.-P., Vanderbilt, V., Wan, Z. M., Teillet, P., and Carneggie, D.: Terrestrial remote sensing science and algorithms planned for EOSMODIS, *International Journal of Remote Sensing*, 15, 3587–3620, <https://doi.org/10.1080/01431169408954346>, 1994.
- Samsonov, S., Tiampo, K., and Cassotto, R.: SAR-derived flow velocity and its link to glacier surface elevation change and mass balance, *Remote Sensing of Environment*, 258, 112 343, <https://doi.org/10.1016/j.rse.2021.112343>, 2021.

- Santanello, J. A., Dirmeyer, P. A., Ferguson, C. R., Findell, K. L., Tawfik, A. B., Berg, A., Ek, M., Gentile, P., Guillod, B. P., van Heerwaarden, C., Roundy, J., and Wulfmeyer, V.: Land–Atmosphere Interactions: The LoCo Perspective, *Bulletin of the American Meteorological Society*, 99, 1253 – 1272, <https://doi.org/10.1175/BAMS-D-17-0001.1>, 2018.
- Santi, E., Paloscia, S., Pettinato, S., Brocca, L., Ciabatta, L., and Entekhabi, D.: On the synergy of SMAP, AMSR2 AND SENTINEL-1 for retrieving soil moisture, *International Journal of Applied Earth Observation and Geoinformation*, 65, 114–123, <https://doi.org/10.1016/j.jag.2017.10.010>, 2018.
- Saxton, K. E., Rawls, W. J., Romberger, J. S., and Papendick, R. I.: Estimating Generalized Soil-water Characteristics from Texture, *Soil Science Society of America Journal*, 50, 1031–1036, <https://doi.org/10.2136/sssaj1986.03615995005000040039x>, 1986.
- Scambos, T., Hulbe, C., and Fahnestock, M.: Climate-Induced Ice Shelf Disintegration in the Antarctic Peninsula, in: *Antarctic Peninsula Climate Variability: Historical and Paleoenvironmental Perspectives*, pp. 79–92, American Geophysical Union, ISBN 9781118668450, <https://doi.org/10.1029/AR079p0079>, 2003.
- Schaphoff, S., von Bloh, W., Rammig, A., Thonicke, K., Biemans, H., Forkel, M., Gerten, D., Heinke, J., Jägermeyr, J., Knauer, J., Langerwisch, F., Lucht, W., Müller, C., Rolinski, S., and Waha, K.: LPJmL4 – a dynamic global vegetation model with managed land – Part 1: Model description, *Geoscientific Model Development*, 11, 1343–1375, <https://doi.org/10.5194/gmd-11-1343-2018>, 2018.
- Schuldt, B., Buras, A., Arend, M., Vitasse, Y., Beierkuhnlein, C., Damm, A., Gharun, M., Grams, T. E., Hauck, M., Hajek, P., Hartmann, H., Hiltbrunner, E., Hoch, G., Holloway-Phillips, M., Körner, C., Larysch, E., Lübke, T., Nelson, D. B., Rammig, A., Rigling, A., Rose, L., Ruehr, N. K., Schumann, K., Weiser, F., Werner, C., Wohlgemuth, T., Zang, C. S., and Kahmen, A.: A first assessment of the impact of the extreme 2018 summer drought on Central European forests, *Basic and Applied Ecology*, 45, 86–103, <https://doi.org/10.1016/j.baae.2020.04.003>, 2020.
- Schwinger, J., Kollet, S. J., Hoppe, C. M., and Elbern, H.: Sensitivity of Latent Heat Fluxes to Initial Values and Parameters of a Land-Surface Model, *Vadose Zone Journal*, 9, 984–1001, <https://doi.org/10.2136/vzj2009.0190>, 2010.
- Sein, D. V., Gröger, M., Cabos, W., Alvarez-Garcia, F. J., Hagemann, S., Pinto, J. G., Izquierdo, A., de la Vara, A., Koldunov, N. V., Dvornikov, A. Y., Limareva, N., Alekseeva, E., Martinez-Lopez, B., and Jacob, D.: Regionally Coupled Atmosphere-Ocean-Marine Biogeochemistry Model ROM: 2. Studying the Climate Change Signal in the North Atlantic and Europe, *Journal of Advances in Modeling Earth Systems*, 12, e2019MS001646, <https://doi.org/10.1029/2019MS001646>, 2020.
- Sellar, A. A., Jones, C. G., Mulcahy, J. P., Tang, Y., Yool, A., Wiltshire, A., O’Connor, F. M., Stringer, M., Hill, R., Palmieri, J., Woodward, S., de Mora, L., Kuhlbrodt, T., Rumbold, S. T., Kelley, D. I., Ellis, R., Johnson, C. E., Walton,

- J., Abraham, N. L., Andrews, M. B., Andrews, T., Archibald, A. T., Berthou, S., Burke, E., Blockley, E., Carslaw, K., Dalvi, M., Edwards, J., Folberth, G. A., Gedney, N., Griffiths, P. T., Harper, A. B., Hendry, M. A., Hewitt, A. J., Johnson, B., Jones, A., Jones, C. D., Keeble, J., Liddicoat, S., Morgenstern, O., Parker, R. J., Predoi, V., Robertson, E., Siahayan, A., Smith, R. S., Swaminathan, R., Woodhouse, M. T., Zeng, G., and Zerroukat, M.: UKESM1: Description and Evaluation of the U.K. Earth System Model, *Journal of Advances in Modeling Earth Systems*, 11, 4513–4558, <https://doi.org/10.1029/2019MS001739>, 2019.
- Sellers, P. J., Dickinson, R. E., Randall, D. A., Betts, A. K., Hall, F. G., Berry, J. A., Collatz, G. J., Denning, A. S., Mooney, H. A., Nobre, C. A., Sato, N., Field, C. B., and Henderson-Sellers, A.: Modeling the Exchanges of Energy, Water, and Carbon Between Continents and the Atmosphere, *Science*, 275, 502–509, <https://doi.org/10.1126/science.275.5299.502>, 1997.
- Seneviratne, S. I., Lüthi, D., Litschi, M., and Schär, C.: Land–atmosphere coupling and climate change in Europe, *Nature*, 443, 205–209, <https://doi.org/10.1038/nature05095>, 2006.
- Seneviratne, S. I., Corti, T., Davin, E. L., Hirschi, M., Jaeger, E. B., Lehner, I., Orlowsky, B., and Teuling, A. J.: Investigating soil moisture–climate interactions in a changing climate: A review, *Earth-Science Reviews*, 99, 125–161, <https://doi.org/10.1016/j.earscirev.2010.02.004>, 2010.
- Slater, T., Shepherd, A., McMillan, M., Leeson, A., Gilbert, L., Muir, A., Munneke, P. K., Noël, B., Fettweis, X., van den Broeke, M., and Briggs, K.: Increased variability in Greenland Ice Sheet runoff from satellite observations, *Nature Communications*, 12, 6069, <https://doi.org/10.1038/s41467-021-26229-4>, 2021.
- Snell, R. S., Huth, A., Nabel, J. E. M. S., Bocedi, G., Travis, J. M. J., Gravel, D., Bugmann, H., Gutiérrez, A. G., Hickler, T., Higgins, S. I., Reineking, B., Scherstjanoi, M., Zurbriggen, N., and Lischke, H.: Using dynamic vegetation models to simulate plant range shifts, *Ecography*, 37, 1184–1197, <https://doi.org/10.1111/ecog.00580>, 2014.
- Soto-Navarro, J., Jordá, G., Amores, A., Cabos, W., Somot, S., Sevault, F., Macías, D., Djurdjevic, V., Sannino, G., Li, L., and Sein, D.: Evolution of Mediterranean Sea water properties under climate change scenarios in the Med-CORDEX ensemble, *Climate Dynamics*, 54, 2135–2165, <https://doi.org/10.1007/s00382-019-05105-4>, 2020.
- Statbel: Land use in Belgium from 1980, <https://statbel.fgov.be/en/themes/environment/land-cover-and-use/land-use#figures>, visited on 2025-02-25, 2025.
- Strengers, B. J., Müller, C., Schaeffer, M., Haarsma, R. J., Severijns, C., Gerten, D., Schaphoff, S., van den Houdt, R., and Oostenrijk, R.: Assessing 20th century climate–vegetation feedbacks of land-use change and natural vegetation dynamics in a fully coupled vegetation–climate model, *International Journal of Climatology*, 30, 2055–2065, <https://doi.org/10.1002/joc.2132>, 2010.

