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Water and productivity accounting using WA+ framework for sustainable water resources management: Case study of northwestern Iran

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ABSTRACT

An exhaustive evaluation of water resources is a prerequisite for evidence-informed planning and implementing sustainable management strategies. However, the lack of sufficient information on water supply and consumption, alongside the technical limitations on comprehensive accounting for inter-relations and interactions between the subsystems, has resulted in decisions with often long-lasting outcomes and undesirable consequences. Water accounting is a tool for systematic acquisition, analysis, and reporting of water-related information to fill the existing knowledge gap on water flows and fluxes. In this study, Water Accounting Plus (WA+) framework is applied to the western region of Lake Urmia, a dying hyper-saline lake, to assess water use and crop water productivity (CWP) from 2010 to 2016. Remotely sensed information along with a distributed hydrological model (SPHY) is used to fill the information gap on water resources and inform effective policy actions. Our analysis reveals that the agricultural sector is neither productive nor efficient while there is a considerable scope to ameliorate water productivity and beneficial water use by adopting proper water management practices. Average CWP values for wheat, sugarbeet, vineyard, and apple vary between 0.38 and 0.55, 5.1–5.6, 1.5–1.7 and 1.9–2.3 (kg/m^3), respectively while storage changes show consistent depletion, especially during dry year, up to 117 MCM. The results indicate that a 40% reduction in blue water use is achievable to supply additional water to revive Lake Urmia. This study highlights the importance of water accounting and information flow for decision-makers, practitioners, and farming communities to define practical targets and enhance productivity in water-scarce regions.

1. Introduction

Monitoring and evaluating water resources systems is the key step for the recognition of the status of the resources, implementation of appropriate policies, and moving towards good governance by adopting the right decisions (FAO, 2018). Water scarcity and ever-increasing competing demands by different sectors have led to the over-exploitation of water resources far beyond sustainable levels. A thorough evaluation of water resources can provide decision makers with a comprehensive picture of the real status of water resources in a basin, reducing outcome uncertainty, improving decision-facilitating information and stakeholder participation (Dobbins et al., 2007; Megdal et al., 2017; FAO, 2018). Nevertheless, the required information and data for such reliable analysis is not always available at spatiotemporal resolutions. As a prerequisite for sustainable development, it is essential to acquire a clear understanding of hydrological processes, water consumptions and human-water interactions in the basin to address drought policy, stewardship issues and, planning effectively (Molden, 2013; Simons et al., 2017; FAO, 2018a; Cai et al., 2021).

With the aim of bringing together a wide range of water-related information under a coherent system, the concept of water accounting was formed by the International Water Management Institute (IWMI) to provide a standard reporting system regarding the state of water resources and water productivity for policymakers in order to bring transparency to stakeholders and avoid suboptimal outputs derived from unclear premises and decisions (Molden, 1997; Godfrey and Chalmers, 2012; Karimi et al., 2013a; FAO, 2018). Developed in the foundation of IWMI-WA, Water Accounting Plus (WA+) is a new

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framework that shares the same principles and definitions as IWMI-WA for water depletion, but with detailed mechanisms (Karimi et al., 2013a). Moreover, WA + creates bound with land use classes to distinguish manifold consumptions in the domain.

The main obstacle for applying water accounting in an operational context is the lack of related data and information, which makes it rather challenging (Karimi et al., 2013b). Even sophisticated models without improved data collection fall short of achieving improvements in water resources management (Silberstein, 2006). Remote sensing offers a promising solution with reliable estimates of hydrological state variables over large basins. A wide variety of data can be acquired from satellite measurements to fill the information gap necessary for water accounting in ungauged or poorly gauged basins including simulation of hydrological models (López López et al., 2017; Herman et al., 2018), crop management (Bastiaanssen et al., 2000; Huang et al., 2019) and meteorology (Wambura, 2020; Ghorbanpour et al., 2021), which demonstrates high capabilities of remote sensing techniques in water accounting and management as an alternative source. On the other hand, On the other hand, the limited spatial coverage of existing field data and their disperse distribution restrain their use in reliable measurement of the water cycle components at basin-scale (Teixeira and Bastiaanssen, 2012, Wambura, 2020). Another source of obtaining relevant data for accounting is through hydrological simulation and water allocation models (Pedro-Monzonís et al., 2016; Esen and Hein, 2020). Furthermore, such models can be used for the evaluation of future management scenarios under climate change or analyzing the possible trends in the past (Wijngaard et al., 2018; Rodgers et al., 2019).

Lake Urmia located in the northwestern part of Iran has been drying rapidly for the last two decades (UNEP, 2012). In recent years, up to 80% of the surface area of the lake has been rendered to the saline body (AghaKouchak et al., 2015), making the region subject to aerosol pollution and dust storms (Ghale et al., 2021). Different studies have attributed the shrinkage of Lake Urmia to anthropogenic impacts including overuse of water resources, construction of man-made dams, expansion of irrigated lands and inefficient agricultural practices (Alborzi et al., 2018; Ghale et al., 2021; Haghighi et al., 2018; Khazaei et al., 2019) while others blame the climate change as the primary reason for the desiccation (Hosseini-Moghari et al., 2020; Schulz et al., 2020). Ghale et al. (2021) investigation on the role of human activities and climate factors from 1985 to 2010 reveals that anthropogenic and climate factors have 80% and 20% effects on the desiccation of Lake Urmia, respectively. Chaudhari et al., (2018) report that by 86%, human-induced activities are responsible for the shrinkage of the lake. Moreover, the lack of information on irrigation and water use has limited the ability to effectively assess and monitor water resources, making water and productivity accounting even more challenging (AghaKouchak et al., 2015; Danesh-Yazdi and Ataie-Ashtiani, 2019).

This study aims at presenting an operational approach for practical water and productivity accounting at spatial and temporal resolutions by employing remotely-sensed data and a fully distributed hydrological model named SPHY (Terink et al., 2015) to fill the information gap in the west of Lake Urmia Basin (WLUB), linking them to WA + water accounts. Though previous studies have mainly used drought and trend analysis to describe the underlying drivers behind the shrinkage of Lake Urmia, this study intends to present the current water-related problems from the water accounting perspective. Additionally, crop water productivity (CWP) recognized as one of the Sustainable Development Goals (SDGs2.3 and SDGs6.4) for ensuring future food security, is implemented to benchmark CWP and address its gap and potentials for four major crop types including wheat, apple, vineyard and sugarbeet. This study focuses mainly on the open-access earth observation data, such as WaPOR (The FAO Water Productivity Open-access portal), MODIS satellite imagery (Moderate Resolution Imaging Spectroradiometer), and GLDAS (Global Land Data Assimilation System) (Rodell et al., 2004), as a viable source for overcoming data collecting challenges in data-scarce regions and complementing water accounts in order to paint a bigger picture of the current issues occurring in the basin regarding sustainable water resources management.

