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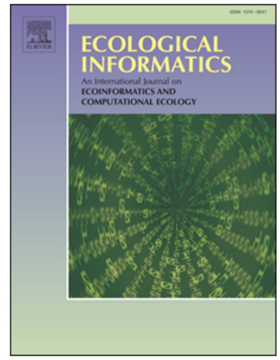

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Simulation of thermal stratification and water Temperature Dynamics in the Joumine reservoir (Tunisia)

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Abstract:

Thermocline stratification has become increasingly important under climate change conditions, impacting the water bodies' quality, by changing the epilimnion thickness, particularly the biological quality related to phytoplankton communities. Advanced modelling techniques based on the new Derived EOLE Joumine Model (DEOLE-J) and metaheuristic approaches were used to model thermocline stratification in the Joumine reservoir in the North of Tunisia. Relative Water Column Stability (RWCS) and thermocline parameters such as thermocline depth and strength index (TSI) were used to assess the water temperature profile and the impact of the thermocline on the phytoplankton community distribution and abundance. Monthly samplings were conducted at eight gauging stations from May 2021 to August 2021. Water samples were collected to measure physical and biological parameters. Joumine's thermal stratification can be divided into three periods: Mixing, Formative, and Stable. During the Mixing period, TSI and air temperature had a significant negative correlation. Similarly, significant negative correlations were observed between TSI, air temperature, and RWCS during the Formative period. Our results reveal that weaker stratification in spring is primarily driven by increased inflow discharge, while summer stratification intensifies, creating sharp thermal gradients. The model successfully captures seasonal thermocline fluctuations and shows that wind speed plays a critical role in regulating vertical mixing. However, moderate wind speeds typical of the Joumine region have limited impact on the deeper layers of the reservoir, particularly during summer. A comparison of model estimates and measured data indicates a bias due to distant meteorological stations and the exclusion of horizontal fluxes, such as water withdrawal and throughflow. Despite these limitations, the DEOLE-J provides valuable insights into the thermal dynamics of reservoirs, showing that prolonged stratification periods reduce vertical mixing and nutrient circulation, potentially degrading water quality. These findings have significant implications for water quality management, particularly in the context of climate change, where extended stratification periods are expected leading to exacerbate water quality issues. Future research should explore two-dimensional models to enhance temperature estimation accuracy and include horizontal fluxes. Keywords: DEOLE-J, Thermal stratification, Joumine reservoir, Thermocline strength, Thermocline depth, phytoplankton distribution, water temperature

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1. Introduction

Understanding the processes and mechanisms driving a lake's thermal stratification and identifying its key factors is essential for effective water-quality management within lake ecosystems (Hutchinson, 1957; Zhang et al., 2014). Changes in thermal stratification affect water mixing, convection, nutrient cycles (Cermeño et al., 2008; Noori et al., 2021), and the vertical distribution of dissolved oxygen and particles (Liu et al., 2019; Zhang et al., 2014). These dynamics shape aquatic ecosystems, particularly influencing phytoplankton community composition (Bockwoldt et al., 2017; Pasztaleniec and Ochocka, 2021; Shi et al., 2022; Wang et al., 2020; Winder et al., 2009; Zhang et al., 2014).

Thermal stratification is a critical phenomenon in reservoirs, particularly in regions with Mediterranean-type climates like North Africa. These areas are highly vulnerable to climate change, which can intensify stratification by increasing surface water temperatures. This has implications for water quality, as it leads to the establishment of a more stable thermocline enabling mixing that also leads to reduced oxygen levels in deeper waters, disrupted nutrient cycling, and increased risks of eutrophication and harmful algal blooms (Cozannet et al., 2021; Woolway et al., 2022). In reservoirs like Joumine, climate-driven changes are further exacerbated by anthropogenic pressures, such as water extraction and agricultural nutrient pollution. The IPCC highlights that rising global temperatures will likely lengthen stratification periods, impacting the ecological balance in Mediterranean reservoirs and threatening water quality (Cozannet et al., 2021). Therefore, monitoring and understanding stratification dynamics under future climate scenarios are critical for sustainable water management (Ladwig et al., 2021; Woolway et al., 2022).

Thermal stratification influences phytoplankton community dynamics by altering light availability, nutrient distribution, and temperature gradients—factors crucial for determining species composition and productivity (Zhou et al., 2022). During stratification, the epilimnion is typically nutrient-poor but receives ample light, favoring species adapted to low-nutrient conditions. In contrast, the hypolimnion is nutrient-rich but light-deprived, creating distinct ecological niches that drive shifts in phytoplankton species composition over seasons. Stratification can influence the timing and duration of phytoplankton blooms, particularly under nutrient-rich conditions, leading to shifts in community structure and productivity.

Thermal stratification is primarily driven by temperature differences that separate surface water from deeper layers (Shi et al., 2022; L. Wang et al., 2024). Factors such as lake morphometry (mean depth, surface area, volume) (Kraemer et al., 2015; Liu et al., 2019), and meteorological parameters including wind, air temperature, and solar radiation (Fee et al., 1996; Saros et al., 2016; L. Wang et al., 2024; Yang et al., 2020) significantly influence thermal structure. Seasonal and spatial variations in thermal profiles are largely driven by heat flux and light penetration (Liu et al., 2019; Zhang et al., 2014), with transparency playing a key role in solar radiation absorption in surface waters (Liu et al., 2019; Saros et al., 2016). This adversely affects the lake ecosystem. During summer, thermal stratification inhibits the mixing of warm surface water (epilimnion) with colder deep water (hypolimnion). This lack of mixing, combined with the absence of light in the hypolimnion, can lead to oxygen depletion, eventually leading to anoxic conditions (Elçi, 2008; Zhang et al., 2014). Stratification thus facilitates the development of anoxic conditions, which can significantly contribute to water quality deterioration in many reservoirs (Elçi, 2008; Wilhelm and Adrian, 2008; Zhang et al., 2014).

Understanding how lakes react to changes in thermal dynamics and mixing processes is crucial, particularly in the context of climate change (Liu et al., 2019; Y. Wang et al., 2024), and the thermocline parameters are key to this understanding (Castrillo et al., 2024; Stainsby et al., 2011). Rising temperatures can prolong stratification periods, altering nutrient cycles and potentially reducing aquatic productivity (Paerl and Paul, 2012; Woolway et al., 2022). Human activities, especially nutrient-rich agricultural runoff, compound these effects by triggering harmful algal blooms and further degrading water quality (Qi et al., 2021). The combined effects of climate change and nutrient enrichment emphasize the need for adaptive management strategies to mitigate impacts on lake ecosystems (Castrillo et al., 2024; Paerl and Huisman, 2009).

Numerical modeling is crucial for simulating and predicting thermal stratification and water temperature distribution, particularly regarding climate change studies (Castrillo et al., 2024; Ishikawa et al., 2022). Models vary by dimensionality—1D, 2D, and 3D—each offering distinct levels of spatial resolution and complexity. For example, 1D models like the DYRESM and EOLE simulate vertical temperature gradients with lower computational demands, making them effective for assessing thermal stratification. The EOLE model, in particular, employs an integral mixed-layer approach for the epilimnion, where the mixing zone depth and temperature are variable (Salençon, 1997).

More complex 2D models, such as Cequal W2, and 3D models like ELCOM and DELFT 3D FLOW, provide enhanced spatial data but require extensive datasets and computational resources (Gaillard et al., 2022; Madani et al., 2020; Yaghouti et al., 2023). Recent advances in modeling have incorporated machine learning techniques, such as artificial neural networks (ANNs) and random forests, which effectively predict temperature profiles and stratification characteristics under specific conditions (Castrillo et al., 2024).

The choice of the EOLE model is based on the fact that the epilimnion is represented using an integral mixed-layer model (Salençon, 1997). In this approach, the depth of the mixing zone is treated as a variable alongside temperature, which directly affects its calculation. This modelling technique is applied within the EOLE thermal model (Salençon, 1997). In our application, we assume that the density of the water varies linearly regarding temeparture, as the water temperature in the Joumine reservoir never drops below 5°C. This assumption is supported by the fact that the reservoir is located in a sub-humid to semi-arid climate zone, where temperatures are less extreme (range between 5°C and 40°C). Furthermore, we assume that the length of the lake remains constant throughout its depth, simplifying the model and ensuring more manageable computational dynamics. The Joumine reservoir, situated northwest of Tunisia, encompasses an upstream watershed area of 418 km². The Joumine reservoir has faced water-quality challenges, including intermittent algal blooms (Limam, 2003) attributed to high concentrations of nutrients loaded due to intensive agricultural activities in the watershed (Fathalli et al., 2011). Therefore, assessing thermal stratification is crucial to understanding better and forecasting the process of algal blooms as it significantly impacts aquatic systems (Li et al., 2022, 2018; Zhang et al., 2021). Simultaneously, understanding the thermal regime and its influencing factors is essential for developing strategies to manage water quality in reservoirs adaptively (Zhang et al., 2014). This is particularly important because changes in thermal structure can alter circulation patterns, impacting the vertical distribution of chemical factors like nutrients and oxygen concentration(Wilhelm and Adrian, 2008; Zhang et al., 2014).

