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Socioeconomic impact of agricultural water reallocation policies in the Upper Litani Basin (Lebanon): a remote sensing and microeconomic ensemble forecasting approach

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ABSTRACT

The integration of remote sensing and socio-economic data is crucial for policy making in regions suffering from water scarcity and climate change. We present a framework that combines remotely sensed estimates of biomass and water use from FAO's Water Productivity Open-access portal (WaPOR) (V2) with an ensemble of calibrated mathematical programming models to assess the impact of water reallocations on rain-fed and irrigated land use and production in water-stressed basins. We evaluated our model in the Upper Litani Basin of Lebanon using two water reallocation policies: (i) quotas that progressively reduces water allocation for irrigation up to 100%, at 1% intervals and (ii) a pricing policy that increases the agricultural water price up to 0.25 USD/m^3, at 0.0025 USD/m^3 intervals. Our results reveal that 1) the impacts of water availability reductions due to quotas on profit and employment are less-than-proportional when water allocation is reduced by <50%, but abruptly increase when water allocation is reduced by >50%; 2) irrigators responses to prices are inelastic until a price increase of 0.03 USD/m^3, become significantly more elastic afterwards, and again become inelastic above a price increase of 0.06 USD/m^3; 3) higher water prices progressively reduce profit and labor, significantly reduce water use over the elastic interval (where irrigators cultivating low value-added crops shift to rainfed agriculture), and increase tariff revenue during the inelastic interval (where irrigators largely stick to their crop portfolios and pay the higher water prices). Our results reveal nontrivial uncertainties and tipping points, thus highlighting the value of combining reliable water use data with multi-model and multi-scenario ensembles in informing robust policies.

1. Introduction

Climate change and growing water demand amplify water scarcity and the frequency and intensity of droughts across the Mediterranean region (IPCC, 2021), which are causing substantial damages to farmers, households, industries, and ecosystems–as well as growing conflicts among these groups of stakeholders (UNDRR, 2021). Addressing ongoing water security crises will require a coordinated adoption of not only promising technological solutions (e.g., wastewater re-use, climate and irrigation services), but also behavioral instruments that align individual choices with collectively agreed water policy objectives such as sustainable and equitable growth (Damania et al., 2017; OECD, 2015). This holds particularly true for the agricultural sector, the largest water user and the one concentrating the least valuable uses of the resource–and thus holding the largest potential for much needed water savings ((FAO, 2021). Although relying solely on rainfall would be adequate for rainfed crop cultivation, the availability of irrigation water plays a vital role in enhancing yields and facilitating the production of agricultural goods. This is especially significant for regions experiencing a dry and hot climate during the summer. Considering irrigation seasonality, the strategic application of irrigation water becomes essential for optimizing crop productivity, underscoring the critical role of irrigation in mitigating the challenges posed by climatic conditions. Yet, decision makers face two major obstacles to the design of sensible water policy conducive towards sustainable water use behaviors by farmers, which mutually reinforce each other: (1) limited and/or biased data on the location, timing and quantity of water withdrawals and consumption by irrigators, as well as on land use and land use change (Castilla-Rho

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et al., 2019; Loch et al., 2020); and (2) limited understanding of irrigators' adaptive behavior and their responses to climate change and reduced water availability, and water reallocation instruments, as well as the associated uncertainties (Pérez-Blanco et al., 2021; Puy et al., 2022). These obstacles hold particularly true for developing countries, where data and information constraints have limited socioeconomic analyses of irrigated agriculture in the past (Maneta et al., 2020).

Recent research has significantly advanced remote sensing techniques, offering unprecedented data precision and granularity for land and water utilization. These advances have been instrumental in various agricultural applications, including precision agriculture, water use optimization, land-use change and forestry (LULUCF), and the intricate evaluation of satellite image processing – e.g. (Bastiaanssen et al., 1998; Fisher et al., 2020; Jaafar et al., 2022; Servia et al., 2022; Xu et al., 2022). Concurrently, the development of Mathematical Programming Models (MPMs) has been offering increasingly sophisticated models that provide insights into the behavior and responses of irrigators (Cortignani and Severini, 2012; Gómez-Limón et al., 2016; Mérel and Howitt, 2014), including through the use of ensemble techniques to better quantify and address uncertainties inherent in agricultural modeling (Pérez-Blanco et al., 2022; Sapino et al., 2022b).

However, despite these scientific and technological advancements, the integration of remote sensing with MPMs and their application in socio-economic assessments of agricultural water management, including under climate change, remains limited. Dalezios et al. (2018) combined satellite-derived indices of drought and vegetation health obtained from images the Advanced Very High-Resolution Radiometer by the National Oceanographic and Atmospheric Administration (NOAA/AVHR) with a Weighted-Goal Programming (WGP) multi-objective model, a type of MPM that in this case adopts an objective function aiming at maximizing gross margin and minimizing total labor and fertilizer costs. The authors calibrated the model in Thessaly, Greece, and used it to identify optimal policy solutions to water scarcity challenges. Maneta et al. (2020), coupled a Positive Mathematical Programming (PMP) model, another type of calibrated MPM, with a semi-distributed and deterministic hydrological model, and embedded the resulting hydro-economic model in a stochastic data assimilation framework that adjusts the parameters of the economic model based on remote sensing data on land and water use. The data feeding the model came from images of three sources: Landsat 5/7, Moderate-Resolution Imaging Spectroradiometer (MODIS), and MODIS Global Terrestrial Evapotranspiration 8-Day Global 1 km data by the National Aeronautics and Space Administration (NASA MOD16A2). The authors illustrated their proposed method with a calibration exercise in the State of Montana (USA) and showed that satellite data provides sufficient information to calibrate the hydro-economic model and to update its calibration periodically as new satellite images become available, thus overcoming some of the limitations that have previously hindered the use of hydro-economic models to inform agricultural water management policies, in particular the need of expensive field surveys, the false sense of precision associated to deterministic models, and the problem of overfitting parameters to specific conditions or years. Similarly, Lauffenburger et al. (2022) combined climate projections informed by remote sensing data with an hydro-economic model (with a PMP model as economic component) to determine agents adaptive responses to climate change. Hazimeh and Jaafar (2024) compared the effect of water use and biomass model choices on economic irrigation water productivity results using remote sensing. To this end, the authors considered the worst possible climate conditions, namely the Representative Concentration Pathway (RCP) 8.5 scenario, and images form the refined NASA MOD16A2. Finally, other authors such as Medellín-Azuara et al. (2015) have used remote sensing data to *ex-post* validate the impact of droughts predicted in their MPM, although this type of approach does not involve an integration of both methods for *ex-ante* prediction like the other studies above.

The studies above adopt a variety of satellite-based water monitoring mechanisms (including mixed approaches that combine remote sensing and on-site appraisals) and MPMs of human behavior, and methods for the integration thereof (agroclimatic indices, decision support systems, and deterministic/stochastic data assimilation). The outputs provided by these studies include profit, labor, and crop production. Landsat is the preferred source for satellite data, with a pixel granularity of up to 30 ×30 m, which is sometimes complemented with the use of other satellite images with coarser resolution, time availability, and reliability (e.g., NOAA/AVHR, MODIS, NASA MOD16A2, or satellite-derived indices). All the studies above highlight the increase in spatial resolution and better accuracy of satellite-based water use data as compared to survey-based and agronomic or ecohydrologic estimates and suggest that the combination of survey-based economic data with satellite-based water use data can improve the predictive performance and reduce calibration errors in MPMs through ground-truthing. Despite these advantages, these studies also reveal at least two relevant shortcomings: first, the number of studies that integrate satellite-based water use data into MPM is limited (and focused on a sub-sample of PMP models), and so are applications, with the literature on water reallocation performance assessments still being dominated by MPMs that adopt irrigation water use estimates obtained from agronomic or eco-hydrological models (Sapino et al., 2022a)—which are regarded as less accurate than satellite observations (Jaafar et al., 2022; Pôças et al., 2020); second, the uncertainty inherent to socioeconomic predictions, particularly the modeling uncertainty in the context of MPMs, is typically ignored. Moreover, these studies focus on developed countries where data availability is typically larger than in developing countries. These gaps limit the practical adoption of remote sensing data into socioeconomic models and assessments that inform policy design, particularly in developing contexts.

This research proposes a novel approach that integrates remote sensing water use data into a multi-model ensemble of MPMs, a methodology not yet explored to the best of our knowledge. The integrated approach leverages the accuracy of remote sensing data from earth observations to limit the uncertainties emerging from the sensitivity of socioeconomic models to conventional water and land use estimates from surveys or modeling. Furthermore, we address the aspect of modeling and scenario uncertainty by employing an ensemble approach (Sapino et al., 2020).

The objective of this research is to contribute to the literature above through the integration, for the first time to the best of our knowledge, of remote sensing data into multi-model ensembles of MPMs. We use advanced remote sensing data and techniques to identify and quantify water consumption and yields through FAO's Water Productivity Open-access portal (WaPOR) (V2) (FAO, 2022a). WaPOR V2 monitors agricultural land use, evapotranspiration, and crop biomass via remote sensing in countries of Africa and the Middle East with historical data constraints on these variables – which in turn have limited socioeconomic analyses of irrigated agriculture in the past. Water use and crop yield data from WaPOR V2, alongside other input data, is integrated into a multi-model ensemble of MPMs to elicit the drivers of irrigators' behavior and predict their responses to behavioral instruments under climate change, while accounting for modeling uncertainties. Methods are illustrated in the context of a developing country with an assessment of policy impacts and responses by irrigators in the Bekaa agricultural plain in Lebanon. The adoption of increasingly accurate remotely sensed water and land use data enhances the accuracy and reliability of policy performance assessments as compared to conventional methods that employ water use data derived from agronomic or ecohydrological models. Moreover, the integration of remote sensing data into multi-model ensembles of MPMs allows us to 1) expand the applicability of remote sensing data to a wider range of MPMs while 2) more thoroughly exploring modeling and scenario uncertainties, and thus identifying and understanding potential vulnerabilities of the irrigation system to policy and climatic changes through the ensemble spread (AgMIP, 2023; CMIP6, 2023). Multi-model and multi-scenario ensembles are a widely used technique for the prediction of plausible futures in complex climatic, agronomic, water and other ecological systems (e.g., CMIP6, 2023; ISIMIP, 2023), albeit their adoption in socioeconomic modeling and assessments is still very limited (Sapino et al., 2020). Our work, therefore, not only contributes a novel integration technique between remote sensing and socioeconomic modeling but also delivers a method to quantify and thus better manage uncertainty.

2. Materials and methods

The proposed framework combines remote sensing methods and data on actual evapotranspiration and yields with economic data and multi-model ensembles to generate socio-economic assessments of agriculture and water use under alternative water allocation and policy scenarios. We use WaPOR V2 to derive reliable ET and crop yield data over a 4-year period (2018–2021) at the district level within the Upper Litani Basin in Lebanon. We then assimilate data on irrigation efficiency, agricultural commodity prices, costs and use of fertilizers, pesticides, seeds, diesel, operation, land rental, and labor to calibrate the ensemble of MPMs for our study area. We perform two simulations with the coupled remote sensing and MPMs that address stakeholders' recommendations during a workshop in Beirut in April 2023, namely the impact of quotas, i.e., water use restrictions, and the impact of a pricing policy. We simulate the impact of both policies on water withdrawals, profit, and employment. Fig. 1 provides a schematic representation of the coupled remote sensing and MPMs modeling framework.