2. Material and methods

2.1. Study area and data used

Lake Urmia Basin is located at 35.6°N-38.5°N latitude and 44.1°E−47.8°E, covering a surface area of 52000 km^2 including the Lake Urmia area, 34,000 km^2 of mountainous areas, and 13,000 km^2 of flat lands. Being an endorheic basin, all the generated runoff ends in Lake Urmia through the rivers. The selected study area, the west of Lake Urmia Basin (WLUB) with a total area of around 7000 km^2, is one of the important segments of Lake Urmia Basin in terms of socio-economic and hydrological aspects. (Fig. 1). Roughly 20–30 percent of the inflows to Lake Urmia are supplied from this part of the basin. Shahar Chay dam is the main reservoir in this basin. Elevation varies from about 1250 m to 3000 m above sea level, and the average annual precipitation is approximately 300 mm in the study area.

Once the second-largest hypersaline lake in the world, Lake Urmia has undergone a dramatic decline of surface area from 5000 km^2 to below 2000 km^2 in recent years. Several anthropogenic factors such as the expansion of cultivation and aggressive development plans in conjunction with climate change have been introduced as the main drivers for the lake shrinkage (AghaKouchak et al., 2015; Bakhshianlamouki et al., 2019), and if the current situation continues, Lake Urmia will share the same fate as the Aral Sea in Eurasia (Small et al., 2001; UNEP, 2012).

With alfalfa typically planted underneath the apple trees, the most irrigated crop in the study area is apple, followed by grape, wheat, and sugar beet. The economy of the study area depends mainly on agriculture using surface and groundwater resources.

All the provided data and their sources for the case study are shown in Table 1. Only the ground stations with continuous data were considered. Two stations were used for calibration of the hydrological model and four discharge stations at the end of each river were used to estimate the total inflow to the lake. Rain gauge records were interpolated using IDW to create daily precipitation maps. All the meteorological inputs to the hydrological model were preprocessed to the extent of the study area and resampled to 1 km resolution. Land-Use Land-Cover (LULC) map was used as the base map to extract information for each category. The data preparation, processing, post-processing, and simulation were performed in pure Python programming language. Moreover, an open-source Python package named *watertools* was developed for collecting a wide range of remote sensing data from online sources to facilitate data processing and is freely available on GitHub (https://github.com/TimHessels/watertools). Fig. 2 shows the overall implementation of WA+ in this study.

Since there was no active lysimeter to record the evapotranspiration in the area, it was not possible to evaluate the WaPOR ET product directly. However, (Javadian et al., 2019) assessed and compared the WaPOR- and METRIC-based estimates of ET over Lake Urmia Basin, and found the accuracy of WaPOR ET favorable. The performance of WaPOR products relative to field measurements and other related products has been evaluated and found acceptable in terms of accuracy in different regions (FAO and Delft, 2019; Blatchford et al., 2020). WaPOR data portal is a perfect tool to be used in monitoring water use in agriculture (FAO, 2019) and assessment of irrigation schemes (Blatchford et al., 2020).

2.2. Water Accounting Plus (WA+) framework and implementation

As stated before, WA+ is a standard framework that provides information on water depletion to support integrated water resources management, elucidating the latent problems by helping water professionals to see the whole picture (Karimi et al., 2013a). WA +

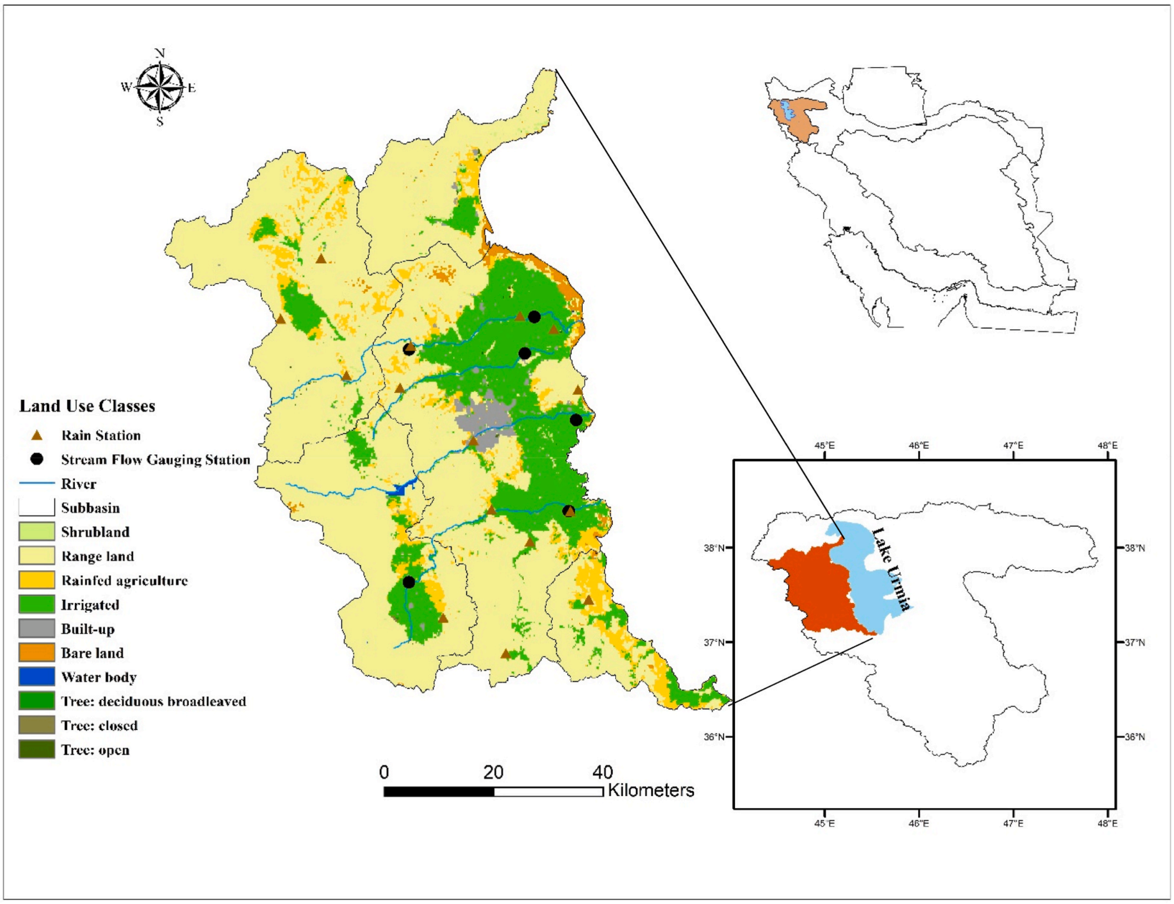

Fig. 1. Location of study area and its land use classes.

summarizes information on water resources into four sheets: (i) a *resource base sheet*, (ii) an *evapotranspiration sheet*, (iii) a *productivity sheet*, and (iv) a *withdrawal sheet*. Land use classes are categorized into four groups to address management options and information on land use with common characteristics (Karimi et al., 2013a): *Protected Land Use* (PLU), *Utilized Land Use* (ULU), *Modified Land Use* (MLU), and *Managed Water Use* (MWU). MWU refers to land that water is intentionally withdrawn, pumped or diverted by man-made infrastructure such as dams. Examples are irrigated agriculture and domestic water use. MLU represents lands that are modified by human activities. Plantation trees and rainfed crops are examples of this category. ULU considers lands with minimum human interferences. It is often used for ecosystem services that it provides (e.g. for grazing or timber). PLU includes conserved lands such as national parks.

