Modeling Earth Systems and Environment (2024) 10:1203–1213
https://doi.org/10.1007/s40808-023-01841-z

ORIGINAL ARTICLE

# Estimating agricultural water productivity using remote sensing derived data

Celine Safi[1] · Sajid Pareeth[1] · Seleshi Yalew[1] · Pieter van der Zaag[1] · Marloes Mul[1]

Received: 25 April 2023 / Accepted: 6 July 2023 / Published online: 15 July 2023


## Abstract

The 2030 Agenda aims at ending extreme poverty, inequality, injustice and climate change. Progress is evaluated through a set of Sustainable Development Goals (SDGs), targets and indicators. However, there are various challenges affecting regular and timely reporting. Remote sensing (RS) derived data has been shown to provide a valuable complementary data source in reporting SDGs. This study focuses on how RS derived data could support SDG 6 related to water, and in particular SDG indicator 6.4.1 - change in Water Use Efficiency (WUE) over time presented in USD per $m^3$ of water withdrawn. Although water withdrawals cannot be monitored through RS, water use in agriculture, globally withdrawing the largest amount of water, can be monitored through RS based evapotranspiration.

Two approaches were modelled to compute the progress of SDG 6.4.1 in the agricultural sector. The first approach uses the standard equation of SDG 6.4.1, replacing water withdrawal with blue evapotranspiration in the irrigation sector. The second approach distributes the gross value added to the gross domestic product by irrigated agriculture according to the land productivity in irrigated agriculture as observed by RS. The results of these two approaches were compared to the standard way SDG 6.4.1 is calculated. The analyses were carried out for Lebanon, which faces critical water challenges while experiencing a difficult economic and political situation.

The results for Lebanon show that the different approaches to estimate $A_{wp}$ show similar trends as $A_{we}$, initially showing an increasing trend followed by a sharp decline in 2019 due to the deteriorating economic situation in the country. However, the absolute values differ substantially, largely due to discrepancies between the estimated irrigated area from RS data and the static data reported in AQUASTAT. The results illustrate the spatial variability of $A_{wp}$ in Lebanon, with the area that contributes significantly to the agricultural production nationally (Bekaa and Baalbek) shows lower land and water productivity compared to irrigated areas in other governorates. The contribution of agriculture to the overall SDG 6.4.1 indicator was relatively small, although agriculture is a major consumer of water.

**Keywords** Water productivity · Remote sensing · SDG · WaPOR · Earth Observation

## Introduction

In 2015, the United Nations (UN) together with the heads of the state of 193 countries agreed to adopt the 2030 Agenda as a response to global challenges such as population growth, changing lifestyles, and climate change which deplete resources and stress the earth system (Bhaduri et al. 2016). They were built on the achievements of the Millennium Development Goals (MDGs) and are far more ambitious in scope of global development (Purvis et al. 2019). It consists of 17 Sustainable Development Goals (SDGs), 169 targets and 231 indicators (UN 2017; WWAP and UN-Water 2018; Eisenmenger et al. 2020). The 2030 Agenda now also incorporates a specific target focussing on achieving sustainable management of clean water and sanitation (SDG 6) (UN 2015). This is in recognition of the fact that water availability supports economic growth and the wellbeing of people and has been identified as one of the main challenges for human survival (Steffen et al. 2015).

SDG 6 consists of two indicators, one focusses on overall water scarcity (SDG indicator 6.4.2) and the other one

✉ Marloes Mul
m.mul@un-ihe.org

[1] Department of Land and Water Management, IHE Delft Institute for Water Education, PO Box 3015, Delft 2601 DA, the Netherlands

focusses on efficient use of water from an economic perspective (SDG indicator 6.4.1). These indicators take into consideration water withdrawals of three main economic sectors – agriculture, industries and services and compare them to their economic contribution to the economy (6.4.1) and the total water available (6.4.2) (UN-Water 2021). SDG indicator 6.4.1 is a composite of the water use efficiency (WUE) of the three sectors, expressed into economic value added per unit of water withdrawn (in USD/$m^3$). As a composite, this indicator is dominated by the high value, low water use sectors such as industry and therefore to be able to provide sector specific recommendations, literature suggests to evaluate each sector's water use efficiency separately (Hellegers and van Halsema 2021).

Monitoring WUE for the agricultural sector, and thus Agricultural Water Use Efficiency ($A_{we}$), is also important for SDG indicator 6.4.2 as it is responsible for over 70% of the globally withdrawn water (FAO 2015). Even though the methodology for monitoring SDG indicator 6.4.1 has been clearly defined (FAO 2019), there is an ongoing debate on the rationale for using water withdrawn as it doesn't take into consideration return flows which could be used elsewhere or is returned to the environment (Hellegers and van Halsema 2021; Vanham 2018). An alternative recommended approach therefore is to evaluate the agricultural productivity against the water consumed in the form of evapotranspiration (ET) (Hellegers and van Halsema 2021), which is also known as agricultural water productivity. One of the discrepancies between considering water withdrawals compared to water consumed is that the latter includes water stemming from rainfall. It is therefore important to consider the water consumed from irrigation only (also called blue ET ($ET_b$) (Chukalla et al. 2015).

The progress of the SDGs is monitored by the countries themselves through comprehensive data collection (Connor 2015; Reyers et al. 2017). However, this is a costly effort and most countries do not collect this information on a regular basis (Roopnarine et al. 2019). In 2019, OECD (2019) reported that on average countries reported on just 55% of the SDG indicators since 2015, with only few countries providing data for all years. The low level of progress compared to the MDG monitoring, which was 68% in 2015, can be explained by the fact that the SDGs has more indicators (231 vs. 48) and more complex computing workflows (MacFeely 2018).

Remote Sensing (RS) is considered as a reliable source of data which can support the monitoring and reporting of the SDG indicators on a regular and near-real time basis (Calera et al. 2017; Hakimdavar et al. 2020; Kavvada et al. 2020). FAO, one of the custodian agencies for reporting several SDGs is therefore actively promoting the uptake of amongst other data, the use of Earth Observation (Gennari et al. 2019). Open data platforms such as Global surface water explorer (Pekel et al. 2016) and the Freshwater Ecosystems Explorer (Lu et al. 2021) contribute significantly to the periodical estimation of indicators related to SDG 6.Recent publications demonstrate the use of satellite data in mapping of wetlands contributing to SDG 6.6.1 (Weise et al. 2020), mapping land degradation to support SDG 15 (Giuliani et al. 2020), and collect evidence on slavery from space supporting SDG 8 (Foody et al. 2019; Boyd et al. 2018). RS based ET has been used to monitor various aspects of water management such as estimation of water allocation to various sectors (Droogers et al. 2010) and irrigation performance assessment (Karimi et al. 2019), however, the use of RS based ET for monitoring the SDGs is still relatively new (Biancalani and Marinelli 2021). There are various RS based ET products available which can be utilised to support reporting of SDG 6 indicators (e.g. SSEBop: Senay et al. 2013; CMRSET: Guerschman et al. 2009; SEBS: Chen et al. 2013; MOD16: Mu et al. 2011).

There are multiple global initiatives globally to coordinate the efforts of monitoring SDG's using RS data. One of the major initiatives is Group on Earth Observations (GEO) which is a partnership of more than 100 national governments and organizations with major objective being main streaming Earth observation data for decisions and actions towards sustainable development (Anderson et al. 2017). GEO initiated the development of Global Earth Observation System of Systems (GEOSS: Nativi et al. 2020) with the Committee on Earth Observation Satellites (CEOS) contributing to the technical side of the development including initiatives to promote RS for SDG monitoring such as EO4SDG (Kavvada et al. 2022).