2.1. Study area: the Upper Litani Basin, Lebanon

We chose the Bekaa agricultural plain situated in the Upper Litani River Basin as a study area to test our coupled remote sensing and microeconomic analysis. Once an area facing water and land use data constraints that limited socioeconomic analysis, the Litani River is now a pilot study area for the implementation of WaPOR tool. The Litani River is a critical component in Lebanon's socioeconomic development, as it is a central host of agricultural and human activities. The 176 km Litani river feeds the country's breadbasket, the Bekaa agricultural plain, and irrigates thousands of hectares of farmland, while providing the water needs of over a million people (Jaafar et al., 2016). The Upper Litani Basin is home to more than 45,000 ha of irrigated agriculture, and it hosts half a million Syrian refugees (Jaafar et al., 2020, 2016). More than 320 million cubic meters of water is estimated to be pumped from groundwater in this basin (Jaafar and Ahmad, 2020). Approximately 60% of water withdrawals originate from irrigated agriculture, primarily sourced from groundwater extractions, surpassing the annual recharge rate. The Valley experiences a semi-arid climate, characterized by an average annual grass reference evapotranspiration of 1.5 m. The majority, specifically 70%, of this evapotranspiration takes place from April to September (Jaafar et al., 2017). Groundwater resources in the Upper Litani River Basin experience an annual depletion of approximately 57.5 million cubic meters, with piezo-metric levels falling by 10–12 m over a 5-yr period in some parts of the basin (Jaafar et al., 2016). Agriculture generates around 31% of the basin's income, and is the primary source of income for 6% of the basin's inhabitants (LRA et al., 2007). Similar to other river basins around the world, the Litani River Basin has attracted high population densities over the years,

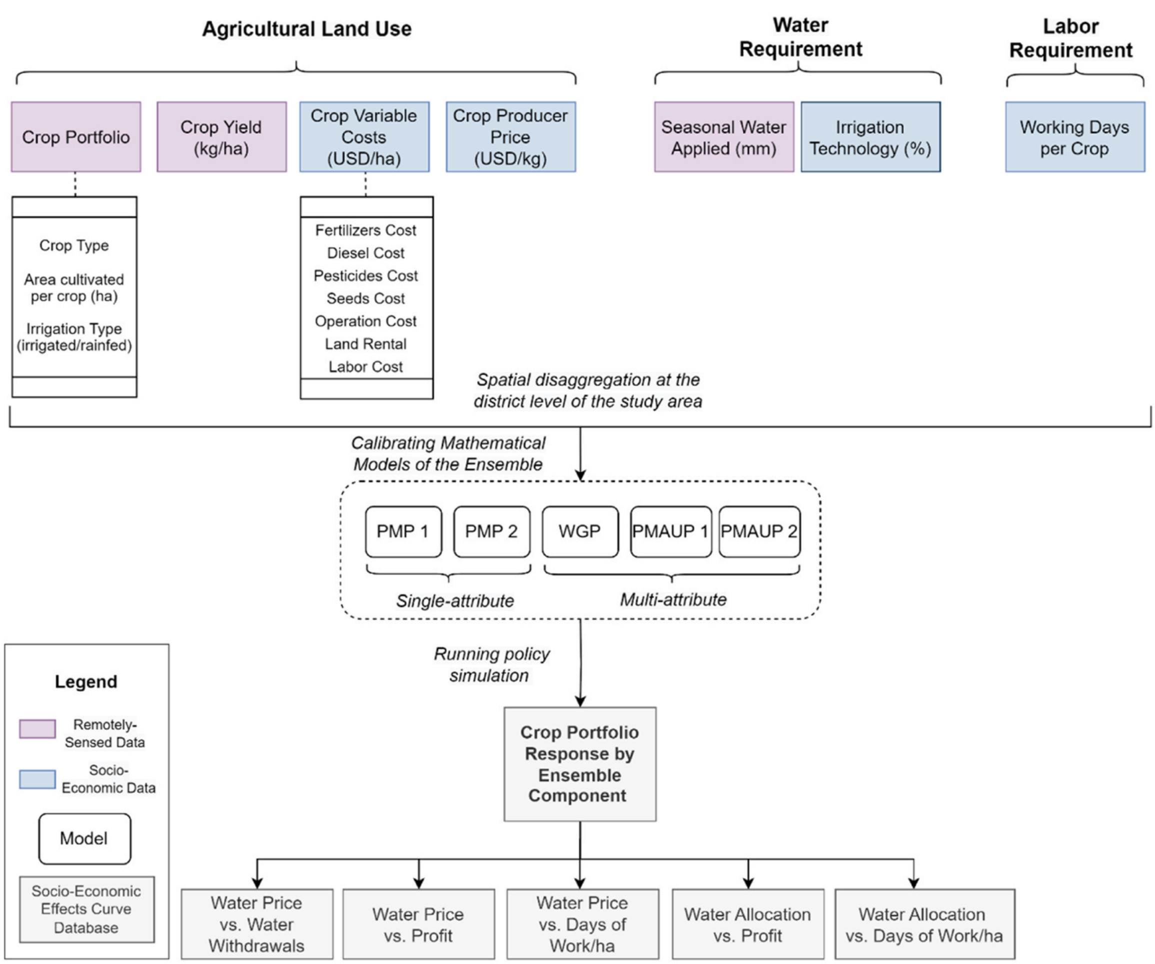

Fig. 1. Workflow of the modeling framework for the coupled remote sensing and the multi-model ensemble of MPMs.

thereby becoming a hub of socio-economic problems. The three districts of Zahleh, Baalbak, and West Bekaa were considered as spatial disaggregation for this study (Fig. 2). The study area, lies within the two parallel Lebanese Eastern and Western mountain ranges running north to south, constitutes Lebanon's biggest agricultural share, accounting for 47% of the country's total utilized agriculture area (IDAL, 2018). The catchment, including the Upper and Lower Litani Basins, covers a total area of 2176 km^2 (FAO and IHE-Delft, 2019). The Upper Litani Basin, where multi-cropping is a common practice, has the highest agricultural water demand in Lebanon (Jaafar et al., 2016). This part of the basin covers an area of 1800 km^2, or 18% of the total country area.

The main source of water in the area is precipitation, which includes snow and rain. The average annual precipitation over the river basin area is 630 mm/year (Jaafar et al., 2016). Due to Bekaa's Mediterranean climate characterized by hot and dry summers and wet winters, most agricultural crops are irrigated from April to October. Agricultural water use within the Litani River Basin has been over-drafting the underlying aquifer as pumping exceeds annual recharge (Jaafar and Ahmad, 2020; Jaafar et al., 2016).

2.2. Data inputs from remote sensing techniques

2.2.1. Crop portfolio and yields

i) Crop Portfolio

The remote sensing and socio-economic modeling frameworks of this research were applied to four major crops grown in the Bekaa: wheat- rain-fed (R) and irrigated (I), early season potatoes (mutually exclusive with irrigated wheat), table grapes (rain-fed and irrigated), and onions. These crops were chosen due to their high area coverage, as well as their key role in contributing to Lebanon's socio-economic development and agricultural production for food security. We derived the observed area shares per crop i ($x_{obs,i}$) using the WaPOR V2 Land Cover Classification datasets of years 2018–2021 over the three districts. We conducted a field survey on the crops in the Bekaa in summer 2021 during the months of May, June, July, and August. The survey consisted of 17 trip days spanning 777 fields of around 30 crops including the studied crops, namely potato, wheat, table grapes, and onions.

ii) Crop Yields

We estimated yields of the study crops over the growing season using field-boundary maps on a district-disaggregated scale. FAO WaPOR V2 data components for yield estimation were utilized for 2018–2021, namely Net Primary Production (NPP) (gC/m^2) datasets and Land Cover Classification (LCC) datasets, both of which are available at 30 m resolution every 10 days at the subnational level. User-defined crop-specific parameters were used to quantify yield figures per crop.

a) Land Cover Classification

Available WaPOR V2 Land Cover Classification (LCC) datasets were used for the years 2018–2021. WaPOR V2 raster LCC was used to generate the vector crop-type map. Given that the WaPOR

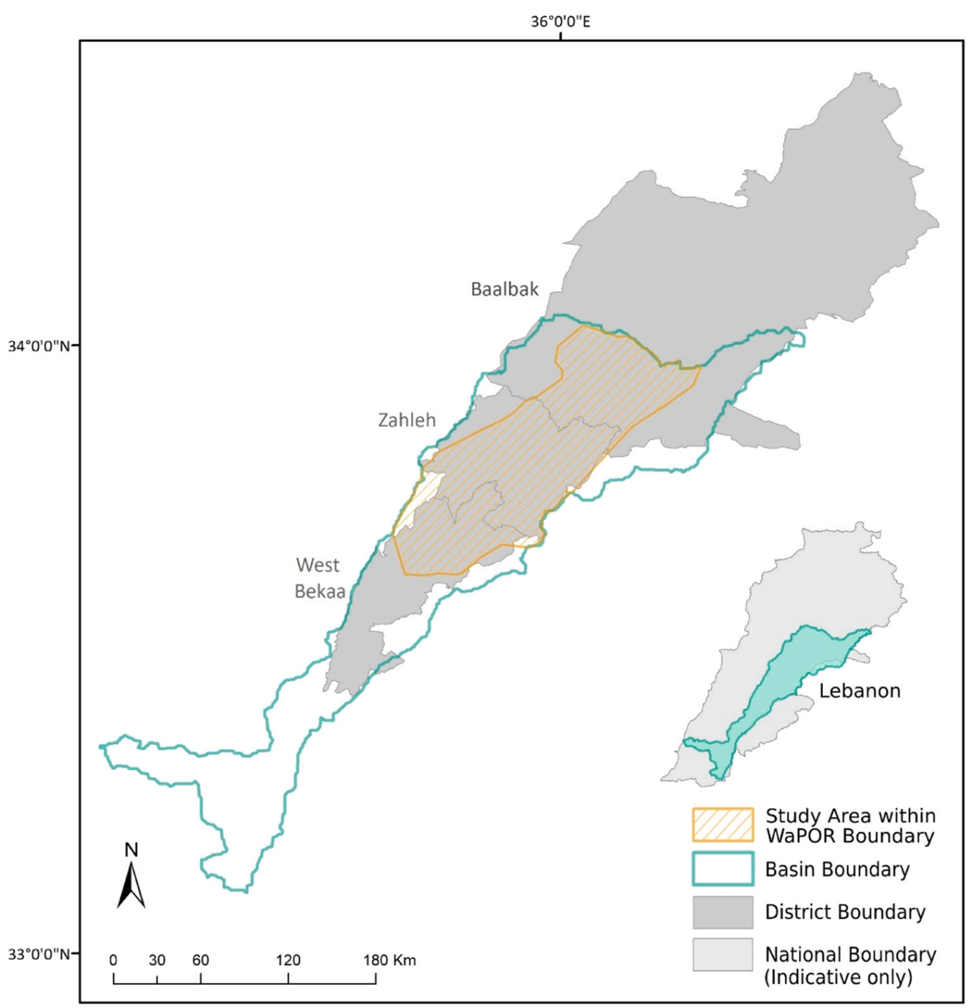

Fig. 2. Geographic location of the study area as delineated by the Water Productivity Open-access Portal (WaPOR) V2 across the districts of Baalbak, Zahleh, and West Bekaa within the Litani River Basin in Lebanon.

database does not classify onions, we considered the irrigated vegetables class representative of onions, since the areas of the vegetable fields and their locations are in line with our 2021 field survey results (7.5% of the surveyed fields were onions, ranking 4th in area percentage after wheat, potatoes, and cannabis). For potatoes and wheat, WaPOR V2 LCC datasets corresponding to the full canopy were used for the second dekad of May and March respectively. For onions and table grapes, the second dekad crop-type map of June was used when both crops are seasonally ripe. The use of WaPOR V2 may constrain the potential for replicating our methodological framework in countries beyond its geographical coverage in the Middle East and North Africa. This limitation prompts the exploration of alternative remote sensing data processing methods.

b) Yields Estimation

The FAO (2020c) WaPOR V2 quality assessment report suggested that the mean derived WaPOR L3 yield values of potato and wheat in the Bekaa valley were reasonable compared to the reported values by farmers. The report's key findings regarding the Bekaa valley indicate that the Net Primary Production (NPP) to transpiration (by vegetation) ratio from WaPOR V2 is in the expected range for C4 crop. We calculated crop yields over the four years by district: Zahleh, Baalbak, and West Bekaa from Start of Season (SOS) to End of Season (EOS). SOS and EOS of each crop are presented in Table 1 based on the crop calendar and agricultural cultural practices in the Bekaa. Crop-field areas per district were summarized using WaPOR V2 LCC data for 2018–2021.

Crop yields were calculated using WaPOR V2 Net Primary Production (NPP) (gC/m^2) datasets (Fig. 3). The conversion of carbon dioxide into biomass by photosynthesis is expressed as NPP, which is a fundamental feature of an ecosystem. Here we used WaPOR V2 NPP datasets at a 10-day temporal resolution, where the pixel value corresponds to the mean daily NPP for that specific dekad. WaPOR V2 applies the methodology improved within the framework of the Copernicus Global Land Component (Swinnen et al., 2021) which incorporates biome-specific light-use efficiencies (LUEs), as well as the addition of a reduction factor for soil moisture stress to account for lowered water availability. NPP is determined by six basic factors: daily input from weather data (Tmin/Tmax) and solar radiation, dekadal inputs from *f*APAR and soil moisture stress, as well as the seasonal indirect input from land cover specific light use efficiency and CO_2. However, CO_2 concentration is assumed to be constant across the globe while accounting for its overall increasing trend using a linear function obtained from the NOAA-ESRL cooperative air sampling network's 15-year annual 'spatial' mean of globally-averaged marine surface (CO2) data (FAO, 2020b).

