Agricultural Water Management 261 (2022) 107373

Contents lists available at ScienceDirect

Agricultural Water Management

journal homepage: www.elsevier.com/locate/agwat

Translating open-source remote sensing data to crop water productivity improvement actions

Abdur Rahim Safi [a,*], Poolad Karimi [a], Marloes Mul [a], Abebe Chukalla [a], Charlotte de Fraiture [a,b]

[a] Land and Water Management Department, IHE Delft Institute for Water Education, The Netherlands
[b] Water Resources Management Department, Wageningen University and Research, The Netherlands

ARTICLE INFO

Handling Editor - J.E. Fernández

Keywords:
WaPOR
Crop water stress
Water scarcity
Agronomic practices
Irrigation practices
Bekaa Valley

ABSTRACT

A widely promoted approach to tackle food insecurity and water shortage challenges simultaneously is to enhance crop water productivity (WP). Therefore, multiple international organizations have featured WP improvements as their major policy goal, and substantial public and private investments have been made in this domain. Advances in remote sensing allow accurate, rapid, and cost-effective WP analysis for agricultural monitoring. However, translating the data to actionable information seems fraught with difficulties, as it only provides spatial and temporal variability in WP and no information on the causes of the variability. This paper introduces a standard approach using open-source remote sensing data for diagnosing reasons behind WP variations, comparing high performing fields (bright spots) with low performing fields (hotspots). The framework is applied to a case study on the Bekaa Valley in Lebanon considering wheat, potato and table grapes. Six factors (crop water stress, irrigation uniformity, soil salinity, nitrogen application, crop rotation and soil type) were analysed to identify their influence on WP and yield. This paper reveals that the growth of wheat and potatoes is negatively affected by water stress in the critical crop growth stages, non-uniform irrigation and nitrogen stress. Also, it was found that potatoes grown on clay-loam soil has better WP and yield than potatoes grown loam soil. Such information with regard to WP factors assists practitioners to identify priority areas and actions aiming at cropfield level WP improvement. While acknowledging errors, uncertainties and caveats inherent to the use of remote sensing data, this paper shows the feasibility and practical usefulness of the diagnostic framework.

1. Introduction

A significant challenge for the current and future generations is to ensure food security with the sustainable use of limited land and water resources. Globally, 820 million people face hunger (FAO, 2019). At the same time, about four billion people face water scarcity during at least one month of the year (UNESCO World Water Assessment Programme WWAP, 2019). In the future, the situation is expected to get worse due to climate change. Farmers will be exposed to increased agricultural water supply variability, growing unpredictability, and frequent droughts and floods (FAO, 2011). Due to the increased competition with industrial and domestic sectors, water availability for agriculture production will decrease (Zwart and Bastiaanssen, 2007; Bakkes et al., 2009). Therefore, a widely promoted approach to cope with the water and food insecurity challenges is to increase agricultural water productivity. Thus, multiple international organisations including World Water Council (WWC); the International Water Management Institute (IWMI); WWAP; and FAO have featured water productivity improvement as a major policy goal (Scheierling and Tréguer, 2018).

The term water productivity (WP) was introduced to emphasise that increasing local irrigation efficiency might not lead to basin-wide water savings (Seckler, 1996). Since then, many other authors have defined WP differently, revolving around crop per drop (Scheierling and Tréguer, 2018). Kijne et al. (2003) defined WP as the ratio of the value or amount of product to the value or volume of water depleted or diverted. Molden et al. (2010) have defined it as the net benefit from the plant, fishery, livestock and mixed agricultural system per unit water used. For this research study, we define WP as the amount of marketable biomass (economic product of a specific crop) in kilograms produced per unit volume of actual evapotranspiration and interception (ET).

Capturing and analyzing spatial and temporal variability in WP paves the way for identifying the potential for improving WP (Zwart and Bastiaanssen, 2007). Remote sensing is an excellent tool that allows comprehensive analysis and requires comparatively little ground

* Correspondence to: Westduinweg 172C, 2583 AG The Hague, The Netherlands.
E-mail address: abdur.rahim@eleaf.com (A.R. Safi).

https://doi.org/10.1016/j.agwat.2021.107373
Received 12 May 2021; Received in revised form 16 November 2021; Accepted 28 November 2021
Available online 9 December 2021

information (Cai and Sharma, 2010). It enables WP estimation with acceptable accuracy, with errors ranging from 7% to 22%—for the best-case scenario (Blatchford et al., 2019). Finally, remote sensing is low cost compared to the ground measurements and offers a rapid scan of the WP in a rather large extent of area (Zwart and Leclert, 2010). In combination with other spatial information, it can diagnose the causes of low performance and identify interventions for improving WP.

Since the first applications of remote sensing for agricultural monitoring using the energy balance to estimate evapotranspiration (Bastiaanssen et al., 1998), open-source remote sensing products have become more available. Not only are there various remote sensing products for evapotranspiration, in combination with vegetation related products such as Leaf Area Index (LAI), Normalized Difference Vegetation Index (NDVI) and Net Primary Production (NPP), it can also provide spatial and temporal WP estimates. However, observing the variability of WP on its own does not contribute to improving WP. The data has to be translated to actionable information, by identifying the causes for the variability. This study, therefore, evaluates how open-source spatial data products can be used to identify reasons behind low performances. This study developed a standard procedure (framework) that can be used to utilize open-source remote sensing data for identifying reasons behind WP variations.