- Stuecker, M. F., Bitz, C. M., Armour, K. C., Proistosescu, C., Kang, S. M., Xie, S.-P., Kim, D., McGregor, S., Zhang, W., Zhao, S., Cai, W., Dong, Y., and Jin, F.-F.: Polar amplification dominated by local forcing and feedbacks, *Nature Climate Change*, 8, 1076–1081, <https://doi.org/10.1038/s41558-018-0339-y>, 2018.
- Sun, S., Pattyn, F., Simon, E. G., Albrecht, T., Cornford, S., Calov, R., Dumas, C., Gillet-Chaulet, F., Goelzer, H., Golledge, N. R., and et al.: Antarctic ice sheet response to sudden and sustained ice-shelf collapse (ABUMIP), *Journal of Glaciology*, 66, 891–904, <https://doi.org/10.1017/jog.2020.67>, 2020.
- Swanson, A. C., Kaplan, D., Toh, K.-B., Marques, E. E., and Bohlman, S. A.: Changes in floodplain hydrology following serial damming of the Tocantins River in the eastern Amazon, *Science of The Total Environment*, 800, 149 494, <https://doi.org/10.1016/j.scitotenv.2021.149494>, 2021.
- Taylor, C. M., Harding, R. J., Thorpe, A. J., and Bessemoulin, P.: A mesoscale simulation of land surface heterogeneity from HAPEX-Sahel, *Journal of Hydrology*, 188-189, 1040–1066, [https://doi.org/10.1016/S0022-1694\(96\)03182-4](https://doi.org/10.1016/S0022-1694(96)03182-4), 1997.
- Taylor, K. E., Stouffer, R. J., and Meehl, G. A.: An Overview of CMIP5 and the Experiment Design, *Bulletin of the American Meteorological Society*, 93, 485 – 498, <https://doi.org/10.1175/BAMS-D-11-00094.1>, 2012.
- Tedesco, M. and Fettweis, X.: Unprecedented atmospheric conditions (1948–2019) drive the 2019 exceptional melting season over the Greenland ice sheet, *The Cryosphere*, 14, 1209–1223, <https://doi.org/10.5194/tc-14-1209-2020>, 2020.
- Tedesco, M., Abdalati, W., and Zwally, H. J.: Persistent surface snowmelt over Antarctica (1987–2006) from 19.35 GHz brightness temperatures, *Geophysical Research Letters*, 34, 1–6, <https://doi.org/10.1029/2007GL031199>, 2007.
- Tedesco, M., Colosio, P., Fettweis, X., and Cervone, G.: A computationally efficient statistically downscaled 100 m resolution Greenland product from the regional climate model MAR, *The Cryosphere*, 17, 5061–5074, <https://doi.org/10.5194/tc-17-5061-2023>, 2023.
- Termonia, P., Fischer, C., Bazile, E., Bouyssel, F., Brožková, R., Bénard, P., Bochenek, B., Degrauwe, D., Derková, M., El Khatib, R., Hamdi, R., Mašek, J., Pottier, P., Pristov, N., Seity, Y., Smolíková, P., Španiel, O., Tudor, M., Wang, Y., Wittmann, C., and Joly, A.: The ALADIN System and its canonical model configurations AROME CY41T1 and ALARO CY40T1, *Geoscientific Model Development*, 11, 257–281, <https://doi.org/10.5194/gmd-11-257-2018>, 2018.
- Teuling, A. J., Seneviratne, S. I., Stöckli, R., Reichstein, M., Moors, E., Ciais, P., Luyssaert, S., van den Hurk, B., Ammann, C., Bernhofer, C., Dellwik, E., Gianelle, D., Gielen, B., Grünwald, T., Klumpp, K., Montagnani, L., Moureaux, C., Sottocornola, M., and Wohlfahrt, G.: Contrasting response of European forest and grassland energy exchange to heatwaves, *Nature Geoscience*, 3, 722–727, <https://doi.org/10.1038/ngeo950>, 2010.
- The IMBIE Team: Mass balance of the Antarctic Ice Sheet from 1992 to 2017, *Nature*, 558, 219–222, <https://doi.org/10.1038/s41586-018-0179-y>, 2018.

- Theeuwens, J. J. E., Staal, A., Tuinenburg, O. A., Hamelers, B. V. M., and Dekker, S. C.: Local moisture recycling across the globe, *Hydrology and Earth System Sciences*, 27, 1457–1476, <https://doi.org/10.5194/hess-27-1457-2023>, 2023.
- Toreti, A., Bavera, D., Acosta Navarro, J., Arias Muñoz, C., Barbosa, P., De Jager, A., Di Ciollo, C., Fioravanti, G., Hrašt Essenfelder, A., Maetens, W., Magni, D., Masante, D., Mazzeschi, M., McCormick, N., and Salamon, P.: Drought in Europe - August 2023 - GDO analytical report, Publications Office of the European Union, <https://doi.org/10.2760/928418>, 2023.
- Toreti, A., Bavera, D., Acosta Navarro, J., Acquafresca, L., Azas, K., Barbosa, P., De Jager, A., Ficchi, A., Fioravanti, G., Grimaldi, S., Hrašt Essenfelder, A., Magni, D., Mazzeschi, M., McCormick, N., Salamon, P., Santos Nunes, S., and Volpi, D.: Drought in Europe - July 2024 - GDO analytical report, Publications Office of the European Union, <https://doi.org/10.2760/420832>, 2024.
- Torres, R., Snoeij, P., Geudtner, D., Bibby, D., Davidson, M., Attema, E., Potin, P., Rommen, B., Floury, N., Brown, M., Traver, I. N., Deghaye, P., Duesmann, B., Rosich, B., Miranda, N., Bruno, C., L’Abbate, M., Croci, R., Pietropaolo, A., Huchler, M., and Rostan, F.: GMES Sentinel-1 mission, *Remote Sensing of Environment*, 120, 9–24, <https://doi.org/10.1016/j.rse.2011.05.028>, 2012.
- Trusel, L. D., Frey, K. E., Das, S. B., Munneke, P. K., and van den Broeke, M. R.: Satellite-based estimates of Antarctic surface meltwater fluxes, *Geophysical Research Letters*, 40, 6148–6153, <https://doi.org/10.1002/2013GL058138>, 2013.
- Trusel, L. D., Frey, K. E., Das, S. B., Karnauskas, K. B., Munneke, P. K., Meijgaard, E. V., and Broeke, M. R. V. D.: Divergent trajectories of Antarctic surface melt under two twenty-first-century climate scenarios, *Nature Geoscience*, 8, 927–932, <https://doi.org/10.1038/ngeo2563>, 2015.
- Tuinenburg, O. A., Theeuwens, J. J. E., and Staal, A.: High-resolution global atmospheric moisture connections from evaporation to precipitation, *Earth System Science Data*, 12, 3177–3188, <https://doi.org/10.5194/essd-12-3177-2020>, 2020.
- Turner, D. P., Ritts, W. D., Cohen, W. B., Gower, S. T., Running, S. W., Zhao, M., Costa, M. H., Kirschbaum, A. A., Ham, J. M., Saleska, S. R., and Ahl, D. E.: Evaluation of MODIS NPP and GPP products across multiple biomes, *Remote Sensing of Environment*, 102, 282–292, <https://doi.org/10.1016/j.rse.2006.02.017>, 2006.
- van den Broeke, M. R., Enderlin, E. M., Howat, I. M., Kuipers Munneke, P., Noël, B. P. Y., van de Berg, W. J., van Meijgaard, E., and Wouters, B.: On the recent contribution of the Greenland ice sheet to sea level change, *The Cryosphere*, 10, 1933–1946, <https://doi.org/10.5194/tc-10-1933-2016>, 2016.
- van der Ent, R. J., Savenije, H. H. G., Schaeffli, B., and Steele-Dunne, S. C.: Origin and fate of atmospheric moisture over continents, *Water Resources Research*, 46, <https://doi.org/10.1029/2010WR009127>, 2010.