In this study, the water accounting was carried out on annual basis for three water years, Oct 2010–Sep 2011 (normal year), Oct 2013–Sep 2014 (dry year), Oct 2015–Sep 2016 (wet year) with 320 mm, 270 mm, and 365 mm precipitation respectively, and the six-year average during Oct 2010–Sep 2016 in order to present a bigger picture of water use and productivity in WLUB. Water type was defined according to the long-term precipitation as the threshold in the study area.

2.3. Water and productivity accounting

The accounting for water and productivity is accomplished by analyzing the water sources, evapotranspiration, water withdrawal, and productivity. Water sources cover the inflows from precipitation and storage changes, outflows, and water depletion of each land use class. Here, water depletion is defined as the net water consumption, which is actual evapotranspiration (Karimi et al., 2013a). Following the common terminology of blue and green water described by Falkenmark and Rockström (2006), the actual evapotranspiration (ET_{actual}) from direct rainfall is denoted as ET_{green}, and ET_{actual} from surface and groundwater sources termed as ET_{blue}:

$$ET_{actual} = ET_{blue} + ET_{green} \quad (1)$$

Partitioning ET_{actual} into ET_{blue} and ET_{green} may be accomplished using the analytical formulation based on the Budyko hypothesis at a multi-annual scale (Simons et al., 2020 (. Since this hypothesis assumes precipitation is the only source of inflow available for evapotranspiration with negligible storage changes, the original Budyko formulation is no longer applicable in areas under human influences (Chen et al., 2020). In this study, we use the spatial ET_{green} maps derived from the hydrological model. Estimation of ET_{green} in this way will be more realistic since it accounts for human interferences and climate variabilities. For the Irrigation fields, ET_{blue} was estimated by subtracting ET_{green} from ET_{actual}.

To understand water use performance-wise, evapotranspiration is divided into three components: transpiration, evaporation from soil and water bodies, which may partially be manageable. Manageable ET includes evapotranspiration from lands with human interferences such as irrigated fields, and non-manageable ET relates to natural land uses such as grasslands and forests. Also, it contains information on how water is consumed, whether beneficial or non-beneficial. Beneficial consumption is the amount of water consumed by natural plants and agricultural crops through the transpiration process. The amount of water leaving the system with no benefit is considered non-beneficial including soil evaporation, water evaporation, interception, and conveyance losses.

As mentioned earlier, Crop Water Productivity (CWP) plays an important role in promoting sustainable development goals and ensuring food security. CWP is an indicator for the assessment of irri-

Table 1
Data description, characteristics, and sources.

Data type	Resolution	Characteristics	Source
DEM	90 m		The Shuttle Radar Topography Mission (Farr et al., 2007), http://srtm.csi.cgiar.org/
Soil	1 km	Soil information including saturated hydraulic conductivity, saturated water content and water content at pF2, pF3 and pF4.2	HiHydroSoil https://www.futurewater.eu/2015/07/soil-hydraulic-properties/
Temperature	0.25°	Minimum, maximum and average temperature maps at a daily scale	Global Land Data Assimilation System (GLDAS ver 2.1) (Rodell et al., 2004) https://hydro1.gesdisc.eosdis.nasa.gov/dods/
Precipitation	–	15 stations at a daily scale	Ministry of Energy
River discharge	–	6 stations at a monthly scale	Ministry of Energy
Water use and withdrawal records	–	–	Ministry of Energy, West Azerbayjan Regional Water Agency (WARWA)
Agricultural data	–	Crop yield, planting and harvesting date	Ministry of Jahade-Agriculture
Crop type map	30 m	–	Modares (2018)
NDVI	250 m	Time series with maps each 16-days (total 346 maps)	MOD13Q1 (Justice et al., 2002) https://e4ftl01.cr.usgs.gov
WaPOR products	250 m	Monthly maps of net primary production, actual evapotranspiration and land use-land cover (LULC)	Water Productivity Open-access Portal https://wapor.apps.fao.org/home/WAPOR_2/1

gation performance, defined as the crop yield (kg/ha) per unit of water (mm) consumed by crop (Zwart and Bastiaanssen, 2004):

$$CWP = \text{Crop yield} / 10 \sum_{SOS}^{EOS} ET_{actual} \tag{2}$$

Crop yield and ET_{actual} is accumulated on a seasonal basis, from the start of season (SOS) to the end of season (EOS) (Table 2), and 10^{-1} is the conversion factor to convert ET_{actual} from mm to m^3ha^{-1}. CWP is the reflection of the idea for “producing more food per drop of water”. CWP is an indicator convenient to be used on a comparative basis and not as an absolute value (Blatchford et al., 2019).

Net primary production (NPP) is the net amount of carbon stored by plants as biomass through photosynthesis. In agricultural applications, NPP, expressed in gC m^{-2}, is converted to Dry Matter (kg ha^{-1}) by the conversion factor 0.045:

$$DM = \frac{NPP}{0.045} \tag{3}$$

Finally, the crop yield (CY) is then derived using the Harvest Index (HI), shoot-root ratio (f) and the moisture content (θ) of the harvested product (FAO and Delft, 2019):

$$CY = f * HI * \sum_{SOS}^{EOS} DM / (1 - \theta) \tag{4}$$

HI is defined as the harvested portion of the total dry matter. HI and θ is crop- and location-specific (Zwart et al., 2010), and often adjusted accordingly (e.g. Bastiaanssen and Ali, 2003; Bastiaanssen and Steduto, 2017). For this study, these parameters are fine-tuned in a specific range (Table 3) as reported in the literature (Bastiaanssen and Ali, 2003;

Table 2
Start of season (SOS) and end of season (EOS) for main crops in the study area.

Crop	SOS	EOS
Wheat	1-Oct	1-Jul
Apple	10-Apr	20-Nov
Grape	10-Apr	10-Nov
Sugar beet	20-Mar	1-Jul