In this paper, we investigate how RS can support monitoring of SDG 6.4.1 on water use efficiency. We modelled the agricultural component of SDG 6.4.1. with RS data using two different approaches: (i) using volume of consumptive water use (actual evapotranspiration) and (ii) using the water productivity concept. We applied both approaches to the country Lebanon as a case study and compared the results to the standard calculations using AQUASTAT data.

## Methodology

### Case study: Lebanon

Lebanon has an area of 10,452 $km^2$ and is divided into 7 governorates (Fig. 1). The annual rainfall ranges between 700 and 1,500 mm/year, averaging 910 mm/year. Lebanon is considered rich in water resources compared to its surrounding countries, with 12 permanent watercourses with a

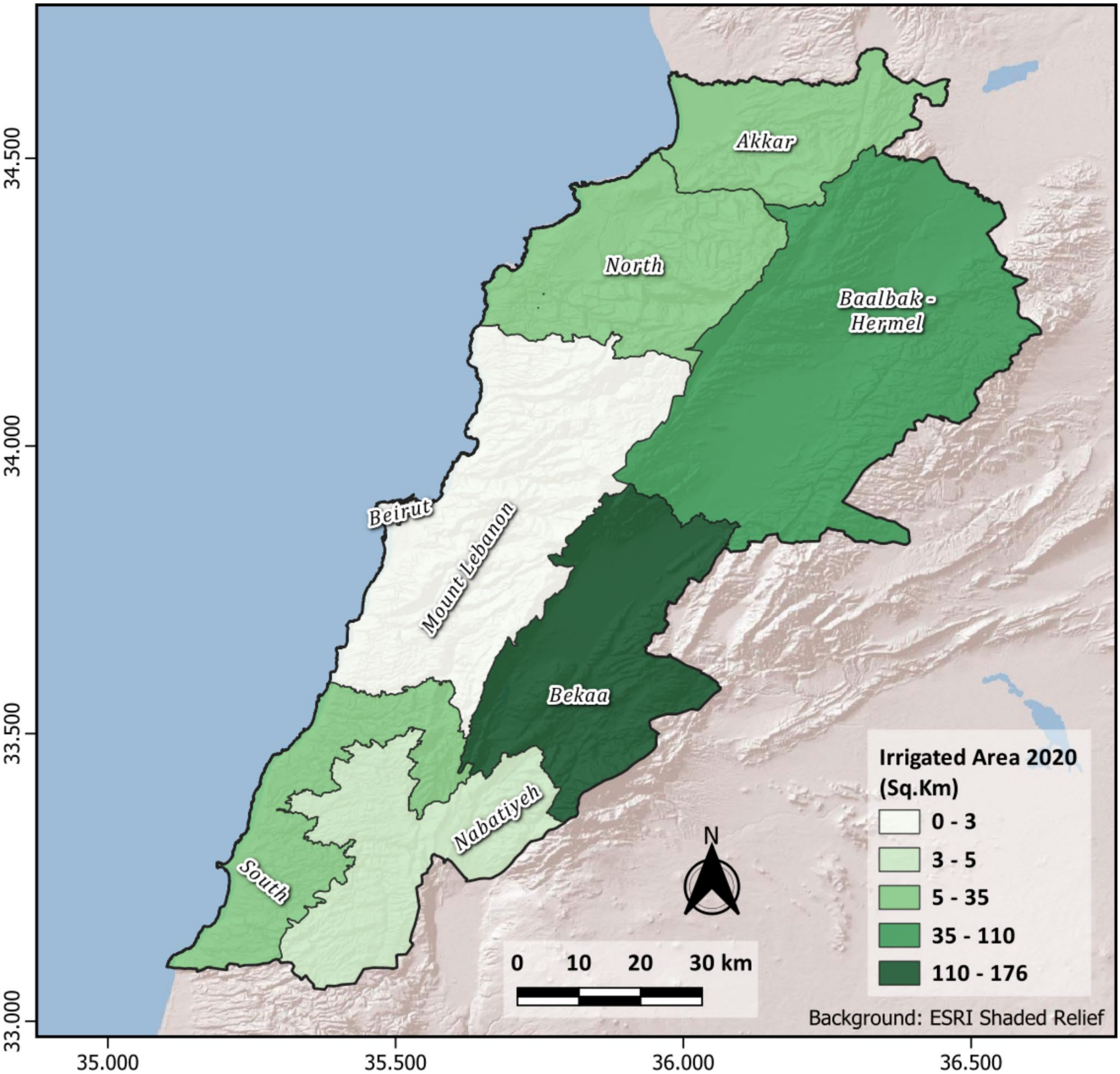



**Fig. 1** Map of Lebanon showing distribution of irrigated areas in governorates in 2020. (source of data: WaPOR)

discharge of 3,542 million $m^3$/year along with 2,000 major springs which provide 630 million $m^3$/year (Shaban 2020).

Agricultural lands occupy more than one third of the area (3,600 $km^2$), of which 1040 $km^2$ is equipped for irrigation and 900 $km^2$ was actually irrigated as recorded in the 1998 census (FAO 2008). About 42% this area is located in the Bekaa Valley (FAO 2008). The main irrigated crops are wheat (24%), potatoes (18%), citrus (16%) and vegetables (14%). The source of water for irrigation is evenly distributed between surface water (48%) and groundwater (52%) (Shaban 2014). The agricultural sector contributes 5% of GDP and employs 8% of the labour force (FAO-Lebanon 2022).

## Methods

This study focuses on modelling the agricultural component of the SDG indicator 6.4.1 ($A_{we}$) using two different RS-based approaches ($A_{wp}$) and compare the results to the standard equation of $A_{we}$. The analysis was conducted using annual timesteps for a 5-year period starting with the baseline for the SDG in 2015 to 2020. We used a geospatial modelling approach (Chen et al. 2020; Koubarakis 2023) to provide a comprehensive analysis of water use efficiency and productivity in agricultural systems.

The standard equation for the agricultural component of SDG indicator 6.4.1 ($A_{we}$) is defined in FAO (2019) as:

$$A_{we} = \frac{GVA_a(1 - c_r)}{V_a} \tag{1}$$

Where:
$A_{we}$ represents the water use efficiency of irrigated agriculture in USD/m$^3$.

$GVA_a$ is the Gross Value Added to gross domestic product (GDP) by agriculture in USD/year.$c_r$ is the proportion of agricultural $GVA_a$ produced by rainfed agriculture.

$V_a$ is the volume of water used by the agricultural sector in m$^3$/year.

The equation focusses on the gross value added to GDP by irrigated agriculture (represented by $GVA_a$* (1 - $c_r$)) as this is where the water withdrawals contribute to. This ensures that the $A_{we}$ calculation focuses solely on the efficiency of the water withdrawals in agriculture.

For the RS-based approaches for modelling the agricultural component of SDG 6.4.1, we developed two approaches. The first approach modifies Eq. 1 by replacing the water withdrawn ($V_a$) with the total volume of the blue water consumed ($V_{ETb}$) derived from water supplied through irrigation (Eq. 2).

$$A_{wp1} = \frac{GVA_a\,(1 - C_r)}{V_{ETb}} \tag{2}$$

Where:$A_{wp1}$ is the water productivity of irrigated agricultural in USD/m$^3$ using approach 1

$V_{ETb}$ is the volume of water consumed by irrigation (blue ET) in m$^3$/year.

