ENVIRONMENTAL RESEARCH
WATER

PURPOSE-LED PUBLISHING™

Part of the ENVIRONMENTAL RESEARCH SERIES

PAPER • **OPEN ACCESS**

Remote sensing model choice drives water pricing forecasts in water-scarce basins

To cite this article: Hadi H Jaafar *et al* 2026 *Environ. Res.: Water* **2** 015005

ENVIRONMENTAL RESEARCH
WATER

Check for updates

OPEN ACCESS

RECEIVED
19 May 2025

REVISED
22 January 2026

ACCEPTED FOR PUBLICATION
28 January 2026

PUBLISHED
10 February 2026

PAPER

Remote sensing model choice drives water pricing forecasts in water-scarce basins

Hadi H Jaafar[1,*], Rim Hazimeh[1], Francesco Sapino[2] and C Dionisio Pérez-Blanco[2]

[1] Department of Agriculture, Faculty of Agriculture and Food Sciences, American University of Beirut, Bliss St., Beirut 2020-1100, Lebanon
[2] IMDEA WATER, Av. Punto Com, 2, 28805 Alcalá de Henares, Madrid, Spain
[*] Author to whom any correspondence should be addressed.

E-mail: hj01@aub.edu.lb

Keywords: evapotranspiration, WaPOR V3, HSEB, biomass, socio-economic modeling, mathematical programming, behavioral instruments

Supplementary material for this article is available online

Abstract

Evapotranspiration (ET) and biomass data are critical inputs for the economic models used to forecast the impacts of water management interventions. In water-scarce basins where ground-based data is limited, these forecasts rely heavily on remote sensing (RS) products. This study conducts a comparative analysis to quantify how the choice of RS input data influences the ex-ante performance assessment of water pricing policy simulations for Lebanon's upper Litani River Basin driven by two distinct RS datasets: FAO WaPOR V3 and a hybrid single source surface energy balance (HSEB) model coupled with the Global Yield and Evaporation Mapper in Earth Engine (GYMEE). Results indicate that while biomass estimates correlate strongly, WaPOR V3 consistently estimates higher yields (up to 66%). Conversely, HSEB estimates significantly higher Actual ET than WaPOR V3 (34% to 66%), reversing trends observed in previous WaPOR versions. When integrated into a microeconomic ensemble, these biophysical discrepancies lead to fundamentally divergent policy performance forecasts. Models informed by HSEB predict a highly elastic response to pricing, suggesting significant water savings and a shift to rainfed crops. In contrast, WaPOR V3 inputs drive a nearly inelastic response, forecasting minimal water savings and higher initial farmer profits. Consequently, maximum tariff revenue estimates differ by 9% solely based on the RS input chosen. These findings demonstrate that policy performance assessments are highly sensitive to the underlying water use data. The study highlights that in the absence of ground validation, relying on a single RS product can lead to unquantified uncertainty in policy design, underscoring the need for sensitivity analyzes in hydro-economic modeling.

1. Introduction

The sustainable management of agricultural water resources has become an imperative, particularly in semi-arid and water-scarce basins where groundwater abstraction underpins food security, rural livelihoods, and regional economies (FAO 2020 a, Elshall *et al* 2022, Connor 2024). In these regions, the 'tragedy of the commons' often manifests as unsustainable aquifer depletion, necessitating robust intervention strategies (Ostrom 1990, Grafton *et al* 2022). Quantifying crop actual evapotranspiration (ETa) and biomass production is fundamental for assessing water use efficiency and productivity, serving as the biophysical basis for conservation interventions ranging from irrigation scheduling to allocation planning (Foster *et al* 2020, FAO 2021). Earth observation systems have emerged as indispensable tools for monitoring these variables at policy-relevant scales, overcoming the spatial limitations of *in-situ* measurements (Bastiaanssen *et al* 1998, Jaafar, Mourad and Schull 2022). These remote sensing (RS)-derived datasets are increasingly utilized to design behavioral economic instruments—specifically water pricing schemes—intended to internalize the environmental costs of extraction and influence irrigator decision-making (Molle and Closas 2021, Hazimeh and Jaafar 2024).

To operationalize these data for policy analysis, recent frameworks have integrated RS inputs with mathematical programming models (MPMs). These bio-economic ensembles leverage the high spatiotemporal resolution of RS data to calibrate simulations of irrigator behavior, allowing researchers to generate ex-ante assessments of policy performance under uncertainty (Graveline 2016, Sapino *et al* 2024). While the theoretical potential of water pricing to encourage conservation is well-established (Dinar and Subramanian 1997), its projected effectiveness is highly sensitive to the price elasticity of water demand. In agriculture, this elasticity is often inelastic, implying that substantial price increases are required to achieve modest water savings—a dynamic that can severely impact farmer profitability and social equity (Booker *et al* 2012, Scheierling and Treguer 2016, Albiac *et al* 2020). Consequently, the design of these pricing schemes requires precise data to avoid exacerbating user conflicts or driving marginal farmers out of production (Kerr 2007, Tu *et al* 2023).

However, a critical methodological gap remains in the literature: the sensitivity of these microeconomic policy performance assessments to the specific choice of the underlying RS model. While previous research has extensively validated the biophysical accuracy of various RS products (e.g. comparing FAO WaPOR V2 against energy balance models like hybrid single source surface energy balance (HSEB)) (Blatchford *et al* 2019, Hazimeh and Jaafar 2024), and others have utilized single-source RS data for economic modeling (Sapino *et al* 2020), no study has yet quantified how the algorithmic differences between these models propagate through economic simulations to alter policy design recommendations. Differences in model architecture (e.g. the Penman–Monteith approach of WaPOR versus surface energy balance approaches), input forcing data, and parameterization can lead to divergent estimates of baseline water use and yield.

We hypothesize that these biophysical divergences are not merely technical artifacts but can lead to substantially different forecasts regarding farmer responses to pricing, labor demand, and tariff revenues. This study addresses this gap by conducting a comparative sensitivity analysis of water pricing simulations within a microeconomic ensemble forecasting framework. We contrast the simulated policy outcomes derived from two distinct, state-of-the-art RS datasets: the FAO's updated WaPOR V3 (utilizing ETLook) and a HSEB model coupled with the Global Yield and Evaporation Mapper in Earth Engine (GYMEE). Focusing on the Upper Litani River Basin (ULRB) in Lebanon—a representative data-scarce region facing critical groundwater stress (Jaafar *et al* 2016, 2024)—we integrate these datasets into calibrated MPMs.

It is important to clarify that the objective of this study is not to validate these RS models against ground truth, nor to assess the credibility of the water pricing policy itself. Rather, we aim to diagnose the sensitivity of the policy performance assessment to the input data. We explicitly frame this as a local sensitivity analysis, designed to demonstrate the existence and direction of RS-driven variance in simulated outcomes, rather than to globally quantify uncertainty across all model inputs. While Hazimeh and Jaafar (2024) established the biophysical discrepancies between HSEB/GYMEE and FAO WaPOR V2, that analysis was limited to the validation of physical variables (ET and Yield). The current study advances this framework by integrating the updated WaPOR V3 into a hydro-economic model, shifting the analytical focus from data accuracy to policy performance assessment sensitivity. The primary innovation of this work is to demonstrate that RS model selection is a non-neutral variable in ex-ante policy analysis; the choice of model significantly influences simulated water withdrawal reductions and economic outcomes under incremental pricing scenarios. By highlighting these dependencies, this research underscores the necessity of rigorous model selection and uncertainty analysis for developing robust, equitable water management policies in challenged basins worldwide.

2. Methods

2.1. Overall framework

This study employs an integrated framework coupling RS analysis with microeconomic modeling to evaluate the impact of RS model choice on water pricing simulations in Lebanon's ULRB. The central hypothesis is that the selection between different, plausible RS-derived datasets can significantly alter simulated policy outcomes.