2. Material and methods

2.1. Study area

The Bekaa Valley was chosen as the case study for developing and testing the diagnostic framework due to the availability and accessibility of both field data and high-resolution RS imagery. The Bekaa Valley, located in eastern Lebanon, has a total area of 90,000 ha and is situated between Anti-Lebanon and Mount Lebanon to the east and west, respectively (Fig. 1). The Valley has a Mediterranean climate with average annual rainfall ranging from 700 mm year^{-1} in the southern part to 250 mm year^{-1} in the northern part (Chalak and Sabra, 2007). The major crops grown in the Valley are wheat, early potatoes and vegetables (Caiserman et al., 2019). Next to seasonal crops, many perennial fruit trees are grown in the Bekaa Valley, including apples, grapes, citrus, cherries, almonds, apricots, peaches, plums and pears (Verner et al., 2018).

During summer—the main cropping season—the reference evapotranspiration exceeds the precipitation. Irrigation supply is therefore essential to meet the evaporative demand of the crops (Fig. 2). A large portion of the irrigation water (72%) is supplied from groundwater (FAO and IHE Delft, 2019). Based on the field survey, most of the farmers in the Valley use sprinkler irrigation (65%), followed by drip irrigation (22%), micro-sprinklers (6%) and furrow irrigation (4%) (Jaafar et al., 2017). Potatoes and table grapes are grown under full irrigation, while supplementary irrigation is practiced for wheat (Stokvis, 2017). This research is carried out on three major crops, potatoes, wheat and table grapes.

The Bekaa Valley is known as the country's food basket, and 42% of the total agricultural land is concentrated in the Valley (Verner et al., 2018). However, insufficient rainfall and its seasonality, make water a primary constraint for agricultural production (Saab et al., 2014). Therefore, improving water productivity is of vital importance in the Valley, to sustain food production in light of growing water scarcity.

2.2. Remote sensing data

2.2.1. WaPOR data

FAO's portal to monitor water productivity through open access of remotely sensed derived data (WaPOR) contains datasets for estimating WP. It comes in three levels with different resolutions (FAO, 2018). For the Bekaa Valley, the highest resolution (30 m) is available and was used for this study. The most recent WaPOR version (2.1) was accessed through https://wapor.apps.fao.org/home/WAPOR_2/3. Table 1 shows the different WaPOR datasets used in this study.

2.2.2. Other remote sensing data

Data from the Landsat 8 and Sentinel 2 satellite missions have been acquired. This data is used to calculate leaf moisture, soil salinity and leaf nitrogen, described separately in the later sections. On-demand surface reflectance Landsat 8 data is downloaded from the official United States Geological Survey (USGS) website. Then, clouds and shadows were removed using the "Cloud masking for Landsat products" plugin in QGIS. Sentinel 2 data was downloaded from THEIA, which had already been atmospherically and slope corrected. The clouds and shadows were removed by using the masks already provided with the data. Soil-type data is acquired from SoilGrids—a global soil-properties mapping system that is based on state-of-the-art machine learning methods (Hengl et al., 2017).

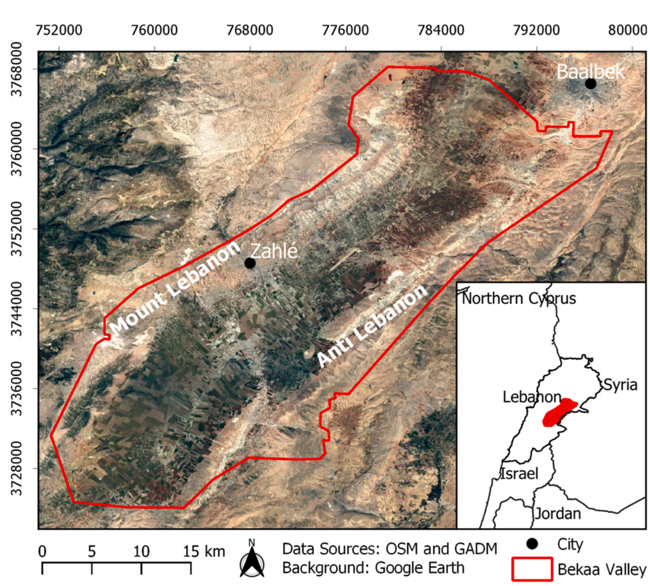

Fig. 1. Geographic location of the case study area (Bekaa Valley).

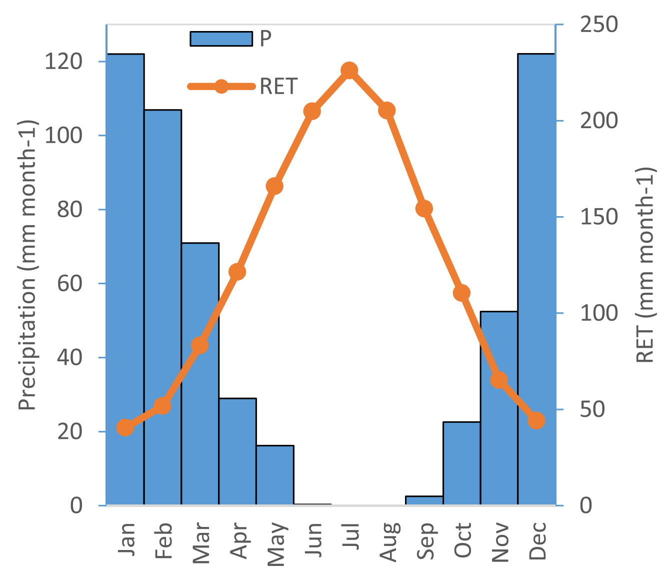

Fig. 2. Monthly average precipitation (P) and reference evapotranspiration (RET) in the Bekaa Valley.
Data source: WaPOR 2009–2017.