This study aims to enhance the understanding of thermal stratification mechanisms in the Joumine Reservoir through a novel statistical approach. Specifically, the research will elucidate how these methods contribute new insights into the stratification processes and contextualize these findings within the effects of climate change and human activities on thermal dynamics. Furthermore, the study will explore how changes in thermal stratification affect the reservoir's overall ecosystem functionality, particularly in terms of phytoplankton community dynamics.

2. Methods

2.1.Study area

The Joumine Reservoir (36°59′49″ N, 9°36′49″ E) is situated in northwestern Tunisia **Fig. 1**. According to data from the National Observatory of Agriculture (Onagri, 2022), the reservoir's current water volume is approximately 26 Mm^3. It has a height of 52 meters and a total storage capacity of 118 Mm^3. Constructed in 1983, the Joumine Dam serves multiple purposes: irrigation for 1800 hectares of downstream land, supplying drinking water to the Plaine Mateur area, and flood control (Limam, 2003). It plays a crucial role in the North Water Master Plan. Indeed, the construction of this dam is part of a sustainable water resource management framework and the mobility of hydraulic resources.

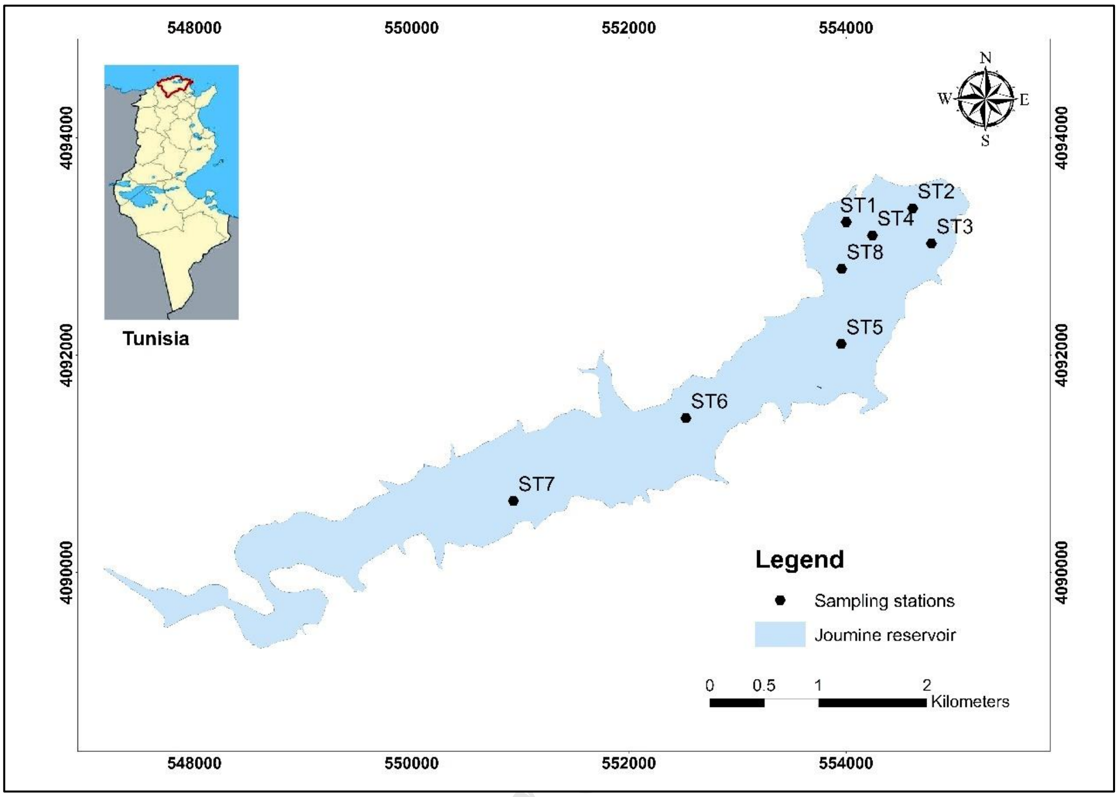

Fig. 1. Map of the study region and the water quality monitoring sites

2.2.Data collection and sources

To study water temperature variations in the reservoir, we used several types of data:

2.2.1 In situ data:

- Sampling was conducted at eight monitoring sites in the Joumine reservoir, from the surface to 20 meters depth, over three months (May, June, and August 2021). Phytoplankton samples were collected in 1-litre bottles, preserved with 10 ml of 35% formaldehyde, and later analyzed using sedimentation chambers and an inverted microscope based on (Utermöhl, 1958). This approach allowed for the identification and quantification of phytoplankton species. This allowed us to calculate the abundance of phytoplankton species and therefore calculate the contribution of groups of phytoplankton in density (%).
- The water temperature (WT) was measured directly using a multiparameter probe (WTW multi 340i)

2.2.2 Data:

- Bathymetry (2013): The bathymetry data, provided by the General Directorate for Dams and Major Hydraulic Works, consists of depth measurements and surface-area curves to assist in understanding the reservoir's shape and volume (**Fig. 2**).
- Meteorological Data (2021): We used weather data such as air temperature, wind speed, cloud cover, solar radiation, and humidity from the INM Beja weather station.

Since hourly air temperature data were missing, we reconstructed it using a metaheuristic approach.

2.2.3 Reconstruction of Missing Data

To fill gaps in the 2021 hourly air temperature data, we used the ERA5 atmospheric reanalysis dataset from the European Center for Medium-Range Weather Forecasts (ECMWF). This dataset, available since 1950, offers global weather data with hourly resolution and a spatial resolution of 31 km. We downloaded the 2021 data in NetCDF format from the Copernicus Climate Data Store (Hersbach et al., 2020).

For accurate results, we defined the geographical area of interest using the latitude and longitude coordinates of the study area. The data's precision depends on these boundaries.

Since hourly air temperature data were missing, we applied a metaheuristic method to estimate it. We first analyzed the average air temperature trends from the ERA5-Land data and compared these with measurements of the local meteorological station (R^2 = -0.82). Despite some discrepancies in the absolute values, the hourly temperature patterns from ERA5 proved to be reliable.

We then grouped the data by season and calculated the average temperature for each hour of the day within each season. A polynomial adjustment was applied to these averages, allowing us to estimate hourly temperature values for each season. For detailed results, refer to Appendix A.

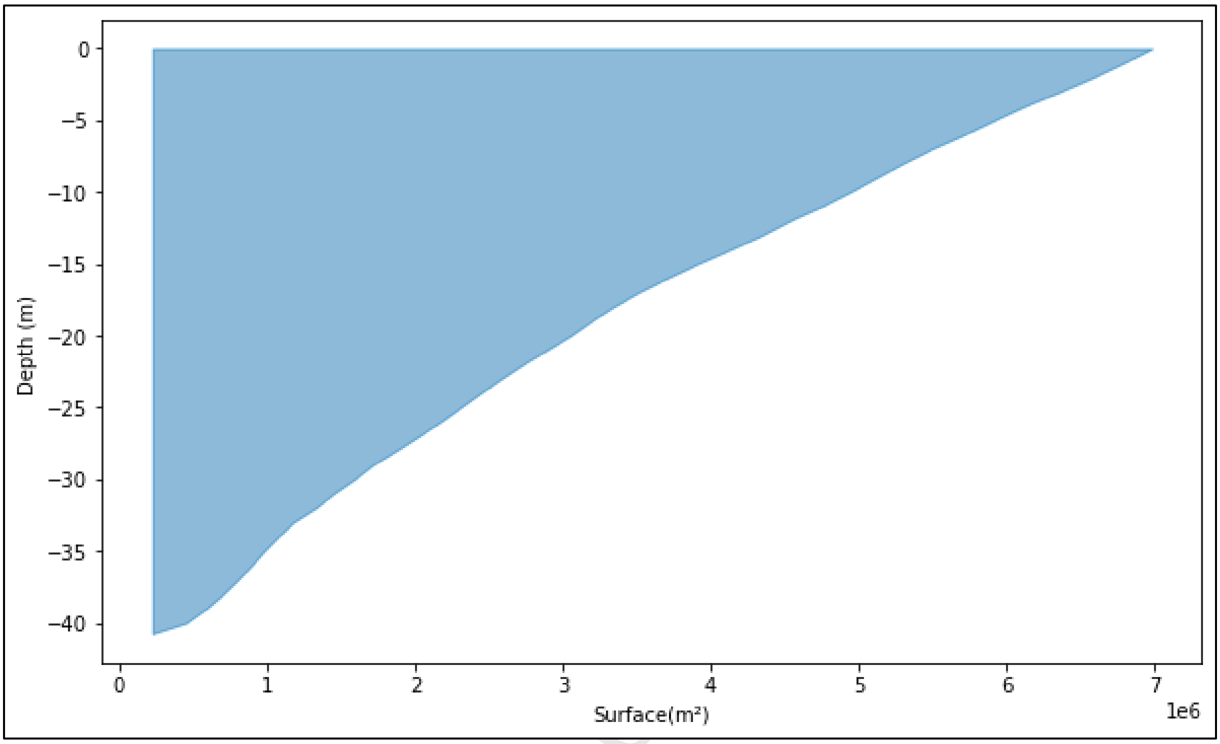

Fig. 2. Bathymetry of Joumine reservoir of 2013

2.3.Overview of the Conceptual EOLE model

The Conceptual EOLE Model is a well-established one-dimensional vertical model designed to simulate thermal processes in water bodies by dynamically representing the depth of the epilimnion boundary, using an integral mixed-layer approach (Salençon, 1997). In this method, the mixing zone's depth and the water temperature are considered dynamic variables that influence each other. This relationship allows for more accurate calculations of the mixing zone depth based on temperature changes (Prats et al., 2017; Salençon, 1997).