As illustrated in the workflow diagram (figure 1), the framework's core involves processing and comparing inputs from two distinct, contemporary RS sources:

1. FAO's water productivity open access portal version 3 (WaPOR V3): Providing estimates of ETa and biomass/yield.

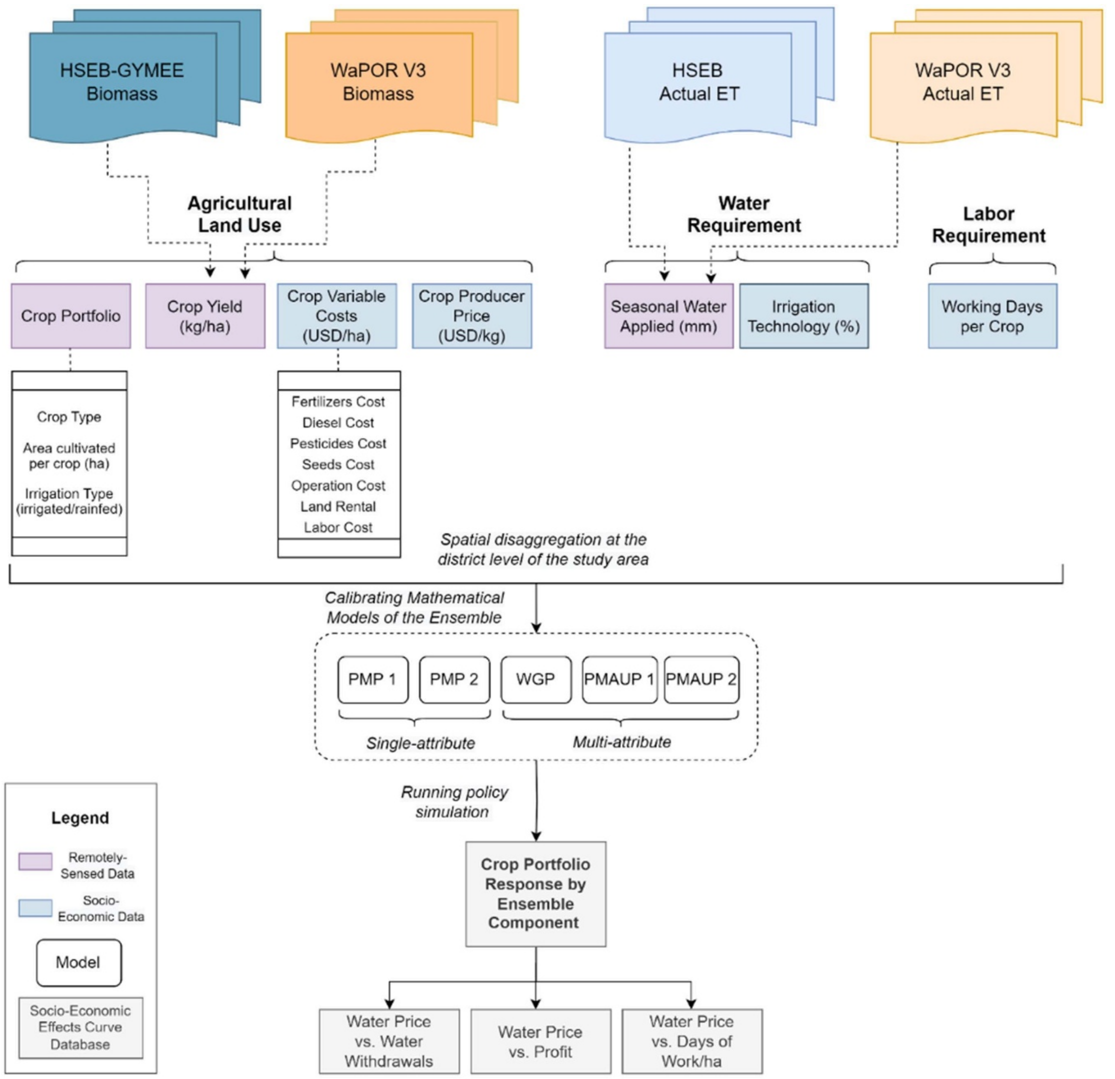

Figure 1. Workflow for the modeling framework of the coupled remote sensing and the multi-model ensemble of MPMs using both the HSEB and FAO WaPOR V3 models.

2. A HSEB model combined with the Global Yield and Evaporation Mapper in Earth Engine (GYMEE): Providing an alternative set of ETa (from HSEB) and biomass/yield (from GYMEE) estimates.

These parallel RS data streams serve as crucial biophysical inputs driving the subsequent economic analysis. Specifically, the ETa estimates from each source are used to calculate crop-specific water requirements and the seasonal volume of irrigation water applied, considering local rainfall and irrigation technology efficiencies. Concurrently, the biomass estimates are converted into marketable crop yields, forming the basis for calculating potential farm revenue (figure 1). These RS-derived biophysical parameters (water applied, crop yield) are then integrated with essential socio-economic data pertinent to the ULRB context. This includes district-level information on crop producer prices, variable production costs (such as fertilizers, diesel for pumping, pesticides, seeds, labor, etc.), typical irrigation technologies employed, and crop-specific labor requirements (working days per crop), as depicted in figure 1.

This combined biophysical and socio-economic dataset feeds into an ensemble of five distinct, calibrated MPMs. Adapted from previous work by Sapino *et al* (2024, 2020), this ensemble (comprising positive mathematical programming (PMP), weighted goal programming (WGP), and positive multi-attribute utility programming (PMAUP) model types—see figure 1 and section 2.6) is designed to simulate farmer decision-making, primarily concerning crop choice (the crop portfolio), under conditions of economic and resource constraints. By relying on an ensemble rather than a single specification, we explicitly account for model (structural) uncertainty, capturing a range of plausible behavioral responses to policy changes instead of imposing one behavioral assumption.

The overall workflow follows several key steps (figure 1): (i) Derivation and processing of ETa and yield estimates from both the WaPOR V3 and HSEB-GYMEE sources for the study period and crops. (ii) Integration of these RS inputs with collected socio-economic data at the district level. (iii) Calibration of the five MPMs within the ensemble to replicate baseline agricultural land use patterns, performed separately using inputs derived from each RS source. (iv) Simulation of farmer responses to incremental water pricing scenarios using the calibrated models, run independently with WaPOR V3-derived inputs and HSEB-GYMEE-derived inputs. (v) Comparative analysis of the key simulated socio-economic outputs resulting from each RS input stream, focusing on agricultural water withdrawals, farmer profitability, and labor demand, generating policy-relevant effect curves.

This dual-input simulation strategy directly isolates and quantifies the sensitivity of projected policy impacts to the choice of RS model, representing a key advancement over previous studies that typically relied on a single RS dataset (e.g. WaPOR V2 in Sapino *et al* 2024). The analysis spans the 2018–2021 agricultural seasons for four economically significant crops in the ULRB: wheat, early-season potatoes, table grapes, and onions, conducted across the basin's three main administrative districts (Baalbeck–Hermel, Zahleh, and West Bekaa). This period was chosen strategically to capture significant inter-annual climatic variability (ranging from wet to dry years) as well as the onset of severe economic instability in Lebanon. This variability is essential for testing the models under diverse environmental and economic stress conditions.

2.2. Study area: ULRB

The study focuses on the ULRB, located within Lebanon's Bekaa Valley (figure 2). This fertile valley, situated between the Mount Lebanon range to the west and the Anti-Lebanon range to the east, constitutes the country's primary agricultural heartland, accounting for approximately 40% of the national cultivated area. The ULRB itself covers roughly 180 000 ha, characterized by a relatively flat valley floor suitable for extensive farming, with elevations typically ranging between 800 and 1100 m above sea level.

The region experiences a semi-arid Mediterranean climate (Köppen classification Csa), marked by pronounced seasonality. Hot, dry summers with infrequent rainfall necessitate irrigation for crop production, while cool, wet winters concentrate the majority of the annual precipitation (averaging around 500–800 mm, varying spatially) between November and April. Summer temperatures often exceed 30 °C, leading to high potential ET rates during the primary irrigation season, which spans from May to October.

Hydrologically, while the Litani River flows through the basin, its discharge is highly seasonal and often insufficient to meet the substantial agricultural water demand during peak summer months. Consequently, the agricultural sector is heavily reliant on groundwater, which accounts for an estimated 60% of total water withdrawals in the basin (Jaafar *et al* 2016). This groundwater is predominantly abstracted via a large number of privately owned wells, often operating without effective regulation or monitoring. This largely uncontrolled abstraction significantly exceeds the natural recharge occurring from rainfall infiltration and snowmelt runoff from the adjacent mountain ranges, resulting in chronic groundwater depletion estimated at approximately 57.5 MCM/year and associated declines in water table levels (Jaafar *et al* 2016, Molle and Closas 2021).

Approximately 25% of the ULRB's area is dedicated to irrigated agriculture. For this analysis, we specifically focus on four representative crops: wheat, potatoes, table grapes, and onions. According to land-use surveys by Jaafar *et al* (2016) and Ministry of Agriculture data, these cultivars dominate the regional production profile: wheat accounts for ∼90% of cereal cultivation, potatoes and onions are the primary summer cash crops, and table grapes constitute the main orchard crop. These agricultural activities are fundamental to the regional economy and local livelihoods. Irrigation practices vary, encompassing traditional surface irrigation methods as well as more modern sprinkler and drip systems. Energy for pumping groundwater is a significant operational cost for farmers, often relying on diesel generators due to the unreliability of the national electricity grid. Water governance in the basin remains fragmented, hindering coordinated efforts to manage resource abstraction sustainably. The socio-economic fabric has also been impacted by the influx of a large number of Syrian refugees since 2011, placing additional strain on already stressed water resources and infrastructure (Jaafar *et al* 2020).

Furthermore, the ULRB exemplifies conditions common to many data-scarce agricultural basins worldwide. Ground-based monitoring networks for meteorological data, streamflow, groundwater levels, and actual agricultural water use are sparse and often inconsistent. Comprehensive agricultural surveys detailing cropping patterns, yields, and input use are also limited. This lack of reliable ground data underscores the importance and potential utility of RS techniques for water resource assessment and monitoring in the region.