To estimate $V_{ETb}$ the first step is to separate ET into water from rainfall (ET green) and irrigation ($ET_b$) (Chukalla et al. 2015). Various models exist to separate ET, which have different level of complexity and without clear validation data it is not possible to identify the best model (Msigwa et al. 2021). Therefore, for this purpose, we used a rather simple model by considering effective rainfall as ET green with the remainder of ET to be attributed to $ET_b$. The effective rainfall and $ET_b$ is calculated on a monthly basis and summed to an annual value using Eq. 3:

$$ET_b = \sum_{n=1}^{12} max(ET - P_e, 0) \tag{3}$$

Where:
$ET_b$ is in mm/year,
ET is in mm/month, and
$P_e$ is effective rainfall in mm/month.

$P_e$ is computed from monthly precipitation by applying the conditions in outlined in the Eq. 4, adapted from Brouwer and Heibloem (1986):

$$Pe = \max(0.8 * P - 25, 0),\ \text{if P} > 75\ \text{mm/month} \tag{4}$$
$$Pe = \max(0.6 * P - 10, 0),\ \text{if P} \leq 75\ \text{mm/month}$$

Annual $ET_b$ is then converted to volume ($V_{ETb}$) in m$^3$/year by multiplying the average $ET_b$ of the irrigated areas ($\bar{ET_b}$) with the irrigated area ($A_{irr}$) as given in Eq. 5.

$$V_{ETb} = \overline{ET_b} \times A_{irr} \tag{5}$$

The second approach starts with calculating Biomass Water Productivity ($WP_b$) at pixel scale in kg/m$^3$. $WP_b$ is derived from dividing the Total Biomass Production or Land Productivity (LP in kg/ha) by the irrigation water consumed ($ET_b$). This is represented by the following equation (Eq. 6):

$$WP_b = \frac{LP}{ET_b} \tag{6}$$

$WP_b$ is converted to economic water productivity by multiplying the average price per unit of annual biomass production from irrigated agriculture as presented in the following equation (Eq. 7):

$$A_{wp2} = WP_b \times \bar{p} \tag{7}$$

Where:
$A_{wp2}$ is the agriculture water productivity in USD/m$^3$ using approach 2.

$WP_b$ is the Biomass Water Productivity in kg/m$^3$.

$\bar{p}$ is the average value added in USD per kg of annual biomass production

The average price is obtained by dividing $GVA_a$ of irrigated agriculture with the total LP of the irrigated area. This second approach is modelled at the grid or pixel level, which fills the gap that national level indicators are not able to provide all the required information for decision makers (Giuopponi et al. 2018; Saner et al. 2020). The analyses enables the spatial disaggregation of the results to sub-national levels (governorates and villages), and thereby providing an assessment of spatial variability of $A_{wp}$ within a country.

**Table 1** Data and corresponding sources employed in each of the approaches

| Variables | Description | Units | Temporal resolution | Spatial resolution | $A_{we}$ | $A_{wp1}$ | $A_{wp2}$ | Source |
|---|---|---|---|---|---|---|---|---|
| $V_a$ | Volume of agricultural water withdrawal | $m^3$/year | Static | Country | X | | | AQUASTAT |
| $GVA_a$ | Gross Value added to GDP from agriculture | USD/year | Yearly | Country | X | X | X | AQUASTAT |
| $c_r$ | Proportion of $GVA_a$ produced by rainfed agriculture | - | Static | Country | X | X | X | AQUASTAT |
| LCC | Land cover classification – irrigated & rainfed area | -- | Yearly | 100 m | | X | X | WaPOR |
| ET | actual EvapoTranspiration and Interception | mm/month | Monthly | 100 m | | X | X | WaPOR |
| P | Precipitation | mm/month | Monthly | 5 km | | X | X | WaPOR |
| LP | Land Productivity[2] | kg/ha/year | Yearly | 100 m | | | X | WaPOR |

[2] In WaPOR the layer is called Total Biomass Production.

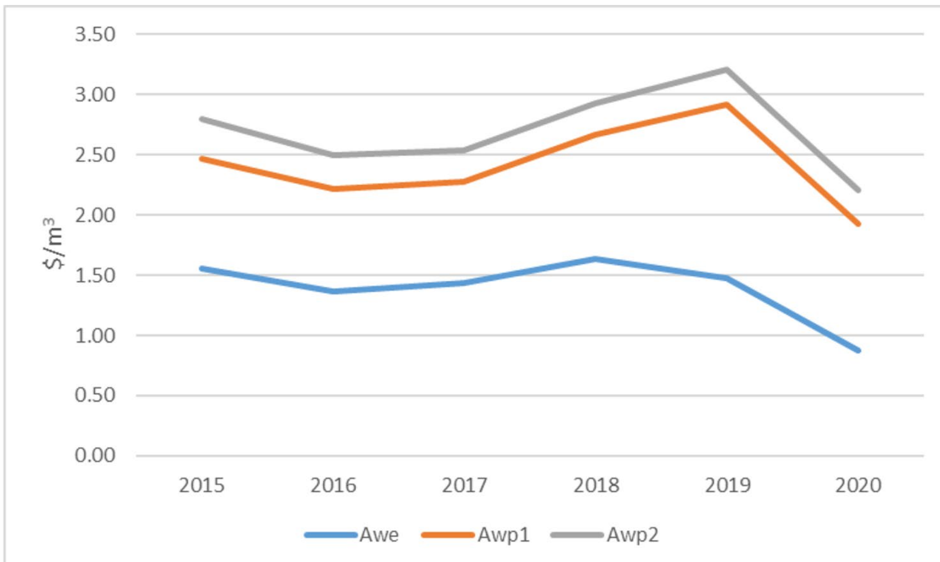



**Fig. 2** Comparison between $A_{we}$ and the two approaches for estimating $A_{wp}$

## Data sources

Table 1 shows an overview of the data used in this research and for each approach, it consists of both secondary data and RS derived data. $A_{we}$ is calculated using solely the secondary data from AQUASTAT (FAO 2022). This secondary data consists of annual country-level data on agricultural water withdrawals ($V_a$), gross value added to GDP from agriculture ($GVA_a$), and the Proportion of $GVA_a$ produced by rainfed agriculture ($c_r$). Except for $V_a$, this data was also used to model the two RS-based approaches. For the RS-based approaches, the data is complemented by RS based ET and LP. This data was obtained from FAO's portal to monitor water productivity through open access RS derived data (WaPOR) (FAO 2023). WaPOR data is available in three resolutions, for Lebanon the highest resolution available covering the entire country of 100 m (WaPOR level 2) was used in this study.

## Results and discussion

### National level

The results of the two approaches for calculating $A_{wp}$ were compared to $A_{we}$ (Fig. 2). The values of $A_{wp1}$ range between 1.93 USD/$m^3$ in 2020 to 2.46 USD/$m^3$ in 2015, with $A_{wp2}$ showing a slightly higher estimation compared to $A_{wp1}$. The three curves show similar trends over time, with a decline from 2015 to 2016, a general increase from 2016 to 2019 and a sharp decline in 2020. The results show a high correlation between $A_{wp1}$ and $A_{wp2}$ ($r^2 = 0.9$), and lower correlation between the two approaches for $A_{wp}$ and $A_{we}$ ($r^2 = 0.5$).

