

EARTH OBSERVATION AND SMART METERING TO SPATIALIZE AGRICULTURAL WATER USES IN MEDITERRANEAN CONTEXT

OBSERVATION DE LA TERRE ET COMPTAGE INTELLIGENT POUR SPATIALISER LES USAGES AGRICOLES DE L'EAU EN CONTEXTE MÉDITERRANÉEN

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ABSTRACT

Mediterranean irrigated agriculture is increasingly exposed to recurrent drought, high evaporative demand and growing competition for water resources. Managing the irrigation systems delivering these precious resources needs new ways of innovation to ensure resilience. In the Provence-Alpes-Cote d'Azur; South region of south-eastern France, water volumes delivered to farms are accurately recorded at irrigation hydrants, but their spatial allocation to irrigated plots and crop types remains difficult. This paper presents the IAGO-ASICs framework, an operational approach designed to spatialize agricultural water uses by combining Earth Observation, in situ measurements and smart-metered consumption data. IAGO produces seasonal land-use and irrigated-area maps from Sentinel-1 and Sentinel-2 time series using Random Forest classification supported by field observations. ASICs then integrates these products with precipitation, OPTRAM-derived surface soil moisture from Sentinel-2 and Landsat 8/9, and REImu smart-meter records to detect irrigation events, identify plausible hydrant-parcel connections and allocate consumed volumes to active irrigated surfaces. By merging Earth Observation outputs with hydrant-level water consumption records, the framework also provides valuable reference information that helps validate and reinforce the quality and reliability of irrigation mapping. Application to a service area ranging over 80,000 ha managed by the Societe du Canal de Provence shows that the framework provides consistent land-use mapping, irrigation detection and operational indicators such as total irrigated area, volume per hectare and crop-specific water demand. The approach supports collective irrigation management by transforming measured volumes into spatially explicit information that can guide planning, monitoring and adaptation under increasing climate constraints.

Keywords: Earth Observation; irrigation mapping; smart metering; soil moisture; OPTRAM; water governance.

RÉSUMÉ

L'agriculture irriguée méditerranéenne est de plus en plus exposée aux sécheresses récurrentes, à une forte demande évaporative et à une concurrence croissante pour les ressources en eau. La gestion des systèmes d'irrigation qui distribuent ces précieuses ressources nécessite de nouvelles approches innovantes afin de garantir leur résilience. Dans la région Provence-Alpes-Côte d'Azur, dans le sud-est de la France, les volumes d'eau fournis aux exploitations sont enregistrés avec précision au niveau des bornes d'irrigation, mais leur affectation spatiale aux parcelles irriguées et aux types de cultures reste difficile. Cet article présente le cadre IAGO-ASICs, une approche opérationnelle conçue pour spatialiser les usages agricoles de l'eau en combinant l'observation de la Terre, des mesures in situ et des données de consommation issues de compteurs intelligents. IAGO produit des cartes saisonnières de l'occupation du sol et des surfaces irriguées à partir de séries temporelles Sentinel-1 et Sentinel-2, au moyen d'une classification par forêts aléatoires étayée par

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des observations de terrain. ASICs intègre ensuite ces produits aux précipitations, à l'humidité superficielle du sol dérivée d'OPTRAM à partir des données Sentinel-2 et Landsat 8/9, ainsi qu'aux relevés des compteurs intelligents REImu, afin de détecter les épisodes d'irrigation, d'identifier les raccordements plausibles entre bornes et parcelles et d'affecter les volumes consommés aux surfaces irriguées actives. En fusionnant les résultats de l'observation de la Terre avec les relevés de consommation d'eau au niveau des bornes, le cadre fournit également de précieuses informations de référence qui contribuent à valider et à renforcer la qualité et la fiabilité de la cartographie de l'irrigation. Son application à une zone de desserte de plus de 80 000 ha gérée par la Société du Canal de Provence montre que le cadre fournit une cartographie cohérente de l'occupation du sol, une détection fiable de l'irrigation et des indicateurs opérationnels tels que la superficie irriguée totale, le volume par hectare et les besoins en eau propres à chaque culture. Cette approche soutient la gestion collective de l'irrigation en transformant les volumes mesurés en informations spatialement explicites susceptibles d'orienter la planification, le suivi et l'adaptation face à des contraintes climatiques croissantes.

Mots clés : Observation de la terre; Cartographie de l'irrigation; Comptage intelligent; Humidité du sol; OPTRAM; Gouvernance de l'eau.

INTRODUCTION

Mediterranean regions are among the most vulnerable to climate change (Ali et al., 2022). They face longer droughts, more frequent heat waves and higher summer temperatures. At the same time, water availability decreases during the main growing season because precipitation tends to become more seasonally contrasted and evaporative demand increases. These changes directly affect agricultural systems, crop production and the ability of water managers to provide reliable irrigation services.

In Provence-Alpes-Cote d'Azur (PACA, France), irrigation is one of the key adaptation levers for maintaining agricultural production. However, irrigation practices are highly variable because they depend on pedo-climatic conditions, crop variability, phenological stages, soil conditions, equipments and farmers' strategies. This heterogeneity makes it difficult to predict water use at territorial scale and to anticipate demand during periods of resource tension.

Recent developments in connected monitoring tools, such as smart metering systems, provide new opportunities to better quantify water use in irrigated systems.