A mean value composite of the NPP_{max} images is computed at the end of each dekad. The final NPP product is obtained by multiplying the mean value composite NPP_{max} with the *f*APAR, soil moisture stress and the land cover dependent light use efficiency values (1) (FAO, 2020b).

$$NPP_{10} = fAPAR_{10} \times SM \times \varepsilon_{LUE} \times NPP_{\max,10} \quad (1)$$

$$\text{With} \quad NPP_{\max,10} = \frac{\{\sum NPP_{\max,1}\}}{N_d} \quad (2)$$

NPP in agricultural applications is converted to Dry Matter Production (DMP) using a constant scaling factor where $1gC/m^2/day$ (NPP) = 22.2 kgDM/ha/day (DMP) (1) (FAO, 2020b). The seasonal Above-Ground Biomass Production (AGBP) (kg/ha/season) is then calculated using Eq. (3) for DMP (Dry Matter Production in kgDMP/ha/dekad) and Eq. (4) where AoT is the ratio between AGBP and total biomass production. The subscript j refers to the number of days since the start of season (SOS). EOS is the end of season. Yield is derived using Eq. (5) to arrive at seasonal yields per crop i.

$$DMP_j = NPP \times 22.222 \times Nd_j \quad (3)$$

$$AGBP_s = \sum_{j-SOS}^{EOS} DMP_j \times AoT \quad (4)$$

$$Y_i = \frac{AGBP \times HI \times C_4}{(1 - m_c)} \quad (5)$$

Harvest Indices (HI), Moisture Contents (mc) - the wet weight basis plant moisture content, and AGBP are then used to calculate crop yields. Since all crops are C3 crops, the C4 factor was 1.00 (Table 2). The Harvest Index is used to distinguish between fractions of harvestable and non-harvestable biomass production, and typically indicates how much of the biomass output contributes to the harvestable fraction of a crop (FAO, 2020b), herein denoted by yield.

It is essential to acknowledge uncertainties in model estimations of yield that may arise from uncertainties in crop-specific parameters, weather inputs, model structure and natural variability (Ramirez-Villegas et al., 2017). The increase in the number of crops occurring per pixel may decrease the accuracy of the model applied to 1.1 km pixels (Bastiaanssen and Ali, 2003). Differences in the sizes of fields of every crop may contribute to inconsistencies in yield results (FAO, 2020c). Moreover, given that the calculation of yield relies on three primary equations, uncertainties may exist in the intermediate steps that transform AGBP into yield.

2.2.2. Water requirements

i) Seasonal water applied

Sub-national 30 m spatial resolution Actual Evapotranspiration and Interception (ETIa) datasets derived from WaPOR V2 on a monthly temporal resolution over the Bekaa were used in conjunction with Land Cover Classification (LCC) datasets to generate seasonal ETIa quantities for each crop. FAO (2020c) cross-validates WaPOR V2 L3 ETIa values through a comparison to literature data over the Bekaa valley. ETIa raster data were scaled as per WaPOR V2 conversion factor, and monthly sum ETIa was calculated for each crop following the crop calendar. Zonal statistics were performed over the fields to derive the mean monthly actual ET of each crop. We summarized mean crop actual ET over the growing season (mm) per district (Baalbak, Zahleh, and West Bekaa) by accumulating monthly actual ET values (mm) from start of season to end of season. We summarized irrigation ET per crop by summing ETIa values during the summer months when irrigation was applied.

We quantified water applied by farmers per crop i (w_i) per district (Eq. 6) based on crop seasonal ET and effective rain, while accounting for the irrigation system efficiency (Table 3). The efficiency of an irrigation system represents the portion of irrigation water applied that is beneficially utilized by the crop. The integration of modern irrigation technologies, as suggested by (Perry, 2007), can contribute to enhancing this efficiency. The adaptation of irrigation system efficiencies and types in the Bekaa region is based on the work of Jaafar et al. (2016). Their study surveyed the irrigation practices in the study area to evaluate irrigation abstraction for major crops cultivated there. Based on our summer 2021 survey, more than 96% of potato fields use sprinklers for irrigation. Water applied for rain-fed table grapes and wheat is

Table 1
Growing seasons for crop yield estimation of potato, wheat, table grapes, and onions in the Upper Litani Basin in Lebanon.

Crop Type	Start of Season	End of Season
Potato	March 01	July 30
Wheat	December 01	June 30
Table Grapes	April 01	November 30
Onions	March 01	September 30

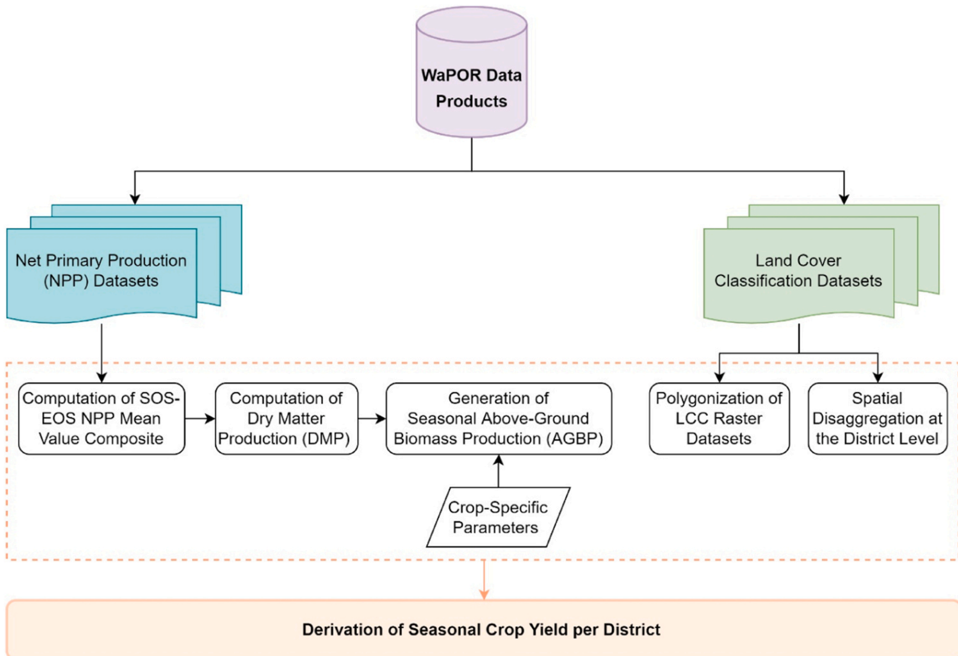

Fig. 3. Workflow for the estimation of seasonal crop yield per district with user-defined crop specific parameters using the Net Primary Production (NPP) and Land Cover Classification datasets of the Food and Agriculture Organization (FAO) Water Productivity Open-access Portal (WaPOR).

Table 2
Crop-specific parameters for yield estimation of potato, wheat, table grapes, and onions (AoT = ratio between above-ground and total biomass production; C4 = crop that utilizes the C4 carbon fixation pathway).

Crop Type	Harvest Index	Moisture Content	AoT	C4
Potato	0.79–0.8 (Darwish et al., 2006; FAO, 2020c)	0.79–0.8 (Darwish et al., 2006; FAO, 2020c)	1	1 (Safi et al., 2022)
Wheat	0.39 (Karam et al., 2009)	0.15 (FAO, 2020c)	0.72	1
Table Grapes	0.31 (Safi et al., 2022)	0.75 (Safi et al., 2022)	1	1
Onions	0.7	0.88 (Djaeni et al., 2017)	1	1

Table 3
Irrigation system type efficiency per crop type after (Jaafar et al., 2016).

Crop Type	Irrigation System Type	Irrigation System Efficiency
Potato	Sprinkler	75%
Wheat	Sprinkler	75%
Table Grapes	Drip	80%
Onions	Sprinkler	75%

considered zero. Although uniform efficiency per crop across all fields using a specific irrigation system is assumed based on the responses obtained from the surveyed farmers, variations in maintenance, operation, and environmental conditions may lead to different efficiencies in different fields, slightly impacting the accuracy of the calculated irrigation water applied.

$$w_i = \frac{Irrigation \quad ET_{seasonal}}{Irrigation \quad System \quad Efficiency} \tag{6}$$

i) Irrigation technology

Winter crops in the Bekaa are usually rain-fed except for wheat which is under supplemental irrigated for the most part. Spring and summer crops, including potatoes are irrigation dependent. Given the dry and hot climate of the Bekaa during summer, most cultivated crops are irrigated (Jaafar et al., 2016), with 72% of the crops fully or supplementary irrigated (Nasrallah et al., 2020). Jaafar and Kharroubi (2021) examined current irrigation management practices used by farmers in Lebanon, and their study revealed that a large percentage of farmers rely on drip (34.6%), sprinkler (22.5%), and drip and sprinkler jointly (12.7%), among other irrigation system types. More than 96% of potato fields use sprinklers for irrigation as surveyed in summer 2021. This figure is in line with the study of Jaafar et al. (2016) where sprinkler irrigation is largely used to produce potatoes. For growing table grapes, drip irrigation is increasingly being used in new vineyards, especially where irrigation water is scarce.

2.3. Other data inputs: crop prices and variable costs

We quantified variable costs for the study-crops over the 2018–2021 period. The variable costs of fertilizers, pesticides, seeds or cuttings, diesel, operation, and land rental (USD/ha), as well as unitary labor costs (USD/working day) were determined from official national reports and e-news, in-person interviews with farmers, TV-recorded interviews, datasheets of the national Ministry of Agriculture and the Ministry of Energy and Water, and local newspaper articles. The costs related to fertilizers and pesticides encompass the expenses involved in acquiring these inputs (USD/ha) of cultivated crops during each growing season, aligning with the cultural practices observed among local farmers in the basin. The expenses associated with diesel costs pertain to the fuel utilized for powering and operating irrigation pumps and systems, calculated per crop per growing season and measured in USD/ha. Operation costs encompass expenses directly linked to crop production, covering those for activities such as plowing, spraying, pruning, and tractor works for the cultivated crop. The seeds or cuttings cost pertains to the expenditures associated with procuring seeds for planting crops per season (measured in USD/ha). In the case of table grapes, the initial cost of cuttings is annualized over a 20-year period. The land rental cost denotes the expenses borne by farmers or producers when renting or leasing agricultural land for crop cultivation, expressed in USD/ha per growing season and categorized by district.

Data on labor requirements per crop and hectare, namely working days per crop and year for each of the four crops, was collected from interviews with local potato, wheat, onion, and table grapes growers (Saikali, 2022). Labor costs refer to the expenses associated with labor wages for agricultural workers involved in various tasks, including planting, harvesting, irrigation, pest control, and other farm operations. The labor cost adheres to the prevailing local pay range commonly observed in the three districts of the basin. The interviewed farmers reported that, on average, potatoes, onions, table grapes, and wheat, require around 90, 120, 250 (I), 100 (R), 35 (I), and 5 (R) working days respectively from SOS till EOS as per each crop calendar. The agricultural cost in the study area is high, driven by several factors. One prominent reason is the substantial reliance on hired labor, coupled with the intensive application of fertilizers and pesticides—practices often encouraged by input suppliers (Aw-Hassan et al., 2018). On a national level, the Lebanese agricultural sector serves as the primary income source for 30–40% of the population. Notably, regional disparities exist, with agriculture remaining a key economic activity for a significant portion of the population in the Bekaa. The variation in labor intensity across regions is notable, with West Bekaa exhibiting a higher demand for permanent labor, averaging one permanent worker for every 3 ha of land (majorly due to the prevalence of family-based agriculture), with a high demand for seasonal workers. In contrast, in Baalbak, the rate stands at approximately 1 worker for every 6.6 ha of land along with seasonal workers (MoA, 2012).

We computed the total variable cost per crop by summing the costs of input variables (USD/ha). We performed an in-house crop cost economic study for wheat and potato. We collected crop producer prices paid at the farm gate through a field survey. The method assumes uniformity in costs across different farms for a specific crop. Agricultural practices and input prices can vary, and the method might not capture these nuances adequately. Moreover, additional pertinent economic factors could be integrated into the analysis to provide a more comprehensive representation of the actual production costs incurred by farmers. This may include factors like storage costs, marketing costs, or miscellaneous unforeseen expenditures.

