The University of Liege
Faculty of Sciences
Department of Environmental Science and Management

Population vulnerability to drought and other extreme weather events in the context of climate change – a case study in the Central Highlands of Vietnam

Nguyen Thi Thanh Thao

Thesis presented with a view to obtaining
of the degree of Doctor of Science
July 2022

Members of the jury :

President :	Dr Célia Justo, ULiège, FS
Promotor:	Prof. Bernard Tychon, ULiège
Co-promotor:	Prof. Dao Nguyen Khoi, Vietnam National Univ
Lecteurs :	Prof. Le Hung Anh, Univ. of Industry, HCM
	Prof. Luong Van Viet, Univ. of Industry, HCM
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With the support of

To my mother Nguyen Thi Dieu;
To my father Nguyen Quoc Trang;
To my siblings Nguyen Thi Mai Huong;
Nguyen Tien Trinh;
Nguyen Thi Bich Hanh;
To my twin sister Nguyen Thi Thanh Hieu;
And to you;

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Abstract

Drought is a natural phenomenon caused by a lack of precipitation over a long period in a specific area. It happens throughout the world, affecting large areas and causing significant human and economic losses. Recently, climate change has become more visible worldwide. In Vietnam, a visible consequence of climate change is an increase in frequency and severity of drought. Recently, severe drought occured in the Central Highlands of Vietnam due to the continuing El Niño-Southern Oscillation (ENSO) phenomena, causing varying degrees of damage to agriculture and residents' livelihoods in 2014, 2015, and 2016.

The Central Highland of VietNam is an important agricultural area of Vietnam. It holds the Srepok River basin that plays a significant role in the Central Highland and where this study was located. This study examines regional socio-natural climate vulnerability and adaptive response capacities of local people to drought in the Srepok River basin region of Central Highland. As a mean of population vulnerability reduction, a monitoring system for the forecast of primary agriculture products such as coffee crops is proposed.

The findings of this study indicated that water (sensitivity) and livelihood strategies (adaptive capacity) are two major causes of high vulnerability to drought for all districts and surveyed communities. The study also found that there is a significant difference in climate change perceptions and observations of climate change-related extreme events, depending on different socio-economic and demographic household characteristics: in particular, education, preferred media sources and income sources have significant effects on local people’s perceptions regarding drought. Besides, this study is the first to develop and assess a coffee yield forecasting method at the regional scale for Dak Lak province, in the Central Highlands of Vietnam, by using the Crop Growth Monitoring System Statistical Tool (CGMSstatTool – CST) software and vegetation biophysical variables (NDVI, LAI, and FAPAR) derived from satellite remote sensing (SPOT-VEGETATION and PROBA-V).

These results might help assess the needs in terms of actions and designing site-specific intervention strategies to reduce the vulnerability of agriculture smallholders to climate change.

Keywords: livelihood vulnerability, drought, perception, drought trends, coffee yields, prediction model, LAI, FAPAR, NDVI, phenological metrics, CGMStatTool, Spirits sofware tool, Central Highland of Vietnam.

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Abbreviations and Symbols

AC	Adaptive capacity
Adj.R^2	Adjusted coefficient of determination
adn	Largest decrease between subsequent periods
Aup	Largest increase between subsequent periods
BMT	Buon Ma Thuot
C(d)	Estimated for each day of each year.
CDD	Consecutive dry days
CGLS	Copernicus Global Land Service
CGMS	Crop Growth Monitoring System
CRED	Centre for Research on the Epidemiology of Disassters
CST	CGMSstatTool - the Crop Growth Monitoring System Statistical Tool
CV	Coefficient of variation
CWD	Consecutive wet days
D	Drought
ddn	Relative date of (last) Largest decrease
dmn	Relative date of (first) Minimum value
dmx	Relative date of (last) Maximum value
dup	Relative date of (first) Largest increase
E	Exposure
ENSO	The El Niño-Southern Oscillation
EU	European Union
F	Food
FAPAR	Fraction of Absorbed Photosynthetically Active
H	Health
JRC	Joint Research Centre
LAI	Leaf Area Index
LMB	Lower Mekong Basin
LMCS	Land Monitoring Core Service
LOO	Leave one out
LS	Livelihood strategy
LVI	Livelihood vulnerability index
MAPE	Mean absolute percentage error

MARD	Ministry of Agriculture and Rural Development
MARS	Monitoring Agriculture with Remote Sensing
MODIS	Moderate-Resolution Imaging Spectroradiometer
NAFOSTED	Vietnam National Foundation for Science and Technology Development
NDVI	Normalized difference vegetation index
R(n)	The daily precipitation
R20mm	Number of heavy precipitation days
R25mm	Number of very heavy precipitation days
R95p	Very wet days
RMSEp	Root mean square error of prediction
rrg	Relative range (Maximum – Minimum)
RRMSE	Relative root mean square error
RSD	The Residual Standard Deviation
rsd	Relative Standard deviation (with N as denominator, not N-1)
RX1day	Max 1-day precipitation amount
RX5day	Max 5-day precipitation amount
$\bar{R}$	The climatological annual daily average.
S	Sensitivity
SDII	Simple daily intensity index
SDP	Sociodemographic profile
SN	Social networks
SPI	Standardised Precipitation Indices
SPI12	Standardised Precipitation Indices with 12-month timescales
SPI3	Standardised Precipitation Indices with three-month timescales
SPI6	Standardised Precipitation Indices with six-month timescales
SPIRITS	Software for the Processing and Interpretation of Remotely sensed Image Time Series
STD	Standard deviation
vav	Average value (or Mean)
VI-IPCC	Vulnerability Index-Intergovernmental Panel on Climate Change
vmn	Minimum value
vmx	Maximum value

VND	Vietnamese dong
VNDMA	Vietnam Disaster Management Authority
W	Water
WBI	Wallonie-Bruxelles International

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Chapter 1. Introduction

1.1. Research framework

1.1.1. General context.

Recently, there has been an increasing frequency of extreme weather and climate events. These extreme events favour the natural disasters, especially those related to floods and severe droughts (Cunha et al., 2019). According to the Centre for Research on the Epidemiology of Disasters (CRED) (Wallemacq, 2019), in 1998-2017, extreme weather events and geophysical disasters killed 1.3 million people. In addition, they impacted a further 4.4 billion people, while the majority (91%) of all the cause was floods, storms, drought and other extreme weather events.

Drought is a silent and pervasive hazard, which originates from the deficit of water availability, with devastating impacts on agriculture, water supply and the environment (Dow, 2010; Popova et al., 2014; Yu et al., 2014), causing economic losses and damages to the ecosystem (Dahal et al., 2016; Wilhite, 2000; Wilhite et al., 2007). Droughts happen virtually at all climatic zones and high and low precipitation areas and are a frequent phenomenon that negatively impact natural habitats, ecosystems, society and the economy (Tfwala et al., 2020). In addition, drought has marked impacts on vegetation, air, soil, wildlife; its conditions enhance forest fires risk and land degradation processes and may cause forest mortality, reduce primary production and change biodiversity (Barbosa et al., 2020; Vicente-Serrano et al., 2020).

Droughts have been increasingly common in recent years as rainfall intensity has increased and the number of wet days has decreased. Drought tends to increase in severity and frequency, and the trend is more significant for longer drought time scales. Recent studies show that agricultural production has declined significantly in many parts of the world, including Asia, due to drought's increased frequency and severity (Bakker and Downing, 2000; Dahal et al., 2016). For example, the severe Australian drought in 2006 reduced the national winter cereal crop by 36%, leaving many farmers in a financial crisis (Wong et al., 2010). In the Kingdom of Eswatini, the drought in 2015-2016 occurred, and there were severe adverse effects, causing a 30% reduction in incomes, especially in the agricultural sector (Tfwala et al., 2020). Recently, most regions in Brazil faced the most extreme droughts of the last 60 years (Bevacqua et al., 2021; Cunha et al., 2019). In 2014, a severe drought affected the water supply of 28 million people in southeastern Brazil (Bevacqua et al., 2021; Melo et al., 2016). From 1980 to 2019, the U.S. has sustained 26 drought events, losing the nation cost at least $249 billion, with an average cost of more than $9.6 billion for each event (NOAA, 2020). According to estimates in a new analysis led by UC Merced researchers, the 2021's drought directly affected the California agriculture sector, losing about $1.1 billion and nearly 8750 full – and part-time jobs. (Lorena Anderson, 2022; Medellín-Azuara et al., 2022)

In Thailand, Cambodia, Laos and Vietnam, drought events have severe influences on the socio-economic state of these countries and affect about 85% to 90% of the livelihoods of poor communities and people living in rural areas in the Lower Mekong Basin (LMB) region (MRC, 2019). The LMB, including Thailand, Cambodia, Laos, and Vietnam, has been experiencing extreme drought events in 1992, 1999, 2003, and 2015-2016. They led to massive economic losses due to crops damages, adverse effects on the environment and people's livelihoods (MRC, 2019). The recent extreme drought in 2016 caused 1.7 billion USD damages in Thailand and caused water shortages in 18 out of 25 provinces affecting 2.5 million people in Cambodia. Total 2016 drought costs were assessed at 669 million USD, and costs to recover damages approximately amounted to 1.5 billion USD in Vietnam (MRC, 2019).

El Nino weather events have become more frequent in the last 50 years, causing more typhoons, floods and droughts (Oxfam, 2008). There has been more droughts in the south of Vietnam in recent years, which have tended to last longer. Hoc (2002) reveals a series of drought events in the Central Highlands of Vietnam from 1994 to 1998 that affected winter-spring crops.

In 2016, the El Nino weather event has been blamed in Vietnam for the country's worst drought in 90 years, with drought affecting 52 of the country's 63 provinces; 18 provinces have been declared states of emergency (FAO, 2016a). Droughts would increase in some areas due to rising temperatures and/or rainfall shortfalls during the dry season (e.g. spring and summer in the Southern Central, spring in the South and winter in the North) (Tran et al., 2016).

1.1.2. Drought definitions

The precise drought definition depends on several aspects, such as the main influences on the hydrological, economic, environmental or social factors analysed and the related processes and impacts (Barbosa et al., 2020). Drought is caused by lack of precipitation, high temperature, overuse, and overpopulation. Droughts are to be discriminated from aridity, a stable climatic characteristic, and from water shortage, a situation where the climatologically available water resources are inadequate to satisfy long-term average water demands (Barbosa et al., 2020). Drought includes four main classifications: those are meteorological, hydrological, agricultural, and socioeconomic (Thao et al., 2019; Wilhite, 2000; Wilhite and Glantz, 1985)

- Meteorological drought is a period with an unusual precipitation insufficiency concerning the long-term average conditions for a region (Barbosa et al., 2020). Over time, the meteorological drought leads to other drought categories, such as agricultural, hydrological or socioeconomic droughts.
- Agricultural drought is a consequence of the characteristics of meteorological drought impact on agriculture, precipitation scarcities, differences between actual and potential evapotranspiration, and soil moisture shortage cause of limited water availability for irrigation on agriculture (natural vegetation and crops) (Aksoy et al., 2018).
- Hydrological drought is associated with the impacts of periods of precipitation deficits on the surface or sub-surface water supply such that streamflow, reservoir and lake levels, and groundwater table decline (Barbosa et al., 2020).
- A socioeconomic drought links the supply and requirement of some economic goods or services (e.g., fruits, vegetables, grains, meat, and hydroelectric power) with meteorological, hydrological, and agricultural drought (Wilhite, 2000). Socioeconomic drought happens when economic goods demand can not be satisfied due to a weather-related shortage in water availability.

Besides four classical definitions of drought, Crausbay et al. (2017) proposed a new type of drought – ecological drought – combining the ecological, climatic, hydrological, socioeconomic and cultural dimensions of drought. They define ecological drought "as an episodic deficit in water availability that drives ecosystems beyond thresholds of vulnerability, impacts ecosystem services, and triggers feedbacks in natural and/or human systems" (Crausbay et al., 2017). The environment indicates the many interactions between microbial fauna, wildlife, plants, soil features, atmosphere, water and human effects. Many of the consequences of drought on various ecosystems may be traced back to these human factors such as human activities that can have a significant impact on desertification; given that human management of these systems profoundly changes natural systems, they can also affect water and air quality and other processes such as forest mortality (Vicente-Serrano et al., 2020). Therefore, Vicente-Serrano et al. (2020) prefer to use "environmental" instead of "ecological" drought because they show it better represents the coupled nature of human-environment interactions, including the human use (and misuse) of the environment that is key to this type of drought.

1.1.3. Drought history in Vietnam

In Vietnam, several drought events have occurred in the past, as shown in Table 1.1. This table reveals that drought occurred in the whole country from 1952 until 2020. Recently, El Nino weather events have become more frequent causing more typhoons, floods and droughts (Oxfam, 2008; Van Viet, 2021). There has been more droughts in the south of Vietnam in recent years, which have tended to last longer. In 1976, drought affected 370000 hectares of crops in the northern and north-central regions. The drought destroyed 80,000 hectares of crops in six provinces of the Mekong River Delta in 1982.

Similarly, in 1983, central and southern Vietnam lost 291000 hectares of cereals. In the winter-spring of 1992-1993, paddy production was decreased by 559000 tons in the Mekong River Delta. Moreover, the central region of Vietnam has been experiencing severe drought in 1993 (Nguyen and Shaw, 2011). This drought spread throughout the whole country. It caused losses suffered from approximately 175000 hectares, of which 35000 hectares were completely damaged, with 150000 tons of crops fully lost.

Hoc (2002) reveals a series of drought events in the Central Highlands of Vietnam from 1994 to 1998 that affected winter-spring crops. According to the Ministry of Agriculture and Rural Development (MARD, 1998), Vietnam was affected by a prolonged and widespread drought with two periods of drought from late 1997 to 1998 (OCHA, 1998), which led to enormous consequences for the agricultural production in VietNam; the first period from late 1997 to May 1998, affected more than 600000 households or three million people. About 380000 tonnes of paddy equivalent, 11400 hectares were destroyed by forest fires due to drought, and 19360 ha of water areas used for aquatic production dried up. 274000 households suffered from food scarcity. Total economic losses in the first period were estimated at VND 5290 billion (USD 407 million), excluding possible losses for future harvests due to a fall in production of some crops. From June to August 98, the second period had massive effects on agricultural production in Vietnam's Central and Central Highlands, affecting around 66000 hectares of winter-spring rice, with 50000 ha destroyed. Moreover, over 74500 hectares of rice were affected for summer-autumn crops, in which 41400 hectares were destroyed; 230000 residents did not have access to fresh water. In spring-winter crop 1998-1999, about 361000 hectares were affected by water shortage in Mountainous areas in the North, Red River Delta, North-Centre, Mekong River (OCHA, 1999).

Severe droughts had impacted all provinces in the Mekong Delta, Southern Central, and Central Highland regions since the end of 2015. Reporting period October 2015 - Mar 2016, there were ten provinces in a state of drought emergencies, 976000 people did not have access to water for consumption and domestic use, 159000 hectares of paddy were damaged (Viet Hien, 2016). In Vietnam, the worst drought in 2016 has broken 90 years historical record for country water deficit, with 52 out of 63 provinces (83%) affected by drought; states emergency in 18 provinces were declared, as of June 2016 (FAO, 2016a). During the peak of the drought (February-May 2016), there were 2 million people lacking water for daily consumption, 1.1 million were food uncertain, 1.75 million people lost revenues due to damaged or lost livelihoods because of drought and saltwater intrusion (Conille, 2018).

The onset of the rainy season in 2019 in the Mekong was late compared to recent years, and its cessation ended early. As a result, the total annual flow of the Mekong river was lower than its annual average, even lower than the period 2015 to 2016 when the record drought and saline intrusion occurred. It is the main reason for the early, deep, and prolonged drought and saline intrusion, affecting residents and production in the Mekong Delta (IFRC, 2020). According to the Vietnam Disaster Management Authority (VNDMA), 10 out of 13 provinces with 74 out of 137 districts in the Mekong River Delta are affected by drought and saltwater intrusion. More than 685000 people in the Mekong Delta were affected. Furthermore, the drought and saltwater intrusion influenced Agricultural production, led to losses of about 460000 hectares. In addition, the drought and saltwater intrusion limited access to safe water for 200000 households, who do not have usual and adequate access to water for consumption and other domestic use (IFRC, 2020).

Table 1.1. Drought Events in Vietnam from 1952-2020

Regions	**Years of Drought**			
	Summer	**Summer-Autumn**	**Spring-Summer**	**Winter-Spring**
Mountainous areas in the North	1988, 1990, 1991, 1993, 1998.			1988, 1990, 1991, 1993, 1994, 1996, 1998, 1998, 1999, 2009, 2014, 2015.
Red River Delta	1987, 1990, 1998.			1960, 1961, 1962, 1963, 1964, 1986, 1987, 1988, 1991, 1998, 1999, 2004, 2005, 2007, 2008.
North Central Regions	1982, 1983, 1988, 1992, 1993, 1995, 1996, 1998.	1992, 1993, 1994, 1998, 2004.	1995, 1996	1991, 1992, 1993, 1994, 1998, 1999, 2009, 2014, 201.5
South Central Regions	1983, 1993, 1994, 1997, 1998, 2000, 2004, 2005, 2014, 2015.	1952, 1969, 1970, 1971, 1977, 1978, 1982, 1984, 1985, 1993, 1998, 2000, 2001, 2002, 2004, 2005.		1977-1978, 1983, 1984, 1993, 1998, 2002, 2004, 2005, 2012, 2015, 2016.
Central Highlands	1997, 1998, 2001, 2002, 2004, 2005, 2014, 2015, 2016, 2020.	1983, 1988, 1993, 1995, 1997, 1998		1994, 1995, 1996, 1997, 1998, 1999, 2014, 2015, 2016.
Southeast Regions	1988, 1990, 1992, 1997, 1998.	1988, 1990, 1992, 1998.		1987, 1988, 1990, 1992, 1997, 1998, 2014, 2015.
Mekong River Delta	1981, 1983, 1984, 1985, 1987, 1992, 1994, 1998, 2004.	1981, 1982, 1988, 1992, 1997, 1998, 2019, 2020.		1989, 1992, 1993, 1998, 1999, 2004, 2009, 2010, 2014, 2015, 2016.

Source: *Nguyen (2006), Hoc (2002), Nguyen and Shaw (2011), OCHA (2016, 1999, 1998). And, International Federation of Red Cross And Red Crescent Societies, primary country: Vietnam (IFRC, 2020).*

1.2. Aims and objectives

Drought is a natural disaster and can not be prevented. However, drought damages can be mitigated by adaptation and mitigation strategies. Drought damages depend on the severity of drought and the interactions between socioeconomic and ecological vulnerability in vulnerable systems (UNDP, 2021). Therefore, a better understanding of livelihood vulnerability to drought is a key to build resilience to droughts and develop adequate management and policy strategies. Besides, it is important to consider current local perception and coping capacities of droughts and climate change to assess their ability to reduce their vulnerability. When local people have a correct perception of risk, good adapting and coping capacities, the droughts' damages can be reduced. On the other hand, if the risk is not well identified by vulnerable population, if their capacity to adapt to this more risky new life environment is not present, few or no action to mitigate or reduce their vulnerability will be adopted what will even more increase their vulnerability.

In the study area, agriculture production is the main source of income which is an essential reduction factor of the population vulnerability. At present, it is not possible to avoid farmers' income fall following the impact of droughts in the Central Highlands region. However, the provision of a crop yield forecasting tool is a first step that can help anticipate years with low production and therefore low income. This type of tool, if it is effective, can enable the Vietnamese authorities to prepare well for these difficult conditions and properly take care of populations in difficulty before humanitarian crises take hold; and thus it can reduce the population vulnerability during these difficult episodes linked to agricultural droughts.

Therefore, the objective of this dissertation is to better understand population vulnerability to drought and other extreme weather events in the Central Highlands of Vietnam in the context of climate change.

The purpose of the study was reached by undertaking the following tasks:

- Assessing livelihood vulnerability to drought for selected areas using standard international vulnerability indices.

- Understanding local people's perceptions of drought and investigating the differences between their perceptions and meteorological recorded data in the selected areas.
- Performing regional coffee yield forecasting using remote sensing data and statistical yield forecast models.

1.3. The dissertation outline

The thesis is a set of scientific papers, one accepted and two submitted.

Chapter 1 describes the background of the study and the study objectives. It also provides a general description of the research undertaken in the thesis.

Chapter 2 studies livelihood vulnerability to drought in the study area. This chapter presented here has been published in the *International Journal of Disaster Risk Science*. In this chapter, the Livelihood vulnerability index (LVI) and Vulnerability Index-Intergovernmental Panel on Climate Change (VI-IPCC) were used to evaluate the livelihood vulnerability of households to drought in the study area. Chapter 2 is based on the structure of the paper I.

- **Paper I:** Nguyen Thi Thanh Thao, Dao Nguyen Khoi, Tran Thanh Xuan, Bernard Tychon: Assessment of livelihood vulnerability to drought in the Lower Mekong River Basin: a case sudy in Dak Nong province, Viet Nam. *International Journal of Disaster Risk Science*, accepted in 2019.

After understanding aspects of livelihood vulnerability to drought in the study area, in the following steps, this study will find out about the awareness of locals related to drought because the perceptions of drought are one of the aspects that influence the effective reduction of drought damages. Therefore, chapter 3 analysed local people's perceptions of climate change and related drought. Besides, this study investigates the differences between local people's perceptions and meteorological recorded data in this area. This chapter also analysed meteorological data to assess monthly precipitation and temperature distribution, extreme precipitation events, and precipitation and temperature trends. Finally, this chapter also reveals preliminary analysis results on the assessment of drought using the non-parametric Mann-Kendall trend test and Standardised Precipitation Indices to assess drought in the study area. Chapter 3 is based on the structure of the paper II.

- **Paper II:** Nguyen Thi Thanh Thao, Dao Nguyen Khoi, Luong Van Viet, Joost Wellens, Marie Lang, Bernard Tychon: Comparing local people’s perceptions of climate change and drought using scientific observations in the Lower Mekong Basin: a case study in Dak Lak province, Vietnam. The paper is submitted in Environment, Development and sustainability (ENVI) Journal.

One of the methods to reduce drought impacts on agricultural population is to provide to decision makers a tool (model) to predict crop yields and production, in order to anticipate population livelihood reduction and prepare adapted support. The main crop of the study area is coffee. Therefore, chapter 4 presents an early regional prediction of coffee yield using a statistical approach and satellite remote sensing vegetation biophysical variables (NDVI, LAI, and FAPAR). Chapter 4 is based on the structure of the paper III.

- **Paper III:** Nguyen Thi Thanh Thao, Dao Nguyen Khoi, Antoine Dennis, Luong Van Viet, Joost Wellens, Bernard Tychon: Early Prediction of Coffee Yield in the Central Highlands of Vietnam Using a Statistical Approach and Satellite Remote Sensing Vegetation Biophysical Variables. Remote Sens. 2022, 14(13), 2975; https://doi.org/10.3390/rs14132975. Published: 22 June 2022

Finally, Chapter 5 presents a summary and the conclusions of the study. Recommendations for future work are also presented.

Chapter 1 Introduction

Background of the study and objectives

Chapter 2 Assessment of livelihood vulnerability to drought in the studies area

Calculating the livelihood vulnerability index (LVI)

Calcuating the livelihood vulnerability index – IPCC (LVI-IPCC)

Assessment the vulnerbility of study areas.

Chapter 3 Comparing local people's perception of climate change and drought with scientific observations in the study area.

Analyze local people's perceptions on climate change and related drought

Meteorological data analysis (eight precipitation extremes: RX1day, RX5day, R95p, SDII, R20mm, R25mm, CDD, CWD)

Trend analysis of annual, monthly and seasonal rainfall, temprature,

Identify the onset and cessation of the rainy season.

Trend of the onset and cessation of the rainy season.

Analyze SPI

Investigate the differences between the perceptions of local people and meteorological recorded data in this area

Chapter 4. Early prediction of coffee yield in the Central Highlands of Vietnam using statistical approach and satellite remote sensing vegetation biophysical variables

Model performance

Coffee yield prediction for 2020

Chapter 5 General conlusion and outlook

General conclusion

Outlook

Figure 1.1. Outline of the thesis

Chapter 2. Assessment of livelihood vulnerability to drought in the Central Highlands of Vietnam.

This chapter was adapted from the following publication:

Nguyen Thi Thanh Thao, Dao Nguyen Khoi, Tran Thanh Xuan, Bernard Tychon: Assessment of livelihood vulnerability to drought in the Lower Mekong River Basin: a case sudy in Dak Nong province, Viet Nam. International Journal of Disaster Risk Science, Published in 2019. DOI: 10.1007/s13753-019-00230-4

Abstract

In recent years, droughts have strongly affected the Central Highlands of Vietnam and have resulted in crop damage, yield decline, and serious water shortage. This study investigated the livelihood vulnerability of five communities of farmers who are exposed to droughts in one of the more vulnerable regions of Vietnam—Dak Nong Province. A survey of 250 households was conducted in the five communities to collect data on the region's sociodemographic profile, livelihood systems, social networks, health status, food and water security, drought conditions, and climate variability. Data were aggregated using a livelihood vulnerability index and the IPCC vulnerability index. The survey results indicate that Quang Phu community is the most vulnerable of the study's communities, followed by Nam N'dir, Dak Nang, Duc Xuyen, and Dak D'ro in descending order of vulnerability. Water availability and livelihood strategies are the most important variables in determining the vulnerability of the five surveyed communities. In order to reduce vulnerability to droughts, water management practices and livelihood diversification in farming and nonfarming activities are recommended for the study area.

Keywords: Agricultural drought, Livelihood vulnerability, Vietnam, Vulnerability indicators.

2.1. Introduction

Drought is a recurrent natural disaster that has negative impacts on water resources and socio-economy. Drought results from a considerable hydrological deficit due to climatic factors (e.g. decreases in rainfall) (Mohmmed et al., 2018) or human factors (e.g. land-use change) (Keesstra, 2007). Basically, drought is categorized in four major types, such as meteorological, hydrological, agricultural, and socio-economic droughts, depending on its impacts (Thilakarathne and Sridhar, 2017). Recently, drought frequency and severity have significantly increased due to climate change (IPCC, 2013a). This generates large challenges of socio-economic development for developing countries, especially in agricultural sector. Panthi et al. (2016) indicated that people whose livelihood replies mostly on agricultural activities are particularly vulnerable in the developing countries. Therefore, studies on vulnerability assessment for impacts of climate change and natural disasters are necessary to improve knowledge of people's vulnerability and to help decision-makers in implementing and planning climate change adaptation and disaster risk reduction. According to IPCC (2001), vulnerability is defined as the extent to which geophysical, biological, and societal aspects are disposed to, or at risk of, and are unable to deal with the adverse effect of climate change and variability. Vulnerability assessment depicts a varied set of approaches used to systematically integrate and consider interactions between humans and their environmental surroundings, including physical and social aspects (M.B. Hahn et al., 2009).