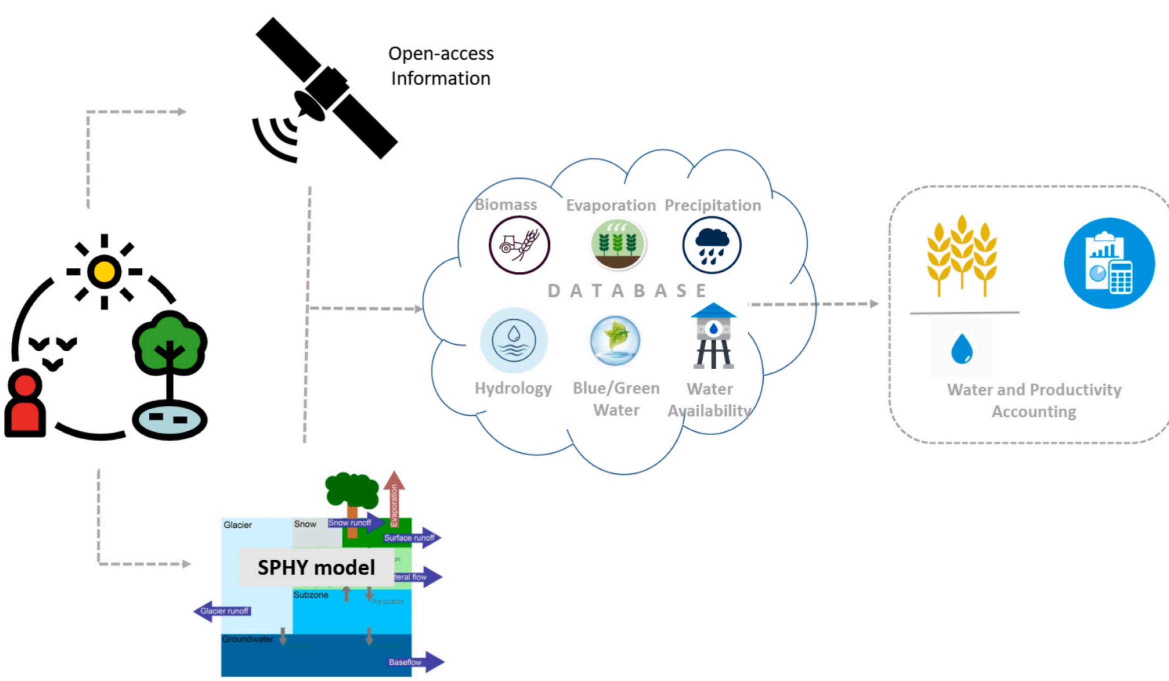

Fig. 2. Overall overview of water accounting procedure in WLUB.

Table 3
Harvest index (HI) and moisture content (θ) Crop parameters for the selected crops in the study area.

Crop	HI min	HI max	Selected HI	Moisture content (θ)	Selected θ
Wheat	0.4	0.5	0.45	0.15	0.15
Apple	0.55	0.7	0.55	0.8	0.75
Vineyard	0.4	0.6	0.5	0.75	0.7
Sugar beet	0.5	0.7	0.65	0.8	0.8

Unkovich et al., 2010; Villalobos and Fereres, 2016, FAO and Delft, 2019). Shoot-root ratio is assumed to be 0.65 as suggested by FAO and Delft (2019) for the estimation of above-ground biomass production based on WaPOR NPP product.

Water withdrawal from surface and groundwater bodies may account for consumed and non-consumed water. The non-consumed water is the difference between applied water and consumed water. These terms are based on the common definition described by Molden (1997), Perry (2007) and Perry et al. (2009). This study focuses only on water withdrawal from irrigated areas.

Given the fact that conveyance losses from canals, soil surface, return flows or percolations are not accounted for, the incremental ET or ET_{blue} is not equal to the volume of water withdrawn from surface water and aquifers. The relationship between ET_{blue} and withdrawn water for irrigation can be described as follow (Van Eekelen et al., 2015):

$$\text{Withdrawal} = ET_{blue} / \text{efficiency} \quad (5)$$

Irrigation efficiency in West Azerbaijan, which includes the selected study area in the current research, is about 21–41 percent (Ardakanian, 2005; Mahab-Ghodss, 2013). Reports show that conveyance and application efficiencies are 0.5–0.7 and 0.5–0.6 respectively, and about 20%–30% of the withdrawal is return flow (Mahab-Ghodss, 2013). Here, efficiency for Eq. (6) is assumed to be 0.7, and 25% of the total withdrawal was considered as return flow in this study. Also, our analysis based on Mahab-Ghodss (2013), Taheri et al. (2019) and the available records of water withdrawal provided by WARWA, shows that the ratio of surface water to total withdrawal in both normal and wet years is about 50–60 percent in WLUB, and 40–50% in dry years. Therefore, the fraction of 0.6 and 0.45 was considered for normal/wet and dry years in this study, respectively.

2.4. Hydrological model

SPHY (Spatial Processes in HYdrology) is a pixel-based, fully distributed hydrological model that is applied on a cell-by-cell basis (Terink et al., 2015). The soil column structure comprises two-layered soil storages (root-zone and sub-zone), and third groundwater storage with surface runoff, lateral flow and base flow as corresponding drainage components. The routing module is based on the flow recession concept. SPHY model adopts the Hargreaves method (Hargreaves and Samani, 1985) for calculating reference evapotranspiration (ET_r), and FAO crop coefficient approach (Allen et al., 1998) for potential evapotranspiration (ET_P):

$$ET_P = Kc * ET_r \quad (6)$$

Kc is crop-specific, depending on land use and cropping season. Regarding the available water in the root-zone layer, ET_{green} is calculated:

$$ET_{green} = ET_P * ET_{red} * ET_{wet} \quad (7)$$

ET_{red} and ET_{wet} are the reduction and stress coefficients for water shortage and excess condition, respectively.

For the calculation of kc, we used an NDVI-based parameterization module implemented in SPHY. SPHY assumes a linear NDVI-kc relationship using minimum and maximum NDVI and kc values for the specific period:

$$Kc = kcmin + (kcmax - kcmin) * (NDVI\text{-}NDVImin) / (NDVImax\text{-}NDVImin) \quad (8)$$

Where kc and NDVI is crop coefficient and NDVI for a given moment, respectively. Here, we assumed the following values: $kc_{min} = 0.35$, $kc_{max} = 1.2$, $NDVI_{min} = 0$, $NDVI_{max} = 0.8$. Such a dynamic parametrization for crop coefficient may result in a realistic estimates of kc at spatial and temporal resolution (Hunink et al., 2017).

All the required inputs for the SPHY model were prepared at 1 km resolution and the model was run on a daily time step. The model was calibrated from 2002 through 2009 with 1 year as initialization (year 2001), and evaluated for 2010–2015 using monthly time-series of discharge data. The calibration was carried out using shuffled complex evolution algorithm (Duan et al., 1993) implemented in a Python package named SPOTPY (Houska et al., 2015). The sensitivity analysis was carried out using FAST algorithm (Fourier Amplitude Sensitivity Test) (Saltelli et al., 1999) embedded in SPOTPY to select the most effective parameters in the calibration process and rule out the rest, which resulted in a total of seven parameters related to the SPHY model: saturated hydraulic conductivity of the root-zone, the recession routing coefficient (*kx*), field capacity of root-zone, root-zone depth, critical temperature (threshold for precipitation to fall as rain or snow), baseflow recession coefficient (αGW), and delay time for water leaving the soil to groundwater (δGW).

First, a visual comparison between the simulated streamflow values and observations was made to evaluate the predictability of the model. Next, the performance of the model was assessed for model evaluation using Nash-Sutcliffe Efficiency (NSE) and Kling-Gupta Efficiency (KGE) as the criteria.