In absolute values, however, $A_{wp1}$ and $A_{wp2}$ are almost a factor 2 higher than $A_{we}$. With the $GVA_a$ for $A_{we}$ and $A_{wp1}$ being the same, the difference is in the estimation of the water withdrawn or consumed. Comparing the annual irrigated areas obtained from the WaPOR and those from AQUASTAT, it shows a significant difference. The WaPOR LCC map estimates an area between 354 and 432 $km^2$ as irrigated, which is less than half of the area reported by the

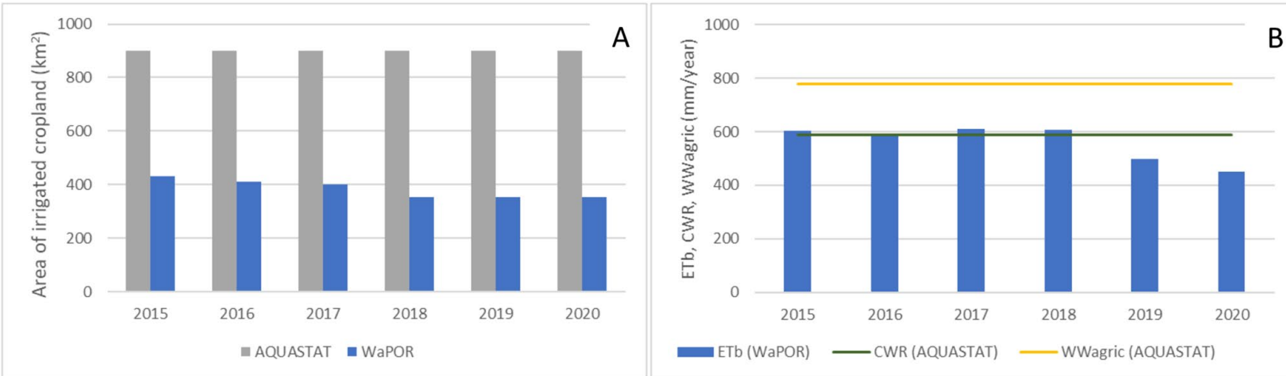
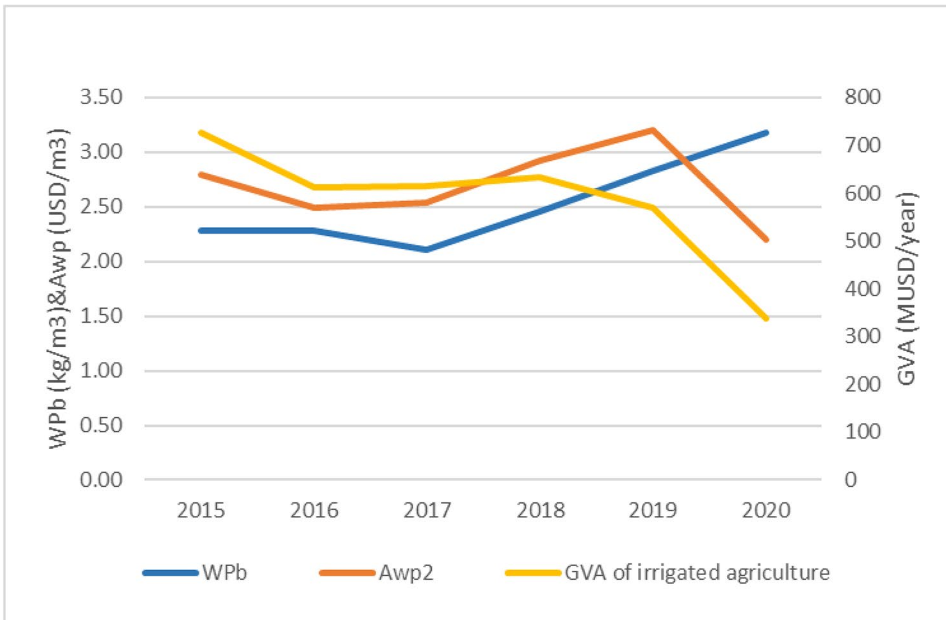



**Fig. 3** **A)** Area under irrigation from WaPOR and AQUASTAT and **B)** average $ET_b$ from WaPOR over irrigated areas versus agricultural water withdrawal ($WW_{agric}$) and estimated crop water requirement (CWR) from AQUASTAT for Lebanon between 2015 and 2020

**Fig. 4** Comparison between $WP_b$, $A_{wp2}$ and $GVA_a$ between 2015–2020, for irrigated agriculture in Lebanon




Lebanese government in AQUASTAT (900 km$^2$) (Fig. 2A). A major distinction between the two is that the AQUASTAT data is based on area equipped for irrigation, which is a static value, whereas WaPOR uses a water deficit index based on precipitation and evapotranspiration to estimate if a cropland is irrigated or not, which varies year by year[1] (FAO 2020).

When comparing the volume of water used for irrigation per area (in mm/year) (Fig. 2B), the values from both sources have a closer match. The WaPOR $ET_b$ data ranges between 449 mm/year in 2020 to 604 mm/year in 2015 (Fig. 2B), while AQUASTAT reports the volume of water withdrawn by agriculture ($WW_{agric}$) to be 0.7 km$^3$/year (equivalent to 777 mm/year), and crop water requirement (CWR) of 0.529 km$^3$/year (equivalent to 587 mm/year). The discrepancy in the last two years could be attributed to fields being abandoned because of the economic hardship faced by farmers in Lebanon. Despite these differences, the order of magnitude in estimated water depth estimated using the WaPOR data are reasonable.

As shown in Fig. 2, the results show a consistent drop in $A_{we}$ and both $A_{wp}$ approaches between 2019 and 2020. Comparing $WP_b$ with $A_{wp2}$ shows that the main culprit for the decline in $A_{wp2}$ is not in efficient water use in the agricultural sector as $WP_b$ shows an overall increasing trend from 2015 to 2020, from 2.1 to 2.2 kg/m$^3$ in 2015 to 3.18 kg/m$^3$ in 2020 (Fig. 4). $A_{wp2}$ followed the same trend as $WP_b$ until 2019, starting at 2.79 USD/m$^3$ in 2015 to reach 3.21 USD/m$^3$ in 2019. After 2019, the two indicators start deviating with $WP_b$ increasing to 3.18 kg/m$^3$, and $A_{wp2}$ dropping to 2.2 USD/m$^3$. The drop in $A_{wp2}$ is therefore not the result of a reduced performance of the agricultural sector but is

[1] Because FAO uses a moving window of 5 years, the last two years are not updated.

due to factors affecting the economy in Lebanon 2020, with $GVA_a$ dropping from 634 million USD in 2018 to 339 million USD in 2020. At the same time, the results show that $WP_b$ continues to increase over time.

## Sub-national level

The spatial disaggregation of LP, $WP_b$ and $A_{wp2}$ per governorates and villages provides additional information related to the performance of the irrigated areas in the different administrative zones (Fig. 5). The highest LP was found in the North and South with a LP between 20 and 25 ton/ha.