2.4. Multi-model ensemble of MPMs

Agricultural economics and water resources research have developed various approaches to represent and model the behavior and responses of farmers, including MPMs, econometrics, field experiments, Data Envelopment Analysis, hedonic pricing, and contingent valuation – among which the most commonly used are MPMs (Graveline, 2016). MPMs are a mathematical reproduction of farmers that aim to mimic their behavior and predict their responses to exogenous shocks, incorporating the "deep parameters" or micro-foundations that arouse from observed preferences, technology, and resource constraints.

A set of constraints (both physical and socioeconomic) limits farmers' adaptation options and it is mathematically depicted through the domain $F(X)$Error!Bookmark not defined. (Graveline, 2016). Farmers are modeled by rational economic agents that seek to maximize their economic return through the choice of the land allocated to every crop. This economic return is represented through a utility function U(**X**) that considers one or more (single- or multi-attribute) utility-relevant attributes (e.g., profit, risk avoidance):

$$Max \quad U(\boldsymbol{X}) = f(z_1(\boldsymbol{X}), \ldots, z_m(\boldsymbol{X})) \tag{7}$$

Subject to:

$$x_i \geq 0 \tag{8}$$

$$\sum\nolimits_{i=1}^{n} x_i = 1 \tag{9}$$

$$X \in F \tag{10}$$

$$\boldsymbol{X} \in \mathbb{R}^n \tag{11}$$

$$z_1(\boldsymbol{X}), \ldots, z_m(\boldsymbol{X}) = \boldsymbol{Z}(\boldsymbol{X}) \in \mathbb{R}^m \tag{12}$$

where the decision variable is the crop portfolio (X), containing the share of land used by each crop x_i which in the baseline scenario, with no reallocation policy, should be as close as possible to the WaPOR estimated $x_{obs,i}$ (Section 2.2.1.i). The crop portfolio is produced on a yearly basis: the irrigation campaign. Each attribute $z(x_i)$ depends on the land allocated to the different crops. Following Sapino et al., (2020), we explore the relevance of three attributes: expected profit; risk avoidance; and management complexity avoidance, which is measured through a proxy: labor avoidance:

Expected profit (z_1), is calculated using the following formula: it is the sum of the expected per hectare gross margin of each crop, denoted as π_i. This gross margin is derived by taking the product of the price (in USD/kg) and the WaPOR estimated yield (Eq. 5) (in kg/ha) for each crop, and then subtracting the variable costs (in USD/ha) from this product. The resulting figure for each crop is then multiplied by that crop's proportion of land use (x_i):

$$z_1(\boldsymbol{X}) = \sum_i x_i \overline{\pi}_i \tag{13}$$

where $\overline{\pi}_i$ is the average gross margin for each crop i in the period 2018–2021.

Risk avoidance (z_2) is quantified as the difference in profit variability between two distinct crop portfolios. Specifically, the profit variability of the profit-maximizing crop portfolio $\widehat{X}$ minus that of an alternative crop portfolio $\boldsymbol{X}$ (Bartolini et al., 2007):

$$z_2 \quad (\boldsymbol{X}) = \widehat{\boldsymbol{X}}^t VCV(\pi)\widehat{\boldsymbol{X}} - \boldsymbol{X}^t VCV(\pi)\boldsymbol{X} \tag{14}$$

where $VCV(\pi)$ is the variance and covariance matrix of profit in the time period for which data is available (2018–2021). The first term, $\widehat{X}^t VCV(\pi)\widehat{X}$, calculates the risk associated with the crop portfolio that maximizes profit, the second term, $X^t VCV(\pi)X$, the one of an alternative crop portfolio. Since there is often a tradeoff between risk and profit (as higher profits tend to be associated with higher risks, as noted by Gutiérrez-Martín and Gómez (2011)), this difference will be positive.

Labor avoidance (z_3) is calculated as the difference between the amount of labor used in the profit-maximizing crop portfolio ($\overline{L}$) and that used in an alternative crop portfolio x:

$$z_3 \quad (\boldsymbol{X}) = \overline{L} - L(x) \tag{15}$$

In which $L(x) = \sum_i x_i L_i$ is the labor requirement per hectare to produce the crop portfolio x.

The set of constraints includes the water availability constraint, described as follows:

$$\sum_{i=1}^{n} (w_i x_i) \leq W_g \tag{16}$$

where w_i represents water consumption by crop i (Eq. 6), $\sum_{i=1}^{n}(w_i x_i)$ indicates the quantity of water consumed by the economic agent, and W_g represents the amount of water allocated to each agent in the observed situation. In our application to the Upper Litani Basin, the economic agents are the districts of Baalbak, Zahleh, and West Bekaa (see Fig. 2). The complete database used for the calibration of MPMs is available in Annex I in the online supplementary material. Annex II provides a comprehensive description of the domain F(**X**) used by the models of the ensemble and its mathematical formulation.

The attributes in the utility function and their parameter values can be elicited using normative methods or positive methods (Buysse et al., 2007). Normative models study the optimal allocation of the resource by adopting an objective function that is defined by the researcher, rather than elicited from observations, typically using the assumption that agents will maximize profit. On the other hand, positive models follow an inductive approach to elicit the objective function of the agent, where the objective is to minimize the gap between observed and modeled choices via model calibration. Positive models demand a larger amount of data than normative models, but enhance accuracy, and are typically favored by researchers when data needs are met. Accordingly, this study uses an ensemble of five positive MPMs following the ones selected by Sapino et al. (2020): two non-linear PMP models, developed by (Howitt, 1995) (PMP 1) and (Júdez et al., 2002) (PMP 2); two non-linear multi-attribute Positive Multi-Attribute Utility Programming (PMAUP) models that follow the calibration proposed by Gutierrez-Martin and Gomez (2011) (PMAUP 1) and Gómez-Limón et al. (2016) (PMAUP 2); and a linear multi-attribute WGP model (Sumpsi et al., 1997).

The key differences across MPMs are defined by the form of the objective function and the calibration method adopted. Regarding the *form* of the objective function, positive MPMs can be single or multi-attribute: single attribute models typically aim at maximizing expected profit; while multi-attribute models include in the objective function, in addition to profit, other potentially relevant attributes to the farmer such as risk and management complexity avoidance (Gómez-Limón et al., 2016; Gutierrez-Martin and Gomez, 2011). Our ensemble includes two single-attribute PMP models, both of which adopt a quadratic objective function (17); and three multi-attributes: the PMAUP models, that adopt a non-linear Cobb-Douglas objective function (18), while the remaining one adopts an additive linear objective function through the WGP method (19):

$$U(\boldsymbol{X}) = \sum\nolimits_{i=1}^{n} (p_i Y_i - c_i(x_i))x_i \tag{17}$$

$$U(\boldsymbol{X}) = \prod\nolimits_{i=1}^{n} \left(z_1(x_i)^{\alpha_1}, z_2(x_i)^{\alpha_2}, z_3(x_i)^{\alpha_3}\right) \tag{18}$$

$$U(\boldsymbol{X}) = \sum\nolimits_{i=1}^{n} \left(w_1 z_1(x_i), w_2 z_2(x_i), w_3 z_3(x_i)\right) \tag{19}$$

Where p_i and Y_i represent the price and WaPOR estimated yield (Eq. 5) of each crop i, respectively, and $c_i(x_i)$ denotes the quadratic cost function. The term $\alpha_{1,2,3}$ indicates the calibration parameter of the Cobb-Douglas function, and $w_{1,2,3}$ the weight of each attribute in the final decision for the additive function.

Regarding the *calibration*, each mathematical programming model used has a unique calibration method, which is discussed in detail in Annex III in the online supplementary material.

3. Results and discussion

3.1. WaPOR yield and water use estimation results

Fig. 4 presents the summary of yield estimates of the studied crops in kg/ha. The estimated potato yield (a) across the three districts ranged between 34.8 MT/ha and 47.4 MT/ha from 2018 to 2021, with the highest yield observed in Zahleh in 2020 and the average yield value over the study period being 41.6 MT/ha. It is observed that onion yield (Fig. 4d) ranges between 44.4 MT/ha and 62.4 MT/ha across the districts, with the highest yield quantified in 2021 in Baalbak district. A noticeable difference in rain-fed and irrigated wheat yield (Fig. 4b) is observed, with the highest average estimated yield of irrigated wheat in the West Bekaa district (5.0 MT/ha) in 2018. This is close to with the average wheat yield (4.6 MT/ha) reported by farmers in West Bekaa (Tawk et al., 2019). Rain-fed wheat yield average figure (2.2 MT/ha) is

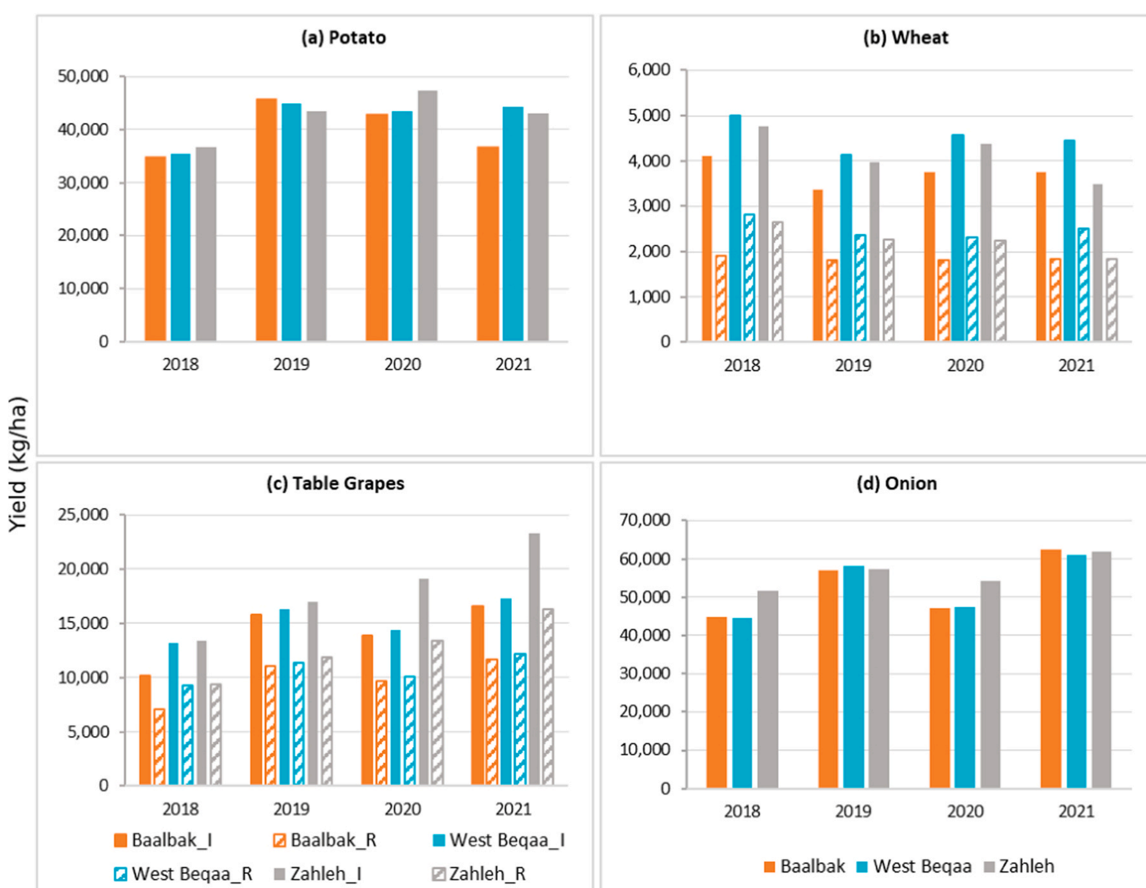

Fig. 4. Seasonal estimates of remotely sensed crop yield in kg/ha of potato (a), wheat (b), table grapes (c), and onion (d) over four years (2018–2021) of WaPOR V2 data components disaggregated by district in the Upper Litani Basin (I = irrigated; R = rain-fed).

almost half of the irrigated wheat yield in all districts over the study period. Onion is the highest yielding crop among other study crops in all districts, followed by potato, table grapes, and wheat. The highest onion yield figures slightly coincide with FAOSTAT data (FAO, 2022b) from 2018 to 2020, where the average onion yield at the country level was 40.0 MT/ha, whereas the estimated average yield at the district level is 53.9 MT/ha.