- Van Tricht, K., Lhermitte, S., Lenaerts, J. T. M., Gorodetskaya, I. V., L'Ecuyer, T. S., Noël, B., van den Broeke, M. R., Turner, D. D., and van Lipzig, N. P. M.: Clouds enhance Greenland ice sheet meltwater runoff, *Nature Communications*, 7, 10 266, <https://doi.org/10.1038/ncomms10266>, 2016.
- Van Wijk, M. T., Dekker, S. C., Bouten, W., Bosveld, F. C., Kohsiek, W., Kramer, K., and Mohren, G. M. J.: Modeling daily gas exchange of a Douglas-fir forest: comparison of three stomatal conductance models with and without a soil water stress function, *Tree Physiology*, 20, 115–122, <https://doi.org/10.1093/treephys/20.2.115>, 2000.
- Verma, A., Lanssens, B., Tölle, M., Jacquemin, I., Chaudhari, T., Hambuckers, A., and François, L.: Integrating high-resolution data and species-level traits for enhanced ecosystem projections using a dynamic vegetation model: Case study in Wallonia, Belgium, *Journal of Environmental Management*, 375, 124 329, <https://doi.org/10.1016/j.jenvman.2025.124329>, 2025.
- Vicente-Serrano, S. M., Beguería, S., and López-Moreno, J. I.: A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index, *Journal of Climate*, 23, 1696 – 1718, <https://doi.org/10.1175/2009JCLI2909.1>, 2010.
- Vincke, C., Bogaerts, G., Chebbi, W., Chebbi, W., Chopin, H., De Ligne, A., Demoulin, L., Douxfls, B., Engelmann, T., Faurès, A., Heinesch, B., Manise, T., Orgun, A., Piret, A., and Thyron, T.: Fluxnet Product from Vielsalm, 1995-12-31–2024-12-31, <https://hdl.handle.net/11676/CYyvunMafV2iXCfCHTW209J0>, 2026.
- Vogel, M. M., Orth, R., Cheruy, F., Hagemann, S., Lorenz, R., van den Hurk, B. J. J. M., and Seneviratne, S. I.: Regional amplification of projected changes in extreme temperatures strongly controlled by soil moisture-temperature feedbacks, *Geophysical Research Letters*, 44, 1511–1519, <https://doi.org/10.1002/2016GL071235>, 2017.
- Wan, Z. and Dozier, J.: A generalized split-window algorithm for retrieving land-surface temperature from space, *IEEE Transactions on Geoscience and Remote Sensing*, 34, 892–905, <https://doi.org/10.1109/36.508406>, 1996.
- Wang, J., Rich, P. M., and and, K. P. P.: Temporal responses of NDVI to precipitation and temperature in the central Great Plains, USA, *International Journal of Remote Sensing*, 24, 2345–2364, <https://doi.org/10.1080/01431160210154812>, 2003.
- Warnant, P., François, L., Strivay, D., and Gérard, J.-C.: CARAIB: A global model of terrestrial biological productivity, *Global Biogeochemical Cycles*, 8, 255–270, <https://doi.org/10.1029/94GB00850>, 1994.
- Westerling, A. L., Hidalgo, H. G., Cayan, D. R., and Swetnam, T. W.: Warming and Earlier Spring Increase Western U.S. Forest Wildfire Activity, *Science*, 313, 940–943, <https://doi.org/10.1126/science.1128834>, 2006.

- Wille, J. D., Favier, V., Jourdain, N. C., Kittel, C., Turton, J. V., Agosta, C., Gorodetskaya, I. V., Picard, G., Codron, F., Santos, C. L.-D., Amory, C., Fettweis, X., Blanchet, J., Jomelli, V., and Berchet, A.: Intense atmospheric rivers can weaken ice shelf stability at the Antarctic Peninsula, *Communications Earth & Environment*, 3, 90, <https://doi.org/10.1038/s43247-022-00422-9>, 2022.
- Woodward, F. I. and Williams, B. G.: Climate and plant distribution at global and local scales, *Vegetatio*, 69, 189–197, <https://doi.org/10.1007/BF00038700>, 1987.
- Wulfmeyer, V., Turner, D. D., Baker, B., Banta, R., Behrendt, A., Bonin, T., Brewer, W. A., Buban, M., Choukulkar, A., Dumas, E., Hardesty, R. M., Heus, T., Ingwersen, J., Lange, D., Lee, T. R., Metzendorf, S., Muppa, S. K., Meyers, T., Newsom, R., Osman, M., Raasch, S., Santanello, J., Senff, C., Späth, F., Wagner, T., and Weckwerth, T.: A New Research Approach for Observing and Characterizing Land–Atmosphere Feedback, *Bulletin of the American Meteorological Society*, 99, 1639 – 1667, <https://doi.org/10.1175/BAMS-D-17-0009.1>, 2018.
- Wyard, C., Scholzen, C., Fettweis, X., Van Campenhout, J., and François, L.: Decrease in climatic conditions favouring floods in the south-east of Belgium over 1959–2010 using the regional climate model MAR, *International Journal of Climatology*, 37, 2782–2796, <https://doi.org/10.1002/joc.4879>, 2017.
- Wyard, C., Scholzen, C., Doutreloup, S., Hallot, E., and Fettweis, X.: Future evolution of the hydroclimatic conditions favouring floods in the south-east of Belgium by 2100 using a regional climate model, *International Journal of Climatology*, 41, 647–662, <https://doi.org/10.1002/joc.6642>, 2021.
- Yang, T., Li, Q., Chen, X., Hamdi, R., De Maeyer, P., Kurban, A., and Li, L.: Improving snow simulation with more realistic vegetation parameters in a regional climate model in the Tianshan Mountains, Central Asia, *Journal of Hydrology*, 590, 125 525, <https://doi.org/10.1016/j.jhydrol.2020.125525>, 2020.
- Yates, D. N., Chen, F., LeMone, M. A., Qualls, R., Oncley, S. P., Grossman, R. L., and Brandes, E. A.: A Cooperative Atmosphere–Surface Exchange Study (CASES) Dataset for Analyzing and Parameterizing the Effects of Land Surface Heterogeneity on Area-Averaged Surface Heat Fluxes, *Journal of Applied Meteorology*, 40, 921 – 937, [https://doi.org/10.1175/1520-0450\(2001\)040<0921:ACASES>2.0.CO;2](https://doi.org/10.1175/1520-0450(2001)040<0921:ACASES>2.0.CO;2), 2001.
- Zeitz, M., Reese, R., Beckmann, J., Krebs-Kanzow, U., and Winkelmann, R.: Impact of the melt–albedo feedback on the future evolution of the Greenland Ice Sheet with PISM-dEBM-simple, *The Cryosphere*, 15, 5739–5764, <https://doi.org/10.5194/tc-15-5739-2021>, 2021.
- Zhang, P., Hu, X., and Ban, Y.: Wildfire-S1S2-Canada: A Large-Scale Sentinel-1/2 Wildfire Burned Area Mapping Dataset Based on the 2017–2019 Wildfires in Canada, in: *IGARSS 2022 - 2022 IEEE International Geoscience and Remote Sensing Symposium*, pp. 7954–7957, <https://doi.org/10.1109/IGARSS46834.2022.9884275>, 2022.

- Zhang, W., Jansson, C., Miller, P. A., Smith, B., and Samuelsson, P.: Biogeophysical feedbacks enhance the Arctic terrestrial carbon sink in regional Earth system dynamics, *Biogeosciences*, 11, 5503–5519, <https://doi.org/10.5194/bg-11-5503-2014>, 2014.
- Zhang, W., Miller, P. A., Jansson, C., Samuelsson, P., Mao, J., and Smith, B.: Self-Amplifying Feedbacks Accelerate Greening and Warming of the Arctic, *Geophysical Research Letters*, 45, 7102–7111, <https://doi.org/10.1029/2018GL077830>, 2018.
- Zhou, Z., Fan, L., De Lannoy, G., Liu, X., Peng, J., Bai, X., Frappart, F., Baghdadi, N., Xing, Z., Li, X., Ma, M., Li, X., Che, T., Geng, L., and Wigneron, J.-P.: Retrieval of High-Resolution Vegetation Optical Depth from Sentinel-1 Data over a Grassland Region in the Heihe River Basin, *Remote Sensing*, 14, <https://doi.org/10.3390/rs14215468>, 2022.
- Zittis, G., Almazroui, M., Alpert, P., Ciais, P., Cramer, W., Dahdal, Y., Fnais, M., Francis, D., Hadjinicolaou, P., Howari, F., Jrrar, A., Kaskaoutis, D. G., Kulmala, M., Lazoglou, G., Mihalopoulos, N., Lin, X., Rudich, Y., Sciare, J., Stenchikov, G., Xoplaki, E., and Lelieveld, J.: Climate Change and Weather Extremes in the Eastern Mediterranean and Middle East, *Reviews of Geophysics*, 60, e2021RG000762, <https://doi.org/10.1029/2021RG000762>, 2022.
- Zwally, H. J. and Fiegles, S.: Extent and duration of Antarctic surface melting, *Journal of Glaciology*, 40, 463–475, <https://doi.org/10.3189/s0022143000012338>, 1994.

