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Satellite-Driven Evaluation of Moisture Dynamics for Irrigation Management in a Semi-Arid Apple Orchard

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Abstract: Sustainable water management is crucial for maintaining long-term productivity in orchard systems situated in semi-arid environments. This study uses satellite-derived spectral and thermal indices to present a six-year remote sensing-based analysis (2020–2025) of moisture variability in a commercial apple orchard. The research integrates multiple metrics to evaluate soil-plant-atmosphere interactions, enabling the detection of hydrological stress periods and recovery phases through spatial and temporal diagnostics. The findings reveal that the orchard experienced critical water stress in 2020 and 2022, characterized by low canopy and surface moisture across most field zones, which coincided with intensified atmospheric water loss. In contrast, 2025 represented a year of partial recovery, where improved spectral responses aligned with lower evapotranspiration intensity. The year 2024 exhibited a notable anomaly: despite low moisture indicators, vegetation performance was sustained, pointing to localized efficiency in water use or unobserved subsurface retention mechanisms. Spatial mapping revealed distinct dry zones recurring across years, primarily in the northern and eastern sectors of the orchard, underscoring the need for spatially adaptive irrigation practices. The combined index approach offered a more nuanced understanding of water distribution patterns than any single metric could achieve alone. These insights support more responsive and data-driven water management strategies under variable climatic conditions. The study contributes to the growing knowledge on the operational use of remote sensing in precision agriculture. It highlights the integration of spectral moisture indices with thermal water loss metrics to improve field-level decision-making, reduce irrigation inefficiencies, and enhance resilience to climate-induced water challenges in fruit production systems.

Keywords: Spectral indices, canopy stress, soil moisture variability, orchard hydrology, thermal analysis, water-use efficiency, precision agriculture

INTRODUCTION

Climate change and the growing scarcity of freshwater resources have made effective irrigation management increasingly essential, particularly in semi-arid agricultural regions. In this context, remote sensing technologies have emerged as powerful tools for evaluating vegetation health, soil moisture, and evapotranspiration (ET)—all critical components for sustainable and efficient water usage. By integrating satellite-derived vegetation indices, such as NDWI and NDMI, with ET modeling, remote sensing offers a scalable, data-driven approach to precision irrigation management (Li et al., 2023).

The Normalized Difference Water Index (NDWI) is extensively utilized to detect the presence of surface water and estimate vegetation water content by analyzing reflectance in the NIR and SWIR bands. Additionally, the Normalized Difference Moisture Index (NDMI) provides a more sensitive measure of canopy moisture status and has demonstrated high accuracy in identifying drought conditions in perennial orchard systems. Additionally, covering the soil surface with crop residues in agricultural areas reduces moisture loss and increases the plant's water use efficiency. Indeed, studies conducted with

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power harrows have reported that leaving crop residues on the surface plays a significant role in conserving soil moisture, and this effect is particularly pronounced in semi-arid areas (Celik & Altıkat, 2022). These indices have proven to be particularly effective in fruit orchards, such as those for apples, olives, pomegranates, and grapes, where irrigation needs are closely linked to phenological stages and soil-plant-atmosphere water dynamics (Caruso & Palai, 2023; Borgogno-Mondino et al., 2022).

Evapotranspiration is a crucial metric for assessing crop water demand, encompassing both soil evaporation and plant transpiration. Utilizing satellite-based ET estimation through platforms like Sentinel-2 allows for continuous monitoring of crop water use with high spatial and temporal resolution (Ippolito, 2023). When combined with NDMI and NDWI, ET models significantly improve irrigation scheduling by linking physiological plant responses to environmental water availability (Dursun et al., 2025).

Recent research utilizing the Normalized Difference Water Index (NDWI) and the Normalized Difference Moisture Index (NDMI) in olive and pomegranate orchards has demonstrated the effectiveness of these indices in mapping water stress patterns within orchards and identifying spatial variability in irrigation needs (Crespo et al., 2025; Borgogno-Mondino et al., 2022). Additionally, time-series analyses of NDWI in kiwifruit orchards have revealed the potential to estimate leaf turgor pressure, which is essential for determining optimal irrigation timing (Jopia et al., 2020). Studies further reinforce these methodologies by indicating that Sentinel-2 imagery can effectively distinguish between irrigated and non-irrigated orchard zones, aiding tactical decision-making and long-term water resource planning (Matarrese et al., 2023).

Integrating NDWI, NDMI, and evapotranspiration modeling offers a robust and scalable framework for data-driven irrigation management. These advances represent a shift from observational to predictive and adaptive systems, enabling growers to manage orchard water use more precisely in the face of increasing climatic variability.