Table 1
Data components acquired from the WaPOR database.

Data component	Level	Temporal resolution	Spatial resolution
Actual Evapotranspiration Interception (ET)	Sub-national	10 days	30 m
Net Primary Production (NPP)	Sub-national	10 days	30 m
Land Cover Classification (LCC)	Sub-national	10 days	30 m
Quality of Land Cover Classification (QI-LCC)	Sub-national	Seasonal	30 m
Quality of Normalized Difference Vegetation Index (QI)	Sub-national	10 days	30 m

Source: WaPOR database

2.2.3. *Unit of analysis*

This study applies the analyses at the crop-field level. The crop-field boundaries (polygons) are delineated based on a 30 m resolution crop mask obtained from WaPOR. As can be seen from Tables 1 and 2, the spatial resolution of the various datasets used varies, with WaPOR and Landsat 8 data being available at 30 m resolution, Sentinel 2 10–20 m, while SoilGrids data is having a coarser resolution of 250 m. While the statistics calculated for crop fields based on Sentinel 2 data is not expected to affect the accuracy of the analysis, the coarser resolution data from SoilGrids could affect the accuracy of the results. Therefore, crop fields laying on multiple soil types were removed from analysis.

2.2.4. *Period of analysis*

The analyses were implemented for the year 2017 when there was an overlap between the crop-type map of WaPOR, available at the time of the study and the Sentinel-2B data. A comparison was done on the water productivity values from 2015 to 2019 to ensure the selected year was not abnormal.

2.3. *Analytical framework*

The analytical framework (Fig. 3) applied in this study consist of four steps. 1) Yield and WP figures for each crop field were calculated using WaPOR data. 2) Bright spots (well-performing crop fields) and hot spots (poor-performing crop fields) were identified in the study area. 3) Based on available WaPOR and other remote sensing data, various indicators were defined to identify factors affecting yield and water productivity. 4) Finally, analyses of WP factors were done between different indicators and the hotspots and the bright spots to diagnose reasons behind yield and WP variations. The framework is applied to three main crops in the Bekaa Valley (wheat, potatoes and grapes). Each step is described in detail in the next sections.

2.3.1. *Yield and water productivity estimation*

The yield and water consumption are calculated for the selected crops using a field-boundary map. This was obtained, for each crop type, by polygonising a raster crop-type map of the study area. For wheat and potatoes, the crop-type map corresponding to the full canopy cover for each crop (for the wheat first decade of March and potatoes last decade of April) from WaPOR were used. For the table grapes, the crop-type mask was provided by Alvarez-Carrion (2018), as WaPOR crop type map does not differentiate between the table-grapes and wine-grapes.

Yield and WP are calculated by using WaPOR data (NPP and ET). The above-ground biomass production is calculated using Eqs. 1 and 2 (FAO, 2018) and finally crop yield is calculated by Eq. 3 (Mul and Bastiaanssen, 2019).

$$DMP_i = NPP \times 22.222 \quad \times Nd_i \tag{1}$$

$$AGBP_s = \sum_{i=SOS}^{EOS} DMP_i \times AOT \tag{2}$$

$$Y = \frac{AGBP \times HI \times C_4}{(1 - m_c)} \tag{3}$$

The DMP_i is dry matter production (kgDMP ha^{-1} dekad^{-1}), NPP is net primary production (gC m^{-2} day^{-1}), N_{di} is the number of days in a dekade (days) and $AGBP_s$ is seasonal above-ground biomass production (kg ha^{-1} season^{-1}) from the start of the season (SOS) to the end of the season (EOS), HI is dry basis harvest index (fraction) and AOT is AGBP over Total Biomass Production (TBP). The fraction, AOT, is used in the calculation of AGBP if the HI of a crop is calculated as yield to above-ground biomass. For wheat, the HI is calculated as yield to above-ground biomass ratio (Abi Saab et al., 2019; Karam et al., 2009). Contrary to this, HI of potatoes is the ratio of the dry weight of the tubers to the dry weight of the entire plant (Darwish et al., 2006; Mazurczyk et al., 2009) and HI of grapes is calculated as the marketable yield divided by the total biomass production (TBP) (Alvarez-Carrion, 2018). Therefore, unlike the wheat crop, the AOT value for potatoes and grapes is “1.00” and can be ignored in AGBP’s equation. Thus, users must be clear on how the HI is defined in the literature consulted. Y is yield (kg ha^{-1} season^{-1}). The light use efficiency of C4 crops is about 80% higher than the C3 crops, therefore, the Y of C4 crops is multiplied by a factor of 1.8 (Mul and Bastiaanssen, 2019). For C3 crops the factor value is “1.00” and can be ignored in Eq. 3. The m_c is wet weight basis plant moisture content (fraction). The SOS and EOS for each crop were identified from the NDVI time series. Whereas the crop-specific parameters were adapted from literature as summarized in Table 3.