Fig. 5 shows that on a district level over the study period, table grapes have the highest area share in Zahleh, wheat is mostly grown in West Bekaa, whereas Baalbak area shares of onion and potato are comparable, with wheat occupying more areas of land than table grapes. However, areas planted with wheat display a general decreasing trend from 2018 to 2021 in Baalbak and West Bekaa districts. This decline in area shares may be attributed to the fact that wheat is no longer as profitable as other crops, hence farmers turn to growing table grapes and potato, which are more water-intensive, to increase profit as shown in Zahleh district in Fig. 5. Of the 43 respondents to a 2019 farmers survey conducted by Tawk et al. (2019) in the Bekaa, 95% asserted that they produce wheat for commercial purposes. Additionally, farmers in 2021 were considerably affected by several governmental actions and ramifications including the lack of provision of subsidies (Salame, 2022), a shrinking purchasing power and lack of liquidity due to the economic and financial crisis that Lebanon is enduring (Dal et al., 2021), and a decreased capability of purchasing diesel, as well as expensive imported fertilizers and pesticides (FAO, 2020a). Prior to 2021, the government of Lebanon used to assist local wheat growers in the form of subsidies. The purpose of subsidies was to protect farmers from the fluctuations of international wheat prices by purchasing the wheat from the farmers at a fixed price and selling it at international market prices (BlomInvestBank, 2016). In a producer-level survey, farmers were asked whether they would continue growing wheat if the Lebanese Government lifted wheat production subsidies. Roughly 42% of the wheat growers responded that they might or definitely would stop growing (Tawk et al., 2019), which matches the results of our remotely-sensed decline in areas of wheat fields. Overall, our study reveals that the Lebanese agricultural sector has moved to a low input system, with lower yields and lower marketable production.

Fig. 6 summarizes water use results in mm of the studied crops as quantified using WaPOR V2 crop Actual Evapotranspiration and Interception datasets distinguished by three districts. Highest seasonal ET are observed for table grapes in the Zahleh District (932 mm), followed onion (691 mm), potatoes (660 mm), and finally wheat (640 mm) in the West Bekaa district. Results of a survey conducted among 678 Lebanese farmers by Jaafar and Kharroubi (2021) reveal that there is a prevalence of reliance on groundwater for irrigation of agricultural fields (68.6%). This may explain the highest seasonal water use observed in the West Bekaa district where proximity to water sources (Qaraoun Reservoir fed by the Litani River) is key to understanding the increased over-exploitation of groundwater resources. Fig. 6 also shows the difference in water use between rain-fed and irrigated crops, which clearly displays its effects on the remotely sensed yields of both crops (see Fig. 4). Snowmelt and local precipitation events, which are limited to 90–100 days between October and April, replenish the Litani River Basin each year. Monthly actual ET values are lower during these rainfall months than during the dry periods at the time when farmers irrigate their crops more extensively.

3.2. MPMs ensemble results and climate change impacts

To illustrate the performance of the integrated remote sensing and MPM ensemble modeling framework, we perform two sets of simulations in our case study site in the Bekaa agricultural plain: (i) the first set of simulations (Section 3.2.1) assesses the impacts of quotas that progressively reduces water allocation for irrigation up to 100%, at 1% intervals; (ii) the second set of simulations (Section 3.2.2) assesses the impact of water price increases (a behavioral instrument) up to 0.25 USD/m^3, at 0.0025 USD/m^3 intervals. For each set of simulations (quotas and pricing) we produce information on water withdrawals, profit, and employment (and for pricing, also revenue from the water tariff) at a district level.

It should be noted that the highest water allocation reduction (100%) in the simulations is higher than the water availability reduction predicted in climate change forecasts for the Bekaa. This is done to offer an in-depth assessment of farmer responses, including any potential nonlinear adaptation responses that may be triggered at higher water allocation reductions than those forecasted by climate change scenarios. According to CMIP6 (2023) simulations and their interpretation by experts (Hausfather and Peters, 2020), the worst-case and “highly unlikely” climate change scenario for the Bekaa (namely, the Shared Socio-Economic Pathways 5 - Representative Concentration Pathway 8.5 scenario, or SSP 5–8.5) should result in a water allocation reduction of up to 9% by the middle of the century (2040–2059) and up to 20% by the end of the century (2080–2099). Milder and more “likely” climate change scenarios, notably the middle-of-the-road SSP 2–4.5 scenario,

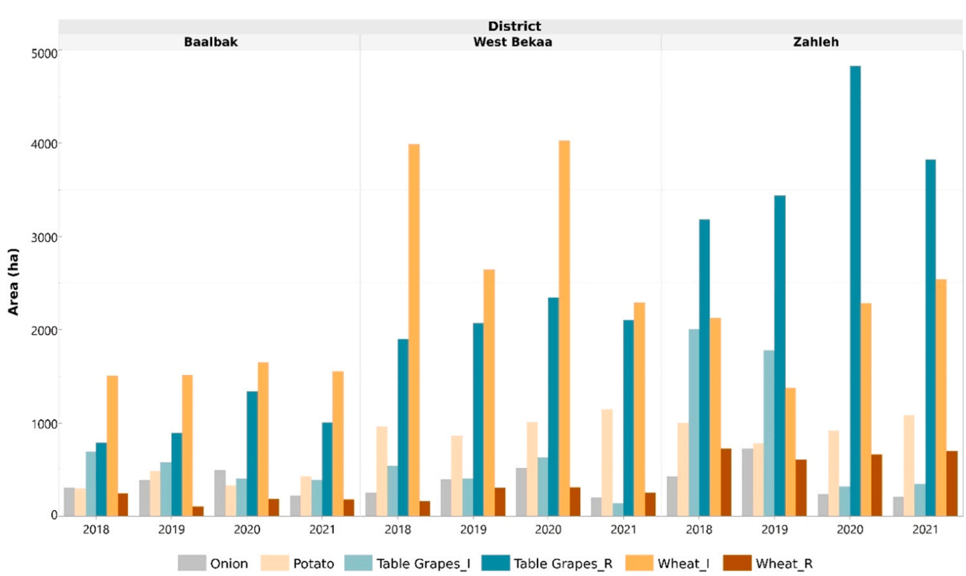

Fig. 5. Area shares of study crops in hectares over four years (2018–2021) distinguished by district in the Upper Litani Basin using WaPOR V2 Land Cover Classification datasets (I = irrigated; R = rain-fed).

Fig. 6. Mean seasonal actual ET estimates of potato (a), wheat (b), table grapes (c), and onion (d) over four years (2018–2021) of WaPOR V2 water use data components distinguished by district in the Upper Litani Basin (I = irrigated; R = rain-fed).

predict a water allocation reduction for the Bekaa of 7% both at the middle (2040–2059) and the end of the century (2080–2099). Critically, the decision to simulate water allocation reductions of up to 100% was validated by river basin planners and other local stakeholders in the context of a workshop held in Beirut in July 2022. Participants in the workshop noted that available climate change simulations focus on surface water resources and showed concern that the significant groundwater overexploitation and aquifer depletion in the upper Bekaa could reduce water allocation (potentially significantly) beyond 20% in some areas across the basin.

The river basin planners and other local stakeholders who participated in the Beirut workshop also supported that the pricing simulation considered an upper threshold of 0.25 USD/m3—although the feasibility of such price increase in the current context was deemed "low" or "very low". According to the (limited) institutional information and the expert judgement of local stakeholders, the cost of water in the study area is approximately 0.25 USD/m^3, which is largely driven by the energy costs of pumping groundwater for irrigation. Stakeholders thus proposed for the simulations a price increase of up to 100% of the current cost of groundwater, both for surface and groundwater (i.e., up to 0.25 USD/m^3 price increase).

3.2.1. Quotas simulations

Fig. 7 reports land use changes in response to water allocation reductions of up to 100%. Up to a 20% reduction in water allocation (a threshold that corresponds to the SSP5–8.5 climate change scenario), low-value-added irrigated wheat and irrigated vineyards are progressively substituted with rain-fed wheat and rain-fed vineyard, respectively. This trend is observed up to a water allocation reduction of 50%. After water allocation is reduced by 50% or more, irrigated wheat and vineyards virtually disappear from the cropping patterns, and water savings focus on higher valued-added crops (potatoes and onion). This crop portfolio outcome appears unlikely under current climate change forecasts for the Bekaa, whose worst-case (and "highly unlikely") SSP5–8.5 scenario (Hausfather and Peters, 2020) suggests a water allocation reduction of up to 9% by the middle of the century (2040–2059) and up to 20% by the end of the century (2080–2099) (CMIP6, 2023). However, according to stakeholder consultations, some areas relying on groundwater may experience significantly larger water reductions, even in the short term, due to aquifer depletion. The five models in the MPM ensemble suggest similar crop portfolio trends, albeit the substitution of irrigated by rainfed crops is slightly faster in the PMAUP and WGP than in PMP models.

Differences among models in the baseline crop portfolios (0% water reduction) are the result of calibration errors in the multi-attribute WGP and PMAUP models. The WGP model, the only MPM in the ensemble with a linear utility function, shows the most significant discrepancy with the observed crop portfolio. This is because linear models often find over-specialized or even corner solutions that can significantly deviate from observed decisions (Graveline, 2016). This linear utility function can result in rigidness: the model allocates all land to the crop with the highest utility until a binding constraint is reached (e.g., the maximum quantity of water available is used), which yields choices often deemed as "too far from reality, at least in the short term" (Graveline, 2016). This poor performance could be used to argue in favor of the exclusion of the WGP model from the ensemble, or of assigning this model a lower relevance through weighting. On the other hand, non-linear PMAUP models can also be overspecialized when the choices are limited, and

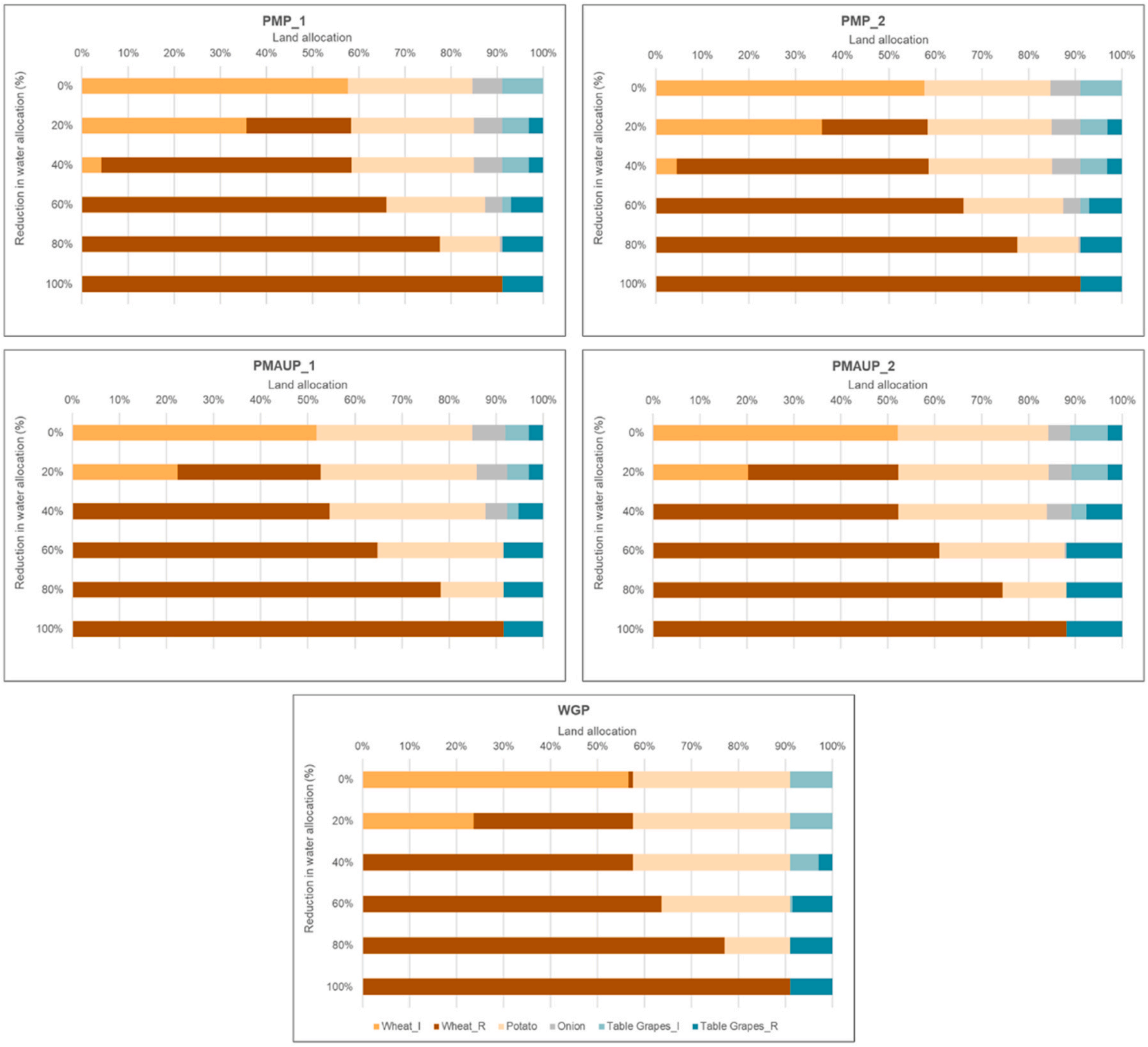

Fig. 7. Land use response to the reduction in water allocation in the Upper Litani Basin (_I = Irrigated; _R = rain-fed).