The EOLE model has proven indispensable in hydrological research and has been validated across numerous studies for its reliability in simulating water temperature, thermal stratification, and reservoir dynamics. For example, it successfully modeled the Bimont Reservoir, accurately reflecting its thermo-hydrodynamic processes and adapting to various climate change scenarios, underscoring its applicability (Prats et al., 2017).

Its versatility is further demonstrated by its application to different reservoirs, such as Lake Pareloup, with a residence time of about one year, and the shorter-residence Rochebut Reservoir, showcasing its robustness (Salençon, 1997). EOLE has also proven its effectiveness in long-term simulations, spanning up to 12 consecutive annual cycles for Lake Pareloup (Salençon, 1997). The model's strong alignment with measured thermal profiles further confirms its effectiveness in capturing water temperature patterns and interannual variations, making it a reliable choice for thermal modeling (Prats et al., 2017; Salençon, 1997).

In this study, we build on the Conceptual EOLE Model to develop the Derived EOLE Joumine Model (DEOLE-J), which has been specifically tailored for the Joumine Reservoir in northern Tunisia. This derivative model maintains the foundational principles of EOLE while incorporating the metaheuristic approach to enhance its calibration and improve its applicability to reservoirs in Mediterranean climates. The metaheuristic approach is used to fine-tune model parameters, optimizing the simulation of thermal dynamics by identifying the best-fitting parameter values that account for seasonal variations, wind patterns, and other regional characteristics specific to the Joumine Reservoir.

2.4. Key features of the model:

One-Dimensional Water Column Structure: adopts a one-dimensional structure, discretizing the water column into horizontal layers with uniform thickness ($\Delta z = 0.25$ m). Only the surface layer can have variable thickness (Salençon, 1997). Each layer, denoted as i, is assumed to be homogeneous (Salençon, 1997). The lake's length is consistent across all depths, leading to varying widths according to the surface area (Salençon, 1997). The interface between adjacent layers is determined from bathymetric data, with surface areas linearly interpolated along the z-axis (Salençon, 1997). The volume of each layer is derived from the calculated surface areas (Salençon, 1997). The reservoir is represented as multiple horizontal layers, each representing temperature zones from the surface to the deeper layers (Salençon, 1997). (Details are provided in Appendix B.)

Forcing Variables: The necessary inputs for this model, which have already been collected and processed (see section 2.2), include the reservoir's bathymetry and important meteorological data such as solar radiation, air temperature, wind speed, relative humidity, cloud cover, and atmospheric pressure. Additional data, like the depth of the Secchi disk, is also included (Prats et al., 2017; Salençon, 1997). (Refer to Appendix B for variable definitions and formulations.)

Model Outputs: The DEOLE-J model operates with an hourly time step and a spatial resolution of 0.25 meters (Salençon, 1997). Its outputs provide the water temperature at each depth and time step in the reservoir, as well as the depth of the thermocline at each time point (**Fig. 3).**

Numerical Resolution: The numerical solution is achieved using a fractional step method, which breaks the solution into three primary steps: solar radiation penetration, convective mixing due to surface cooling, and turbulent mixing due to wind (Salençon, 1997). The details of each step and the intermediate solutions are provided in Appendix D.

Software Implementation: Based on the Conceptual EOLE Model, we developed a new model called the Derived EOLE Joumine Model (DEOLE-J). This model has been implemented using Python 3.10 and specifically applied to the Joumine Reservoir in northern Tunisia. One advantage of DEOLE-J is that it does not require calibration because it uses coefficients that are applicable across different reservoirs.

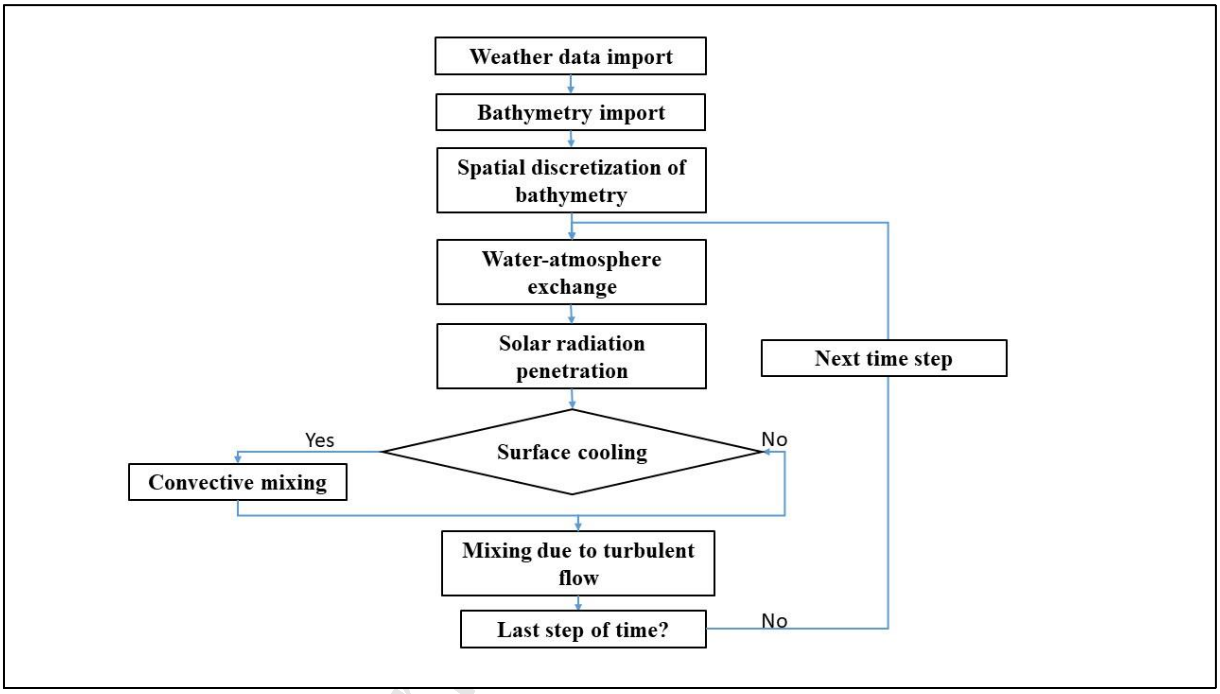

Fig. 3. Flowchart illustrating the key stages in the development of Derived EOLE Joumine Model (DEOLE-J) aimed at efficiently simulating reservoir water temperature (WT) and identifying thermal stratification (Dieden, 2021)

2.5.Statistical Parameters for Accuracy Assessment

Statistical parameter such as the determination coefficient (R^2) was calculated to assess model precision and is calculated as the following equation.

$$R^2 = \left(\frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \right)^2$$

where xi and yi are individual samples taken at points indexed with the variable i and $\bar{x}$ and $\bar{y}$ are the samples mean respectively of x and y.

2.6. Thermal stratification parameters

Two parameters were used to characterize thermal stratification: Relative Water Column Stability (RWCS) and the Thermocline Strength Index (TSI).

RWCS compares the density difference between the bottom (D_b) and surface (D_s) waters with the density difference of pure water at 4°C (D_4) and 5°C (D_5), as outlined in (Padisák et al., 2006). It provides a simple way to assess water column stability.

$$RWCS = \frac{D_b - D_s}{D_4 - D_5}$$

TSI measures the maximum thermal gradient with depth, as established by Horne and Goldman (Horne and Goldman, 1994).

$$TSI = \frac{\Delta T}{\Delta h}$$

Where ΔT and Δh are the differences in WT (° C) and water depth (m), respectively, between the upper and lower boundaries of the thermocline. The TSI directly quantifies the temperature gradient (°C/m) with a minimum threshold of 0.2°C/m required to define the thermocline. The depth of the upper thermocline boundary is used to locate the thermocline.

Finally, the temporal dynamics of stratification were analyzed by defining three key periods. The Formation Period refers to the time from the initial appearance of stratification to the point when it reaches maximum strength. This is followed by the Stationary Period, during which the stratification remains stable and fully developed. Lastly, the Weakening Period marks the phase from the decline of stratification until its complete disappearance (Zhang et al., 2022).