WaPOR data quality index (QI) is produced while compositing the NDVI and indicates the gap between the nearest observation date and reconstruction date (FAO, 2018). For the available and reliable observations, the reconstruction is not needed and thus the QI is set to zero (an ideal condition). The NDVI composites are used as inputs to NPP and ET calculation therefore, the QI depicts the quality of NPP and ET (FAO, 2018). To ensure better accuracy of the data used, the NPP and ET pixels with QI greater than 3 dekades were removed from each image. It means that the data constructed based on a gap longer than 30 days in-between valid observations is discarded. This criterion for QI can adjusted based on the user preferences and local circumstances. As this study uses the crop-field level as the unit of analysis, the average value of all pixels within a crop field is considered for analysis, therefore, removing low-quality pixels did not create data gaps at the field level.

Water Productivity is calculated using the following formula (Chukalla et al., 2021):

$$WP = {}^{Y}\!/_{ET} \times \frac{1}{10} \tag{4}$$

The WP is water productivity (kg m^{-3}), Y is yield (kg ha^{-1} season^{-1}), and ET is seasonal actual evapotranspiration for a specific crop type (mm season^{-1}).

After the yield and WP maps have been prepared, then the crop fields with implausible data were removed by using the following four criteria

Table 2
Other remote sensing data acquired for the study.

Data component	Data source	Temporal resolution	Spatial resolution	Website
Surface Reflectance (Band 5, 6, 8)	Landsat 8	16 days	30 m	https://www.usgs.gov/land-resources/nli/landsat
Surface Reflectance (Band 5, 7, 8 A, 11)	Sentinel 2	5 days	10–20 m	https://theia.cnes.fr/atdistrib/rocket/#/home
Soil types/classes	SoilGrids	Not Applicable	250 m	https://soilgrids.org/

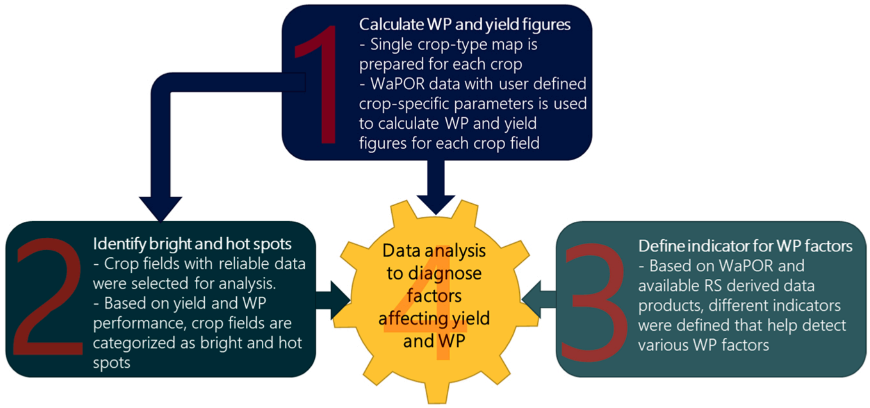

Fig. 3. Analytical framework used to identify factors affecting yield and WP in the Bekaa Valley.

Table 3
Crop specific parameters for yield estimation.

Crop type	Harvest Index		Moisture Content	AOT	C4
	Based on AGBP	Based on TBP			
Wheat	0.39 Average of Abi Saab et al. (2019) and Karam et al. (2009)		15% Karam et al. (2009)	0.72 Figueroa-Bustos et al. (2018)	1.00 (Wang et al., 2012)
Potatoes		0.79 Darwish et al. (2006)	79% Darwish et al. (2006)	1.00	1.00 Wang et al. (2012)
Grapes		0.31Alvarez-Carrion (2018)	75% Jarmain et al. (2007)	1.00	1.00 Morata and Loira (2016)

filter to avoid erroneous conclusions.

– Crop fields with a coefficient of variation of WP (WP_{cv}) greater than 20%. With WP_{cv} calculated using the following equation:

$$WP_{cv} = \frac{\sigma_{wp}}{WP_{mean}} \tag{5}$$

σ_{wp} is the standard deviation of WP within the crop field and WP_{mean} is the mean water productivity of a crop field.

– Crop fields with an area of less than one hectare.
– Crop fields with the yield value higher than the maximum achievable and lower than the minimum recorded, based on literature.
– Crop fields with an average LCC accuracy of less than 80%.

Fig. 4 shows all the selected crop fields, after removal of the fields with implausible data, for the analysis.

2.3.2. Identification of bright and hot spots

Bright spots generally can be defined as the agricultural communities and households which are performing better than their neighbours even with the same social, environmental and demographic pressures (de Vries, 2005). On the other hand, low performing areas are considered hot spots (Karimi et al., 2019). These bright and hot spots can be used to identify the causes behind what is affecting the performance.

Bright spots can be defined in terms of higher yield (e.g. Cai and Sharma, 2010 in India), higher WP or a combination (e.g. Alauddin et al., 2010 in Bangladesh). By focusing on WP improvements alone, ignores the farmers' need to produce crops for food security and income, whilst only focusing on yield improvement may affect the sustainability of the basin water resources. Therefore, in this study, we focused on identifying bright and hot spots based on both yield and WP.