Although the Societe du Canal de Provence (SCP) now measures water volumes delivered through smart meters installed at irrigation hydrants, the allocation of these volumes is not directly known. In practice, several plots may be connected to the same hydrant, while some plots may be irrigated intermittently or only during dry periods. The disconnection between reliable volumetric measurements and spatially explicit information limits the ability of managers to analyze in-depth irrigation practices, allocate water amount to crops and support operational decisions.

Recent advances in Earth Observation (EO) provide new opportunities for monitoring irrigated agriculture. Sentinel-1 radar and Sentinel-2 optical time series provide repeated information on vegetation, land use and surface moisture at spatial resolutions compatible with plot-scale applications. However, the irrigation practices observed in the mediterranean area and in particular in the SCP command area are characterized by the use of drip irrigation in a supplementary mode with low volumes application. Compared to sprinkler irrigation applied on field crops that mobilize high water volumes with important variations of soil moisture, drip irrigation on vineyards or orchards makes the change detection very difficult. When combined with ground observations, meteorological data and frequent metered water volumes, these data can help bridge the gap in time and space between water delivery measurements and actual irrigated surfaces.

The objective of this study was to develop and evaluate an operational methodological framework for quantifying, mapping and spatializing agricultural water use by integrating satellite observations, in situ measurements and metered water volumes. The paper presents the study area and datasets, then describes the IAGO-ASICs processing chain (i.e. land-use classification, irrigation detection, surface soil moisture recalibration, and probabilistic linkage between hydrants and parcels). Results are discussed regarding classification performance, irrigation mapping and decision-support potential.

MATERIALS AND METHODS

Study area

The study area is located in the PACA region in south-eastern France (Figure 1). The region is characterized by a Mediterranean climate with hot, dry summers and strong spatial and temporal variability in precipitation. These conditions generate substantial pressure on water resources and a high dependence on irrigation for many farming systems.

The targeted perimeter corresponds to sectors managed by SCP and covers over 80,000 ha of agricultural land. Cropping systems are diverse and include winter and summer field crops, perennial crops such as vineyards, orchards and aromatic plants, and vegetables. Water requirements and irrigation practices therefore vary widely across crops and over time. The irrigation network is structured around delivery points, or hydrants, equipped with communicating meters that record delivered volumes at fine temporal resolution of 1 hour.



Figure 1. Location of the study area in Provence-Alpes-Cote d'Azur (Region Sud) and spatial extent considered within the SCP concession area.

Datasets

The proposed approach relies on the integration of multi-source datasets combining EO imagery, in situ observations, meteorological forcing data and metered irrigation volumes.

Satellite observations were mainly derived from the Copernicus Sentinel missions for the period from October 2022 to September 2025. Sentinel-2 optical composites were produced approximately every ten days and used to calculate spectral and water-related indices such as NDVI, NDMI and NDWI. Sentinel-1 Ground Range Detected radar images were processed at weekly time step using VV and VH backscatter and the VV/VH ratio, providing information that is less sensitive to cloud cover and complementary to optical observations. The French Land Parcel Identification System, or Registre Parcellaire Graphique (RPG), was used as the main geometric support for plot delineation. In this

study, RPG attributes were not used as a thematic reference but as a spatial framework to aggregate satellite-derived variables at agricultural-unit scale. Meteorological data, including precipitation and other hydro-climatic variables, were used to contextualize vegetation dynamics and distinguish rainfall-driven responses from irrigation signals.

Ground-truth observations were collected during field campaigns over a diversity of irrigated and not-irrigated plots, with a sample size of approximately 3000 plots. For each plot, location, crop type, crop condition and phenological stage were recorded.

In addition, daily in situ soil water content measurements were obtained from capacitive probes installed on 54 monitored plots distributed across the study area. These measurements were used to recalibrate satellite-derived surface soil moisture. Smart meters installed on agricultural hydrants provided hourly water volumes, allowing temporal analysis of irrigation consumption.

General IAGO-ASICs framework

The methodology integrates two complementary approaches:

- IAGO (Irrigated Agriculture Observation) produces land-use and irrigated-area maps from satellite time series and field observations (Figure 2).
- ASICs (Analysis of Irrigated Surfaces and Consumptions) uses IAGO products, measured hydrant volumes and hydro-climatic variables to connect consumption records to parcels and crop types (Figure 3).

