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Loc-Crops: A Spatio-Temporal Framework for Agricultural Planning Under Climatic and Ecological Variability

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Abstract

Planning and locating agricultural varieties in alignment with regional specifications and climatic properties represent significant chal- lenges due to the inherent variability and interaction among numerous parameters. To address this, we propose a decision support system called LocCrops that integrates spatio-temporal analysis with multi-criteria op- timization to efficiently identify areas suitable for large-scale crop pro- duction. The framework leverages diverse environmental data—including climate, soil, and phenological parameters—to develop a forecasting model tailored to specific regions. As a case study, we evaluate olive production in agro-pastoral steppe regions, employing NDVI analysis across differ- ent seasons and extensive field surveys to capture production dynamics. Experimental validation reveals that our framework not only enhances yield prediction accuracy (up to 88.5%) and achieves a high suitability index (0.85), but also demonstrates strong NDVI temporal correlation (0.89). Additionally, the application of the ELECTRE III method success- fully ranks regions based on production, climatic variability, soil quality, and irrigation practices, with Region A emerging as the most favorable for large-scale olive production. These results confirm that LocCrops pro- vides a robust, data-driven approach to optimizing agricultural planning, effectively balancing production potential with ecological constraints in the face of environmental variability.

Keywords: Agricultural Planning · Climatic Properties · Decision Sup- port System · Loc-Crops Framework · Olive Production · NDVI.

1 Introduction

Recent years have witnessed significant efforts to develop decision support sys- tems (DSS) for agro-ecological planning that integrate environmental and cli- matic parameters (e.g. [1, 18]). These systems are broadly categorized into three

generations: first-generation yield-prediction tools, second-generation static soil- climate suitability indices, and emerging third-generation frameworks adopting dynamic spatio-temporal modeling [28]. Early yield-centric models, while estab- lishing baseline agro-climatic zoning, often oversimplify the non-linear interac- tions among soil heterogeneity, microclimate variability, and phenological stres- sors (e.g.[23, 10]). In response, recent studies have emphasized the integration of spatio-temporal dynamics and multi-objective optimization, as exemplified by DSS that combine satellite-derived NDVI with soil moisture sensors [19]. Precision agriculture approaches using machine learning—such as CNNs and reinforcement learning—further enhance crop suitability predictions but face scalability challenges in data-sparse regions (e.g.[29, 9]).

The sustainable cultivation of crops in alignment with regional ecological and climatic conditions presents a critical challenge in modern agricultural planning [7, 22]. Rapid environmental changes—driven by anthropogenic pressures and shifting climatic baselines—coupled with the complex interplay of soil properties, microclimates, and species-specific phenological requirements, demand robust strategies that harmonize agricultural productivity with ecological resilience [12, 14]. This challenge is particularly acute in semi-arid and agro-pastoral regions, where fragile ecosystems, erratic precipitation regimes, and rising temperatures exacerbate risks of land degradation, desertification, and crop failure [6].

Conventional agricultural zoning methods, which often rely on static suitability models or oversimplified climatic analogs, struggle to account for the dynamic spatial and temporal interactions between biophysical variables [15]. Consequently, there remains an urgent need for adaptive, data-driven frameworks that integrate real- time environmental feedback with long-term sustainability goals [25].

To address these limitations, we introduce *Loc-Crops*, a geospatial deci- sion support system designed to optimize agricultural zoning through spatio- temporal analytics and multi-criteria optimization. Building upon advances in precision agriculture and ecological modeling [26], our framework synthesizes heterogeneous environmental datasets—including high-resolution soil composi- tion maps, decadal precipitation trends, diurnal temperature fluctuations, and species-specific phenological thresholds—to dynamically delineate cultivation zones that maximize yield potential while adhering to ecological carrying ca- pacities [27]. By employing machine learning techniques to reconcile conflict- ing objectives (e.g., water-use efficiency versus yield maximization), *Loc-Crops* translates multidimensional agro-climatic parameters into spatially explicit, ac- tionable insights. This enables stakeholders to systematically navigate trade-offs between productivity, biodiversity conservation, and resource efficiency across temporal scales.

The practical utility of *Loc-Crops* is demonstrated through a longitudinal case study on olive cultivation in North Africa's agro-pastoral steppe regions, where climate variability and soil aridity threaten the viability of traditional farming systems. Focusing on this economically vital and cultur- ally symbolic crop, we evaluate its agro-ecological suitability across gradients of elevation, soil hydrology, and microclimate niches by integrating:

(1) phenological stage-specific climatic thresholds (e.g., chilling requirements for flowering), (2) edaphic constraints on rootzone water retention, and (3) satellite-derived NDVI (Normalized Difference Vegetation Index) time-series to quantify veg- etation health and phenophase alignment under climate stress. Ground-truth validation using field surveys from 42 farms reveals that *Loc-Crops* achieves higher accuracy in predicting viable olive cultivation zones. The methodology establishes a replicable workflow for adapting crop zoning strategies to semi- arid environments globally, with particular relevance for Mediterranean-climate regions facing analogous sustainability challenges.

This study makes three primary contributions:

A novel spatio-temporal optimization framework (Loc-Crops) that unifies multi-source environmental data with agro-ecological constraints to dynam- ically map climate-resilient cultivation zones empirical validation of the system through a decade-long case study in North Africa, demonstrating its superiority over static zoning methods in predicting olive viability under drought scenarios

By bridging ecological specificity with computational scalability, Loc-Crops advances the frontier of climate-resilient agriculture, offering policymakers and farmers a pathway to stabilize yields, conserve biodiversity, and mitigate land-use conflicts in vulnerable regions. The implications extend beyond agro-economic optimization, providing a blueprint for reconciling UN Sustainable Development Goals

(SDGs) related to zero hunger, climate action, and terrestrial ecosystem protection.

Paper Organization: Section 2 contextualizes the problem through Study area: Spatio-temporal analysis. The architecture of Loc-Crops, including its data fu- sion pipeline and optimization algorithms, is detailed in Section 3. Section 4 presents experimental results from the North African case study, followed by dis- cussion . Section 5 critically analyzes gaps in existing decision support systems for agro-ecological planning. The paper concludes with future research directions in Section 6.

2 Study area: Spatio-temporal analysis

2.1 Geographical Situation of the Ksar Chellala Area

General Location The Ksar Chellala District, located in the Oued Touil region of Tiaret province, is a strategically positioned area approximately 116 kilome- ters southwest of the city of Tiaret, the provincial capital. This geographical location places Ksar Chellala at a crossroads between several important rural and urban regions in the country. As a result, it enjoys optimal connectivity, facilitating access to various economic, agricultural, and administrative hubs within the region. This area, due to its semi-arid Mediterranean climate, offers fertile ground for various agricultural activities, including arboriculture, which is a key component of the local economy

Geographical Boundaries The Ksar Chellala District is bordered by several administrative and geographical areas, providing it with a rich and diverse array of natural resources and environmental conditions. The district is geographically delimited as follows:

- **To the North and West:** The district borders Djelfa province. This prox- imity to a neighboring region fosters inter-regional cooperation in terms of economic development and resource sharing. Djelfa province is also known for its agriculture, particularly wheat and barley cultivation, creating a com- plementary dynamic with Ksar Chellala.
- **To the East:** The commune of Rechaigua, located to the east of Ksar Chellala, serves as a strategic access point to other agricultural and industrial regions. Its influence on local commercial dynamics is significant, promoting the distribution of agricultural products on a larger scale.
- **To the South:** The commune of Faidja marks the southern boundary of the area. Positioned in the heart of the steppic region, it provides Ksar Chellala with direct contact with less developed areas that are rich in natural resources such as pastures and drier farming zones.

Ksar Chellala is precisely located at the following coordinates:

- **Latitude:** 35°13’ 00” N
- **Longitude:** 2°19’ 00” E

These geographical coordinates place the commune in an ideal position for environmental studies, offering a good representation of southern Algeria’s re- gions, with climatic and ecological conditions typical of semi-arid zones.

2.2 Distances between Ksar Chellala and Neighboring Communes

The commune of Ksar Chellala is characterized by a relatively well-developed transportation network, ensuring mobility between the various communes and facilitating trade. This connectivity is crucial for the region’s economic devel- opment. Here are the key distances between Ksar Chellala and its neighboring communes: (i) **Ksar Chellala – Serguine:** 18 km. This short distance allows for smooth interactions between the two communes, particularly in terms of agricul- tural activities and the marketing of local products. **Ksar Chellala – Zmalet Emir Abdelkader:** 42 km. While this distance is slightly longer, it remains easily accessible, thus facilitating the exchange of goods and services between rural areas. (ii) These short distances play a key role in regional integration, strengthening social and economic ties between Ksar Chellala and its neighbor- ing communes, thereby stimulating cooperation in sectors such as agriculture, trade, and infrastructure. In particular, the proximity to these communes allows Ksar Chellala to develop while maintaining its rural characteristics, benefiting from the resources and markets of its neighbors.

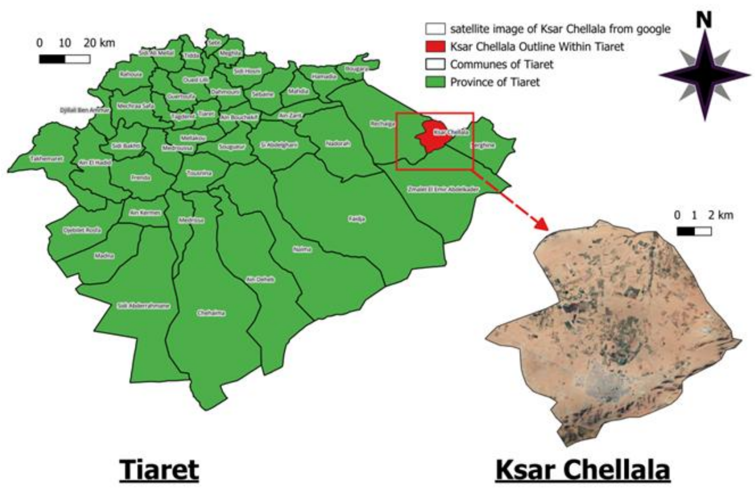


Fig. 1. Geographical Situation of the Ksar Chellala Area.