There is still a debate as to what level defines better performance. For yield, Licker et al. (2010) defined the attainable yield within regions of similar climate at the 90th percentile, whereas Foley et al. (2011) used the 95th percentile. For WP, Alauddin et al. (2010) used the top quartile

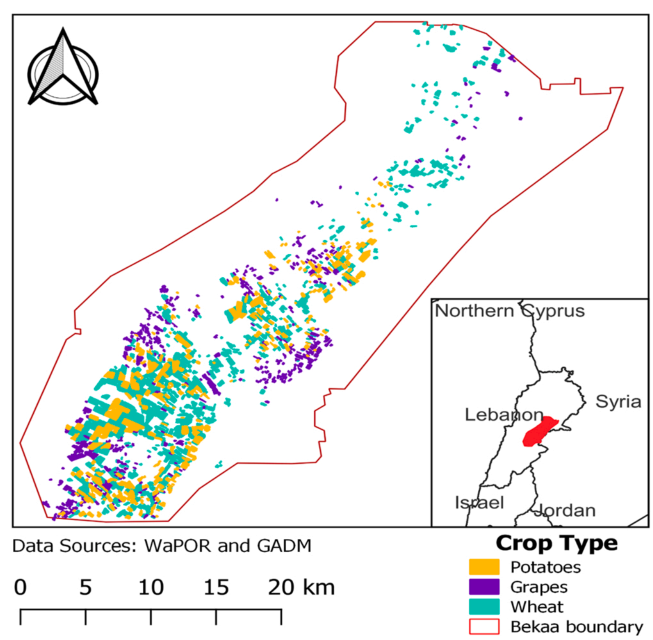

Fig. 4. Location of the selected crop fields for the analysis.

(75th percentile), whereas Zwart and Bastiaanssen (2004) and Zwart et al. (2010) used the 95th percentile to exclude extremes.

The selection of the threshold is arbitrary but has a significant effect on the results. For example, using high threshold values (> 95th) primarily identifies extremes (Zwart et al., 2010) while the focus should be more on values which are attainable under the set conditions (i.e. a lower threshold value). For this study, we tested threshold values (70th to 95th percentile with 5 percentile intervals), and selected the threshold value which provided a sufficiently large number of fields in the bright and hotspots categories (exceeding the threshold levels in both yield and WP) and significantly large performance gap. We, therefore, used the 80th percentile threshold for both yield and WP to be classified as bright spots, while fields below the 20th percentile are categorised as hot spots.

2.3.3. Defining indicators for WP factors

Reasons behind yield and WP variations can be diagnosed by analyzing the internal (genetic) and external (environmental) factors that affect crop production. Six WP factors (external), water stress, irrigation heterogeneity, salinity stress, nitrogen stress and soil type were considered in this study as they can be determined using WaPOR and other remote sensing data. Each factor is analyzed by using one or more indicator(s) to find reasons behind WP variations (see Fig. 5). Each indicator is separately discussed in the following sections.

2.3.4. Water stress

Water stress is assumed to be linked to leaf water content and plant moisture stress. This can be observed using the mid-infrared (MIR) (Carlson et al., 1971; Thomas et al., 1971; Tucker, 1980; Everitt, 1986; Ripple, 1986) and near-infrared (NIR) wavelengths (Hardisky et al., 1983; Everitt, 1986; Ceccato et al., 2001) RS bands. Therefore, various vegetation indices, based on NIR, are proposed for detecting plant moisture stress, we selected the Normalized Difference Moisture Index (NDMI) in this study as it was found to have the highest correlation with leaf and canopy water content ($R^2 = 0.68$) (Zhang et al., 2018).

$$NDMI = \frac{R_n - R_s}{R_n + R_s} \tag{6}$$

R_n and R_s are reflectances for NIR and shortwave infrared (SWIR), respectively. The index is calculated by using Sentinel 2 band 8 A (NIR) and band 11 (SWIR). To increase the temporal resolution of data, NDMI was also calculated by using similar bands on Landsat 8: band 5 (NIR) and band 6 (SWIR). Images acquired on the same date resulted in highly similar NDMI maps, represented by $R^2 = 0.98$ and Mean Bias Error = 0.003.

The crop response to water stress was identified from the change in leaf moisture content and corresponding changes in biomass production. Crop fields identified as bright spots were assumed to have optimal moisture content conditions. Therefore, the average NDMI value of bright spots was considered a benchmark against which the hot spots' NDMI value was compared. In this way, the moisture stress in hotspots was quantified by subtracting the average NDMI of hot spots from the average NDMI of bright spots from SOS to the EOS. The larger difference in NDMI ($NDMI_{diff}$) indicates higher stress in hotspots and vice versa. Similarly, the difference in biomass production (NPP_{diff}) was quantified by subtracting the average NPP of hot spots (NPP_{HS}) from the average NPP of bright spots (NPP_{BS}). The core methodology is to compare $NDMI_{diff}$ with NPP_{diff} to know how crops respond to water stress in terms of changes in biomass production.