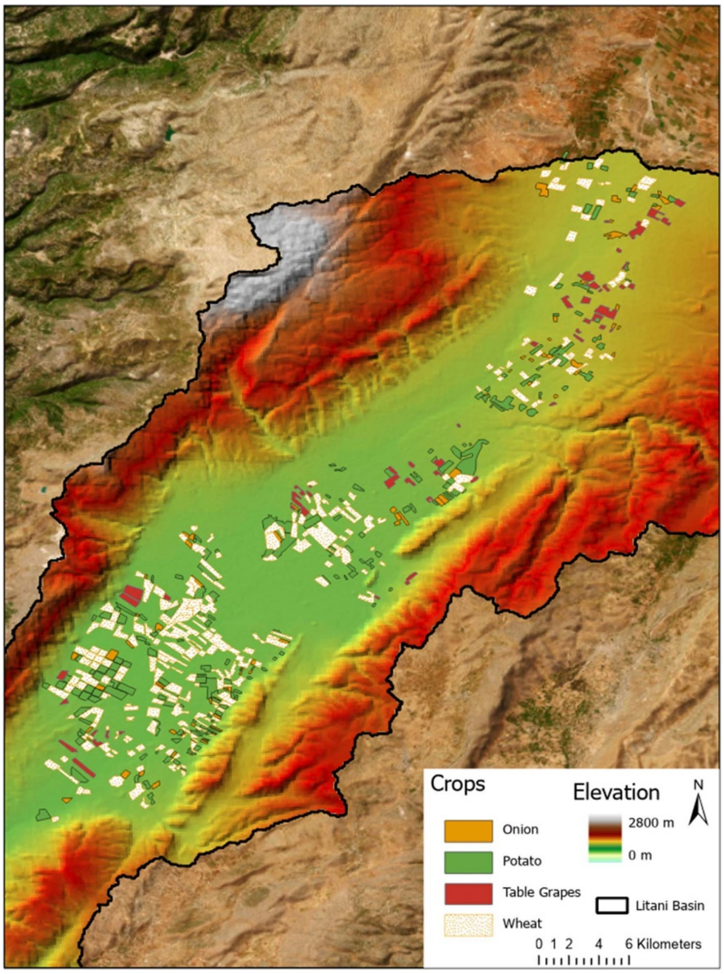

Figure 2. Geographic location of the study area within the upper Litani River Basin in Lebanon.

Given its high dependence on irrigation, critical groundwater overdraft situation driven by unregulated use, significant socio-economic reliance on agriculture, prevailing data scarcity, and the clear policy relevance of exploring demand management instruments like water pricing, the ULRB serves as a highly representative and pertinent case study for investigating how the choice of RS models influences the simulation of water policy impacts. The analysis encompasses the three main administrative districts within the basin: Baalbeck–Hermel, Zahleh, and West Bekaa (figure 2).

2.3. RS data acquisition and processing

2.3.1. Agronomic data collection

The temporal integration of RS data was aligned with the specific phenological windows of each crop in the Bekaa Valley. The four major crops studied are wheat, potatoes, grapes, and onions. Wheat (Winter Cereal) is sown in November–December and harvested in June–July. Irrigation is supplementary, typically occurring during the grain-filling stage in late spring. Potatoes (Spring/Early Summer): Planted in February–March and harvested in July. This crop is highly sensitive to water stress and requires intensive irrigation during tuber initiation and bulking. Onions (Winter–Summer): Sown in November and harvested in July–September, requiring consistent irrigation throughout the hot, dry summer months of the Bekaa. Table Grapes (Perennial): The active growing season spans from bud break in April to harvest in September–October.

2.3.2. ETa estimation

The two compared ET models are FAO WaPOR v3 and the HSEB model. In FAO WaPOR V3, Eta is derived using the ETLook model (Bastiaanssen *et al* 2012, FAO 2020 b, 2022), which employs the Penman–Monteith equation informed by meteorological data and satellite observations, including thermally sharpened land surface temperature (LST) from Landsat/Sentinel-2 and VIIRS (FAO 2023). Data was obtained at 30 m resolution for the growing seasons of the crops in the four years. WaPOR

V3's ETLook relies on the Penman–Monteith equation, incorporating canopy and aerodynamic resistance terms derived from meteorological and satellite data, including thermally sharpened LST. HSEB, as a single-source energy balance model, partitions net radiation based primarily on the surface temperature gradient. It is important to distinguish the WaPOR V3 dataset used here from the V2 version analyzed in previous regional studies (e.g. Hazimeh and Jaafar 2024). Released in 2023, WaPOR V3 represents a significant methodological update. While both versions utilize the ETLook energy balance framework, V3 incorporates: (i) higher spatial resolution for Level 3 data (30 m, compared to 100 m in V2); (ii) improved cloud masking algorithms; (iii) the integration of VIIRS and Sentinel-2 data for superior thermal and optical inputs; and (iv) recalibrated equations for deriving biophysical parameters such as fPAR and canopy resistance. These algorithmic and input refinements are distinct from V2 and are hypothesized to drive the shift in ETa magnitude observed in our results.

HSEB calculates the latent heat flux (and thus ETa) as the residual of the surface energy balance (net radiation, soil heat flux, sensible heat flux) using Landsat/Sentinel-2 data processed via Google Earth Engine (Jaafar *et al* 2022, Jaafar and Sujud 2024). The analysis utilized a fused dataset of Landsat 7 ETM+ (Collection LANDSAT/LE07/C02/T1_L2) and Landsat 8 OLI/TIRS (Collection LANDSAT/LC08/C02/T1_SR) imagery, accessed via Google Earth Engine. These collections provide atmospherically corrected land surface reflectance at 30 m resolution. To resolve the resolution discrepancy between thermal bands (60 m for L7, 100 m for L8) and optical bands, we applied the T-Sharp thermal sharpening algorithm (Agam *et al* 2007) to generate a consistent 30 m LST product for all scenes. Meteorological boundary conditions were derived from the ECMWF ERA5-Land hourly reanalysis dataset (0.1° resolution), selected for its consistency in capturing surface energy cycles (Dee *et al* 2011). To account for the complex topography of the ULRB, 2 m air temperature was downscaled to 30 m. This was achieved by correcting for elevation differences between the ERA5 grid and the local digital elevation model using a dynamic moist air lapse rate, calculated from ERA5 vapor pressure and air density at the exact time of satellite overpass. Wind speed data were ingested without downscaling.

Seasonal irrigation water applied at the field level was calculated for each RS model's ETa estimate by subtracting effective rainfall (calculated based on local precipitation data) from the seasonal ETa and dividing by crop-specific irrigation system efficiencies adopted from Jaafar *et al* (2016). To isolate the sensitivity of the economic model to RS inputs, we adopted a standardized water accounting equation (Chukalla *et al* 2022). We assume that secondary fluxes—specifically capillary rise, soil-moisture carryover, and non-beneficial ET—are constant across the comparative scenarios. This *ceteris paribus* approach ensures that divergences in the simulation results are attributable strictly to the differences between the WaPOR V3 and HSEB-GYMEE datasets,

$$\text{Seasonal Irrigation Water Applied to Field } (w_i) = \frac{\text{Irrigation ET}_{\text{seasonal}} - \text{Effective Rainfall}}{\text{Irrigation System Efficiency}}. \quad (1)$$

2.3.3. Biomass and crop yield estimation

Above-ground biomass (AGB) and marketable yield were estimated using two light-use efficiency (LUE) based models:

FAO WaPOR V3: net primary production (NPP) is calculated based on absorbed photosynthetically active radiation (fPAR), LUE (εLUE, optimized value 2.49 gC MJ^{-1}), and environmental stress factors (equation (2)). Data was obtained at 30 m resolution dekadally.

GYMEE: Above-ground dry matter production (DMP) is calculated similarly, using fPAR, LUE (LUEmax = 2.5 g MJ^{-1}), and stress factors, implemented in Google Earth Engine (Jaafar and Mourad 2021) (equation (3)). Field-scale dekadal DMP values were interpolated to monthly estimates.

While both are LUE models, WaPOR V3 incorporates stress implicitly via the ETLook water balance affecting ETa (which can be linked back), whereas GYMEE applies explicit stress reduction factors (SM, TS, VS) directly to the LUE calculation (Pan *et al* 2014, Servia *et al* 2022).