3. Results

Surface water temperature appears to be well-modelled (**Fig. 4**). The difference between measured and modelled temperatures remains consistent where $R^2 = 0.98$.

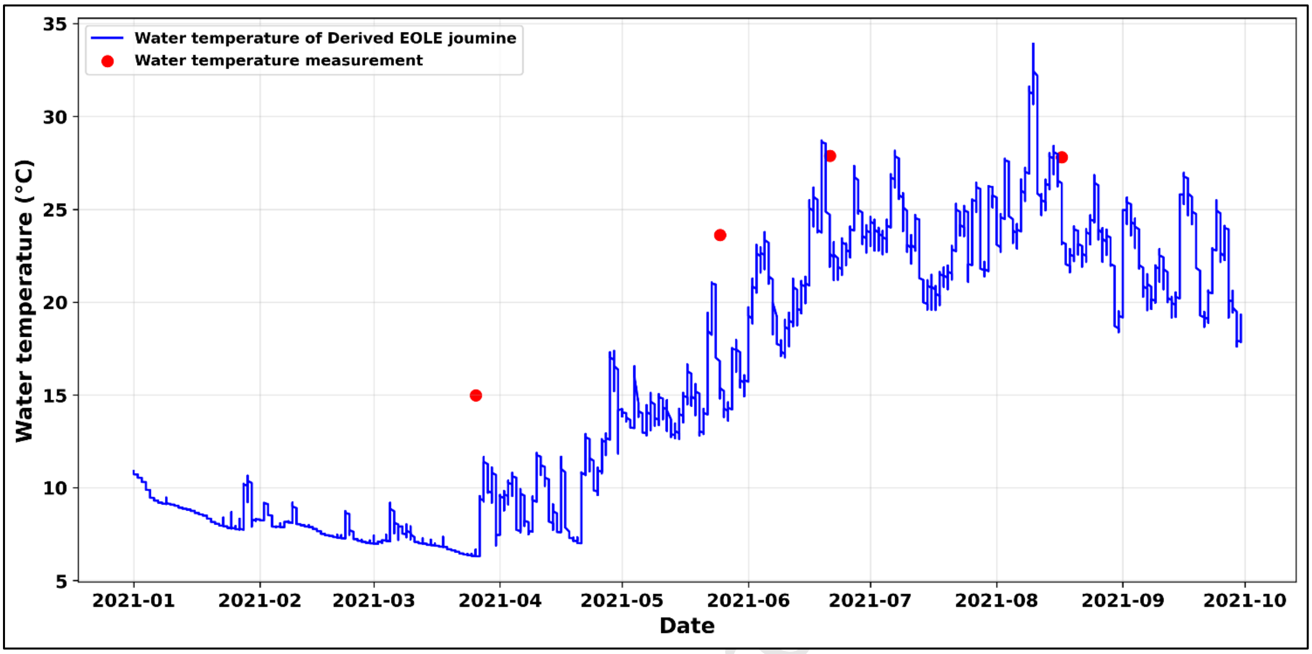

Fig. 4. Variation of water surface temperature generated by the DEOLE-J model and water surface temperature measured in the filed

3.1 Changes with thermocline stratification

Fig. 5 demonstrates that from January to February, due to cold air temperatures, there was minimal temperature stratification in the Joumine reservoir, resulting in the absence of a distinct thermocline. When a thermocline occurs, it is relatively deep and weak. Starting in March, with the increase in air temperatures, water temperature stratification began to develop, leading to a shallower and gradually strengthening thermocline. The thermocline reached its peak strength in August, indicating the most significant stratification during the summer months. Conversely, February had the weakest thermocline. Overall, the thermocline exhibited seasonal strengthening, stabilizing, and weakening cycles. The thermal stratification cycle was categorized into three stages: the mixing period from January to February, the formative period from March to May, and the stable period from June to September.

During the mixing period, the thermocline was deepest, reaching 30 meters. After March, its depth decreased to around 2.5 meters during the formative and stable periods. This indicates vertical mixing in colder months, driven by lower air temperatures and wind. As temperatures increase in spring and summer, the thermocline remains at about 2.5 meters, despite temperature changes.

Wind speed also plays a crucial role in this process. During the mixing period, wind speeds are relatively high, reaching around 2.5 m/s in January. This high wind speed contributed to vertical mixing, preventing strong stratification and resulting in a deep thermocline. As the reservoir enters the formative period (March-May), wind speeds decrease slightly but remain sufficient to maintain a moderate thermocline depth. In the stable period (June-September), wind speeds drop further, averaging around 1 m/s or less. The reduction in wind speed, combined with warmer air temperatures, allows for stronger thermal stratification and stabilizes the thermocline at about 2.5 meters.

The Thermal Stratification Index (TSI) was low during the mixing phase, showing weak stratification. It increased from May, reaching its peak in July and August, marking the strongest stratification. Air temperatures increased from January to July, reaching around 25°C in the summer before decreasing. This pattern corresponds to stronger stratification, reflected in the shallow thermocline depth and high TSI values. Even though air temperatures were higher, the thermocline remained at 2.5 meters. This suggests that factors like solar radiation and wind also play a role in influencing stratification.

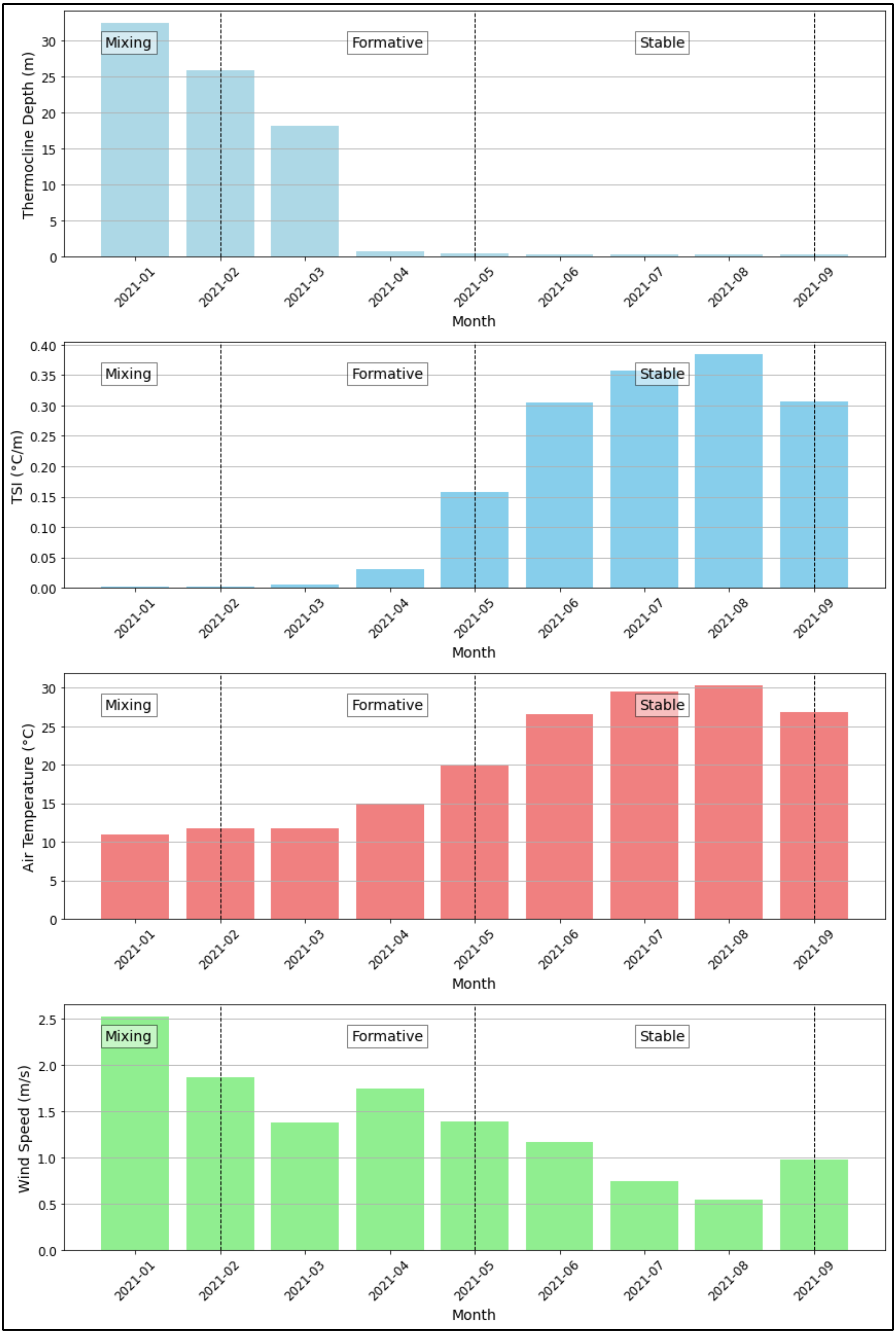
Thermocline Depth (m)
Mixing
Formative
Stable
Month
TSI (°C/m)
Air Temperature (°C)
Wind Speed (m/s)
2021-01
2021-02
2021-03
2021-04
2021-05
2021-06
2021-07
2021-08
2021-09

Fig. 5. Subplot of monthly average values of Air Temperature, Thermocline Depth (TD), Thermocline Strength Index (TSI), and wind speed in reservoir Joumine from January 2021 to September 2021 during three periods: Mixing, Formative and Stable

The temperature gradient in the Joumine reservoir thermocline was significant as shown in **Fig. 6**. During periods of stable stratification, the maximum temperature stratification index (TSI) in the thermocline reached 0.42 °C/m, and this substantial temperature gradient was associated with a corresponding density difference of 15.