Appendix

A Additional elements for Chapter 2

Difference in MODIS mean annual cycle

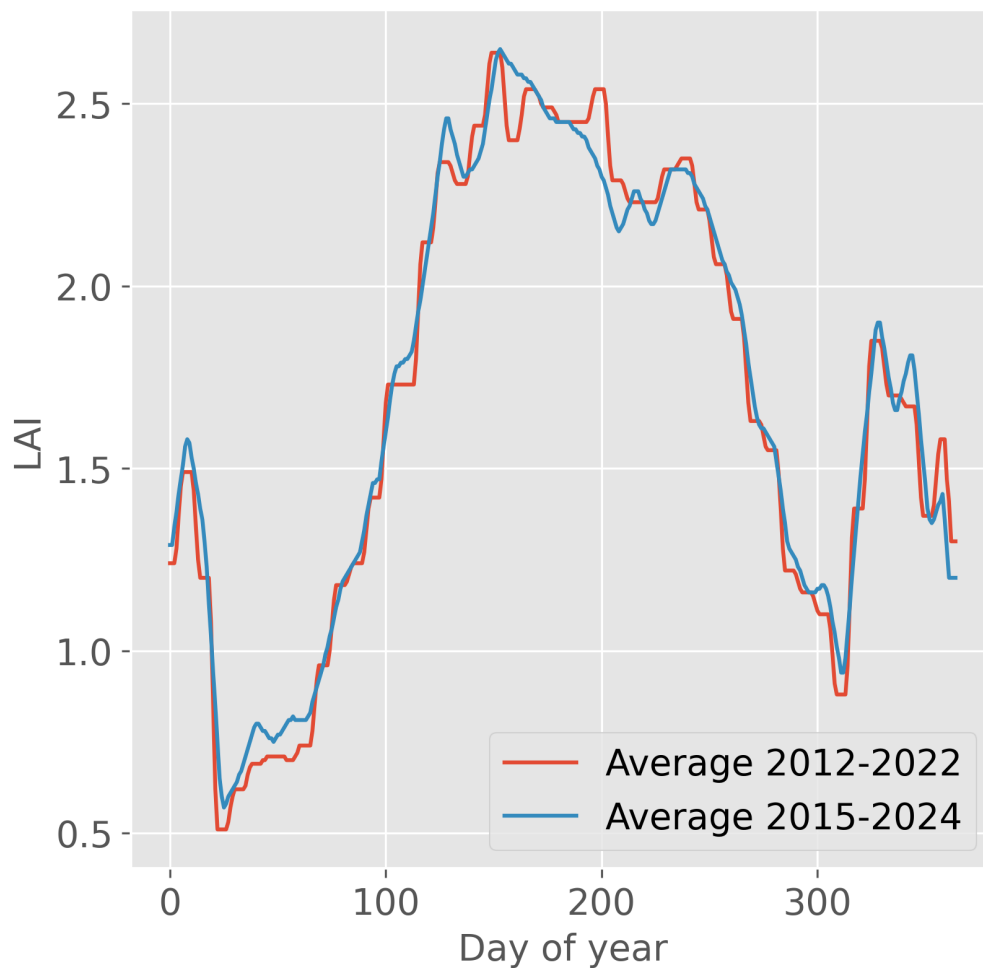


Figure A.01: Comparison of MODIS LAI mean annual cycles calculated using data from 2012–2022 versus 2015–2024.

Difference in LAI in summer

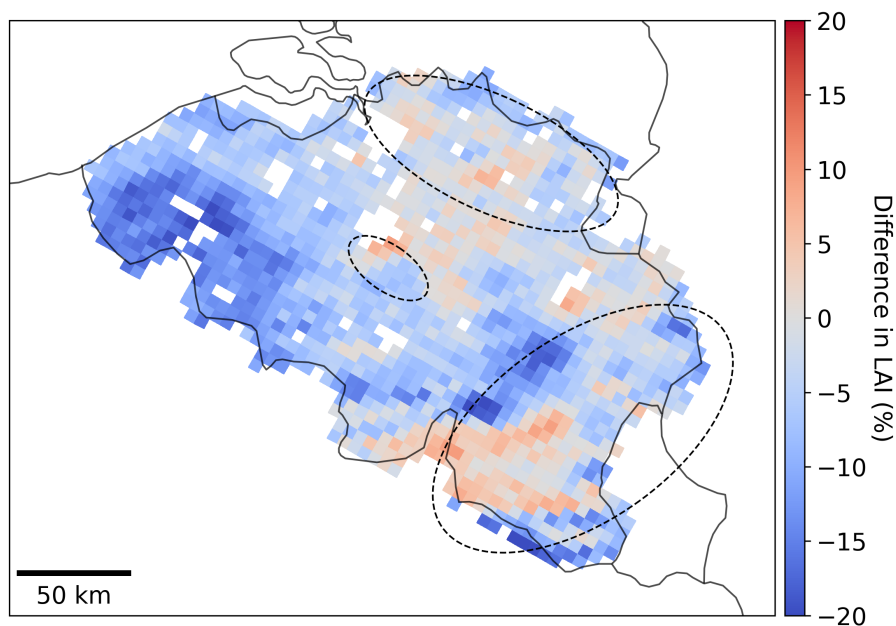


Figure A.02: Map of the average difference (in %) in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2019 in Belgium.

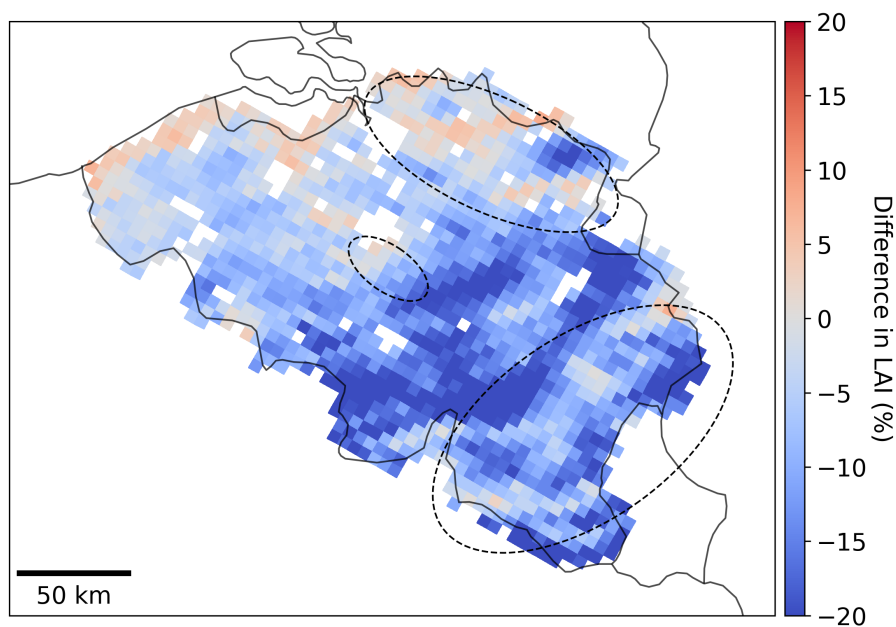


Figure A.03: Map of the average difference (in %) in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2020 in Belgium.

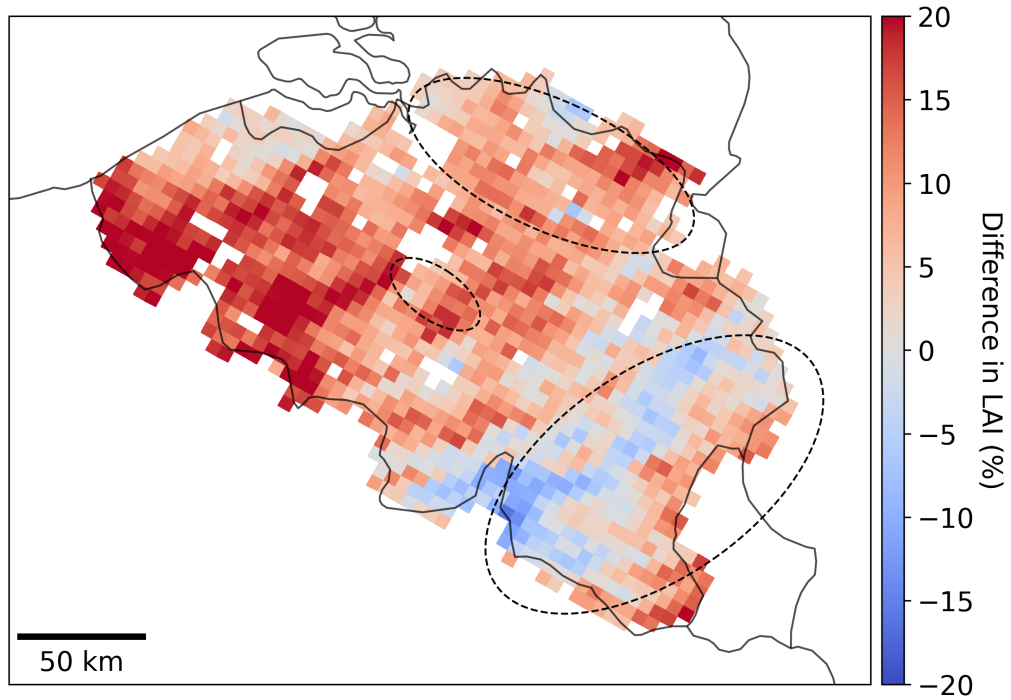


Figure A.04: Map of the average difference (in %) in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2021 in Belgium.