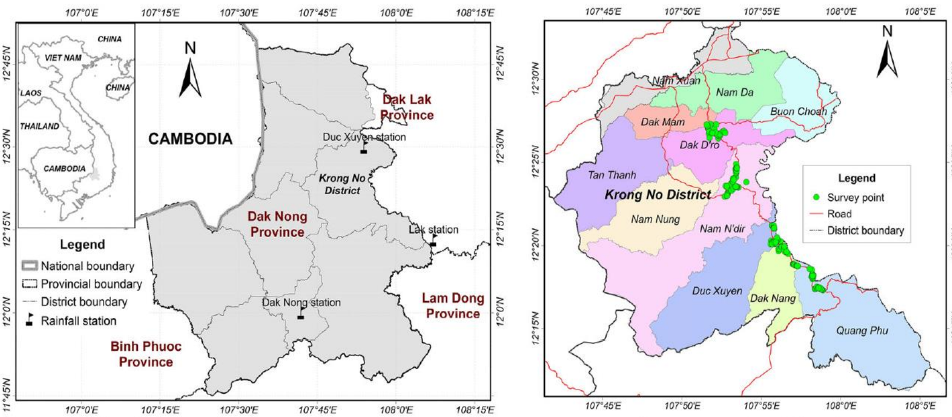
In recent years, studies on vulnerability assessment in the context of climate change natural disasters have been gained more attentions from scientists. A number of approaches of the vulnerability assessment include historical narrative, comparative analysis, statistical analysis, indicator-based method, and agent-base modeling. Among these methods, the indicator-based method is widely used for assessing vulnerability to climate change and natural disasters (Mohmmed et al., 2018; Pandey and Jha, 2012; Salik et al., 2015). In the past decade, Livelihood Vulnerability Index (LVI) has been a useful and popular tool in assessing farmers' vulnerability to climate change and natural disasters around the world (e.g. Addisu Legese et al. 2016; Panthi et al. 2016; Adu et al. 2018; Oo et al. 2018; Williams et al. 2018). Computed and improved by Hahn et al. (2009) based on Intergovernmental Panel on Climate Change (IPCC)'s definition of vulnerability, the LVI approach consists of various variables apprehending the level of smallholder farmers' exposure, sensitivity and adaptive capacity to natural disasters (e.g. drought and flood) and climate change. LVI provides measures to observe likely vulnerability over time and space and to identify the processes that contribute to vulnerability, prioritize strategies for its reduction, and assessing the efficiency of these strategies in different social and ecological environments (Shah et al., 2013). Furthermore, Panthi et al. (2016) indicated that impact of climate change and natural disasters vary from area to area and vulnerability assessment is imperative to be investigated in a regional scale.

Vietnam, a tropical and developing country in Southeast Asia, is identified one of the most vulnerable hotspots affected by climate change and natural disasters (drought and flood) (IMHEN and UNDP, 2015; IPCC, 2013b). In the past two decades, Vietnam suffered approximately 216 natural disasters which caused a loss of approximately 0.55% of Gross Domestic Product (GDP) per year (Eckstein et al., 2017). In the years 2015-2016, Vietnam, especially in the Central Highlands, had faced the most severe prolonged drought in the past 90 years, causing severe damage to agricultural production and farmer’s income (UNDP, 2016a). The Central Highland plays an important place in Vietnam’s economy because this region is a biggest producer of coffee beans in Vietnam and Vietnam is the world’s second largest exporter of coffee. However, in a recent study conducted by Sam et al. (2018), they stated that the droughts in the Central Highlands of Vietnam are becoming more and more severe and prolonged in the near future. This will cause serious impacts on agriculture and people's livelihood in this region. Furthermore, poor and farming communities are identified to be a principal object affected by the climate change and natural disaster in the developing countries since they have insufficient adaptive capacity (IPCC, 2007a). However, livelihood vulnerability of farmers to drought is not well reported in Vietnam, especially in the Central Highlands. A lack of knowledge of drought impacts on farmers’ livelihood is an obstacle to determine suitable livelihood strategies in order to increase farmers’ welfare in the context of drought.

The objective of the present study was to assess livelihood vulnerability of farmers to drought in the Krong No District (Dak Nong province) in the Central Highlands of Vietnam. Five communities in the Krong No district, namely Quang Phu, Nam N’dir, Dak Nang, Duc Xuyen, and Dak D’ro, were selected for the investigation because they were the most vulnerable areas affected by the historical drought in the years 2015-2016 (FAO, 2016b). The results of this study are expected to help local governments find drought adaptations to enhance farmers’ adaptive capacity in the study area.

2.2. Study area

The Krong No District is located in the Central Highlands of Vietnam (Fig. 2.1). The district is positioned between latitudes 12°15′–12°30′N and longitudes 107°45′–108°05′E. This district has an average altitude higher than 2,000 m with an area of 813 km^2 and its population was about 70,604 people in 2014 (Dak Nong Statistical Office, 2015). Krong No District experiences a tropical monsoonal climate with distinct dry and wet seasons. Rainfall is highly seasonal, is concentrated in the monsoon season, and lasts from April or May to November. Average annual temperature is around 25 °C. The months of July, August, and September have the largest precipitation, up to 320 mm. In the dry season, average temperature is around 20 °C and average precipitation is about 4–5 mm in January and February. Average annual relative humidity is approximately 76% and the highest value is 89% in August.



(a) Dak Nong Province (grey area) (b) Krong No District

Figure 2.1 Location of the study area

2.3. Methodology

In this study, the LVI and VI-IPCC were used to evaluate the livelihood vulnerability of households to drought in the Krong No District. The two vulnerability indices were selected for this study because they have been widely used in studies on assessing the vulnerability to climate change and disasters (e.g. Addisu Legese et al. 2016; Panthi et al. 2016; Adu et al. 2018; Oo et al. 2018;

Williams et al. 2018). In the following subsections, we provide the detailed methods of LVI and VI-IPCC used in this study.

2.3.1. Livelihood vulnerability index

According to Hahn et al. (2009), the LVI includes seven major components: sociodemographic profile (SDP); livelihood strategies (LS); social networks (SN); health (H); food (F); water (W); and natural hazard-induced disasters and climate variability. In this study, the LVI was calculated based on these seven major components, and each component contained a different number of subcomponents (Table 2.1) based on available data collected through a survey of households affected by the droughts of 2015–2016 in the study area. As subcomponents were evaluated on diverse scales, they were first standardized. Standardization was based on the Human Development Index (HDI)) (UNDP, 2007).

$$Index\ S_c = \frac{S_c - S_{min}}{S_{max} - S_{min}} \quad (1)$$

where S_c is the original value of the subcomponent for community c, S_{min} and S_{max} are minimum and maximum values reflecting low and high vulnerability of this subcomponent.

Table 2.1. Major components and sub-components comprising the Livelihood Vulnerability Index (LVI) developed for 5 communities in Krong No district, Dak Nong province.

Major components	**Subcomponents**	**Unit**	**Explanation of subcomponents relative to LVI**
Socio-demographic profile (**SDP**)	**SDP1 -** Ratio of dependent people.	-	Higher value reflects less capacity to adapt
	SDP2 - Percentage of female-headed households.	%	Higher value reflects less capacity to adapt Women typically have less adaptive capacity
	SDP3 - Percentage of household heads who have not attended school	%	Higher value reflects less capacity to adapt Education makes people more aware and able to adjust to change in environmental conditions
Livelihood strategies (**LS**)	**LS1** - Livelihood diversification Index which was constructed as the inverse of the number of livelihood activities of	-	Higher value reflects more capacity to adapt Income diversification increases adaptive capacity.

	households +1.		
	LS2 - Percentage of households depending only on agriculture as a source of income	%	Higher value reflects less capacity to adapt Households depending only on agriculture are more vulnerable
	LS3 - Agricultural livelihood diversification index, which was constructed as the inverse of the number of crops cultivated by a household + 1	-	Higher value reflects more capacity to adapt Diverse crops reduce the risk of major losses
Food (**F**)	**F1** - Percentage of households depending only on their farming products as a source for food	%	Higher value indicates vulnerable Limited source for food
	F2 (+) - Monthly living expense.	1000VND/month	Higher value indicates less vulnerable
	F3 - Percentage of households struggling for food. Proportion of households reported that they had at least one month struggling for food.	%	Higher value indicates more vulnerable
Social Network (**SN**)	**SN1** - Percentage of households not having access to communication media (TV/radio, telephone).	%	Higher value indicates more vulnerable. Communication media makes people aware of hazard occurrence and having better preparation
	SN2 - Percentage of households not having access to local government service.	%	Higher value indicates more vulnerable. These services strengthen adaptive capacity.
	SN3 - Percentage of households not having access to funds from government or other organizations.	%	Higher value indicates more vulnerable. Funds sources strengthen adaptive capacity.
Health (**H**)	**H1** - Average distance to health facility.	km	Higher value indicates more vulnerable
	H2 - Percentage of households with family member with chronic illness.	%	Higher value indicates more vulnerable. People with chronic illness are more sensitive.

	H3 - Percentage of households not participating in health insurance.	%	Higher value indicates more vulnerable.
Water (**W**)	**W1** - Percentage of households using natural water sources from well or stream.	%	Higher value indicates more vulnerable.
	W2 - Percentage of households not having stable water from a water treatment plant.	%	Higher value indicates more vulnerable. Family with unstable water supply is more sensitive.
	W3 - Storage water volume of households	m^3	Higher value indicates more vulnerable.
Drought (**D**)	**D1** - Frequency of drought (6-month Standardized Precipitation Index (SPI^)	%	Higher value reflects more exposure
	D2 - Mean standard deviation of monthly precipitation	-	Higher variability implies higher exposure.
	D3 –Mean standard deviation of monthly maximum temperature.	-	Higher variability implies higher exposure.

[a]1 USD = 23.25 VND (exchange rate on 2 September 2019); SPI6 = 6-month standardized precipitation index

After standardizing subcomponents, major component index is calculated by the following equation.

$$M_{jc} = \frac{\sum_{i=1}^{n} indexS_c}{n} \quad (2)$$

where n is the number of sub-components in each major components and M_{jc} is value of major component j for community c. The LVI for community was calculated using the following equation:

$$LVI = \frac{\sum_{i=1}^{n} w_{Mi} M_{ic}}{\sum_{i=1}^{n} w_{Mi}} \quad (3)$$

where w_{Mi} is the weight of each major component, which was estimated by the number of subcomponents that make up each major component.

After calculating the major components and LVI, a radar chart was used to compare the vulnerability level of each major component for each community. The livelihood vulnerability index was scaled in the range from 0 (least vulnerable) to 1 (most vulnerable).

2.3.2. IPCC – Vulnerability index (LVI-PCC)

This study used VI-IPCC to assess livelihood vulnerability based on the IPCC approach. VI-IPCC highlights three major components, including exposure, adaptive capacity and sensitivity. Drought will be framed under "exposure", water, food and health sectors under "sensitivity", and socio-demographic profile, livelihood strategy and social network under "adaptive capacity" (Table 2.2).

Table 2.2. Major components are framed under Exposure, Sensitivity and Adaptive capacity contributing factors to vulnerability.

IPCC contributing factors to vulnerability	Major components
Exposure	Natural disaster and climate variability
Adaptive capacity	Socio-demographic profile
	Livelihood strategies
	Social networks
Sensitivity	Health
	Food
	Water

The exposure is measured by using rainfall data from three rain gauges located in the study area. The sensitivity is measured by assessing the current state of the Dak Nong province's food, water security and health status. The adaptive capacity is quantified by using the socio - demographic profile, types of livelihood strategies and existing social networks in the study area. The same sub-components as for the LVI index as well as the equations 1 and 2 were used to calculate the VI-IPCC index.

The VI-IPCC index is calculated as follows

$$\text{VI} - \text{IPCC} = (\text{exposure} - \text{adaptive capacity}) \text{ x sensitivity} \qquad (4)$$

The VI-IPCC index ranges from -1 (least vulnerable) to 1 (most vulnerable). IPCC-defined contributing factor (exposure, adaptive capacity and sensitivity) is calculated as below:

$$CF_c = \frac{\sum_{i=1}^{n} w_{Mi} M_{ci}}{\sum_{i=1}^{n} w_{Mi}} \qquad (5)$$

where CF_c is an IPCC-defined contributing factor (exposure, adaptive capacity and sensitivity) for community c, w_{Mi} is the weight of each major component determining factor, M_{ci} is the major component for community c indexed i, and n is the number of major components in each contributing factor.

After calculating contributing factor (exposure, adaptive capacity and sensitivity) and VI-IPCC, these results are described by using vulnerability triangle diagram to compare 2 or more study areas. Each vertex of triangle shows each contributing factor.

2.3.3. Data collection

This study used data from both primary and secondary sources. Secondary data on monthly precipitation measured at three rain gauges, including the Lak, Duc Xuyen and Dak Nong stations, were collected. The data were collected for the period 1981-2016 and obtained from the Hydro-Meteorological Data Center of Vietnam (HMDC). In order to estimate drought frequency, the Standardized Precipitation Index (SPI) was used based on the monthly precipitation data. The SPI for 6-month time scale was selected for estimate the drought frequency because it is suitable for describing the seasonal meteorological drought (Spinoni et al., 2014). The procedure of SPI calculation could be referred in McKee et al. (1993).

Primary data was gathered from household questionnaire survey. A structured questionnaire was designed in relation to LVI's components and sub-components. The questionnaire contained socio-economic, demographic and livelihood information at community and district levels in the Krong No district. In addition, it contained questions related to drought, climate change perceptions, adaptive solutions and interventions that each stakeholder is able to support and apply to reduce the negative impacts of drought in each community. The sample size was calculated at a 95% confidence level, precision of ± 10% at an assumed coverage of 50% based on the probability proportional to size method. A household survey was carried out with 250 households who were selected at random in five communities of the Krong No district in the last April 2016, and approximately 50 households in each community, namely Quang Phu, Nam N'dir, Dak Nang, Duc Xuyen, Dak D'ro, respectively. Households were randomly selected from the household lists of all communities. The survey was carried out by six interviewers who were trained. Household heads or other experienced members of the selected households were considered for the survey. Each interview lasted approximately 30 minutes and was conducted in Vietnamese language. Data were inputted, checked and analyzed using MS Excel version 16.0. Major surveys objective was to collect information on indicators mentioned in Table 2.1.

2.4. Results and discussion

The collected information of the survey questionnaires is summarized in Table 2.3, which includes the result of indices in five communes, maximum and minimum values. Table 2.4 shows the result of LVI of the five communities and Krong No district after standardizing and aggregating into seven main components, including Socio-demographic profile (SDP), Livelihood strategies (LS), Food (F), Water (W), Health (H), Social networks (SN) and Drought (D). Table 3 is the result of VI – IPCC for the Krong No district, after aggregating the seven main components into three contributing factors, namely Adaptive capacity (Socio-demographic profile, Livelihood strategies, Social networks), Sensitivity (Health, Food, Water) and Exposure (Drought).

Table 2.3. The result of values of LVI subcomponents for the five communities in the Krong No District in Dak Nong Province, Vietnam

Indices	**Unit**	**Quang Phu**	**Dak D'ro**	**Dak Nang**	**Nam N'dir**	**Duc Xuyen**	**max**	**min**
SDP1	-	0.32	0.21	0.26	0.36	0.29	1	0
SDP2	%	13.95	2.44	4.88	21.43	7.55	100	0
SDP3	%	28.57	10.26	0.00	16.67	2.70	100	0
LS1	-	0.47	0.39	0.43	0.41	0.42	0.50	0.25
LS2	%	88.37	80.49	87.80	78.57	73.58	100	0
LS3	-	0.32	0.30	0.32	0.32	0.31	0.500	0.143
F1	%	30.23	34.15	29.27	33.93	16.98	100	0
F2(+)	1000d/ month	1431.63	1821.46	1790.49	1464.46	2288.87	6000	0
F3	%	30.23	36.59	14.63	32.14	32.08	100	0
W1	%	100.00	56.10	100.00	98.21	37.74	100	0
W2	%	76.74	51.22	75.61	73.21	64.15	100	0
W3(+)	m^3	2.01	1.33	1.03	1.99	0.87	10	0
H1	m	1582.50	1398.78	1235.90	1607.27	1416.98	5000	10
H2	%	65.12	43.90	36.59	46.43	50.94	100	0
H3	%	37.21	4.88	29.27	35.71	20.75	100	0
SN1	%	6.98	4.88	7.32	10.71	1.89	100	0
SN2	%	65.12	48.78	56.10	80.36	71.70	100	0
SN3	%	53.49	26.83	14.63	46.43	33.96	100	0

D1	%	16.06	16.37	16.58	16.57	16.86	100	0
D2	mm	88.25	81.64	73.16	72.38	71.06	168.90	5.68
D3	Celsius	2.03	2.03	2.03	2.03	2.03	2.29	1.75

SDP = Sociodemographic profile; LS = Livelihood strategy; F = Food; W = Water; H = Health; SN = Social networks; D = Drought

Table 2.4. LVI components calculation for five communes in Krong No district

	Quang Phu	Dak D’ro	Dak Nang	Nam N’dir	Duc Xuyen	Krong No district
SDP	0.248	0.113	0.103	0.246	0.130	0.168
LS	0.748	0.603	0.692	0.637	0.624	0.661
F	0.455	0.468	0.380	0.472	0.370	0.429
W	0.855	0.647	0.884	0.839	0.644	0.774
H	0.446	0.255	0.301	0.381	0.333	0.343
SN	0.419	0.268	0.260	0.458	0.358	0.353
D	0.399	0.387	0.370	0.369	0.367	0.378
LVI	**0.510**	**0.392**	**0.427**	**0.486**	**0.404**	**0.444**

SDP = Sociodemographic profile; LS = Livelihood strategy; F = Food; W = Water; H = Health; SN = Social networks; D = Drought; LVI = Livelihood vulnerability index

Table 2.5. VI-IPCC contributing factors calculation for five communities and Krong No district in Dak Nong Province, Vietnam

	Quang Phu	Dak D’ro	Dak Nang	Nam N’dir	Duc Xuyen	Krong No district
Adaptive capacity (AC)	0.496	0.631	0.607	0.505	0.586	0.565
Sensitivity (S)	0.586	0.457	0.522	0.564	0.449	0.515
Exposure (E)	0.399	0.387	0.370	0.369	0.367	0.378
VI-IPCC	**-0.057**	**-0.112**	**-0.124**	**-0.077**	**-0.099**	**-0.096**

The VI-IPCC (Vulnerability Index—Intergovernmental Panel on Climate Change) is scaled and ranges from − 1 (least vulnerable) to + 1 (most vulnerable)

The results indicate that the vulnerability of the Krong No District (average of five communities) estimated by the LVI and VI-IPCC indices is moderate based on the vulnerability scales of 0 to 1 for LVI and − 1 to 1 for VI-IPCC. Specifically, the values of LVI and VI-IPCC are 0.444 and − 0.096. Considering the vulnerability of the five communities, the LVI and VI-IPCC values indicated that households of the Quang Phu community are the most vulnerable, followed by Nam N'dir, Dak Nang, Duc Xuyen, and Dak D'ro communities (Tables 2.3, 2.4).

2.4.1. Drought in the Krong No district

Using the Thiessen polygon method to analyze the station rainfall and drought spatial correlation, the two rain gauges whose rainfall is closely correlated with droughts in the study region are the Duc Xuyen and Lak stations. The Duc Xuyen station rainfall in particular is correlated with droughts in the whole Dak D'ro community, most of Nam N'dir and Duc Xuyen communities, and a part of Dak Nang community. The Lak station rainfall has a close correlation with droughts in the Quang Phu community and the remaining part of the Dak Nang and Duc Xuyen communities (Fig. 2.1). Besides, Fig. 2.2 and Table 2.5 specify the drought levels of the three rain gauges. The associated areas of Duc Xuyen station tend to be more heavily affected by droughts than the other areas. Quang Phu, whose rainfall is closely related to the Lak station, is the least drought-affected community compared to the other communities. In general, drought frequency of Krong No District is about 16% in which moderate drought occupies more than 66% of the area, severe drought occupies about 20%, and extreme drought afflicts about 14%. This suggests that drought in Krong No is a great threat that should be taken into special consideration, especially in those regions measured by the Duc Xuyen station.

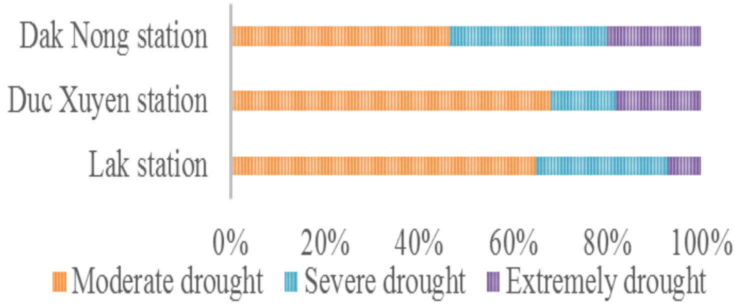


Figure 2.2. Drought frequency in three rain gauges in Krong No district.

Table 2.6. The result of SPI6 in Krong No district

SPI6*	Lak (1981 – 2010)	Duc Xuyen (1981 – 2016)	Dak Nong (1981 – 2013)
Total events	355	427	391
Moderate drought (-1 ÷ -1.49)	37	49	21
Severe drought (-1.5 ÷ -1.99)	16	10	15
Extremely drought (≤ -2)	4	13	9
Total drought events (≤-1)	57	72	45
Drought frequency	**0.16**	**0.17**	**0.12**

* *SPI drought class classification* (T.B. McKee et al., 1993)

Since the income of households is intensely dependent on farming, the condition of food security is frail in the study area. Nearly 30% of Krong No Districts households struggle with food availability; and, according to our survey, this period of difficulty falls in the months when the crop has not yet been harvested (from January to May, with a peak in March, Fig.2.3). It is noteworthy that the period of food shortage also coincides with the time when households lack water for domestic use as well as irrigation (this deficit period also falls between January and May, peaks in March, Fig. 2.3). Once drought seriously occurs, it severely affects the lives of households. Drought leads to crop failure and lack of water, making the people’s lives more difficult in the next period.

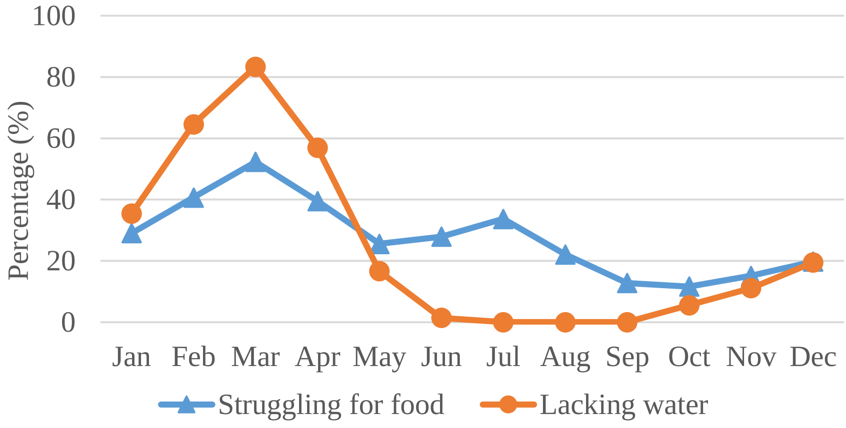
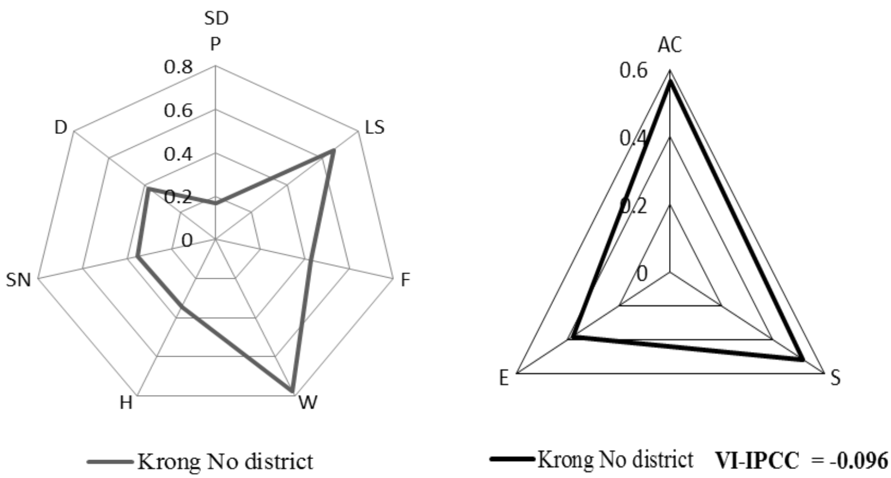


Figure 2.3. Percentage of households struggling for food and lacking water in Krong No district

2.4.2. Livelihood's vulnerability in the Krong No district

Figure 4a presents the diagram for the seven major components of LVI for the Krong No District. There are two imbalance aspects—Water (0.774) and Livelihood strategies (0.661). These aspects are the two main factors that increase the vulnerability of the district. The Sociodemographic aspect of Krong No is quite good. Our surveys show that the sociodemographic profile of most households indicates a relatively low vulnerability (0.168). The burden imposed by a large-sized family, as well as a female-headed household, has significantly decreased since 25 years ago when the family planning program was successfully implemented in rural areas. In the last 10 years, small-sized families and the number of children going to school have increased, which contribute to mitigate the vulnerability of the district.