MATERIALS and METHODS

Materials

Study Area

This research was conducted in a commercial apple orchard (Malus domestica Borkh.) under semi-arid climatic conditions between 2020 and 2025. The study area covers a total of 63,107 m² and utilizes a modern drip irrigation system. High evaporation rates and insufficient rainfall in the region contribute to the manifestation of water stress. In addition, fruit production systems in Iğdır are largely based on traditional management practices and intensive human labor, which increases the sensitivity of irrigation timing and water-use efficiency in orchard systems (Malaslı, Altıkat & Çelik, 2012).

Data Source and Satellite-Based Products

The remote sensing data used in the study were obtained from the Farmonaut® Crop Health Monitoring platform, which processes Sentinel-2 surface reflectance products to provide agricultural decision support outputs (Farmonaut, 2025). Sentinel-2 Level-2A products are ready for use after being preprocessed with the Sen2Cor algorithm, which includes atmospheric correction processes (Louis et al., 2016).

Image selection was made from scenes with low cloud cover during the May–October period, which covers the plant growth season.

Moisture and Canopy Water Content Indices

The water availability in the garden and the moisture status within the plant canopy were assessed using the Normalized Difference Water Index (NDWI) and the Normalized Difference Moisture Index (NDMI). NDWI is widely used to determine surface and leaf liquid water content (Gao, 1996). NDMI is a sensitive indicator for detecting canopy moisture and drought stress (Wilson & Sader, 2002).

The index values were produced using the following equations. Here, NIR (Near Infrared) refers to the near-infrared wavelength band; SWIR1 (Short-Wave Infrared 1) and SWIR2 (Short-Wave Infrared 2) refer to the short-wave infrared spectral regions. (Equation 1 and Equation 2) While the NIR band reflects the internal cellular structure and chlorophyll density of leaves, the SWIR bands are highly correlated with leaf water content and surface moisture. Therefore, the ratio of the difference and total values between the NIR and SWIR bands enables the reliable assessment of plant and surface water conditions.

$$NDWI = \frac{NIR - SWIR1}{NIR + SWIR1} \quad \text{.......(1)}$$

$$NDMI = \frac{NIR - SWIR2}{NIR + SWR2} \quad \text{.......(2)}$$

In this study, five classes were created for both indices: <0.1, 0.1–0.2, 0.2–0.3, 0.3–0.4, and ≥0.4. NDWI values≥ 0.2 and NDMI values≥ 0.2 were used as threshold values to represent moisture-rich or low water stress areas. The literature indicates that NDWI and NDMI indices above 0.2 correspond to a physiological state in which the plant's structural water content is preserved and stomatal closure is not pronounced (Gao, 1996; Wilson & Sader, 2002). Conversely, values < 0.2 are accepted as an indicator of drought and water stress, signaling deterioration in both soil-water interaction and canopy water internal stability. These thresholds ensured that the six-year temporal comparisons in the study could be made consistently and accurately.

Evapotranspiration (ET) Analysis

Evapotranspiration (ET) layers have been examined to assess plant water use behavior and atmospheric water loss. Satellite-based ET models provide a reliable basis for water use efficiency in irrigation planning (Allen et al., 2007; Senay et al., 2013). ET distribution was classified into five categories: Very Low, Low, Medium, High, and Very High, using the Farmonaut platform.

Spatial and Temporal Analysis

The distributions of NDWI and NDMI classes over the study area (m^2) were calculated for each year, and these distributions were used to compare moisture level classes across years. Subsequently, the trends in moisture-rich regions represented by the thresholds NDWI ≥ 0.2 and NDMI ≥ 0.2 were evaluated over the years. Furthermore, evapotranspiration (ET) class distributions, which reflect the water consumption behavior of plants, were analyzed to reveal the annual patterns of surface runoff water relationships. These data were superimposed in multi-year layers, identifying persistent water stress regions recurring over the years, particularly in the northern and eastern sectors. Thus, by not limiting the analysis to the individual interpretation of the indices, but rather evaluating the moisture indicators and ET together and in relation to each other, it was possible to clearly define periods of hydrological collapse, temporary recovery, and partial improvement during the study period.

RESULTS and DISCUSSION

Climatic Stress Footprint: Interannual Variability in Moisture Metrics

A multi-year analysis of moisture-related indices has revealed significant variability in climatic stress over the six years from 2020 to 2025, with important implications for irrigation planning and plant productivity within the semi-arid orchard ecosystem. The spatial and temporal distributions of the NDWI and NDMI indices effectively illustrated the extent of water scarcity and physiological drought experienced at the field level.

2022 was the most moisture-deficient season, with 94% of the orchard area falling within the -1 to 0.1 NDWI range and 100% classified in the 0.1–0.2 NDMI category (Table 1). These figures reflect severe surface and subsurface moisture depletion, indicating extreme drought stress. Similarly, in 2020, the NDWI distribution was primarily low, with approximately 69% of the field (43.277 m²) exhibiting NDWI values between 0.1 and 0.2 and no portion of the field surpassing 0.3. The NDMI values for that year further corroborated the presence of critical water stress conditions.