2.3 Geographical Location of the Serguine Commun

The commune of Serguine, located in the eastern part of the Tiaret province's administrative region, plays a vital role in the agro-pastoral activities of the area. Covering a total area of 36,000 hectares, it stands as a testament to the integration of agricultural and pastoral traditions in Algeria. Positioned between various neighboring communes, Serguine is bounded to the southwest by Zmalte El Emir Aek, to the west by Ksar-Chellala, to the east by Elkhémis, to the north by Sidi-Ladjel, and to the southwest by Elguernini.

The commune is particularly notable for its abundant hydric resources, which are essential for sustaining its agricultural activities. In total, Serguine hosts more than ten artesian wells and seven potable water sources, ensuring a reli- able water supply for its population.

These natural resources support the local inhabitants, who are engaged in various forms of cultivation. In particular, they grow a wide range of vegetables (maraîchage), cereals, and engage in arboricul- ture, focusing predominantly on apricot trees. Alongside crop production, the region also supports a thriving livestock industry, with residents raising sheep and cattle.

Serguine's geographical coordinates are as follows:

- Latitude: 35°16'15" North
- Longitude: 2°30'28" East

This commune, with its combination of rich agricultural practices and natural resources, plays a crucial role in the socio-economic landscape of the region, contributing significantly to both food production and rural livelihoods.

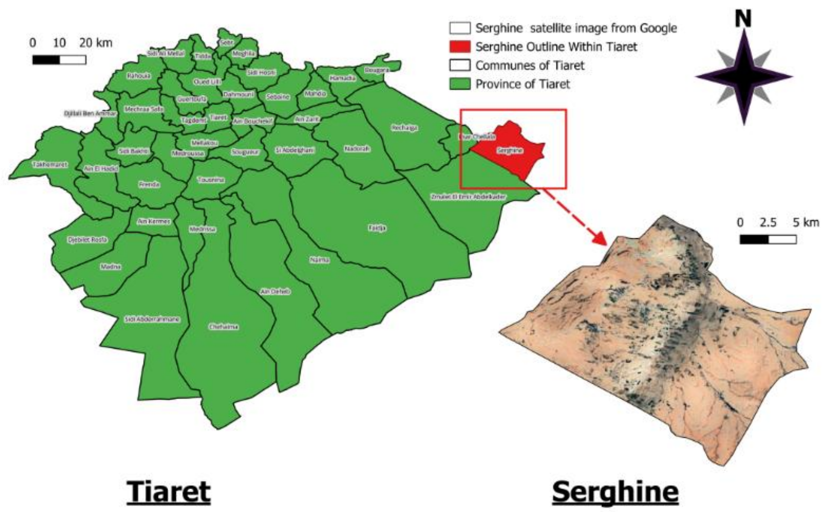


Fig. 2. Geographical Location of the Serguine Area .

2.4 Geographical Location of the Z'MALT AMIR ABD-EL-KADER Area

The Z'MALT AMIR ABD-EL-KADER region is located 160 km south of Ksar Chellala, in the Tiaret province, with a total area of 1189 km^2. Its geographical coordinates are:

- Latitude: 34°53'59" N
- Longitude: 2°18'51" E

This region is bordered by several areas:

- To the northeast by Serguine.
- To the northwest by Ksar Chellala and Rechaïga.
- To the east by Djelfa province.
- To the west by Nadhorah.
- To the south by Djelfa province and Faidja.

The region’s strategic location influences its agricultural and pastoral activ- ities, making it a key area for local economic growth .

Temporal Analysis and Key Parameters: The Z’MALT AMIR ABD-EL- KADER region’s agricultural productivity is influenced by several temporal pa- rameters. The following factors are critical to understanding seasonal trends:

1. Climate Variability: Seasonal variations in temperature, precipitation, and humidity significantly impact crop yields and livestock. The region experi- ences dry summers and mild winters, which affect crop planning and har- vesting times.

2. Soil and Water Resources: Water availability from artesian wells and springs is crucial. Temporal analysis of water levels and soil moisture enables better irrigation strategies.
3. Agricultural Practices and Crop Phenology: Monitoring crop development phases and aligning them with seasonal changes helps optimize planting and harvesting times.
4. Livestock and Pastoral Movements: Temperature and water availability af- fect grazing patterns. Monitoring seasonal trends helps optimize livestock management and prevent overgrazing.

By analyzing these parameters, decision-makers can enhance agricultural practices, leading to higher productivity and sustainability.

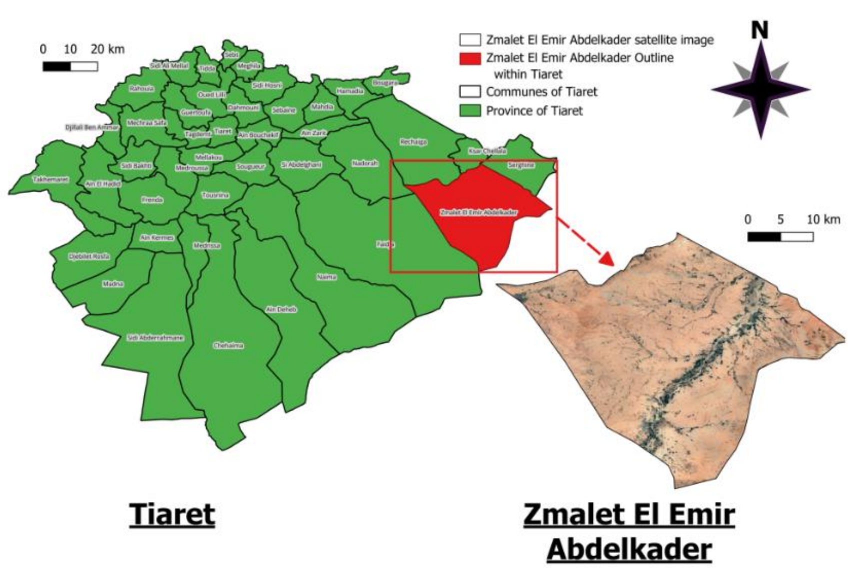


Fig. 3. Geographical location of the Z'MALT AMIR AEK area.

2.5 Geolocation of the Djaib exploitation:

The exploitation is located approximately 27 km from the main town of the Rechaigua municipality (Fig. 4). It covers a total area of 490 hectares, of which 155 hectares are dedicated to olive cultivation. The remaining land is used for growing nectarines, plums, peaches, cherries, and pomegranates. Its geographical coordinates are as follows:

- Longitude: 2° 11' 18,57" and 2° 13' 49.00"
- Latitude: 35° 13' 59.18" and 35° 14' 54.37"

The average altitude is 780 meters. The area slopes gently from the southeast to the northwest with an inclination of approximately 1 to 3%.

Table 1 presents the distribution of different olive varieties across various plots in the *Djaib* farm, along with their respective surface areas.

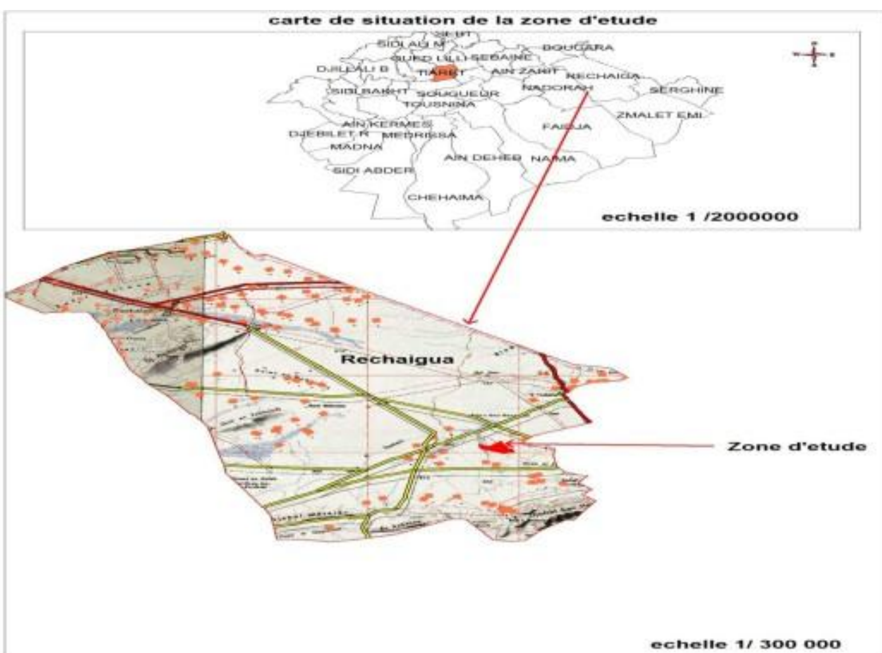


Fig. 4. Geographical location of the jaib exploitation area.

To compare different varieties, we selected various plots from the 32 olive-growing parcels, numbered as shown in Table N°1. The selection was made based on accessibility and the presence of the varieties.

Table 1 : Different Olive Varieties from the Djaib exploitation.