To better understand crop response to water stress, the Stress Sensitivity Index (SSI) was developed in this study. The SSI was calculated by dividing the NPP_{diff} of a decade over the corresponding $NDMI_{diff}$. The SSI was calculated for all decades, from SOS to the EOS. The SSI time series indicates how biomass production is affected by changes in the moisture stress along the crop growth cycle. The crop response to stress is investigated through all phenological stages of each crop type to identify its stress-sensitive growth stages. For this purpose, four general physiological stages introduced by FAO—initial-, developing-, mid-, and late-stage—and more crop-specific growth stages were adapted from literature.

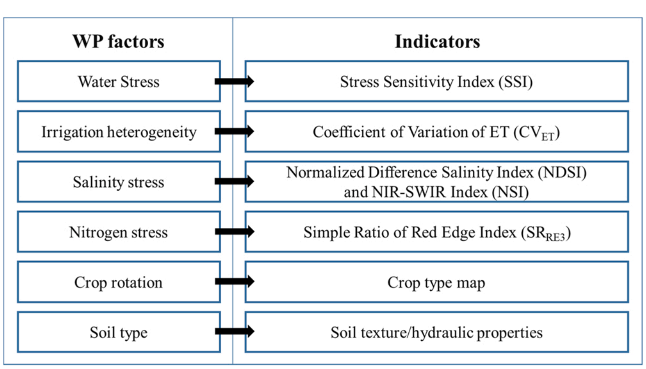

Fig. 5. Indicators used to identify factors affecting WP.

$$SSI = \frac{NPP_{BS} - NPP_{HS}}{NDMI_{BS} - NDMI_{HS}} \tag{7}$$

Where:

SSI is stress sensitivity index (-).

$NDMI_{BS}$ is average normalised difference moisture index of bright spots (-).

$NDMI_{HS}$ is average normalised difference moisture index of hot spots (-).

2.3.5. Irrigation heterogeneity

The variability in evapotranspiration (ET) within a crop field is assumed to be related to the heterogeneity in the water application. The within-field coefficient of variation of ET (CV_{ET}) (Karimi et al., 2019) is calculated and correlated with the yield and WP to assess non-uniform irrigation practices' effect on crop production and water consumption.

2.3.6. Salinity stress

In cases where the salinity stress is coupled with other stresses—moisture, aeration, or diseases—bare soil salinity can help identify the impact of soil salt content on crop production. Al-Khaier (2003) proposed the Normalized Difference Salinity Index (NDSI) that allows accurate salinity detection ($R^2 = 0.86$) of the bare agricultural soil.

$$NDSI = (R_{s1} - R_{s2})/(R_{s1} + R_{s2}) \tag{8}$$

R_{s1} and R_{s2} are reflectances for SWIR1 (band 4) and SWIR2 (band 5) on Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). As ASTER data is not available currently, similar bands of Landsat 8—SWIR1 (band 6) and SWIR2 (band 7)—are used for NDSI calculation. Abuelgasim and Ammad (2019) have also used Landsat 8 data for bare soil salinity detection. They have assessed the accuracy of multiple salinity indices, of which the NIR-SWIR index (NSI) has the highest accuracy (60%).

$$NSI = \frac{R_{s1} - R_{s2}}{R_{s1} - NIR} \tag{9}$$

R_{s1}, R_{s2} and NIR are reflectances for SWIR1 (band 6), SWIR2 (band 7) and NIR (band 5) on Landsat 8, respectively. To identify the effect of salinity, the NDSI and NSI of each crop field are correlated with their yield and WP figures.

2.3.7. Nitrogen stress

A study by Ramoelo and Cho (2018) has exposed that the simple ratio of red edge index (SR_{RE3}), based on Sentinel 2 data, allows an accurate estimate of the leaf nitrogen content, represented by R^2 of 0.75 and RMSE of 0.17 (%N). In this study, the SR_{RE3} is used for leaf nitrogen estimation.

$$SR_{RE3} = \frac{R_{re3}}{R_{re1}} \tag{10}$$

R_{re1} and R_{re3} are respectively reflectances for Visible Red Edge (VRE1) (band 5) and VRE3 (band 7) on Sentinel 2. The SR_{RE3} values of all identified bright spots were averaged for each decade from SOS to the EOS to produce their average leaf nitrogen content time series. A similar time series for hot spots were also produced. Then their average leaf nitrogen content time series were compared with each other to know the role of nitrogen application in biomass production.

2.3.8. Effect of crop rotation on yield and WP

Crop rotation is the growing of a series of various crop types on the same crop field in successive years or seasons (Cottren and Gryder, 2014). For each crop, its preceding crop grown on the same field was identified by using WaPOR LCC of the previous season. The crop fields were categorized as rotated and mono-cropped. For instance, if the preceding crop of a wheat field in 2017 was identified as wheat in 2016, then the field was categorized as mono-cropped. Further, if multiple crops are grown on the same crop field in 2016, then the area of partial rotation is considered. If more than 50% of the crop-field area is covered by crops other than wheat in 2016, then the crop-field is categorised as rotated, otherwise, the crop field is mono-cropped. The yield and WP figures of the two groups—rotated and mono-cropped fields—were tested with the *t*-test to determine the significance of the rotation practices. More detailed information about the *t*-test is provided in the section "Data analysis ↱2.3.4".

2.3.9. Effect of soil type on yield and WP

The raster layer of soil-type (soil classes based on United States Department of Agriculture (USDA) classification) map was acquired from SoilGrids (Table 2). The soil information is then extracted to the polygon of each crop field by using the zonal statistic in QGIS. The yield and WP figures of the crop fields associated with the different soil types were tested with the *t*-test to identify the statistical significance of soil type influence on yield and WP.