In contrast, 2021 and 2023 experienced a temporary recovery, with 100% of the field achieving NDWI and NDMI classifications within the 0.3–0.4 range. This indicates a more favorable soil and canopy moisture period, though still within moderate limits. A relatively improved profile was noted in 2025, when 57% of the field fell within the 0.2–0.3 NDWI range and 91% within the 0.2–0.3 NDMI range, suggesting a partial hydrological recovery (Table 1). Nevertheless, high moisture zones (≥0.4) remained absent.

While 2024 was generally productive in terms of vegetative indices, it presented a hydrological anomaly: over 72% of the field had NDMI values below 0.1, with only 1.4% surpassing 0.3 NDWI. This discrepancy may indicate a spatial decoupling between soil surface moisture and internal plant water content, likely due to variations in irrigation efficiency, subsurface heterogeneity, or the effects of canopy shading.

Table 1. *Field area (m²) distribution for NDWI and NDMI index classes*

Index	Class Range	Years					
		2020	2021	2022	2023	2024	2025
NDWI	<0.1	0	0	59319	0	45823	0
	0.1-0.2	43277	0	3788	0	12375	0
	0.2-0.3	19830	0	0	0	4041	36185
	0.3-0.4	0	63107	0	63107	869	26922
	>0.4	0	0	0	0	0	0
NDMI	<0.1	45267	0	0	0	60349	5718
	0.1-0.2	17840	0	63107	0	2758	57389
	0.2-0.3	0	0	0	63107	0	0
	0.3-0.4	0	63107	0	0	0	0
	>0.4	0	0	0	0	0	0

Figure 1 illustrates the interannual trends, highlighting the percentage of the field area covered by NDWI and NDMI values greater than or equal to 0.2. This chart highlights the years of hydrological breakdown (2020, 2022), the transient recovery observed in 2023 and 2025, and the significant sub-canopy stress experienced in 2024, which was accompanied by strong spectral vegetation indices.

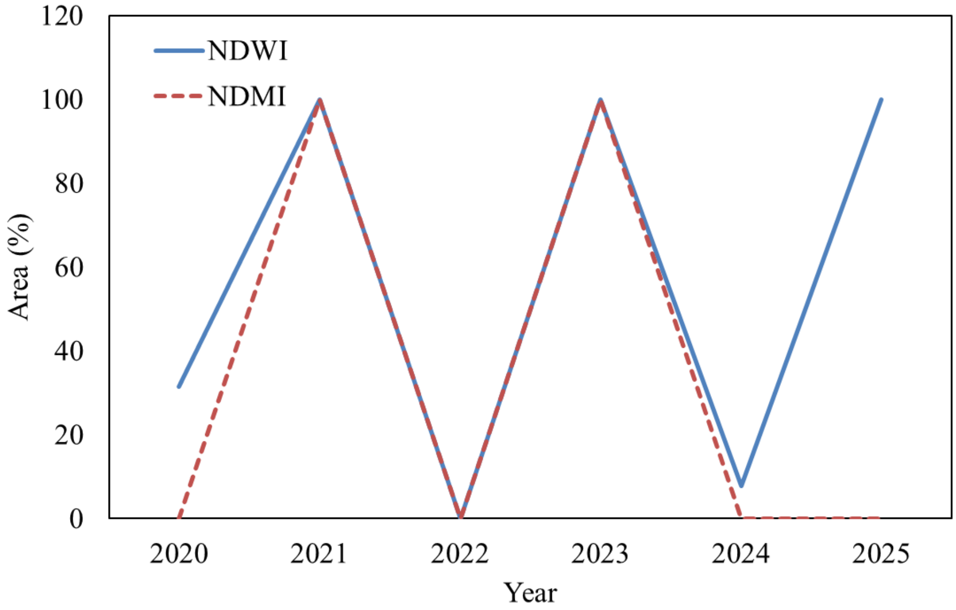

Figure 1. *Temporal trends of moisture-rich zones (NDWI and NDMI ≥ 0.2)*

The NDWI and NDMI trends across six years demonstrate the orchard's vulnerability to climatic variability and its capacity for partial recovery under favorable conditions. These indices provide a robust diagnostic framework to support adaptive irrigation scheduling and site-specific water management.

NDWI and NDMI are remote sensing indices commonly utilized to assess surface water availability and moisture levels in both top and bottom soils, respectively, reflecting plants' water content (Gao, 1996; Jackson et al., 2004). The year 2022 is notable as an extreme drought year, highlighting the sensitivity of these indices for drought detection. This observation is consistent with previous research indicating that NDMI is exceptionally responsive to drought stress (Gu et al., 2008). Similarly, low values of NDWI and NDMI were recorded in 2020, further confirming significant losses in surface and soil moisture during that year.