3. Results and discussion

3.1. Simulation of hydrological processes

To simulate hydrological processes in WLUB, SPHY was calibrated for a period of nine years (2001–2009), and evaluated during 2010–2015 using monthly time-series of two hydrometric stations named Tapik and Hashem-Abad. Fig. 3 shows the simulated streamflow against the observations in conjunction with the calibration and evaluation performance indicators. The visual evaluation shows that the simulated water flows, especially the peak flow discharges, agree well with the observed discharges. The calibration period indicates an acceptable performance for Tapik and Hashem-Abad station with NSE of 0.72 and 0.74, and KGE values of 0.66 and 0.76, respectively. Likewise, the evaluation results show the NSE of 0.71 and 0.61, and KGE of 0.78 and 0.75. According to Moriasi et al. (2007), the model evaluation can be judged acceptable.

Fig. 4 represents the annual ET_{green} and total runoff maps simulated by SPHY along with WaPOR ET for 2013 have been represented in Fig. 4. High rates of ET WaPOR in Fig. 4 (bluish pixels) is related to the irrigated areas while reddish pixels show non-irrigated lands. The dynamic parameterization of crop coefficient was helpful to provide a realistic and spatial estimation of ET_{green}.

3.2. Water accounting plus (WA+) application in WLUB

Based on a remote sensing-based procedure, we applied the WA + framework in WLUB to assess the state of water resources and present four accounting sheets for three water years and the six-year average: Oct 2010–Sep 2011 (normal year), Oct 2013–Sep 2014 (dry year), Oct 2015–Sep 2016 (wet year), and averaged over Oct 2010–Sep 2016 denoted as N, D, W, and A, respectively. As long as it was feasible, the accuracy of the results was evaluated based on the available measured records of water flows.

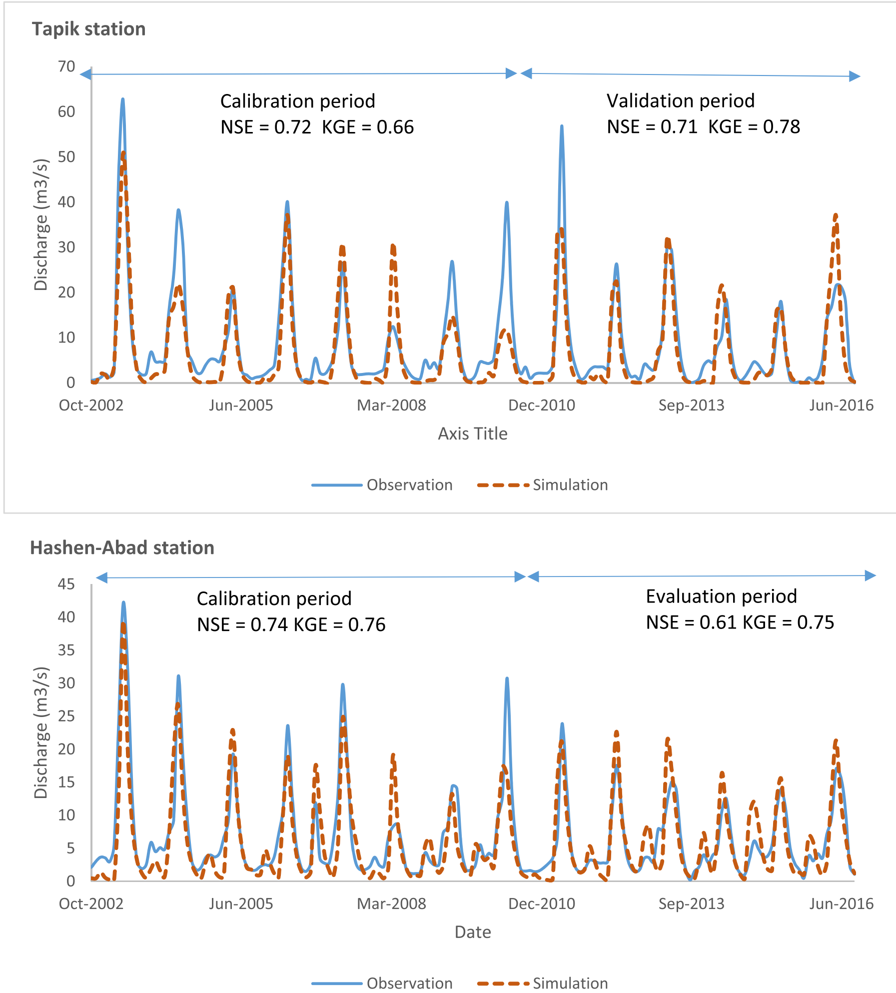

Fig. 3. Comparison of monthly simulated discharge versus measured results at two gauging stations for the calibration and evaluation period.

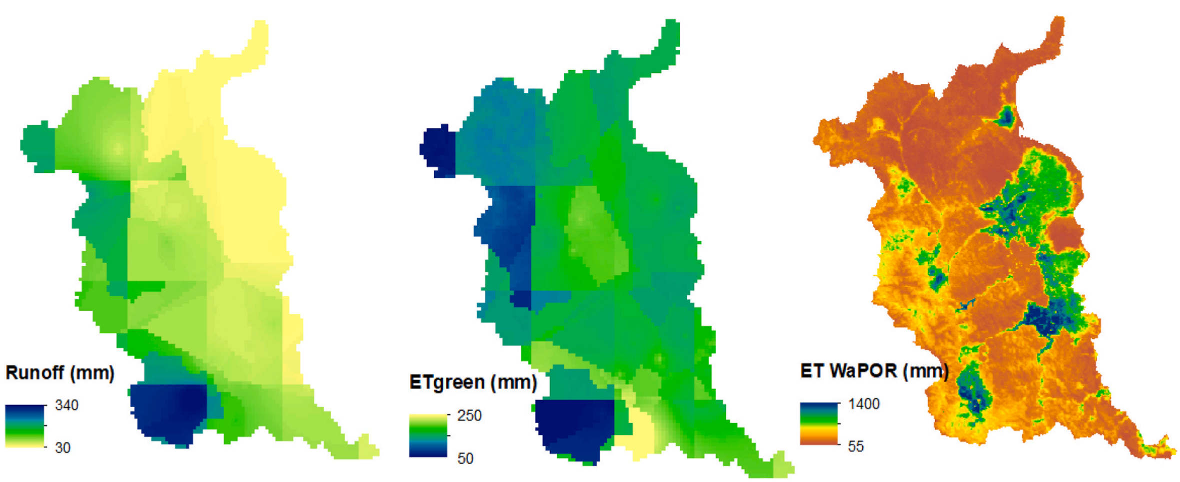

Fig. 4. Maps of streamflow, ET_{green} (based on the SPHY model) and ET_{actual} derived from WaPOR.

