DEVELOPMENT OF A MODEL FOR SUPPORTING AGRICULTURAL DECISION-MAKING BASED ON AGRO-METEOROLOGICAL SENSOR DATA: A CASE STUDY OF THE IMETOSSTATION

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Abstract: *This paper proposes a practical data-driven model that converts hourly observations from an IMETOSstation and connected soil sensors into interpretable indicators for microclimate stress monitoring, irrigation advisory, pesticide spraying windows, and station power-health diagnostics. The case study uses an exported FieldClimate dataset containing hourly air temperature, dew point, solar radiation, vapor pressure deficit (VPD), relative humidity, precipitation, wind statistics, and soil measurements (5TE volumetric water content, dielectric permittivity, soil temperature; Watermark soil-water tension), complemented by daily reference evapotranspiration (ET0). Results demonstrate how raw sensor streams can be operationalized into simple, auditable rules and normalized indices such as soil moisture index (SMI), soil water deficit, heat-stress hours, and spray-suitable hours.*

Keywords: *precision agriculture; agro-meteorological sensors; IMETOS; FieldClimate API; irrigation scheduling; VPD; soil moisture index*

INTRODUCTION

Agricultural decisions more and more depend on constant sensor data. This helps reduce weather risks, use water efficiently, and choose the right time for field work. Although modern stations can measure many variables every hour (or even more often), farmers usually need only a few clear indicators and alerts.

IMETOSis an agro-meteorological monitoring system that connects field sensors to cloud storage and analysis through the FieldClimate platform [1,2]. In this paper, we aim to build and test a full workflow that takes hourly IMETOSdata and converts it into a small set of useful indicators that help day-to-day farm decisions.

2.Background

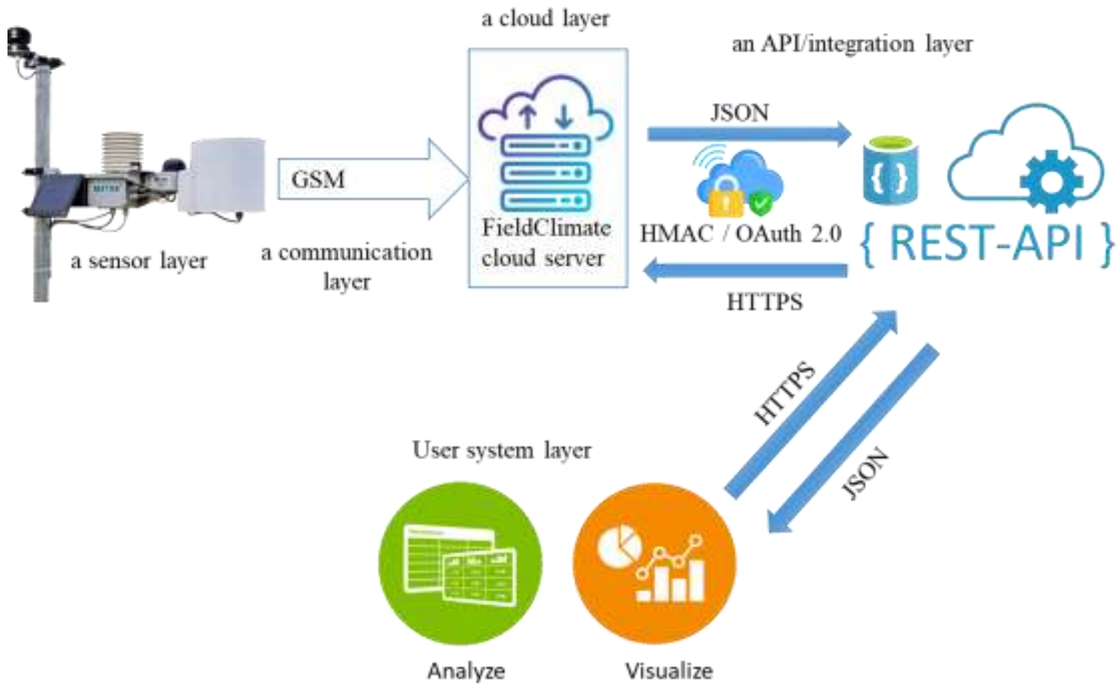

Figure-1. The iMETOSdata-driven flow architecture.

The IMETOSarchitecture can be described as layered data flow: (1) a sensor layer (meteorological and soil probes), (2) a communication layer (e.g., GSM/GPRS, LTE, Wi-Fi, LoRaWAN), (3) a cloud layer where FieldClimate stores, decodes, normalizes, and computes derived variables, and (4) an API/integration layer enabling access from external applications (e.g., GIS tools, databases, dashboards) [1,2]. This modular architecture supports real-time monitoring and systematic integration into information systems for analysis and visualization.