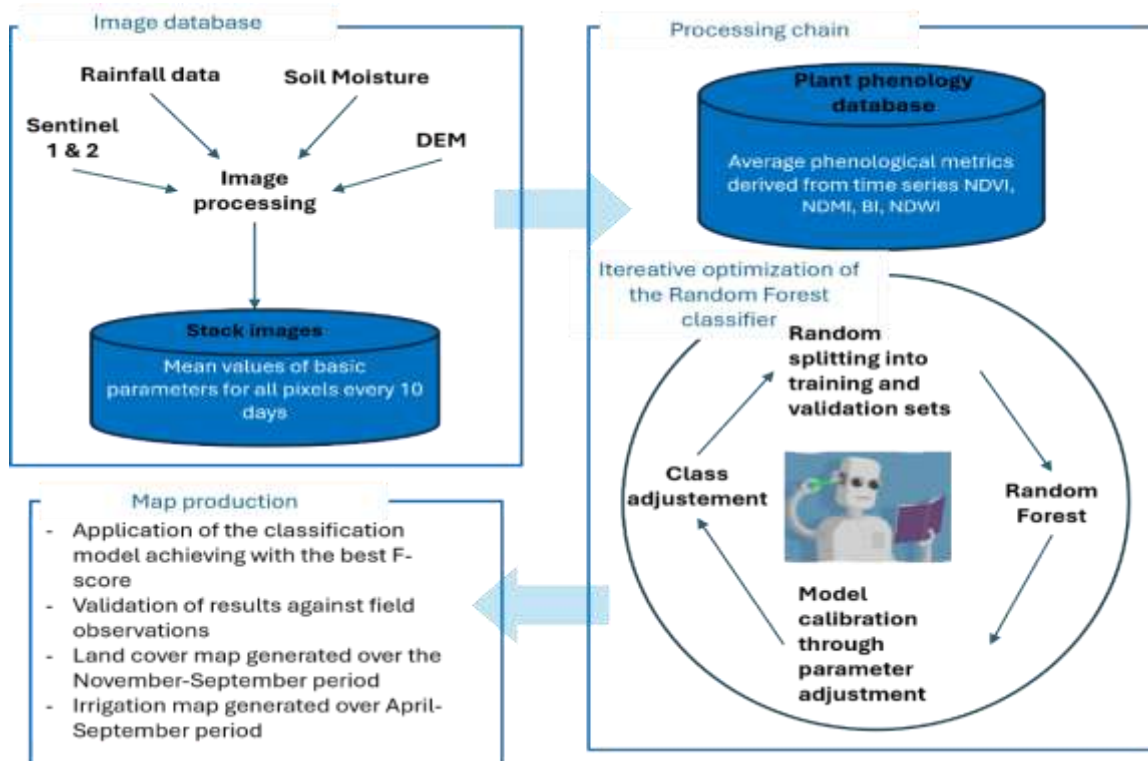


Figure 2. IAGO processing chain for land-use mapping and irrigation detection from satellite time series.

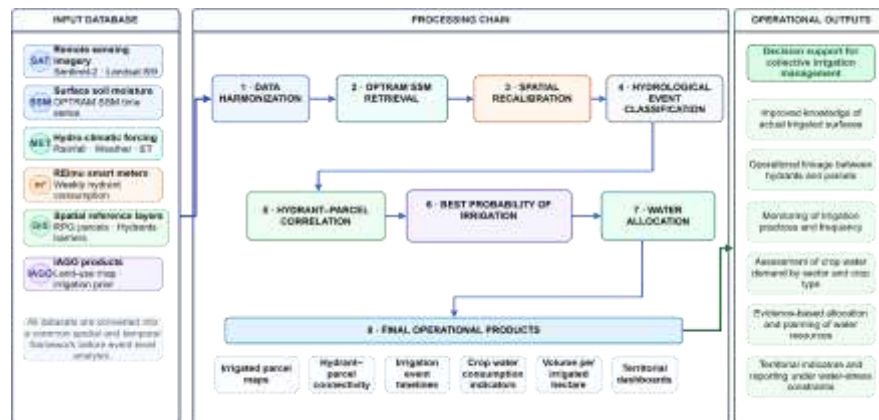


Figure 3. ASICs processing chain for hydrant-parcel linkage and allocation of consumed water volumes

Land-use mapping

Crop classification was performed with the IOTA2 processing chain (Fauvel, 2022). A Random Forest classifier was selected because of its robustness, its ability to handle high-dimensional EO time series and its proven efficiency for crop mapping. The model was trained using variables derived from Sentinel-2 and Sentinel-1 time series aggregated at plot scale using the RPG geometry.

Explanatory variables included spectral reflectance values, radar backscatter, the VV/VH ratio, brightness indicators and normalized vegetation or water indices. The main optical indices used to describe vegetation vigour and water-related spectral response were :

$$\begin{aligned} \text{NDVI} &= (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \text{ (Eq. 1),} \\ \text{NDWI} &= (\text{NIR} - \text{SWIR}) / (\text{NIR} + \text{SWIR}) \text{ (Eq. 2), and} \\ \text{NDRE} &= (\text{NIR} - \text{Red_Edge}) / (\text{NIR} + \text{Red_Edge}) \text{ (Eq. 3),} \end{aligned}$$

where NIR, Red, SWIR and Red_Edge denote near-infrared, red, short-wave infrared and red-edge reflectance, respectively.

Class imbalance was a major issue because some crops were dominant while others were poorly represented in field observations. To reduce this bias, classes with fewer than ten samples were grouped, and the Orfeo Toolbox Sample Augmentation procedure (CNES, 2023) was used during training. Model performance was assessed using stratified cross-validation and an independent validation dataset.

Detection of irrigated plots

Irrigated-plot detection was performed over the April-September irrigation season by jointly analyzing vegetation dynamics, precipitation and surface moisture indicators. The land-use map produced beforehand was used to restrict the analysis to agricultural units. For each unit, NDVI, NDMI, NDWI and soil moisture time series were aggregated, and statistical descriptors were calculated to characterize hydrological and vegetation behaviour throughout the season.

The underlying assumption is that irrigated plots tend to show more stable moisture signatures and higher or more regular vegetation activity than rainfed plots under summer water stress. A supervised Random Forest approach was then used to classify agricultural units according to their hydrological regime. The resulting irrigation map was validated against field observations collected during the irrigation period.