3.2.1. *Assessing water balance components and storage changes*

Resource base sheet for the study period is shown in Fig. 5. By considering each water type, the variation in the components changes accordingly. That is, the more water becomes available, the higher consumption occurs. Of the total precipitation in the catchment, about 55 percent is landscape ET (ET_{green}), which is related to the natural processes, only 10 percent flows into the Lake, and the rest belongs to ET_{blue} from MWU. Exploitable water is the available water that is potentially allocable. Lack of enough water in the dry year puts significant pressure on the surface and groundwater storage so that the deficit of water is compensated for. As a result, it undergoes −117 MCM (Million Cubic Meter) of storage depletion. During the wet year, due to

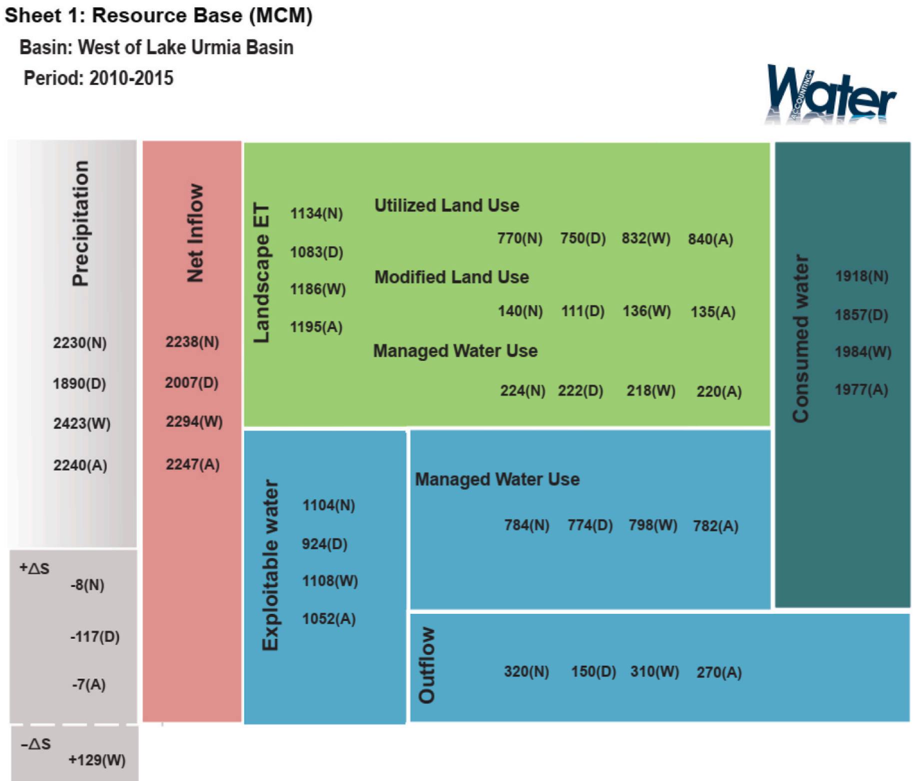

Fig. 5. WA + resource base sheet (MCM/year) for the time period of Oct 2010–Sep 2016

the increase in precipitation, the storage is replenished to some extent. However, the overall water balance is negative in WLUB. As observed, storage depletion for the normal and six-year average are −8 and −7 MCM, respectively, which reveals a consistent decline in the water storage.

Table 4 shows the recorded aquifers and reservoir water storage changes as well as estimated storage change (see Fig. 5) in WLUB for further investigation. It is evident that the WA + estimates are highly in line with these records, following the same trend. Also, the six-year average of storage changes is −3 MCM. The slight difference between WA + estimates and the available data on the storage depletion can be attributed to the fact that the WA + estimations account for soil moisture depletion while the ground measurements miss this component.

Fig. 6 illustrates the accumulated groundwater drawdown (m) from 1981 to 2015 for Urmia plain aquifer. It can be seen that since 1996, it has been on a downward trend. It is worthwhile to mention that the long-term groundwater storage depletion for Urmia plain is −5.5 MCM according to the records.

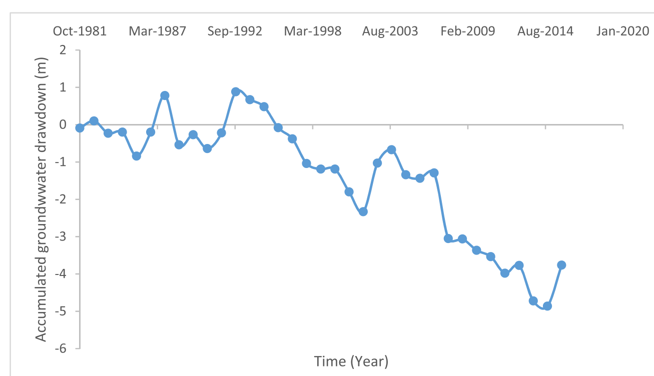

Fig. 6. Accumulative groundwater drawdown for Urmia aquifer for the period of 1981–2015.

3.2.2. *Analyzing evapotranspiration, water availability and beneficial water consumption*

Evapotranspiration sheet quantifies water consumption for different land uses in detail. On the right side of the sheet, beneficial and non-beneficial water consumptions are presented. To be specific, transpiration from crops and natural plants contribute to biomass production and thus are considered as beneficial evapotranspiration (agricultural and environmental beneficial) whereas evaporation from soil or reservoirs, etc. is non-beneficial evapotranspiration.

According to the evapotranspiration sheet in Fig. 7, about 50 percent of the total ET is originated from human-managed processes. Almost half of the water consumed in ULU and MLU is lost to evaporation, while in MWU this ratio is approximated around 30%. In addition, roughly 38% of the consumed water leaves the basin through evaporation without creating any benefits. The results show that a considerable portion of water use in WLUB produces limited benefits while the basin suffers water scarcity and environmental burdens. Similarly, AghaKouchak et al. (2015) also report that agricultural activities in the study area with low efficiency are one of the major drivers affecting sustainable development and management plans. They suggested that a recovery plan

Table 4
Measured surface and groundwater storage change (MCM) along with the estimated storage change in the study area.

Source type	2010	2013	2015	Average storage change (2010–2016)
Aquifers	−5.5	−54.1	60.8	−3.1
Reservoir	3	−50	45	0.1
Storage change	−2.5	−104.1	106.8	−3
Estimated storage change	−8	−117	128	−7

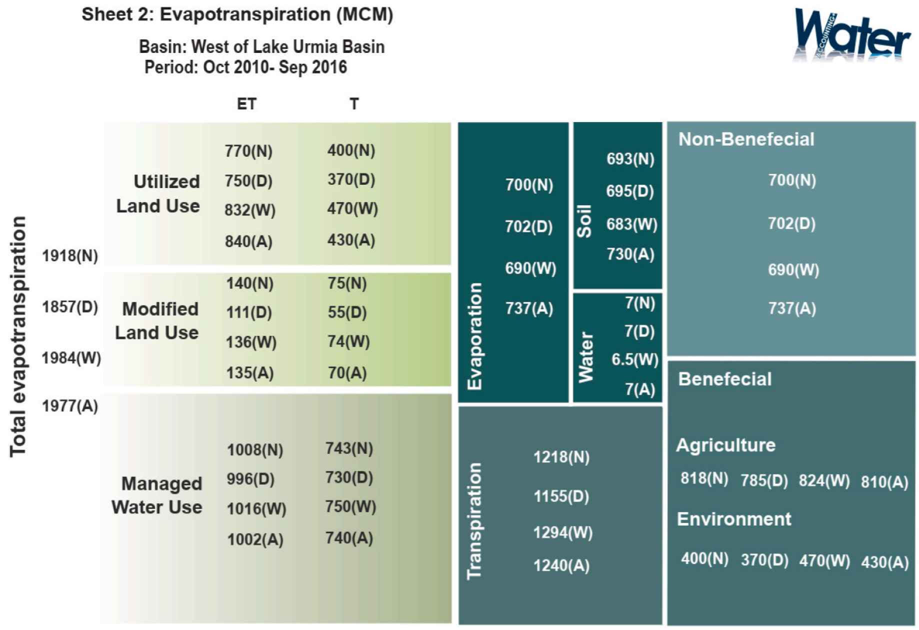

Fig. 7. WA + evapotranspiration sheet (MCM/year) for the time period of Oct 2010–Sep 2016

with emphasis on reducing irrigation water demand and increasing efficiency should be established to sustain productivity in the long run.