The transient rebounds in 2021 and 2023 suggest that moisture indices are sensitive to climatic fluctuations and potential changes in irrigation management. This supports studies suggesting that remote sensing and time series analysis can be used to monitor irrigation strategies (Thenkabail et al., 2005).

The paradoxical scenario in 2024, characterized by low NDMI values paired with high vegetation productivity, suggests a decoupling between crop water content and soil moisture levels. This phenomenon can be attributed to several factors, including variations in irrigation efficiency, subsoil water mobility, and shading effects. Prior studies examining the impacts of heterogeneous irrigation systems have documented such occurrences (Campos et al., 2010).

Overall, this study demonstrates that through comparative analysis of NDWI and NDMI over time, these tools provide powerful diagnostic capabilities that can be utilized for both monitoring climatic fluctuations and informing regional irrigation management decisions.

Evapotranspiration Shifts as a Stress Indicator

Evapotranspiration (ET) patterns observed between 2020 and 2025 indicated significant changes in water loss dynamics, indirectly reflecting the physiological activity and stress conditions within the orchard ecosystem. While the Normalized Difference Water Index (NDWI) and Normalized Difference Moisture Index (NDMI) provided static views of moisture availability, ET maps offered ongoing insights into the interactions between plants and the atmosphere, as well as the actual water demand.

In 2020, evapotranspiration rates were remarkably high, with over 40,000 m² of the orchard area affected. This is illustrated by the extensive dark orange and red zones in the ET raster outputs. These elevated evapotranspiration levels occurred with significant soil moisture deficits, highlighting a substantial atmospheric evaporative demand that intensified water stress.

In contrast, 2021 and 2023 exhibited a notable shift towards lower evapotranspiration (ET) levels, with the combined area of Low and Very Low ET classes exceeding 25,000 m² and 30,000 m², respectively. These years corresponded with NDWI and NDMI values that reflected moderate water availability, suggesting a more balanced usage of plant water relative to the available moisture. This observation is further illustrated in Figure 2, which showcases the changing dominance of ET classes throughout the seasons.

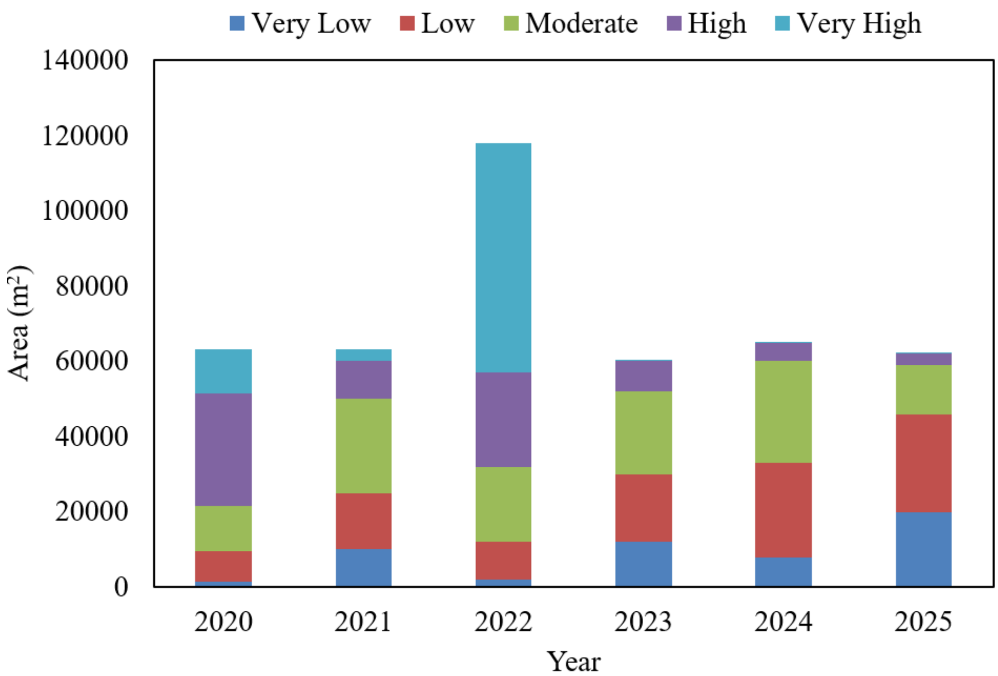

Figure 2. *Annual distribution of evapotranspiration classes*

The most spatially uniform and moderate ET profile occurred in 2024, where over 52,000 m² was categorized within the low–moderate evapotranspiration classes. This alignment with visual vegetation indices (NDVI, RVI) suggests improved crop functioning under targeted irrigation conditions.