(a) LVI major components (b) VI-IPCC major components

Figure 2.4. Vulnerability spider diagram of the livelihood vulnerability index (LVI) major components (a) and Vulnerability Index-Intergovernmental Panel on Climate Change (VI-IPCC) major components pyramid diagram (b) for the Krong No District in Dak Nong Province, Vietnam. Note: SDP = Sociodemographic profile; LS = Livelihood strategy; F = Food; W = Water; H = Health; SN = Social networks; D = Drought; AC = Adaptive capacity; E = Exposure; S = Sensitivity

Water source is the dreadful issue in the district. Our survey reveals that approximately 70% of households lack sufficient water for domestic use and irrigation in the dry season. In three out of the five surveyed communities, 100%

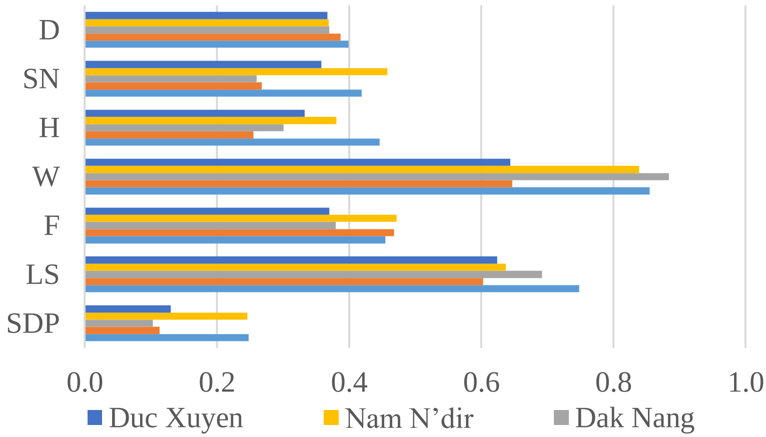
of households are dependent on natural water sources and lack access to a central water supply system (W1 and W2, Table 2.2). Once a dry season is prolonged, the district becomes one of the most vulnerable places in the country. The other main reasons are that households significantly depend on farming and rural poverty has not been completely eliminated. In addition to water, the second prominent problem is the livelihood strategy of the households. Households in Krong No have poor, undiversified livelihood strategies, and they are considered a vulnerable community even when droughts do not occur. This is attributed to the fact that the livelihood of more than 80% of households depends entirely on farming and small-scale livestock production. Most members of these households do not have a job that generates a stable salary; when a drought happens, it leads to severe crop failure and a great impact on the livelihood of households, because they have no other source of income to compensate for the loss. As a result, there is no money to cover living expenses and this leads to food and water shortages, disease, and poverty year after year.

The VI-IPCC index also indicates that the vulnerability of the district is at a medium level (-0.096) based on the vulnerability scale of -1 to $+1$. The VI-IPCC result is presented in a spider chart (Fig. 2.4a) and in different format using three contributing factors (calculated in Eq. 4), aggregated from the seven major components in Fig. 2.4a, and displayed in a pyramid chart (Fig. 2.4b). In general, the adaptive capacity of households just surpasses the average (approximately 0.6), but is not strong enough to respond to the impacts of drought. Sensitivity shows that the living standard of the community is still low and needs more support from the government. The VI-IPCC indicates that both adaptive capacity (AC) and sensitivity (S) should be taken into consideration during drought mitigation efforts in which sensitivity (water, food, and health) should be prioritized. The result suggested that household adaptive capacity also needs to be addressed directly, because community capacity is the key to solving economic, social, and environmental problems. Oo et al. (2018), in addressing similar issues in Myanmar, stated that lack of households adaptive capacity is a main cause of high vulnerability to the impacts of climate change and disasters. Studies in West Africa and in the Himalayas indicated that knowledge (Obayelu et al. 2014) and income (Aryal et al. 2014) are key factors in determining household adaptive capacity and reducing household vulnerability. When knowledge and economy combine to make a community strong, that society will be able to improve its quality of life on their own initiative. Once drought takes place and lasts, strengthened social institution will have enough vitality to survive, mitigate, and recover from drought damages.

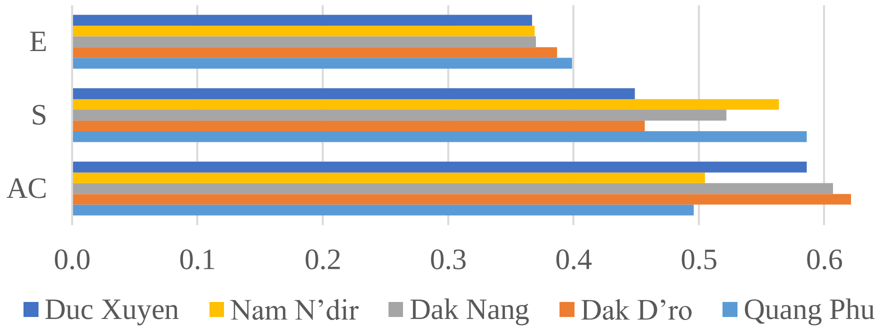
2.4.3. Livelihood's vulnerability of five communes

Vulnerability of the five communities in the Krong No District in decreasing order is: Quang Phu, Nam N'dir, Dak Nang, Duc Xuyen, and Dak D'ro (Table 2.3). Quang Phu (LVI = 0.510) needs special attention, followed by Nam N'dir (LVI = 0.486). Table 2.3 indicates in detail the vulnerability aspects of each community. Through this table, it is easy to see what specific issues need to be addressed for each community. This study presents two aspects that need special attention for all five communes—water availability and diversified livelihood strategies for the residents. Although on issues of water sources, all five communes have serious concerns, the Dak Nang, Quang Phu and Nam N'dir communities are the three most vulnerable areas in the water component with very high LVI values of 0.884, 0.855, and 0.839, respectively (Table 2.3). The water issue seems to be extremely critical, especially when the prolonged dry season leads to droughts that severely affect the lives of the local people. In terms of livelihood strategies, the table also shows that all five communities need attention because their vulnerability is relatively high, and Quang Phu and Dak Nang are considered as the two most vulnerable communities. Finally, the social network component (SN) shows that Quang Phu and Nam Nam N'dir are two communities needing more attention because adequate communication facilities and support policies are not widely present in either community. Quang Phu and Nam N'dir also need more food and health support than do others. Therefore, it is necessary to have appropriate policies for these two communities so that once support policies are proposed and implemented, those initiatives will be effective. For Quang Phu, the order of priority is for support policies that sustain people's livelihoods and reduce the impact of the natural element—drought. The priority sequence is as follows: water > livelihood strategies > food > health > social networks > sociodemographic profile. For Nam N'dir, priority is proposed as follows: water > livelihood strategies > food > social networks > health > sociodemographic profile.

Figure 2.5 indicates that livelihood vulnerability in the five communities mainly comes from two contributing factors—adaptive capacity (AC) and sensitivity (S). In terms of adaptive capacity, VI-IPCC considers household sociodemographic profile, livelihood strategies, and social networks; and in terms of sensitivity, it considers water, food, and health component. Figure 2.5 also clearly shows differences in these two factors, and between two communities (Quang Phu and Nam N'dir) and the other communities. The communities are ranked in order of capacity from low to high: Quang Phu > Nam N'dir > Duc Xuyen > Dak Nang > Dak D'ro. In general, Dak D'ro has the best adaptive capacity in comparison with the other communities, partly because of its location nearing the district center, whereas Quang Phu is the farthest distance from local site to district administrative support center. Finally, the impacts of drought are indirectly shown by the components of the sensitivity factor. The order of sensitivity from high to low are: Quang Phu > Nam N'dir > Dak Nang > Dak D'ro > Duc Xuyen. Again, Quang Phu and Nam N'dir are the two communities with a higher vulnerability factor than the other communities. In summary, all results show that Quang Phu and Nam N'Dir are the two vulnerability hotspots of Krong No District.



(a) LVI major components



(b) VI-IPCC major components

Figure 2.5. Contributing factors of livelihood vulnerability index (LVI) major components (a) and Vulnerability Index-Intergovernmental Panel on Climate Change (VI-IPCC) major components (b) for the five communities in the Krong No District in Dak Nong Province, Vietnam. Note: SDP = Sociodemographic profile; LS = Livelihood strategy; F = Food; W = Water; H = Health; SN = Social networks; D = Drought; AC = Adaptive capacity; E = Exposure; S = Sensitivity

2.5. Discussion

The results of this study indicate that water availability and effective livelihood strategies are the most important factors in determining livelihood vulnerability for the five surveyed communities in Krong No District. According to the survey results, most households in the study area mainly depend on natural sources of water because of the absence of a community water supply system and almost universally their livelihoods lack diversity because they rely only on agriculture for income. This dependence produces high vulnerability to the impacts of climate change and climate variability, especially water shortage in the dry season (M.B. Hahn et al., 2009). In addition, the water problem is attributed to a high reliance of farming on water (Pandey et al., 2015; J. Panthi et al., 2016). Water problems for the study area may increase, because the streamflow is predicted to significantly decrease in the future, especially in the dry season (Sam et al., 2018). Under the impacts of drought, the study area must find alternative water resources, such as wells, ponds, or rainwater harvesting. Moreover, new water management practices, such as drip irrigation, irrigation supplements, and the adoption of stress-tolerant crop varieties, need to be introduced to solve current and future water deficit problems.

Because the main livelihood system of the five surveyed communities in the district is farming, the main income of these communities is more likely to be affected adversely by droughts. The low values of the livelihood diversification indices (LS1 and LS3) of these communities are a reason for the high vulnerability of existing livelihood strategies. This finding is consistent with the insights of Aryal et al. (2014) and Oo et al. (2018). Antwi-Agyei et al. (2013), who pointed out that a household is judged less vulnerable if there are more than two income sources in a family to improve livelihood diversification. In the face of drought impacts, livelihood stability for households in the five communities is emphasized, and livelihood diversification in terms of a mixture of farming and nonfarming activities is recommended to reduce vulnerability from drought impacts on households.

In general, the LVI and VI-IPCC indices are effective in determining household vulnerability for the five study areas. By using these indices, the vulnerability level between different sites within a study area can be compared. However, the same two indices may not be readily compared with other investigations in more distant regions because of different subcomponents (indicators) and contexts. Indeed, Hahn et al. (2009) suggested that selection of subcomponents significantly affects the assessment result of household livelihood vulnerability to climate change and natural hazards. Panthi et al. (2016) also contend that local environment affects the frame and design of the subcomponents. Selection of appropriate subcomponents is a challenge in the use of vulnerability indices. As this study demonstrates, extensive literature review, expert consultation, and stakeholder consultation are recommended for designing subcomponents of the vulnerability indices (LVI and VI-IPCC).

2.6. Conclusion

In this study, livelihood vulnerability of farmers in Krong No District, Dak Nong Province on the Central Highlands of Vietnam was investigated by using two vulnerability indices: LVI and VI-IPCC. The main findings can be summarized as follows: (1) results of LVI and VI-IPCC indicated that the Krong No District is at a medium level of livelihood vulnerability under the impacts of drought (0.444 and -0.096); (2) considering the vulnerability of five surveyed communities, the overall LVI and VI-IPCC values from the major components pointed out that households of the Quang Phu community are the most vulnerable to drought, with indices of 0.510 and − 0.057, followed by Nam N'dir, Dak Nang, Duc Xuyen, and Dak D'ro communities; and (3) this study also indicated that water (sensitivity) and livelihood strategies (adaptive capacity) are two major causes of high vulnerability to the impacts of drought for the district and all surveyed communities. Therefore, this study recommends increasing investment in water management practices and livelihood diversification. In future research, vulnerability under some policy interventions will be investigated to see the effectiveness of planned activities in reducing livelihood vulnerability of communities of the area.

Acknowledgement

This research is funded by the Vietnam National Foundation for Science and Technology Development (NAFOSTED) under Grant Number 105.06-2013.09.

Supplemental data

Table S. 1. The influence of rainfall station per commune according to the Thiessen Polygon Method

Station	Quang Phu	Dak D'ro	Dak Nang	Nam N'dir	Duc Xuyen
Lak	1	0.62	0.06	0	0
Duc Xuyen	0	0.38	0.90	0.95	1
Dak Nong	0	0	0.04	0.05	0
Total Thiessen	1	1	1	1	1

Chapter 3. Comparing local people's perceptions of climate change and drought using scientific observations in the Central Highlands of Vietnam

Abstract

The main purpose of this study was to analyse local people's perceptions of climate change and of climate change-related drought in rural areas of Daklak province in the Central Highlands of Vietnam, located in the Lower Mekong Basin. In addition, this study investigated the differences between the perceptions of local people and the meteorological recorded data in the area. A sample of 354 households was selected using a simple random sampling method. Data were collected from face-to-face interviews with respondents, based on a structured questionnaire. The study found that there is a significant difference in climate change perceptions and observations of climate change-related extreme events, depending on different socio-economic and demographic household characteristics: in particular, education, preferred media sources and income sources have significant effects on local people's perceptions regarding drought. The limits of human perception of slow processes such as climate change or processed noised by strong interannual variability are also shown. If important agreements are observed between farmers' perception and meteorological data for clear trends like global warming, the perceptions are most often in disagreement with meteorological observations when it comes to describing trends in precipitation (volume and duration) due to a much less marked trend and a very high interannual variability. Regarding drought occurrence, the majority (95%) of respondents' perceptions align correctly with scientific observation based on the SPI index. These results provide useful information to local governments and policymakers in building strategies to mitigate the risk of adverse impacts of climate change and drought.

Keywords: Climate change; drought; perception; trend analysis; Vietnam

3.1. Introduction

Today, people all over the world face the reality of climate variability, which in many parts of the world has been shown to cause increased unpredictability of extreme weather events (Eckstein et al., 2019). Additionally, the Intergovernmental Panel on Climate Change (IPCC, 2018) has reported several regional climate change findings, including extreme temperature rises in many places, increasing in frequency and intensity, as well as heavier amounts of precipitation in some cases and more intense or frequent droughts in others. Between 1999 and 2018, approximately 495,000 people died globally and USD 3.54 trillion of losses were suffered (in purchasing power parity) as a direct result of more than 12,000 extreme weather events (Eckstein et al., 2019). Drought is an extreme weather event. It is defined as the naturally occurring phenomenon that exists when precipitation is reduced or deficient over an extended period of time. This shortage will be reflected in decreasing surface and subsurface water levels, causing significant hydrological imbalances that adversely impact land resource production systems, ecosystems and societies (Rezaei et al., 2016).

In recent years, the Lower Mekong Basin, including Thailand, Cambodia, Laos and Vietnam, experienced extreme drought in 1992, 1999, 2003 and 2015–2016. This has led to massive economic losses from damage to crops and adverse effects on the environment and people's livelihoods (MRC, 2019). The recent extreme drought in 2016 cost Thailand USD 1.7 billion in damage, and in Cambodia caused water shortages in 18 out of 25 provinces, affecting 2.5 million people. In Vietnam, the total costs of the 2016 drought were assessed at USD 669 million, and costs to recover damages amounted to approximately USD 1.5 billion (MRC, 2019).

Vietnam has been identified as one of the countries most vulnerable to climate change and natural disasters (drought and flood) (IMHEN and UNDP, 2015; IPCC, 2013b; Thao et al., 2019). From 1999–2018, Vietnam suffered from approximately 226 natural disasters, leading to a loss of 0.47% of annual Gross Domestic Product (Eckstein et al., 2019). During the dry season of 2015–2016, with the effects of the El Niño phenomenon, Vietnam and especially the Central Highlands faced the most severe droughts in 90 years, causing tremendous damage to agricultural production and farmers' incomes (UNDP, 2016b). The Central Highlands region is part of the Lower Mekong Basin and plays a critical role in Vietnam's economy. The region is the biggest producer of coffee beans in Vietnam, ranking second in export (Thao et al., 2019). Nevertheless, a recent study found that in the near future droughts in the Central Highlands of Vietnam will become increasingly extreme and prolonged (Sam et al., 2019). Thus, agriculture and people's livelihoods in this region will continue to be challenged by the adverse effects of drought. While the occurrence of droughts cannot be stopped, they can be predicted by implementing available technological innovations (FAO, 2017). Similarly, the impact of droughts can be reduced and mitigated by appropriate adaptation strategies. Adaptation strategies can be carried out by farmers themselves or by government policies targeted at supporting appropriate and effective adaptation measures. However, these strategies seem to be ineffective without an understanding of local people's perceptions of climate change and drought (Monirul Alam et al., 2017). Famers perceptions of climate change and their responses to change are the two main elements of the climate change adaptation process (Monirul Alam et al., 2017). Moreover, according to Hartter et al. (2012), in order to develop suitable adaptation strategies it is important to take action on natural changes and to understand how climate change and its related hazards—in this case drought—are perceived, experienced and interpreted by local people. Farmers' interest in climate primarily concerns the need to predict the weather to adjust their cropping decisions (Callo-Concha, 2018; Roncoli, 2006). Therefore, a comparison between local people's perceptions of drought and scientific observations is important for identifying the main issues related to the role of local people's perception and knowledge in drought risk management, and in making suggestions for developing adaptation strategies that can mitigate the negative impacts of climate change—such as drought—on people's livelihoods. Recent studies tend to be primarily concerned with the potential of local and traditional knowledge to provide useful insights on local climatic systems, as well as with peoples' vulnerability, resilience and response capabilities (Adger and Pulhin, 2014). However, the combined local and scientific knowledge is still limited due to an incomplete understanding of local knowledge systems, and the lack of approaches and tools to integrate both together (Adger and Pulhin, 2014; Kahsay et al., 2019; Kettle et al., 2014).

This study's objectives were, first, to analyse the perceptions of local people regarding climate change and droughts in Dak Lak province in the Central Highlands of Vietnam. Three districts, namely Buon Don (Eanuol, Cuor Knia and Tan Hoa communes), Cu M'gar (Ea Kiet, Ea Tar and Ea M'droh communes) and Easup (Eale and Cu Kbang communes), were selected for this study because they were the areas most affected by the historical drought in 2015–2016 (FAO, 2016b). Next, the findings of the study of local people's perceptions related to climate change and droughts were compared with meteorological data. We expect studies such as this one to help local governments develop drought-adaptation strategies to enhance the adaptive capacities of local people living in the study area.

3.2. Study area

The study was carried out in Dak Lak province, located in the Central Highland of Vietnam in the Lower Mekong River Basin (Figure 3.1). The total area is 13,125 km^2 and in 2019 the population of Dak Lak province counted 2.127 million people, with 44 ethnic groups (Dak Lak Statistical Office, 2020). The Kinh ethnic group accounts for the greatest portion of Daklak's population (70%). The remaining population (30%) includes ethnic minorities such as the Ede, M'nong, Thai, Tay and Nung ethnic groups. In Dak Lak province, agriculture is the main source of local livelihood. The area's geographic coordinates are from 107°28'57" to 108°59'37" east longitude and from 12°9'45" to 13°25'06" north latitude, with a range elevation of 400–800 m. Generally, the area's climate varies depending on the altitude: below 300 m it is hot all year round, it is hot and humid from 400–800 m, and colder above 800 m. Seasonal rainfall may hinder the development of agricultural production. There are two distinct seasons in Dak Lak province: a rainy season from May to October with approximately 80–85% of annual rainfall and a dry season from November to April which is normally dry and sunny (15–20% of annual rainfall). Dak Lak province is an agricultural area with perennial crops such as coffee, pepper, cashew and fruits. The region also produces annual crops including rice, maize, sweet potato, vegetables, sugarcane, groundnut and soybean (CCAFS-SEA, 2016).

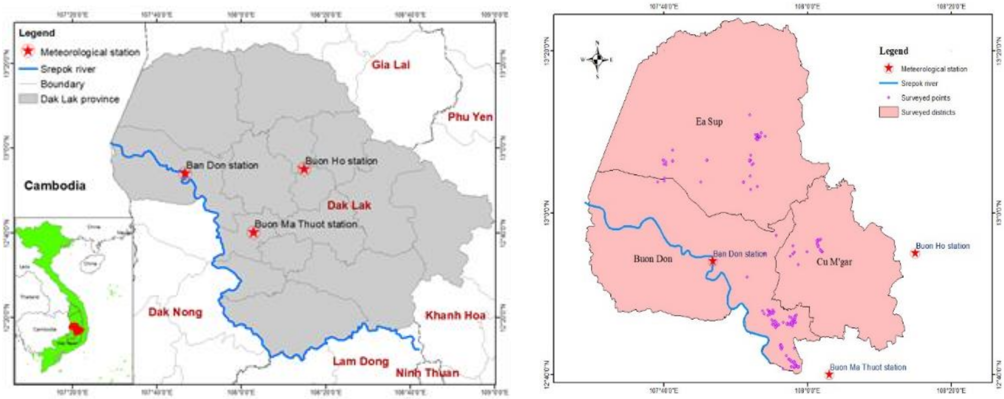


Figure 3.1. Location of Dak Lak province and the three surveyed districts

3.3. Methodology

3.3.1. Data collection

Data collection and field surveys were conducted during the 2019 dry-season months of March and April. Information was collected at the commune level on climatic phenomena and their impact on farming practices. The questionnaire contained information related to socio-economic and demographic characteristics, and to farming practices at commune and district levels in Dak Lak province (the survey was implemented in eight communes spread over three districts, see Table A.2). It also included questions related to climate change, local droughts and adaptation solutions adopted to mitigate the negative impacts of drought in each commune (Table A.2). Before data collection began, the structured questionnaire was tested with ten respondents. Expert advice was also sought to confirm the adequacy of the survey questions and to avoid any unclear or misleading questions. A total of 354 households were surveyed from eight communes in three districts of Dak Lak province, namely: Ea Nuol, Tan Hoa and Cuor Knia (Buon Don district); Ea Tar, Ea Mdroh and Ea Kiet (Cu M'gar district); and Eale and Cu Kbang (Ea Sup district). These were the most vulnerable areas affected by the historical drought of 2015–2016 (FAO, 2016b). Selection of households was done by taking the number of people in each commune respecting the required sample size. The sample size was calculated at a 95% confidence level with a 5.21% margin of error, at an assumed coverage of 50% based on the probability proportional to size method. The households were selected by simple random sampling. Each respondent was interviewed in the Vietnamese language for approximately 30 minutes. The targeted number of households in each commune, shown in Table A.1, depended on the population size of each commune. In case of non-respondents, the interviewers continued with the next household until the targeted number of households in each commune was reached. Table A.2 shows the survey information analysed in this research.

3.3.2. Data analysis

3.3.2.1. Household data analysis

Surveyed data were recorded in Microsoft Excel 2010 for descriptive statistical analysis; missing data were rejected based on a simple deletion approach (Acock, 2005). In addition, Barnard's exact test (Erguler, 2016) was applied using RStudio (version 3.6.2) to better understand household profiles and local perceptions regarding drought-related climate change. For instance, higher educated and literate people are supposed to be able to access various information sources, and hence have a better understanding of issues related to climate change and drought (Habiba et al., 2012; Manandhar et al., 2015). If Barnard's exact test shows a statistically significant difference at the 95% confidence level (p-value ≤ 0.05), the null hypothesis is rejected. Then, the findings of local people's perceptions were compared to the results of meteorological data analysis to assess the differences between local people's experiences and the measured climate change data related to drought and extreme events.

3.3.2.2. Meteorological data analysis.

In this study, meteorological data for the 1981–2018 period were used, with daily precipitation data recorded from three rain gauges (Buon Me Thuot, Ban Don and Buon Ho) and temperature data recorded from one weather station (Buon Ma Thuot station) (Figure 3.1). These data were collected from the Hydro-Meteorological Data Centre of Vietnam. Meteorological data were analysed to assess monthly precipitation and temperature distribution, extreme precipitation events, and precipitation and temperature trends. The non-parametric Mann-Kendall trend test was used to calculate trends with RStudio's (version 3.6.2) 'Kendall' package (McLeod, 2011). In addition, descriptive statistics such as minimum, maximum, median and mean values, standard deviation (STD), coefficient of variation (CV), skewness and kurtosis were analysed to better understand the data characteristics. Furthermore, precipitation extremes (Table 1) were estimated using Rclimdex 1.1 (version 1.0) (Wang and Feng, 2004).

Table 3.1. List of eight precipitation extremes used in this study

Types	Indices	Name	Definitions	Unit
Intensity indices	RX1day	Max 1-day precipitation amount	Monthly maximum 1-day precipitation	mm
	RX5day	Max 5-day precipitation amount	Monthly maximum 5-day precipitation	mm
	R95p	Very wet days	Annual total PRCP when precipitation >95th percentile	mm
	SDII	Simple daily intensity index	Annual total precipitation divided by the number of wet days	mm/day
Frequency indices	R20mm	Number of heavy precipitation days	Annual count of days with daily precipitation ≥20mm	days
	R25mm	Number of very heavy precipitation days	Annual count of days when precipitation ≥25mm	days
Duration indices	CDD	Consecutive dry days	Maximum number of consecutive days with precipitation <1mm	days
	CWD	Consecutive wet days	Maximum number of consecutive days with precipitation ≥1mm	days

To identify the onset and cessation of the rainy season, the study used the method of Liebmann et al. (2012) to calculate 'anomalous accumulation' of precipitation on the day (*d*) (*C(d)*), as follows

$$C(d) = \sum_{n=1}^{day} [R(n) - \bar{R}] \quad (1)$$

where, R(n) is the daily precipitation and $\bar{R}$ is the climatological annual daily average. C(d) is estimated for each day of each year. Start and end dates of the rainy season are defined by finding, respectively, the minimum and maximum curvature points in the cumulative daily precipitation anomaly.

In this study, the Standardised Precipitation Indices with three-month, six-month and 12-month timescales (SPI3, SPI6 and SPI12, respectively) (T. B. McKee et al., 1993) were calculated to assess short-, medium-, and long-term drought episodes. SPI is calculated based solely on precipitation. SPI3 presents the drought effect on agricultural practices, SPI6 shows droughts' impact on reservoir levels and river discharges, and SPI12 generally shows the effect on groundwater. Three-month, six-month and 12-month accumulation periods were used, allowing an integration over the whole-year cycle (Meresa et al., 2016).

3.4. Results and discussion

3.4.1. The meteorological data analysis

3.4.1.1. Analysis of annual, seasonal, and monthly precipitation.

The research used the mean rainy season onset and cessation over 38 years (1981–2018) to analyse the trend. From Table 3.2, the results found that mean rainy season onset is at 118 Julian days (27 April) and the cessation at 298 Julian days (23 October) for the whole study area. Based on the Mann-Kendall trend test analyser, trends were calculated for our 38-year rainfall dataset for the three rain gauge stations in the study area. The estimated Mann-Kendall Z values and magnitude of Sen's slope for each station and for the whole study area for monthly, annual and seasonal timescales are shown in Table 3.3. Seasonal timescales are computed over a period of 38 years for each station and the entire study area.

Table 3.2. Descriptive statistics of onset, cessation and duration of rainy seasons over 37 years for the three stations and the whole study area.

	Parameter	Min	Max	Mean	STD	CV
Buon Ma Thuot	Onset (Julian day)	79	166	123	14.64	0.12
	Cessation (Julian day)	263	348	292	19.22	0.07
	Duration (day)	115	214	171	22.73	0.13
Ban Don	Onset (Julian day)	80	145	119	15.06	0.13
	Cessation (Julian day)	265	332	294	15.78	0.05
	Duration (day)	127	228	176	23.74	0.13
Buon Ho	Onset (Julian day)	76	179	128	21.06	0.16
	Cessation (Julian day)	261	348	301	21.99	0.07
	Duration (day)	101	226	175	27.92	0.16
Study area*	Onset (Julian day)	91	145	118	12.92	0.11
	Cessation (Julian day)	265	348	298	16.95	0.06
	Duration (day)	127	244	180	22.80	0.13

* Study area meteorological variables were obtained by Thiessen Polygons spatial interpolation

The months of August and October for the Buon Ma Thuot station show decreasing trends with the 99% significance level. Statistically decreasing trends were found in September at the 90% significance level for the Buon Ma Thuot and Buon Ho stations. We found no significant trends for most of the monthly, annual and seasonal precipitations for the Ban Don station (Table 3.3).