Surface soil moisture retrieval and recalibration

Surface soil moisture was introduced into the ASICs framework to provide a direct physical indicator of parcel-scale wetting dynamics, helping to distinguish rainfall-driven responses from probable irrigation events and to strengthen hydrant–parcel attribution. It was estimated using the OPTRAM model (Sadeghi et al., 2017) applied to Sentinel-2 and Landsat 8/9 observations (Figure 4). The workflow includes cloud, cirrus, shadow, snow, defective-pixel and water masking, followed by computation of the relationship between NDVI and the shortwave infrared transformed reflectance (STR). Dry and wet edges were estimated monthly for each sub-region of interest in order to account for seasonal and spatial variability.

Initial OPTRAM estimates were compared with in situ measurements from the IRRI Provencal observatory and SCP monitoring sites over 2022–2024. Linear regression and Bayesian optimization were used to correct local biases and improve agreement between satellite estimates and field observations. Performance was assessed with standard indicators including Pearson correlation, coefficient of determination, RMSE, MAE, NSE and Kling-Gupta Efficiency (KGE), using an independent test dataset.

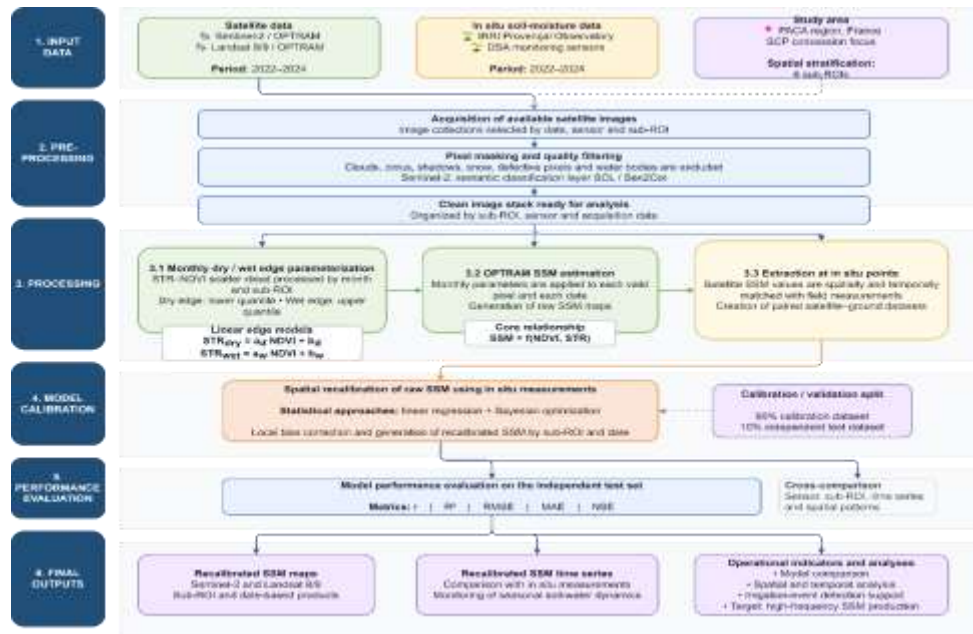


Figure 4. Workflow for OPTRAM-based surface soil moisture retrieval and spatial recalibration using in situ measurements.

Hydrological correlation and water allocation

ASICs integrates soil moisture dynamics, rainfall and measured hydrant consumption to identify irrigation events and associate them with plausible plots. The decision scheme is summarized in Figure 5. Each delivery point is uniquely identified by a combination of the hydraulic code and meter post (HydrantUID = HydrantCode + "___" + HydrantPoste).

For each plot i and interval k bounded by two consecutive surface-soil-moisture observations, the three variables used by the hydrological classifier are defined in Eqs. (4)–(6).

$$\Delta SSM_{i,k} = SSM_i(t_{k+1}) - SSM_i(t_k) \quad (4)$$

$$Psum_{i,k} = \sum P_i(t), \quad t \in [t_k; t_{k+1}] \quad (5)$$

$$V_{h,k} = \sum Conso_h(t), \quad t \in [t_k; t_{k+1}] \quad (6)$$

The hydrological state is then assigned using the decision rules in Eqs. (7a)-(7d). These rules explicitly separate rainfall-driven wetting, probable irrigation, drying or neutral behaviour, and a zone of low sensitivity. The thresholds ε and ζ were set to 0.1 and 1.0 mm, respectively.

$$\Delta\text{SSM}_{i,k} > \varepsilon \text{ and } \text{Psum}_{i,k} > \zeta \Rightarrow \text{rainfall event} \quad (7a)$$

$$\Delta\text{SSM}_{i,k} > \varepsilon \text{ and } \text{Psum}_{i,k} \leq \zeta \Rightarrow \text{probable irrigation event} \quad (7b)$$

$$\Delta\text{SSM}_{i,k} < -\varepsilon \text{ and } \text{Psum}_{i,k} \leq \zeta \Rightarrow \text{drying or neutral condition} \quad (7c)$$

$$|\Delta\text{SSM}_{i,k}| \leq \varepsilon \Rightarrow \text{insensitive signal zone} \quad (7d)$$



Figure 5. ASiCs hydrological decision scheme combining surface soil moisture, rainfall and measured water consumption.