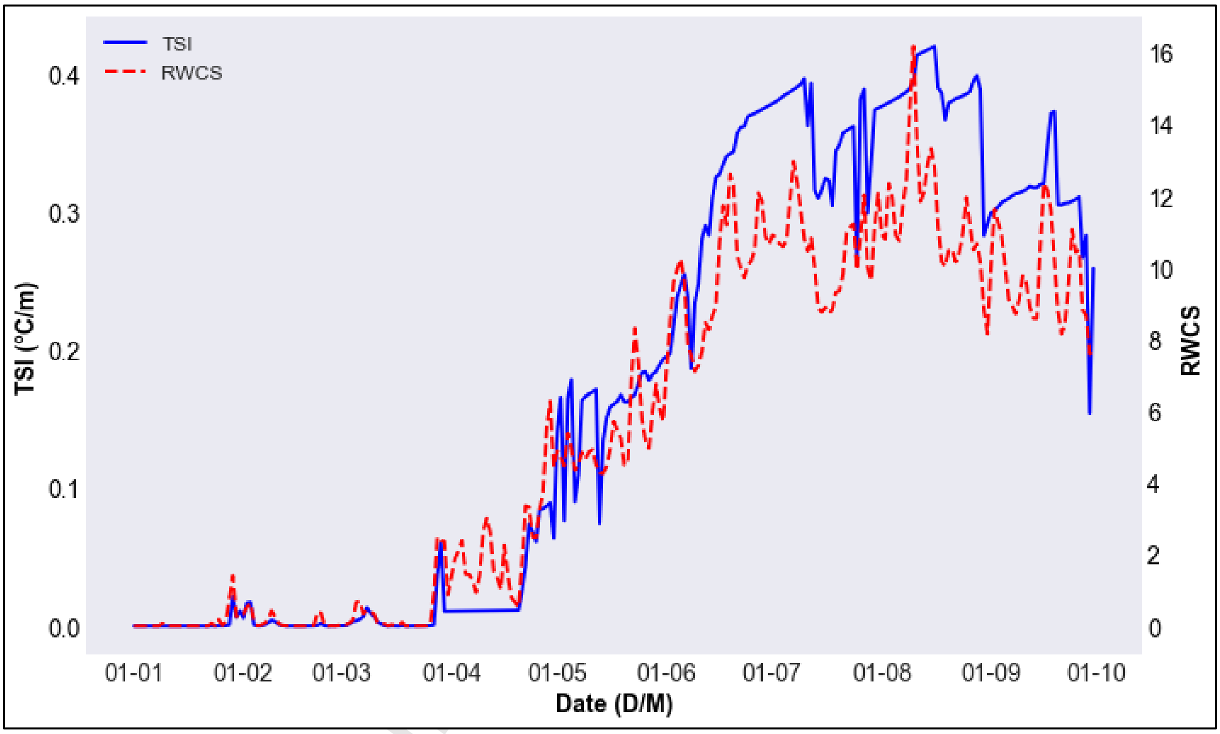

Fig. 6. Time series of thermocline strength index (TSI) and relative water column stability (RWCS) over Joumine reservoir

3.2 Relationships among the Thermal Stratification Parameters

The relationships between the thermal stratification factors are outlined across three periods of thermal stratification.

During **the mixing period** (**Fig. 7**), a significant negative correlation between TSI and thermocline depth and air temperature (R^2=0.42, R^2=0.56 respectively), similar to the formative period. A positive correlation existed between TSI, air temperature and RWCS. These results demonstrated that the depth of heat penetration was a major determinant of thermal stratification during this period.

During **the formative period** (**Fig. 8**), a strong positive correlation existed between TSI and air temperature, Thermocline depth and air temperature and RWCS and TSI (R^2=0.74, R^2=0.40 and R^2=0.84 respectively) indicating that the RWCS and TSI increased with increasing thermocline strength. Furthermore, a negative correlation existed between TSI and thermocline depth, (R^2=0.42).

During **the Stable period** (**Fig. 9**), there was a significantly negative linear relationship between thermocline depth and air temperature (R^2= 0.13) between thermocline strength and thermocline depth (R^2=0.28). Thermocline strength was positively correlated with air temperature (R^2 =0.39). Furthermore, a positive correlation existed between TSI and thermocline depth (R^2=0.52).

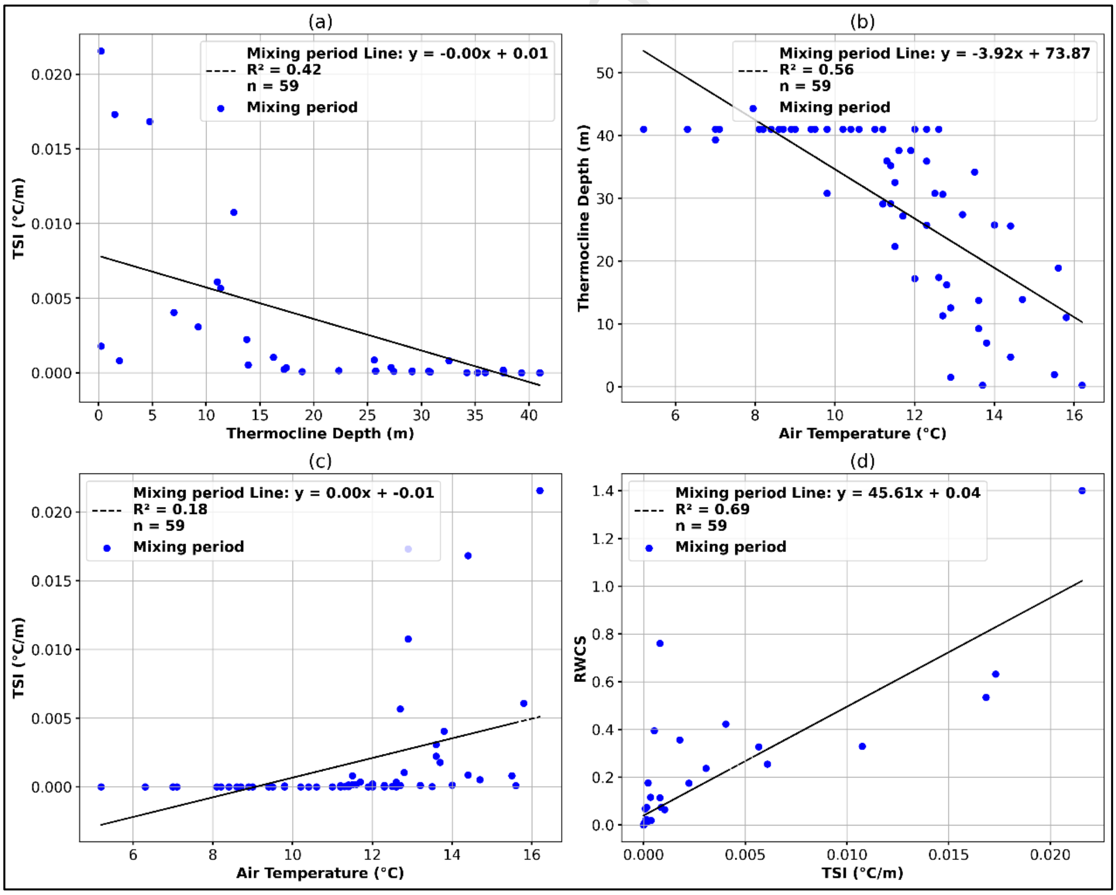

Fig. 7. Linear relationships among the thermodynamic parameters during the mixing period (January 2021–February 2021): (a) thermocline depth and thermocline strength index (TSI), (b) thermocline depth and air temperature, (c) thermocline strength index

and air temperature, and (d) thermocline strength index (TSI) and Relative Water Column Stability (RWCS) over Joumine reservoir