Latitude (X)	Longitude (Y)	Plot 5	Plot 12_13	Plot 14_15	Plot 38_39
35°17'27.95"N 35°14'32.19"N 35°14'24.68"N 35°14'45.06"N	2°13'29.31"E 2°13'27.26"E 2°12'57.13"E 2°12'98.10"E	3 ha	10 ha	3 ha	8 ha
Variety		SIGOISE	SOFIANA	CHEMLAL	AZERADJ

2.6 Ksar Chellala

We conducted a survey in the areas of Ksar Chellala, Serguine, and Z'Malt Al Amir Aek, visiting several olive oil plantations distributed according to their surface areas and varieties, as follows (Table **N°2**, Table **N°3**, and Table **N°5**).

2.7 Serguine

As we can see in Table, 3 olive oil stations visited in the Serguine area, specifying the cultivated variety, surface area, and exact coordinates. It highlights the dom- inance of the Sigoise variety, with other varieties such as *Chemlalle* and *Picual* present in smaller plots. These stations play a key role in olive oil production and regional agricultural planning.

Table 2. Olive Oil Stations Visited in the Ksar Chellala Area

Station Name	Variety	Area (ha)	Latitude	Longitude
BOUDJENAH	PICUAL	13	35.282307	2.292739
DOKMANE	SIGOISE	1	35.293759	2.299084
HADJI	CHEMLLALE	4	35.280000	2.279167
INSID INTERNE	PICUAL	2	35°15'0489	2°17'3266
INSID EXTERNE 1	CHEMLLALE	1	35°15'0489	2°17'5125
INSID EXTERNE 2	SIGOISE	2	35°15'0489	2°17'5.25

WENAS	SIGOISE	2	35.252564	2.299635
BOUHAFES	SIGOISE	2	35.259444	2.316389
BOUDISSA	SIGOISE	2	35.209444	2.316389
NOUIDJEM	SIGOISE	1	35.236726	2.303442
INCONNU 1	CHEMLLALE	2	35°17’24.76	2°17’39.89
INCONNU 2	CHEMLLALE	0.5	35°17’12.02	2°17’48.21
BELAOUBI	ALBIKINA	13.5	35°16’58.66	2°17’32.66
RJEL	CHEMLLALE ALBIKINA	3	35°22’5.87	2°14’12.04
FARAA 1	SIGOISE	1	35°13’51.20	2°18’55.63
FARAA 2	SIGOISE CHEMLLALE	2	35°14’2.933	2°18’55.45
FARAA 3	CHEMLLALE	2	35°14’14.66	2°34’48.55
AEK TORKI 1	SOFIANA PICUAL	1	35°20’18.264	2°18’19.8
AEK TORKI 2	CHEMLLALE	0.5	35°20’18.345	2°18’21.898
LAISSAOUI 1	CHEMLLALE	1	35°19’46.59	2°18’6.498
LAISSAOUI 2	SIGOISE CHEMLLALE	2	35°19’38.789	2°18’11.459
LAISSAOUI 3	SIGOISE	1	35°19’38.789	2°18’11.459

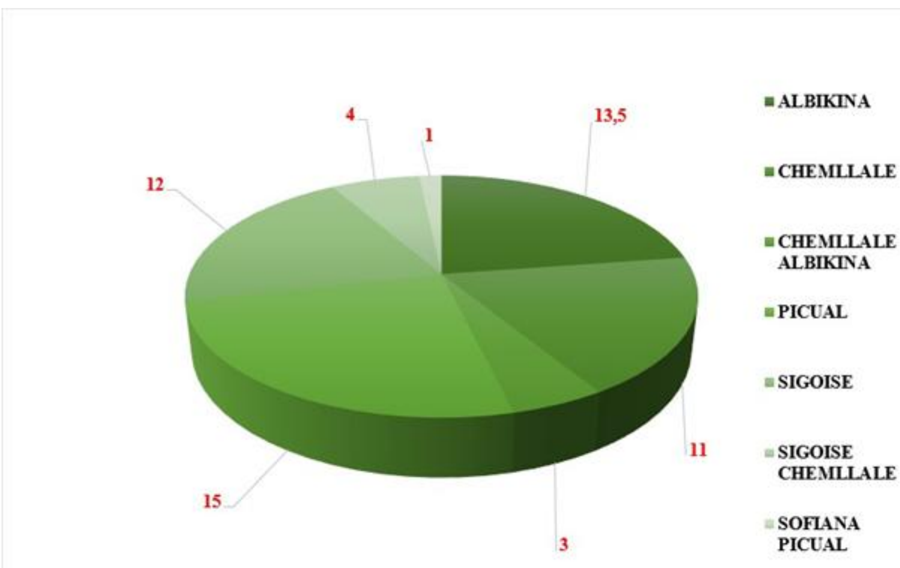


Fig. 5. The different varieties of olive trees in the Ksar Chellala area (ha).

Different Olive Varieties and Their Areas in the Djaib Exploitation are distributed in all of the exploitation,it contain different olives variéties of consomation and oil varieties.

Table 3. Olive Oil Stations Visited in the Serguine Area

Station Name	Variety	Area (ha)	Latitude	Longitude
ZWABLIA	SIGOISE	0.5	35.265813	2.500820
SELMOUNE 1	SIGOISE	1.5	35.260509	2.494518
SELMOUNE 2	SIGOISE	0.5	35.258466	2.492043
TABLATI	CHEMLLALE	0.5	35.234846	2.509687
LAARFI	PICUAL	1	35.234568	2.505884

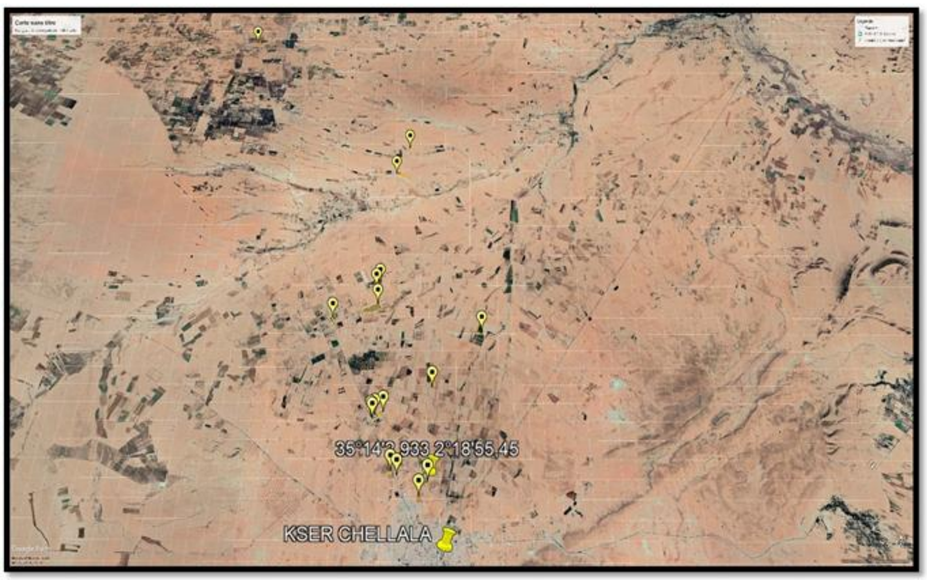


Fig. 6. Location map of the plots in the *Ksar Chellala* area.

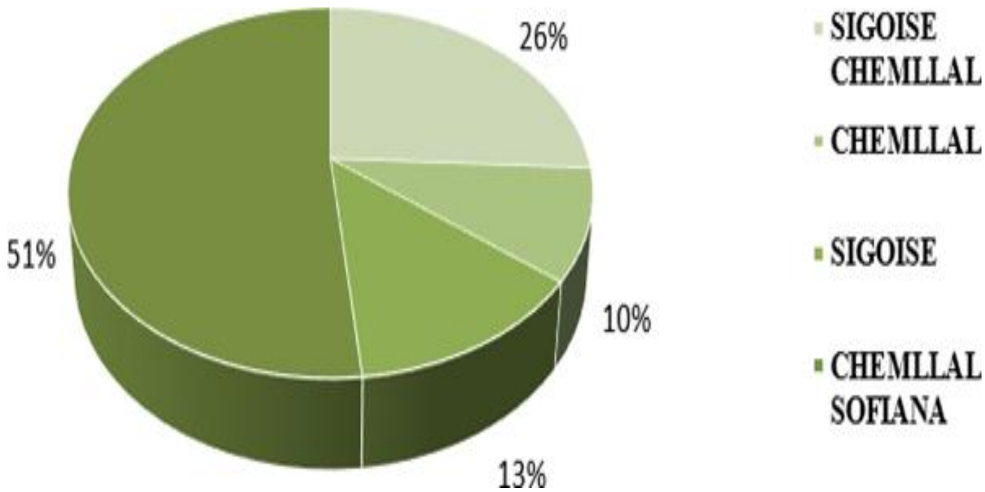


Fig. 7. The different varieties of olive trees in the *Ksar Chellala region* area.

In Table No. 3 and Figure No. 6, we represent the different recorded exploitations in the *Ksar Chellala* region.