Table 3.3. Mann-Kendall trend test and Sen’s slope for monthly, seasonal and annual precipitation for each station and for the entire study area (using Thiessen polygons to calculate the average amount of precipitation over the whole study area using the three stations)

Time series	**Ban Don**		**Buon Ma Thuot**		**Buon Ho**		**Study Area**	
	Z	**Sen's slope**	**Z**	**Sen's slope**	**Z**	**Sen's slope**	**Z**	**Sen's slope**
January	0.06	0	1.41	0	2.76	**0.09****	1.84	**0.04+**
February	-0.58	0	-0.92	0	-0.55	-0.01	-1.09	-0.02
March	-0.76	-0.04	1.04	0.175	-0.54	-0.04	-0.08	-0.01
April	0.55	0.52	-0.30	-0.26	-0.35	-0.25	-0.08	-0.08
May	1.04	1.58	-0.75	-0.958	0.15	0.31	-0.18	-0.12
June	0.00	0.02	-0.93	-1.535	-1.26	-1.66	-0.70	-0.67
July	0.28	0.4	0.73	0.7	1.33	1.67	0.83	1.06
August	-1.61	-1.86	-2.11	**-3.1***	-0.83	-1.20	-1.87	**-2.15+**
September	1.11	1.86	1.89	**2.73+**	1.66	**2.18+**	1.61	1.78
October	-1.53	-2.03	-2.21	**-3.96***	-1.48	-2.47	-1.48	-2.76
November	-0.01	-0.01	0.50	0.43	0.88	1.07	0.48	0.48
December	0.93	0	1.20	0.24	1.56	0.50	1.35	0.34
ANNUAL	-0.60	-1.33	-1.06	-4.07	0.78	3.01	-0.20	-0.47
Rainy season	-0.08	-0.51	-1.66	**-7.13+**	-0.91	-3.88	-1.43	-4.05
Dry season	-0.72	-1.69	0.98	2.79	2.52	**5.63***	1.82	**3.22+**
Onset of rainy season	-1.08	-0.29	-0.22	-0.06	0.08	0	-1.62	-0.36
Cessation of rainy season	-1.43	-0.34	-1.16	-0.3	-0.92	-0.33	-0.75	-0.18
Duration of rainy season.	-0.40	-1.15	-0.63	-0.19	-1.22	-0.6	-0.37	-0.11

Note: **, *, and + indicate that the trends are significant at 99%, 95% and 90% levels of confidence, respectively

The study revealed that the dry-seasonal rainfall had an upward trend at the 95% significance level (values of Z and Sen’s slope are 1.82 and 3.22, respectively). Meanwhile, the rainy-seasonal rainfall showed a downward trend with negative values of Z and Sen's slope, but not statistically significant because of the high inter-annual variability of the recorded meteorological data (as shown in Table A.3). In addition, over the entire study area, seven months (Feb, Mar, Apr, May, Jun, Aug, Oct) give a negative Z value, indicating a decreasing trend, while the other months (Jan, Jul, Sep, Dec) indicate an increasing trend (Table 3.3). However, the trends are not statistically significant, except for January and August, which both have a 90% level of significance. The estimated Sen's slope (S) was also analysed separately for each month. The months of Febuary, March and April gave gently decreasing slope magnitudes, the month of January showed a significant increasing trend, and August a significant decreasing trend at 90% level of significance (Table 3.3). Figure B.1 presents the annual rainfall variations (trends) over the study area and for each station between 1981–2018. From Figure B.1 and Table 3.3 it can be seen that there are no significant changes in annual precipitation data.

If we look at the monthly rainfall trends (Table 3.3), the rainy seasons had a negative trend except for July and September. Among the dry seasons, November, December and January had a positive rainfall trend.

Figure 3.2 shows time series of onset and cessation dates and rainy season durations for the three weather stations and the study area mean. Onset dates are between the middle of March and June, and cessation dates are between the middle of September and November. The rainy season duration trend for the last 38 years (1981–2018) shows a slight increase, suggesting a longer rainy season. In fact, there are no significant trends for the onset, cessation and duration of the rainy season at the three stations (+ mean) because of the high inter-annual variation of the precipitation data.

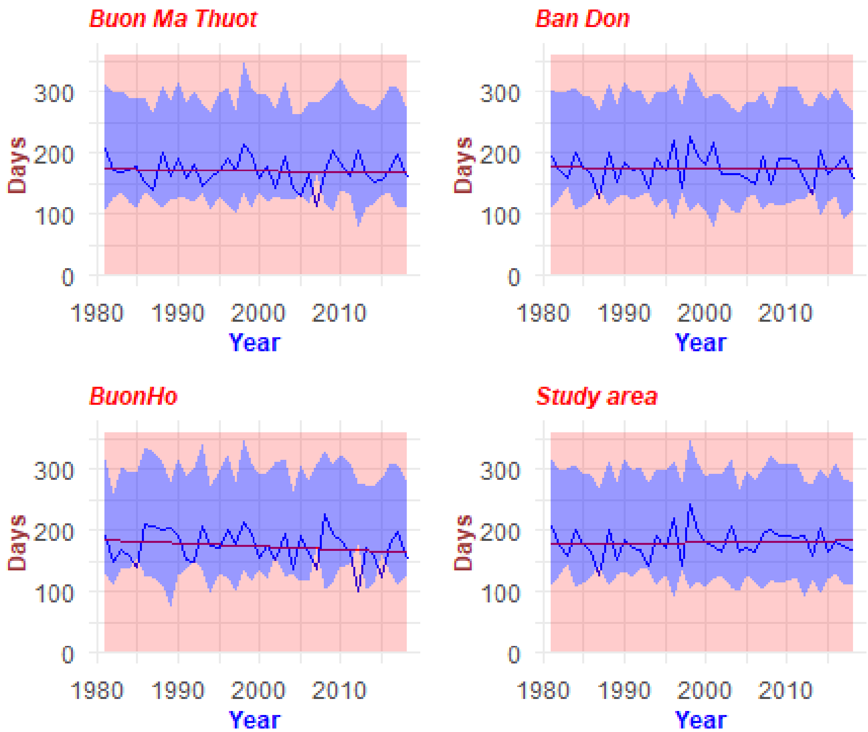
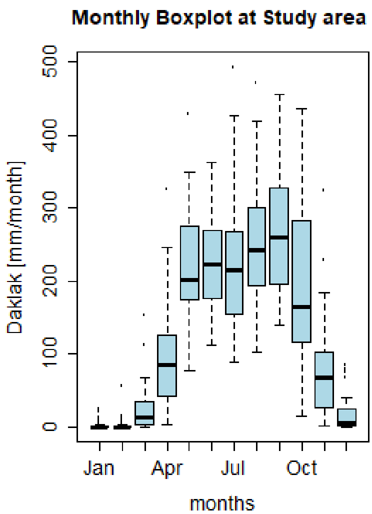


Figure 3.2. Time series of onset and cessation dates, and durations of the rainy season for different weather stations (BMT, Buon Ho and Ban Don stations) and the whole study area (mean). Blue areas indicate rainy seasons, red areas indicate dry seasons; blue line indicates rainy season durations, red line indicates rainy season duration trend.

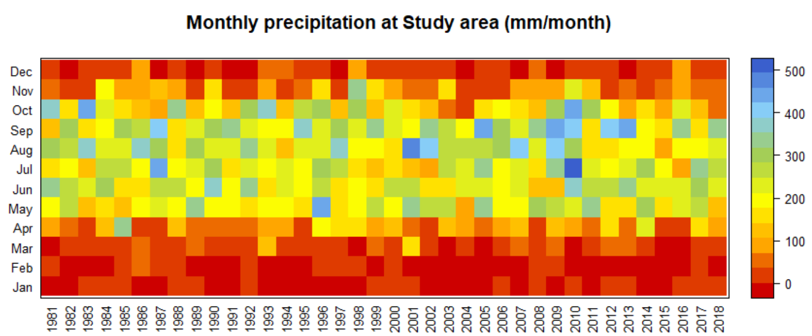
3.4.1.2. Analysis of extreme events related to precipitation

The summary of the descriptive annual precipitation statistics of the study area is presented in Table A.3. The results indicated that western Ban Don province had a higher CV (0.2) than east and central Dak Lak province (0.16 and 0.14, respectively); in other words, rainfall in the west of Dak Lak province showed more year-to-year variability than east and central Dak Lak province. The average annual precipitation of the whole study region is 1619 mm; it ranges between the highest values recorded at Buon Ma Thuot station (1854 mm) and the lowest ones at Buon Ho station (1563 mm).

The 37-year precipitation dataset was analysed on a monthly basis in order to determine the months with the greatest rainfall values in the study area (Figure 3.3). The monthly boxplot (Figure 3.3a) shows that the wettest month of the year is August, followed by September and October. The months with the lowest rainfall are January, February and December. In addition, it can be seen that the major rainfall events start in May, reach their peak in August and September, and remain high until October. In the monthly time series (Figure 3.3), the monthly rainfall distribution for the complete dataset is illustrated; it indicates a clear monthly rainfall peak in July 2010.



(a)



(b)

Figure 3.3. Monthly boxplot precipitation and distribution of monthly precipitation for each year, in the study area of Dak Lak province; (a). monthly boxplot precipitation, (b). distribution of monthly precipitation

Extreme precipitation trends for the whole study area for the period 1981–2018 were assessed using Thiessen polygons of the study area's three stations. We found no significant trend for the eight indices used, due to the high inter-annual variability of the recorded meteorological data. Regarding the intensity indices, slope of mean values RX5day decreased lightly, and RX1day, SDII and R95p increased gently during the study period, but the trends are not significant at 5% significance level (Figure B.2). The annual mean values of RX5 ranged from 86.3 mm/5 days to 297.1 mm/5 days. For the annual mean values of RX1day, the highest value was 186.4 mm in 2010 and the smallest 51.7 mm in 1999. The values of R95p varied between 54.5 mm and 1264.5 mm from 1981–2018, with the lowest level in 1994 and the highest in 2010. Regarding duration indices, the mean values of consecutive dry days (CDD) had a gently increasing trend, while the slope of the trend of consecutive wet days (CWD) decreased gently.

Table 3.4. Slope of trends in climatic extreme indices of precipitation for the three stations and the whole study area (average values of the three stations)

Station	RX1day (mm)	RX5day (mm)	SDII (mm/day)	R20mm (days)	R25mm (days)	CDD (days)	CWD (days)	R95p (mm)
Ban Don	0.049	-0.457	0.003	0	0.028	-0.143	-0.046	0.899
BMT	-0.026	0.149	-0.006	-0.047	-0.019	-0.035	-0.082	0.181
Buon Ho	-0.073	0.968	0.006	0.013	0.027	-0.355	-0.024	0.312
Study area	0.091	-0.364	0.009	0.045	0.057	0.015	-0.087	0.266

Note: **, *, and + indicate that the trends are significant at 99%, 95% and 90% levels of confidence, respectively

Regarding duration indices, the results of Table 3.4 illustrate that the trends of CDD and CWD tend to decrease for most stations. However, increasing trends of CDD were found for the whole study area. The mean values of CDD varied from 35 to 135 days, with the highest value at Ban Don station and the lowest at Buon Ho station. A longer CDD was observed in the western station (Ban Don) while shorter durations were detected in north-eastern and central parts. Moreover, the number of CWD indicated a decreasing trend for most of the stations. CWD values were between 8 and 28 days.

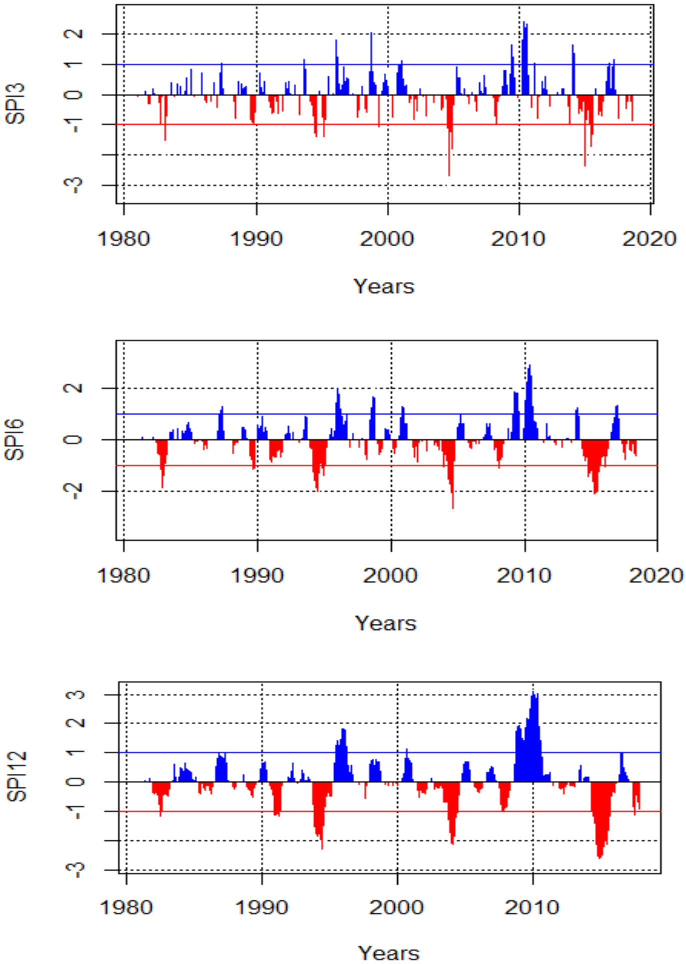
For the frequency indices (R20mm, R25mm), there were no significant differences in the spatial distributions. The values of R20mm and R25mm ranged from 12–37 days and 9–33 days, respectively. Additionally, both R20mm and R25mm showed no longer precipitation durations for the southern station (BMT station) than for northern ones (Ban Don and Buon Ho stations).

The values of SDII over the study area fluctuated between 8.8–17.7 mm/day. Higher values of precipitation intensity of 27.8 and 25 mm/day were found in western areas. The values of R95p of Buon Ma Thuot, Ban Don and Buon Ho have gently increasing trends.

3.4.1.3. Drought analysis

Figure 3.4a presents the three-month SPI, six-month SPI and 12-month SPI patterns for the study area using the weighted (derived from the Thiessen polygons method) average precipitation 1981–2018 dataset. This figure illustrates how different categories of droughts have occurred over the years. The maximum number of drought events are found to occur in Buon Ma Thuot station (144 events) for the three-month SPI across the 1981–2018 period (with threshold values SPI <-0.5). For whole study area, there were 131 drought events on SPI3, 128 events on SPI6 and 100 events on SPI12. Among the 131 total drought events (SPI3), 53.4% are slight drought, 25.2% moderate drought, 12.2% severe drought and 9.2% extreme drought; with 21.5% of severe droughts occurring in Buon Ma Thuot station. Values of SPI3, SPI6 and SPI12 showed extreme droughts in 1983, 1995, 2004, 2005, 2015 and 2016. Meanwhile, SPI3, which is often used to monitor agricultural drought, seems to show drier conditions over the last 15 years, especially in 2015, with extreme and severe drought conditions in the first and last three months of that year. The analysis of short, medium and long-term SPI values demonstrated that drought was a frequent event in the study area of Dak Lak province. Moreover, SPI values indicated that dry conditions last longer and are more frequent.

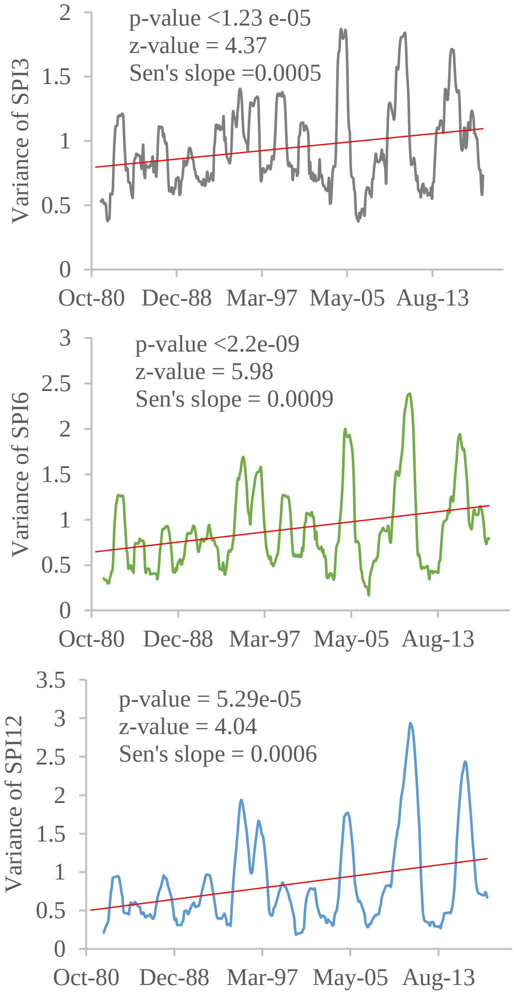
The results of the Mann-Kendal analysis applied to the variance of SPI values and variance trends, using a moving average of 12 months, are presented in Figure 3.4b. The p-values of all SPIs show that the climate trends (flood, drought or both) were significantly changing. The slopes of all trends were significantly positive, clearly showing more variability in climate phenomena (flood, drought).



SPI values

Extremely wet	>2.0
Severe wet	1.5 ~1.99
Moderate wet	1 ~ 1.49
Slight wet	0.5 ~ 0.99
Normal	-0.49 ~ 0.49
Slight drought	-0.99 ~ -0.5
Moderate drought	-1.49 ~ -1
Severe drought	-1.99 ~-1.5
Extreme drought	-2 and less

(a).



(b).

Figure 3.4. (a). Evolution of Standardised Precipitation Index (SPI3, SPI6, SPI12) from 1981–2018 for the study area. Blue and red colours denote positive and negative values, respectively. (b). Variances of SPI3 – SPI6 – SPI12 using a moving average of 12 months with the red line showing trend of variances of each SPI (SPI3, SPI6, SPI12).

3.4.1.4. Analysis of annual, seasonal, and monthly temperature.

The descriptive statistics for minimum and maximum temperature were calculated using daily temperature data from the Buon Ma Thuot station for the period 1981–2018. Table A.4 and Figure B.3 show that the highest monthly minimum and maximum temperatures of 25.7°C and 38.7°C are measured in April, and the lowest monthly minimum and maximum temperatures of 10.3°C and 16.7°C are recorded in December. The table also shows a slight negative skewness in minimum (-1.02) and maximum temperatures (-0.22). Both minimum and maximum temperature also had slight positive kurtosis (1.4 and 0.11, respectively) as shown in Table A.4.

As Table 3.5 shows, minimum temperature trends in rainy seasons are positive, with a Sen's slope of 0.052 and a Z-value of 5.98 at 99% confidence level. The rainy season trend for Tmax was significantly increasing at 99% confidence level with Sen's slope 0.035 and Z-value 4.4.

Table 3.5. Mann-Kendall trend and Sen's slope for annual and seasonal minimum and maximum temperatures in Dak Lak province

Time series	**Tmin**		**Tmax**	
	Z	**Sen's slope**	**Z**	**Sen's slope**
January	0.55	0.009	1.94	**0.043⁺**
February	-2.56	**-0.044****	1.61	0.034
March	-2.43	**-0.031***	1.9	**0.042⁺**
April	-0.77	-0.011	1.3	0.022
May	1.67	**0.013⁺**	0.67	0.013
June	5.63	**0.035*****	0.34	0.006
July	5.59	**0.037*****	-1.52	-0.01
August	5.29	**0.038*****	0.75	0.011
September	5.62	**0.034*****	0.29	0.003
October	3.94	**0.033*****	1.24	0.014
November	4.01	**0.046*****	1.52	0.028
December	2.97	**0.035****	1.22	0.024
ANNUAL	3.17	**0.017****	2.26	**0.018***
Dry	-1.37	-0.013	-0.3	-0.004
Rainy	5.98	**0.052*****	4.40	**0.035*****

Note: ***, **,*, and + indicate that the trends are significant at 99,9%, 99%, 95% and 90% level of confidence, respectively

For monthly temperature trends, minimum temperatures from May to December showed a (significantly) positive trend with Z values varying between 1.67 and 5.63, and a negative trend was seen in February and March. On the other hand, maximum monthly temperatures were only found to increase in a significant way in January and March.

The results demonstrated that both annual maximum and minimum temperature trends were positive. There were also significant trends at 95% and 90% levels of significance, respectively. The increasing slopes of 0.018°C/year for maximum temperature and 0.017°C/year for minimum temperature are shown in Table 3.5. A significant rising trend of annual minimum and maximum temperatures illustrates that there is an alarming global warming signal expressed over the entire study area.

3.4.2. Perceptions of local people concerning concepts relating to climate change and drought

Agricultural practices depend on weather conditions, therefore farmers must pay attention to local weather and climate variations. Of all respondents, approximately 56% had heard of climate change from various sources such as mass media, communication with friends or at school (Figure B.4). Climate change information also came from radio/television and internet/mobile phone, respectively for 46.6% and 13.8% of respondents, as presented in Figure B.4. These access sources are limited and thus the climate change awareness of local people seems limited. Approximately 46% of the surveyed households perceived climate change concepts and 46.6% understood that climate change has already increased some extreme events in number and intensity. This demonstrates that access to information on climate change is an important issue that influences the likelihood of local people taking measures to mitigate the risk of adverse effects of climate change.

Table A.5 presents the characteristics of the surveyed households. Respondents interviewed in this survey were 51.1% male, 48.9% female and had different degrees of farming experience. Length of farming experience varied and ranged: 0 years (0.6%), 1- 10 years (19.5%), between 10 and 19 years (41.9%), between 20 and 29 years (26%) and >=30 years (18%). Demographic characteristics were further used in Barnard's exact test to test the relationship between local people's demographic characteristics and their perceptions relating to climate change and drought (Table 3.6). The analysis found that gender, education, ethnic group and the ability to access information are factors that significantly influence local people's perceptions of climate change and drought; with statistically significant values for gender at a 95% confidence level and for education, ethnic group and ability to access information at a 99.9% confidence level (Table 3.6).

3.4.3. Perceptions of local people regarding climate change as related to extreme events.

Irrespective of interviewees' demographic profile, over 91% of interviewees had noticed changes in climate (precipitation and temperature) and extreme events over time (Figures 3.5 and Figure B.5). Regarding annual mean precipitation and temperature, the results showed that over 95% of the surveyed respondents had noticed a decrease in rainfall and over 95% had noticed temperatures increasing over the last 5–10 years (Figures 3.5). A large proportion of interviewees (96%) had noticed considerable climatic changes in the last 5–10 years. In addition, Barnard's exact test did not show any significant differences in perceptions of climate change and drought between interviewees with less than or equal to 30 years farming experience and residence time and those with over 30 years farming experience and residence time (see Table A.5). Moreover, Barnard's exact test also illustrated that there were no significant differences in climate change perception between respondents with and without agricultural income sources. However, there was a significant difference in perceptions relating to drought between respondents with agricultural and non-agricultural income sources (see Table A.5). These results are in agreement with those of (Manandhar et al., 2015). The findings indicated that most of the surveyed respondents perceived that local precipitation has tended to decrease and temperature has tended to increase, while the number of rainy days during the dry season and the number of days with heavy rain were less than before (Figure 3.5a).

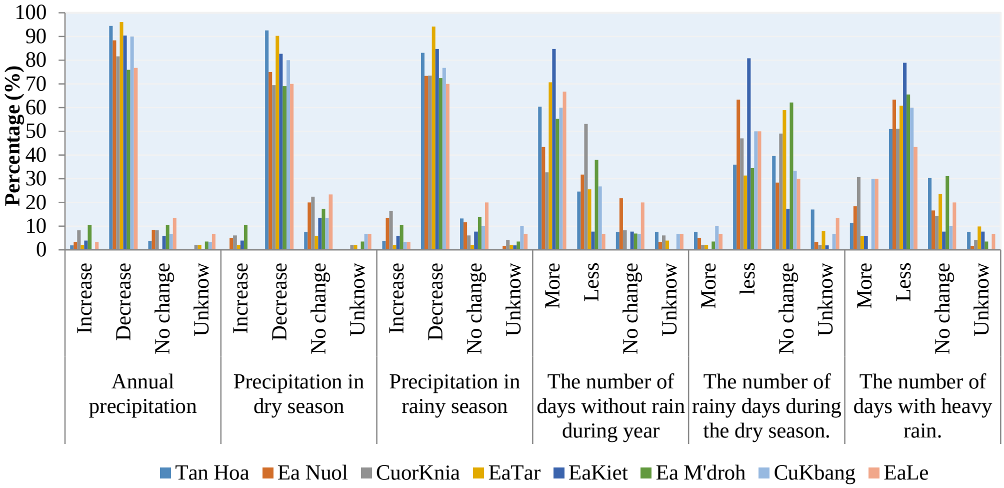
Regarding extreme event occurrences in the previous ten years, over 96.04% of interviewees (70.0% in Eale) reported one or more droughts in their locality and over 34.75% attested to being affected by tornadoes. Less reported were floods (7.06%) and storms and landslides (combined, 1.69%) (Figure B.5).