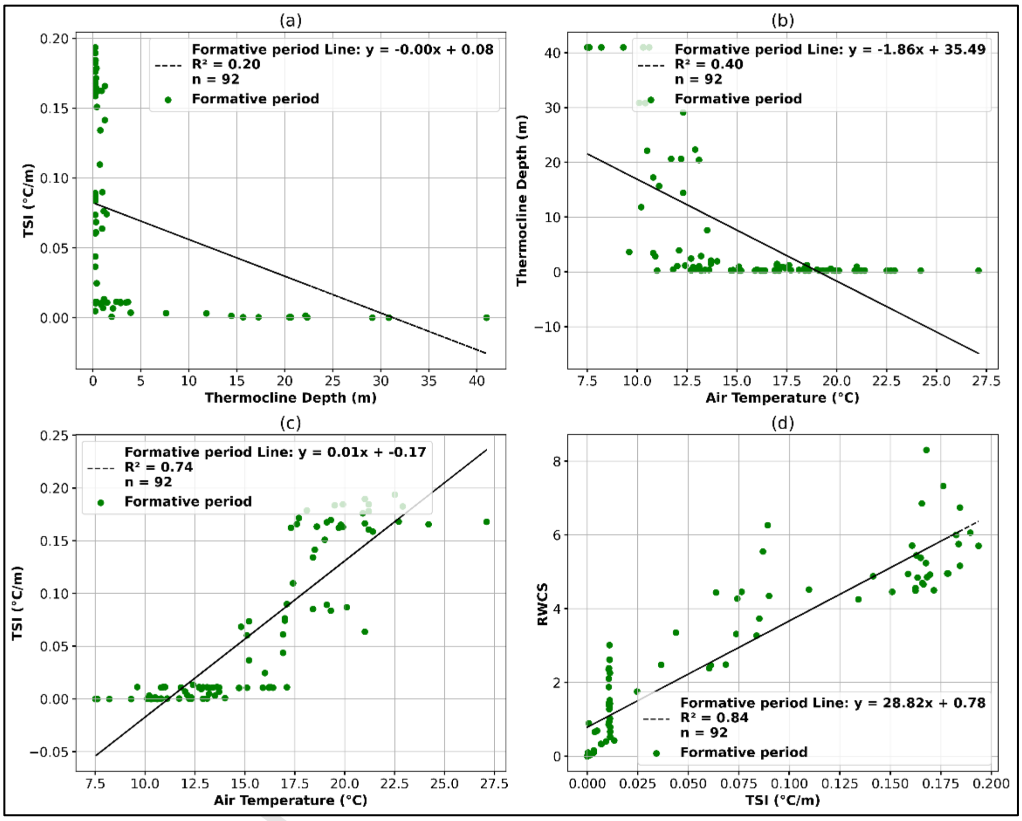

Fig. 8. Linear relationships among the thermodynamic parameters during the formative period (March 2021–May 2021): (a) thermocline depth and thermocline strength index (TSI), (b) thermocline depth and air temperature, (c) thermocline strength index and air temperature, and (d) thermocline strength index (TSI) and Relative Water Column Stability (RWCS) over Joumine reservoir

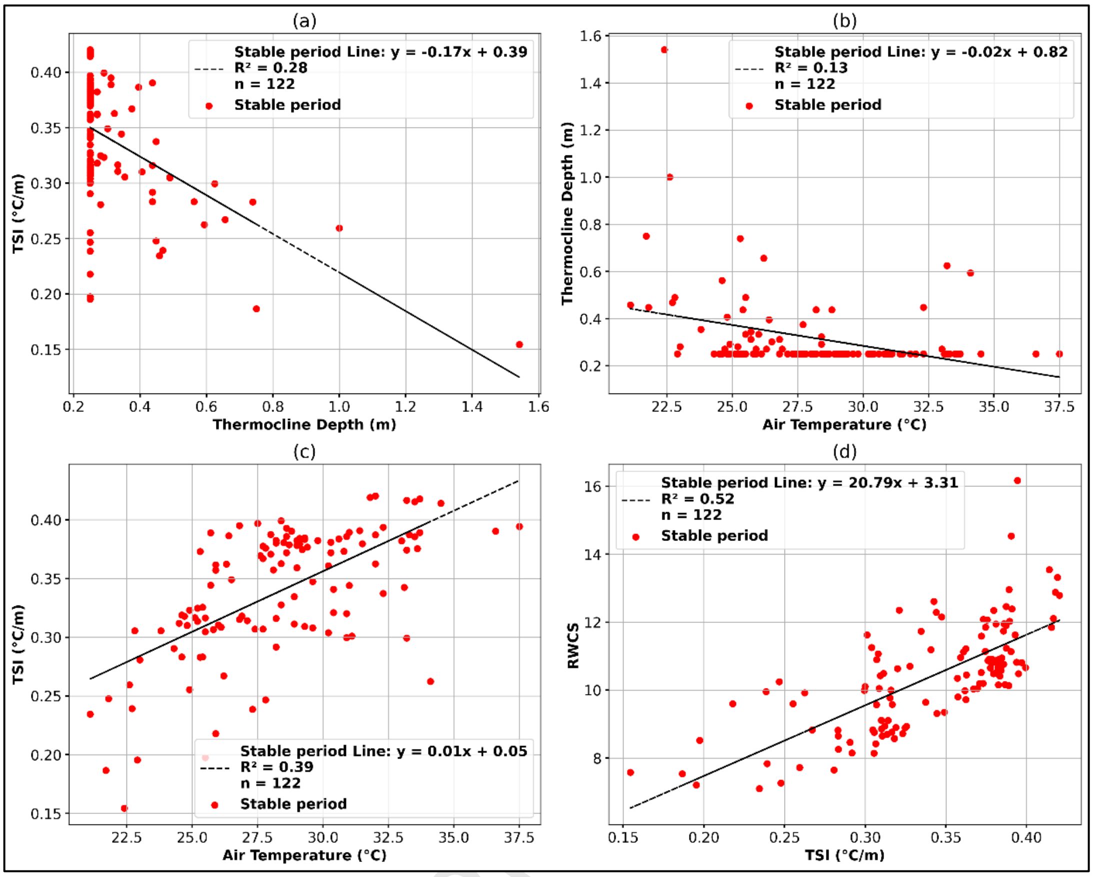

Fig. 9. Linear relationships among the thermodynamic parameters during the stable period (June 2021–Septembre2021): (a) thermocline depth and thermocline strength index (TSI), (b) thermocline depth and air temperature, (c) thermocline strength index and air temperature, and (d) thermocline strength index (TSI) and Relative Water Column Stability (RWCS) over Joumine reservoir

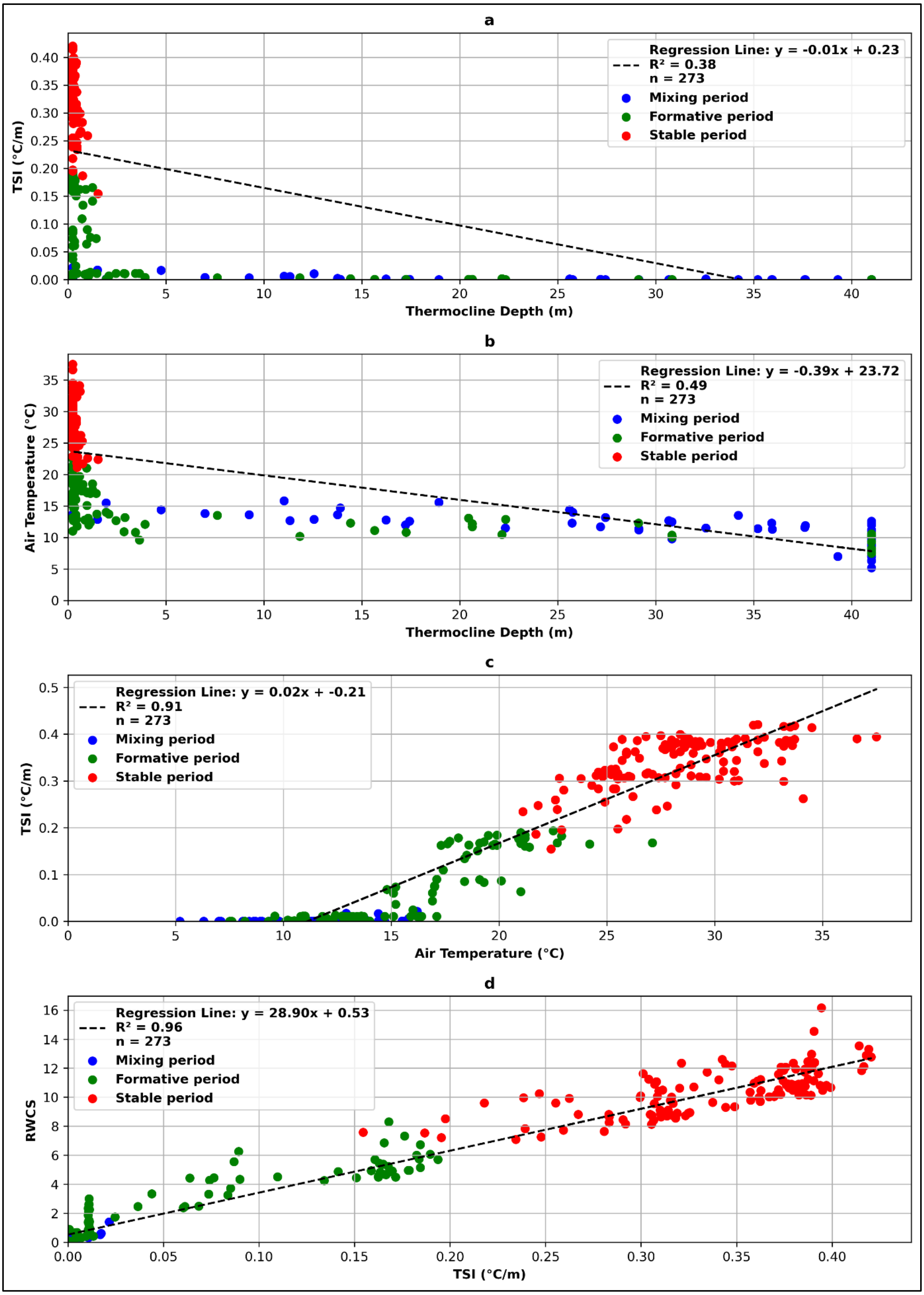

Fig. 10. Relationship between thermocline depth and the thermocline strength index (TSI) (a), thermocline depth and air temperature (b), thermocline strength index (TSI) and air temperature