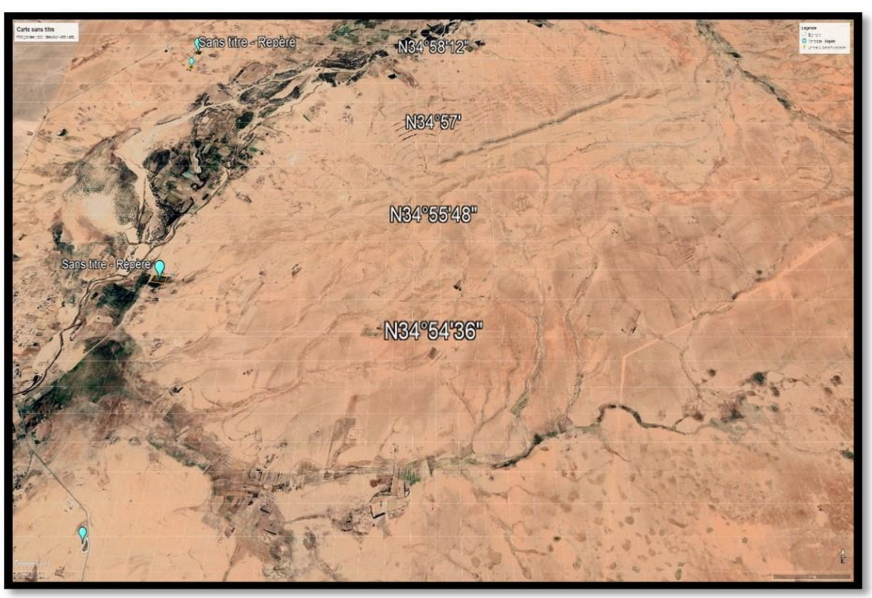


Fig. 8. location map of plots in the Z'MALT AMIR ABD-EL-KADER area.

Table 4. Different Olive Varieties in the Djaib Exploitation

Variety	Area (ha)

Chemllal	120
Sigoise	22.5
Sofiana + Azerag	7.5

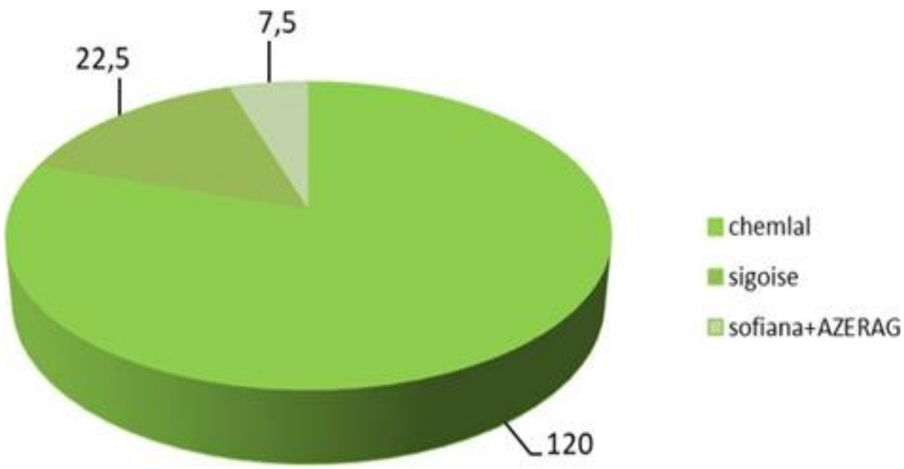


Fig. 9. The different varieties of olive trees from the djaib farm.

2.8 Djaib Exploitation

In this section, we present the geolocation of the exploitation and the distribution of different olive crop varieties, along with their yield production.

2.9 Comparison of Different Olive Varieties

In order to compare the different varieties, we selected various plots from the 32 olive groves, numbered as follows in Table 5. The selection was made based on accessibility and the existence of the varieties.

Table 5. Different Olive Varieties in the Djaib Exploitation

Name	Latitude	Longitude	Area (ha)	Variety
Parcelle 5	35°17’27.95"	2°13’29.31"	3	Sigoise
Parcelle 12_13	35°14’32.19"	2°13’27.26"	10	Sofiana
Parcelle 14_15	35°14’24.68"	2°12’57.13"	3	Chemllal

Parcelle 38_39	35°14’45.06"	2°12’98.10"	8	Azeradj

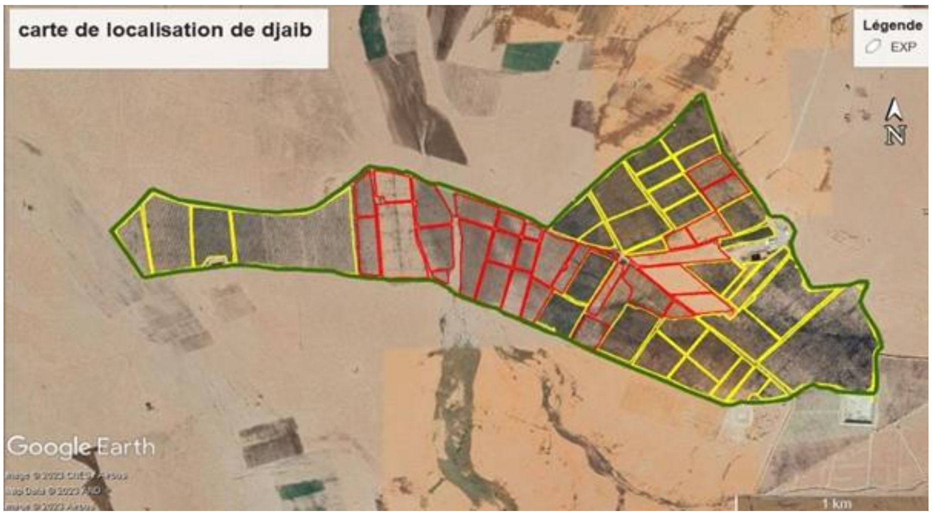


Fig. 10. Location and distribution map of The different varieties of olive trees from the Djaib exploitation.

1 Our framework and its theoretical foundations

Our framework LocCrops emphasizes two stages: the synthetic phase of analy- sis for the collection of parameters and data, and the analytical phase, which relies on a multi-criteria and spatio-temporal analysis to identify the optimal re- gions based on production potential. The spatio-temporal framework leverages climatic and ecological variability to efficiently assess and plan agricultural ac- tivities across regions.

Figure 12 illustrates the comprehensive preview of our methodology.

The crop management and monitoring system integrates data extraction, persistence, and analytical processing to provide actionable recommendations to breeders and managers. The system collects critical data from agricultural fields, including tree plots, geolocation, irrigation details, pruning schedules, and tree disease records. A tracker logs agricultural events and stores them in a ro- bust database for further analysis. The analytical phase extracts relevant data through a combination of queries, machine learning algorithms, and statistical analysis to derive valuable insights. A data analyst then interprets these insights through dashboards, performing descriptive, diagnostic, and predictive analy- ses to inform decision-making. Recommendations derived from the analysis are converted into actionable guidance, covering areas like irrigation adjustments, disease management, and optimal pruning strategies. These recommendations are designed to support breeders and managers in enhancing agricultural prac- tices. The integration of data-driven insights ensures that farming technique are sustainable and tailored to local conditions, improving both productivity and environmental compatibility.

The spatio-temporal analysis in LocCrops enables the identification of optimal agricultural regions by considering the interaction of multiple parameters, such as soil type, climate, irrigation methods, and phenological data. By evaluating these parameters over time and across different locations, the system helps determine which regions are most suitable for large-scale crop production.

Incorporating the ELECTRE III method, the framework also applies multi- criteria decision analysis to rank different regions based on various factors such as climatic variability, soil quality, irrigation practices, and crop suitability. This method helps prioritize regions based on their overall production potential, sup- porting informed and strategic decision-making for large-scale agricultural plan- ning.

Steps involved in the framework:

- Data collection from agricultural fields (tree plots, geolocation, irrigation, etc.)
- Logging events and storing them in a database
- Extracting data using queries and machine learning algorithms
- Performing descriptive, diagnostic, and predictive analysis
- Interpreting insights through dashboards and reports
- Generating recommendations based on analysis
- Implementing interventions such as irrigation adjustments, pruning, and dis- ease management

This decision support system aims to enhance crop productivity and optimize farming practices by leveraging climatic, ecological, and socio-economic factors in a dynamic, multi-dimensional framework. By integrating ELECTRE III and spatio-temporal analysis, the framework offers a powerful tool for balancing pro- duction potential with ecological constraints, thus ensuring more sustainable and efficient agricultural management.

1.1 Theoretical foundations of LocCrops

In this section, we model the localization problem to optimize arboricultural production.

Data:

- M : set of all physical resources required for arboricultural production (e.g., agricultural equipment, cultivation machinery), where $m = |M|$.
- N : set of tasks related to arboricultural production (e.g., planting, harvest- ing, irrigation), where $n = |N|$.
- Ji : set of operations associated with task $i \in N$, such that operation $j \in Ji$ must be performed before operation $j + 1 \in Ji$.
- $Mij \subset M$: set of resources that can perform operation $j \in Ji$ of task $i \in N$.
- $Pijk$: duration of operation $j \in Ji$ of task $i \in N$ on resource $k \in Mij$.
- B : an integer representing a very large value used for constraints or limits.
- $ELECETRE\ III$: set of electrical resources or specific constraints (e.g., electricity usage limits) relevant to the arboricultural production process

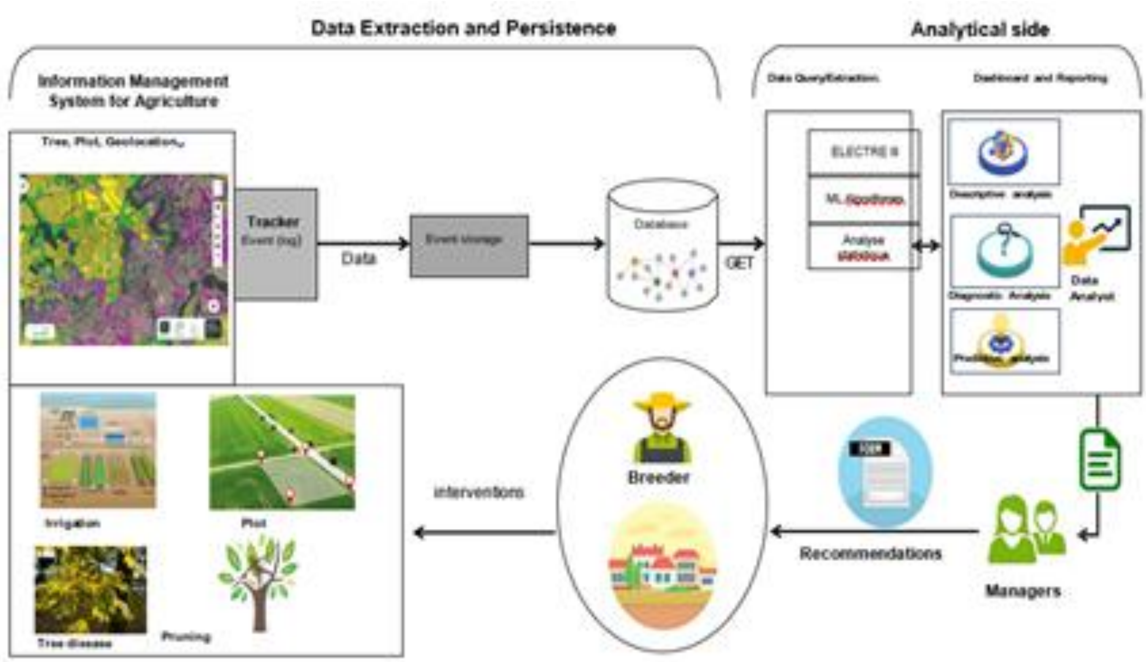


Fig. 12. Our framework LocCro.