2.3.10. Data analysis

Various approaches were adapted for analysis based on the data type. In this study, three kinds of data analysis were performed. Each is described separately in the below sections.

2.3.11. Bright and hot spots time series comparison

The NDMI, NPP, SSI and SR_{RE3} of each crop is changing from time to time during the growth period. Therefore, time series from SOS to the EOS for these indicators were produced to track their fluctuations along the crop growth cycle. To increase the significance of the results, average time series were produced for the bright and hot spots categories. For example, the NDMI time series of all wheat bright spots were averaged into one average wheat bright spot NDMI time series. Similarly, one average wheat hot spot NDMI time series were produced. Variations in these average time series were analysed to understand various factors affecting crop yield.

2.3.12. T-test analysis

The crop fields can be clustered into a specific number of groups based on their soil type. For instance, they were grouped as loam and clay loam soils. Then the yield and WP figures of both groups were tested with the *t*-test to determine whether the difference between the means of the groups is significant or not. If the t-score exceeds its critical value (at $p < 0.05$), then the difference is significant and vice versa. A significant difference implies that the factor (soil type) has affected yield or WP.

2.3.13. Correlation analysis

For the CV_{ET}, NDSI and NSI, all crop fields have a single value for a season. Therefore, their time series cannot be produced. Besides, for these indicators, all crop fields have a unique value. Therefore, they cannot be categorised into groups. Thus, CV_{ET}, NDSI and NSI of the individual crop fields were correlated with their corresponding yield and WP figures. Correlation evaluates the relationship between two variables quantitatively. A higher correlation indicates a stronger relationship between variables, whereas a weak correlation implies that the variables are not related to each other.

3. Results and discussion

3.1. Yield and water productivity estimation

Crop yield and WP maps of each crop type for all crop fields were estimated. The summary is presented in Table 4 and Fig. 6.

The average estimated wheat yield (3203 kg ha^{-1}) and potatoes yield (31,495 kg ha^{-1}) are quite comparable with the reported wheat yield (3000 kg ha^{-1}) (Tohmé Tawk et al., 2019) and potatoes yield (32, 533 kg ha^{-1}) (Awad, 2019) in the Valley. The average grapes yield in Lebanon, based on FAOSTAT (2020) data from 2008 to 2018, is 8741 kg ha^{-1}, whereas the calculated grapes yield in this study is 17, 858 kg ha^{-1}. The discrepancy is because the FAOSTAT (2020) reports the average yield of both wine and table grapes and this study considers only table grapes. Also, the reported yield is the average value at the country level, while the estimated yield value is only for the Bekaa Valley. Furthermore, the estimated average WP of wheat (0.82 kg m^{-3}), potatoes (8.05 kg m^{-3}) and grapes (2.40 kg m^{-3}) are within their respective global WP ranges 0.62–2.00 kg m^{-3} (Foley et al., 2019), 4.00–11.00 kg m^{-3} (Steduto et al., 2012) and 1.3–4.5 kg m^{-3} (Alvarez-Carrion, 2018).

Although, the yield and WP estimations using the WaPOR data—-with the single HI value—show a good correlation with figures from the field. But, the HI should be adjusted, upward or downward, depending on the timing, crop phenological stage and extent of various stresses and sensitivity of the crop to these stresses (Steduto et al., 2012). Whereas in this study, based on literature, one constant HI value is used, thus, considering the HI dynamics, yield estimated by using a single HI value might not depict the real crop yield variations.

The analyses further presented in the paper reflect the diagnostic analysis for the year 2017, which is an average year of Table 4.

3.2. Identified bright and hot spots

Table 5 summarises the total number of crop fields and the number of crop fields categorised as bright and hot spots for each crop type.

The spatial distribution of bright and hot spots of wheat, potatoes and grapes is shown in Fig. 7. An example of a scatter plot of yield versus WP for potatoes with the identified bright and hot spots are shown in Fig. 8.

A single threshold value is used for the entire Valley to identify bright and hot spots. But the Valley has various climatic zones, therefore, the threshold value might be too high or low for certain areas. Thus, it is recommended to determine and delineate various agro-climatic zones and apply separate thresholds to each zone.

3.3. Analysis of WP factors

3.3.1. Water stress

Fig. 9-A shows that before 12th March the wheat NPP_{diff} is marginal, even though the $NDMI_{diff}$ around February is very high. From the booting stage onward, despite a decrease in $NDMI_{diff}$, the NPP_{diff} soars. The SSI curve further demonstrates the influence of moisture stress on

Table 4
Calculated water productivity figures based on five years of data from WaPOR (2015–19).

Crop type	Mean WP (kg m^{-3})	Mean yield (kg ha^{-1})	Mean ET (mm $season^{-1}$)
Wheat	0.82 (0.02/0.03)	3203 (331/0.10)	393 (43/0.10)
Potatoes	8.05 (0.52/0.06)	31,495 (1729/0.05)	367 (67/0.18)
Table Grapes	2.40 (0.25/0.10)	17,858 (1427/0.07)	752 (62/0.08)

Water productivity (WP), evapotranspiration (ET). In parenthesis (standard deviation/coefficient of variation).