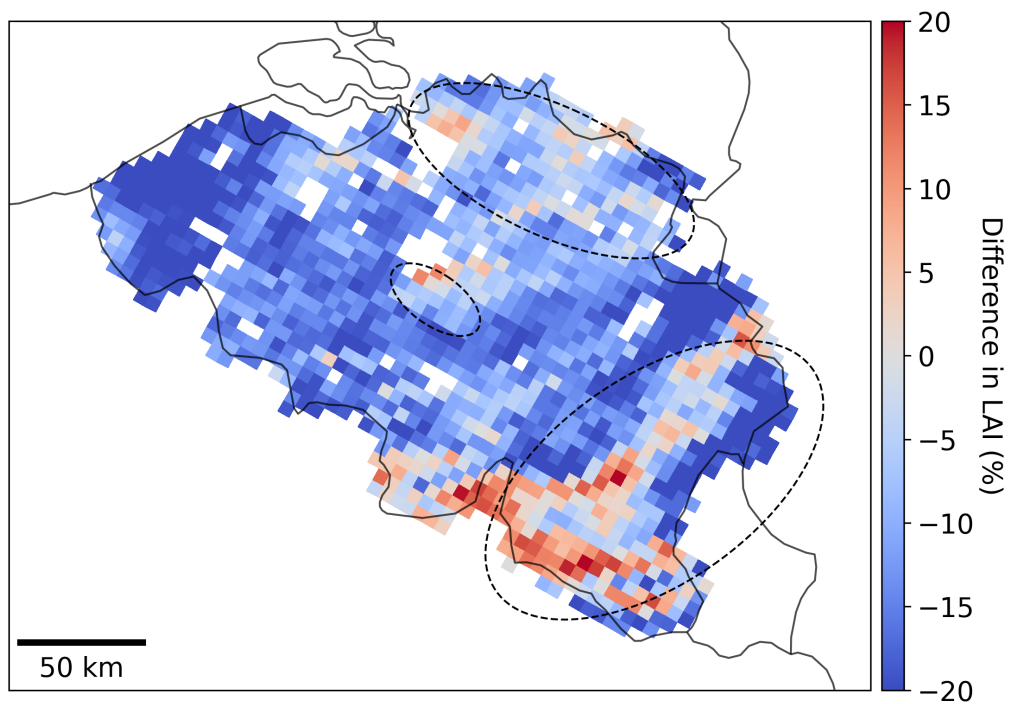


Figure A.05: Map of the average difference (in %) in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2022 in Belgium.

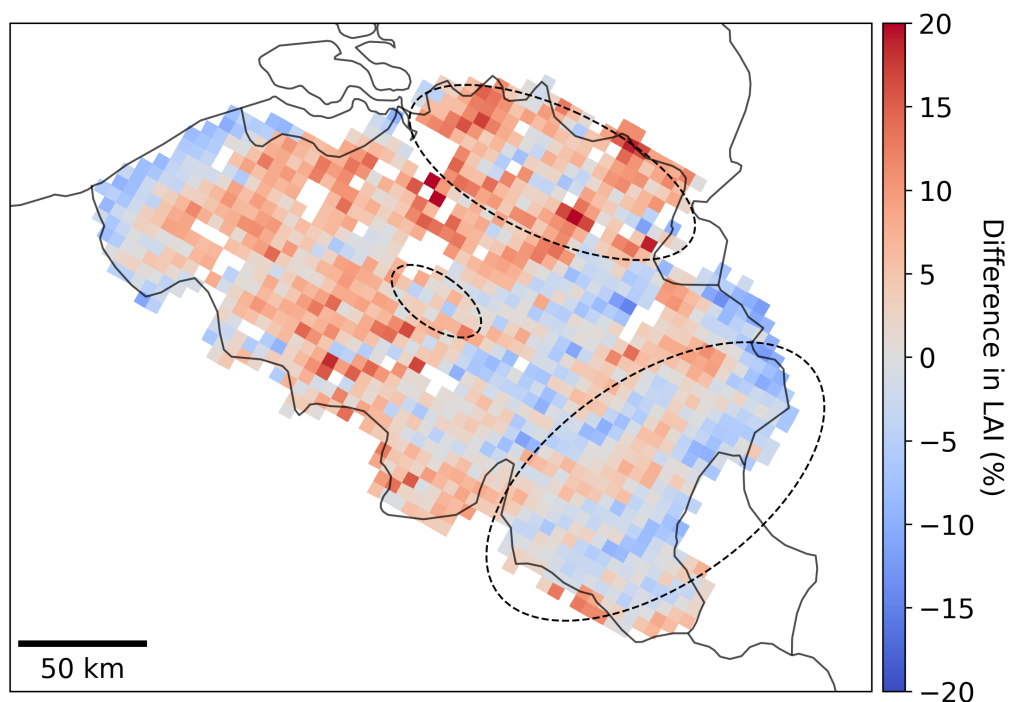


Figure A.06: Map of the average difference (in %) in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2023 in Belgium.

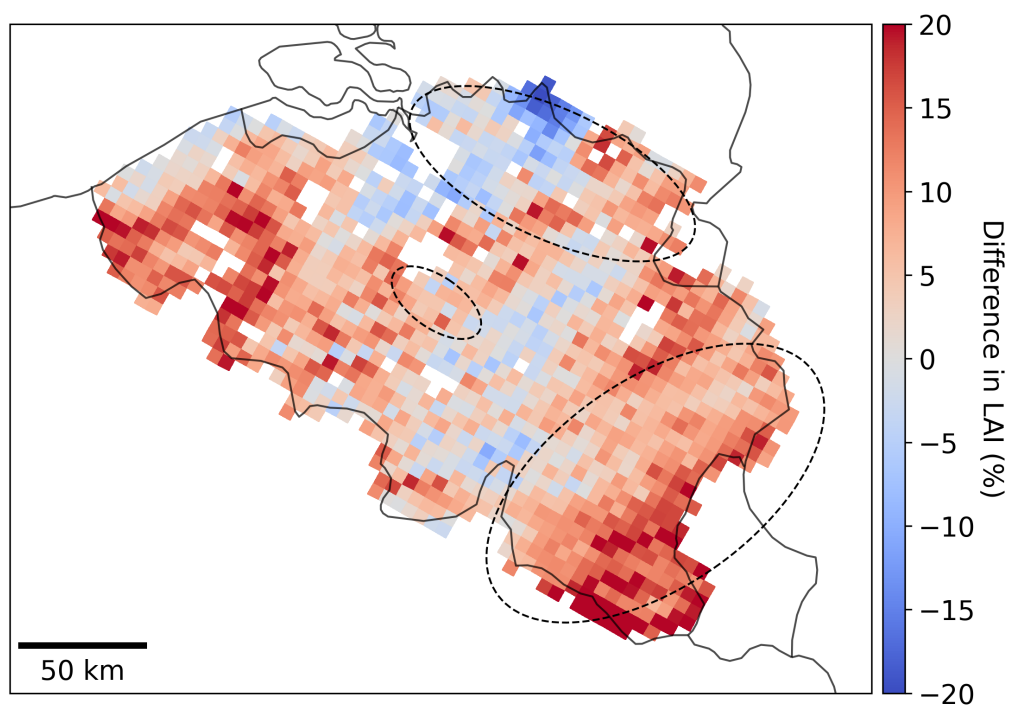


Figure A.07: Map of the average difference (in %) in LAI between the MODIS LAI mean annual cycle (used in $MAR_{MODIS_{cyc}}$) and the 8-day MODIS LAI data (used in MAR_{MODIS}) in July and August 2024 in Belgium.

B Additional elements for Chapter 4

Statistics for the 2020-2021 melt season

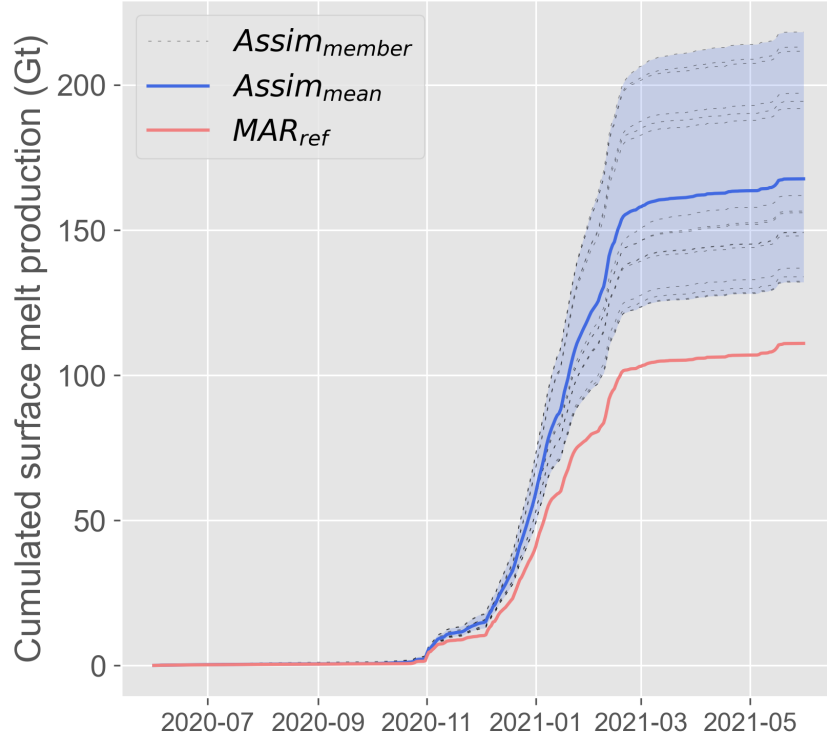


Figure B.01: Cumulated surface melt production (Gt) for the 2020-2021 melt season as modelled by MAR without assimilation (MAR_{ref} in light red), with data assimilation ($Assim_{member}$ in dashed lines), and their averaged value ($Assim_{mean}$ in blue). Shaded areas represent the range of the assimilations.