2025 ET levels experienced another decline, with 20,000 m² categorized in the “Very Low” class, despite signs of partial recovery in soil and canopy moisture indicators. This disconnection could indicate a delay in canopy development or lingering physiological stress from previous dry seasons. Overall, the ET metrics enhanced the static moisture indices (NDWI and NDMI), providing a dynamic diagnostic layer for assessing real-time interactions between crops and climate. As illustrated in Figure

2, the annual evolution of ET classes highlights critical transitions in orchard water behavior, thereby offering a valuable framework for adaptive irrigation scheduling and water budgeting at the field scale.

Hydrological Recovery and Breakdown Years

Analysis of the combined NDWI, NDMI, and ET datasets delineated distinct periods of hydrological breakdown and partial recovery within the six-year observational window. These transitions were instrumental in identifying vulnerable and resilient periods in the orchard's water dynamics.

2022 is notable for experiencing a significant breakdown period characterized by exceptionally low moisture indices. As indicated in Table 2, more than 93% of the orchard area was categorized under NDWI < 0.1, and 100% was classified within NDMI 0.1–0.2, underscoring a pervasive water deficiency in soil and vegetation. Concurrently, the evapotranspiration metrics presented in Table 2 reveal that Very High and High ET levels encompass approximately 51.000 m², highlighting an unsustainable imbalance between water availability and atmospheric water loss.

Table 2. *Hydrological recovery breakdown*

Year	NDWI ≥ 0.2 Area (m²)	NDMI ≥ 0.2 Area (m²)	High/Very High ET Area (m²)	Low/Very Low ET Area (m²)
2020	19830	0	41607	9500
2021	63107	63107	13107	25000
2022	0	0	50107	12000
2023	63107	63107	8507	30000
2024	4910	0	5102	33000
2025	63107	57389	3107	46000

The year 2024 presented a complex scenario: while vegetative indices were promising, NDMI data from Table 2 indicated that over 95% of the area remained below 0.2, suggesting a disconnect between vegetative performance and the internal water status of plants. Nevertheless, the balanced distribution of ET shown in Table 2 suggests potential improvements in irrigation targeting or localized soil water-holding capacity. Furthermore, by 2025, there were signs of partial hydrological recovery. Table 1 illustrates that 57% of the area attained NDWI values in the 0.2–0.3 range, with over 90% reaching NDMI values of 0.2–0.3. This diagnostic approach, which integrates soil moisture, plant water status, and evapotranspiration dynamics, effectively differentiates between years of decline and recovery. It also aids in developing index-based water risk models adapted to seasonal variations.

Optimal Moisture and Irrigation Conditions in 2024 and 2025

2024 and 2025 marked two contrasting cases regarding moisture distribution and evapotranspiration behavior, offering unique insights into the orchard's irrigation response capacity under different climatic and management scenarios.

In 2024, NDWI values indicated limited surface water presence, with only 4.910 m² (7.8%) of the orchard reaching an NDWI value of≥ 0.2, while over 72% remained below the 0.1 NDMI class. Despite this, evapotranspiration data showed a high proportion of the field within Low and Moderate ET classes, accounting for over 52,000 m². This discrepancy suggests the possibility of localized irrigation efficiency or improved canopy water regulation, resulting in relatively balanced ET even under suboptimal root-zone moisture conditions.

In contrast, 2025 presented a scenario in which both indices aligned more consistently. According to Table 1, 100% of the orchard area exceeded NDWI 0.2, and over 90% of the field reached NDMI values between 0.2 and 0.3. This reflects a broader spatial recovery in both soil and plant moisture status. Simultaneously, evapotranspiration rates significantly declined, with Low and Very Low ET zones covering over 46,000 m² of the orchard area. The transition is further supported by Figure 3, demonstrating a substantial reduction in High and Very High ET zones compared to prior years.