Table 3.6. Barnard test performed between respondents' characteristics and their perceptions of climate change and extreme events, including drought

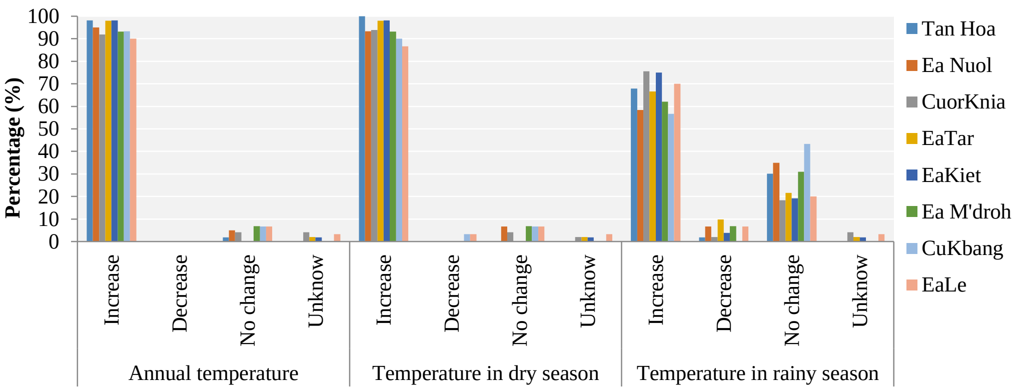
	Climate change concepts			Climate change related to extreme events			Drought concepts		
	Number of respondents		Barnard test p-value	Number of respondents		Barnard test p-value	Number of respondents		Barnard test p-value
Gender	disagree	agree		disagree	agree		disagree	agree	
Female	103	70	**0.042**	103	70	**0.042**	40	133	0.606
Male	88	93		86	95		37	144	
Education									
Primary school or Less	78	20	**1.80E-09**	78	20	**7.38E-10**	35	63	**2.51E-04**
Secondary school or higher	113	143		111	145		42	214	
Ethnic group									
Kinh	96	120	**6.80E-06**	94	122	**3.00E-06**	42	174	0.197
Ethnic minorities	95	43		95	43		35	103	
Ages									
>50 years old	68	51	0.515	68	51	0.359	25	94	0.836
<=50 years old	123	112		121	114		52	183	
Access to information on climate change									
No	144	11	**3.80E-42**	144	11	**3.1E-43**	46	109	**0.003**
Yes	47	152		45	154		31	168	
Income source									
Agriculture	182	150	0.228	181	151	0.102	68	264	**0.025**
Non-agriculture	9	13		8	14		9	13	
Time resident in current area									
>30 years	61	48	0.641	60	49	0.721	29	80	0.145
<=30 years	130	115		129	116		48	197	
Farming experiences									
>30 years	17	22	0.184	17	22	0.228	10	29	0.606
<=30 years	173	141		171	143		67	247	

p-value<0.05 statistically significant at the 95% confidence level, p-value <0.001 statistically significant at the 99.9% confidence level

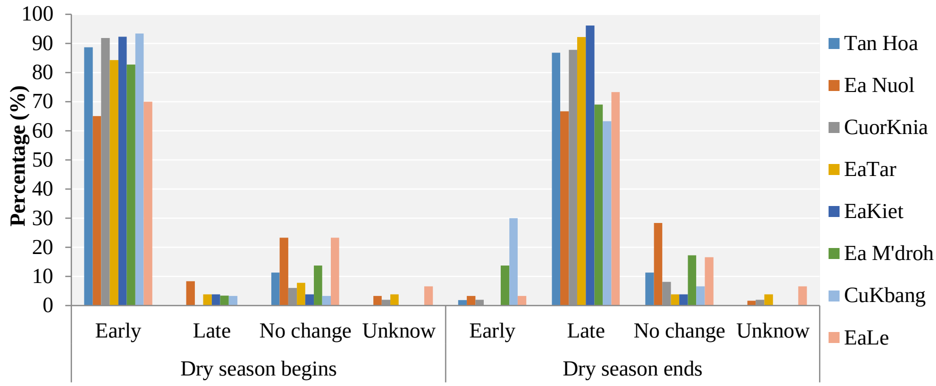
Local people simply perceived drought as a long duration with scarce, late or no rainfall. Overall, 96.04% of households had experienced droughts. They had also noticed dry seasons beginning earlier and ending later, with ranges between 65.0–93.3% and 63.3–96.2% of respondents, respectively (Figure 3.5c). Furthermore, the majority noticed that in their locality over the last ten years drought had become more frequent, intensity more serious and duration lasted longer (Figure B.6). Most local people (54.24%) claimed that land-use change was a cause of drought (Figure B.7); 39.6%, 27.1% and 28.2% of them assumed it was due to lack of rain, high temperature or climate change, respectively.



(a). Local people's perceptions of changes in precipitation



(b). Local people's perceptions of changes in temperature



(c). Local people's perceptions of changes in season

Figure 3.5. Percentage of households in the eight communes of the study area perceiving changes related to local (a) precipitation, (b) temperature, (c) season

3.4.4. Perceptions of local people regarding the impacts of drought in their locality in recent years.

The results indicated that local people have suffered various impacts of drought in their locality (Figure B.8). Over 96% of respondents (Eale 70%) had noticed drought problems in the last ten years. The majority of interviewees in all communes (over 60%) pointed to serious reductions in the water levels of surface water resources (rivers, streams, lakes, etc.) and of groundwater wells. Such declines in surface water and groundwater resources affected farming practices and households' water use. In addition, over 55% of the respondents interviewed recognised that drought had a serious economic impact on them because of its effects on agriculture, the main livelihood in the study area. Over 55% (36% in Eale) of interviewees said that drought caused crop plants to wilt and 60% (40% in Eale) said that drought reduced plant growth.

Approximately 68% (43% in Eale) of households faced crop yield losses and over 56% faced serious income reductions. Furthermore, 30% of interviewees also reported damage to their property (e.g. house and farm-related machinery) and health problems due to drought. Most of the respondents said that their local and livelihood activities faced difficulties due to drought. However, over 46–80% of the households in all communes did not adjust their farming practices and had no or few solutions to mitigate the effects of drought (see figure B.9). Climate change adaptation measures suggested were changing crops, adopting advanced irrigation, timely drought forecasts, regulating reservoirs, recycling water, and agricultural insurance. Of the households in Eakiet and Eale communes, 40% and 44%, respectively, accorded high and medium priorities to adopting the adaptation strategies of crop changes and advanced irrigation. In Eale, 20% of households gave a medium priority and 40% gave a high priority to regulating the reservoir for storing water.

3.4.5. Comparison between perception's local people and meteorological data

Local people's perceptions of climate change regarding changes in precipitation, temperature or other markers of a changing climate (survey choices were 'increase', 'decrease', 'no change' and 'I don't know' for changes in annual precipitation, precipitation during the dry season, precipitation during the rainy season, and seasonal change in precipitation); temperature (survey choices were 'increase', 'decrease', 'no change' or 'I don't know' for changes in annual temperature, temperature during the dry season and temperature during the rainy season); and the occurrences of extreme events (drought, flood, etc.) were compared with meteorological data from local stations.

3.4.5.1. Precipitation and temperature

Observations of the interviewees in the study area agreed with the recorded temperature data. The annual temperature and minimum temperature trends in the rainy season in Dak Lak province increased with high Z-values: 3.17 and 5.82, at 99.9% confidence level of significance (Table 3.5). And local people in the communes of all three districts in Dak Lak province felt that in the last ten years there had been increases in annual temperatures (90–98% of respondents), dry season temperatures (86.7–100% of respondents) and rainy season temperatures (56.7–75.5% of respondents), as seen in Figure 5b. Thus, the results indicated that the majority of local people correctly perceived temperature changes. However, 19.2–43.3% of local people perceived no temperature changes in the rainy season.

Figure 3.5a shows local people's perceptions relating to precipitation trends. Most noticed changing rainfall patterns and more frequent extreme events. The majority had notice a decrease in annual (75.9 – 96.1%), rainy season (70.0 – 94.1%) and dry season (69.0 – 92.5%) rainfall. In contrast, nearly 0.0—10.3% of respondents reported an increase in annual precipitation over the last ten years, 0.0—10.3% reported an increase in dry-season precipitation over the same period and 2.0–16.3% reported an increase in rainy season precipitation over the same period. Table 3.3 shows the annual and rainy-season precipitation for the entire study area as a decreasing trend with negative Z value and Sen's slope. But the decrease is not significant at all because of the high variation in inter-annual precipitation, while dry-season precipitation has significantly increased over the 38 years from 1981–2018. Local people's perceptions relating to dry-season precipitation were not consistent with the meteorological data: only 0.0–10.3% thought that the amount of precipitation in the dry season had increased.

Figure 3.5a also shows that 32.7–84.6% of local people perceived an increase in the annual number of days without rain, 6.7–53.1% noticed a decrease in the annual number of days without rain, 43.3–78.8% considered that the annual number of days with heavy rain is lower than it was ten years ago and 7.7–31% had noticed 'no change' in the annual number of days with heavy rain in recent years. Table 3.4 indicates that CDD for the entire study area has increased with no statistical significance. This means that, in terms of the annual number of days without rain, the perception of most local people is not in agreement with the meteorological data analysis; only 6.7–21.7% of them agree with the meteorological data that there has been no change. In addition, Table 3.4 illustrates that R20 and R25 trends have increased, but not significantly; and only 7.7–31% of local people's observations are therefore in line with the recorded data.

3.4.5.2. Onset and cessation of rainy season.

In Dak Lak province, most local people's livelihoods are in agriculture. Thus, they pay particular attention to the features of the rainy season. Over 70–96.7% of local people interviewed noticed a long-term change in the onset and cessation of the dry season (Figure 3.5c). The majority said they thought the onset of the dry season had got earlier over the last ten years (65–93.3%), while 0–8.3% reported later onset dates and 3–11% thought that onset dates had not changed. Looking at the meteorological data, trends in rainy-season cessation dates for the period 1981–2018 reveal a slight but not significant decrease, suggesting an earlier end to rainy seasons, having shifted over the last 38 years from November to October (Table 3.3, Figure 3.2). However, according to the statistical data analysis there is no clear trend showing a change in the onset date for the dry season. There is therefore no agreement between the meteorological data and local's people perception about increasingly early onsets dates for the dry season. Moreover, there is a mismatch between the meteorological data and local people's perceptions concerning dry season end dates (Figure 3.5c, Table 3.3). According to 63.3–96.2% of respondents, dry season cessation dates in their locality have been delayed in recent years (Figure 3.5c), While the meteorological data shows that the trend for rainy season onset dates seems to be earlier (negative sen slope, but not significant), meaning the end of the dry season is earlier. From Figure 3.2 it can be seen that average rainfall onset fluctuates between April and May. However, the latest rainy season onset dates were for 2015–2016, when the end of the dry season was very late. People tend to reminisce about impressive recent experiences (Manandhar et al., 2015). Therefore, the cessation dates of the dry season in recent years are in line with local people's perceptions of extreme drought as they experienced it in 2015–2016. Moreover, Table 3.3 indicates that the trend of rainy season duration has a declining tendency with a negative Z-value. In other words, the length of the rainy season seems to be shorter, but due to high inter-annual variability of the meteorological data this trend is not statistically significant for the onset or cessation of the rainy season.

3.4.5.3. Drought events

Interviewees also noticed that there were (more) extreme events in their locality in the last ten years (Figure B.5) and over 95% of them had observed droughts. The findings described in Figure B.6 show that most of the respondents believed that drought events had increased, became more serious and lasted longer compared to previous years. This trend is confirmed by Table 3.4 and Figure B.2, which show the trend of CDD increasing over the last 38 years in the study area, while the trend of CWD is decreasing. However, these trends are not significant due to high inter-annual variability of precipitation. In addition, SPI3 values (moderate drought with threshold <-1) reveal a higher frequency of drought events for eight of the last ten years (2008–2018). Figure 3.4b shows that extreme events (flood and drought) were significantly increasing. Those results are in agreement with local people's perceptions, as demonstrated in Figure B6 which indicates that over 80–98% of respondents claimed there had been an increase in drought frequency. Furthermore, most interviewees said that the intensity of droughts was more serious in the last ten years (84–96%) and their duration lasted longer (80–98%) (Figure B.6). In the past five years (2014–2018), the study area has experienced severe droughts in 2014, 2015 and 2016—with SPI3, SPI6, and SPI12 indices less than -1.5 (severe and extreme droughts). Especially in 2015, there were extremely severe drought conditions in the first and last three months of the year. Thus, local people's perceptions of the frequency, intensity and duration of droughts in the period 2014–2018 are in agreement with the scientific observations based on SPI indices in the study locations over the same period (Figure 3.4).

3.5. Discussion

In recent years it has become more important to integrate local people's perceptions of climate change and drought with the kind of measured meteorological data that informs adaptation measures (Manandhar et al., 2015). This study analysed local people's perceptions regarding changes in precipitation and temperature, and compared these perceptions with scientific observations. Nearly 46% of the surveyed interviewees are aware of concepts relating to climate change and 56% of them have accessed knowledge on climate change and drought from various sources. In addition, a majority (over 91%) have observed climatic changes (in rainfall amount and temperature) in their locality over the last ten years. The results of this study reveal a significant difference (at the 95% and 99.9% confidence level) in perceptions of climate change and extreme events related to climate change, between different demographic and socio-economic features of households (along the lines of gender, education level, ethnicity and access to information about climate change) (Table 3.6). Other studies have suggested that famers' perceptions relating to climate change and the adaptive measures they adopt depend on their level of education (Ayanlade et al., 2017; Roco et al., 2015), their social environment and income (Ayanlade et al., 2017; Zheng and Dallimer, 2016). The findings in this study confirm that education level, media (i.e. access to information) and income are important factors that influence the perceptions of local people in conceiving adaptation strategies to cope with climate change and drought. These results are useful for supporting risk management for local governments that wish to develop programmes focusing on local people's understanding of drought adaptation measures.

The results of this study reveal that the majority of local people (over 86%) correctly observed increases of annual minimum and maximum temperatures in the rainy season, in agreement with the meteorological data. In contrast, while 80% of the respondents thought that precipitation patterns had changed during the last ten years and that there had been a decrease in annual, rainy and dry season rainfall, this was not confirmed by analysing the meteorological rainfall data. Local people's observations related to long-term decline in precipitation could be explained by the reliance of their perceptions on recent experiences of precipitation variability (increasing consecutive dry days, changes in late onset and early cessation of rainy season, and precipitation distribution) rather than on observed average amounts of annual precipitation (Amadou et al., 2015). Hence, this might be the reason why local people perceive a decrease in annual and dry season precipitation even though the actual measured data shows no significant change in trend (Amadou et al., 2015). In addition, most interviewees' perceptions did not agree with the historical meteorological data concerning the rising trend for dry season precipitation; only 2–16% of them correctly observed this.

Rainy season characteristics (onset, cessation and length) are key information for agricultural activities in the study area. The majority of local people therefore pay a lot of attention to these features. However, it appears that they incorrectly perceived the evolution of rainy season characteristics. They believed that the dry season now starts earlier and ends later compared to the past ten years. This is not correct, since the analysis of rainy season data showed that both onset and cessation dates occur earlier, and the length of the rainy season is only a little shorter, but with no significant trend due to high fluctuation in the onset, cessation and length of the rainy season over the last 38 years.

It seems impossible for inhabitants of this region to have a correct perception of the evolution of rainy season characteristics because the inter-annual variability of precipitation is too great and masks the slow evolution of rainy season characteristics linked to climate change.

Climate change is a slow process, which people find very difficult to pinpoint because they find it difficult to precisely recall past events. They are very strongly influenced by events of the recent past, which heavily skew perceptions of a slow phenomenon like climate change. In this case, the survey was carried out in the dry season after people had experienced significant droughts in the recent past; events that left traces on people's memory. If the survey had been carried out in the rainy season after relatively rainy years, perceptions of local people would probably have been very different. Human's observations of climate are therefore very imperfect and we must be wary of them when analysing events taking place over a long term (i.e. several decades).

Regarding drought occurrences and amplitudes in their locality, the perceptions of an overwhelming majority (95%) of respondents aligned correctly with the scientific observations based on the trend of SPI variance indices (Figure 3.4, Figure B.5). Both local people's perceptions and the meteorological data showed that timing and pattern, especially precipitation variability, had changed, despite the fact that there is no significant change in trend of rainfall amount nor SPI values. Despite the absence of rainfall amount trends, dry seasons were getting dryer because of temperature increases in the study area. Similarly, (Hasan and Kumar, 2019), Mkonda et al. (2018) and Ayanlade et al. (2017) also demonstrated that farmers' perceptions of temperature trends were consistent with meteorological data. In the study area, most local people perceived a change in the climate, but over 46–80% of households in all communes did not adjust their farming practices and had applied no or few solutions to mitigate the effects of drought (see Figure B.9). These results provided useful information for local government and decision-makers in developing local people's capacity to cope with drought and in planning for water resource management in Dak Lak province.

3.6. Conclusion

The study's findings reflect that local people's values and observations influence their actions, and that their perception of weather and climate may be taken into consideration as a consistent indicator of their awareness. Besides, people tend to reminisce about impressive recent experiences. Thus, local people's perceptions of climate change are correct only for a short recent period, which is not enough for monitoring a slow process such as climate change. The study results also reveal that the majority of local people had observed impacts of climate change and drought on their localities such as decreasing water levels in surface and groundwater, fading crops, plant stress, reduction in crop yields, reduction in income, and damage to property and health. However, most of them did not have adaptation strategies to mitigate the impact of drought such as changing crops, moving to advanced irrigation, drought early warning and forecasting, regulating reservoirs, recycling water, or agricultural insurance. Moreover, poor farming communities have been declared to be the most vulnerable group in developing countries to climate change and natural disasters, as they have insufficient adaptive capacities (IPCC, 2007b). Improving the livelihoods and adaptation capacities of people in these localities is therefore increasingly urgent. Furthermore, this study also reveals that access to information on climate change is an important factor with considerable effect on the likelihood of local people taking measures to mitigate the negative impacts of drought. Thus, the findings of this study provide valuable information to local governments and policymakers in improving local people's livelihoods. First, improved drought early warning and forecasting systems in each commune should give timely notice to local people, thereby advancing their preparedness in adaptation measures to cope with the negative impacts of climate change and drought. Second, local governments and policymakers should organise information dissemination or training sessions to raise local people's awareness of adaptation strategies such as diversification of crop types and varieties, changing to drought-resistant varieties, advanced irrigation and agricultural insurance.

Acknowledgements

This research was supported under the project MP10 2.21 funded by Wallonie-Bruxelles International organisation.

Supplementary material

Appendix - A

Table A. 1. Summary of households interviewed

District	Buon Don			Cu M'gar			Ea Sup	
n = 354	Tan Hoa	Ea Noul	Cuor Knia	Eatar	EaKiet	Ea Mdroh	EaLe	CuKbang
Number of households interviewed	53	60	49	51	52	29	30	30
Crop farmers (%)	86.79	90.00	81.63	98.04	96.15	100.00	96.67	96.77
Livestock famers (%)	20.75	15.00	24.49	13.73	13.46	13.79	16.67	54.84
Both crop and livestock farmers (%)	16.98	11.67	16.33	11.76	13.46	13.79	16.67	54.84
Others (%) (service+others)	18.87	35.00	18.37	3.92	19.23	3.45	23.33	0.00

Table A. 2. The surveyed information analyzed in this research.

Variable	Question	Type
Household information	- Gender - Age - Ethnic group - Education level - Monthly income - Resident time - Income source - Years of farming experience or livelihood activity	Ordinal Nominal Ordinal Ordinal Ordinal Ordinal Ordinal Ordinal
Perception of climate change	- What is your understanding of climate change? Climate change is: Long-term changes in temperature, rainfall, humidity… Extreme weather events (drought, flood, and tsunami) frequently occur and have a severe impact - Through which channels/sources of information did you hear about 'climate change'? - Over the last 10 years, what has the weather been like in your locality: Rainfall (dry season rainfall, rainy season rainfall, dry season onset and cessation)	Ordinal Ordinal Ordinal

	Dry season temperature and rainy season temperature Extreme weather and local disasters (what kinds of natural disasters occur frequently? extent of damage, frequency, time of disasters)	
Perception of drought	- What is your understanding of drought? - Causes of drought - Have you ever experienced any droughts? - If any, in how many of the past 10 years did drought occur. - Over the past 10 years, what has been the drought frequency, influence, and drought period?	Ordinal Ordinal Ordinal Ordinal Ordinal
The impacts of drought	- Decreasing water levels in rivers, streams and ponds - Decreasing groundwater levels - Crop plants (coffee, pepper…) withering - Reduced crop growth time - Reduced crop yields (coffee, pepper, etc…) - Reduced income - Poverty damage (pumps, water containers, houses, etc…) and damage to health (flu, dengue fever, etc…) - Other opinion (if any)	Ordinal Ordinal Ordinal Ordinal Ordinal Ordinal Ordinal Ordinal
Measure to reduce the impacts	- Change crops (adjust planting plan) or use plants that consume less water - Change to advanced irrigation solutions: drip irrigation, saving irrigation - Communication, timely forecast information - Regulation of local reservoirs and irrigation works - Recovering water through farm ponds or reservoirs - Agricultural insurance	Ordinal Ordinal Ordinal Ordinal Ordinal Ordinal

Table A. 3. Descriptive statistics for annual precipitation data series over the period 1981–2018 at three rainfall stations

Stations	**Min. (mm)**	**Max. (mm)**	**Median (mm)**	**Mean (mm)**	**SD (mm)**	**CV (-)**	**Skewness (-)**	**Kurtosis (-)**
Buon Ma Thuot	1347	2598	1800	1854	303.90	0.16	0.48	-0.45
Ban Don	930.4	2788	1544	1599	319.64	0.20	1.18	3.52
Buon Ho	1158	1970	1605	1563	221.95	0.14	-0.21	-1.00
Study area	1023	2546	1576	1619	272.86	0.17	0.82	2.34

SD: standard deviation; CV: coefficient of variation

Table A. 4. Descriptive statistics for annual temperature data series over the period 1981–2018 at Buon Ma Thuot station

	Min. (°C)	Max. (°C)	Median (°C)	Mean (°C)	SD (-)	CV (-)	Skewness (-)	Kurtosis (-)
Tmin	10.3	25.7	21.1	20.68	1.81	0.09	-1.02	1.40
Tmax	16.7	38.7	29.7	29.55	2.87	0.10	-0.22	0.11

Table A. 5. Summary of demographic and farming characteristics

Variables	Mean or percentage (%)
Education of interviewees	
No education	9.9
Primary	19.5
Secondary	45.8
High school	23.4
College	7.5
Ethnic group	
Kinh	61
Nung	11.3
Tay	6.2
Thai	0.3
Dao	4.2
E de	16.1
Tho	0.3
M'nong	0.6
Gender of interviewees	
Male	51.1
Female	48.9
Length of farming experience (years)	
1-10 years	19.5
10–19 years	41.9
20–29 years	26
>= 30 years	18
No experience	0.6
Livelihood strategies	
Crop farming	84.5
Livestock	19.2
Crop and livestock	16.7
Others	16.7
N	**354**

Appendix – B

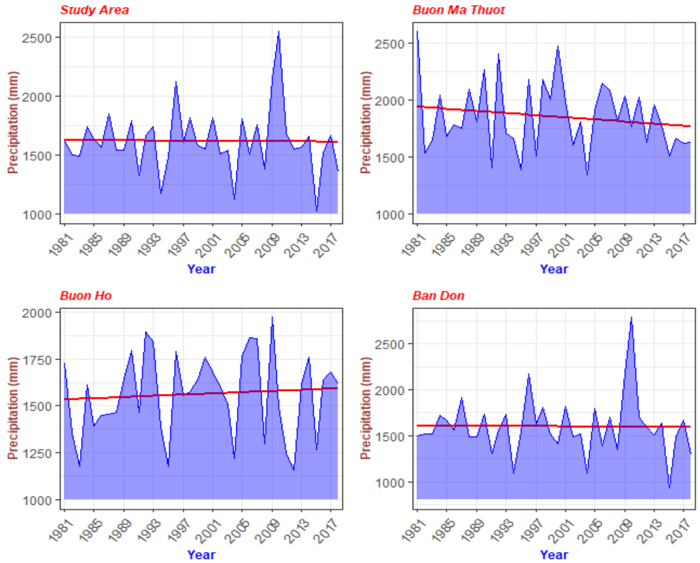


Figure B. 1. Annual precipitation trend analysis for the whole study area and the three stations (BMT, Ban Don, Buon Ho station)

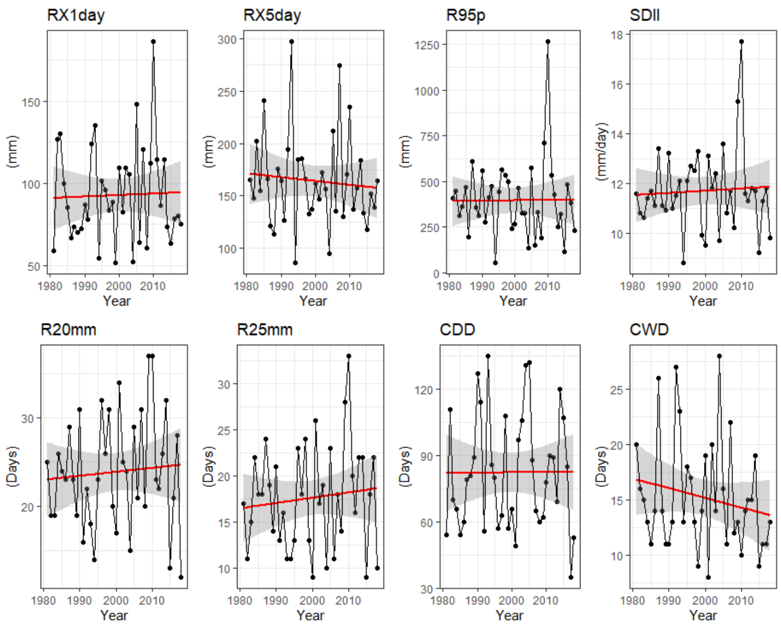


Figure B. 2. Inter-annual variations of spatially averaged extreme precipitation indices for the period 1981–2018. The grey solid line indicates arithmetic average values of the three stations. The black dotted line indicates the annual average level. The red line shows the trends.