According to the sheet 1 (Fig. 5), less than 50% of inflow can be managed for socio-economic, environmental and agricultural needs, and the rest is lost as landscape ET, implying that climate change variables could limit the exploitable water to some extent. Most importantly, a significant imbalance between demand and exploitable water could be imminent as a result of the projected increase in population, expansion of irrigated lands with lower efficiency and aggressive development plans. This is in agreement with the studies carried out by AghaKouchak et al. (2015) and Danesh-Yazdi and Ataie-Ashtiani (2019) where they warn that continuation of the anthropogenic activities and climate change will exacerbate water shortage and environmental issues in Lake Urmia basin. This may result in a drastic pressure on groundwater to compensate for water shortage as it is discerned from Fig. 6. Therefore, there is an urgent need for mitigation of pressure on water resources, especially aquifers during dry years, through proper management and adaptation strategies according to the current situation.

3.2.3. *Productivity accounting and potentials for filling the gap*

Productivity sheet for the selected crops in WLUB is shown in Fig. 8 regarding each cropping season for 2010, 2013, and 2015. The estimations of the components in this sheet is based on the crop type map from (Modares, 2018), LULC, evapotranspiration, and net primary production maps provided by WaPOR portal. Productivity sheet is mainly designed for the assessment of agricultural production in terms of water productivity, providing extra attention to the cropping system and identifying opportunities for ameliorating productivity and efficiency.

As it can be seen in Fig. 8, the estimated yield based on the remotely sensed compares well with the reported yield by Centre of Ministry of Jahade-Agriculture. The slight difference between the reported and estimated yield can be attributed to the errors in the classification of crop type map and remote sensing-based estimates of crop yield. Overall, according to the productivity sheet, the remote sensing-based estimates of crop yield are in acceptable ranges. At the bottom of the productivity sheet, CWP of each crop for the corresponding year is calculated.

As stated earlier, CWP values should be used in a relative manner not as absolute values. Therefore, proper standard values are vital to benchmark CWP values and evaluate the results derived from the progress of CWP improvements so that decision-makers become aware of target values and define right decisions and policies accordingly.

Sheet 3: Agricultural services
Land productivity (ton/ha) and water productivity (kg/m3)

Basin: West of Lake Urmia Basin
Period: Oct 2010- Sep 2016

	Crop			
	Wheat	Sugarbeet	Vineyard	Apple
Land productivity	2.3(N) 2.6(D) 3(W)	53(N) 50(D) 55(W)	11.9(N) 10.5(D) 12.1(W)	20(N) 19(D) 22(W)
Observed yield	2.7(N) 2.8(D) 3.4(W)	54(N) 58(D) 59(W)	12.3(N) 11.7(D) 14(W)	17(N) 18(D) 20(W)
Water productivity	0.38(N) 0.44(D) 0.55(W)	5.3(N) 5.1(D) 5.7(W)	1.7(N) 1.5(D) 1.7(W)	2.0(N) 1.9(D) 2.3(W)

Fig. 8. WA + productivity sheet for the time period of Oct 2010–Sep 2016

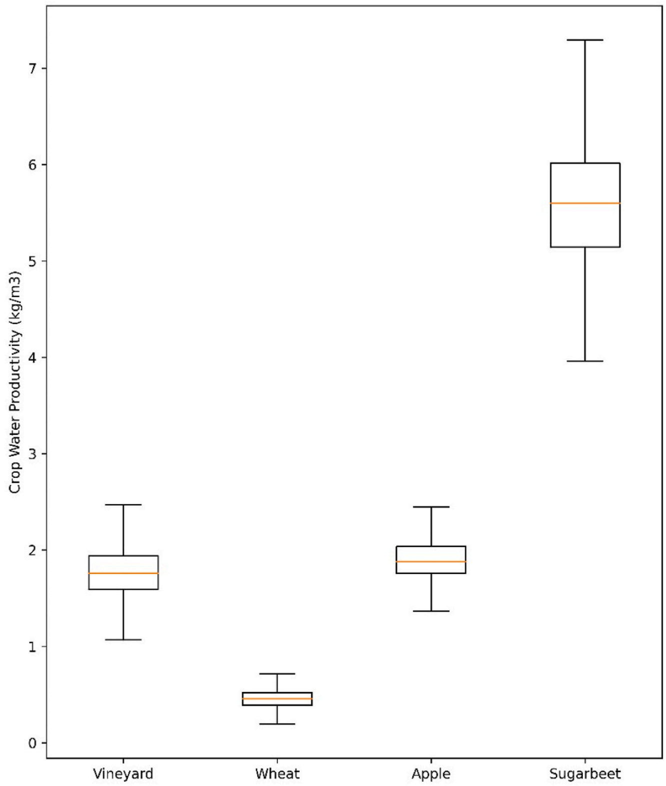

Fig. 9. Spatial variability of crop water productivity (CWP) for the selected crops in WLUB.

Fig. 9 shows the box-plot for CWP for major selected crops in the study area. As it can be perceived, average CWP for vineyard, wheat, apple and sugarbeet are distributed around 1.7, 0.5, 2 and 5.5 (kg/m^3). However, some fields with better on-farm practices display higher CWP values, which can be discerned in Fig. 9. In fact, CWP could potentially be optimized by 60% for wheat, 47% for vineyard, 26% for apple and 30% for sugarbeet. CWP gap may be bridged towards upper CWP percentiles either by increasing crop yield with the same water use or decreasing water use while sustaining crop yield. The latter could significantly reduce water consumption in WLUB as this approach is most relevant in water scarce regions (Blatchford et al., 2018). This proves that it is feasible to improve water productivity by adopting proper on-farm water management practices. This sheet shows that agricultural sector in WLUB is neither productive nor efficient. Studies show that applying supplemental irrigation in agricultural areas does not necessarily improve CWP, on the contrary, a reduction in irrigation may result in significantly higher CWP (Ilbeyi et al., 2006; Geerts and Raes, 2009).