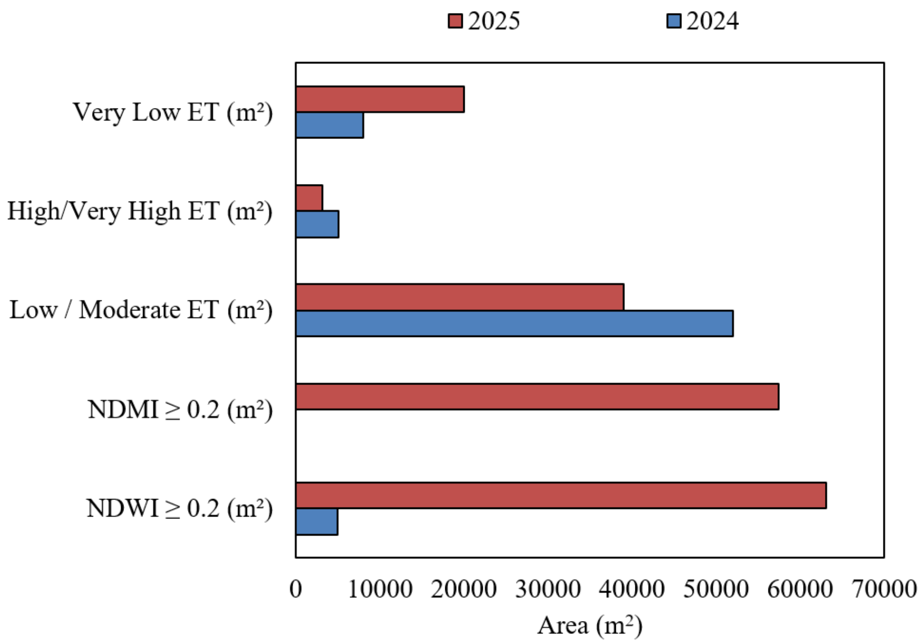

Figure 3. *Optimal moisture irrigation*

This alignment between higher moisture availability and lower atmospheric water loss in 2025 suggests that irrigation timing and distribution were more synchronized with plant water demand. Conversely, the 2024 results highlight how evapotranspiration data alone may not capture latent sub-surface stress, emphasizing the importance of integrating multiple indices for precise irrigation evaluation.

The combined interpretation of moisture and ET indices in these two years emphasizes the complexity of orchard water dynamics. While NDWI and NDMI signal potential water stress, ET values provide an operational lens into how water is utilized and lost, allowing for a nuanced assessment of irrigation effectiveness.

Spatial Disparities in Field-Level Water Availability

The spatial heterogeneity of water availability across the orchard was distinctly observable in the multi-index evaluation, which combined NDWI, NDMI, and ET datasets. At the same time, temporal trends revealed specific interannual patterns of moisture stress and recovery, while spatial analyses identified localized zones of persistent water scarcity or surplus, which are often obscured in field-level averages.

In 2022 and 2024, the orchard exhibited apparent spatial disparities, with NDWI and NDMI values concentrated in the lower classes (≤ 0.2), particularly in the northern and eastern subregions. These zones consistently aligned with low ET signatures, reinforcing the presence of cumulative water stress driven by insufficient infiltration, poor retention capacity, or suboptimal irrigation coverage. In contrast, the southwestern quadrant in 2025 exhibited elevated NDWI (0.2–0.3) and NDMI (0.2–0.3) values, indicating improved surface and canopy-level moisture conditions. Dominant low-to-moderate ET levels supported these spatial gains in moisture availability, implying a more efficient water use pattern under similar atmospheric conditions.

Interestingly, the 2024 spatial maps revealed a hydrological mismatch—while certain zones displayed moderate ET levels, their corresponding NDMI and NDWI values remained critically low, suggesting possible hydraulic decoupling or deep percolation losses that were not captured in the surface indices. These inconsistencies emphasize the importance of using integrated spatial diagnostics rather than relying on single indices for moisture assessment. These trends are numerically summarized in Table 3, which illustrates the spatial distribution of dry zones (NDWI ≤ 0.2), canopy-level drought (NDMI ≤ 0.2), and ET-based water loss zones, clearly demonstrating temporal field heterogeneity.

Overall, spatial disparities across the orchard confirm that uniform irrigation strategies are insufficient under semi-arid field conditions. Site-specific interventions based on high-resolution remote sensing data are crucial for reducing local stress hotspots and achieving equitable water distribution. These findings underscore the operational value of spatial analytics in advancing precision agriculture and enhancing resilience to hydrological variability.

Table 3. *Spatial water availability (m^2)*

Year	NDWI ≤ 0.2 (Dry Zone)	NDMI ≤ 0.2 (Dry Canopy)	ET (High/Very High)	ET (Low/Moderate)	ET (Very Low)
2020	63107	63107	-	-	-
2021	0	0	-	-	-
2022	63107	63107	-	-	-
2023	0	0	-	-	-
2024	58228	63107	3400	48800	10907
2025	0	5718	1782	39000	22325

Synchronized Index Behavior as a Diagnostic Tool

The concurrent evaluation of NDWI, NDMI, and ET datasets across the 2020–2025 period reveals a strong diagnostic potential when used in an integrated framework. Rather than interpreting these indices in isolation, their co-behavioral trends provide more precise insights into moisture availability, vegetative stress, and irrigation effectiveness over time.

As illustrated in Figure 4, years with low NDWI and NDMI values, such as 2020 and 2022, also recorded the highest average evapotranspiration (ET), indicating a critical imbalance between water availability and atmospheric water demand. During these seasons, the field was subject to simultaneous soil and canopy water deficits, while experiencing elevated atmospheric moisture loss, which exacerbated overall plant stress.

In contrast, 2025 demonstrates a more synchronized hydrological recovery. NDWI and NDMI averages improved to 0.28 and 0.27, respectively, while ET values decreased significantly to 0.20. This alignment reflects a balanced plant–soil–atmosphere interaction, suggesting that the vegetation utilized the water supply more effectively.