Seasonal biomass was aggregated from dekadal/monthly estimates. Marketable crop yield (Y) was derived from seasonal AGB using crop-specific dry basis harvest indices (HIs) and wet basis moisture content (MC), following Zwart and Bastiaanssen (2004) and Hazimeh and Jaafar (2024) (equation (4),)

$$\text{NPP}_{\text{WaPOR V3}} = \text{NPP}_{\max} \times \text{fPAR} \times \text{SM} \times \text{LUE} \quad (2)$$

where:
NPP: *(gC m^{-2})*
NPP$_{max}$: *maximum **NPP** (gC m^{-2})*

***fPAR**: fraction of photosynthetically active radiation equals to 1.257xNDVI—0.161 in WaPOR V3 similar to that of GYMEE (previously 0.8642xNDVI—0.0814 in WaPOR V2)*
εLUE: Light use efficiency at optimum conditions (g MJ^{-1}), taken as 2.49 g MJ^{-1} in WaPOR V3 (previously as 2.7 g MJ^{-1} in WaPOR V2)

$$\mathrm{DMP}_{\mathrm{GYMEE}} = \mathrm{APAR} \times \mathrm{LUE}_{\max} \times \mathrm{SM} \times \mathrm{TS} \times \mathrm{VS} \times 0.864 \tag{3}$$

where:
***DMP**: above-ground DMP (kg ha^{-1})*
***APAR**: fraction of absorbed photosynthetically active radiation (W m^{-2})*
***SM**: soil moisture stress reduction factor*
***TS**: temperature stress according to (*Stewart 1988*) after (*Jarvis 1976)
***VS**: vapor stress*
***0.864**: unit conversion factor*

$$Y = \frac{\mathrm{AGBs} \times \mathrm{HI} \times C_4}{(1 - \mathrm{MC})} \tag{4}$$

where:
***Y**: seasonal crop marketable above ground biomass production (kg ha⁻/season)*
***AGB_s**: seasonal AGB, defined as sum of the above-ground dry matter produced during the crop growing season (kg ha⁻/season)*
HI**: dry basis crop **HI
MC**: wet basis crop **MC
***C4**: factor set to 1.00, as all crops are C3 crops*

2.4. Economic data collection

Economic data (crop prices, input costs) were gathered to calculate crop net profit, defined as total production value (marketable yield × farm gate price) minus total production costs (Bellù 2013, Young and Loomis 2014). Data sources included desk-based research (Lebanon's Ministry of Agriculture, Lebanon's Ministry of Energy and Water) and localized cost assessments with four representative farmers in the ULRB for the four key crops. Costs included operational expenses, fertilizers, pesticides, labor, diesel, land rental, and seeds/cuttings. Some costs were assumed fixed per hectare, while others were proportional to yield, acknowledging this as a simplification necessary due to data limitations. A complete list of the economic parameters and their numerical values is provided in the supplementary information.

2.5. Statistical indicators for model comparison

Outputs (ETa, Biomass) from the two RS modeling approaches (WaPOR V3 vs HSEB for ETa; WaPOR V3 vs GYMEE for Biomass) were compared using standard statistical metrics: correlation coefficient (r), root mean square error (RMSE), mean bias error, coefficient of determination (R^2), and percent relative error (%RE). Equations are provided below (equations (5)–(9)),

$$\text{Root Mean Square Error:RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (A_i - P_i)^2}{n}} \tag{5}$$

$$\text{Mean Bias Error : MBE} = \frac{\sum_{i=1}^{n} (A_i - P_i)}{n} \tag{6}$$

$$\text{Relative Error : \%RE} = \frac{|\text{Absolute Error}|}{A} \times 100 \tag{7}$$

$$\text{Correlation Coefficient : } r = \frac{\sum_{i=1}^{n} (A_i - \bar{A})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (A_i - \bar{A})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}} \tag{8}$$

$$\text{Coefficient of Determination : } R^2 = \frac{\sum_{i=1}^{n} (A_i - \bar{A})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n} (A_i - \bar{A})^2 \sum_{i=1}^{n} (P_i - \bar{P})^2}}. \tag{9}$$

2.6. Microeconomic modeling framework

To investigate farmer decision-making responses to varying water prices, we utilized an ensemble modeling approach, adapting five distinct, calibrated MPMs based on previous work by Sapino *et al* (2024, 2020). This ensemble was strategically composed to capture a range of potential farmer behaviors and included two PMP models, one WGP model, and two PMAUP models. The fundamental principle underlying each model is the maximization of a specific utility function, representing farmer objectives, subject to prevailing resource constraints. The primary decision variable optimized within this framework is the allocation of crop area across the available land.

The objective functions driving these models varied in complexity. The PMP models adopted a traditional economic perspective, focusing solely on the maximization of expected net profit. In contrast, the multi-attribute models (WGP and PMAUP) were designed to maximize a composite utility reflecting a broader set of farmer motivations, incorporating not only expected net profit but also considerations for risk avoidance and the minimization of management complexity. Expected net profit was calculated using yield estimates derived from RS data (from both models, WAPOR V3 and GYMEE) combined with relevant economic parameters. Risk avoidance was typically proxied by minimizing income variance or prioritizing crops with historically stable yields, while management complexity avoidance was represented by minimizing labor requirements.

All models operated within a set of critical constraints reflecting real-world limitations. Key among these were the finite availability of land within each district and, crucially, water availability. The latter was directly linked to the calculated irrigation water applied per crop, with input data derived from two alternative sources for comparative analysis: either the HSEB model coupled with the GYMEE or the FAO's WaPOR V3 database. While not explicitly detailed here, potential agronomic constraints, such as crop rotation limits, could also be incorporated into such frameworks.

To ensure the models realistically represented baseline conditions, they underwent a calibration process. For the PMP and PMAUP models, this involved established PMP techniques, while the WGP model was calibrated through the adjustment of goal weights. The common objective was to replicate observed historical cropping patterns, a standard practice in agricultural economic modeling aimed at grounding simulations in empirical reality (Graveline 2016). It is acknowledged, however, that this calibration primarily ensures baseline replication and does not substitute for extensive validation against independent datasets. All MPMs share a common structure: they maximize a utility function—specific to each modeling family (equation (10))—subject to a set of constraints (equation (11)):

$$\text{Max } U(\boldsymbol{X}) = f(z_1(\boldsymbol{X}), \ldots, z_m(\boldsymbol{X})). \\ \text{Subject to:} \tag{10}$$

$$x_i \geq 0 \tag{11}$$

$$\sum_{i=1}^{n} x_i = 1 \tag{12}$$

$$\boldsymbol{X} \in F \tag{13}$$

$$\boldsymbol{X} \in \mathbb{R}^n \tag{14}$$

$$z_1(\boldsymbol{X}), \ldots, z_m(\boldsymbol{X}) = \boldsymbol{Z}(\boldsymbol{X}) \in \mathbb{R}^m \tag{15}$$

where the crop portfolio ($\boldsymbol{X}$), representing the share of land used by each crop x_i, is the sole decision variable and is determined annually, reflecting the irrigation campaign. The attribute $z(\boldsymbol{X})$ in the utility function, which depends on the land allocated to different crops, captures expected profit in the case of PMP models. For multi-attribute models, it also incorporates two additional attributes: risk avoidance and management complexity avoidance, the latter being measured using a proxy—labor avoidance.

Expected profit z_1 is defined as the sum of the expected gross margin per hectare for each crop, weighted by that crop's share of total cultivated area. For each crop, the gross margin is computed as the product of the crop price (USD/kg) and the RS-based yield estimate (equation (4), kg ha^{-1}), minus the variable costs (USD/ha). The term $\overline{\pi}_i$ denotes the average gross margin of crop i over 2018–2021,

$$z_1(\boldsymbol{X}) = \sum_i x_i \overline{\pi}_i. \tag{16}$$

Risk avoidance z_2 is measured as the reduction in profit variability when moving from a profit-maximizing crop portfolio to an alternative portfolio. More precisely, it is the difference between the variance of profits associated with the profit-maximizing portfolio and that of an alternative portfolio, based on the variance–covariance matrix of profits over 2018–2021. Because higher expected profits are typically linked to higher risk (Gutiérrez-Martín and Gómez 2011), this difference is positive,

$$z_2(\boldsymbol{X}) = \widehat{\boldsymbol{X}}^t \mathrm{VCV}(\pi)\widehat{\boldsymbol{X}} - \boldsymbol{X}^t \mathrm{VCV}(\pi)\boldsymbol{X}.. \tag{17}$$

Labor avoidance z_3 is defined as the difference in total labor requirements between the profit-maximizing portfolio and an alternative portfolio. Labor use is obtained by multiplying the per-hectare labor requirement of each crop by its corresponding cropped area,

$$z_3(\boldsymbol{X}) = \bar{L} - L(x). \tag{18}$$

The model also includes a water availability constraint,

$$\sum_{i=1}^{n} (w_i x_i) \leq W_g. \tag{19}$$

Total water use—calculated as water consumption by crop (equation (1)) aggregated across the portfolio—must not exceed the water volume allocated to each economic agent in the baseline situation (W_g).

Following calibration, the ensemble was employed to simulate farmer responses under various incremental water pricing scenarios, ranging from no increase to a 0.25 USD m^{-3} rise in steps of 0.0025 USD m^{-3}. This price was set following stakeholder input from a workshop held in Beirut in 2024. Experts indicated that the new tariff could, at most, double the existing water cost, which is estimated at 0.25 USD m^{-3} (primarily due to the energy cost of groundwater pumping) (Sapino *et al* 2024).