Decision Variables:

– $Xijk$: binary variable equal to 1 if operation $j \in Ji$ of task $i \in N$ is assigned to resource $k \in Mij$, and 0 otherwise.

– $Zijhgk$: binary variable equal to 1 if operation $j \in Ji$ of task $i \in N$ precedes operation $g \in Jh$ of

– task $h \in N$ on resource $k \in Mij \cap Mhg$, and 0 otherwise.

– $Sijk$: start date of operation $j \in Ji$ of task $i \in N$ on resource $k \in Mij$.

– $Cijk$: end date of operation $j \in Ji$ of task $i \in N$ on resource $k \in Mij$.

– Ci : end date of task $i \in N$.

– C_{max} : makespan, i.e., the total processing time for all tasks.

– $ELECETRE\ III_{u}se$: binary variable equal to 1 if electrical resources from the set $ELECETRE\ III$ are used for operation j of task i, and 0 otherwise.

Objective The main objective of this model is to optimize the localization of various agricultural operations (e.g., planting, maintenance, harvesting) consid- ering ecological constraints specific to each region (e.g., soil, climate, phenology) and the available material resources, including the management of electrical re- sources from the set $ELECETRE\ III$. This model aims to determine the dates and resources needed for each step of the arboricultural production process, in order to maximize efficiency and profitability while respecting natural, technical, and energy-related constraints.

Constraints

– Tasks must be executed in a specific order based on dependencies between the operations.
– Resources are limited, and each resource can only be used for one operation at a time.
– Operations must be scheduled to respect time constraints and production deadlines to avoid delays in harvesting or maintenance.
– Climatic and ecological variations affect operation durations and must be accounted for to adjust the necessary dates and resources.

This mathematical model enables efficient planning of arboricultural produc- tion by considering both available resources and local ecological conditions. By using binary variables and specifying operation durations for each resource, the model optimizes the localization of tasks and resource management, ensuring optimal production on a large scale.

Example 1. This table illustrates the scheduling of arboricultural tasks, resource assignments, and the use of electrical resources (ELECETRE III).

Table 6. Resource Assignment and Scheduling for Arboricultural Tasks

Step	Task	Operation	Resource	Duration	Start	End
1	Planting	Soil Prep	Tractor (m_1)	3 hrs	2025-02-21 08:00	2025-02-21 11:00
2	Planting	Planting	Tractor (m_1)	4 hrs	2025-02-21 11:00	2025-02-21 15:00
3	Harvesting	Harvesting	Harvester (m_2)	5 hrs	2025-02-22 08:00	2025-02-22 13:00
4	Harvesting	Post-Harvest	Harvester (m_2)	3 hrs	2025-02-22 13:00	2025-02-22 16:00

Electrical Resources (ELECETRE III): $ELECETRE\ III\_use_1 = 1$ for ir- rigation during planting, and $ELECETRE\ III\_use_2 = 1$ for post-harvest pro- cessing. Objective Calculation: The makespan is:

$$\boxed{\text{Makespan} = 2025 - 02 - 2216 : 00 - 2025 - 02 - 2108 : 00 = 32 \text{ hours}}$$

2 Result and Discussion

In this section, we evaluate the Loc-Crops framework by presenting field survey results and key inventory data across multiple agricultural zones . We analyze parameters such as production, climatic variability, soil quality, and irrigation methods to assess crop performance and sustainability. Statistical and sensitiv- ity analyses are conducted to identify the most influential factors affecting yield predictions and regional suitability. Finally, we apply the ELECTRE III method to rank the regions, demonstrating Loc-Crops' effectiveness in optimizing agri- cultural planning.

2.1 Survey Results

After conducting the field survey, we summarized the findings in the tables below:

Table 7. Inventory Table for the Ksar Chellala Zone.

Station Name	Variety	Area (ha)	Production (q/ha)	Irrigation
BOUDJENAH	PICUAL	13	35	**Drip Irrigation**
DOKMANE	SIGOISE	1	18	**Drip Irrigation**
HADJI	CHEMLLALE	4	30	**Drip Irrigation**
INSID INTERNE	PICUAL	1.5	2.5	**Drip Irrigation**
INSID EXTERNE 1	CHEMLLALE	0.25	1.5	**Drip Irrigation**
INSID EXTERNE 2	SIGOISE	0.25	1.5	**Drip Irrigation**
WENAS	SIGOISE	2	7	**Non-irrigated**
BOUHAFES	SIGOISE	2	13	**Furrow Irrigation**
BOUDISSA	SIGOISE	2	8	**Furrow Irrigation**
NOUIDJEM	SIGOISE	1	13	**Furrow Irrigation**
INCONNU 1	CHEMLLALE	2	40	**Furrow Irrigation**
INCONNU 2	CHEMLLALE	0.5	4	**Furrow Irrigation**
BELAOUBI	ALBIKINA	13.5	37	**Drip Irrigation**
RJEL	CHEMLLALE ALBIKINA	3	55	**Furrow Irrigation**
FARAA 1	SIGOISE	1	6	**Furrow Irrigation**
FARAA 2	SIGOISE CHEMLLALE	2	12	**Drip Irrigation**
AEK TORKI 1	SOFIANA PICUAL	1	10	**Furrow Irrigation**
AEK TORKI 2	CHEMLLALE	0.5	/	**Drip Irrigation**
LAISSAOUI 1	SIGOISE CHEMLLALE	1	/	**Furrow Irrigation**
LAISSAOUI 2	SIGOISE CHEMLLALE	1	/	**Furrow Irrigation**
LAISSAOUI 3	**SIGOISE CHEMLLALE**	**1**	**/**	**Furrow Irrigation**

We note that the most common varieties in the Ksar Chellala zone are the Chemllelle and Sigoise varieties, followed by Picual. We observe that the most common varieties in the Ksar Chellala zone are the Chemllelle and Sigoise vari- eties, followed by Picual.

Table 8. Inventory Table for the Serguine Zone.

Station Name	Variety	Area (ha)	Production (q/ha)	Irrigation
ZWABLIA	SIGOISE	0.5	10	**Furrow Irrigation**
SELMOUNE 1	SIGOISE	2	13	**Furrow Irrigation**
SELMOUNE 2	SIGOISE	0.5	13	**Furrow Irrigation**
TABLATI	**CHEMLLALE**	**0.5**	**15**	**Furrow Irrigation**

We observe that the most common varieties are Chemllelle and Sigoise. From this table, we note that the Sofiana and Chemllelle varieties are more prominent in the ZEA zone, followed by Sigoise. We observe that in all three zones, the dominant varieties are Sigoise and Chemllelle, which are local varieties with moderately high production under irrigation systems ranging from furrow irrigation to drip irrigation.

Table 9. Inventory Table for the Z'MALT AMIR AEK Zone.

Station Name	**Variety**	**Area (ha)**	**Production (q/ha)**	**Irrigation**
FAREM DE SALMANI	SIGOISE	4	16	Drip Irrigation
KAMADA	SIGOISE	1	6	Drip Irrigation
MEKHETARYA	SIGOISE	2	10	Drip Irrigation
DJAFI	CHEMLLALE SOFIANA	8	37.5	Drip Irrigation

EL MHAKA	CHEMLLALE	0.5	6	Furrow Irrigation

2.2 Supporting Tool

To enhance the user experience, we have developed a comprehensive support tool for our framework. This tool enables users to navigate through various re- gions and their plots, allowing for the editing and management of information and parameters related to geographical, climatic, and environmental factors. Furthermore, the tool utilizes the ELECTRE III method to recommend optimal locations or personnel based on the specific characteristics of olive varieties, con- sidering user-defined constraints and preferences. The system also incorporates advanced decision-making processes to provide personalized recommendations, optimizing agricultural planning and resource allocation. Figure 13 shows the prototype tool of our framework.