Interestingly, 2024 exhibited a divergence in index behavior: the NDWI and NDMI averages remained low (0.15 and 0.11), while ET was relatively moderate (0.22). This suggests that vegetation effectively regulated transpiration under low moisture conditions, possibly due to short-term rainfall events, improved irrigation efficiency, or reduced leaf area index.

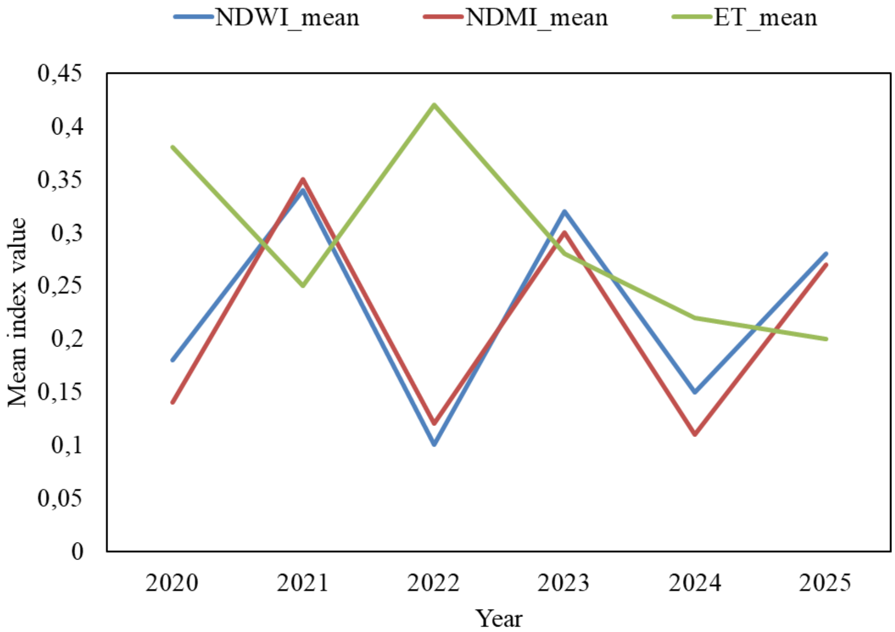

Figure 4. *Temporal trends of NDWI, NDMI, and ET indices*

The multi-index trends in Figure 4 confirm the value of synchronized evaluation. They highlight the transition from critical drought to partial recovery, offering a nuanced understanding of hydrological dynamics that extends beyond what a single index can deliver. This approach supports more accurate field-level diagnostics and informed decision-making in irrigation planning and drought response strategies.

CONCLUSION

This study demonstrated the effectiveness of integrating satellite-derived NDWI, NDMI, and evapotranspiration (ET) indices in monitoring moisture stress and guiding irrigation strategies in a semi-arid apple orchard over six years. The combined use of these indices enabled a detailed characterization of surface and canopy-level water dynamics. It provided valuable insight into the interaction between plant water availability and atmospheric water loss. Similar research has shown that soil moisture dynamics and soil–atmosphere gas exchange processes can be successfully modeled using artificial neural networks and hybrid predictive frameworks, demonstrating the applicability of data-driven approaches in semi-arid agricultural systems (Altikat, Gulbe, Kucukerdem, & Altikat, 2020).

The results highlighted 2020 and 2022 as critical drought years, marked by severely low NDWI and NDMI values across the field. Conversely, 2025 emerged as a recovery year, with widespread improvements in indices and concurrent reductions in evapotranspiration intensity. The divergence observed in 2024, where moderate ET values coincided with low internal plant moisture, emphasized the importance of interpreting these metrics in concert rather than in isolation.

Spatial analyses revealed significant within-field variability, underscoring the limitations of uniform irrigation practices and supporting the implementation of zone-based irrigation strategies. On the other hand, temporal trends highlighted the dynamic nature of moisture availability and underscored the need for real-time monitoring under changing climatic conditions.

Ultimately, the study offers a replicable and scalable remote sensing framework for precision irrigation management. By aligning soil moisture, canopy hydration, and evapotranspiration metrics, this approach enhances water-use efficiency, supports drought resilience, and contributes to sustainable orchard productivity in water-limited environments.

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AUTHOR CONTRIBUTIONS

The authors contributed equally to this study.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

Allen, R. G., Pereira, L. S., Howell, T. A., & Jensen, M. E. (2007). Evapotranspiration information reporting: I. Factors governing measurement accuracy. Agricultural Water Management, 95(4), 529–543.