Candidate plots are identified within an operational radius around each hydrant and then evaluated based on topological constraints. The method does not rely only on Euclidean distance: road or hydrographic barriers and the length of admissible paths are also considered and hydraulic limits attainable by the network available pressure. The spatial filtering criteria are expressed in Eqs. (8)-(10), where R is approximately 300 m and $L_{h,i}$ is the shortest admissible path between hydrant h and plot i .

$$d(h,i) \leq R, \text{ with } R \approx 300 \text{ m} \quad (8)$$

$$\text{Segment}(h,i) \cap \text{Barriers} = \emptyset \quad (9)$$

$$L_{h,i} = \min \sum l_e \text{ over admissible paths between } h \text{ and } i \quad (10)$$

The hydrological score in Eq. (11) measures the recurrence of irrigation signals, while the topological probability in Eq. (12) decreases as the admissible path length increases. The final Best Irrigation Probability (BPI) in Eq. (13) combines these two terms with the irrigation prior derived from IAGO outputs.

$$\text{Hydro_Prob}_i = 0.70 \times (N_{\text{irrigation}_i} / N_{\text{total}_i}) + 0.30 \times \min(N_{\text{irrigation}_i} / 3 ; 1) \quad (11)$$

$$\text{Topo_Prob}_{h,i} = \exp(-L_{h,i} / 250) \quad (12)$$

$$\text{Best_Irri_Prob}_{h,i} = 0.60 \times \text{Hydro_Prob}_i + 0.25 \times \text{Topo_Prob}_{h,i} + 0.15 \times \text{Irrigation_Prior}_i \quad (13)$$

A plot is classified as actively irrigated when both the number of consistent irrigation events and the BPI index exceed the decision thresholds in Eq. (14). At event scale, active irrigated areas linked to the same hydrant are aggregated with Eq. (15), and the measured hydrant volume is converted into a volume-per-area indicator with Eq. (16).

$$S_i = 1 \text{ if } \text{Irri_cor}_i \geq 2 \text{ and } \text{Best_Irri_Prob}_{h,i} \geq 0.50 \quad (14)$$

$$S_{h,k} = \sum S_i \text{ for active parcels } i \text{ linked to hydrant } h \quad (15)$$

$$\text{VSI}_{h,k} = V_{h,k} / S_{h,k} \quad (16)$$

When several plots or crops are detected as irrigated during the same event, the hydrant volume is distributed proportionally to irrigated areas using Eqs. (17)-(18). Allocated volumes can then be aggregated by crop, hydrant, hydraulic sector or territory through Eq. (19).

$$\text{Part}_{i,k} = S_i / \sum S_j \quad (17)$$

$$V_{i,k} = V_{h,k} \times \text{Part}_{i,k} \quad (18)$$

$$V_{\text{culture}} = \sum_k \sum_{i \in \text{culture}} V_{i,k} \quad (19)$$

RESULTS

Land-use and irrigation maps

The classification process allowed to produce a land-use map for the 2025 agricultural season (Figure 6). The map provides a spatially explicit description of the agricultural landscape in the Puylobier sector, where agricultural water consumption is important and vineyards strongly dominate the cultivated area. The results highlight the continuous distribution of vineyards, whereas other classes are more fragmented and localized, reflecting local diversity in production systems and agro-climatic conditions.

In addition to land use, IAGO produced an irrigated-area map that characterizes the spatial distribution of irrigation practices (Figure 7). Irrigated areas are mainly concentrated in areas equipped with hydraulic infrastructure or benefiting from easier access to water resources. In vineyards, irrigation appears heterogeneous, reflecting supplemental irrigation, non-irrigated management and intra-parcel variability. Non-irrigated areas show stronger dependence on climatic conditions, with more variable vegetation profiles during the summer period.