3.Materials and methods

3.1.IMETOSstation and connected sensors

The case study is based on an IMETOSagro-meteorological station that integrates on-site sensing, local logging, and cloud-based storage/visualization through the FieldClimate platform [1,2]. In typical off-grid deployments, the station operates continuously using a solar panel and battery, and transmits measurements to the cloud for near real-time monitoring and analytics.

Meteorological (microclimate) sensing

At the station level, meteorological observations include air temperature, relative humidity, dew point, solar radiation, precipitation, and wind statistics. Air temperature and relative humidity are core drivers for derived microclimate indicators such as vapor pressure deficit (VPD) and dew/condensation risk—both important for interpreting crop transpiration demand, heat stress exposure, and operational decisions such as spraying.

Solar radiation provides a proxy for surface energy load and is used to contextualize evapotranspiration and heat stress conditions. Precipitation directly affects irrigation suppression logic and field access windows, while wind speed and gusts are critical safety constraints for pesticide application and other field operations.

Soil and plant sensing

For below-ground monitoring, the station is connected to soil probes that quantify the root-zone water and temperature regime. In the exported dataset, soil measurements include volumetric water content, dielectric permittivity, and soil temperature measured by a 5TE-type probe [5], and soil-water tension (matric potential proxy) measured by a Watermark-type sensor [6].

Power diagnostics and reliability (maintenance relevance)

Because IMETOSis often deployed in remote, off-grid fields, power diagnostics—solar panel voltage, battery voltage, and sensor board battery voltage—are critical for maintenance planning and data continuity [1].

3.2. Data acquisition and preprocessing

Hourly measurements were collected using an IMETOSstation deployed in the Khorezm region (Uzbekistan) and exported from the FieldClimate platform as an Excel dataset. Data acquisition can alternatively be automated using the FieldClimate REST API [3], including endpoints for listing stations, retrieving last measurements, and downloading hourly time-series for a selected period.

Preprocessing included timestamp harmonization, numeric conversion, outlier removal, and computation of derived indicators.[11,12]

3.3. Decision-support model and derived indicators

The decision-support model converts the raw variables into a compact set of actionable indicators grouped into four decision domains:

● Microclimate stress (heat load and atmospheric demand)

● Irrigation advisory (soil-water availability and deficit status)

● Field-work windows (spraying suitability)

● Station operation health (power diagnostics and data continuity)

The model is designed to be transparent: each indicator is computed using explicit formulas and threshold-based rules (rather than black-box predictions), allowing agronomists to review and adjust parameters for crop type, phenological stage, soil conditions, and local management practice.

Table 1. Derived indicators calculated from hourly IMETOSobservations.

Indicator	Formula / rule	Inputs	Interpretation / action
Dew point depression (DPD, °C)	DPD = T_air - T_dew	Air temp, dew point	Low DPD suggests condensation risk

Soil Moisture Index (SMI)	SMI = (VWC−P10)/(P90−P10), clipped to [0,1]	VWC; dataset percentiles	Normalized soil wetness (0=dry, 1=wet)
Soil Water Deficit	Deficit = 1 − SMI	SMI	Relative deficit for irrigation prioritization
Heat-stress hour	T_air ≥ 35°C	Air temp (avg)	Potential heat stress; adjust threshold by crop
High-VPD hour	VPD ≥ 3 kPa	VPD (avg)	High atmospheric demand; consider irrigation / shading
Combined stress	Heat-stress AND High-VPD	Air temp, VPD	Critical stress window
Spraying window (SprayOK)	Wind ≤ 3 m/s AND gust ≤ 5 m/s AND Prec=0 AND T_air ≤ 30°C	Wind, gust, precipitation, air temp	Suitable hour for spraying/atomization
Irrigation suggestion	(SMI ≤ 0.3 OR Deficit ≥ 0.7) AND High-VPD AND (6h precip sum = 0)	SMI/Deficit, VPD, precipitation	Rule-based advisory for irrigation timing
Power health	Monitor battery voltage trends; solar panel voltage day–night pattern	Battery, panel, board battery	Detect low-power risk affecting data continuity

3.4.Evaluation approach

Because the case study dataset covers a limited multi-day period and does not include independent agronomic ground truth (e.g., yield or field irrigation logs), evaluation focuses on: (i) descriptive statistics of the recorded environment, (ii) coherence checks between variables (e.g., high temperature aligning with high VPD and high radiation), and (iii) demonstration of decision outputs (stress hours, spray windows, irrigation suggestions) with timestamps.

4.Results

4.1.Data overview and quality

The dataset contained 91 hourly records with high-temperature and high-VPD conditions and no recorded precipitation.