Table B.01: Surface mass balance (SMB), and average snowpack density (ρ) and snowpack liquid water content (LWC) for MAR_{ref} , the reference assimilation ($Assim_{ref}$) and the mean value of the assimilations ($Assim_{mean}$) over the Antarctic Peninsula for the 2020-2021 melt season. The range comprises all 19 assimilations. LWC and ρ are taken at a depth of 0.2 m and 1 m while the other variable are given as a snowpack cumulated value.

	ME (Gt yr ⁻¹)	RU (Gt yr ⁻¹)	SMB (Gt yr ⁻¹)	$\rho_{0.2m}$ (kgm ⁻³)	ρ_{1m} (kgm ⁻³)	$LWC_{0.2m}$ (kgkg ⁻¹)	LWC_{1m} (kgkg ⁻¹)
MAR_{ref}	111	36	559	429	432	0.003	0.003
$Assim_{ref}$	149	49	546	447	450	0.002	0.003
$Assim_{mean}$	168	52	544	448	452	0.002	0.003
Range	132 - 218	44 - 61	534 - 551	442 - 452	446 - 457	0.002 - 0.003	0.002 - 0.004
Evolution (%)	51.1	43.7	-2.7	4.3	4.4	-17.8	-18

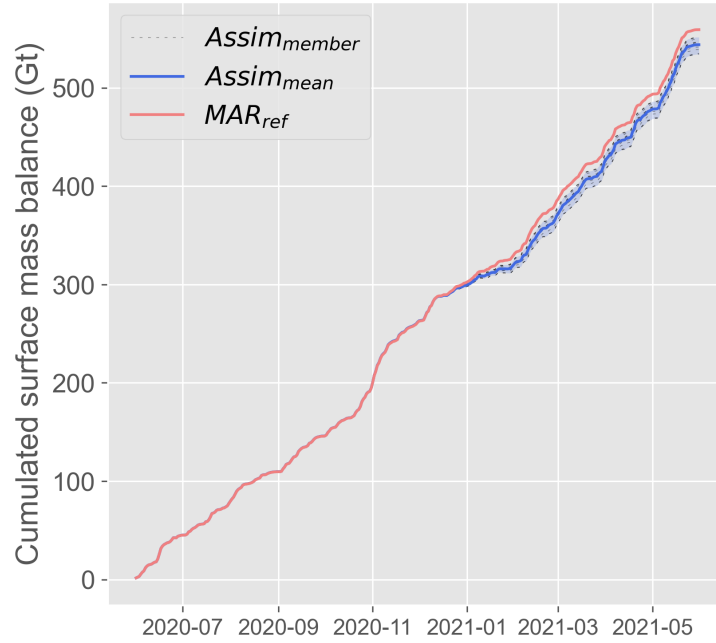


Figure B.02: Cumulated surface mass balance (Gt) for 2020-2021 melt season as modelled by MAR without assimilation (MAR_{ref} in red), with data assimilation ($Assim_{member}$ in dashed lines), and their averaged value ($Assim_{mean}$ in blue). Shaded areas represent the range of the assimilations.

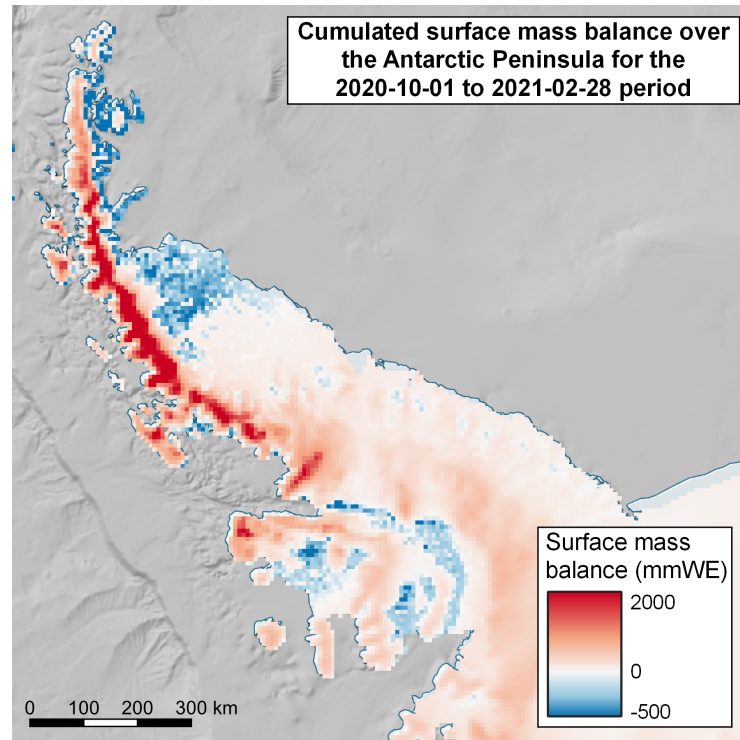


Figure B.03: Cumulated SMB (mmWE) from 2020-10-01 to 2021-02-28 over the AP as modelled by $Assim_{ref}$. Larsen C is outlined in purple, Georges VI in green, and Wilkins in red. The ice shelves and the northernmost coastlines are experiencing a decrease in SMB in opposition to the rest of the AP.

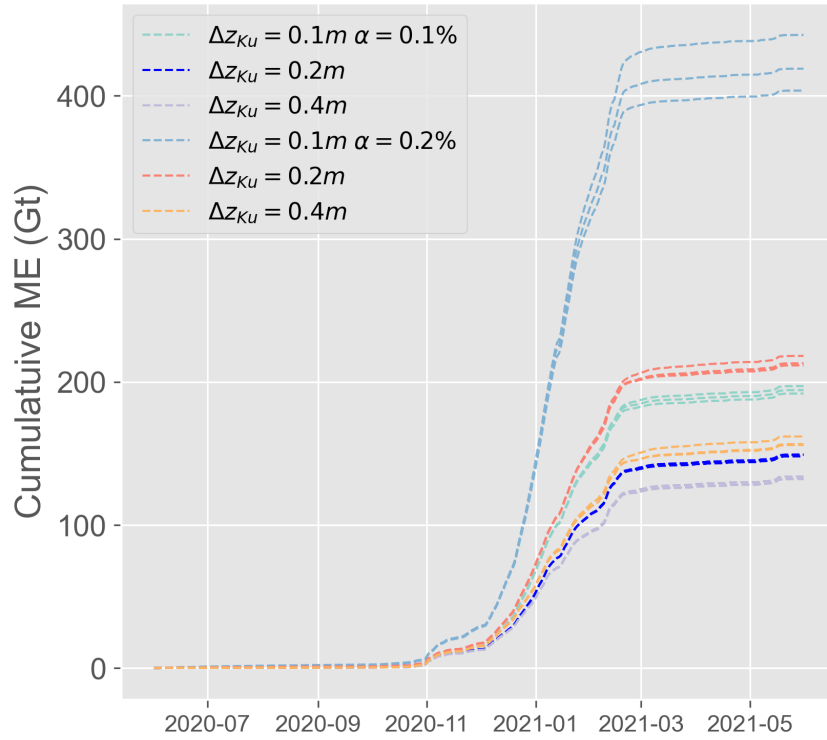


Figure B.04: Cumulated surface melt production (Gt) for 2020-2021 melt season as modelled by the different assimilation. Curves of the same color have different Δ_z for the C-band sensors.