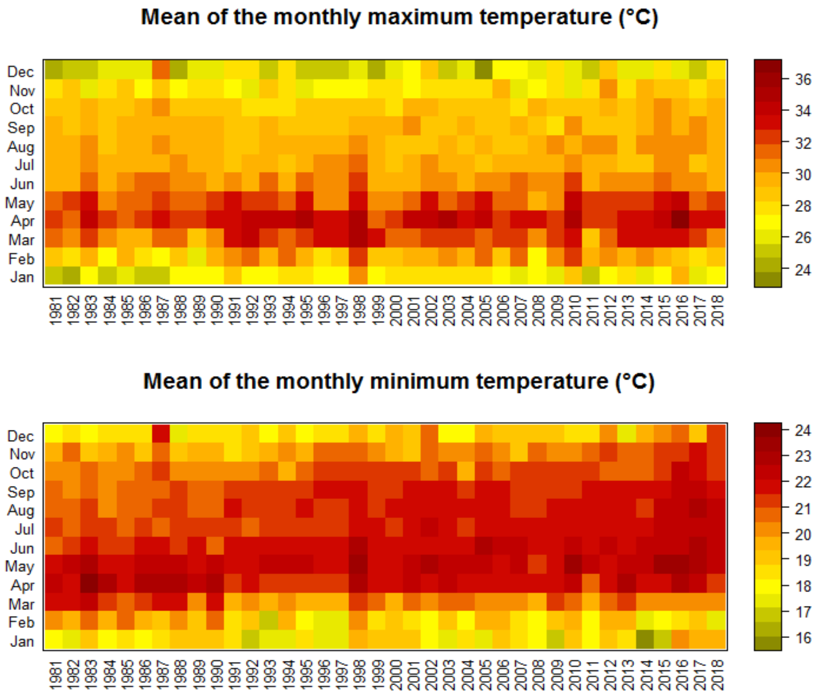


Figure B. 3. Monthly min and max temperature for each year at Dak Lak (BMT Station)

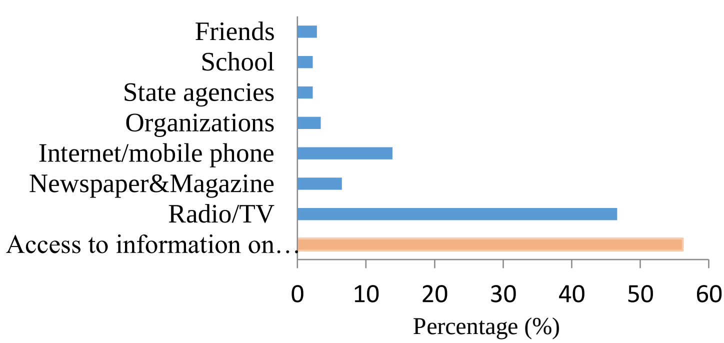


Figure B. 4. Percentage of people aware of climate change in the study area, and their information sources

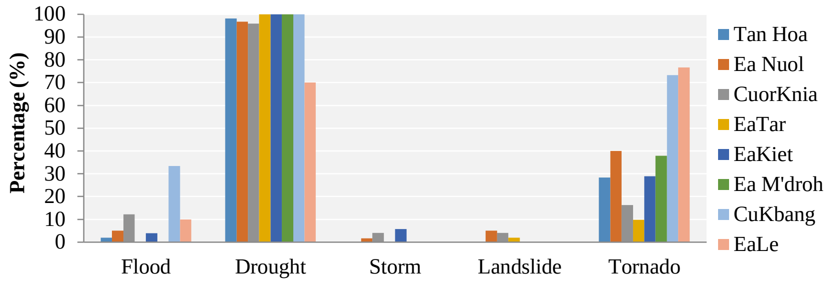


Figure B. 5. Percentage of respondents who observed occurrences of extreme events in Dak Lak province in the last 10 years

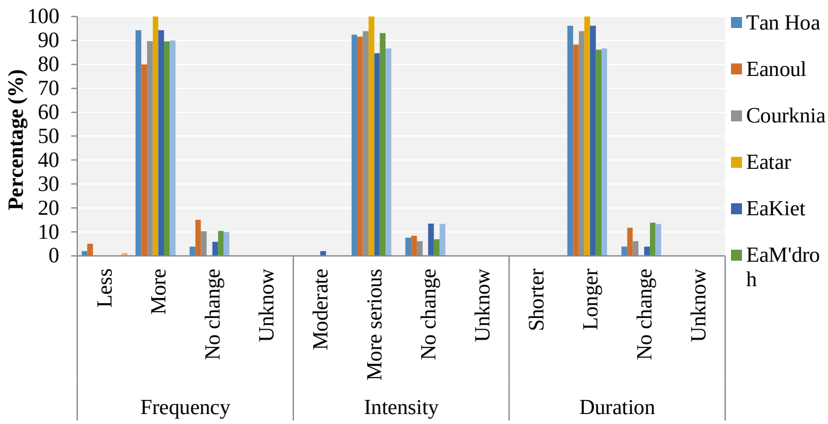


Figure B. 6. Households' perceptions of drought characteristics in their locality

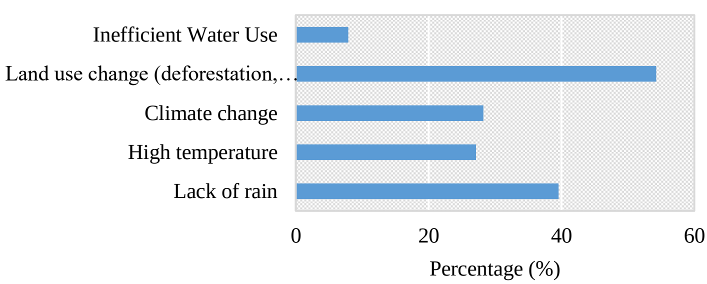


Figure B. 7. Percentage of households perceiving the cause of drought in their locality

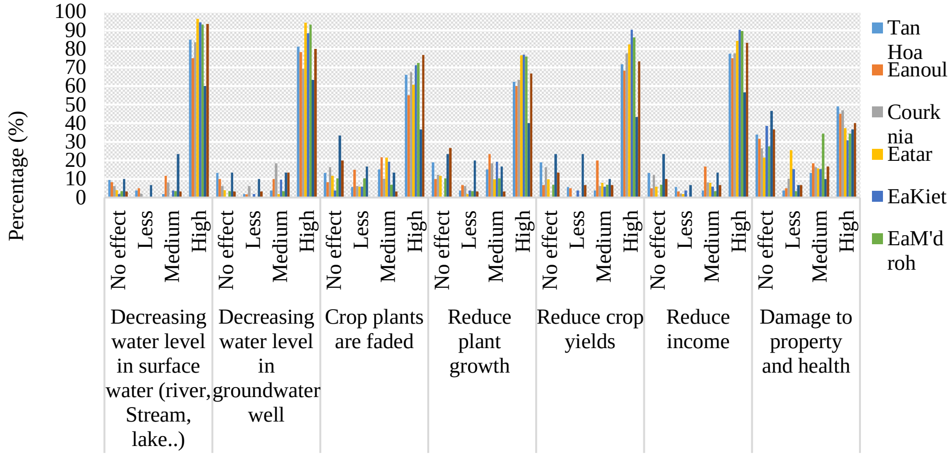


Figure B. 8. Local people's perceptions of the impacts of drought in their locality in recent years

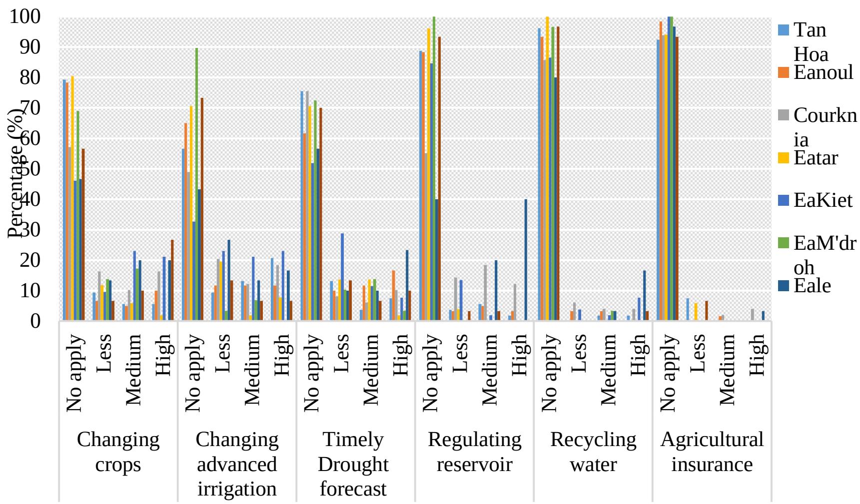


Figure B. 9. Local people's solutions to mitigate the effects of drought in their locality

Chapter 4. Early prediction of coffee yield in the Central Highlands of Vietnam using a statistical approach and satellite remote sensing vegetation biophysical variables

This chapter was adapted from the following publication:

Nguyen Thi Thanh Thao, Dao Nguyen Khoi, Antoine Dennis, Luong Van Viet, Joost Wellens, Bernard Tychon: Early Prediction of Coffee Yield in the Central Highlands of Vietnam Using a Statistical Approach and Satellite Remote Sensing Vegetation Biophysical Variables. *Remote Sens.* 2022, *14*(13), 2975; https://doi.org/10.3390/rs14132975. Published: 22 June 2022

Abstract

Given the present climate change context, accurate and timely coffee yield prediction is critical to all farmers who work in the coffee industry worldwide. This study aims to develop and assess a coffee yield forecasting method at the regional scale of Dak Lak province, in the Central Highlands of Viet Nam, by using the Crop Growth Monitoring System Statistical Tool (CGMSstatTool–CST) software and vegetation biophysical variables (NDVI, LAI, and FAPAR) derived from satellite remote sensing (SPOT-VEGETATION and PROBA-V). There has been no research yet on applying this approach to this specific crop, which is the main contribution of this study. The findings of this research reveal that the elaboration of multiple linear regressions models based on the combination of information coming from satellite-derived vegetation biophysical variables (LAI, NDVI, and FAPAR) corresponding to the first six months of the years 2000–2019 resulted in coffee yield forecast models presenting satisfactory accuracy (Adj.R2 = 64 to 69%, RMSEp = 0.155 to 0.158 ton/ha, and MAPE = 3.9 to 4.7%). These results demonstrated that the CST may efficiently predict coffee yields on a regional scale by using only satellite-derived vegetation biophysical variables. This study's findings are likely to aid local governments and decision makers in precisely forecasting coffee production early and promptly, as well as in recommending relevant local agricultural policies.

Key words: coffee yield forecast, remote sensing vegetation biophysical variables, early prediction, CGMSstatTool, Viet Nam, LAI, NDVI, FAPAR

4.1. Introduction

Coffee is one of the most crucial agricultural products in the world market, playing a significant part in the economy of several developing countries in equatorial and subequatorial regions (Africa, America, and Asia) (Kouadio et al., 2021; Pohlan and Janssens, 2015; Ubilava, 2012). Currently, two coffee bean species, *Coffee arabica* L. (Arabica coffee) and *C.canephora* Pierre ex A. Froehner (Robusta coffee) account for 99% of coffee production in the world coffee trade (DaMatta et al., 2019; Kouadio et al., 2021). Coffee is grown in approximately 80 tropical countries and contributes to the economic basis of many of these countries. In addition, about 25 million farmer families produce coffee worldwide, with most being smallholders and families whose source of revenue largely depends on this crop (DaMatta et al., 2019). Coffee is a climate-sensitive perennial plant, likely to be highly influenced by changes in climate. The rising climate variability may lead to coffee yield decrease, to coffee areas damage, and threaten coffee production in producing areas worldwide (Pham et al., 2019; Piato et al., 2020). Extreme weather events such as severe droughts or excess precipitation in these parts of the world associated with the El Nino Southern Oscillation (ENSO) significantly influence the coffee production in the world market (Kouadio et al., 2021; Ubilava, 2012).

Viet Nam has been the world’s second largest exporter of coffee beans with a total coffee production of 25.73 million 60 kilogram bags (1544 million metric tons) on average in the period 2011–2021, accounting for roughly 20 percent of the world’s coffee production (ICO, 2021; USDA Foreign Agricultural Service, 2021), and the largest world producer of robusta coffee (Kouadio et al., 2021). The Central Highlands area is one of the most critical places for Vietnam’s economy because it is the largest producer of coffee beans in Vietnam (Kouadio et al., 2021; Thao et al., 2019) with mainly robusta coffee (Kouadio et al., 2021). Robusta coffee yield is influenced by the interaction of precipitation, temperature, and phenological stages. Robusta coffee reacts better to rising temperatures than arabica coffee (Jayakumar et al., 2017; Kath et al., 2020; Piato et al., 2020) and is considered more resistant to climate change than other coffee species (Kath et al., 2020). In recent years, the increasing temperatures and variability of precipitation in Vietnam’s sub-regions were associated with the El Nino Southern Oscillation. (Nguyen et al., 2014; Van Viet, 2021). Weather data indicated lower precipitation and higher average temperatures than mean conditions in Vietnam's major coffee-growing areas for the first five months of the calendar year 2020, causing lower yields and reduced production (Vo, 2021). Therefore, it is necessary to provide decision makers with support tools enabling forecasting of coffee yield and production in order to facilitate the development of management strategies and of the economic evaluation of coffee production for the different stakeholders of the coffee industry, from smallholder farmers to governmental authorities.

Several studies have already developed models to simulate and predict coffee production. Gutierrez et al. (1998) developed a model to simulate the vegetative growth process of arabica coffee as age–mass structured populations of stem, root, and leaves and enabled branch level computation of leaf area index at any stage of coffee development. Furthermore, Rodríguez et al. (2011) built a model to simulate the phenology, growth, and development of the coffee plants, based on the physiologically based models of Gutierrez et al. (1998). The model inputs consisted of soil parameters (e.g., nitrogen and water) and daily meteorological data. This model easily incorporated other coffee varieties in different ecological zones where coffee is cultivated (Rodríguez et al., 2011). The model has been successfully calibrated for the Colombian and Brazilian regions, two areas with different climates and flower phenology (subtropical and equatorial) (Vezy et al., 2020). Van Oijen et al.(2010) also developed a simple dynamic model of coffee agroforestry systems that models the physiology of vegetative and reproductive growth of coffee plants and their response to different cultivating conditions. The strengths of this model are its ease of use, its speed, and that it can be run under changing climates. Growing conditions such as weather conditions (temperature, rain, light, humidity, and wind), soil conditions (initial organic matter and nitrogen content, water balance, etc.), tree management (choice of species, density, etc.), and coffee management (rotation length, fertilization, and pruning regime) are addressed as inputs by the model. Rahn et al. (2018) applied it in two sites of East Africa with different climates. It was also calibrated and modified successfully in two different coffee-growing sites in Costa Rica and Nicaragua by Ovalle-Rivera et al. (2020). In addition, Vezy et al. (2020) designed a DynAC of model to incorporate a plant-scale reproductive phenology formalism of the Rodríguez et al. (2011) model. It was based on canopy temperature, with distinct sub-modules in order to obtain suitable adjustment of coffee and shade tree management, density, and tree species, as in the model of Van Oijen et al. (2010) (i.e., canopy temperature-dependent phenology and the submodules for agroforestry system management). Kouadio et al. (2021) also successfully tested a process-based model using satellite remote sensing data (LAI) and model-based gridded climate data for predicting robusta coffee yield in the Central Highlands of Vietnam. Kouadio et al. (2021) indicated that one of the limitations they encountered was the unavailability of distinct production statistics for arabica and robusta coffee. Aside from the process-based model (Kouadio et al., 2021), Kouadio et al. (2018) developed a model based on an artificial intelligence approach using soil fertility properties for predicting robusta coffee yield in the Lam Dong province of Vietnam. Furthermore, Molina et al. (2018) successfully calibrated the Aquacrop model for predicting arabica coffee in Colombia. The input databases for this application contained the parameters associated with the climatic variables, soil, crops, and management practices.

Most of the aforementioned models simulate coffee yields accounting for the growing conditions. These models mainly depend on the data collected on the field and observed weather data. The accuracy of such models depends also on the accurate descriptions of crop management practices (e.g., crop variety, sowing date, fertilization, irrigation), while collecting such data in a sufficiently accurate manner is difficult at the regional scale (Fall et al., 2021). Furthermore, several years of experimental data to train and calibrate models to the local environmental conditions are necessary for these crop models, and when they are applied in other regions, they have to be recalibrated (Fall et al., 2021).

Due to the limitations of these models, statistical models such as multiple linear regression have been widely utilized to link crop yields to climate variables (Laudien et al., 2020; Tebaldi and Lobell, 2008) or even intermediate output variables from process-based crop models (Nain et al., 2004). Despite not being directly based on the mechanisms of plant growth, statistical models can effectively predict crop production (Fall et al., 2021). The main benefits of statistical models are their limited dependence on field calibration data and their clear assessment of model uncertainties (Lobell and Burke, 2010). Statistical models typically perform better as the availability and quality of observable data improve (Fall et al., 2021).

Among the various tools and methods that enable the development of statistically based models, the “Crop Growth Monitoring System Statistical Tool” (CgmsStatTool – CGMS statistical tool - CST) (Goedhart et al., 2019) is independent software for forecasting crop yield based on initial indicator databases derived from crop models, climate data, or remote sensing data (Kerdiles et al., 2017). The CST was developed by the MARS (Monitoring Agriculture with Remote Sensing) unit of the European Union (EU) Joint Research Centre (JRC) to support the development and selection of crop yield forecast models in order to assist national or sub national crop yield forecasting activities (Goedhart et al., 2019). The CST plays a crucial role in scientific decision-making in the EU agricultural economy (Goedhart et al., 2019). The CST has been effectively applied to some main crops' growth monitoring and yield forecasting in Northeast China (Qing et al., 2012). Fall et al. (2021) also used the CST to predict millet yield at a regional scale in Senegal with input data containing weather data combined with variables derived from remote sensing indicators (NDVI). The CST enables simple examination of data quality, analysis of crop yield time trend, and construction of crop yield forecasting models through three methods: (1) multivariate regression analysis; (2) scenario analysis, which is a method of forecasting that looks for the previous years that are most similar to the current year based on a set of indicators and combines their yields (Fall et al., 2021); (3) the moving average analysis model that is simply based on the average yields of the most recent years, preceding the target year. The CST calculates a number of statistics that allow choosing the best crop yield forecast model for a given region and time of prediction. Another advantage of the CST is its ability to test multiple models rapidly (Fall et al., 2021; Goedhart et al., 2019).

With the development of satellite imagery, agricultural monitoring systems have been using agro-meteorological indices coming from the spectral reflectance of the vegetation to provide timely and concise information about seasonal vegetative growing (Rembold et al., 2015). Remote sensing derived vegetation indices (e.g., the Normalized difference vegetation index, NDVI) and biophysical variables (e.g., the Fraction of Absorbed Photosynthetically Active

Radiation, FAPAR; the Leaf Area Index, LAI) can be used to predict crop yield, either directly or indirectly (Balaghi et al., 2010; De Wit et al., 2012). In addition, remote sensing vegetation variables enable estimating crop growth variability to quantify the crops' relative development and health conditions (Araya et al., 2017). Such vegetation indices and biophysical variables are the most common satellite products utilized for these purposes (Rembold et al., 2015). At the national and regional levels, satellite systems can contribute effectively to early warning of crop stress during the growing period and in forecasting harvest yields (López-Lozano et al., 2015; Rembold et al., 2015). Bernardes et al., (2012) observed, in the Brazilian largest coffee-exporting province and from a dataset covering the 2002-2009 period, correlations between variations of the yield of coffee plots and variations of MODIS derived EVI and NDVI vegetation indices computed from pure coffee crop 250 m pixels overlapping the same coffee plots. The vegetation index metrics best correlated to yield were the amplitude and the minimum values over the growing season. The best correlations were obtained between the variation of yield and variation of vegetation indices of the previous year ($R^2 = 0.55$). In another study, Nogueira et al., (2018) evaluated the relationships between coffee productivity of some coffee plantations in Brazil and values of NDVI, SAVI and NDWI vegetation indices derived from LANDSAT-8-OLI sensor for different coffee phenological phases. They concluded that the best phenological phases of coffee to determine coffee productivity from spectral indices were the stages of dormancy and flowering. The results also indicated that the NDVI was the best index to estimate the productivity of coffee trees, with the coefficient of determination (R^2) ranging from 0.58 to 0.90.

The objective of this research is to develop and assess a coffee yield forecasting method at the regional scale of Dak Lak province, in the Central Highlands of Vietnam, by using the Crop Growth Monitoring System Statistical Tool (CGMSstatTool – CST) software and vegetation biophysical variables (NDVI, LAI, and FAPAR) derived from satellite remote sensing (SPOT-VEGETATION and PROBA-V).

The findings of this study are expected to assist local governments and decision-makers in accurately forecasting coffee yields early and in a timely manner, as well as in recommending appropriate strategies for local agriculture.

4.2. Study area

The study was carried out in Dak Lak province, located in the Central Highlands of Vietnam in the Lower Mekong River Basin. The total area is 13125 km2, and in 2019 the population of Dak Lak province was 2.127 million people. Currently, Dak Lak province includes Buon Ma Thuot city, Buon Ho town, and 13 districts.

In Dak Lak province, agriculture is the main source of local livelihoods. The area’s geographic coordinates are from 107° to 109° east longitude and from 12° to 13° north latitude (Figure.4.1), with an elevation range of 400–800 m. Dak Lak province is dominated by a humid tropical climate. Generally, the area’s climate varies depending on the altitude: below 300m it is hot all year round, and in the range of 400–800 m, it is hot and humid (DakLak provincial people’s committee, 2022). There are two distinct seasons in Dak Lak province: a rainy season from May to October with approximately 80–85% of annual rainfall and a dry season from November to April, which is generally dry and sunny (15–20% of annual rainfall). Dak Lak province is an agricultural area with perennial crops such as coffee, pepper, cashew, and fruits which play an important part in its economy. The region also produces annual crops such as rice, maize, sweet potato, vegetables, sugarcane, groundnut, and soybean (CCAFS-SEA, 2016). Dak Lak has 209955 ha of coffee area, accounting for nearly 31% of the country's coffee area (DakLak Statistical Office, 2021). For Dak Lak province, coffee exports represented 86% of the total agricultural exports and over 60% of total yearly province income. In addition, coffee production employs more than 300000 direct workers and more than 100000 indirect workers (Huong and Anh, 2019). The vast majority of coffee trees are part of coffee tree plantations where coffee trees are the main vegetation story. Irrigation was applied one to four times per year from 2008 across robusta coffee in Dak Lak province (on average 1345 litre/tree/year, i.e. 148 mm/year). The stated irrigation quantities varied based on rainfall patterns during the coffee growing season (Byrareddy et al., 2020).

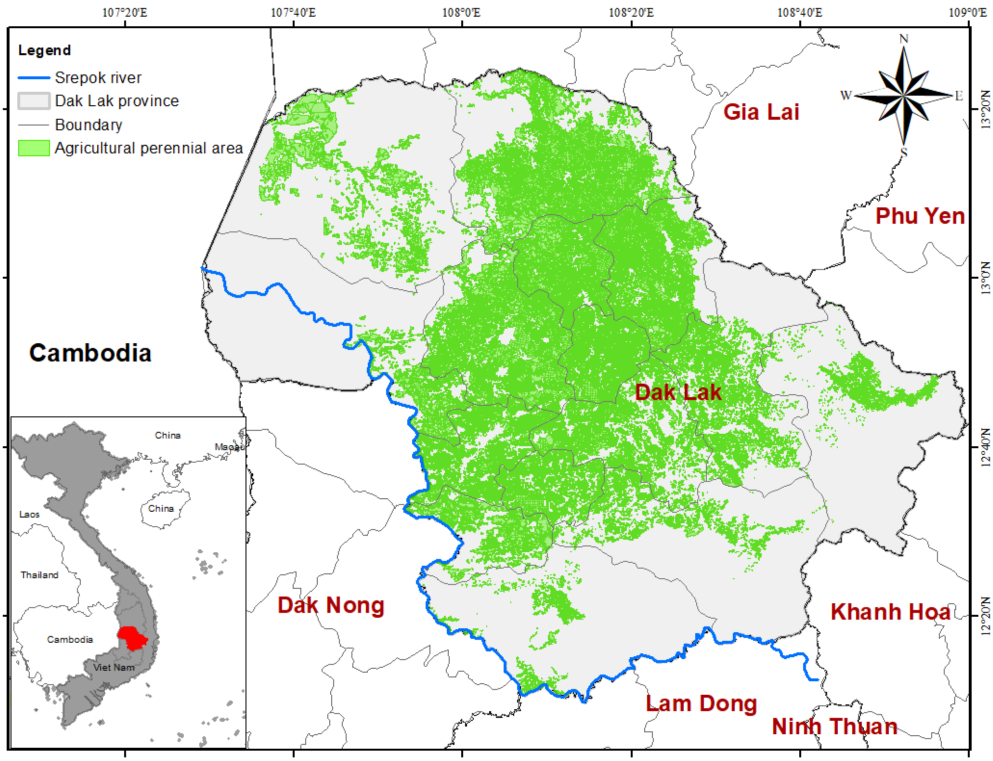


Figure 4.1. Dak Lak province with the agricultural perennial planted area in green.

4.3. Methodology

The proposed methodology is based on multiple linear regression modeling using, on the one hand, the official coffee yields of Dak Lak province and, on the other hand, phenological variables derived from the seasonal dynamics of the satellite-derived biophysical variables NDVI (normalized difference vegetation index), LAI (leaf area index), and FAPAR (fraction of absorbed photosynthetically active radiation).

The general methodology workflow followed in the research is presented in Figure 4.2 and further detailed below.

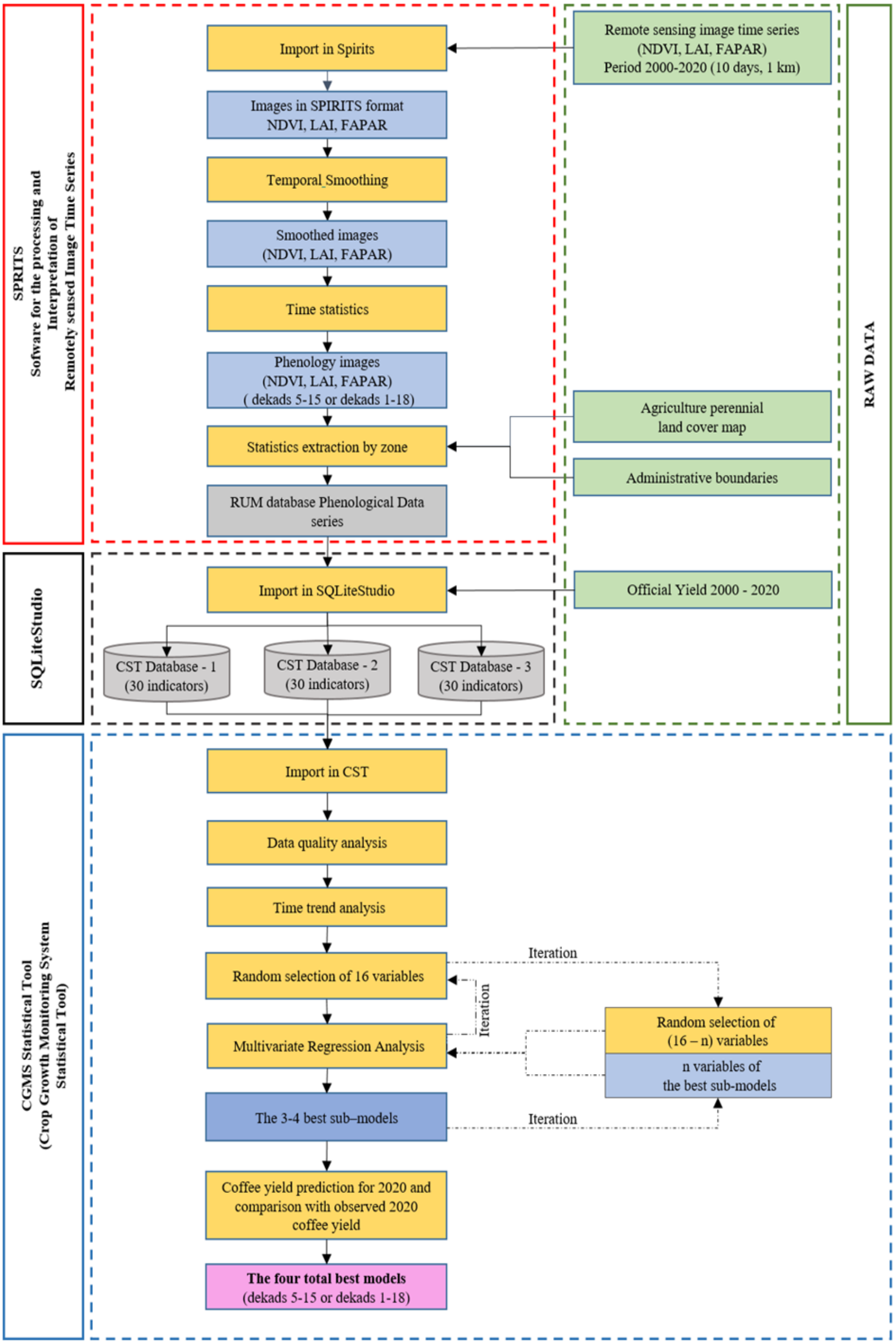


Figure 4.2. General workflow of the coffee yield forecasting method. Green rectangles: raw input data; yellow rectangles: data processing; blue rectangles: intermediate data; gray rectangles: variable databases; and pink rectangle: final results.