Several channels in the export were fully missing (notably the generic 'Soil temperature' fields), indicating either a disconnected sensor channel or an export template mismatch. The proposed preprocessing layer flags such channels and continues computation with available variables.

4.2.Microclimate stress patterns

Using the simple thresholds in Table 1, the period contained 9 heat-stress hours (T_air ≥ 35°C) and 25 high-VPD hours (VPD ≥ 3 kPa). All 9 heat-stress hours coincided with high VPD, indicating that temperature extremes occurred under strong evaporative demand. The most critical windows were concentrated around midday and early afternoon, coinciding with peak solar radiation.

4.3.Irrigation advisory from soil sensors

Soil-water status was assessed using two complementary channels: volumetric water content (VWC) from the 5TE probe [5] and soil-water tension from the Watermark sensor [6]. Because site-specific calibration parameters (field capacity/wilting point) were not provided, the Soil Moisture Index (SMI) was computed by normalizing VWC using the 10th and 90th percentiles of the observed distribution (P10=8.15%, P90=15.63%). This yields a dimensionless wetness scale suitable for short-term decision support and anomaly detection.

The rule-based irrigation suggestion produced 7 advisory hours, all occurring on 2025-08-15 between 11:00 and 17:00. During this window, VPD exceeded 3 kPa while SMI dropped below 0.3, indicating increasing atmospheric demand coinciding with low measured soil water content. This type of combined soil–atmosphere reasoning is consistent with irrigation scheduling approaches that integrate soil moisture sensing with evapotranspiration-based demand [8].

Table 2. Example hours flagged by the irrigation advisory rule.

Timestamp	T_air (°C)	VPD (kPa)	VWC (%)	SMI
2025-08-15 11:00	30.71	3.14	8.65	0.07
2025-08-15 12:00	31.48	3.45	8.45	0.04
2025-08-15 13:00	31.34	3.34	8.24	0.01
2025-08-15 14:00	31.35	3.31	7.95	0.00
2025-08-15 15:00	31.36	3.28	7.71	0.00
2025-08-15 16:00	31.20	3.23	7.49	0.00
2025-08-15 17:00	30.49	3.01	7.30	0.00

4.4. Spraying windows and operational safety

Operational planning was demonstrated via a spraying-suitability classifier (SprayOK) based on wind and temperature constraints. Across the analyzed period, 58 out of 91 hours satisfied the conservative criteria of wind ≤ 3 m/s, gust ≤ 5 m/s, no rainfall, and air temperature ≤ 30°C. This output can be directly used to propose daily work windows and reduce drift-related risk.

4.5. ET0 context and station health diagnostics

The export includes a daily ET0 channel, which can serve as a baseline estimate of atmospheric water demand and support water-balance reasoning when combined with precipitation and irrigation logs. In FieldClimate, ET0 is typically computed as reference evapotranspiration; the FAO-56 framework provides the canonical definition and calculation guidance [7].

5. Discussion

This case study demonstrates a practical workflow for converting hourly IMETOSstation measurements into decision-ready indicators that are easier to use in daily farm management.

A central design choice is transparency: instead of relying on a black-box predictor, the model uses explicit derived indicators and rule-based logic. For example, microclimate stress is captured through VPD-driven atmospheric demand, temperature exposure, and radiation context; irrigation advisory combines 5TE volumetric water content with Watermark tension to represent both “water amount” and “plant extraction difficulty”; spraying suitability is framed through wind (including gusts), precipitation, and humidity/temperature conditions; and station health is monitored using solar and battery channels to anticipate data continuity issues. Because each indicator is defined by formulas and thresholds, agronomists can audit the logic and adjust parameters to crop type, soil texture, and management goals [13].

The 5TE family relies on dielectric response, and Watermark sensors reflect soil-water tension; both require correct installation and soil-context interpretation as described in vendor documentation [5,6].

These extensions are feasible because IMETOSdata can be accessed programmatically via the FieldClimate platform and its API, supporting integration with external information systems (databases, dashboards, and GIS modules) [2,3].

6. Conclusions

This paper presented a case study on developing a decision-support model using agro-meteorological data collected from an IMETOSstation. Based on an hourly FieldClimate export, the workflow demonstrated data harmonization, basic quality control, and the computation of actionable indicators across operational domains. Power diagnostics (solar and battery voltages) add a reliability layer that is often overlooked but critical for continuous monitoring in remote fields.

Even with a limited observation period, the results show that combining meteorological and soil measurements can produce interpretable, decision-ready outputs such as stress-hour summaries, time-stamped safe spraying periods, and irrigation advisories.

The model is lightweight, transparent, and suitable for integration into external information systems through FieldClimate data access and API-based workflows, enabling practical deployment and iterative refinement as longer datasets and ground-truth records become available.

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