Altikat, S., Gulbe, A., Kucukerdem, H. K., & Altikat, A. (2020). Applications of artificial neural networks and hybrid models for predicting CO_2 flux from soil to atmosphere. International Journal of Environmental Science and Technology, 17(10), 4719–4732. https://doi.org/10.1007/s13762-020-02799-6

Borgogno-Mondino, E., Farbo, A., Novello, V., & Palma, L. (2022). A fast regression-based approach to map the water status of pomegranate orchards with Sentinel-2 data. Horticulturae, 8(9), 759. https://doi.org/10.3390/horticulturae8090759

Campos, I., Neale, C. M. U., Calera, A., Balbontín, C., & González-Piqueras, J. (2010). Assessing satellite-based basal crop coefficients for irrigated grapes (Vitis vinifera L.). Agricultural Water Management, 98(1), 45–54.

Caruso, G., & Palai, G. (2023). Caruso, G. and Palai, G. (2023) 'Assessing grapevine water status using Sentinel-2 images', Italus Hortus, 30(3), pp. 70-79. doi: 10.26353/j.itahort/2023.3.7079

Celik, A., & Altikat, S. (2022). The effect of power harrow on the wheat residue cover and residue incorporation into the tilled soil layer. Soil & Tillage Research, 215, 105202. https://doi.org/10.1016/j.still.2021.105202

Crespo, N., Pádua, L., & Paredes, P. (2025). Spatial-Temporal Dynamics of Vegetation Indices in Response to Drought Across Two Traditional Olive Orchard Regions in the Iberian Peninsula. Sensors. https://pmc.ncbi.nlm.nih.gov/articles/PMC11946650/

Dursun, G., Yilgan, F. & Dogan, S. Monitoring of Moisture and Temperature Regime on Agricultural Land Parcels Using Landsat-8 Remote Sensing Data in the Mardin Province, Türkiye. J Indian Soc Remote Sens 53, 1875–1890 (2025). https://doi.org/10.1007/s12524-024-02114-7

Farmonaut. (2025). Farmonaut Crop Health Monitoring Platform. https://www.farmonaut.com

Gao, B. C. (1996). NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sensing of Environment, 58(3), 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3

Gu, Y., Brown, J. F., Verdin, J. P., & Wardlow, B. (2008). A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophysical Research Letters, 35(6). https://doi.org/10.1029/2006GL029127

Ippolito, M. (2023). Assessing crop water requirements and irrigation scheduling at different spatial scales in Mediterranean orchards using models, proximal and remotely sensed data [PhD dissertation]. https://tesidottorato.depositolegale.it/handle/20.500.14242/172965

Jackson, T. J., Chen, D., Cosh, M., Li, F., Anderson, M., Walthall, C., ... & Doriaswamy, P. (2004). Vegetation water content mapping using Landsat data-derived normalized difference water index for corn and soybeans. Remote Sensing of Environment, 92(4), 475–482. https://doi.org/10.1016/j.rse.2003.10.021

Jopia, A., Zambrano, F., & Pérez-Martínez, W. (2020). Time series of vegetation indices (VNIR/SWIR) derived from Sentinel-2 (A/B) to assess turgor pressure in kiwifruit. ISPRS International Journal of Geo-Information, 9(11), 641. https://doi.org/10.3390/ijgi9110641

Li, X., Liu, Y., Wang, D., & Zhang, F. (2023). Integrating multi-source remote sensing data for real-time irrigation management in orchards. Remote Sensing Applications: Society and Environment, 30, 100995. https://doi.org/10.1016/j.rsase.2023.100995

Louis, J., Debaecker, V., Pflug, B., Main-Knorn, M., & Gascon, F. (2016). Sentinel-2 Level-2A atmospheric correction using Sen2Cor. Proceedings of SPIE, 10005. https://doi.org/10.1117/12.2232262

Malaslı, M. Z., Altıkat, S., & Çelik, A. (2012). Iğdır ili kayısı tarımının mekanizasyon sorunları ve çözüm önerileri. Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 2(3), 47–54.

Matarrese, R., Portoghese, I., & Mirra, L. (2023). Mapping irrigated crops through Sentinel-2 satellite images: evidence from Southern Italy. IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/10424152/

Senay, G. B., Bohms, S., Singh, R. K., Gowda, P. H., Velpuri, N. M., Alemu, H., & Verdin, J. P. (2013). Operational evapotranspiration mapping using remote sensing and weather datasets: A new parameterization for the SSEBop model. Journal of the American Water Resources Association 49:3 577-591.

Thenkabail, P. S., Schull, M., & Turral, H. (2005). Ganges and Indus River Basin land use/land cover (LULC) and irrigated area mapping using continuous streams of MODIS data. Remote Sensing of Environment, 95(3), 317–341.

Wilson, E. H., & Sader, S. A. (2002). Detection of forest harvest type using multiple dates of Landsat TM imagery. Remote Sensing of Environment, 80(3), 385–396. https://doi.org/10.1016/S0034-4257(01)00318-2