The highest $WP_b$ during these five years was Bekaa governorate in 2020. However, the highest average $WP_b$ of all the governorates was Akkar with 2.8 kg/m$^3$ and the lowest was recorded in the North Governorate with 2.4 kg/m$^3$ (Fig. 5D). Overall, $WP_b$ per governorate was increasing over the years (Fig. 6A), however $A_{wp2}$ was decreasing, especially in the last year of the analyses (Fig. 6B).

While Lebanon's average $A_{Wp2}$ between 2015 and 2020 was 2.78 USD/m$^3$, the spatial disaggregation per governorate or even village shows high variability, with $A_{wp2}$ in the range between 1.8 and 3–3.5 USD/m$^3$ (Fig. 6B). These results show that reporting of $A_{wp2}$ (and therefore

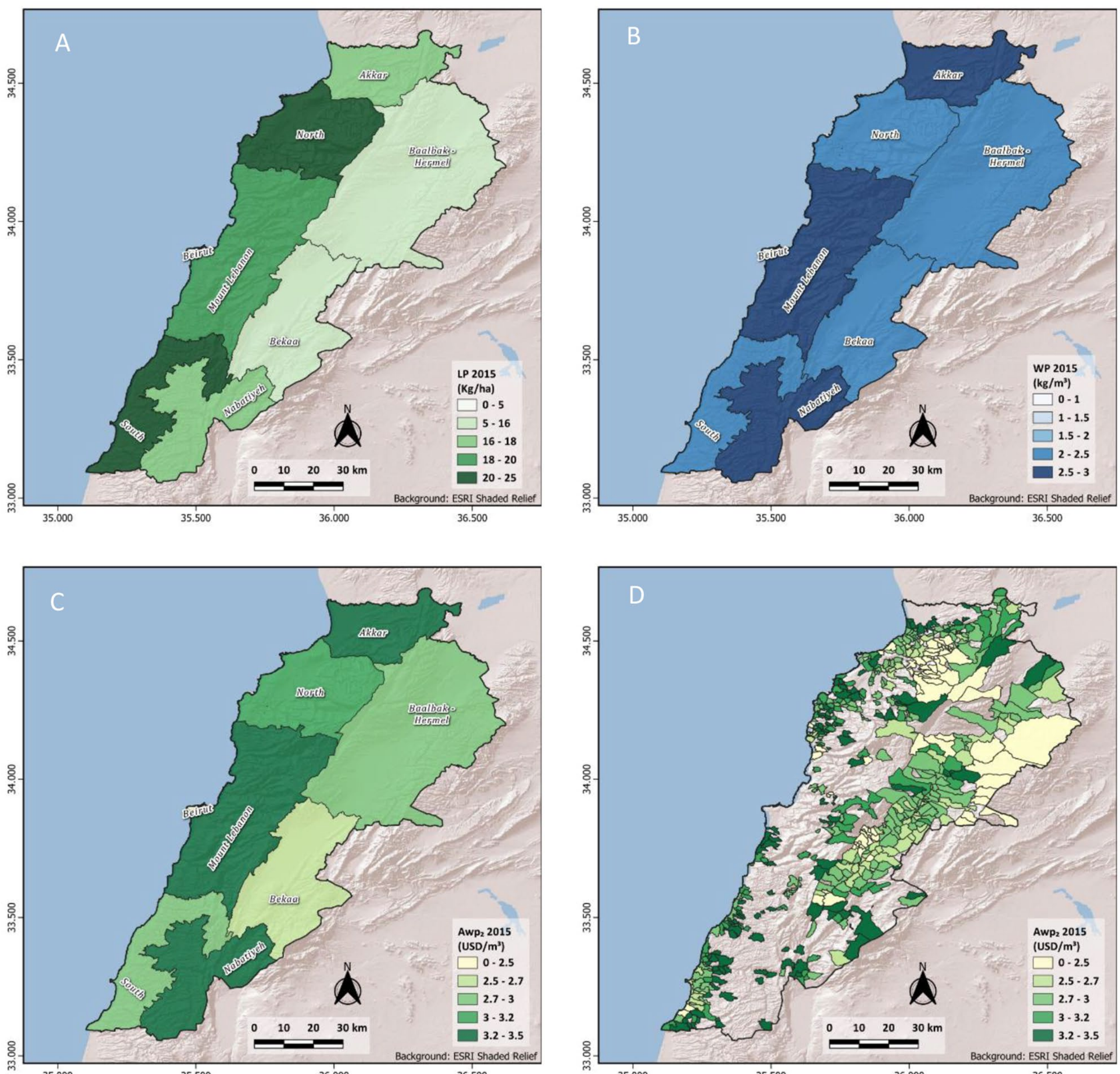



**Fig. 5** **A)** Water Productivity ($WP_b$), **B)** Land Productivity (LP) and **C)** $A_{wp2}$ per governorates in 2015; **D)** $A_{wp2}$ per village in 2015