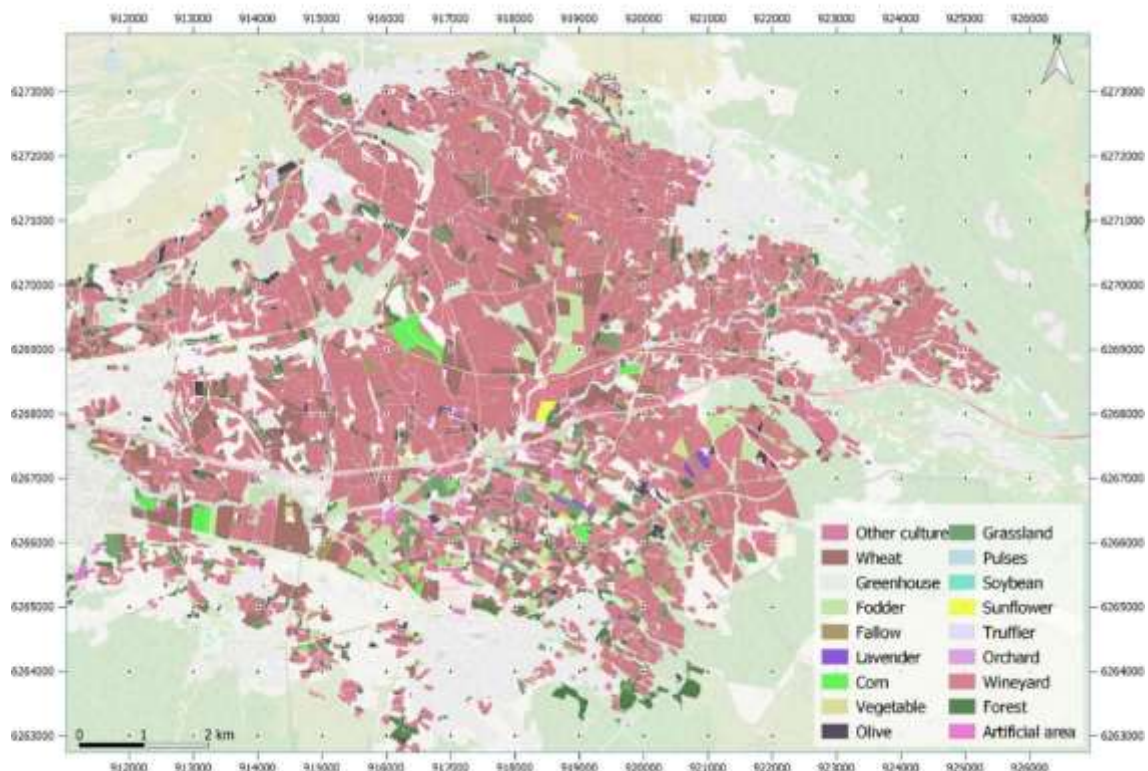


Figure 6. Land-use map produced by IAGO in the Puylobier sector for the 2025 agricultural season.

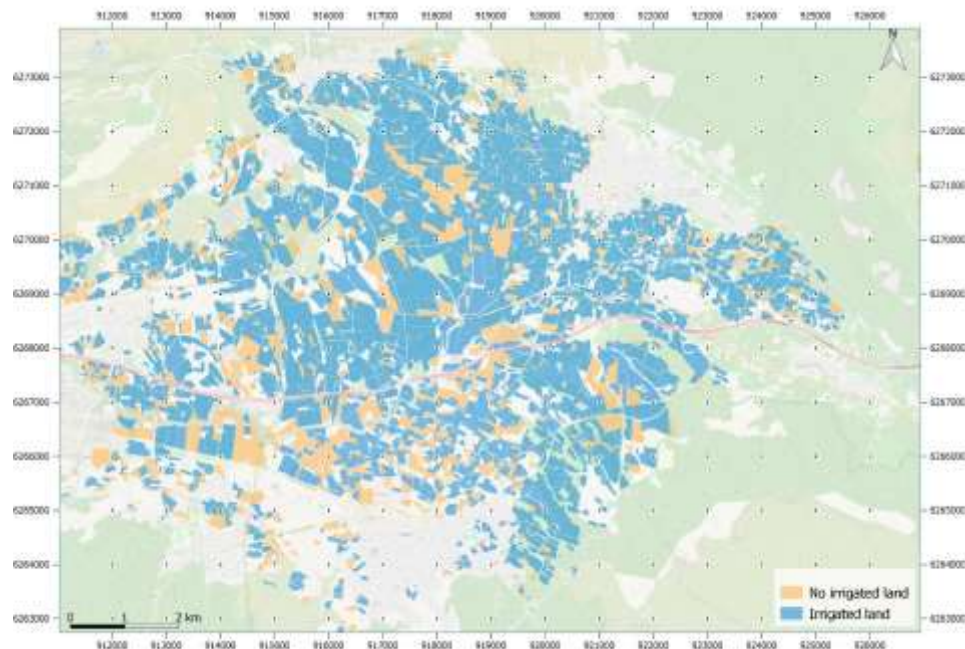


Figure 7. Irrigated and non-irrigated surfaces derived from IAGO products.

Hydrant-plot association and operational indicators

Using land-use and irrigation-area maps from IAGO, the ASICs hydrological correlation analysis linked agricultural hydrants to the plots they most probably supplied (Figure 8). Green parcels are identified as irrigated and assigned to a hydrant, whereas red parcels are considered non-irrigated. Black lines represent spatial connections used to allocate irrigation volumes.

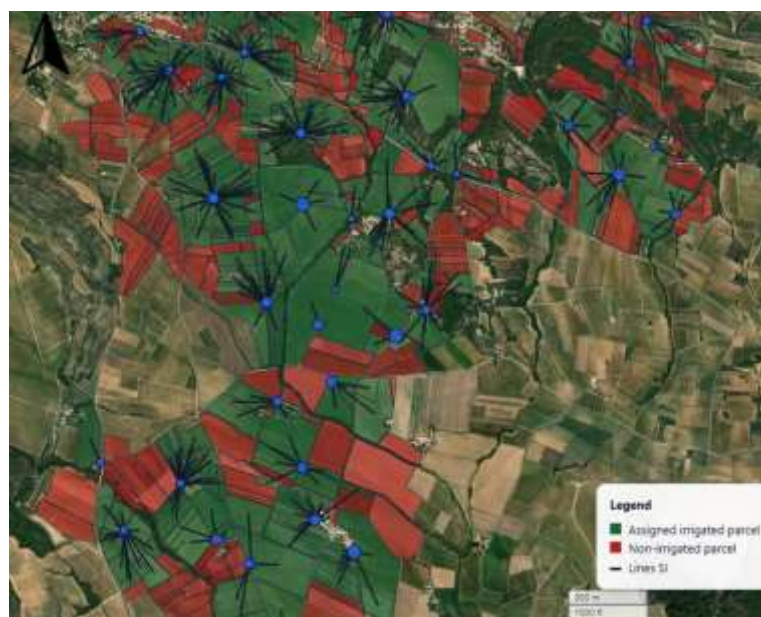


Figure 8. Spatial correlation between irrigation hydrants (blue dots), assigned irrigated plots and non-irrigated plots.