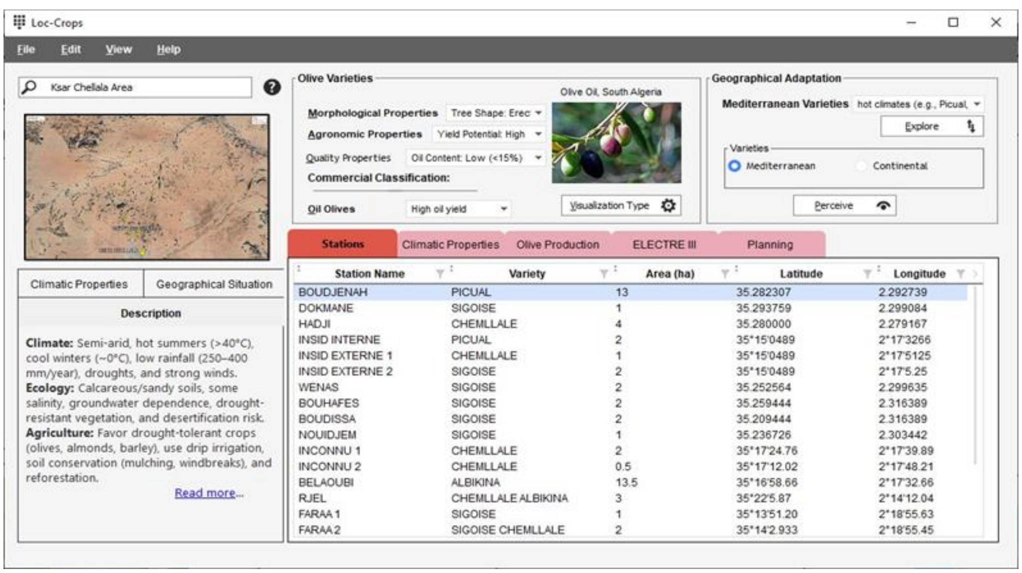


Fig. 13. Supporting Tool of LocCrops.

2.3 *Loc-Crops* Evaluation

In this section, we analyze key parameters of the *Loc-Crops* framework using Sensitivity, Statistical Distribution, and Correlation Analysis.

Parameter Analysis To identify the most influential parameters, we con- ducted a sensitivity analysis to evaluate the impact of key input variables on the results. This process includes examining the domain values, variability range, and probability distributions of the parameters. In this section, we assess two main aspects of *Loc-Crops*: the sensitivity analysis of database parameters and the use of effect

plots for visualization. We applied three methods to distin- guish between crucial and non-crucial parameters: **(i)** Sensitivity Analysis, **(ii)** Statistical Data Distribution Analysis, and **(iii)** Correlation Analysis.

Sensitivity Analysis To identify the most important parameters, we employed feature selection techniques validated by expert input. The significance of each predictor was assessed in a model-agnostic manner using a filter approach. This

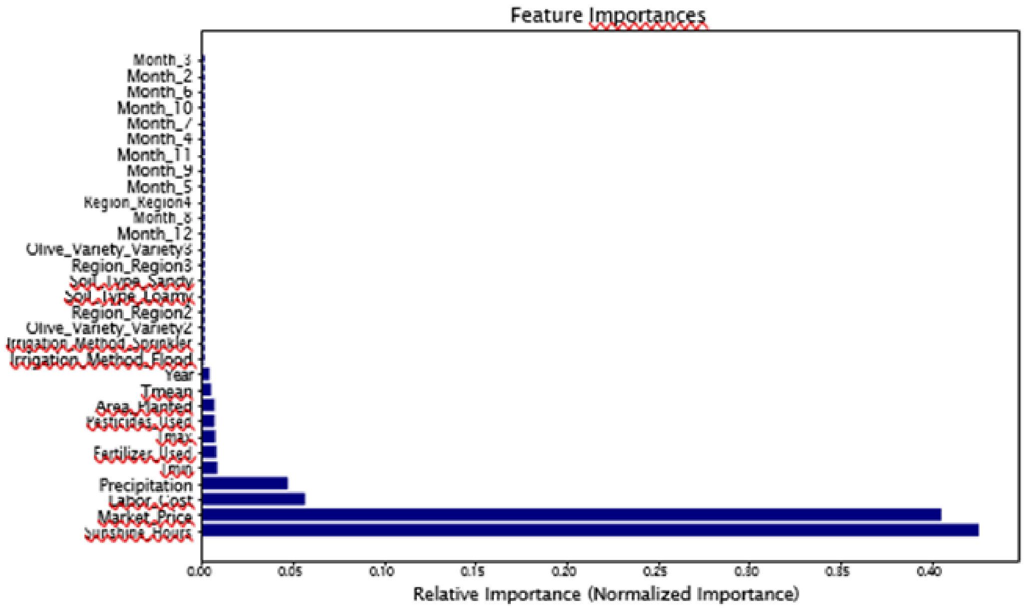
resulted in a ranked list of Prod parameters based on their importance. Figure 14a shows the relative importance of all parameters, highlighting their cumula-tive contribution to predictions.

We used the PCA algorithm to reduce the dimensionality of the dataset to the top 17 most critical features. These are visualized in relation to their normalized importance, with the total summing to 1. Figure 14b presents the cumulative importance as a function of the number of features, with a vertical line marking the threshold for cumulative importance. importance, set at 95% in this instance.

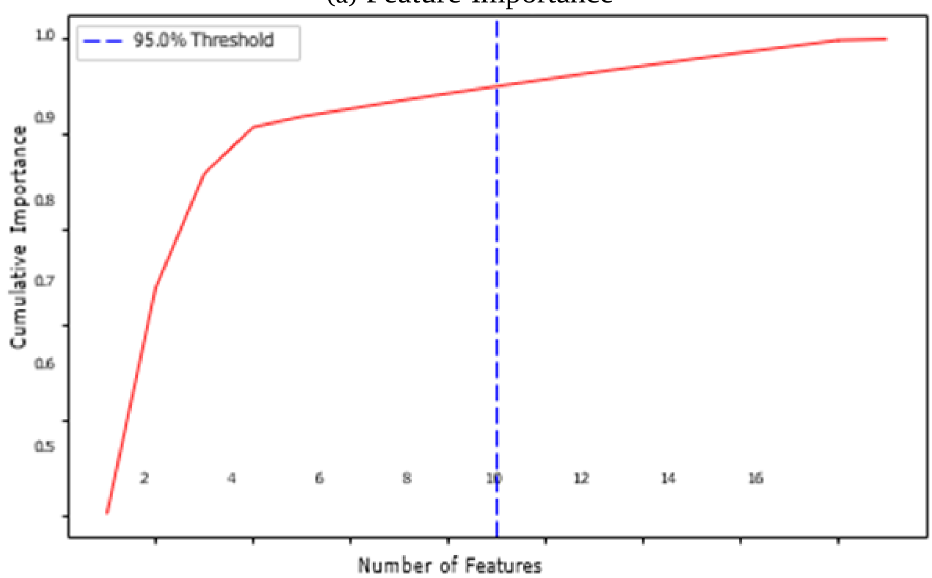
Statistical Data Distributions Analysis Figure 15 illustrates the evaluation of variable linearity by visualizing the distribution patterns of key parameters, offering insight into data variability. The parameters encompass agricultural factors such as soil fertility and crop density, environmental conditions like temperature, humidity, and soil type, as well as technological metrics, includ- ing irrigation efficiency and machinery energy consumption. Moreover, the figure incorporates an uncertainty region to account for future climatic conditions and market demand.

These variables are key inputs for the model. The visualization underscores the challenge of capturing complex interactions, as it does not explicitly ad- dress non-linear dependencies between the production parameters Prod and the output.

Correlation Analysis of parameters A separate boxplot is presented for each input parameter, illustrating the impact of Prod parameters and how vari- ations in their values influence performance. In these boxplots, the upper and lower bounds represent the 75th and 25th percentiles, respectively, capturing the middle 50.



(a) Feature Importance



(b) Cumulative Feature Importance

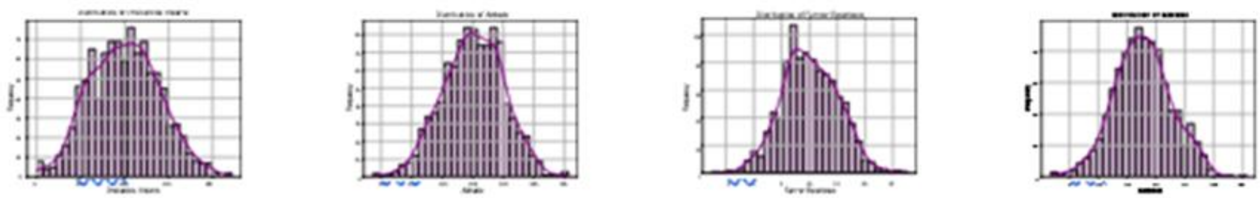
Fig. 14. Sensitivity analysis of *Prod* parameters

The selection of parameter domain values is critical, as it affects the disper- sion of values used in the cost model. Figure 16a visualizes the distribution of key input parameters such as *soil fertility*, *crop density*, *temperature*, *humidity*, *soil type*, *irrigation efficiency*, and *machinery energy consumption*.

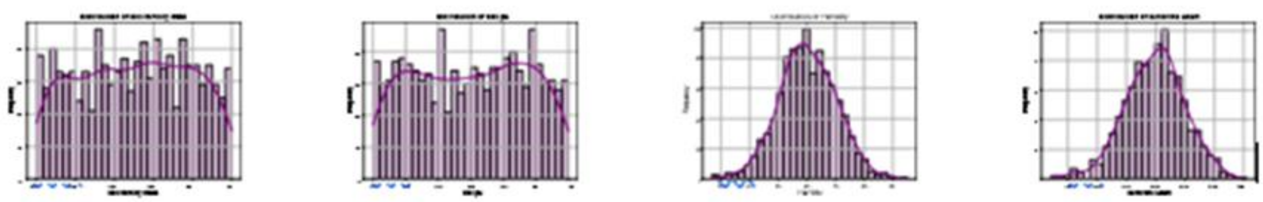
Notably, the median values for several parameters, including *soil fertility* and *crop density*, appear similar across different cases. Moreover, *irrigation efficiency* exhibits a stronger influence on results compared to other factors.