(c), and thermocline strength index (TSI) and Relative Water Column Stability (RWCS) (d) within the annual thermal stratification cycle

There was a significantly negative linear relationship between thermocline depth and air temperature (**Fig. 10**.a) and between the thermocline strength index and thermocline depth (**Fig. 10**.b) during the annual thermal stratification cycle (R^2 =0.49, R^2= 0.52 respectively).

The variability of thermocline depth within the air temperature in **Fig. 10**.b range of 10-15°C (0-42m) can be attributed to several factors. First, wind-driven mixing and atmospheric conditions can cause fluctuations in the water column, influencing the thermocline even when air temperatures remain relatively stable. Additionally, thermal inertia means that water responds more slowly to temperature changes than air does; therefore, even slight shifts in air temperature may not immediately result in corresponding changes in water temperature. This lag can lead to variability in the thermocline. Local inflows or outflows can also contribute by introducing water at different temperatures, which affects the stratification at specific depths. Furthermore, the shape and depth of the reservoir, along with hydrodynamic factors such as currents and turbulence, can create areas of resistance to mixing. These conditions might result in localized stratification, causing the thermocline to shift unpredictably, even in the presence of stable air temperatures. Together, these factors explain the observed variability in thermocline depth.

A significant positive linear relationship between the thermocline strength index (TSI) and air temperature (**Fig. 10**.c) and between Relative Water Column Stability (RWCS) (**Fig. 10**.d). These show that the thermocline strength index is a good indicator of the thermal structure of the Joumine reservoir.

3.3 Changes in phytoplankton species composition under the various stratification stages

The distribution of phytoplankton species composition differed during Formative and stable periods. The contribution of groups of phytoplankton was calculated based on the Phytoplankton total abundance (2.2), which was higher during the thermocline stable period, and the Cyanobacteria the most abundant (24,7%) of the total density during the formative period. Klebsormidiophycae (86%) was dominant in the stable period (**Fig. 11**). The most common phytoplankton taxa abundance belongs to Cyanobacteria and Chlorophyceae during the two thermal periods.

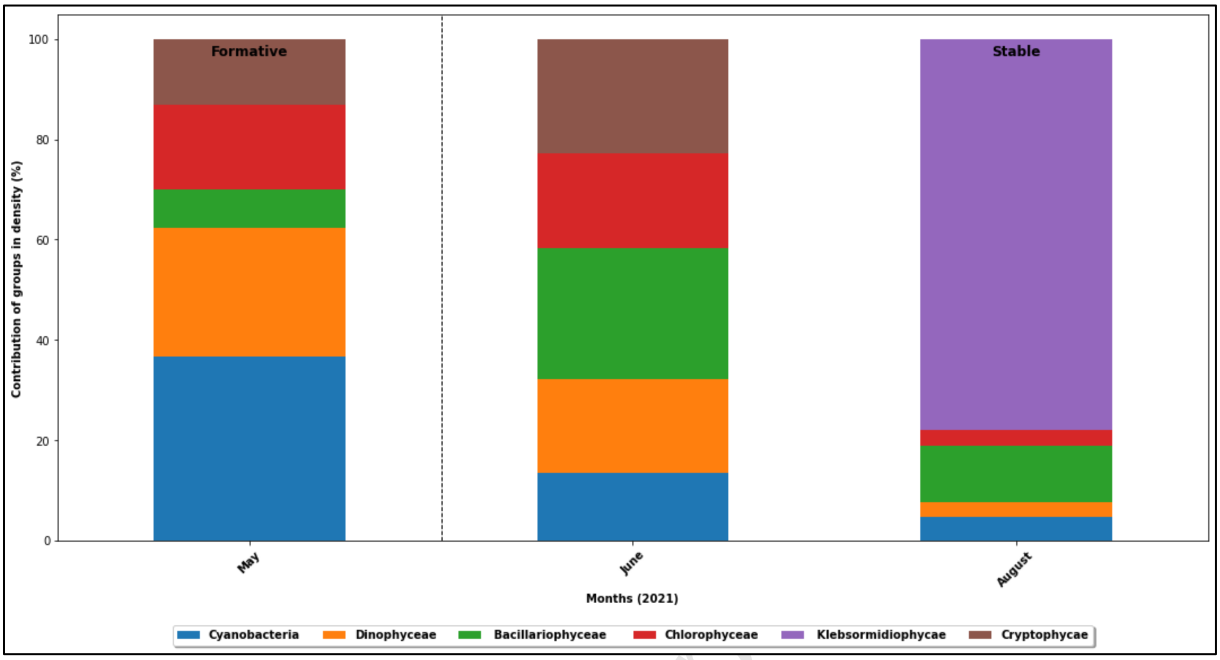

Fig. 11. Stratification period differences in community composition and the contribution of groups of phytoplankton in density in the Joumine reservoir

4. Discussion:

The EOLE conceptual logic and equation were used to implement a new Derived EOLE Joumine Model (DEOLE-J) to simulate the evolution of thermal stratification in the Joumine Reservoir. The model incorporates physical processes and thermal exchanges at the air-water interface to enhance understanding of these complex dynamics (Salençon, 1997). The DEOLE-J aims to represent the one-dimensional vertical structure. Our choice of model is based on the fact that the epilimnion is described with an integral mixed-layer model, and the discretization used is the finite volume method (Salençon, 1997).

The DEOLE-J model calibration emphasizes precision and reliability through a structured metaheuristic approach comprising three primary steps. First, polynomial fitting is employed to enhance data quality by identifying and removing outliers, normalizing variables, and optimizing polynomial degrees through cross-validation to prevent overfitting. Second, the calibrated values are validated against target averages and realistic physical ranges, with residual analysis used to uncover and correct any systematic errors. Finally, the calibration process ensures that the limited dataset sufficiently represents all hours and seasonal periods, minimizing potential biases in hourly or seasonal averages. This comprehensive approach integrates with the metaheuristic method to generate hourly air temperature data, which serves as input for the DEOLE-J model.

Despite the constraints of a limited observed dataset, the outputs of the DEOLE-J model were evaluated for physical consistency by analyzing seasonal patterns, thermal gradients, and responses to meteorological inputs. The model accurately simulated seasonal variations in surface water temperatures, with warmer conditions in summer (peaking in July–August) and cooler conditions in winter (January–February), consistent with findings by (Prats et al., 2017), who observed similar trends in the Bimont reservoir using the EOLE model. The DEOLE-J model also simulated reasonable thermal gradients, with a thermocline strength index (TSI) reaching 0.42°C/m in summer, aligning with the expected behavior of Mediterranean reservoirs. The thermocline depth ranged from 30 m during winter mixing to 2.5 m during stable summer stratification, comparable to those observed by (Salençon, 1997) in Pareloup and Rochebut lakes. The model effectively captured the influence of external drivers such as wind speed and air temperature. High wind speeds in winter (~2.5 m/s) drove vertical mixing, leading to deeper thermoclines. In comparison, reduced wind speeds in summer (~1 m/s) and increased air temperatures stabilized the thermocline at 2.5 m, reflecting similar findings by (Prats et al., 2017) and (Salençon, 1997), who identified wind and temperature as key drivers of stratification. The simulated surface temperatures ranged from 5°C to 32°C, consistent with the observed range in Mediterranean reservoirs, further demonstrating the robustness of the DEOLE-J model in capturing thermal dynamics.