Once hydrant-plot associations are established, irrigation events can be detected and the relationship between irrigated plots and supplied volume can be analyzed. Figure 9 illustrates an operational example. The map identifies plots associated with a hydrant, the timeline shows the sequence of rainfall and irrigation events during the season, and the table summarizes crop type, irrigated area, hydrological irrigation probability, best irrigation probability, total consumed volume and equivalent irrigation depth.

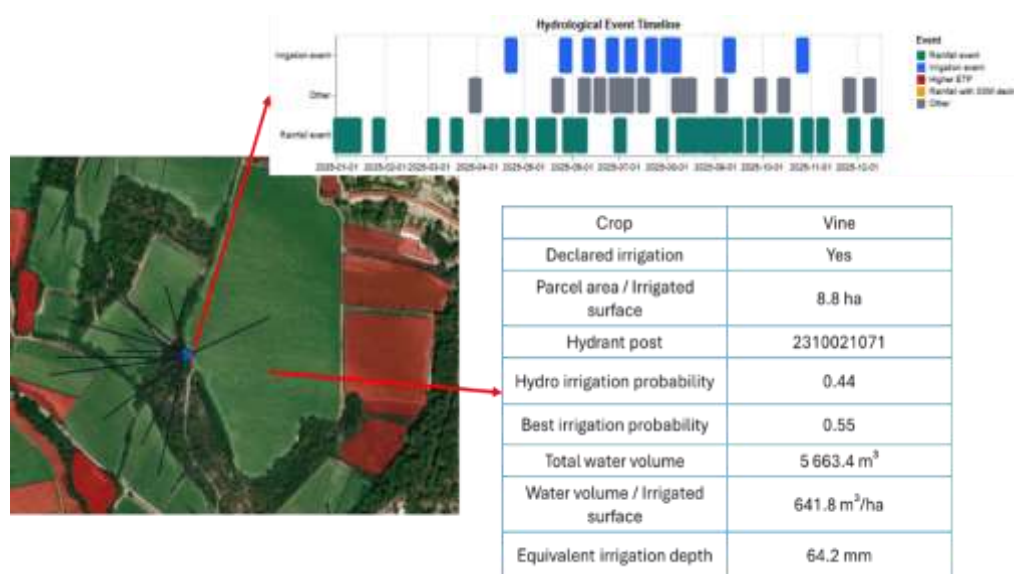


Figure 9. Operational example of a hydrant-pilots association, hydrological event timeline and volume-per-area indicators.

Validation

Land-use classification was evaluated using an independent reference dataset collected in the field, with 1200 plots (40%) dedicated to validation. Overall accuracy reached approximately 95%, with higher performance for vineyards and cereal classes, which are better characterized both spectrally and spatially. The confusion matrix and class-level indicators show that minor or heterogeneous classes obtained lower scores because of intra-class variability and similarities in spectral-phenological signatures (Figure 10).

Irrigation detection reached an overall accuracy of approximately 80%, with the best performance in intensively irrigated and well-equipped areas. The main limitations concerned localized or low-intensity irrigation, especially drip irrigation, which is more difficult to detect using satellite data.

The OPTRAM soil moisture estimates recalibrated with capacitive-probe data were consistent with field observations. Validation indicators showed satisfactory performance (KGE = 0.70, Pearson r = 0.67 and ubRMSE = 4.6%). The scatter plot in Figure 11 confirms the relationship between Sentinel-2 OPTRAM estimates optimized through Bayesian calibration and in situ soil moisture measurements at 10 cm depth.

DISCUSSION

The results confirm the value of an integrated approach combining EO, ground observations, hydro-climatic data and operational metering to improve knowledge of agricultural water use in Mediterranean conditions. IAGO provides consistent information on land use and irrigation practices, while ASICs transforms measured hydrant volumes into spatially explicit indicators linked to plots and crop types. This combination enables moving beyond a purely volumetric representation of irrigation.

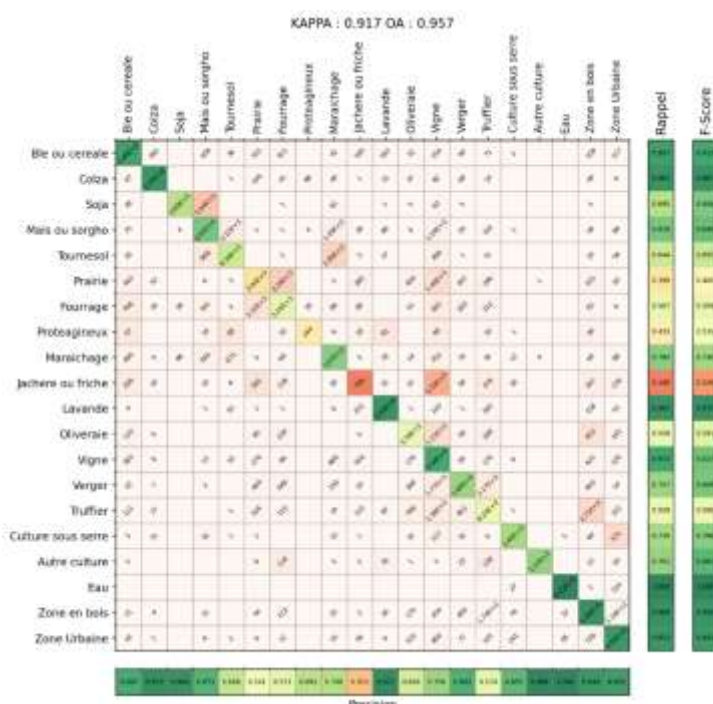


Figure 10. Confusion matrix and performance indicators for the land-use classification.