To further analyze relationships between variables, Figure 16b presents a correlation matrix, where each cell indicates the correlation coefficient between features and the output. The correlation plot highlights both positive and neg- ative correlations, particularly in the off-diagonal blocks.

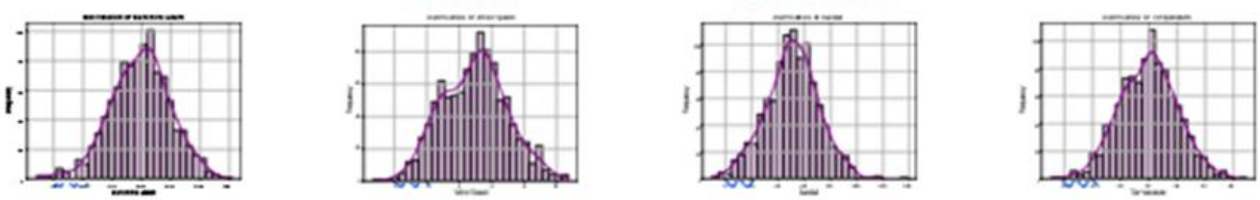
Figure 18 shows the fluctuations in the NDVI level are observed during flow- ering due to environmental conditions and the late and early flowering of certain varieties.



(a) Production Volume (b) Altitude (c) Farmer Experi- ence (d) Subsidies

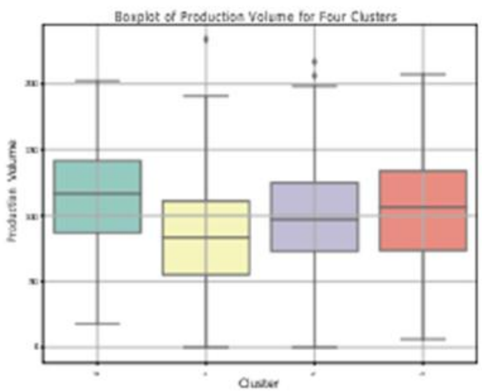


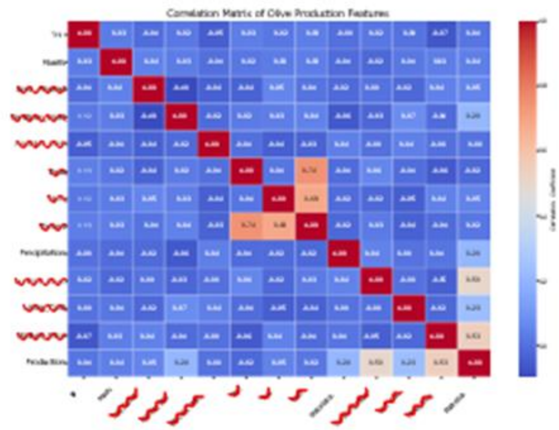
(e) Soil Fertility Index (f) Soil pH distri- bution (g) Humidity dis- tribution (h) Sunshine Hours distribution



(i) Sunshine Hours (j) Wind Speed (k) Rainfall (l) Temperature

Fig. 15. Excerpt of Sample Distributions of Chosen Parameters.





(a) Boxplot (Olive Production) (b) Correlation coefficients of the parameters.

Fig. 16. Partial view of the *Prod* parameters correlation analysis.

Results and Analysis The validation experiments demonstrate the effective- ness of the *Loc-Crops* framework in optimizing agricultural planning. Table 10 presents a comparative analysis of the different test scenarios based on key per- formance metrics.

As shown in Figure 17, it is noted that the NDVI collected by the two methods is not different during the production period except for the case of station 4, in the case of severe pruning we observe a clear decrease

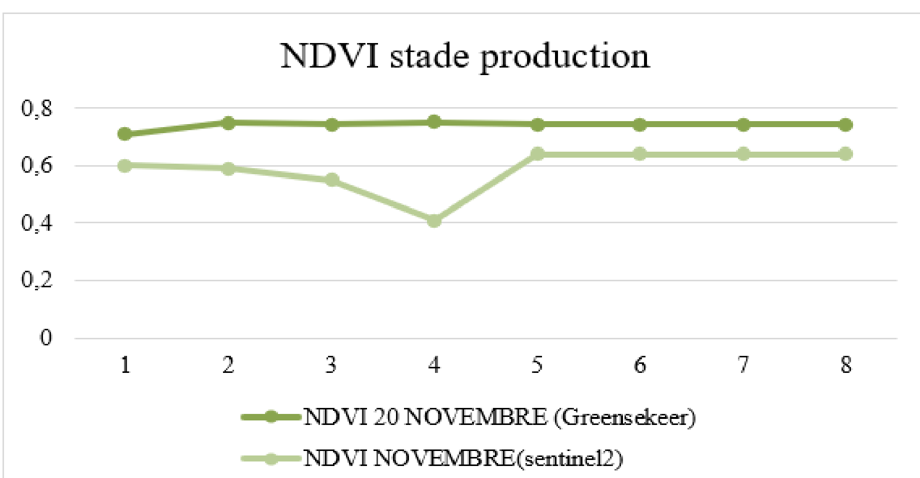


Fig. 17. Graphical representation of NDVI (production stage).

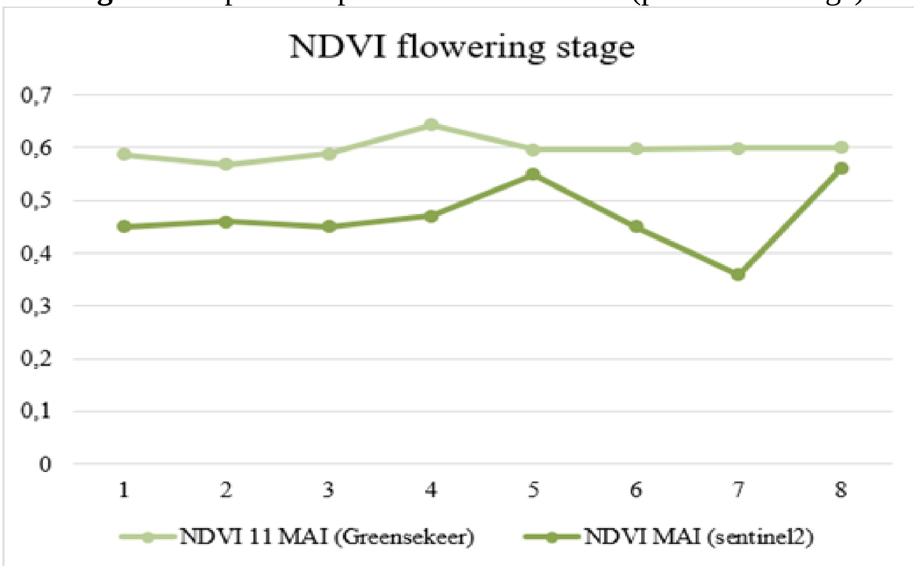


Fig. 18. Graphical representation of NDVI (flowering stage).

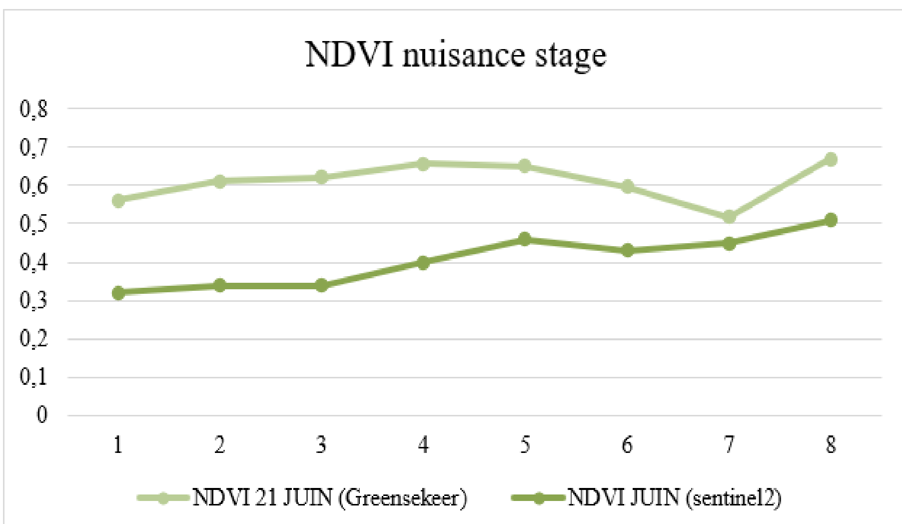


Fig. 19. Graphical representation of NDVI (Nuisance stage).

Based on the result on Figure **19**, we can see that there is no significant difference during the nuisance stage except for the two stations 7 and 8.

Table 10. Comparative Analysis of Test Scenarios

Metric	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Suitability Index (0-1)	0.42	0.65	0.78	0.85
Yield Prediction Accuracy (%)	55.3	72.8	80.1	88.5
NDVI Temporal Correlation	0.32	0.58	0.82	0.89
Computational Efficiency (s)	1.2	2.8	3.5	4.7

– **Suitability Index:** The *Loc-Crops* framework improves the selection of suitable areas, with Scenario 4 achieving the highest index (0.85) due to multi-criteria integration.

– **Yield Prediction Accuracy:** The framework significantly enhances yield prediction accuracy, reaching 88.5% in Scenario 4.

– **NDVI Temporal Correlation:** The use of NDVI data in Scenario 3 and Scenario 4 results in a stronger correlation (0.82 and 0.89), demonstrating the advantage of integrating vegetation monitoring.

– **Computational Efficiency:** More complex scenarios require additional processing time, with Scenario 4 taking the longest (4.7s), but still within an acceptable range for decision-making.

Table 11. Seasonal variations in vegetation indices and climatic parameters.