few crops are available (see Annex III for more information on the calibration methodologies and calibration errors). Moreover, while the PMP calibration techniques yield a calibration error of zero, their forecasting capacity has not been validated yet in any application in the literature, and we should expect (potentially nontrivial) forecasting errors. It should be noted that the ecological ensembles that assign weights to alternative models and their predictions typically do so based on their forecasting errors (Taner et al., 2019). Critically, measuring forecasting errors in MPMs via rolling origin or other technique in our case study site is precluded by the limited data available, which covers the period 2018–2021—just enough time for robust calibration.

Rather than selecting the models that have the lowest calibration errors, or assigning them a higher weight, in our application we consider all the models in the ensemble of MPMs and adopt an un-weighted approach. Due to the limited data available, we do not have evidence to conclude that the WGP predicts worse than the other models that have lower calibration errors. On the contrary, a model with a relatively high calibration error may predict better than one with relatively low calibration errors (Pindyck, 2017). Without further information, notably on forecasting errors (including under climate change), assigning weights to models becomes a subjective process that implies a priori assumptions regarding the weights and the accuracy of the models (Tebaldi and Knutti, 2007). By including all the models in the MPMs ensemble via an unweighted approach, we consider a larger number of potential outcomes, which can help in reducing regret in decision making.

Fig. 8 shows the impact of water allocation reductions on farmers' profit. All models in the ensemble suggest a progressive and less-than-proportional reduction of profit in response to quotas in the range 0%-50%, followed by a steep decline when water allocation is reduced by 50% or more (an unlikely scenario). This non-linear response is typical of positive MPMs: irrigators first choose to reduce the surface of those crops yielding a lower utility (which are usually those that are also less profitable), and only after this option is exhausted the surface of higher-utility crops is reduced–which results in a steep decline in profit. The ensemble models yield a narrow prediction range (which has to do with the limited crop choices available to irrigators in the Bekaa), with the decline in profit starting slightly earlier for PMP models (at 50% water allocation reduction) than PMAUP and WGP models (60% reduction). Importantly, all models of our ensemble display a similar behavior even if they start from a different baseline due to calibration errors (see Annex III). Noteworthy, the two PMP models almost overlap each other, presenting only minor differences.

Regarding employment, the ensemble yields an even narrower prediction range. Fig. 9 shows the reduction in working days (per hectare) following reductions in water availability. This reduction is caused by the substitution of irrigated crops by relatively less labor-intensive rain-fed crops. The reduction in working days is almost proportional to the reduction in water allocation and shows no relevant tipping points.

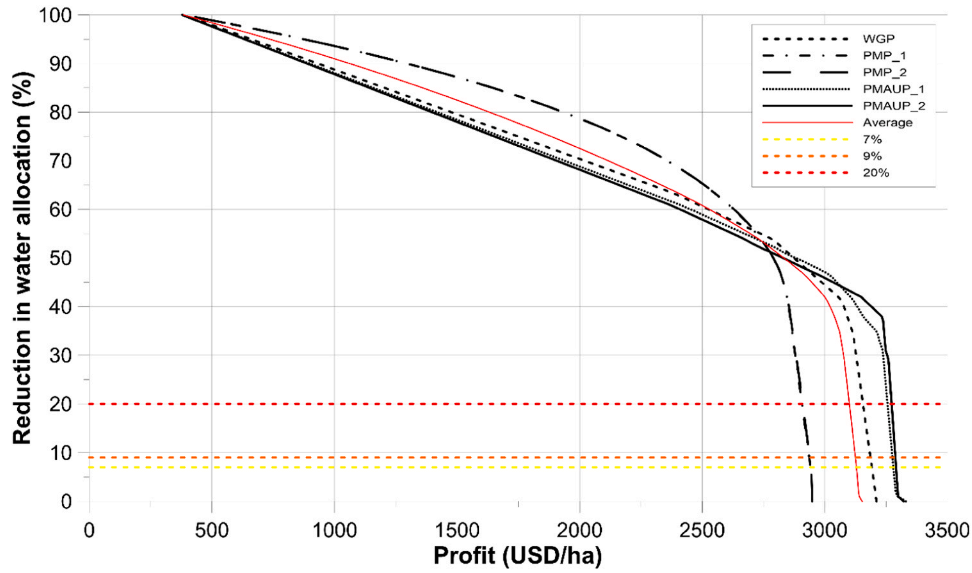

Fig. 8. Irrigators' profit response (USD/ha) to the reduction in water allocation (%) using the multi-model ensemble of MPMs. 7%, 9%, and 20% reduction thresholds refer to the expected reduction in water availability according to SSP2-4.5 and SSP5-8.5 scenarios respectively.

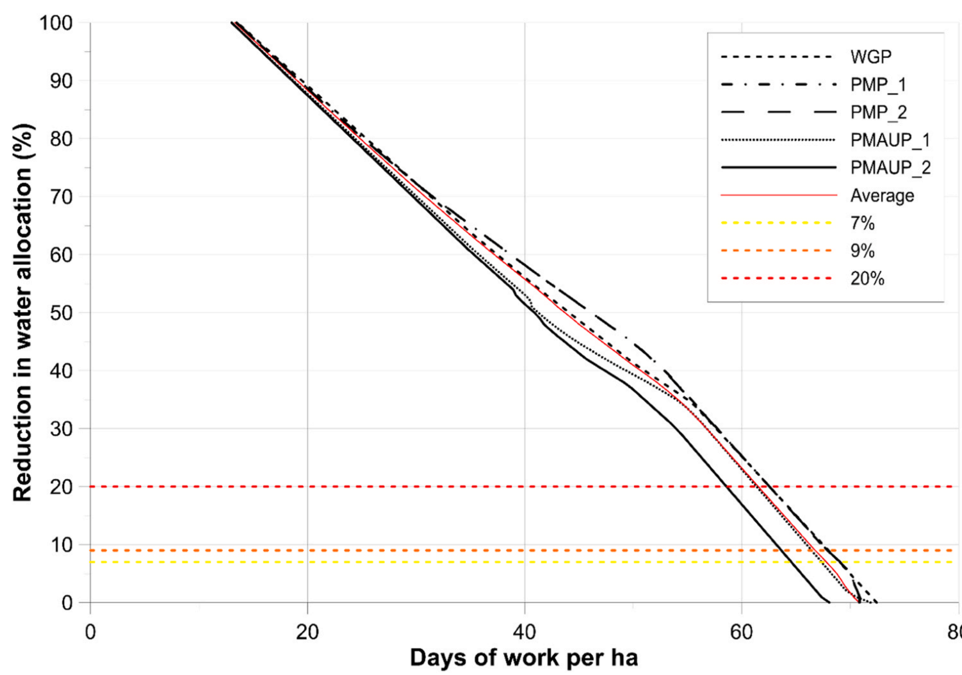

Fig. 9. Labor response (days of work/ha) to the reduction in water allocation (%) using the multi-model ensemble of MPMs. 7%, 9%, and 20% reduction thresholds refer to the expected reduction in water availability according to SSP2-4.5 and SSP5-8.5 scenarios respectively.

3.2.2. Water pricing simulations

Fig. 10 reports irrigators' crop portfolio responses to a price increase of up to 0.25 USD/m^3, at 0.0025 USD/m^3 intervals. All models predict an almost stable area for the highest value-added crop (potato) under all water prices considered. However, they show significant differences in land allocations to other crops. The two PMP models and the WGP model predict a gradual substitution of irrigated wheat with rain-fed wheat, while the two PMAUP models predict a tipping point at a price increase of >0.03 USD/m^3, where the entire surface of irrigated wheat switches to rain-fed agriculture. After irrigated wheat is completely substituted by rain-fed wheat, irrigated vineyards also transition to rain-fed agriculture, although the pace of transition is different in each model. In all models the transition from irrigated to rain-fed vineyard is progressive (no tipping point), except for the WGP, where the entire surface of vineyard transitions to rain-fed for an increase of >0.1 USD/m^3.

It is worth noting that the transition from irrigated to rain-fed agriculture under the pricing simulation fully removes the surface (and consequently water use) of a given crop across all districts before jumping to another crop, rather than simultaneously reducing the surface of several crops across multiple districts (as happens with quotas simulations). This is because rather than homogeneously reducing water allocation across all districts, as quotas simulations in Section 3.2.1 do, pricing penalizes those crops and districts with a lower utility return on water (i.e., those with a larger share of low value-added crops). Accordingly, while under the quotas simulation we can observe a simultaneous reduction in the irrigated surface of low (in districts that

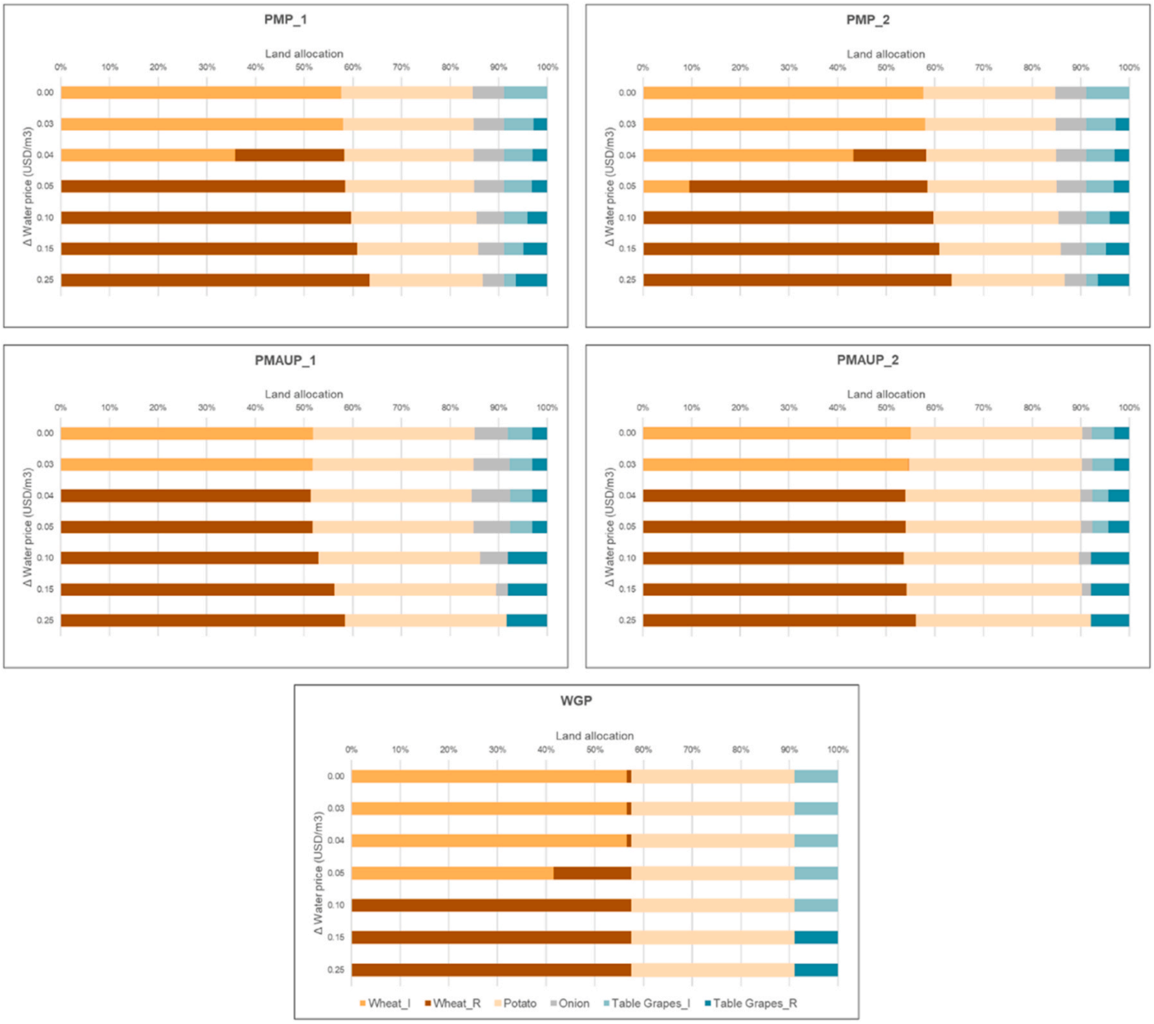

Fig. 10. Irrigators' crop portfolio responses to water price increase in the Upper Litani Basin using the multi-model ensemble of MPMs.

have allocated a relatively larger share of water to low-value added crops, and therefore have a larger "buffer" stock) and high (in districts with a larger share of water allocated to high value-added crops) value-added crops across different districts, under the pricing simulation we observe a sequential phase-out of crops across all districts, from low to higher value-added.