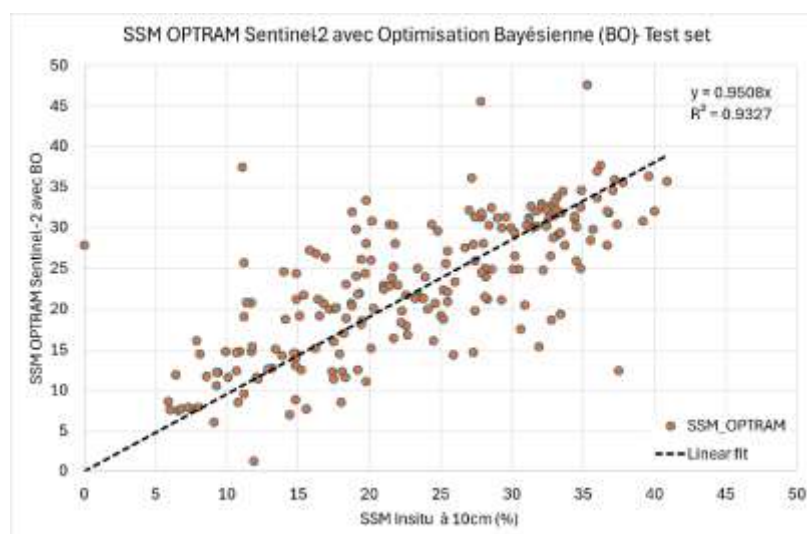


Figure 11. Validation of Sentinel-2 OPTRAM surface soil moisture optimized by Bayesian calibration on the independent test dataset.

Classification performance is encouraging but remains constrained by the structure of the agricultural landscape and by the available training data. Perennial crops such as vineyards, orchards and olive groves are generally well discriminated, as are several annual crops. Conversely, fallow land, mixed vegetation and vegetable systems are more difficult to separate because their temporal signatures may overlap. A more balanced and spatially distributed field dataset would improve robustness for minority classes.

For irrigation detection, the framework achieves the best performance when irrigation events are frequent enough to generate clear moisture and vegetation responses. Drip irrigation, deficit irrigation and short irrigation events may remain weakly visible in satellite time series, especially when acquisition dates do not coincide with irrigation timing. Increasing the temporal density of in situ measurements and improving the recalibration of surface soil moisture across soil and crop contexts are therefore critical for future improvements.

The graph-based hydrant-plot association is a key contribution because it reduces errors that would arise from simple distance-based allocation. By combining hydrological signals, plausible connection paths and IAGO-derived prior information, ASICs provides an evidence-based probability of irrigation and enables the calculation of operational indicators such as active irrigated area, water volume per hectare and crop-specific water supply. These indicators can support monitoring, diagnosis of atypical uses and collective planning under water scarcity.

A limitation applies to soil-moisture-based irrigation detection. While surface soil moisture can provide a direct indicator of recent wetting events, its signal may be weak or highly localized in drip-irrigated systems, which are common in Mediterranean vineyards. In such cases, water is applied to narrow soil zones beneath or along crop rows, making the moisture increase difficult to detect at satellite pixel scale, unlike sprinkler-irrigated crops where wetting is more spatially homogeneous. This may reduce the sensitivity of OPTRAM-derived surface soil moisture for detecting short or low-volume irrigation events. In this context, future work should explore high spatial and temporal resolution thermal imagery to derive actual evapotranspiration (ETa) as a complementary indicator. ETa could provide additional information on crop water use and water-stress dynamics, particularly in vineyard systems where irrigation effects are subtle, spatially heterogeneous and influenced by canopy structure, exposed soil and inter-row cover crops.

Operational validation of the inferred links remains necessary. Field protocols should be implemented to verify actual hydraulic connections, effectively supplied surfaces and farmers' irrigation practices. Such validation would strengthen confidence in the system and support its deployment as a decision-support tool for water managers.

CONCLUSION

This paper presents an operational methodology combining EO and smart-metered data to spatialize and quantify agricultural water use in a Mediterranean irrigation context. The IAGO-ASICs framework produces consistent and spatially explicit information on land use, irrigated areas, irrigation dynamics and water-volume allocation at plot scale. The results demonstrate the relevance of combining satellite time series, in situ soil moisture measurements, rainfall information and hydrant consumption records. The approach provides robust outputs for territorial-scale applications and delivers indicators that can inform water allocation, irrigation monitoring and adaptive management. In the context of climate change and increasing pressure on water resources, this type of integrated framework is well suited to support more efficient, transparent and sustainable irrigation governance. Future developments should focus on improving irrigation detection models, strengthening field validation, integrating predictive approaches and extending the framework to other territories.

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