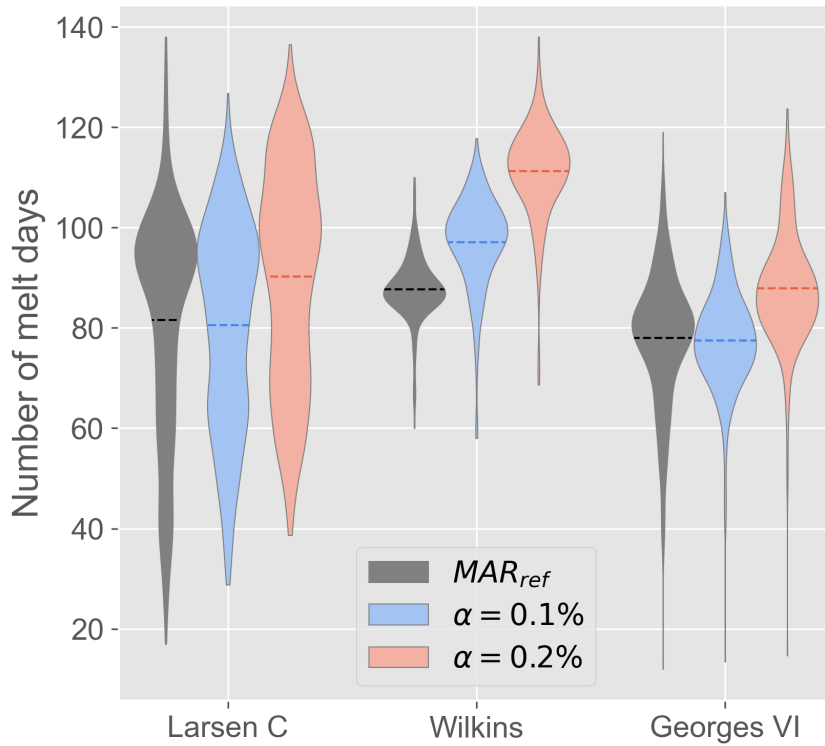


Figure B.05: Distribution of the number of melt days for the 2020-2021 melt season as modelled by MAR_{ref} and the assimilations for the two values of α for the three studied ice shelves. Dashed lines represent the mean value of the distribution.

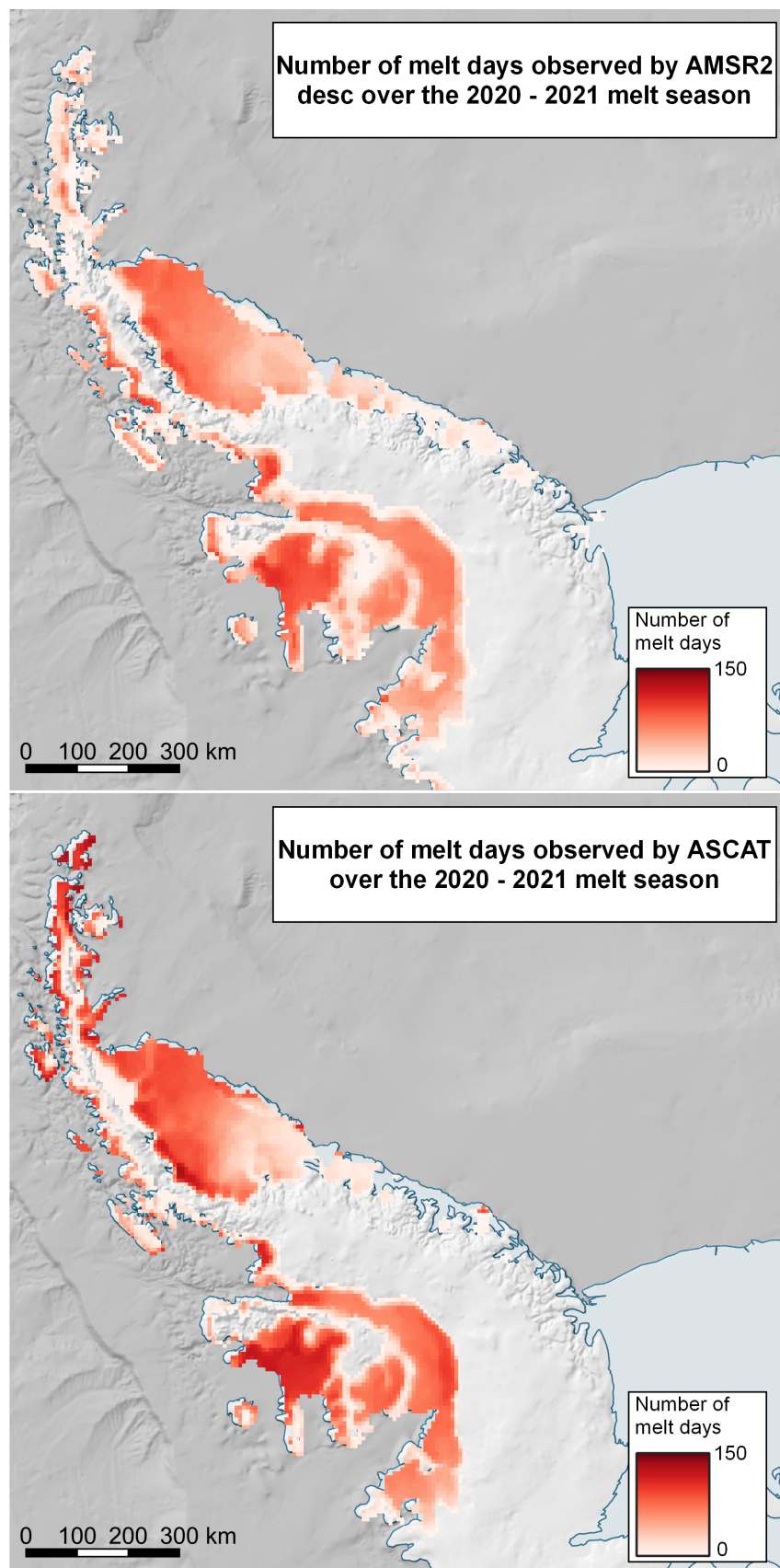


Figure B.06: a) Number of melt days observed by AMSR2 on the AP for the 2020-2021 melt season. b) Number of melt days observed by ASCAT on the AP for the 2019-2020 melt season.

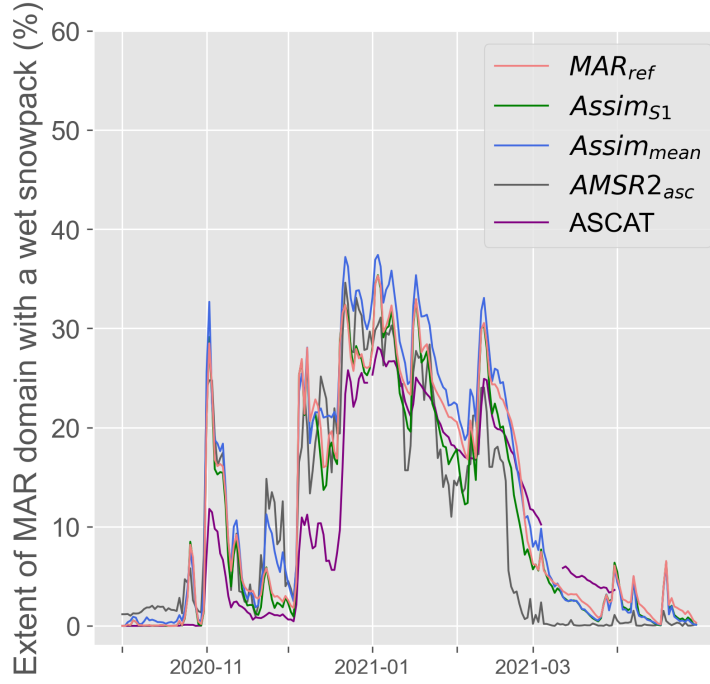


Figure B.07: Evolution of the surface melt extent during the 2020-2021 melt season as modelled by MAR_{ref} (in light red), $Assim_{mean}$ (in blue), the assimilation of only Sentinel-1 melt mask ($Assim_{S1}$, in green), and as observed by AMSR2 in ascending orbit (in grey), and by ASCAT (in purple).

Table B.02: Evolution of surface melt production (ME), runoff (Ru), surface mass balance (SMB), snowpack density (ρ), and snowpack liquid water content (LWC) for MAR_{ref} , the reference assimilation ($Assim_{ref}$) and the mean value of the assimilations ($Assim_{mean}$) over the 3 studied ice shelves for the 2020-2021 melt season. LWC and ρ are given at a depth of 0.2 m and 1 m while the other variable are given as a snowpack average value.