Simulations were performed using input parameters derived separately from both the WaPOR V3 and HSEB-GYMEE datasets. This dual-input approach facilitated a comparative analysis aimed at assessing how the choice of RS-based water and yield estimation model affects a set of key, policy-relevant economic outcomes. In particular, we focus on four variables: (i) agricultural water allocation, as an indicator of environmental pressure on the resource; (ii) farmer profit; (iii) labor (working days), representing labor income; and (iv) tariff revenue, representing public income. These indicators were selected because they allow us to examine the trade–off between environmental performance (water use) and economic performance (surplus, approximated through profit and labor income), and analyze how this surplus is distributed between private actors (farm owners and workers) and the public sector (through tariffs). They are also standard outputs of MPM applications in agricultural economics. Detailed model equations, calibration procedures, and parameters are provided in the supplementary information.

3. Results

3.1. Divergence in RS estimates of biomass, yield, and ET

Our analysis reveals significant, policy-relevant discrepancies between the two state-of-the-art RS approaches for estimating key agricultural variables in the ULRB. While biomass estimates from GYMEE and FAO WaPOR V3 show strong statistical agreement ($r > 0.9$, RMSE < 2 t ha^{-1}, bias < 1.5 t ha^{-1} across crops for 2021; figure 3), a systematic difference emerges. WaPOR V3 consistently estimates slightly higher biomass (6%–9% RE higher in 2021 depending on the crop) compared to GYMEE. This finding contrasts with comparisons involving WaPOR V2 (Hazimeh and Jaafar 2024), suggesting the V3 update influences biomass estimation, potentially aligning it more closely with GYMEE in pattern but maintaining a magnitude difference. Wheat showed the strongest congruence (RMSE 1.05 t ha^{-1}), while potatoes exhibited the largest divergence (RMSE 1.61 t ha^{-1}).

This systematic difference in biomass propagates into significant variations in estimated crop yields (figure 4). Across all four years (2018–2021) and three districts, WaPOR V3 consistently produced higher or equal yield estimates compared to GYMEE for all studied crops (onion, potato, table grapes, wheat).

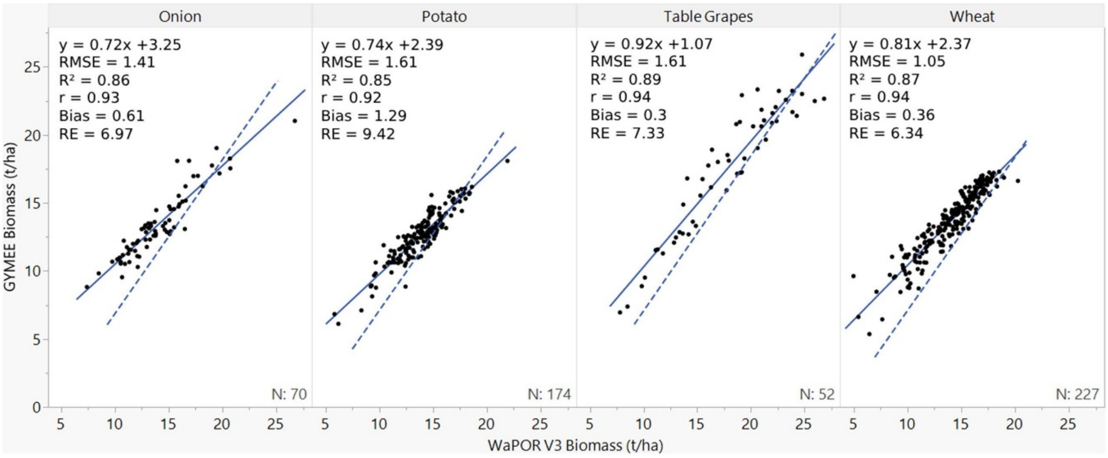

Figure 3. Scatterplots comparing modeled biomass estimates derived from GYMEE and FAO WaPOR V3 for onion, potato, table grapes, and wheat during 2021 growing season in the study area within the Litani River Basin in Lebanon.

Figure 4. Bar charts comparing crop yields (t ha^{-1}) of onion, potato, table grapes, and wheat using GYMEE and WaPOR V3 models during 2018, 2019, 2020, and 2021 growing seasons in the study area within the upper Litani River Basin in Lebanon.

The magnitude of this difference can be substantial; for instance, 2018 onion yields in Baalbeck were estimated at 94 t ha^{-1} by WaPOR V3 versus 32 t ha^{-1} by GYMEE, and potato yields were 49 t ha^{-1} versus 29 t ha^{-1}. While differences narrowed in some years/crops (e.g. 2021 wheat in Zahleh: 7 vs 6 t ha^{-1}), the persistent trend of higher WaPOR V3 yields (often 30%–60% higher, sometimes exceeding 100%) directly impacts the baseline profitability calculated within the subsequent microeconomic models. This highlights an upward adjustment in WaPOR V3 yield estimations compared to findings using V2 (Hazimeh and Jaafar 2024).

Crucially, the comparison of ETa reveals a reversal of trends observed with previous WaPOR versions (figure 5). While WaPOR V3 and HSEB ETa estimates maintain moderate to strong correlations

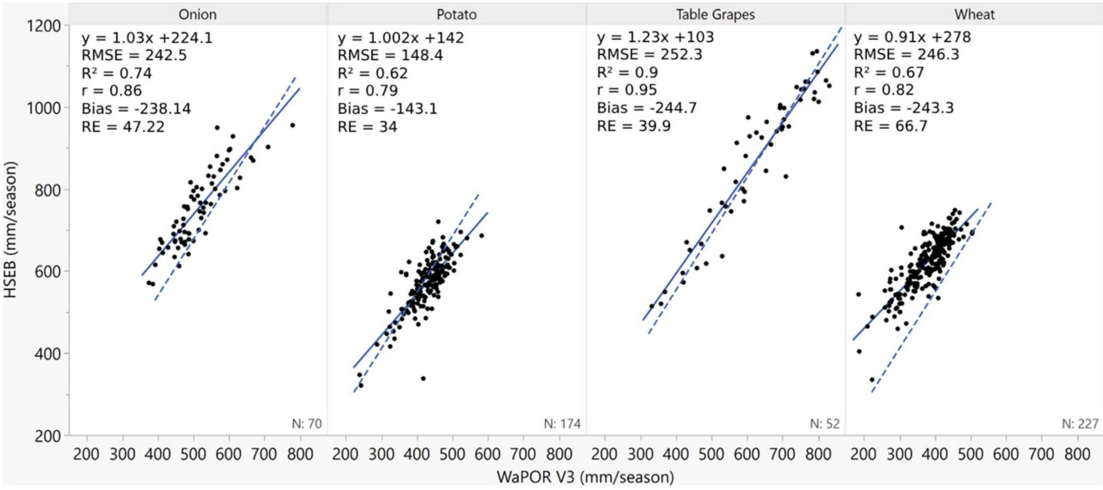

Figure 5. Scatterplots comparing modeled actual evapotranspiration (ETa) estimates derived from HSEB and FAO WaPOR V3 for onion, potato, table grapes, and wheat during 2021 growing season in the study area within the Litani River Basin in Lebanon.

(r = 0.79–0.95), HSEB consistently estimates higher seasonal ETa than WaPOR V3 across all crops. The difference is substantial, ranging from 34% higher for potatoes (bias −143 mm) to 67% higher for wheat (bias −243 mm). This contrasts sharply with Hazimeh and Jaafar (2024), where WaPOR V2 estimates were generally higher than HSEB. This reversal suggests significant changes in the underlying algorithms, input data, or calibration between WaPOR V2 and V3, potentially related to the ETLook model implementation or LST data sources in V3 (FAO 2023). The tighter agreement previously observed between HSEB and WaPOR V2 raises questions about potential biases or uncertainties introduced in V3. Regardless of the cause, the higher ETa from HSEB translates directly into higher calculated irrigation water requirements, a critical input for simulating farmer responses to water pricing.

3.2. RS model choice fundamentally alters simulated policy outcomes

The discrepancies in RS-derived yield and ETa estimates propagate through the microeconomic modeling framework, leading to fundamentally different simulations of farmer behavior and projected policy effectiveness under water pricing scenarios (0–0.25 USD m^{-3} increase).

The most striking divergence occurs in the simulated water demand response (figure 6). When informed by HSEB data (higher ETa, lower yields), the MPM ensemble projects a relatively elastic response to water pricing. Increased water costs, driven by higher baseline water use estimates, incentivize significant reductions in water withdrawals and shifts towards rainfed agriculture within the model. While the overall trend differed significantly between RS inputs, the ensemble approach also revealed intra-scenario variability; for instance, under HSEB inputs, the WGP model showed the most elastic demand response (figure 6). Conversely, when using WaPOR V3 inputs (lower ETa, higher yields), the ensemble predicts a largely inelastic response across most MPMs. The lower perceived water requirements and higher baseline profitability buffer farmers against price increases, resulting in minimal water withdrawal reductions within the simulated price range. This stark contrast underscores a critical policy challenge: the projected effectiveness of water pricing as a conservation tool is highly sensitive to the choice of RS model used for input data. A policy assessment based on WaPOR V3 might suggest pricing is ineffective, whereas one based on HSEB (or WaPOR V2, see Sapino *et al* 2024) would indicate significant potential for demand reduction, potentially leading to drastically different policy decisions depending on the data source employed.