3.2.4. *Water use efficiency and opportunities for reviving Lake Urmia*

Fig. 10 shows WA + withdrawal reporting sheet. This sheet focuses on blue water consumption in irrigated lands. The non-consumed water returns to water resources as return flow. Although the return flows may be assumed to be lost, they are typically recovered or reused in the catchment (Wu et al., 2019). Incremental ET in wet year is high compared to the other years due to the increasing cultivation and water availability. In wet and normal years, water abstraction from surface water (river and reservoir) is the main source for irrigation, but in dry year, as water becomes scarce, farmers turn to extract required water from groundwater resources. Table 5 demonstrates groundwater withdrawal estimates (see Fig. 10) and records from aquifers in WLUB. Based on this table, water withdrawal from aquifers reaches its pinnacle (606 MCM) in the dry year 2013, while in the normal year and wet year it is 341 and 472 MCM, respectively. The main reason that the groundwater consumption in wet year is more than normal year can be related to the cropping system, increase in demand and unauthorized pumping in WLUB. Notably, WA + -based estimates of groundwater withdrawal corresponds well with the records.

By comparing ET_{blue} (Incremental ET) with the results derived from CWP (see Fig. 9), it becomes apparent that consumed water could be reduced accordingly. In other words, up to 26–60% of on-farm

Table 5
Estimated and measured records of groundwater withdrawal during 2010–2015 in the study area.

Year	2010	2013	2015	2010–2015
Groundwater withdrawal (MCM)	341	606	472	470.8
Estimated groundwater withdrawal (MCM)	427	580	434	423

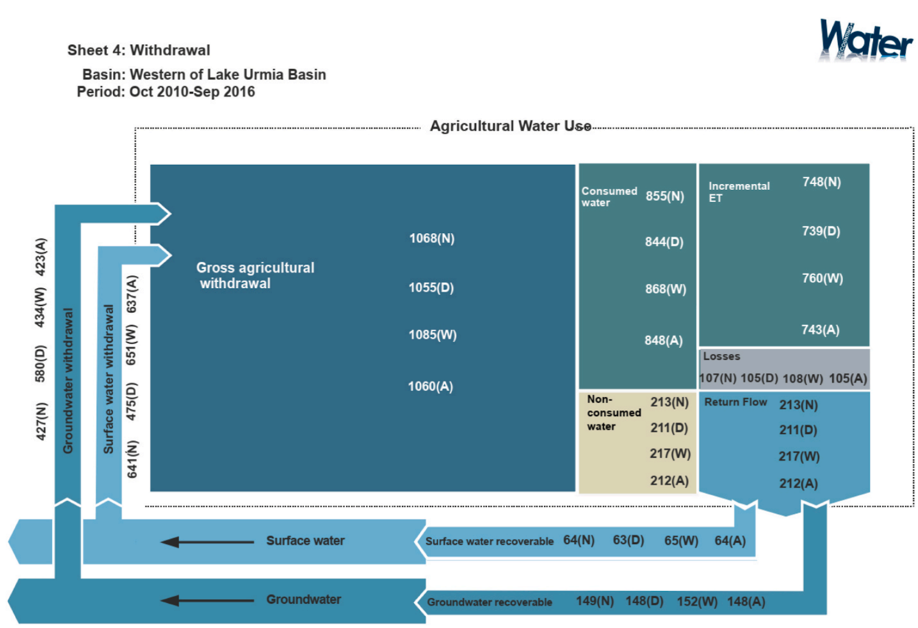

Fig. 10. WA + withdrawal sheet (MCM/year) for the time period of Oct 2010–Sep 2016

consumption, which is none-beneficially lost through the application losses such as weed transpiration or soil evaporation, could have been potentially saved if water had been used more efficiently. One of the main objectives of the Lake Urmia restoration program are to decrease agricultural water consumption by 40%, which has the highest contribution in sustaining the lake's ecological level (Danesh-Yazdi and Ataie-Ashtiani, 2019). From this point of view, it is feasible that such a reduction could be achievable as the results perceive it. Proceeding on these premises, on average, 300 MCM additional water potentially can stream to the lake. Therefore, it can be argued that proper water-efficient practices should be implemented to increase beneficial blue water consumption with economic advantages for farmers.

3.2.5. *Application of WA + for promoting sustainable development*

WA + facilitates the decision-making process by providing a clear understanding of the current status of water resources to diagnose water-related issues and promote sustainable management for the future. Sheets 1 and 2 clearly show that water is not used beneficially while the continuation of the imbalance between water supply and demand negatively contributes to the water scarcity in WLUB. The productivity sheet indicates that the agricultural sector possesses significant capacities for improving CWP and thus, water-saving strategies should be applied to increase efficiency and productivity. The evidence from Sheet 4 proves that blue water use can be decreased by enhancing green water use in exchange for blue water. The substitution between green and blue water is an effective adaptation for achieving sustainable management in regions with water insecurity (Zhao et al., 2021). With such systematic presentations of the current status, it is possible to track the progress of sustainable development goals and adapt proper policy guidelines. Studies also note that any encouragements and support to maximize beneficial water use should be avoided in the absence of a proper water accounting system and controlled water allocations (Pfeiffer and Lin, 2014; Perry et al., 2017; Grafton et al., 2018). In fact, any projected development trajectories and transformational change towards sustainable water resources management may be accompanied by transparent water accounting, accurate assessment and evaluation of possible trade-offs and outcomes.

4. . Summary and conclusions

The objective of this research was to implement the WA + water accounting framework in the west of Lake Urmia to understand the current complexities associated with water resources management. This is an essential step to provide professionals and stakeholders with necessary information on water use, availability, and distribution within time and space for supporting decision making and promoting effective policy actions. In order to make the water accounting procedure applicable even in data-scarce regions, the majority of data used in this research was obtained from remotely-sensed and open-access earth observation data. The SPHY hydrological model and remote sensing datasets were integrated to extract relevant information for compiling WA + reporting sheets.

Owing to the high consumption rate in the agricultural sector, storage changes were negative in WLUB. In dry years, over-exploitation from groundwater takes place as surface sources wane, causing a significant decline in groundwater storage. Assessment of crop water productivity (CWP) in WLUB revealed that there is a considerable scope to ameliorate water productivity and water use efficiency by implementing best on-farm practices. Analysis indicates that the idea of a reduction in agricultural water use by 40% as outlined by the Lake Urmia restoration program is not out of reach.

Validation of the results derived from the WA + procedure showed acceptable accuracy against ground measurements, which demonstrates that remote sensing datasets are of great value, especially for poorly gauged regions. Also, WaPOR-based estimates of crop yield exhibit great accuracy compared to in-situ observations. Nevertheless, uncertainties and errors in satellite measurements and remote sensing-based models are inevitable. Such errors and biases can bring about overestimation or underestimation of estimated variables, suggesting that future studies continue to address and mitigate these errors.

We presented a practical approach to estimate the WA + components and water accounts. Though the framework is applied to the west of Lake Urmia, it can be extended to the entire basin and respond to the current issues concerning the future of the basin. The evidence concurs that the continuation of the current trend may exacerbate the future of the area with unforeseen socio-economic disadvantages. It calls for action to address the governance and stewardship issues as well as coordination among different institutions and stakeholders to preclude unintended outcomes with lasting consequences. Water accounting is an effective tool for identifying sustainable development opportunities and facilitating decision making and governance challenges at local and global scales. Water accounting is a prerequisite for integrated water resources management and pre-assessment of any measure before being implemented. It is highly recommended for areas facing water-related problems.

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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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