Fig. 11 shows irrigators' aggregate demand function, i.e., how water withdrawals change in response to an increase in water price. The

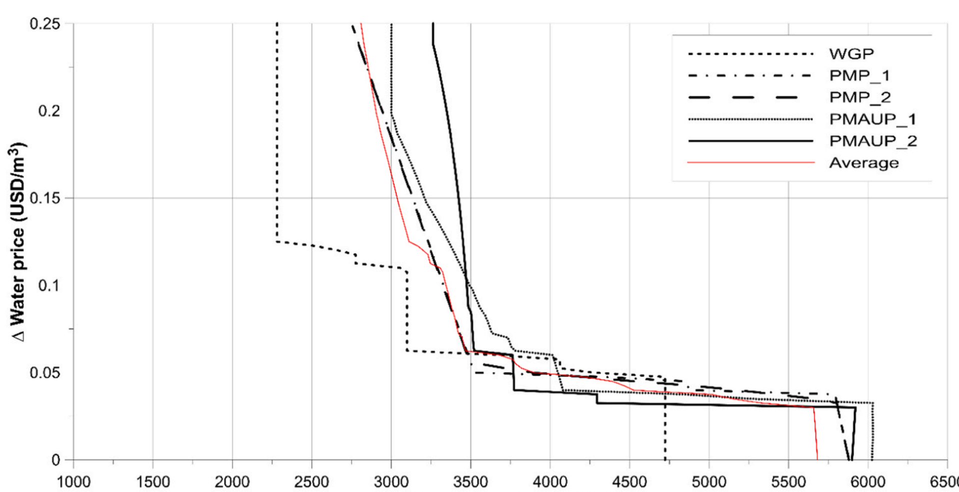

Fig. 11. Agricultural water demand response (m^3/ha) to water price increase up to 0.25 USD/m^3, at 0.0025 USD/m^3 intervals, in the Upper Litani Basin using the multi-model ensemble of MPMs.

demand function shows an inelastic stretch (i.e., no significant reductions in water quantity emerge following price increases) until a 0.03 USD/m^3 price increase, followed by a more elastic response that generates significant water savings in the range between 0.03 and 0.06 USD/m^3, and again an inelastic stretch above a price increase higher that 0.06 USD/m^3. In this case the prediction range is wider than under the quotas simulations, which may result in significant differences across models in thresholds (e.g., in the case of the WGP model the final inelastic stretch starts at a price increase of 0.13 USD/m^3, more than twice as much as in the other models). Albeit positive non-linear models usually display smooth responses, the limited range of crop choices and autonomous adaptation data/options (only extensive –land reallocations towards less water intensive crops– and super-extensive margin –land reallocations from irrigated to rain-fed agriculture– adaptation data is available, while intensive adaptation –deficit or supplementary irrigation– cannot be simulated) yields a "jumpy" demand function for the Bekaa for all models considered.

Figs. 12 and 13 show the impact of water pricing on irrigators' profit and employment, respectively. In all models profit decreases progressively alongside higher prices, with profit reductions ranging between 24 – 33% for a 0.25 USD/m^3 price increase depending on the model. The same price increase leads to a substantial reduction in water withdrawals by 45 – 53% depending on the model. Employment follows a similar trend to the water demand curve: over the inelastic stretches of the water demand function where the surface of irrigated crops is mostly stable, labor demand is largely unaffected; while over the elastic stretches where water demand falls alongside the surface of irrigated crops, labor demand is sharply reduced, due to the higher labor intensity of irrigated crops as compared to rainfed crops. Overall, employment falls by up to 37 – 43% for the maximum price increase of 0.25 USD/m^3 depending on the model. While pricing is effective in saving water for other uses at an overall lower economic cost, the reallocation of water towards high value-added crops and districts (in our case, from the Zahleh and Baalbak districts to the West Bekaa district) raises non-trivial equity issues that call for complementary policies such as (decoupled) subsidies. Moreover, water saving comes at the expense of lower yields of key commodities such as wheat, which may call for higher imports (possibly at less competitive, higher prices) that worsen the trade balance of the country and generate other problems. We come back to these aspects in the discussion in Section 3.3.

Fig. 14 presents the tariff revenue obtained through higher water prices in the Bekaa. Noteworthy, this tariff revenue only accounts for direct contributions from irrigators and does not include indirect impacts on public revenue, such as the decrease in income tax due to declining farmers' profits. Tariff revenue typically increases with higher water prices, reaching between 570.4 – 815.8 at the maximum price, depending on the model used. However, during the elastic stretches of the demand curve where irrigators respond to price increases by abruptly switching from water-intensive crops to rain-fed alternatives, tariff revenue may decrease despite the price increase. This result highlights the complex and often nonlinear relationship between pricing policies, irrigators responses, and public revenue.

3.3. Policy comparison: quotas vs. prices

Fig. 15 compares the aggregated socioeconomic and environmental performance for the two water reallocation policies explored. This is done by calculating the Gross Value Added (GVA) for each simulation and policy, and then plotting it against the corresponding reduction in water allocation, where GVA is calculated as the sum of profit, labor, and tariff revenue (the latter being relevant only for the pricing policy). This yields a two-dimensional plot that displays the broader economic costs of water allocation reductions/water savings.

For all models and water allocation reductions simulated, the pricing policy delivers a larger GVA than the quotas policy. This reflects on the higher efficiency of pricing policies, which penalize low value-added crops that cannot afford the price increase, while allowing higher value-added crops to continue using water—only at a higher price. This increases efficiency in resource allocation while raising public revenue via the tariff. The higher efficiency of pricing policies becomes apparent with larger water allocation reductions, where quotas reduce water availability for higher value-added crops, while pricing policies allow them to continue using water. On the other hand, quotas show higher water saving effectiveness than pricing, which eventually hits an inelastic interval that prevents further water savings. Admittedly, additional water savings could be achieved via higher prices, but the cost of the policy may be so disproportionate that a price increase beyond 0.25 USD/m^3 was deemed "unfeasible" by stakeholders.

It is worth noting here the crucial role of the ensemble approach in providing a comprehensive understanding of the agricultural responses under our policy scenarios. By incorporating a range of MPMs, each with its assumptions and mechanisms, the ensemble allows for a broader

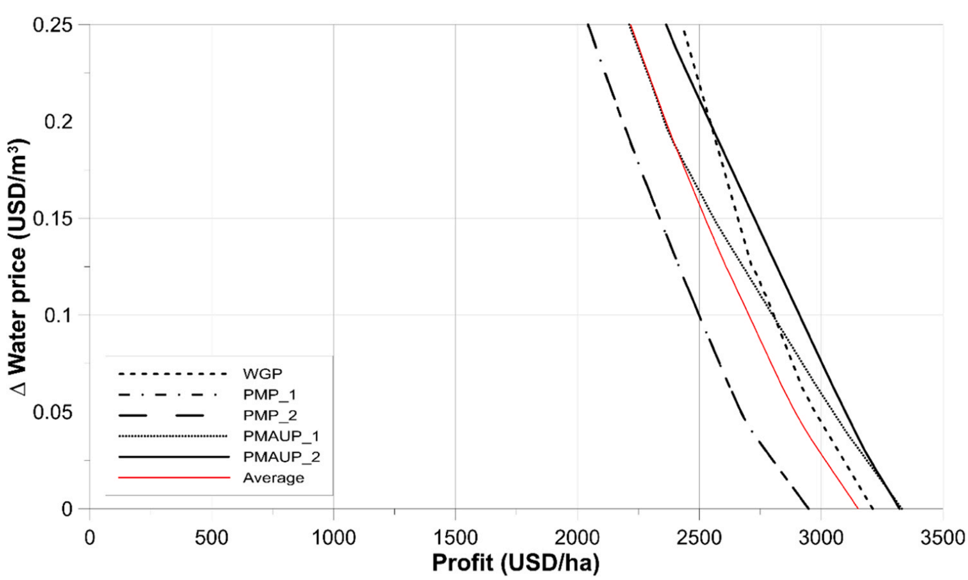

Fig. 12. Profit response (USD/ha) to water price increase up to 0.25 USD/m^3, at 0.0025 USD/m^3 intervals, in the Upper Litani Basin using the multi-model ensemble of MPMs.

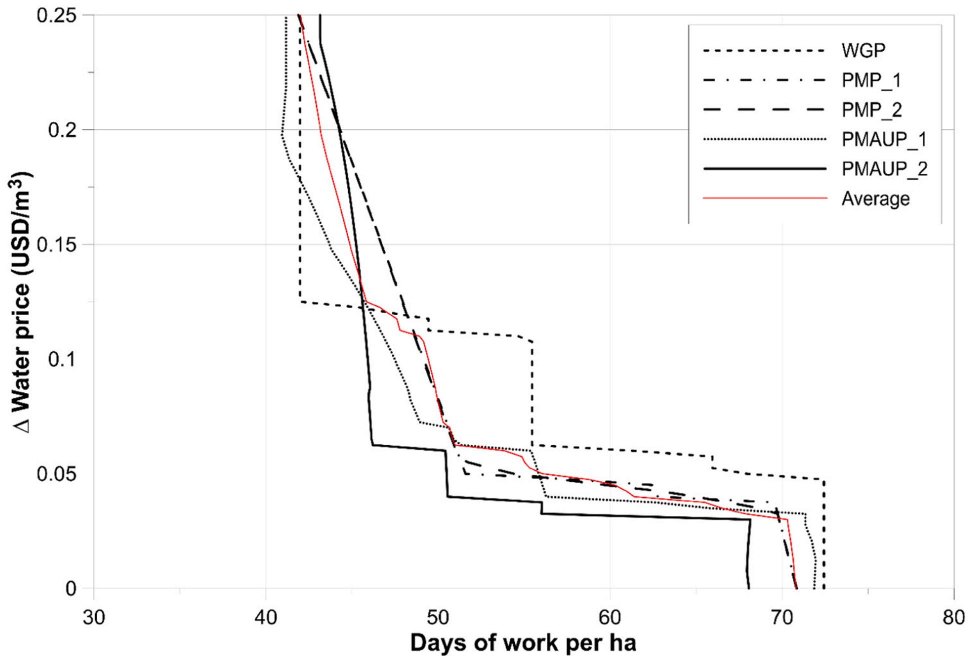

Fig. 13. Labor response (days of work/ha) to water price increase up to 0.25 USD/m^3, in the Upper Litani Basin using the multi-model ensemble of MPMs.