By selecting a suitable time step, we can ensure that meteorological data accurately represent the environmental conditions affecting biological phenomena. This alignment helps prevent energy losses that might occur due to inaccuracies in temporal representation, thereby enhancing the reliability and relevance of studies focusing on biological aspects (Imberger, 1979; Salençon, 1997). Considering the importance of precision and quality of input data in accurately describing the system (Salençon and Thébault, 1994), we used an average value for the extinction coefficient due to the lack of specific data. This may affect the accuracy of the water temperature estimates generated by the Derived EOLE Joumine Model. The extinction coefficient, which varies with seasonal changes, impacts biomass and is crucial in light absorption and the vertical thermal structure (Salençon, 1997). Additionally, the difference between the water temperature measured and estimated by the model (R^2= 0.34) could be caused by the distance between the meteorological station located several kilometres away and the lake. In this version, we used the Derived EOLE Joumine Model. In this one-dimensional vertical model, horizontal fluxes, such as throughflow in the reservoir (rivers, pumping) and water withdrawal from the reservoir were neglected. This could explain the bias between the measured and estimated water temperatures. The 2-D model might be a solution to improve temperature estimation accuracy. Moreover, water withdrawal from the reservoir significantly impacts water temperature, especially when managing water quality downstream or within the reservoir (Salençon, 1997).

ERA5 data is useful for estimating weather conditions in areas without available measurements (McNicholl et al., 2022). The bias between measured and estimated average air temperature is significant. However, the inter-hourly variation is more reliable. The metaheuristic approach was employed to correct ERA5 data based on the measured data while preserving the same inter-hourly variation.

Our results indicate that weaker thermal stratification observed in spring is primarily driven by increased inflow discharge, as suggested by (Y. Wang et al., 2024). The DEOLE-J model successfully simulates this transition, linking seasonal air temperature variations with water inflow, consistent with findings from (Long et al., 2022) that deeper mixed layers reduce light penetration and nutrient availability, leading to unfavorable conditions for phytoplankton blooms. The model calculates seasonal fluctuations in the thermocline, showing phases of strengthening, stabilizing, and weakening throughout the year. The Relative Water Column Stability (RWCS) index, which reflects the energy required to disrupt stratification (Boehrer and Schultze, 2008), confirmed that as air temperature rises, thermocline depth decreases, consistent with findings from (Tian et al., 2017; Y. Wang et al., 2024).

In addition to temperature data, wind speed is another key factor influencing stratification dynamics. (Y. Wang et al., 2024) and (Pöschke et al., 2015) demonstrated that wind regulates heat exchange and water movements, influencing turbulent transport. In the Joumine Reservoir, recorded wind speeds of around 2.5 m/s in winter were sufficient to promote some vertical mixing. However, as (Zhou et al., 2022) noted, even higher wind speeds do not always penetrate the hypolimnion deep enough to mix the water column fully. This was corroborated by our findings, where the thermocline remained stable despite variations in wind speed.

Reservoir size also affects the response to wind-induced mixing. (Liu et al., 2020) found that smaller reservoirs can mix more effectively at lower wind speeds, while larger reservoirs like

Joumine require stronger winds. Our study supports this observation, showing that moderate wind speeds had limited effects on thermocline depth and intensity, except during winter mixing.

Temperature significantly impacts stratification. (Stetler et al., 2021) showed that higher summer temperatures intensify thermal stratification without substantially affecting its depth. Our results corroborate this, indicating that summer surface temperatures sharpen the thermal gradient, while the thermocline remained stable at a depth of 2.5 meters. Thus, although air temperature influences thermal intensity, wind speed predominantly controls stratification depth.

(Morales-Marin et al., 2021) emphasized that climate change can extend the stratification duration, reducing vertical mixing and nutrient distribution, potentially leading to algal blooms. Our observations during stable periods confirm that extended stratification limits mixing, which may further deteriorate water quality. The depth of the thermocline, used as a measure of thermal stratification strength, showed a significant negative correlation with the thermocline strength index (Tian et al., 2017; L. Wang et al., 2024). Therefore, a shallow thermocline depth corresponds to higher thermocline strength.

Furthermore, The Joumine reservoir shows temporal phytoplankton succession (Madyouni et al., 2023). The temporal distribution of phytoplankton groups varied with changing stratification conditions. Thermal stratification dynamics notably influenced the prevalence of phytoplankton species in the reservoir (Cantin et al., 2011). For instance, Cyanobacteria dominated during formative periods, while Klebsormidiophyceae became predominant during stable thermal periods. This pattern supports the findings of (Y. Wang et al., 2024) and (Cantin et al., 2011), which indicate that stratification limits nutrient circulation, favoring buoyant species.

5. Conclusions

The Derived EOLE Joumine Model was coded to simulate the evolution of thermal stratification in reservoirs, considering thermal exchanges at the air-water interface. The model has a one-dimensional vertical structure, a process-based approach, a description of the epilimnion with an integral mixed-layer model, and finite volume discretization. The comparison with field measurements primarily focuses on representing thermal stratification, which could be enhanced by employing a 2-D model to account for horizontal fluxes. This study found that the Joumine reservoir exhibits three distinct thermal stratification periods: mixing, formative, and stable. Seasonal changes in air temperature and thermocline depth were key factors influencing the Joumine reservoir's thermal stability. During the mixing period, there was a notable negative correlation between the thermocline strength index (TSI) and air temperature. Similarly, significant negative correlations were observed among TSI, air temperature, and relative water column stability (RWCS) during the formative period. Across the entire dataset, thermocline depth was significantly negatively correlated with TSI. Furthermore, phytoplankton abundance and distribution were linked to thermal stratification, with Cyanobacteria particularly prevalent during the formative period. Using the results from the model, we will be able to calculate the volume of the thermocline, which is an important parameter that affects the distribution of nutrients and light in the water column. This understanding is crucial for phytoplankton species, particularly buoyant species like cyanobacteria. Cyanobacteria thrive in conditions where they can access both nutrients from deeper waters and adequate light from the surface, often leading to their rapid growth during favorable climatic conditions. By accurately determining the volume of the thermocline, we will enhance our ability to predict when and where cyanobacterial blooms may occur. These blooms can significantly impact water supply strategies due to their potential to degrade water quality, posing risks to both human health and aquatic ecosystems.

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Conflicts of Interest: The authors declare that they have no conflict of interest.

Data Availability Statement: A part of the data and code supporting the findings of this study are publicly available to ensure transparency and reproducibility of the research. The dataset, Python code used for model preparation, and python code employed in generating graphs of this study, can be accessed at this link: (https://github.com/HaifaMadyouni/Thermocline_file).

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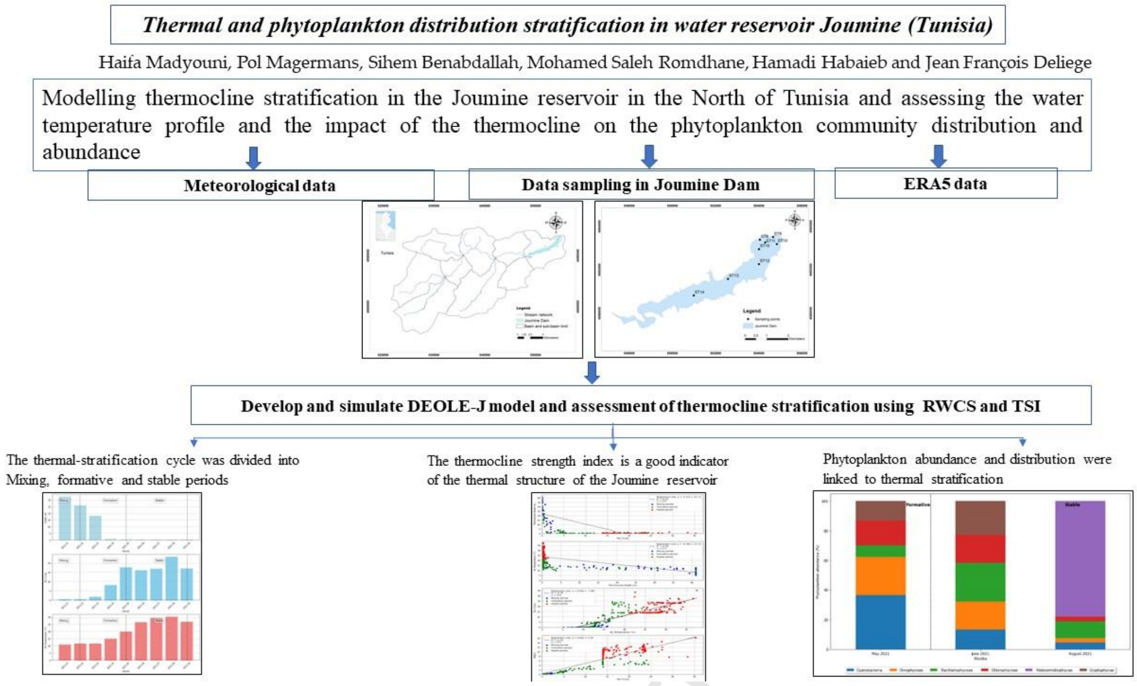
Graphical abstract



Highlights

- The thermal-stratification cycle was divided into Mixing, formative and stable periods.
- Phytoplankton abundance and distribution were linked to thermal stratification
- Thermocline depth was significantly negatively correlated with Thermocline strength index
- The thermocline strength index is a good indicator of the thermal structure of the Joumine reservoir.