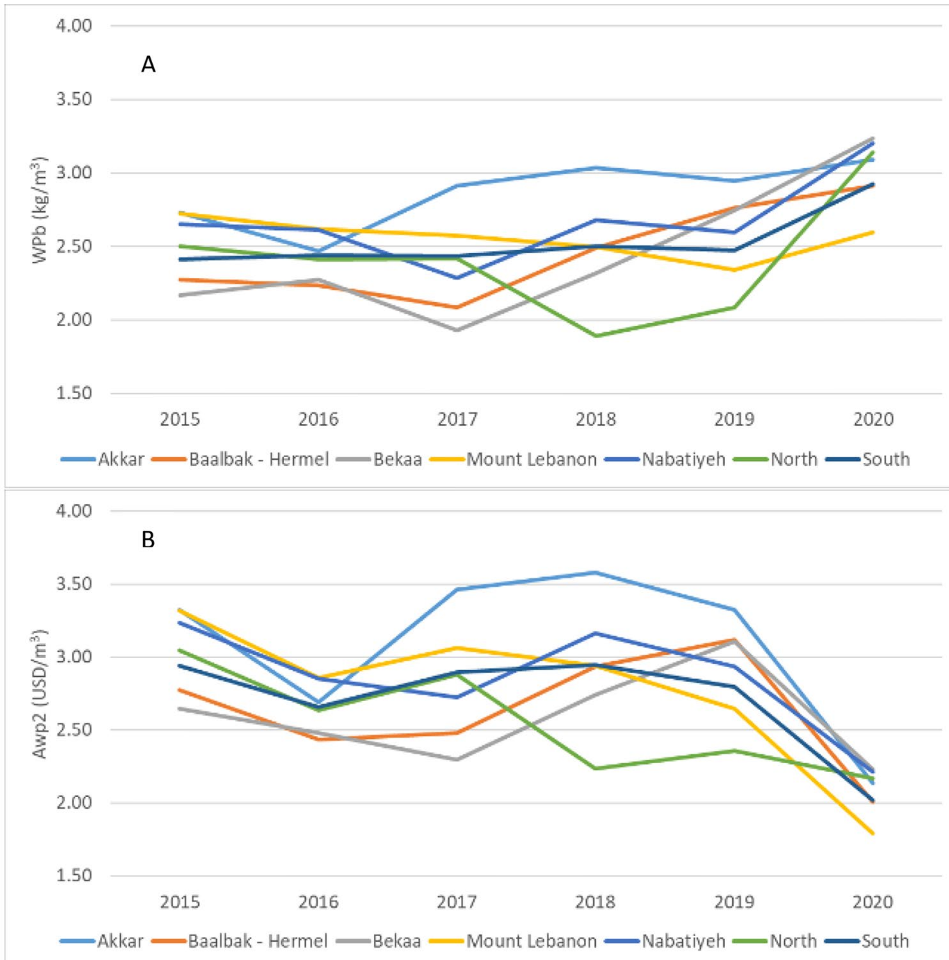



**Fig. 6** **A)** Annual $WP_b$ and **B)** annual $A_{wp2}$ per governorate in 2015

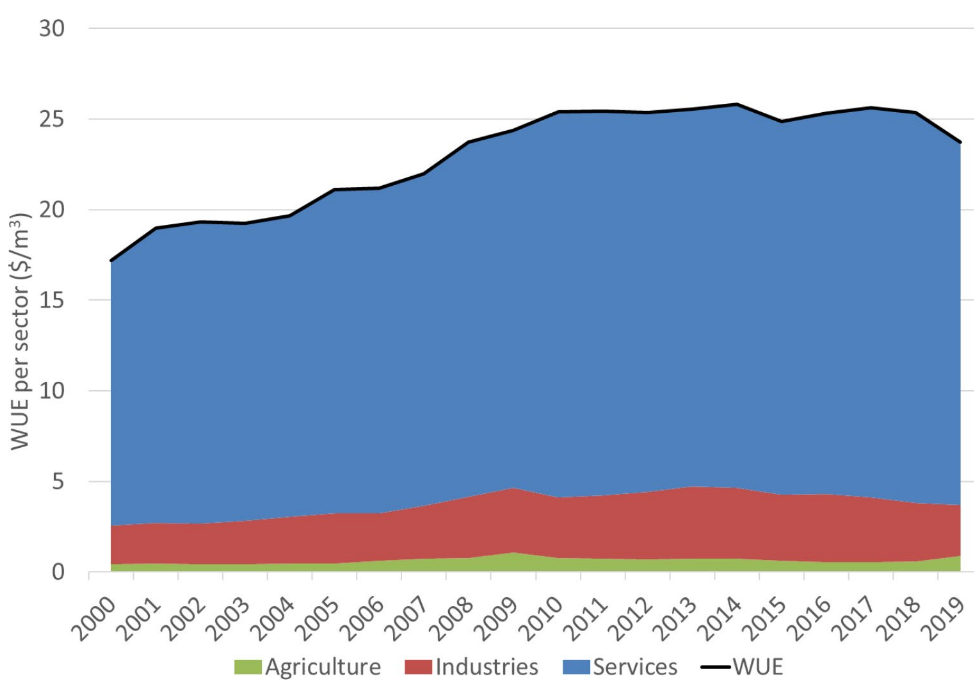



**Fig. 7** Contribution of the different sectors to SDG Indicator 6.4.1 water use efficiency for Lebanon over time between 2000 and 2019. (Source of data: UN-Water 2022)

$A_{we}$) at country level masks the spatial variability within a country and thereby hiding the issues shown when data is

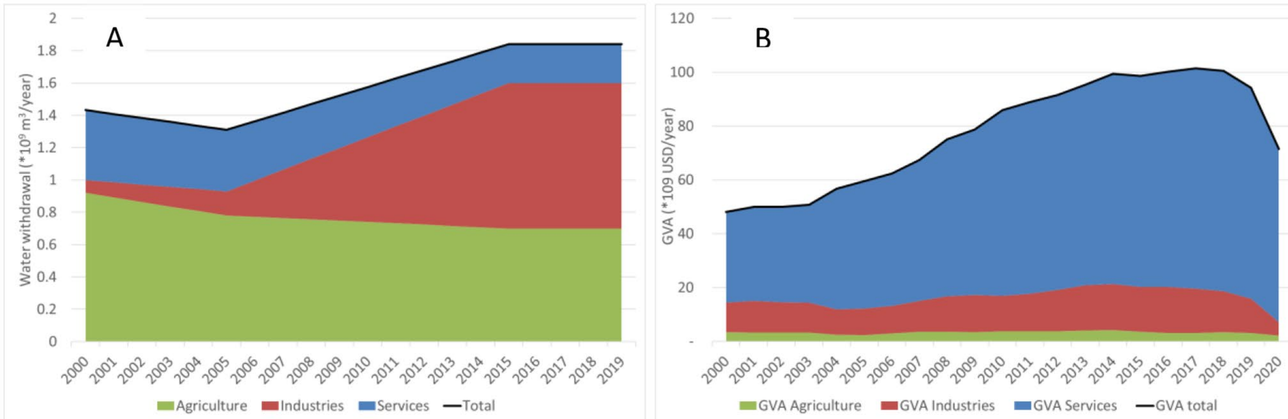



**Fig. 8** **(a)** water withdrawal per sector; **(b)** GVA per sector over time between 2000 and 2019. (Source of data: UN Water 2022)

disaggregated. Thus, the spatial disaggregation can actually identify hotspots and assist in identifying factors that can explain successes and thus measures for improvement.

## Implications for SDG 6 reporting

In the context of reporting SDG indicator 6.4.1 for Lebanon, Fig. 7 shows the indicator increasing from 17.5 USD/$m^3$ in 2000 to 25 USD/$m^3$ in 2019. While the analysis shows that the indicator increased significantly over this period, the changes since 2015 (the baseline of the SDGs) were negligible. The contribution of agriculture to the WUE was relatively small (Fig. 7), although agriculture is a major consumer of water (Fig. 8a).

The data breakdown for SDG indicator 6.4.1 reveals that water withdrawals for the agricultural sector decreases over time while its contribution to the GVA remains relatively constant. The main jump in the overall SDG indicator 6.4.1 between 2000 and 2015 is thus clearly related to the increase in industrial water withdrawals, which has grown nine-fold from 2000 to 2017, surpassing agriculture, while its GVA contribution declines (Fig. 8A and B).

## Conclusion

The results of the different approaches show that RS based data can be a valuable source of data for regular reporting and monitoring of SDG indicator 6.4.1. By replacing the water withdrawn by the water consumed, the latter of which can be observed by RS, a proxy to the conventional indicator is estimated. The results of these different approaches to estimate $A_{wp}$ show similar trends as $A_{we}$. While the overall results on trends are encouraging, the absolute values differ substantially. One main factor is the large inconsistencies in the data on area irrigated in Lebanon between the WaPOR data and the data reported in AQUASTAT. A possible explanation of this discrepancy can be related to the different definitions used in AQUASTAT where the irrigated area is the area equipped with irrigation, whereas WaPOR uses the water deficit index to identify areas that are actually irrigated (FAO 2020). Arguably, monitoring progress benefits more from information on actually irrigated areas and the water consumed in those areas compared to the potential irrigated areas and the estimated water supply to these areas as reported in AQUASTAT.

A second source of discrepancy is that the $A_{wp}$ approaches only estimate water productivity in irrigated areas and does not consider the aquaculture and livestock components as per the definition of SDG indicator 6.4.1. In the case of Lebanon, the volume of water consumed by irrigation contributes to an important part of the total water withdrawn by agriculture, and therefore will not affect the results.

The methodology used in this paper can be easily extended globally. The combination of spatial and temporal analysis can give a better understanding of the spatial variations and can help incorporate policy changes, decisions, and actions toward Agenda 2030. Before applying the methodology to other countries, it is recommended to validate the RS based estimates to improve the reliability of the analysis and to evaluate if the assumption that irrigated agriculture is the largest consumer of water in agriculture is valid.