Impacts on farmer profitability also differ significantly, primarily driven by the baseline yield estimates (figure 7). Models using WaPOR V3 inputs start with substantially higher average profits (∼66% higher) due to the higher yield estimates. As water prices increase, profit declines almost linearly, reflecting the inelastic water demand and lack of crop substitution. Models using HSEB inputs start with lower profits and show varying degrees of reduction, with some models (like WGP) showing smaller absolute losses due to adaptation (shifting crops), while others show steeper declines relative to their lower baseline. While nonlinear models (PMP, PMAUP) show broadly similar patterns of profit loss relative to their starting points regardless of RS input, the absolute profit levels and the interpretation of economic impact differ markedly.

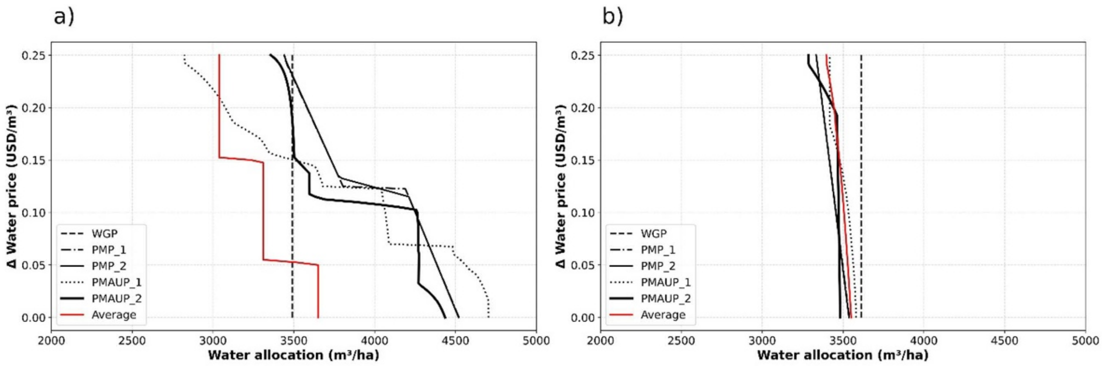

Figure 6. Agricultural water allocation response ($m^3\ ha^{-1}$) to water price increases up to 0.25 USD m^{-3}, evaluated at intervals of 0.0025 USD m^{-3}, in the ULRB using a multi-model ensemble of MPMs, with yield and water requirement inputs derived from (a) HSEB and (b) WaPOR V3.

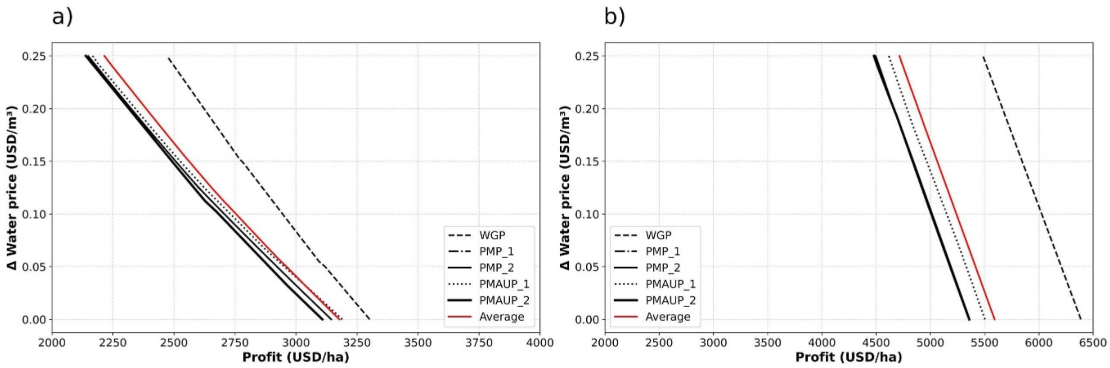

Figure 7. Profit response (USD ha^{-1}) to water price increase up to 0.25 USD m^{-3}, at 0.0025 USD m^{-3} intervals, in the ULRB using a multi-model ensemble of MPMs, with yield and water requirement inputs derived from (a) HSEB and (b) WaPOR V3.

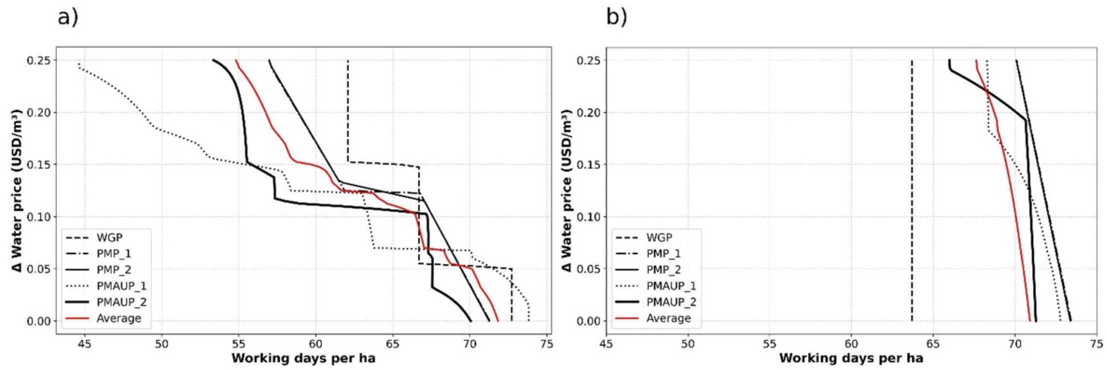

Figure 8. Labor response (days of work/ha) to water price increase up to 0.25 USD m^{-3}, in the ULRB using a multi-model ensemble of MPMs, with yield and water requirement inputs derived from (a) HSEB and (b) WaPOR V3.

These behavioral differences directly influence simulated labor demand (figure 8). The inelastic response simulated using WaPOR V3 inputs translates to minimal changes in labor requirements. In contrast, the shift towards rainfed agriculture simulated using HSEB inputs leads to a pronounced decrease in labor demand as irrigation-intensive activities decline. This highlights potential socio-economic trade-offs associated with water pricing that are only apparent when using RS inputs that trigger adaptive behavior within the models.

Finally, potential tariff revenue generation reflects the simulated demand elasticity (figure 9). With WaPOR V3 inputs, the inelastic demand leads to steadily increasing revenue as prices rise, reaching 821–902 USD ha^{-1} at the maximum tariff. With HSEB inputs, revenue initially increases, then declines in

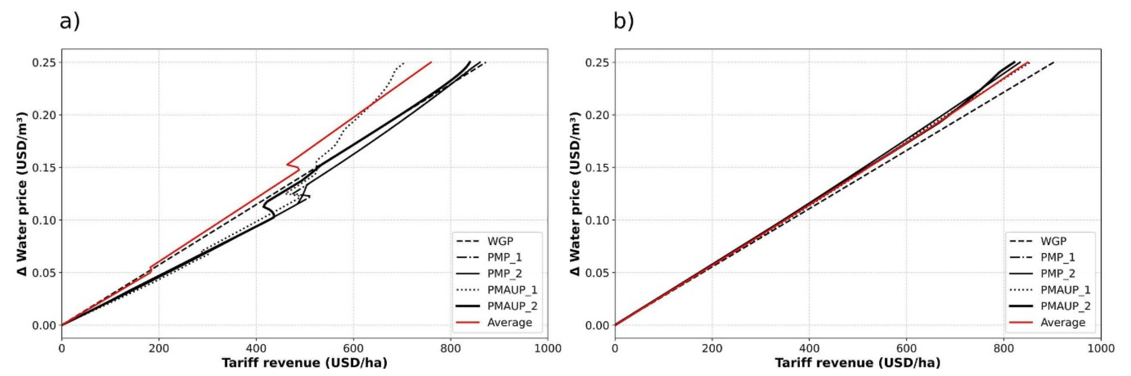

Figure 9. Tariff revenue (USD ha^{-1}) with water price increase up to 0.25 USD m^{-3}, in the ULRB using a multi-model ensemble of MPMs, with yield and water requirement inputs derived from (a) HSEB and (b) WaPOR V3.

most models as farmers reduce water consumption significantly, before increasing again (reaching 705–872 USD ha^{-1})—reflecting the classic shape of a revenue curve under elastic demand. This difference has clear implications for assessing the fiscal sustainability of water management schemes.