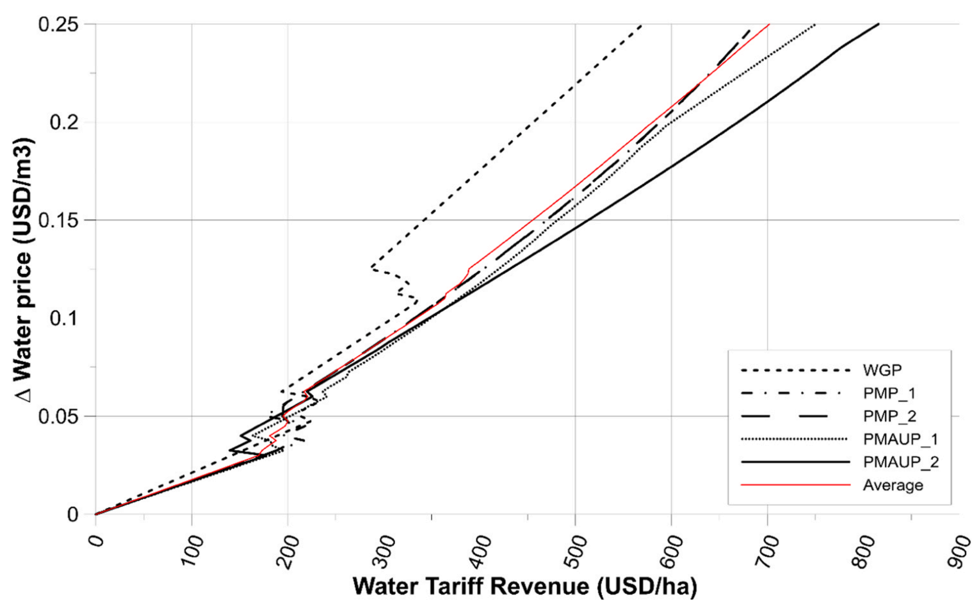

Fig. 14. Tariff revenue (USD/ha) in response to water price increase up to 0.25 USD/m3, in the Upper Litani Basin using the multi-model ensemble of MPMs.

exploration of plausible futures. The ensemble approach mitigates the risk of relying on a single model's predictions, which might be overly specific or fail to capture the full range of possible futures. Furthermore, the ensemble enables a more robust analysis by capturing the variability and extremes (minimum and maximum impacts depending on the model) of the scenarios considered. This is particularly valuable in uncertain decision-making contexts where having information on many potential outcomes and their range, including extreme outcomes, is equally or more relevant than the having information on the average outcome or a specific scenario (Marchau et al., 2019).

4. Discussion and conclusions

This paper integrates, for the first time to the best of our knowledge, remote sensing evapotranspiration and yield data from WAPOR V2 into a multi-model ensemble of MPMs. Remote sensing is used to provide critical information on land use and the location, timing and quantity of water withdrawals and consumption through the monitoring of satellite data at the appropriate spatial and temporal scale, and this information serves as an input to MPMs that are used to assess the repercussions of water reallocation policies on irrigators decisions, and their economic and environmental impacts. In our research, we found distinct responses in the agricultural sector to quotas and pricing policies. For quotas, the impact on profit and employment were less-than-proportional for water allocation reductions of less than 50%, but they increased abruptly for reductions greater than 50%. In the case of water pricing, irrigators' responses were initially inelastic until a price increase of 0.03 USD/m^3, more elastic with further price increases, and then inelastic again beyond 0.06 USD/m^3. This study highlights the efficiency of behavioral policies like water pricing over quotas in terms of resource allocation

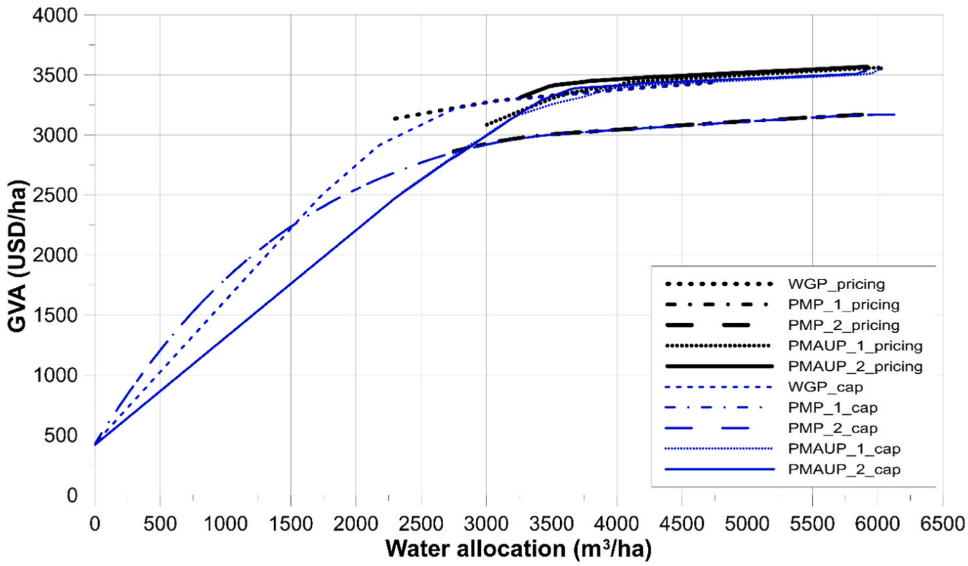

Fig. 15. Quotas v. pricing: GVA (USD/ha) responses to reductions in water allocation, in the Upper Litani Basin using the multi-model ensemble of MPMs.

and revenue generation, especially when facing substantial water allocation reductions. These findings offer valuable insights for developing more effective water management strategies under varying conditions of water scarcity. The presence of nontrivial uncertainties and tipping points in our results underscores the importance of combining reliable water use data with multi-model and multi-scenario ensembles for developing robust water management policies. The application of our proposed methodology to the Bekaa agricultural plain in Lebanon highlights its potential applicability in regions traditionally constrained by limited water and land use data.

We have identified six key features for future research to expand and improve our work. *First*, in our ensemble, we follow conventional mathematical programming modeling where the decision variable is land allocation. This allows to represent extensive (i.e., the shift from water-intensive to less water-intensive crops) and super-extensive (i.e., the shift from irrigated to rain-fed crops) margin adjustments by irrigators, but excludes intensive margin adjustments (i.e., deficit/supplementary irrigation). Koundouri (2004) highlights the relevance of the latter adaptation strategy for irrigators, especially in water stressed basins. Accordingly, researchers are developing a new generation of MPMs that allow for intensive margin adjustment by incorporating water-yield production functions (e.g., the reader can refer to (Mérel et al., 2011; Sapino et al., 2022a)). This makes MPMs more realistic, and potentially more accurate, in explaining and predicting irrigators' responses. However, this type of MPM is data intensive and requires on site information on yield responses to water application under climate change that can be readily transformed into crop-water production functions, which is often not available—as is the case in our study site.

Second, while exploring uncertainty in the microeconomic system, our methodological framework does not account for potential uncertainties arising from remote sensing data processing. Satellite-based models are subject to errors and inherent uncertainties, and there is a need for enhanced transparency in understanding how these data can be deployed alongside traditional in-situ monitoring (Foster et al., 2020). Errors in satellite-based models, stemming from uncertainties in both model inputs and the representation of processes, have the potential to result in socioeconomic losses for farmers. This extends to an examination of how these measurement errors influence the effectiveness of irrigation water use policies designed to address diverse short- and long-term ramifications, as well as critical aspects of decision-making and resource allocation. This could be addressed by incorporating multiple data inputs (e.g., Sentinel, Copernicus) and remote sensing data processing methods into the framework to complement WaPOR (see for example (Calera et al., 2017; D'Urso et al., 2009). The resultant multi-system and multi-model ensemble would allow us to quantify uncertainties more thoroughly within each relevant system, as well as the cascading uncertainties across systems. At present, using WaPOR V2, the application of alternative remote sensing data processing methods in Lebanon and other developing nations is still limited. However, with WaPOR V3 offering global coverage, there exists a heightened potential for replicability of our methodological framework and comparison with other remote sensing methods.

Third, additional relevant scenarios and system models could be incorporated into the analysis to assess modeling outcomes and uncertainty even more scrupulously. For example, our methodology uses climate stationary agricultural data, as well as constant input and output prices—all presumably influenced by climate change (AgMIP, 2023) and other systemic shocks such as the recent Russo-Ukrainian War, which has exposed non-trivial vulnerabilities of international food markets and greatly affected commodity prices (and farmers' choices). This is particularly relevant in the case of Lebanon, which imports almost 80% of the wheat it consumes (a key commodity in the local market, with a per capita consumption of nearly 80 kg), largely from Ukraine. Climate change can aggravate this situation by reducing water availability, constraining the global supply of key agricultural commodities, and increasing their prices—thus creating trade imbalances and potentially economic downturn and even social instability (De Châtel, 2019; Eklund et al., 2022; Ide, 2018; Kelley et al., 2015). Pricing and quotas can further aggravate this situation by reducing local production in favor of higher value-added crops, although this trend may be mitigated as the prices of agricultural commodities increase due to scarcity (e.g., wheat). This micro-macroeconomic feedback needs to be accounted for to avoid unintended and negative consequences in the Bekaa, Lebanon and elsewhere. Moreover, higher detail on the impacts of climate change on groundwater availability in the Bekaa are also necessary to better guide expert judgement in policy design. These gaps can be addressed via modelling, either exogenously to our modeling framework by incorporating new scenarios; or endogenously by coupling other systems and their models to our framework, e.g., a macroeconomic model to assess changes in prices, or hydro-geologic models to enable us anticipating changes in future groundwater availability (Parrado et al., 2020; Pérez-Blanco et al., 2022). Integrating more systems into the modeling framework will reveal nontrivial feedback that better informs the complexities of designing comprehensive policy packages for sustainable growth. Such policy packages will need to look beyond the water and agricultural sectors and consider other adaptation and mitigation strategies beyond water pricing/quotas alone (e.g., trade balance policies, public budget, etc.). It should be noted, though, that all these modelling add-ons can reduce the tractability of the problem for bounded rational decision makers. Knowledge limitations and time constraints affect the decision-making process reducing the availability of relevant information, and this results in a tradeoff between the researcher's objective of thoroughly quantifying uncertainty and the delivery of actionable science that is accessible to stakeholders. With sufficient resources, this limitation can be addressed through training via serious games or other stakeholder engagement methods–albeit this is costly, time-consuming, and often infeasible.

Fourth, higher granularity in MPMs would allow for a more detailed representation of economic agents closer to the actual irrigator (e.g., irrigation communities instead of the districts currently used), albeit this is presently limited by (socioeconomic, in the case of the Bekaa) data constraints.

Fifth, a comprehensive analysis of climate change adaptation in the irrigation sector needs to consider other behavioral and/or engineering instruments that can complement, or substitute, the role of quotas and water pricing. In our pioneering application of the proposed methodological framework in the Bekaa agricultural plain, the focus on quotas and pricing was warranted since stakeholders identified these policies in a workshop held at the American University of Beirut in July 2022. In fact, future responses to water scarcity in the Bekaa agricultural plain and elsewhere in northern Africa and the Middle East will likely come from green engineering and demand-side behavioral instruments, including pricing; but also, buyback, insurance mechanisms and nature-based solutions—whose performance and associated uncertainties will need to be assessed in future research. This expanded scope would provide stakeholders with a valuable tool to identify the most effective strategies for sustainable water and agricultural management.

An alternative is to ration water, setting quotas per hectare or at the farm level, and allow trading in these quotas. This has several advantages: first, less productive farmers will have an incentive to reallocate their quota to more productive farmers (and be paid for it); second, farm incomes are not reduced by an increase in the cost of production unless a farmer opts voluntarily to buy-in more water; and third, the policy instrument (the quota) relates directly to the policy objective (reduced water use) rather than indirectly in setting a price that it is hoped will induce a reduction in demand to the target level.

Finally, before implementing policy solutions such as water pricing or technological interventions, establishing a robust governance framework is essential. This framework should encompass clear regulations, effective enforcement mechanisms, transparency, and stakeholder engagement, along with capacity building within water institutions. Only with such foundational governance improvements can other solutions be effectively implemented and sustained, ensuring that the strategies employed are as equitable and effective as possible in mitigating the impacts of climate change and addressing the complex challenges of water management (Araral and Wang, 2015; Nouri et al., 2023).

CRediT authorship contribution statement

Francesco Sapino: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Writing – review & editing. **Hadi Jaafar:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Methodology, Investigation, Funding acquisition, Conceptualization. **Rim Hazimeh:** Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **C. Dionisio Pérez-Blanco:** Writing – review & editing, Conceptualization, Funding acquisition, Investigation, Methodology, Project administration, Resources, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2024.108805.

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