Season	Autumn	Winter	Spring	Summer
NDVI	0.25	0.23	0.21	0.23
NDWI	0.003	-0.03	-0.04	-0.0223333
RR (mm)	17.84	18.6	67.51	34.65
TT (°C)	16.29	7.56	14.85	12.9
Tm (°C)	10.19	2.79	7.29	6.76
TM (°C)	24.51	14.91	23.38	20.93

These results confirm that integrating spatio-temporal analysis and multi- criteria optimization enhances decision-making in agricultural planning, partic- ularly for olive production in agro-pastoral regions. From these results in Table 11, a strong correlation relationship between the NDVI and the NDWI. According to the table the analysis of the seasonal data of the NDVI we noticed an evolution of the values of the vegetation index from spring to autumn passing through summer with a remarkable regression in winter so we can say that the seasonal values of the NDVI in a relationship with the vegetative cycle of the olive tree.

During its annual development cycle, the olive tree goes through the follow- ing phases: (1) January, February: induction, initiation, and floral differentiation;
(2) Throughout March: growth and development of inflorescences at the axils of leaves on the previous year's branches; (3) April: full flowering; (4) Late April - early May: fertilization and fruit set; (5) June: beginning of fruit development and enlargement; (6) September: veraison; (7) October: fruit ripening and oil en- richment; (8) May - November to January: fruit harvest. Thus, the most intense period of the annual cycle occurs in summer. During this phase, the tree's water and nutrient requirements are at their peak. However, concerning the NDWI, it is generally linked to climatic conditions, particularly precipitation and temper- ature.

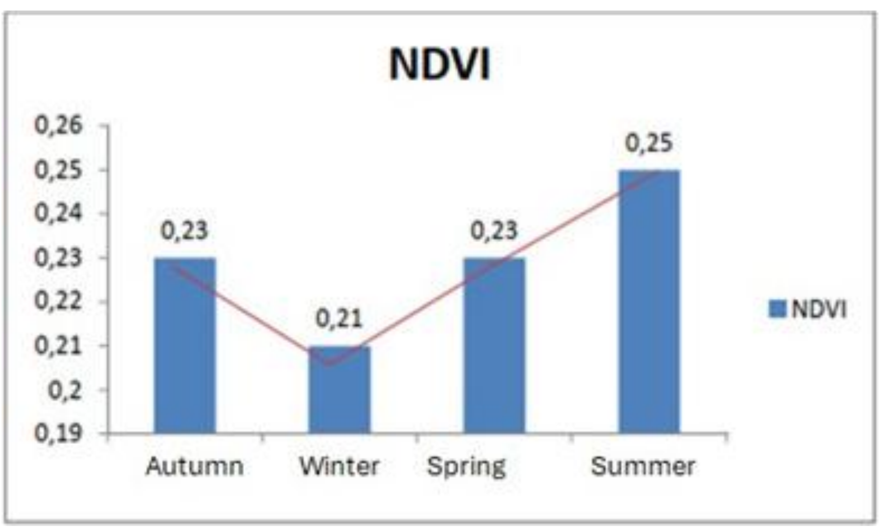


Fig. 20. Graphical representation of NDVI (Nuisance stage).

Ranking Agricultural Regions for Crop Planning Using ELECTRE

The table presents the results of applying the ELECTRE **III** multicriteria decision-making method to rank regions based on several agricultural planning criteria. These criteria include production (in quintals per hectare), climatic variability, soil quality, and irrigation type, with the objective of selecting the most suitable regions for agricultural development. The regions are ranked from the best to the least favorable based on their overall performance across all criteria.

- **Region A**: Region A ranks highest (Rank 1) due to its relatively high pro- duction of 35 quintals per hectare, combined with excellent soil quality and the use of drip irrigation. Despite having medium climatic variability, its overall performance places it as the most suitable region for agricultural planning.
- **Region B**: Region B comes in second place (Rank 2). Although it has slightly lower production (28 q/ha), it benefits from low climatic variability and good soil quality. Its irrigation method, furrow irrigation, is considered effective but not as optimal as drip irrigation, which may have impacted its ranking.
- Region D: Region D holds the third rank with a production of 30 q/ha. Its low climatic variability and excellent soil quality are positive factors. Like Region B, Region D uses drip irrigation, which adds to its advantages, though its slightly lower production compared to Region A led to its third- place ranking.
- Region E: Region E ranks fifth (Rank 5), with a production of 32 q/ha. It faces medium climatic variability and good soil quality, and uses furrow irrigation. Despite its fairly good production, its lower irrigation quality and climatic variability issues have placed it lower on the scale.
- Region C: Region C ranks lowest (Rank 4), with production at 25 q/ha. High climatic variability and non-irrigated land are key challenges that make this region the least favorable for agricultural production, even though its soil quality is medium.

This ranking process highlights the importance of not only considering pro- duction potential but also the climatic and soil conditions, along with the irri- gation method, in agricultural planning. Region A emerges as the most suit- able area for large-scale agricultural development, followed by Region B and Region D, which offer more favorable conditions despite minor differences in production. Region E and Region C show challenges that could hinder their potential, particularly concerning irrigation and climatic factors. The ELECTRE III method provides valuable insights into the multi-dimensional nature of agri- cultural planning and aids in identifying regions that offer the best combination of conditions for optimal crop production.

Table 12. ELECTRE III Ranking Results for Agricultural Planning

Criterion	Region A	Region B	Region C	Region D	Region E
Production (q/ha)	35	28	25	30	32
Climatic Variability	Medium	Low	High	Low	Medium
Soil Quality	Excellent	Good	Medium	Excellent	Good
Irrigation	Drip Irrigation	Furrow Irrigation	Non-irrigated	Drip Irrigation	Furrow Irrigation
ELECTRE III Ranking	1 (Best Region)	2	4 (Worst Region)	3	5

Summary of Experimental Findings*:* The experimental validation of the *Loc-Crops* framework underscores its effectiveness in addressing the complex challenge of planning and locating agricultural varieties in diverse ecological settings. Comparative analysis across four test scenarios reveals that Scenario 4, which integrates multi-criteria optimization, achieves the highest suitability index (0.85) and yield prediction accuracy (88.5%), with NDVI temporal cor- relation reaching 0.89. These metrics indicate that the framework reliably cap- tures the dynamic interactions among climatic, soil, and phenological parame- ters. Moreover, the application of the ELECTRE III method for regional ranking

shows that Region A—characterized by high production (35 q/ha), excellent soil quality, and the efficient use of drip irrigation—is the most favorable for large-scale olive production, while Region C ranks lowest due to high climatic variability and limited irrigation. Overall, these findings demonstrate that *Loc- Crops* provides a robust, data-driven decision support tool that can significantly enhance forecasting models and optimize agricultural planning in agro-pastoral steppe regions.

3 Related work

As we said before, there has been many efforts to develop decision support systems for agro-ecological planning that integrate environmental and climatic parameters (e.g., [24, 2]). In [17], the authors provide a comprehensive review of existing systems, highlighting their focus on yield prediction while often over- looking the dynamic interactions among climatic, soil, and phenological factors. In the same direction, authors in [20] propose a model that emphasizes static environmental datasets, yet their approach does not fully capture real-time vari- ability. Many recent research papers start studying the spatio-temporal dynamics of agricultural systems to address these limitations (e.g., [5]).

In [11], the authors explored which climatic and ecological variables most significantly impact crop yield, while at the same time, several studies propose solutions to enhance decision-making through the integration of multi-criteria optimization (e.g., [21]). Similarly, [13] presents a pilot study of the implementa- tion of an integrated decision support system tailored to specific agro-ecological contexts. In another line of research, the authors of [4] addressed the case of pre- cision agriculture by leveraging remote sensing data to improve spatial planning. In a similar trend, the authors in [16] present a novel framework that incorpo- rates dynamic environmental monitoring into agricultural planning models. Sim- ilar efforts have been conducted using machine learning techniques and advanced spatio-temporal analysis to provide more adaptive and responsive decision sup- port systems (e.g., [3]).

Despite these advancements, a comprehensive framework that effectively merges granular, real-time environmental data with dynamic decision models re- mains an open challenge. Our work aims to fill this gap by proposing the LocCrops framework, which integrates spatio-temporal analysis and multi-criteria opti- mization while critically addressing ecological and climatic variability in agro- ecological planning (e.g., [8]).

4 Conclusion and Future Work

In this study, we introduced a novel decision support framework, LocCrops, designed to address the localization problem in optimizing arboricultural pro- duction. By seamlessly integrating ecological and climatic parameters into our model, we empower decision-makers to pinpoint areas that are not only highly productive but also ecologically sustainable for large-scale agricultural develop- ment. Our case study on olive production in the agro-pastoral steppe region vividly illustrates the framework's capacity to capture the complex interplay between environmental variability and production outcomes, thereby enhancing planning precision through a robust, data-driven approach.

The experimental validation of LocCrops—demonstrated by high yield pre-diction accuracy, a strong suitability index, and effective regional ranking via multi-criteria methods such as ELECTRE III highlights its potential to trans- form agricultural planning. This framework not only offers immediate practical benefits but also lays the groundwork for more adaptive and resilient agricultural systems in the face of climate variability.

Looking ahead, several promising avenues warrant further exploration. Fu- ture work will focus on incorporating more granular datasets, including detailed soil composition, microclimatic variations, and pest management strategies, to further refine predictive accuracy. The integration of advanced machine learning techniques for dynamic optimization is also envisioned, enabling the framework to continuously adapt to evolving climate conditions and agricultural practices. Moreover, extending the application of LocCrops to other crop types and diverse regional contexts will enhance its generalizability and impact, contributing to sustainable agricultural development on a global scale.

Overall, LocCrops represents a significant step forward in leveraging spatio- temporal analysis and multi-criteria optimization for informed, resilient, and sustainable agricultural decision-making.

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