**Acknowledgements** This study was supported by the “Monitoring land and water productivity by Remote Sensing (WaPOR phase 2) project” funded by the Ministry of Foreign Affairs of the Netherlands. The MSc fellowship of the main author was funded through IHE Delft Partnership Programme for Water and Development (DUPC2) MENA scholarship.

**Funding** This study was supported by the “Monitoring land and water productivity by Remote Sensing (WaPOR phase 2) project” funded by the Ministry of Foreign Affairs of the Netherlands.

**Data Availability** The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

## Declarations

**Competing interests** 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. The authors declare the following financial interests/personal relationships which may be considered as potential competing interests.



## References

Anderson K, Ryan B, Sonntag W, Kavvada A, Friedl L (2017) Earth observation in service of the 2030 agenda for Sustainable Development. Geo Spat Inf Sci 20(2):77–96. https://doi.org/10.1080/10095020.2017.1333230

Bhaduri A, Bogardi J, Siddiqi A, Voigt H, Vörösmarty C, Pahl-Wostl C, Bunn S, Shrivastava P, Lawford R, Foster S, Kremer H, Renaud F, Bruns A, Osuna V (2016) Achieving Sustainable Development Goals from a Water Perspective. Front Environ Sci 4:64. https://doi.org/10.3389/fenvs.2016.00064

Biancalani R, Marinelli M (2021) Assessing SDG indicator 6.4. 2 'level of water stress' at major basins level. UCL Open: Environ 1–7. https://doi.org/10.14324/111.444/ucloe.000026

Boyd DS, Jackson B, Wardlaw J, Foody GM, Marsh S, Bales K (2018) Slavery from space: demonstrating the role for satellite remote sensing to inform evidence-based action related to UN SDG number 8. ISPRS J Photogramm Remote Sens 142:380–388. https://doi.org/10.1016/j.isprsjprs.2018.02.012

Brouwer C, Heibloem M (1986) Irrigation water management: irrigation water needs. Training manual, 3. Available at https://www.fao.org/3/S2022E/s2022e00.htm#Contents. Accessed 20 October 2022

Calera A, Campos I, Osann A, D'Urso G, Menenti M (2017) Remote sensing for crop water management: from ET modelling to services for the end users. Sensors 17:1104. https://doi.org/10.3390/s17051104

Chen X, Su Z, Ma Y, Yang K, Wen J, Zhang Y (2013) An improvement of roughness height parameterization of the Surface Energy Balance System (SEBS) over the Tibetan Plateau. J Appl Meteorol Climatol 52(3):607–622. https://doi.org/10.1175/JAMC-D-12-056.1

Chen J, Peng S, Chen H, Zhao X, Ge Y, Li Z (2020) A comprehensive measurement of progress toward local SDGs with geospatial information: methodology and lessons learned. ISPRS Int J Geo-Inf 9(9):522. https://doi.org/10.3390/ijgi9090522

Chukalla AD, Krol MS, Hoekstra AY (2015) Green and blue water footprint reduction in irrigated agriculture: effect of irrigation techniques, irrigation strategies and mulching. Hydrol Earth Syst Sci 19:4877–4891. https://doi.org/10.5194/hess-19-4877-2015

Connor R (2015) The United Nations world water development report 2015: water for a sustainable world (Vol. 1). UNESCO publishing. Available at https://unesdoc.unesco.org/ark:/48223/pf0000231823 Accessed 20 October 2022

Droogers P, Immerzeel WW, Lorite IJ (2010) Estimating actual irrigation application by remotely sensed evapotranspiration observations. Agric Water Manag 97(9):1351–1359. https://doi.org/10.1016/j.agwat.2010.03.017

Eisenmenger N, Pichler M, Krenmayr N, Noll D, Plank B, Schalmann E, Wandl MT, Gingrich S (2020) The Sustainable Development Goals prioritize economic growth over sustainable resource use: a critical reflection on the SDGs from a socio-ecological perspective. Sustain Sci 15(4):1101–1110. https://doi.org/10.1007/s11625-020-00813-x

FAO (2015) Water at a Glance: the relationship between water, agriculture, food security and poverty. Rome. 15 pp. https://www.fao.org/3/ap505e/ap505e.pdf

FAO (2023) FAO's portal to monitor Water Productivity through Open access of Remotely sensed derived data. Available at: https://wapor.apps.fao.org/home/WAPOR_2/1. Accessed on 10 March, 2023

FAO (2022) AQUASTAT - FAO's global information system on water and agriculture. Available at: https://www.fao.org/aquastat/en/. Accessed on 10 October, 2022

FAO (2020) WaPOR database methodology: Version 2 release. FAO, Rome. 78 pages. Available at https://doi.org/10.4060/ca9894en

FAO (2019) GEMI – Integrated Monitoring Initiative for SDG 6 Step-by-step monitoring methodology for SDG Indicator 6.4.1. FAO, Rome, 35 pages. Available at https://www.fao.org/3/ca8484en/ca8484en.pdf

FAO (2008) Country profile – Lebanon. FAO AQUASTAT reports. Available at https://www.fao.org/3/ca0344en/CA0344EN.pdf Accessed 30 June 2023

FAO-Lebanon (2022) : Lebanon at a glance. Available at: https://www.fao.org/lebanon/fao-in-lebanon/lebanon-at-a-glance/en/. Accessed on: 10 October, 2022

Foody GM, Ling F, Boyd DS, Li X, Wardlaw J (2019) Earth observation and machine learning to meet sustainable development goal 8.7: mapping sites associated with slavery from space. Remote Sens 11(3):266. https://doi.org/10.3390/rs11030266

Gennari P, Rosero-Moncayo J, Tubiello FN (2019) The FAO contribution to monitoring SDGs for food and agriculture. Nat plants 5(12):1196–1197. https://doi.org/10.1038/s41477-019-0564-z

Giuliani G, Mazzetti P, Santoro M, Nativi S, Van Bemmelen J, Colangeli G, Lehmann A (2020) Knowledge generation using satellite earth observations to support sustainable development goals (SDG): a use case on land degradation. Int J Appl Earth Obs Geoinf 88:102068. https://doi.org/10.1016/j.jag.2020.102068

Giupponi C, Gain AK, Farinosi F (2018) Spatial assessment of water use efficiency (SDG indicator 6.4.1) for regional policy support. Front Environ Sci 6:141. https://doi.org/10.3389/fenvs.2018.00141

Guerschman JP, Van Dijk AI, Mattersdorf G, Beringer J, Hutley LB, Leuning R, Pipunic RC, Sherman BS (2009) Scaling of potential evapotranspiration with MODIS data reproduces flux observations and catchment water balance observations across Australia. J Hydrol 369(1–2):107–119. https://doi.org/10.1016/j.jhydrol.2009.02.013

Hakimdavar R, Hubbard A, Policelli F, Pickens A, Hansen M, Fatoyinbo T, Lagomasino D, Pahlevan N, Unninayar S, Kavvada A, Carroll M, Smith B, Hurwitz M, Wood D, Schollaert Uz S (2020) Monitoring water-related ecosystems with Earth Observation