4.3.1. Phenological variables from remote sensing time series

4.3.1.1. Vegetation biophysical variables.

Coffee yield forecasting is based on satellite imagery from Copernicus Hub 2022 (source: *https://land.copernicus.vgt.vito.be*), namely NDVI, LAI, and FAPAR available at a decadal (10-day) time step for the entire study area in Dak Lak province and the same years as the official coffee yield statistics (Table 1). The 2000–2020 time series of decadal LAI, NDVI, and FAPAR products (21 years x 36 dekads/year) derived from the SPOT-VEGETATION and PROBA-V instruments were used in this study. The products are freely available at a 1km Global spatial resolution.

"The normalized difference vegetation index (NDVI) is an indicator of the greenness of the vegetation biomes." (source: https://land.copernicus.eu/global/products/ndvi). NDVI has theoretical values ranging from -1 to +1, where negative values mostly correspond to clouds, water, and snow, while values near zero primarily correspond to rocks and bare soil (Fall et al., 2021). NDVI rises progressively with vegetation development.

"The Leaf Area Index is defined as half the total area of green elements of the canopy per unit horizontal ground area. The satellite-derived value corresponds to the total green LAI of all the canopy layers, including the understory which may represent a very significant contribution, particularly for forests. Practically, the LAI quantifies the thickness of the vegetation cover." (source: https://land.copernicus.eu/global/products/lai).

"The FAPAR quantifies the fraction of the solar radiation absorbed by live leaves for the photosynthesis activity. Then, it refers only to the green and alive elements of the canopy." (source: https://land.copernicus.eu/global/products/FAPAR).

In Vietnam, the coffee phenology can be presented in five periods: (i) the flower-bud initiation and blooming season is from January to March; (ii) the fruit setting period is from April to May; (iii) the cherry development period is from May to August; (iv) the maturity stage is from September to October; (v) the ripening/harvest period is organized from October to December (Kouadio et al., 2021). Two periods were considered in this study to compute the explanatory variables used in the search for coffee yield prediction models. The first period corresponds to 11 dekads, from mid-February to the end of May (dekads 5 to 15). This period was considered because it corresponds to the crucial period of growth and development of the coffee bush (Titus and Pereira, 2017). February to May are normally dry months in Viet Nam, and coffee requires irrigation to guarantee blossom and cherry settings (Vo, 2021). The second period corresponds to 18 dekads, from January to June (dekads 1 to 18). This period was considered because a longer period may be more representative of the global coffee development conditions and consequently result in variables that have a higher explanatory power. Additionally, the objective of the methodology developed in this research being to produce models that enable to forecast coffee yield well in advanced compared to the harvest period of October to December, it was decided to make the coffee yield forecast at the end of June at the latest. Indeed, using the first six months of the year to predict coffee yield will give planners sufficient time to consider or find solutions before the end of the coffee season

4.3.1.2. Processing of satellite images in SPIRITS software

The NDVI, LAI, and FAPAR satellite image time series were processed in the free Software for Processing and Interpreting of Remote Sensing Image Time Series (SPIRITS) (Eerens and Dominique, 2013) (Figure 4.2).

- First, images were imported and temporally smoothed with the SWETS algorithm (Swets et al., 1999) that was set with a maximum of 75% of missing values in each pixel profile, and the lowest physical value Ymin for cloud-free land pixels was kept at the default.
- Second, the 11 phenological variables presented in Table 2 were computed from each of the 3 biophysical products (NDVI, LAI, and FAPAR), considering 2 periods (dekads 5 to 15 and dekads 1 to 18) by using the “time statistics” function of SPIRITS, which resulted in phenological images (Figure 4.2).
- Third, zonal statistics were extracted for these phenological variable images for the perennial agricultural vegetation zone of the Dak Lak province thanks to an extraction mask coming from the official 2015 land use map of Dak Lak province collected from the Department of Agriculture and Rural Development of Dak Lak province (Figure 4.1). This land use map did not contain a class specific to coffee plants but only a broad class

relative to agricultural perennial plants containing approximately 62.5 to 68.2% of coffee only, from 2015 to 2018 (DakLak Statistical Office, 2021, 2019, 2015, 2010). No pure coffee crop mask was available and it was not possible for the authors to produce such mask in the framework if this study. The extracted statistics corresponded to the final 33 coffee yield predictors.

Table 4.1. Remote sensing vegetation biophysical products used in this study and downloaded from Copernicus Global Land Service (CGLS) (https://land.copernicus.vgt.vito.be/)

Remote sensing vegetation biophysical products	**Definition**	**Period**
FAPAR	Fraction of Absorbed Photosynthetically Active Radiation	2000–2020
LAI	Leaf Area Index	2000–2020
NDVI	Normalized Difference Vegetation Index	2000–2020

Table 4.2. The 11 phenological variables derived from FAPAR, LAI, and NDVI time series (extracted using the time statistics function of SPIRITS (Eerens and Haesen 2013) for 2 periods: dekads 5 to 15 and dekads 1 to 18, from 2000 to 2020).

No.	**variables**	**Definition**	**Dekads**
1	vav	Average value (or Mean)	5–15; 1–18
2	vmn	Minimum value	5–15; 1–18
3	vmx	Maximum value	5–15; 1–18
4	aup	Largest increase between subsequent periods	5–15; 1–18
5	adn	Largest decrease between subsequent periods	5–15; 1–18
6	rsd	Relative standard deviation (with N as denominator, not N-1)	5–15; 1–18
7	rrg	Relative range (Maximum–Minimum)	5–15; 1–18
8	dmn	Relative date of (first) minimum value	5–15; 1–18
9	dmx	Relative date of (last) maximum value	5–15; 1–18
10	dup	Relative date of (first) largest increase	5–15; 1–18
11	ddn	Relative date of (last) largest decrease	5–15; 1–18

4.3.2. Official coffee yield datasets.

The coffee yields considered in this study are provincial coffee yields and were computed by dividing the official provincial coffee production by the official provincial coffee area coming from the Dak Lak Statistical Yearbook

2009, 2014, 2018, and 2020 (DakLak Statistical Office, 2021, 2019, 2015, 2010). The period from 2000 to 2020 was considered. These coffee yields correspond to coffee dry grain yield.

4.3.3. Crop yield forecasting model in the CST software

In this study the free software "Crop Growth Monitoring System Statistical Tool" (CgmsStatTool – CGMS statistical tool - CST) (Goedhart et al., 2019) was used to generate the coffee yield forecasting models.

The CST approach that we used in this study was multivariate regression analysis to assess the linear relationship between coffee yield (Y) and one or more independent variable(s) (the predictor(s) X1, X2…) through the following equation 1:

$$Y= \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_n X_n + \varepsilon \quad (1)$$

In eq.1, ε is the random error assumed to follow a normal distribution of mean 0 and constant variance σ^2. Errors for different years are assumed to be independent. In the annotation for the X-variables, the subscript n represents which X-variable it is. $\beta_0 \ldots \beta_n$ are the regression coefficients to be calculated through the ordinary least square method minimizing the difference between the observed and fitted yield values. The CST tests various models, using potentially the crop yield time trend and from 1 to 4 independent variables and, then, exports standard statistics and plots that enable to assessment of the quality of these models.

Analysis in the CST was carried out as follows: (1) check for possible errors in the database of official yields and indicators; (2) assess both linear and quadratic crop yield time trend at a significance level of 0.025; (3) assess the correlation between the indicators, with and without time trend (if any); and (4) search for the best multivariate regression models.

"CST takes the potential time trend into account by adding a term in the model that corresponds to that time trend, if applicable. To increase numerical precision, the regression coefficient for the linear time trend is for "year – offset" rather than "year" itself. The offset is fixed at 1965 by default in CST. Likewise, the regression coefficient for the quadratic time trend is for (year - offset)^2 (Goedhart et al., 2019)."

The period 2000–2019 was used to search and build the best models through the multivariate regression method of the CST.

As the CST can only work with a database containing a maximum of 30 variables, 3 databases of 30 variables were built from the 33 input variables and were used sequentially. With 20 years of calibration data (2000-2019), the CST allows 16 variables to be tested at a time in the regression analysis. Therefore, we iterated a random selection of 16 input variables to find the best models (Figure 4.2).

The automatic selection and ordering of the best models by CST at each CST iteration for a given set of candidate variables was based on the root mean square error of prediction (RMSEp) (equation 2). RMSEp indicates the model's quality under prediction conditions (Fall et al., 2021).RMSEp calculated by the CST is based on the leave one out residual or PRESS residual (Goedhart et al., 2019). Predictions become increasingly precise as RMSEp approaches 0 and R^2 approaches 1. Among each CST iteration the 3 to 4 best sub-models were manually selected based on the RMSEp and on the Adjusted coefficient of determination (Adj.R^2) (equation 3). Adj.R^2 is a statistical measure of the model's goodness of fit in a regression model which shows the proportion of variation explained by the estimated regression line.

$$RMSEp = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(P_i - O_i\right)^2} \qquad (2)^*$$

where:

P_i and O_i are the predicted and observed values for each year i, respectively;

$\bar{O}$ and $\bar{P}$ express the means of observed and predicted values, respectively;

n is the number of samples (years);

k is the number of independent variables in the regression equation

* Note: in Eq.2, P_i-O_i is the difference between the i^{th} observation and the predicted value for the i^{th} observation based on a model fit to the remaining

observations, i.e., without the i^th observations (adapted from(Goedhart et al., 2019)).

$$Adj.R^2 = 1 - \left(1 - R^2\right)\left[\frac{n-1}{n-\left(k+1\right)}\right] \tag{3}$$

Four other statistical parameters (equations 4 to 7) were also used to appreciate the models' performance, but not to select them.

The R-squared (R^2) corresponds to the percentage of variance explained by the model (equation 4) (Fall et al., 2021).

$$R^2 = \left(\frac{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)\left(P_i - \bar{P}\right)}{\sqrt{\sum_{i=1}^{n}\left(O_i - \bar{O}\right)^2}\sqrt{\sum_{i=1}^{n}\left(P_i - \bar{P}\right)^2}}\right)^2 \tag{4}$$

The Relative Root Mean Square Error (RRMSE) is calculated by dividing RMSEp with the mean value of observed data (equation 5).

$$RRMSE(\%) = \frac{RMSEp}{\bar{O}} \times 100 \tag{5}$$

The Mean Absolute Percentage Error (MAPE) (equation 6).

$$MAPE = \left(\frac{1}{n}\right)\sum_{i=1}^{n}\left(\frac{\left|O_i - P_i\right|}{\left|O_i\right|}\right) \times 100 \tag{6}$$

The Residual Standard Deviation (RSD) is the square root of the residual mean square (Goedhart et al., 2019).

$$RSD = \sqrt{\frac{\sum_{i=1}^{n}\left(P_i - O_i\right)^2}{df}} \tag{7}$$

where df is the degrees of freedom. Here, df is equal to the sample size minus the number of parameters in the model. For example: Y= $\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$.

Therefore: df = n-3, where n is the sample size, and the number of parameters is 3.

The year 2020 was used to assess the performance of selected models with an independent year not used in model calibration, by comparing the observed and predicted yield for 2020 and computing the related residuals.

The final selection of the best models was based on a combination of model performance in calibration (2000–2019) and in prediction for 2020.

4.4. Results

4.4.1. Model performance

Using the CST time trend analysis mode, Dak Lak province showed a significant upward linear time trend (p-value of 0.0012) for coffee yields over the period 2000 – 2019 (Figure 4.3).

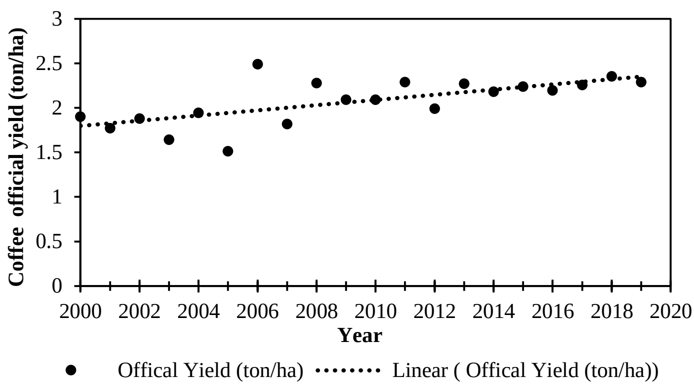


Figure 4.3. Time trend for official coffee yield of Dak Lak province for the period 2000–2019.

Details of the eight best coffee yield models for the Dak Lak province provided by the multivariate regression method of the CST for the two periods considered (mid-February to end of May and early January to end of June), are presented in Table 4.3 and Figure 4.4.

Overall, the forecast coffee yield models performed satisfactorily in both time periods with the RMSEp varying between 0.155 and 0.178 ton/ha, the RRMSE varying between 7.5% and 8.6 %, and the Adjusted-R^2 varying between 62.8% and 68.8% (Table 4.3 and Figure 4.4). The models built on the 18-dekad period provided systematically better results than those built on the 11-dekad period when considering RMSEp and RRMSE only. For models computed on 18 dekads, the RMSEp ranged from 0.155 to 0.158 ton/ha, the Adj. R^2 was between 64.2 and 68.8 %, and the RRMSE ranged from 7.5 to 7.6%. For models calculated on 11 dekads, the RMSEp ranged from 0.174 to 0.178 ton/ha, the Adj. R^2 was between 62.8 and 67.6 %, and the RRMSE ranged from 8.4 to 8.6%.

It seems difficult to clearly identify one best model among those of the 18-dekad period given they all presented very similar global statistical performance when considering all statistical parameters. For example, for the18-dekad period, the best model according to the Adj-R^2 (model 4, Adj-R^2 of 68.8%) is the worst according to the RMSEp (0.158 ton/ha).

The results show that model 0, which corresponded to the linear time trend only, performed less efficiently (RMSEp = 0.202 ton/ha, RRMSE = 9.7%, Adj.R^2 = 41.8%) than models combining a linear time trend with phenological variables derived from the remote sensing data (Table 4.3, Figure 4.4).

For the period considering dekads 1–18 (from January to June), all selected models used three variables in addition to the time trend. Model 1 and model 2 used only the LAI variables; model 3 combined the LAI and NDVI variables; and model 4 combined the LAI and FAPAR variables. For the period considering dekads 5-15, all models used four explanatory variables in addition to the time trend. Model 5 combined the LAI and NDVI variables; models 6, 7, and 8 combined the LAI, NDVI, and FAPAR variables. When considering the 8 best models, LAI derived variables occur 18 times, while NDVI derived variables 6 times and FAPAR derived variables 4 times only. This observation suggests that LAI derived variables are more efficient than NDVI and FAPAR ones for coffee yield forecasting. A relatively high negative or positive correlations was observed between some variables selected in some of the best models (R varies in the range from -0.863 (for Adn_LAI and Dmn_LAI in model 5) to 0.795 (for Vmn_LAI and Dmx_LAI in model 1)) figure 4.5). When considering the period of dekad 1 (start of January) to dekad 18 (end of June) of the years 2000 to 2019, the analysis of the Pearson correlation coefficient of the 11 phenological variables between the three biophysical satellite products LAI, NDVI and FAPAR (figure 4.6) shows a highly variable level of correlation between these phenological variables, from, in absolute value, 0.00 to 0.97, i.e. from no correlation to a very high level of correlation. For this period, the phenological variables derived from FAPAR and NDVI are the most correlated (average absolute correlation of 0.59, 3rd column of figure 4. 6) while those derived from LAI are less correlated to NDVI and FAPAR variables, especially for FAPAR (average absolute correlation of 0.30, 1st column of figure 4.6). The low correlation values observed for at least some phenological variables in each pair of biophysical products (LAI and FAPAR, LAI and NDVI, FAPAR and NDVI) suggests that these three products may bring some non-redundant (uncorrelated) information, and thus be complementary at some point, and consequently that it is relevant to consider the three of them in the search for the best coffee yield prediction models. In addition, the results also showed that models utilizing satellite data from January to June (models 1 to 4) were more suitable for estimating coffee yields in Dak Lak province than models using satellite data from Mid-February to May (lower RMSEp and higher Adj-R^2 for models 1 to 4).

Table 4.3. Details of the eight best coffee yield models for the Dak Lak province based on phenological variables derived from NDVI, FAPAR and LAI for the 2000−2019 time period, with their related statistical perfomrances. Models 1 to 4 are based on the dekads 1 to 18 (January to June) and models 5 to 8 are based on dekads 5 to 15 (mid-Feb to end of May). Model 0 corresponds to the model achieved with the coffee yield linear time trend only.

	Parameter	**Estimate**	**s.e.**	**tvalue**	**RMSEp (ton/ha)**	**RRMSE (%)**	**R^2 (%)**	**MAPE (%)**	**RSD (ton/ha)**
Model 0	Constant	0.774	0.342	2.26					
No dekad	Time trend linear	0.029	7.63E-03	3.83	0.202	9.7	44.8	4.3	0.197
	Constant	0.496	0.361	1.37					
	Time trend linear	0.018	7.30E-03	2.46					
Model 1	dmx-LAI	-0.013	3.84E-03	-3.48	0.155	7.5	71.7	4.3	0.154
Dekads 1-18	rrg-LAI	0.048	0.016	2.91					
	vmn-LAI	0.727	0.231	3.14					
	Constant	0.494	0.362	1.37					
	Time trend linear	0.018	7.30E-03	2.47					
Model 2	dmx-LAI	-0.013	3.85E-03	-3.47	0.155	7.5	71.7	4.3	0.154
Dekads 1-18	vmn-LAI	0.155	0.186	0.83					
	vmx-LAI	0.572	0.197	2.91					
	Constant	0.415	0.346	1.2					
	Time trend linear	0.019	7.39E-03	2.56					
Model 3	dmx-LAI	-8.74E-03	4.27E-03	-2.05	0.155	7.5	72.3	3.9	0.153
Dekads 1-18	dmx-NDVI	-3.58E-03	3.53E-03	-1.01					
	vmx-LAI	0.567	0.194	2.93					
	Constant	1.708	0.592	2.88					
	Time trend linear	0.013	6.79E-03	1.92					
Model 4	ddn-LAI	0.011	3.00E-03	3.65	0.158	7.6	75.4	4.7	0.144
Dekads 1-18	rsd-FAPAR	-0.119	0.046	-2.56					
	vmn-LAI	0.35	0.139	2.52					
	Constant	-0.344	0.412	-0.84					
	Time trend linear	0.015	7.86E-03	1.85					
Model 5	adn-LAI	0.152	0.062	2.43	0.174	8.4	72.6	4.7	0.157
Dekads 5-15	ddn-NDVI	9.96E-03	4.54E-03	2.19					
	dmn-LAI	0.019	6.24E-03	2.97					
	vmx-LAI	0.382	0.144	2.66					

	Constant	3.218	0.972	3.31					
	Time trend linear	0.025	6.10E-03	4.13					
Model 6	adn-NDVI	-9.122	2.602	-3.51	0.177	8.5	76.1	5.6	0.147
Dekads 5-15	ddn-LAI	-0.01	4.03E-03	-2.55					
	ddn-NDVI	0.014	4.44E-03	3.05					
	dmx-FAPAR	-0.028	9.69E-03	-2.9					
	Constant	1.917	0.738	2.6					
	Time trend linear	0.015	9.21E-03	1.67					
Model 7	adn-LAI	0.081	0.039	2.06	0.178	8.6	73.2	5.0	0.156
Dekads 5-15	aup-FAPAR	-1.74	0.673	-2.58					
	rrg-NDVI	-0.067	0.043	-1.55					
	rsd-LAI	0.152	0.055	2.79					
	Constant	1.878	0.754	2.49					
	Time trend linear	0.016	9.36E-03	1.69					
Model 8	adn-LAI	0.081	0.04	2.04	0.178	8.6	72.7	5.3	0.157
Dekads 5-15	aup-FAPAR	-1.806	0.67	-2.7					
	rsd-LAI	0.165	0.063	2.6					
	rsd-NDVI	-0.221	0.151	-1.46					

s.e = standard error, Adj.R^2 = Adjusted R-squared, R^2 = R-squared, RSD = Residual Standard deviation, RMSEp = Root mean square error for prediction, RRMSE = Relative root mean square error (%).

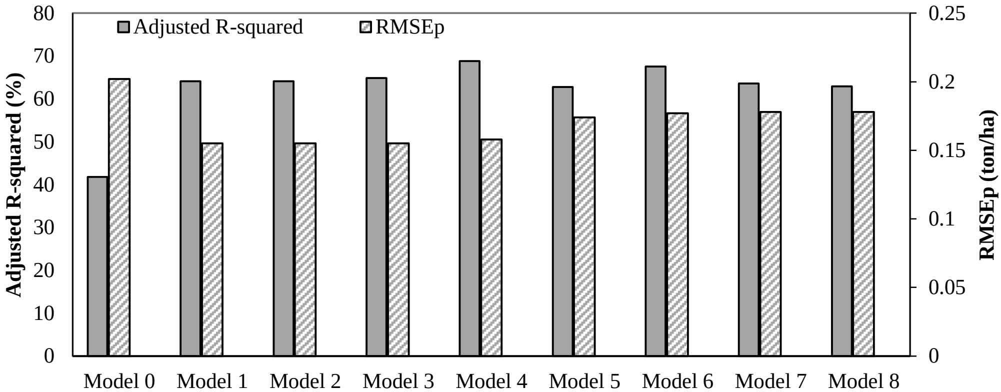


Figure 4.4. Adjusted R-squared and RMSEp of the eight best coffee yield models based on phenological variables derived from NDVI, FAPAR and LAI for the 2000–2019 time period. Models 1 to 4 are based on the dekads 1 to 18 (January to June) and models 5 to 8 are based on dekads 5 to 15 (mid-Feb to end of May). Model 0 corresponds to the model achieved with the coffee yield linear time trend only.

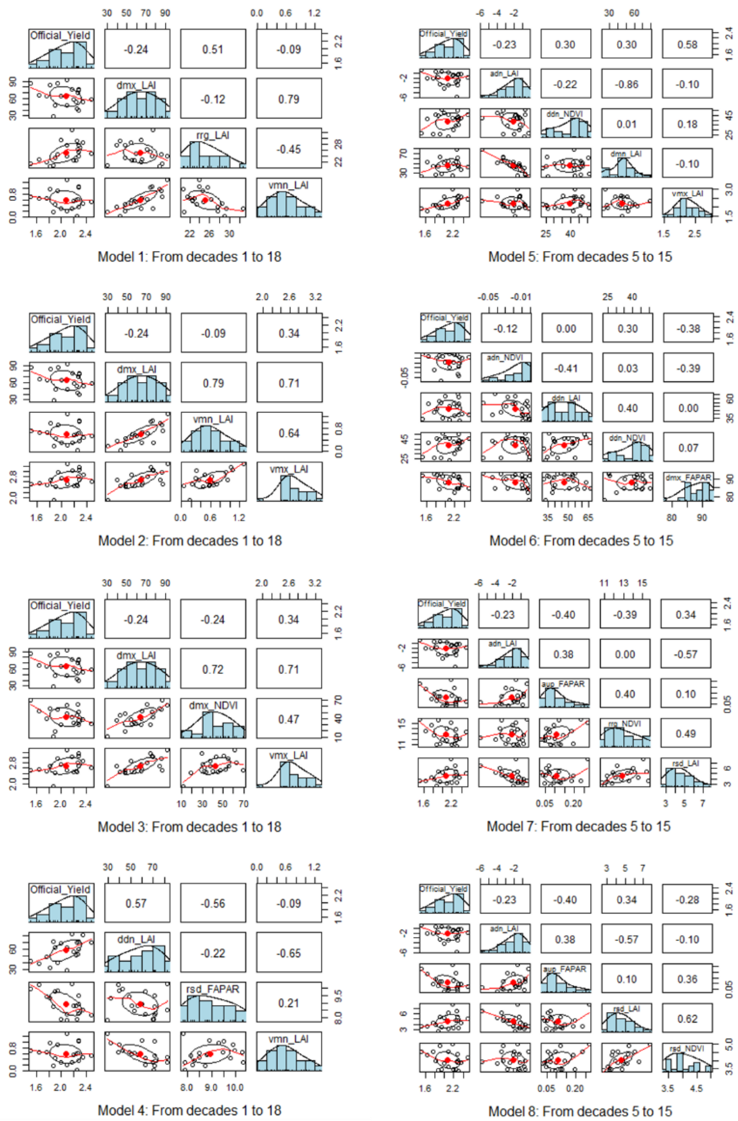


Figure 4.5: Correlation between the phenological variables derived from NDVI, FAPAR, and LAI for the 2000–2019 time period and selected in the eight best coffee yield models. Models 1 to 4 are based on the dekads 1 to 18 (January to June) and models 5 to 8 are based on dekads 5 to 15 (mid-Feb to end of May). The values in the upper right parts of the plots (above the diagonal) are the pearson correlation coefficients between the two variables intersecting the corresponding row and column. On the diagonal is the histogram of each variable, which shows the lowess locally fit regression line. The plots below the diagonal are the bivariate scatter plots of each pair of variables. These scatter plots show an ellipse around the mean (the red point), with the axis length reflecting one standard deviation of the column and row variables. The red line is the smoothed regression lines of the bivariate scatter plots of each pair of variables.