4. Discussion

Our findings demonstrate a critical point: the selection of contemporary RS models for ETa and biomass/yield estimation is not merely a technical detail, but a fundamental factor shaping the ex-ante performance assessment of water management policies like pricing. The stark divergence in predicted water demand elasticity, farmer profitability, labor demand, and tariff revenue potential—driven solely by switching between WaPOR V3 and HSEB-GYMEE inputs—reveals a significant source of uncertainty inherent in policy analysis frameworks reliant on such data. This highlights a critical oversight in current hydro-economic modeling: while recent efforts have focused on quantifying parameter uncertainty (Soriano *et al* 2025), our study identifies input data uncertainty as an equally critical, yet often overlooked, driver of variance in policy forecasts.

Relying on performance assessments derived from a single, potentially unvalidated RS dataset carries substantial risks: policies might be ineffective if based on overly optimistic assumptions (e.g. the inelastic demand suggested by WaPOR V3 in our case) or cause unforeseen negative consequences like abrupt economic disruption if reality aligns more closely with an alternative model's predictions (e.g. HSEB's elastic response). This observation adds a new dimension to the debate on agricultural water pricing. While previous studies often attribute low elasticity to structural constraints such as a lack of alternative crops or market rigidities (Scheierling and Treguer 2016, Albiac *et al* 2020), our results demonstrate that simulated elasticity is also a function of the biophysical data source. The elastic response observed with HSEB aligns with frameworks emphasizing crop substitution potential (Pérez-Blanco *et al* 2016), whereas WaPOR V3 inputs mimic the rigidities often cited in pessimistic assessments of pricing effectiveness.

Although our empirical application focuses on the upper Litani River Basin, these insights regarding the sensitivity of assessment tools are directly relevant to other water–stressed agricultural regions where RS-based indicators are increasingly used to support water pricing and allocation decisions. In such contexts, the choice of RS products can translate into very different policy choices: using a dataset that underestimates demand elasticity may encourage overly ambitious price reforms that fail to deliver expected water savings, while a dataset that overestimates elasticity may lead to excessively cautious pricing, under-recovery of costs, or overestimation of social impacts.

We acknowledge that the study is geographically bounded to the ULRB and temporally limited to the 2018–2021 period. Furthermore, to isolate the sensitivity of the economic model to RS inputs, we adopted a ceteris paribus approach, holding secondary fluxes (e.g. capillary rise, soil moisture carryover) constant. We recognize that these assumptions are non-neutral in semi-arid, groundwater-dependent systems and may interact with the RS inputs to influence results. Additionally, while the models were calibrated to replicate baseline cropping patterns—a standard procedure in agricultural economic modeling—we acknowledge that reproducing a static baseline does not guarantee that the simulated behavioral responses (elasticities) perfectly capture real-world farmer decision-making under stress. To mitigate this, rather than relying on a single behavioral assumption, we employed an ensemble of five distinct MPMs to capture a range of plausible responses and account for structural uncertainty. While this allows for a high-resolution analysis of farm-level decision-making under specific climatic and economic stresses, future research should extend this comparative framework to basins with different agro-climatic regimes to test the transferability of these findings. Nevertheless, the fundamental finding—that policy simulation outcomes are highly sensitive to RS model choice—is likely applicable to other data-scarce regions utilizing RS-derived water accounting.

This underscores the imperative for rigorous, site-specific validation of RS model outputs against ground-truth data before their integration into policy-informing microeconomic models. This is particularly crucial in data-scarce regions like the ULRB where such integrated models are increasingly employed. Our results caution against generalizing model performance across regions or even between different versions of the same model family (e.g. WaPOR V2 vs V3), highlighting that ensuring the accuracy of biophysical inputs is paramount for building trust in, and ensuring the effectiveness and equity of, water resource management strategies. The observed reversal in ETa trends between WaPOR V2 and V3 relative to HSEB warrants specific investigation, potentially stemming from changes in ETLook parameterization, changes to the fPAR derivation equation from NDVI, the assimilation of different LST data sources (VIIRS/Landsat), or cloud-masking procedures in V3. These findings resonate with broader concerns about the 'validation gap' for global RS products (Blatchford *et al* 2019) and the and the risks of applying global products to local management without calibration (Foster *et al* 2020). Despite these challenges, WaPOR V3 can be particularly useful for water pricing design as an open, spatially and temporally consistent source of information on crop water use and productivity in data-scarce regions. Its greatest value lies in providing a transparent baseline for exploratory pricing analyzes, which should then be complemented by alternative RS products and local validation when informing concrete tariff reform, provided that the conditional nature of the resulting policy assessments is explicitly recognized.

From a water pricing design perspective, our results suggest three broad implications that extend beyond the study basin. First, when possible, tariff reforms should be informed by multiple RS products or by RS ensembles, rather than by a single dataset, to characterize a plausible range of assessment outcomes (e.g. a range of potential water demand elasticities). Second, pricing scenarios should be interpreted as conditional on the chosen RS input: robust policy recommendations are those whose desirability does not change qualitatively across RS datasets, whereas policies whose projected performance is highly sensitive to RS choice should be treated with caution or complemented by additional data collection. Third, RS-based modeling should not be used in isolation: targeted farmer surveys, pilot pricing schemes, or experimental designs can be combined with RS to progressively learn about true behavioral elasticities and update tariffs accordingly. It is important to note that our analysis is limited to these model-based responses and does not assess institutional feasibility issues or distributional incidence across heterogeneous farm types; such aspects would require a separate, implementation-focused assessment building on the type of information generated here.

5. Conclusion

This study demonstrates that the selection of RS models—specifically between FAO WaPOR V3 and the energy-balance based HSEB-GYMEE—is a critical, non-neutral determinant in the performance assessment of water pricing policies. By integrating these distinct datasets into an ensemble of microeconomic models for the upper Litani River Basin, we quantified how biophysical input discrepancies propagate into divergent socio-economic forecasts. Specifically, WaPOR V3 inputs suggested higher yields and near-inelastic water demand, whereas HSEB-GYMEE inputs indicated higher ET rates and a considerably more elastic response to pricing.

While this integrated framework offers a powerful tool for ex-ante policy assessment, our results highlight that its reliability is highly contingent on the accuracy of the chosen RS inputs. The substantial differences observed serve as a clear case study of this dependency. Therefore, consistent improvement and validation of RS-derived datasets, complemented by targeted field observations (e.g. plot-level yields and economic surveys), are essential. Further investigation is specifically needed to reconcile discrepancies between model versions (e.g. WaPOR V3 vs V2) and distinct algorithms against ground truth. Crucially, future efforts must focus not only on validating absolute accuracy but also on understanding how observational uncertainty propagates through coupled socio-economic models to influence sensitive policy design choices.

To refine this approach, we recommend that future research expands the comparative assessment framework in two key directions. First, studies should deepen **behavioral realism** by systematically incorporating dynamic economic factors (e.g. market volatility), social considerations (e.g. equity and labor dynamics), and agronomic constraints. Second, research must address **modeling uncertainty** more rigorously. While this study implemented local sensitivity analysis, the field must advance toward Global Sensitivity Analysis (GSA) of model inputs and parameters. Although such protocols are not yet standard in MPMs (Soriano *et al* 2025), their development is critical for ensuring that water management strategies are theoretically sound, practically effective, and that decision-makers are fully aware of the uncertainty bounds surrounding policy performance forecasts.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

Acknowledgments

The research leading to these results has been developed with the support of the Partnership for Research and Innovation in the Mediterranean Area (PRIMA)'s TALANOA-WATER (Talanoa Water Dialogue for Transformational Adaptation to Water Scarcity under Climate Change) Project and the Spanish Research and Innovation Plan's IRENE (Integrated Socioeconomic and Environmental Modeling using Remote Sensing Data for the Management of Unauthorized Water Abstractions) Project, and American University Research Board-funded Project—104514 -'Impact of Evapotranspiration and Biomass Remote Sensing Model Choices on Water Pricing Schemes using Microeconomic Ensemble Forecasting in Water-Scarce Basins'. HJ would like to thank Google.org and the Tides foundation for generously supporting the development of the HSEB model.