Data in support of sustainable development goal (SDG) 6 reporting. Remote Sens 12:1634. https://doi.org/10.3390/rs12101634
Hellegers P, van Halsema G (2021) SDG indicator 6.4.1 "change in water use efficiency over time": methodological flaws and suggestions for improvement. Sci Total Environ 149431. https://doi.org/10.1016/j.scitotenv.2021.149431
Karimi P, Bongani B, Blatchford M, de Fraiture C (2019) Global satellite-based ET products for the local level irrigation management: an application of irrigation performance assessment in the Sugarbelt of Swaziland. Remote Sens 11(6):705. https://doi.org/10.3390/rs11060705
Kavvada A, Metternicht G, Kerblat F, Mudau N, Haldorson M, Laldaparsad S, Friedl L, Held A, Chuvieco E (2020) Towards delivering on the Sustainable Development Goals using Earth observations. Remote Sens Environ 247:111930. https://doi.org/10.1016/j.rse.2020.111930
Kavvada A, Ishida C, Juárez J, Ramage S, Merodio P, Friedl L (2022) EO4SDG: A GEO Initiative on Earth Observations for Sustainable Development Goals. Chapter 9 in Kavvada (ed) Earth Observation Applications and Global Policy Frameworks 145 – 57. https://doi.org/10.1002/9781119536789.ch9
Koubarakis M (2023) Geospatial data modeling. Chapter 2. In: Koubarakis M (ed) Geospatial Data Science: a Hands-on Approach for Building Geospatial Applications using Linked Data Technologies. Association for Computing Machinery New York, pp 9–30. https://doi.org/10.1145/3581906.3581909, United States
Lu S, Jia L, Jiang Y, Wang Z, Duan H, Shen M, Tian Y, Lu J (2021) Progress and prospect on monitoring and evaluation of United Nations SDG 6 (Clean Water and Sanitation) Target. Bull Chin Acad Sci (Chinese Version) 36(8):904–913. https://doi.org/10.16418/j.issn.1000-3045.20210705007
MacFeely S (2018) The 2030 Agenda: An Unprecedented Statistical Challenge. Friedrich-Ebert-Stiftung, Global Policy and Development. Available at https://library.fes.de/pdf-files/iez/14796.pdf accessed 20 October 2022
Msigwa A, Komakech HC, Salvadore E, Seyoum S, Mul ML, van Griensven A (2021) Comparison of blue and green water fluxes for different land use classes in a semi-arid cultivated catchment using remote sensing. J Hydrol Reg Stud 36:100860. https://doi.org/10.1016/j.ejrh.2021.100860
Mu Q, Zhao M, Running SW (2011) Improvements to a MODIS global terrestrial evapotranspiration algorithm. Remote Sens Environ 115(8): 1781 – 800. https://doi.org/10.1016/j.rse.2011.02.019
Nativi S, Santoro M, Giuliani G, Mazzetti P (2020) Towards a knowledge base to support global change policy goals. Int J Digit Earth 13(2):188–216. https://doi.org/10.1080/17538947.2018.1559367
OECD (2019) Measuring Distance to the SDG Targets 2019: An Assessment of Where OECD Countries Stand, OECD Publishing, Paris, 141 pages. https://doi.org/10.1787/a8caf3fa-en
Pekel J-F, Cottam A, Gorelick N, Belward AS (2016) High-resolution mapping of global surface water and its long-term changes. Nat 540:418–422. https://doi.org/10.1038/nature20584
Purvis B, Mao Y, Robinson D (2019) Three pillars of sustainability: in search of conceptual origins. Sustain Sci 14:681–695. https://doi.org/10.1007/s11625-018-0627-5
Reyers B, Stafford Smith M, Erb KH, Scholes R, Selomane O (2017) Essential variables help to focus Sustainable Development Goals monitoring. Curr Opin Environ Sustain 26–27:97–105. https://doi.org/10.1016/j.cosust.2017.05.003
Roopnarine A, Montoute M, Walter L, McLean S, Lewis S, Geoghagen-Martin J (2019) SDG 6 Monitoring Guide for Caribbean SIDS. Global Water Partnership. Ghana. 39 pages Retrieved from https://www.gwp.org/globalassets/global/gwp-c-files/monitoring-guide---sdg-6-in-caribbean-sids.pdf on 09 Nov 2022
Saner R, Yiu L, Nguyen M (2020) Monitoring the SDGs: Digital and social technologies to ensure citizen participation, inclusiveness and transparency. Dev Policy Rev 38(4):483–500. https://doi.org/10.1111/dpr.12433
Senay GB, Bohms S, Singh RK, Gowda PH, Velpuri NM, Alemu H, Verdin JP (2013) Operational evapotranspiration mapping using remote sensing and weather datasets: a new parameterization for the SSEB approach. Am J Water Resour 49(3):577–591. https://doi.org/10.1111/jawr.12057
Shaban A (2014) Physical and Anthropogenic Challenges of Water Resources in Lebanon. J Sci Res Rep 3(3):164–179. https://doi.org/10.9734/JSRR/2014/6990
Shaban A (2020) Water resources of Lebanon. Berlin/Heidelberg, Germany: Springer International Publishing. 229 pages. https://doi.org/10.1007/978-3-030-48717-1
Steffen W, Richardson K, Rockström J, Cornell SE, Fetzer I, Bennett EM, Biggs R, Carpenter SR, Vries W, Wit CA, Folke C, Gerten D, Heinke J, Mace GM, Persson LM, Ramanathan V, Reyers B, Sörlin S (2015) Planetary boundaries: guiding human development on a changing planet. Sci 347:1259855. https://doi.org/10.1126/science.125985
UN (2015) Transforming our World: 2030 Agenda for Sustainable Development Res. A/70/L.1 Available at https://documents-dds-ny.un.org/doc/UNDOC/GEN/N15/291/89/PDF/N1529189.pdf?OpenElement Accessed 20 October 2022
UN (2017) Revised List of Global Sustainable Development Goal indicators. New York, NY: United Nations. Available at https://unstats.un.org/sdgs/indicators/official%20revised%20list%20of%20global%20sdg%20indicators.pdf Accessed 20 October 2022
UN-Water (2021) Analytical brief water-use efficiency. UN-Water Technical Advisory Unit, Geneva, Switzerland. Available at https://www.unwater.org/publications/un-water-analytical-brief-water-use-efficiency Accessed 20 October 2022
UN-Water (2022) The UN-Water SDG 6 Data Portal. Available at: https://www.sdg6data.org/en/charts/bar. Accessed on 10 October, 2022
Vanham D (2018) Physical water scarcity metrics for monitoring progress towards SDG target 6.4: an evaluation of indicator 6.4.2 "Level of water stress. Sci Total Environ 613–614:218–232. https://doi.org/10.1016/j.scitotenv.2017.09.056
Weise K, Höfer R, Franke J, Guelmami A, Simonson W, Muro J, O'Connor B, Strauch A, Flink S, Eberle J, Mino E, Thulin S, Philipson P, van Valkengoed E, Truckenbrodt J, Zander F, Sánchez A, Schröder C, Thonfeld F, Fitoka E, Scott E, Ling M, Schwarz M, Kunz I, Thürmer G, Plasmeijer A, Hilarides L (2020) Wetland extent tools for SDG 6.6.1 reporting from the Satellite-based Wetland Observation Service (SWOS). Remote Sens Environ 247:111892. https://doi.org/10.1016/j.rse.2020.111892
WWAP and UN-Water (2018) The UN World Water Development Report 2018, Nature-based Solutions for Water. Paris, UNESCO. 139 pages. Available at https://unesdoc.unesco.org/ark:/48223/pf0000261424

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.