	LAI and FAPAR	LAI and NDVI	NDVI and FAPAR
Adn	-0.09	0.57	0.35
Aup	-0.12	0.47	0.19
Ddn	0.02	0.34	0.63
Dmn	0.00	0.46	0.44
Dmx	0.75	0.72	0.55
Dup	0.45	0.69	0.60
Rrg	-0.42	-0.02	0.47
Rsd	-0.26	-0.11	0.67
Vav	0.59	0.67	0.97
Vmn	-0.20	0.14	0.85
Vmx	0.38	0.17	0.75
Average of absolute correlation value	0.30	0.40	0.59

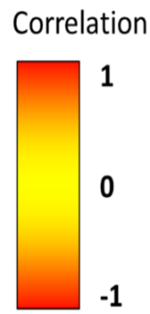


Figure 4.6: Pearson correlation coefficient of the 11 phenological variables, computed over the period of dekad 1 (start of January) to dekad 18 (end of June) of the years 2000 to 2019, between the three biophysical satellite products LAI, NDVI and FAPAR.

4.4.2. Coffee yield predictions for 2020

Table 4.4 shows the residuals and percentage residuals of predicted coffee yields for the target year 2020 for the eight selected models. For models based on dekads 1 to 18 (models 1 to 4), the absolute residuals were in the range of 0.054 to 0.134 ton/ha, and the absolute percentage residuals were in the range of 2.2 to 5.5%. For models based on dekads 5 to 15, three models presented absolute residuals in the range of 0.248 to 0.571 ton/ha and absolute percentage residuals in the range of 10.2 to 23.6% , and one model (model 5) with a better performance presented a residual of 0.082 ton/ha and a percentage residual of 3.4%. The best model in terms of prediction for 2020 was model 3 with a residual of 0.054 ton/ha and a percentage residual of 2.2%. The 2020 residuals for the models 1–4 (Table 4.4) were all smaller than the corresponding RMSEp of the period 2000–2019 (Table 4.3), while the 2020 residuals for the models 5–8 (Table 4.4) were generally much higher than the corresponding RMSEp of the period 2000–2019 (Table 4.3).

Table 4.4. Coffee yield predictions for 2020 based on each model

	Predicted yield (ton/ha)	Yields offical (ton/ha)	Residual (ton/ha)	Percentage Residual (%)
Model 1	2.558	2.424	0.134	5.5
Model 2	2.558	2.424	0.134	5.5
Model 3	2.478	2.424	0.054	2.2
Model 4	2.298	2.424	-0.126	-5.2
Model 5	2.506	2.424	0.082	3.4
Model 6	2.995	2.424	0.571	23.6
Model 7	2.176	2.424	-0.248	-10.2
Model 8	2.171	2.424	-0.253	-10.4

Observed versus model-predicted coffee yields for the period 2000–2020, are presented in a series of scatterplots in Figure 4.7. The predicted values used in these plots were those predicted with the models calibrated on the 2000–2019 period.

These plots revealed the highest R^2 (0.76) for model 4, combining Ddn-LAI, rsd-FAPAR, vmn-LAI, and yield linear time-trend as predictor variables (Figure 4.7). For models based on data from January to June, the four selected models (model 1 to model 4) indicated an R^2 in the range of 0.73 to 0.76 and a p-value of <0.0001 (Figure 4.7).

The models based on data from mid-February to May presented an R^2 ranging from 0.66 to 0.75 and a p-value of <0.0001 (Figure 4.7).

In 2006, most models underestimated the official yields by approximately 0.249 to 0.470 ton/ha.

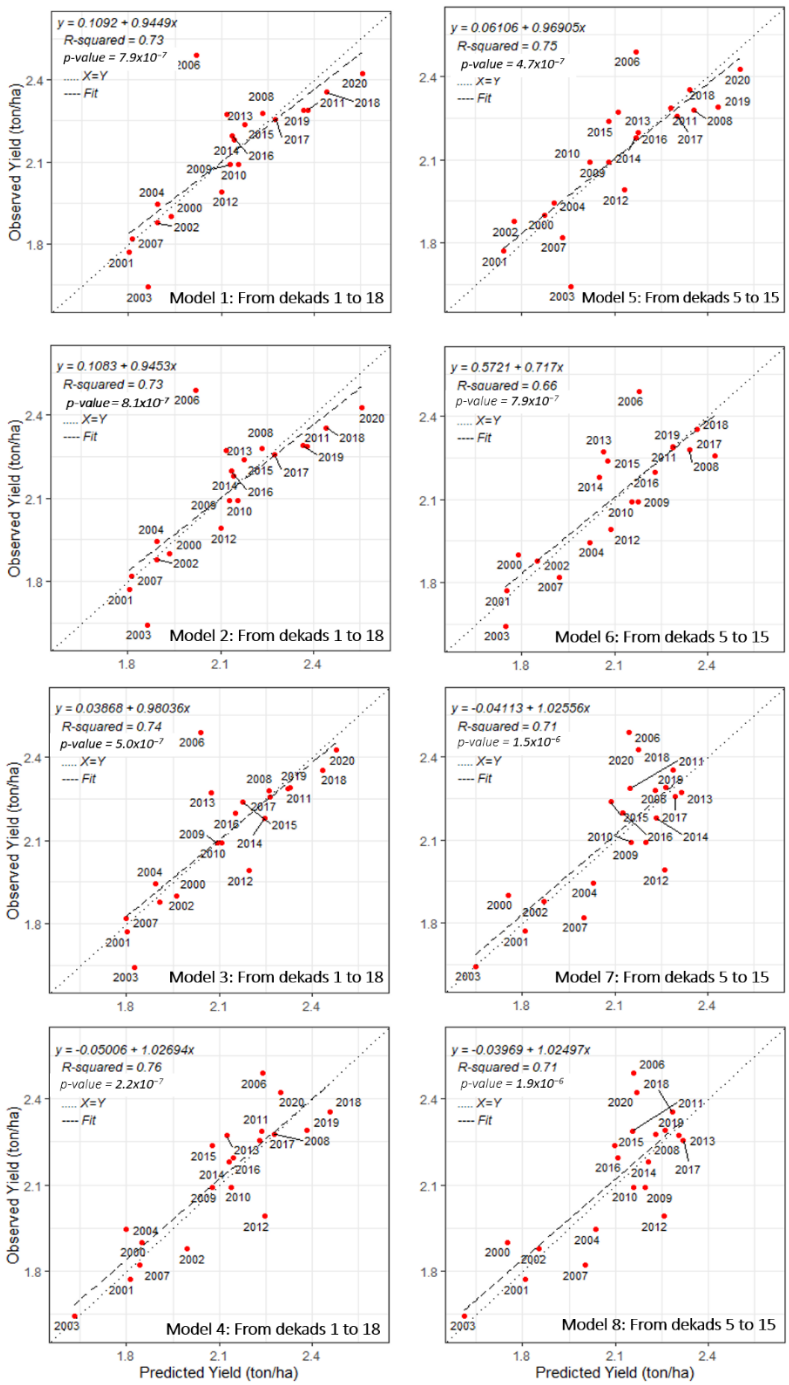


Figure 4.7. Scatter plot of observed versus model-predicted coffee yields for the years 2000 to 2020, using the eight best selected models based on satellite data for the period from dekads 1 to 18 (models 1 to 4) and for the period from dekads 5 to 15 (models 5 to

8). For model 6, the predicted value for the year 2020 is 3.0 ton/ha that is outside the plot frame. R-squared and p-values reported on this figure are those of the relation between observed versus predicted yield for the full period 2000-2020.

4.5. Discussion

The observed positive coffee yields time trend in Dak Lak province over the past 20 years can be explained by a combination of factors including investments in irrigation infrastructure, a heavy reliance on irrigation in coffee farms, the affordability of fertilizer, and the increasing adoption of new management techniques in the province (Byrareddy et al., 2020; Kouadio et al., 2021).

Existing coffee models usually simulate and forecast coffee yields at a local or regional level by including as parameters the main growth and development processes as impacted by climate variations. However, in this study, the results showed that it is possible to predict coffee yield at a regional scale, here in the Dak Lak province of Viet Nam, six months before the harvest based on remote sensing data only. Thus, such models can be an essential tool for indirectly assessing the impacts of weather variability or farmer practices' improvement on coffee yields at the provincial or district level in Viet Nam or any other coffee-growing regions or countries under climate change conditions.

We noticed from Figures 4.3 and 4.5 that 2006 showed the highest observed coffee yield, which corresponded also to the year with the lowest model accuracy. We have no information that could explain such a high yield in 2006. In particular, the precipitation in 2006 was not particularly high.

Compared to the coffee yield forecast models developed by Kouadio et al. 2018 and Kouadio et al. 2021, most of the models developed in this study showed a higher accuracy (RMSEp = 0.155 to 0.178 ton/ha, RMSE = 0.123 to 0.134 ton/ha, RRMSE = 7.5 to 8.6%, and MAPE = 3.9 to 5.3%) (Table 4.3). Indeed, the model of Kouadio et al. 2018 that consisted of an Extreme Learning Machine (ELM) model using as explanatory variables the soil organic matter (SOM), available potassium, and available sulphur, provided coffee yield estimates for Lam Dong provinces (belonging to Central Highlands of Viet Nam) with an RMSE of 0.496 ton/ha, an RRMSE of 13.6%, and MAPE = 7.9%. In addition, the simple process-based model developed by Kouadio et al. 2021 for simulating and forecasting robusta coffee yield at the regional scale in Viet Nam showed a RMSE of 0.24 to 0.33 ton/ha and a MAPE = 9 to 14%, and that model was successfully tested using satellite remote sensing data (LAI) and model-based gridded climate data (maximum and minimum temperatures, solar radiation, and rainfall): MAPE ≤ 12% and RMSE ≤ 0.29 ton/ha.

This study reveals that the method enabled building models that can forecast the coffee yield satisfactorily with a low RMSEp and a high Adj.R^2 for Dak Lak province. It was also shown that the period considered for the production of the model explanatory variables (dekads 1 to 18 versus dekads 5 to 15) has an important impact on the accuracy of the resulting models, with better accuracy for those considering a more extended period. The models based on a longer period were also composed of fewer explanatory variables (three variables + the time trend) than those based on a shorter period (four variables + the time trend).

When selected in models, the variables aup-FAPAR, dmx-LAI, dmx-FAPAR, and dmx-NDVI presented systematically negative values, which may mean that the smaller the "largest increase between subsequent periods" of the FAPAR will be, and the sooner the "date of maximum" LAI, FAPAR, and NDVI occur, the higher the coffee yield will be. Furthermore, the variables derived from the LAI product were shown as more efficient for coffee yield forecast model than those derived from NDVI and FAPAR, though some complementarity was observed between these products for some models (Table 4.3).

No other research was carried out before on combining NDVI, FAPAR, and LAI remote sensing derived phenological variables in the CST to create the coffee yield prediction model, which is the main contribution of this study. The data used in this study were derived from the SPOT-VEGETATION and PROBA-V instruments at a 1km global spatial resolution. Therefore, future studies should consider using the more recent and similar products derived at 300m spatial resolution.

The main technical limitations we encountered in this research are related to the fact that the CST cannot handle a database containing more than 30 variables, and that, with 20 years of data used for model calibration, the CST cannot consider more than 16 variables at a time during the multiple linear regression model search. These two technical limitations of the CST make its use more difficult than it should be.

In this research, we used a multiple linear regression technique in order to produce coffee yield prediction models. Such technique is particularly suited to identify and use the linear relationships between the predictors and the dependent variable. However the linearity of the relationship between coffee yield and the phenological variables was not assessed in this study and it may be possible that some variables present a nonlinear relationship with yield. Consequently, further research might be interested in testing other nonlinear modelling approaches for predicting coffee yield from biophysical variables such those used in this study.

The findings of this study show that satellite data such as the NDVI, LAI, and FAPAR products provided by the Copernicus Global Land service are a good source of information for estimating and forecasting coffee yield in a challenging situation, where there is a deficit of information about management practices, soil characteristics, irrigation schedule, phenology of coffee trees, etc.

We think that a main source of improvement of the coffee yield forecast model developed in this research would probably be the use of a more detailed land use map containing a class specific to coffee. Indeed, the official 2015 land use map of Dak Lak province used to extract satellite derived vegetation biophysical variables did not contain a class specific to coffee plants but only a broad class relative to agricultural perennial plants containing approximately 62.5 to 68.2% of coffee only, from 2015 to 2018 (DakLak Statistical Office, 2021, 2019, 2015, 2010).

4.6. Conclusions

This research is the first to develop and assess a coffee yield forecasting method at the regional scale for Dak Lak province, in the Central Highlands of Vietnam, by using the Crop Growth Monitoring System Statistical Tool (CGMSstatTool – CST) software and vegetation biophysical variables (NDVI, LAI, and FAPAR) derived from satellite remote sensing (SPOT-VEGETATION and PROBA-V).

The findings of this research reveal that the elaboration of multiple linear regressions models based on satellite-derived vegetation biophysical variables

(LAI, NDVI, and FAPAR) corresponding to the first six months of the years 2000–2019 resulted in coffee yield forecast models presenting satisfactory accuracy (Adj.R^2 = 64 to 69%, RMSEp = 0.155 to 0.158 ton/ha, and MAPE = 3.9 to 4.7%). These results demonstrated that the CST may efficiently predict coffee yields on a regional scale by using only satellite-derived vegetation biophysical variables. This study's findings are likely to aid local governments and decision-makers in precisely forecasting coffee production early and promptly, as well as in recommending relevant local agricultural policies.

Further research may consider applying the developed method to search for coffee yield forecast models at other scales (at district and national levels), with enhanced input data (finer spatial resolution for satellite images, and more accurate coffee maps) and with other explanatory variables.

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Chapter 5. General conclusions and outlook

5.1. General conclusion

Drought phenomena are common in Vietnam, and the government has been strongly concerned in recent years. It can happen at any point throughout the rainy season due to a long-term rainfall deficit, although it usually occurs during the dry season, especially in the Central Highlands. Like other natural disasters such as flooding and typhoons, droughts can harm people's livelihoods and economic development, but they are difficult to spot because of their insidious effect.

In this study, we sought to better understand how the drought evolved, how the populations realized its evolution, how their perceptions of this change sometimes deviated greatly from the meteorological reality observed on the ground. In the last chapter, we have developed, as a solution to future droughts which should affect the overwhelmingly agricultural populations, a forecast model for the yields of the main crop in the Region in order to allow the authorities to anticipate supports and other helps in difficult years. These research works are likely to play a significant role in the social development and the livelihood of people.

The study's main goal is to better understand population vulnerability to drought and other extreme weather events in the Central Highlands of Vietnam in the context of climate change. To reach this goal, after an in depth state of the art on the study questions, many and different kinds of data were analysed :

- A 38-year dataset of meteorological observations (rainfall, temperature, humidity),
- A 21-year dataset of several satellite-based vegetation products (NDVI, LAI, FAPAR),
- Official product yield statistics,
- Several household questionnaire surveys.

Then, the study's goal was divided into three particular goals, resulting in open questions being explored in three steps (i.e., chapters 2, 3 and 4 of dissertation).

5.1.1. Livelihood vulnerability to drought

<u>Objective 1:</u> Assessing livelihood vulnerability to drought for selected areas.

Drought effects on farmers' livelihoods are unknown, making difficult determining appropriate livelihood solutions to improve farmers' welfare in the face of drought. This study aims to determine how vulnerable farmers on the regional scale are to droughts. A brief summary of how this study met these objectives is given here: (1) According to the LVI and VI-IPCC results, the Krong No District has a medium degree of livelihood risk due to drought (0.444 and 0.096, respectively); (2) The general LVI and VI-IPCC values from the principal components revealed that households in the Quang Phu community are the most vulnerable to drought, with indices of 0.510 and 0.057, followed by Nam N'dir, Dak Nang, Duc Xuyen, and Dak D'ro communities; (3) Water (sensitivity) and livelihood strategies (adaptive capacity) were also identified as two primary sources of high susceptibility to drought consequences for the districts and all examined communities in this study.

Droughts are more likely to negatively affect the major income of the five surveyed villages in the district because farming is their primary source of revenue. The significant susceptibility of existing livelihood strategies is due to the low values of these communities' livelihood diversification indexes (LS1 and LS3). This result is in line with the findings of of Aryal et al. (2014), Oo et al. (2018), and Antwi-Agyei et al. (2013), who found that having more than two income sources in a family improves livelihood diversity and makes a household less vulnerable. Therefore, in the face of drought, the households in the five communities should prioritize livelihood stability, and livelihood diversification in the form of a mix of agricultural and nonfarming activities is recommended to reduce household vulnerability to drought consequences.

5.1.2. Local people's perceptions of climate change and drought

<u>Objective 2.</u> Understanding local people's perception of drought and examine the discrepancies between local people's perceptions and meteorological data in the selected areas.

Besides assessing livelihood vulnerability to drought, this study analysed local people's perceptions of climate change and climate change-related drought.

Moreover, comparing the differences between local's people perceptions and meteorological data were examined. The study discovered that different socio-economic and demographic household characteristics significantly affect local people's perceptions of drought and observations of climate change-related extreme events. In particular, education, preferred media sources, and income sources significantly affect local people's perceptions. In addition, the limitations of human perception of slow processes like climate change or processed noise caused by sizeable interannual fluctuation are also demonstrated. The study's findings reveal that local people's values and observations influence their actions, and that their awareness of weather and climate may be taken into consideration as a consistent indicator of their perception.

Furthermore, people are prone to reminiscing about memorable recent events. As a result, local people's impressions of climate change are only accurate for a brief period, which is insufficient for monitoring a slow process like climate change. According to the study, most local people had observed the repercussions of climate change and drought on their communities, such as decreased water levels in surface and groundwater, fading crops, plant stress, crop yield reductions, income reductions, and property and health damage's findings. However, most of them lacked drought adaptation measures such as crop rotation, sophisticated irrigation, drought early warning and forecasting, reservoir regulation, water recycling, and agricultural insurance.

Although there are significant agreements between farmers' perceptions and meteorological data for clear trends such as global warming, perceptions are frequently at odds with meteorological observations when describing trends in precipitation (volume and duration) due to a much less marked tendency and high interannual variability. However, most respondents' perceptions (95%) match scientific observations based on the SPI index when it comes to drought occurrence. These findings will aid local governments, and policymakers develop ways to decrease the likelihood of adverse climate change and drought effects.

5.1.3. Coffee yield estimation using remote sensing data (NDVI, FAPAR, LAI)

Objective 3. Performing regional coffee yield forecasting using remote sensing data and Crop yield forcasting model approaches.

The study's findings support the assertion that the CGMSstatTool (CST) can be used to generate specific forecast coffee yields models by using databases of satellite-derived vegetation biophysical variables (LAI, NDVI, and FAPAR) without the use of meteorological data, phenology of coffee, or management practices to estimate the production of coffee crops with low RMSEp and high Adj.R^2 (over 62%). The model provided in this study is one of the first to estimate the yield of coffee crops using only satellite remote sensing data (SPOT-VEGETATION and PROBA-V) and the CST.

The findings of this research reveal that the elaboration of multiple linear regressions models based on satellite-derived vegetation biophysical variables (LAI, NDVI, and FAPAR) corresponding to the first six months of the years 2000–2019 resulted in coffee yield forecast models presenting satisfactory accuracy (Adj.R2 = 64 to 69%, RMSEp = 0.155 to 0.158 ton/ha, and MAPE = 3.9 to 4.7%). These results demonstrated that CST may efficiently predict coffee yields on a regional scale by using only satellite-derived vegetation biophysical variables. This study's findings are likely to aid local governments and decision makers in forecasting coffee production early and promptly, as well as in recommending relevant local agricultural policies. According to the results, CST enables the creation of the best model for predicting production values of coffee crops on a regional scale. The evaluation of the performed coffee model showed that the projected and official reported coffee yields for Dak Lak province were in good agreement. This study significantly adds to forecasting models for perennial plants in as case of coffee plants. Therefore, the forecasting yield model is critical in managing and contributing to the province's agricultural development strategy by using the first six months of all past years to estimate the year's coffee yields.

The results showed that combining phenological vegetation indices (LAI, NDVI, and FAPAR) produced a forecast of coffee yield with reasonable accuracy, with four models using data from the first six months of each year (models 1 to 4) presenting good Adj.R^2 and RMSEp. Besides, the findings also revealed that LAI is an essential index in contributing to the coffee yield prediction models.

The results demonstrated that CST could effectively estimate coffee crop models on a regional or national scale using only satellite data without meteorological data, management techniques, soil characteristics, fertilizer management, and so on. The outcomes of this study are anticipated to help local governments and decision-makers forecast coffee production accurately and quickly and recommend suitable local agricultural policies.

5.2. Outlook

Following the objectives of the study, several statistical tools that assess livelihood vulnerability to drought, drought trends, analyze people perception related to drought/climate change, estimate and forecast main crops (coffee crops) availability at the end of the growing season in the Vietnamese Central Highland areas, were developed and discussed in this PhD dissertation. Overall, this study contributed to the challenging task of monitoring and mitigating livelihood vulnerability to drought under climate change context in the Central Highlands of Vietnam.

The LVI and VI-IPCC indices help identify household vulnerability for the five study sites. In addition, the vulnerability level of numerous places within a research region can be compared using these indicators. However, the two indices may not be readily compared with other investigations in more distant areas due to differences in subcomponents and contexts. Indeed, according to Hahn et al. (2009) the subcomponents chosen have a considerable impact on assessing household livelihood vulnerability to climate change and natural hazards. Panthi et al. (2016) further claim that the local environment influences the frame and design of the subcomponents. Therefore, the usage of vulnerability indices presents a problem in selecting acceptable subcomponents. For creating subcomponents of vulnerability indices, substantial literature analysis, expert consultation, and stakeholder consultation are recommended, as this study indicates (LVI and VI-IPCC). Depending on the characteristics of the regions, subcomponents of vulnerability indices will be developed to assess LVI and VI-IPCC. The assessment result will reveal the most vulnerable of the aspects and areas. The government might develop strategies to mitigate each local livelihood vulnerability based on the assessment results.

Besides, the study's findings show that local people's values and observations impact their actions and that their perception of weather and climate may be used as a constant indicator of their awareness. Furthermore, people are prone to reminiscing about memorable recent events. As a result, local people's impressions of climate change are only accurate for a brief period, which is insufficient for monitoring a slow process like climate change.

Climate change is a slow process that individuals find difficult to define since they have trouble recalling specific occurrences from the past. Furthermore, current events significantly impact them, which bias impressions of a slow-moving process like climate change. In this scenario, the survey was conducted during the dry season, after people had recently suffered substantial droughts, leaving a lasting impression on their minds. If the study had been conducted during the rainy season after a particularly wet year, the results would almost certainly have been considerably different. As a result, human observations of climate are inherently flawed, and we must be cautious when analyzing long-term events (i.e. several dekads).

Furthermore, this research shows that having access to climate change information is a critical factor influencing residents' willingness to mitigate the adverse effects of drought. As a result, the study's findings can assist local governments and politicians enhance inhabitants' livelihoods. First, enhanced drought early warning and forecasting systems should offer communities timely notice, allowing them to better prepare for climate change and drought adaptation techniques. Second, local governments and politicians should hold informational or training sessions to improve the understanding of adaptation techniques such as crop diversification and variety, switching to drought-resistant cultivars, sophisticated irrigation, and agricultural insurance among the general public.

On the other hand, developing the model that predicts the local's main crops yield and production is essential to ensure the local livelihood. This study concentrated on solving the technical requirement of implementing tools to predict coffee yield at the end of the harvest season, the main crop in the study areas. All variables of phenological metrics of LAI, FAPAR, and NDVI (33 indices) were computed as input indicators. The number of variables over the limited number of available input indicators of the CST is a limitation in this study. The "Best subset selection" method in the CST is limited in selecting the best models with multiple indicators. These two technical limitations of the CST make its use more difficult than it should be. Therefore, electing input variables process might be considered in a subsequent research, or, increase the numbers of input datasets in CST.

The proposed project suggests using the CST to construct a model for estimating coffee crop yields. No such research has been done on employing this technology for this specific crop, which is a significant study contribution. In this regard, this study aims to evaluate the CST models for forecasting coffee yield at a regional scale in Vietnam using just remote sensing data (Dak Lak province).

It is found that satellite data from services like the Copernicus Global Land provide a good source of information about the NDVI, LAI, and FAPAR for estimating coffee with very few information available – no need for information about management practices, soil characteristics, irrigation, and phenology of the coffee tree, among other things. In this context, the yield forecast models for perennial crops could be based on the combination of satellite-derived vegetation biophysical variables (LAI, NDVI, and FAPAR). Further research is needed to improve our understanding of the relationship between vegetation biophysical variables (LAI, NDVI, and FAPAR) and coffee yield. Another aspect is that the recently launched SENTINEL-3 satellite will provide near-real-time biophysical variables with a finer spatial resolution of 300m. As a result, the crop prediction models will be modified to maintain the continuity of the developed grading systems. Different data sources, such as MODIS-TERRA/AQUA, should be tested to uncover additional enhancing potential and assure interoperability with Copernicus Global Land products.

Further research may consider applying the developed method to search for coffee yield forecast models at other scales (at district and national levels), with enhanced input data (finer spatial resolution for satellite images and more accurate coffee maps) and with other explanatory variables.

The study was about reducing disaster impact and population's vulnerability in the Central Highlands. Much can still be done to reduce population vulnerability and strengthen its resilience as for example :

- Increase population means through education, information access, higher income, better skills, increased solidarity between farmers, agricultural insurance, disaster forecasting systems, yields forecasting models, etc...

- Strenghten the resilience capacity of agricultural systems to climate change in the study area by planting crops (including perenial crops) that are more adapted to future climate conditions and by reducing drought damage through access to irrigation. This will definitely help building a more sustainable future.
- The findings reveal that water and livelihood strategies are the major components that influence the local's livelihood. Therefore, this study recommends increasing investment in water management practices, improving integrated water resources management such as building irrigation dam systems and livelihood diversification. In future research, vulnerability under some policy interventions will be investigated to see the effectiveness of planned activities in reducing livelihood vulnerability of communities of the area.
- A natural disaster can not be prevented in the short term. However, in the long term, it can be mitigated by minimizing the factors that contribute to generating natural disasters, such as stopping deforestation and minimizing actions that generate greenhouse gases.

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