Larsen C	ME (Gt yr ⁻¹)	RU (Gt yr ⁻¹)	SMB (Gt yr ⁻¹)	$\rho_{0.2m}$ (kg m ⁻³)	ρ_{1m} (kg m ⁻³)	$LWC_{0.2m}$ (kg kg ⁻¹)	LWC_{1m} (kg kg ⁻¹)
MAR	30	5.7	20	605	595	0.0006	0.0008
$Assim_{ref}$	41	9.2	16	625	633	0.0005	0.0007
$Assim_{mean}$	47	11	14	629	639	0.0005	0.0007
σ_0	11	1.5	1.1	111	41	0.0005	0.0006
Wilkins	ME (Gt yr ⁻¹)	RU (Gt yr ⁻¹)	SMB (Gt yr ⁻¹)	$\rho_{0.2m}$ (kg m ⁻³)	ρ_{1m} (kg m ⁻³)	$LWC_{0.2m}$ (kg kg ⁻¹)	LWC_{1m} (kg kg ⁻¹)
MAR	5.9	1.4	5.8	564	605	0.0002	0.0002
$Assim_{ref}$	8.6	3.7	3.5	626	675	0.0002	0.0002
$Assim_{mean}$	10	4.1	3.1	634	678	0.0002	0.0002
σ_0	2.7	1.4	1.4	82	80	0.0002	0.0002
Georges VI	ME (Gt yr ⁻¹)	RU (Gt yr ⁻¹)	SMB (Gt yr ⁻¹)	$\rho_{0.2m}$ (kg m ⁻³)	ρ_{1m} (kg m ⁻³)	$LWC_{0.2m}$ (kg kg ⁻¹)	LWC_{1m} (kg kg ⁻¹)
MAR	10	1.9	11	592	590	0.0003	0.0004
$Assim_{ref}$	13	3.4	10	624	627	0.0003	0.0004
$Assim_{mean}$	15	3.5	10	620	621	0.0003	0.0004
σ_0	3.2	3.5	0.7	87	66	0.0003	0.0003

Table B.03: Comparison between the melt season length and number of melt days modelled for the three studied ice shelves for MAR_{ref} and the assimilations for the 2020-2021 melt season.

Larsen C	Melt season length (days)	Number of melt days modelled
MAR_{ref}	209	113
$\alpha = 0.1 \%$	208	116
$\alpha = 0.2 \%$	209	127
Wilkins	Melt season length (days)	Number of melt days modelled
MAR_{ref}	200	99
$\alpha = 0.1 \%$	201	119
$\alpha = 0.2 \%$	207	132
GeorgesVI	Melt season length (days)	Number of melt days modelled
MAR_{ref}	200	98
$\alpha = 0.1 \%$	200	95
$\alpha = 0.2 \%$	200	113

List of Publications

Publications in Peer-Reviewed Journals

Dethinne, T., Glaude, Q., Amory, C., Kittel, C., & Fettweis, X. (2022). Comparison Between Surface Melt Estimation From Sentinel-1 Synthetic Aperture Radar and a Regional Climate Model. Case Study Over the Roi Baudouin Ice Shelf, East Antarctica. *Bulletin de la Société Géographique de Liège*, 78(2022), 113-122. doi:10.25518/0770-7576.6644.

Glaude, Q., **Dethinne, T.**, Lambin, C., & Fettweis, X. (2023). Discussing an extreme mock/what-if scenario over the antarctic peninsula: the effect of intense melt on surface mass balance. *Bulletin de la Société Géographique de Liège*, 80 (2023/1). doi:10.25518/0770-7576.7039.

Dethinne, T., Glaude, Q., Picard, G., Kittel, C., Alexander, P., Orban, A., & Fettweis, X. (2023). Sensitivity of the mar regional climate model snowpack to the parameterization of the assimilation of satellite-derived wet-snow masks on the antarctic peninsula. *The Cryosphere*, 17 (10), 4267-4288. doi:10.5194/tc-17-4267-2023.

Seehaus, T., Sommer, C., **Dethinne, T.**, & Malz, P. (2023). Mass changes of the northern Antarctic Peninsula Ice Sheet derived from repeat bi-static synthetic aperture radar acquisitions for the period 2013-2017. *The Cryosphere*, 17 (11), 4629-4644. doi:10.5194/tc-17-4629-2023.

Gorodetskaya, I. V., Durán-Alarcón, C., González-Herrero, S., Clem, K. R., Zou, X., ... **Dethinne, T.**, & Picard, G. (2023). Record-high Antarctic Peninsula temperatures and surface melt in February 2022: a compound event with an intense atmospheric river. *npj Climate and Atmospheric Science*, 6 (202). doi:10.1038/s41612-023-00529-6.

Seehaus, T., Shahateet, K., & **Dethinne, T.** (2025). Three decades of ice discharge and mass balance assessment throughout the Antarctic Peninsula (>70° S). *Journal of Glaciology*. [In Review]

Dethinne, T., Ghilain, N., Kittel, C., Lecart, B., Fettweis, X., & Jonard, F. (2025). Assessing Regional Climate Model Sensitivity to Vegetation Dynamics Informed by Remote Sensing. *EGUsphere*, 1-43. doi:10.5194/egusphere-2025-3907. [In Review]

Sacré, I., **Dethinne, T.**, Pohl, B., Bonnardot, V., Quénol, H., & Doutreloup, S. (2026). Seventy years of change: How climate change is redefining viticulture in Belgium. *ONEO one*. [In Review]

Dethinne, T., Ghilain, N., François, L., Lecart, B., Fettweis, X., & Jonard, F. (2026). RAVEL 1.0: A Regional Atmosphere-Vegetation Model Based on the Coupling of the Regional Climate Model MAR and the Dynamic Vegetation Model CARAIB. *Geoscientific Model Development*. [In Preparation]

National and International Conferences

Dethinne, T., Kittel, C., Glaude, Q., Orban, A., & Fettweis, X. (26 May 2022). Interest of the Assimilation of Surface Melt Extent Derived From Passive and Active Microwave Satellites Into the Regional Climate Model MAR Over the Antarctic Peninsula [Oral presentation]. EGU General Assembly 2022, Vienne, Austria. doi:10.5194/egusphere-egu22-5913.

Dutrievoz, N., Gorodetskaya, I., Durán-Alarcón, C., Leroy-Dos Santos, C., ..., **Dethinne, T.**, & Kittel, C. (12 October 2022). Summer atmospheric rivers during February 2022 at the Antarctic Peninsula: large-scale circulation, moisture sources and precipitation [Oral presentation]. International Atmospheric River Conference 2022, Santiago, Chile.

Seehaus, T., Sommer, C., Malz, P., **Dethinne, T.**, Navarro, F., & Shahateet, K. (24 May 2023). Mass balance of the northern Antarctic Peninsula Ice Sheet [Oral presentation]. EGU2023, Vienne, Austria. doi:10.5194/egusphere-egu23-11256

Seehaus, T., Sommer, C., Malz, P., **Dethinne, T.**, & Shahateet, K. (July 2023). Glacier changes throughout the northern Antarctic Peninsula Ice Sheet [Oral presentation]. General Assembly of the International Union of Geodesy and Geophysics (IUGG), Berlin, Germany. doi:10.57757/IUGG23-0561

Ghilain, N., **Dethinne, T.**, Van Schaeybroeck, B., Fettweis, X., Hamid, R., ..., & Termonia, P. (19 February 2024). Towards a mini-ensemble of Regional Earth System Models for climate services over Belgium [Poster presentation]. Belgian Science for Climate Action Conference, Brussels, Belgium.

Dethinne, T., Ghilain, N., Fettweis, X., & Jonard, F. (15 March 2024). Predicting the response of forest ecosystems to climate extremes using MODIS data in the Regional Climate Model MAR during the 2018 drought in Belgium [Poster presentation]. Belgian Geographers Days, Namur, Belgium.

Gorodetskaya, I., Durán-Alarcón, C., Zou, X., Rowe, P., Park, S.-J., Favier, V., **Dethinne, T.**, ..., & Ralph, F. M. (24 June 2024). Precipitation and melt over the Antarctic Peninsula: the role of intense atmospheric rivers [Oral presentation]. International Atmospheric Rivers Conference 2024, La Jolla, United States - California.

Ghilain, N., Grailet, J.-F., **Dethinne, T.**, Strebelle, J., Moutier, W., ..., & van Schaeybroek, B. (28 January 2025). CM-SAF datasets uses for verification of Belgian Regional Climate Models: case studies [Poster presentation]. EUMETSAT Climate Monitoring SAF User workshop, Bonn, Germany.

Dethinne, T., Ghilain, N., Lecart, B., Fettweis, X., & Jonard, F. (28 March 2025). Sensitivity of the Regional Climate Model MAR to Vegetation Dynamics in Forested Areas [Poster presentation]. EGU General Assembly 2025, Vienne, Austria. doi:10.5194/egusphere-egu25-11286.

Ghilain, N., Francois, L., Lecart, B., **Dethinne, T.**, Jonard, F., & Fettweis, X. (4 May 2026). Modeling fire occurrence and tree mortality in Belgium for the 21st century using downscaled CMIP6 climate simulations [Poster presentation]. EGU General Assembly 2026, Vienna, Austria. doi:10.5194/egusphere-egu26-19149.

Timmermans, G., Brice, N., Kittel, C., **Thomas, D.**, Nicolas, G., ..., & Xavier, F. (6 May 2026). Evaluation of MARv3.14 over Greenland and the Impact of Model Resolution [Oral presentation]. EGU General Assembly 2026, Vienna, Austria, doi:10.5194/egusphere-egu26-11626.