Author contributions

Hadi H Jaafar 0000-0003-2612-3191
Conceptualization (equal), Data curation (lead), Formal analysis (equal), Funding acquisition (equal), Investigation (equal), Methodology (equal), Project administration (equal), Resources (equal), Software (equal), Supervision (equal), Validation (equal), Visualization (supporting), Writing – original draft (equal), Writing – review & editing (lead)

Rim Hazimeh
Conceptualization (supporting), Data curation (equal), Formal analysis (equal), Investigation (equal), Methodology (equal), Resources (supporting), Software (supporting), Supervision (supporting), Validation (equal), Visualization (equal), Writing – original draft (lead), Writing – review & editing (supporting)

Francesco Sapino 0000-0002-9812-2334
Conceptualization (equal), Data curation (equal), Formal analysis (equal), Funding acquisition (supporting), Investigation (equal), Methodology (equal), Project administration (equal), Resources (equal), Software (equal), Supervision (equal), Validation (supporting), Visualization (equal), Writing – original draft (equal), Writing – review & editing (equal)

C Dionisio Pérez-Blanco 0000-0002-7777-4317
Conceptualization (equal), Data curation (supporting), Formal analysis (supporting), Funding acquisition (lead), Investigation (equal), Methodology (equal), Project administration (lead), Resources (lead), Software (equal), Supervision (equal), Validation (equal), Visualization (supporting), Writing – original draft (supporting), Writing – review & editing (supporting)

References

Agam N, Kustas W P, Anderson M C, Li F and Neale C M U 2007 A vegetation index based technique for spatial sharpening of thermal imagery *Remote Sens. Environ.* **107** 545–58

Albiac J, Calvo E, Kahil T and Esteban E 2020 The challenge of irrigation water pricing in the water framework directive *Water Altern.* **13** 674–90 (available at: www.water-alternatives.org/index.php/alldoc/articles/volume-13/issue-3-1/587-a13-3-5/file)

Bastiaanssen W G, Menenti M, Feddes R and Holtslag A 1998 A remote sensing surface energy balance algorithm for land (SEBAL). 1. Formulation *J. Hydrol.* **212** 198–212

Bastiaanssen W, Cheema M, Immerzeel W, Miltenburg I and Pelgrum H 2012 Surface energy balance and actual evapotranspiration of the transboundary Indus Basin estimated from satellite measurements and the ETLook model *Water Resour. Res.* **48** W11512

Bellù L G 2013 Value chain analysis for policy making: methodological guidelines and country cases for a quantitative approach (Food and Agriculture Organization) (available at: https://openknowledge.fao.org/handle/20.500.14283/at511e)

Blatchford M L, Mannaerts C M, Zeng Y, Nouri H and Karimi P 2019 Status of accuracy in remotely sensed and *in-situ* agricultural water productivity estimates: a review *Remote Sens. Environ.* **234** 111413
Booker J F, Howitt R E, Michelsen A M and Young R A 2012 Economics and the modeling of water resources and policies *Natural Resour. Model.* **25** 168–218
Chukalla A D *et al* 2022 A framework for irrigation performance assessment using WaPOR data: the case of a sugarcane estate in Mozambique *Hydrol. Earth Syst. Sci.* **26** 2759–78
Connor R 2024 The United Nations world water development report 2024: water for prosperity and peace; executive summary (available at: https://unesdoc.unesco.org/ark:/48223/pf0000388948)
Dee D P *et al* 2011 The ERA-interim reanalysis: configuration and performance of the data assimilation system *Q. J. R. Meteorol. Soc.* **137** 553–97
Dinar A and Subramanian A (ed) 1997 Water pricing experiences: an international perspective World Bank technical paper ; no. WTP 386 (The World Bank) (available at: http://documents.worldbank.org/curated/en/580151468768597034)
Elshall A S, Castilla-Rho J, El-Kadi A I, Holley C, Mutongwizo T, Sinclair D and Ye M 2022 Sustainability of groundwater *Imperiled: The Encyclopedia of Conservation* (Elsevier) pp 157–66
FAO 2020a The state of food and agriculture 2020. Overcoming water challenges in agriculture (available at: https://openknowledge.fao.org/items/a2dc7490-735d-4b5d-92a2-a36bfb380e02)
FAO 2020b WaPOR database methodology: version 2 release (FAO) (available at: https://openknowledge.fao.org/server/api/core/bitstreams/d3db4794-fb5b-444c-9b3a-c5fb154c5f9f/content)
FAO 2021 The state of the world's land and water resources for food and agriculture—systems at breaking point *Synthesis Report* (available at: https://openknowledge.fao.org/server/api/core/bitstreams/ecb51a59-ac4d-407a-80de-c7d6c3e15fcc/content)
FAO 2022 pyWaPOR repository—ETLook (available at: www.fao.org/aquastat/py-wapor/_etlook.html)
FAO 2023 WaPOR version history (FAO) (available at: www.fao.org/in-action/remote-sensing-for-water-productivity/wapor-database/database-history/en)
Foster T, Mieno T and Brozovic N 2020 Satellite-based monitoring of irrigation water use: assessing measurement errors and their implications for agricultural water management policy *Water Resour. Res.* **56** e2020WR028378
Grafton R Q, Horne J and Wheeler S A 2022 Rethinking water markets *Oxford Research Encyclopedia of Environmental Science* (Oxford University Press)
Graveline N 2016 Economic calibrated models for water allocation in agricultural production: a review *Environ. Modelling Softw.* **81** 12–25
Gutiérrez-Martín C and Gómez G 2011 Assessing irrigation efficiency improvements by using a preference revelation model *Spanish J. Agric. Res.* **9** 1009–20
Hazimeh R and Jaafar H 2024 Impact of ET and biomass model choices on economic irrigation water productivity in water-scarce basins *Agric. Water Manage.* **292** 108651
Jaafar H H and Sujud L H 2024 High-resolution satellite imagery reveals a recent accelerating rate of increase in land evapotranspiration *Remote Sens. Environ.* **315** 114489
Jaafar H, Karimi P and Borgomeo E 2024 Economic irrigation water productivity of wheat and potato: an earth observation perspective on policy implications in the Litani Basin, Lebanon *Agric. Water Manage.* **306** 109180
Jaafar H, King-Okumu C, Haj-Hassan M, Abdallah C, El-Korek N and Ahmad F 2016 *Water Resources within the Upper Orontes and Litani Basins* (International Institute for Environment and Development)
Jaafar H and Mourad R 2021 GYMEE: a global field-scale crop yield and ET mapper in Google Earth Engine based on Landsat, weather, and soil data *Remote Sens.* **13** 773
Jaafar H, Mourad R, Kustas W and Anderson M 2022 A global implementation of single-and dual-source surface energy balance models for estimating actual evapotranspiration at 30 m resolution using Google Earth Engine *Water Resour. Res.* **58** e2022WR032800
Jaafar H, Mourad R and Schull M 2022 A global 30-m ET model (HSEB) using harmonized Landsat and Sentinel-2, MODIS and VIIRS: Comparison to ECOSTRESS ET and LST *Remote Sens. Environ.* **274** 112995
Jarvis P 1976 The interpretation of the variations in leaf water potential and stomatal conductance found in canopies in the field *Phil. Trans. R. Soc. B* **273** 593–610
Kerr J 2007 Watershed management: lessons from common property theory *Int. J. Commons* **1** 89–109
Molle F and Closas A 2021 Groundwater metering: revisiting a ubiquitous 'best practice' *Hydrogeol. J.* **29** 1857–70
Ostrom E 1990 *Governing the Commons: The Evolution of Institutions for Collective Action* (Cambridge University Press)
Pan S, Tian H, Dangal S R, Ouyang Z, Tao B, Ren W, Lu C and Running S 2014 Modeling and monitoring terrestrial primary production in a changing global environment: toward a multiscale synthesis of observation and simulation *Adv. Meteorol.* **2014** 965936
Pérez-Blanco C D, Standardi G, Mysiak J, Parrado R and Gutiérrez-Martín C 2016 Incremental water charging in agriculture. A case study of the regione Emilia Romagna in Italy *Environ. Modelling Softw.* **78** 202–15
Sapino F, Hazimeh R, Pérez-Blanco C D and Jaafar H H 2024 Socioeconomic impact of agricultural water reallocation policies in the upper Litani Basin (Lebanon): a remote sensing and microeconomic ensemble forecasting approach *Agric. Water Manage.* **296** 108805
Sapino F, Pérez-Blanco C D, Gutiérrez-Martín C and Frontuto V 2020 An ensemble experiment of mathematical programming models to assess socio-economic effects of agricultural water pricing reform in the Piedmont Region, Italy *J. Environ. Manage.* **267** 110645
Scheierling S M and Treguer D O 2016 Investing in adaptation: the challenge of responding to water scarcity in irrigated agriculture *Econ. Rev.* 01612387
Servia H, Pareeth S, Michailovsky C I, de Fraiture C and Karimi P 2022 Operational framework to predict field level crop biomass using remote sensing and data driven models *Int. J. Appl. Earth Obs. Geoinf.* **108** 102725
Soriano G, Sapino F and Pérez-Blanco C D 2025 A review of economic calibrated mathematical programming models for agricultural water reallocation *Environ. Modelling Softw.* **193** 106628
Stewart J 1988 Modelling surface conductance of pine forest *Agric. For. Meteorol.* **43** 19–35
Tu C, D'Odorico P, Li Z and Suweis S 2023 The emergence of cooperation from shared goals in the governance of common-pool resources *Nat. Sustain.* **6** 139–47
Young R A and Loomis J B 2014 *Determining the Economic Value of Water: Concepts and Methods* (Routledge)
Zwart S J and Bastiaanssen W G M 2004 Review of measured crop water productivity values for irrigated wheat, rice, cotton and maize *Agric. Water Manage.* **69** 115–33