Fig. 6. Box plot showing WP (A), Y (B) and ET (C) for wheat, potatoes and table grapes.

Table 5
Summary of the number of crop fields.

Crop type	Number of total crop fields	Number of bright spots	Number of hot spots
Wheat	544	32	34
Potatoes	341	52	58
Table Grapes	383	57	64

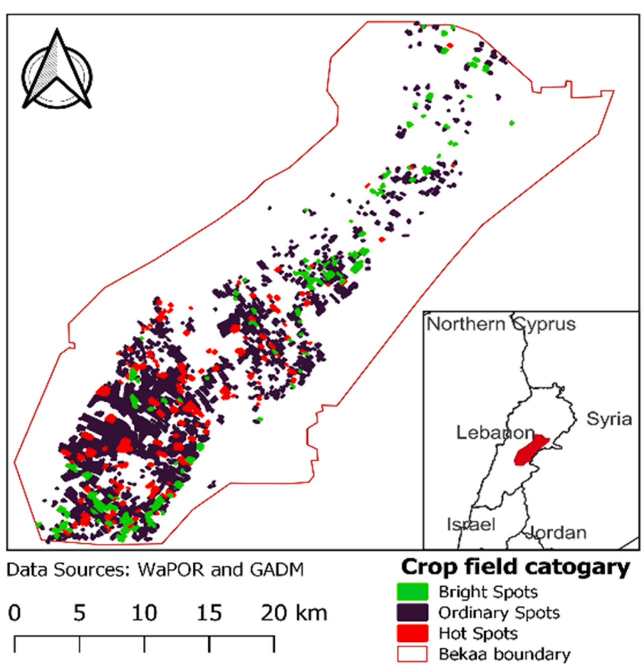

Fig. 7. Spatial distribution of bright and hot spots of all crops under the study.

biomass production (Fig. 9-B). The SSI remains close to zero from the initial to the mid of the developing stage (start of booting). While with the onset of the booting stage, the SSI mounts and remains higher till the end of the grain filling stage. This indicates that the wheat biomass is more sensitive to moisture stress from the mid-developing to grain filling stage. Zhang and Oweis (1999) have also found that wheat sensitivity to water stress in the Mediterranean region is higher from the booting stage to grain filling and then reduces at the late-stage (Table 6).

Biomass loss in the potatoes has occurred from the tuber initiation until maturity (Fig. 9-C). At tuber initiation and the start of tuber filling, the moisture deficit has a real-time effect on biomass production; the

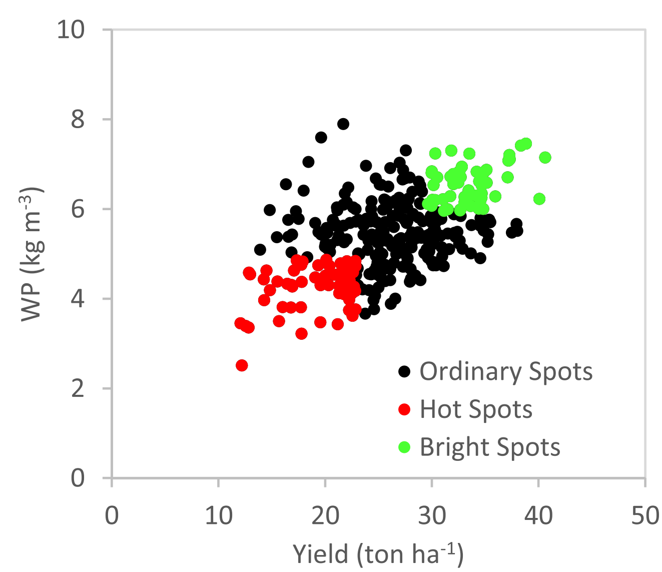

Fig. 8. Potatoes bright and hot spots shown in Yield-WP scatter plot.

NPP_{diff} soars as the $NDMI_{diff}$ rises. However, in the mid tuber filling, the decreases in $NDMI_{diff}$ do not affect the gained momentum of the NPP_{diff} curve. It is because water deficit during tuber initiation limits the number of tubers formation (Obidiegwu et al., 2015), which reduces biomass accumulation during tuber filling. The SSI for the potato crop (Fig. 9-D) demonstrates that yield response to stress is peaking in the tuber filling stage and then sharply declines at maturity (late-stage). Steduto et al. (2012) also reported that the yield response factor (k_y) for potatoes sharply declines from 0.7 in the mid-stage to 0.2 in the late-stage (Table 6). The SSI of potatoes remains low from the establishment to mid tuber initiation while Table 6 shows a very high potatoes sensitivity to stress at the initial stage. At this period, the potatoes are not stressed (NDMI diff remains almost zero, see Fig. 9-C), therefore crop response in terms of yield reduction is not captured. Thus, to better understand crop response to stress at each stage, crops should be intentionally stressed at every phenological stage.

Many grape varieties—some are listed by Leeters (2018) and Alvarez-Carrion (2018)—in the Valley causes significant heterogeneity in phenological stages and in harvest time within and between the groups—bright and hot spots. Therefore, a comparison of NDMI and NPP figures does not give sufficient information about the grapes stress response to biomass production. This also signifies that the SSI analysis for intercropping leads to erroneous results due to differences in biomass production, HI and ET of various crops in the same crop-field.

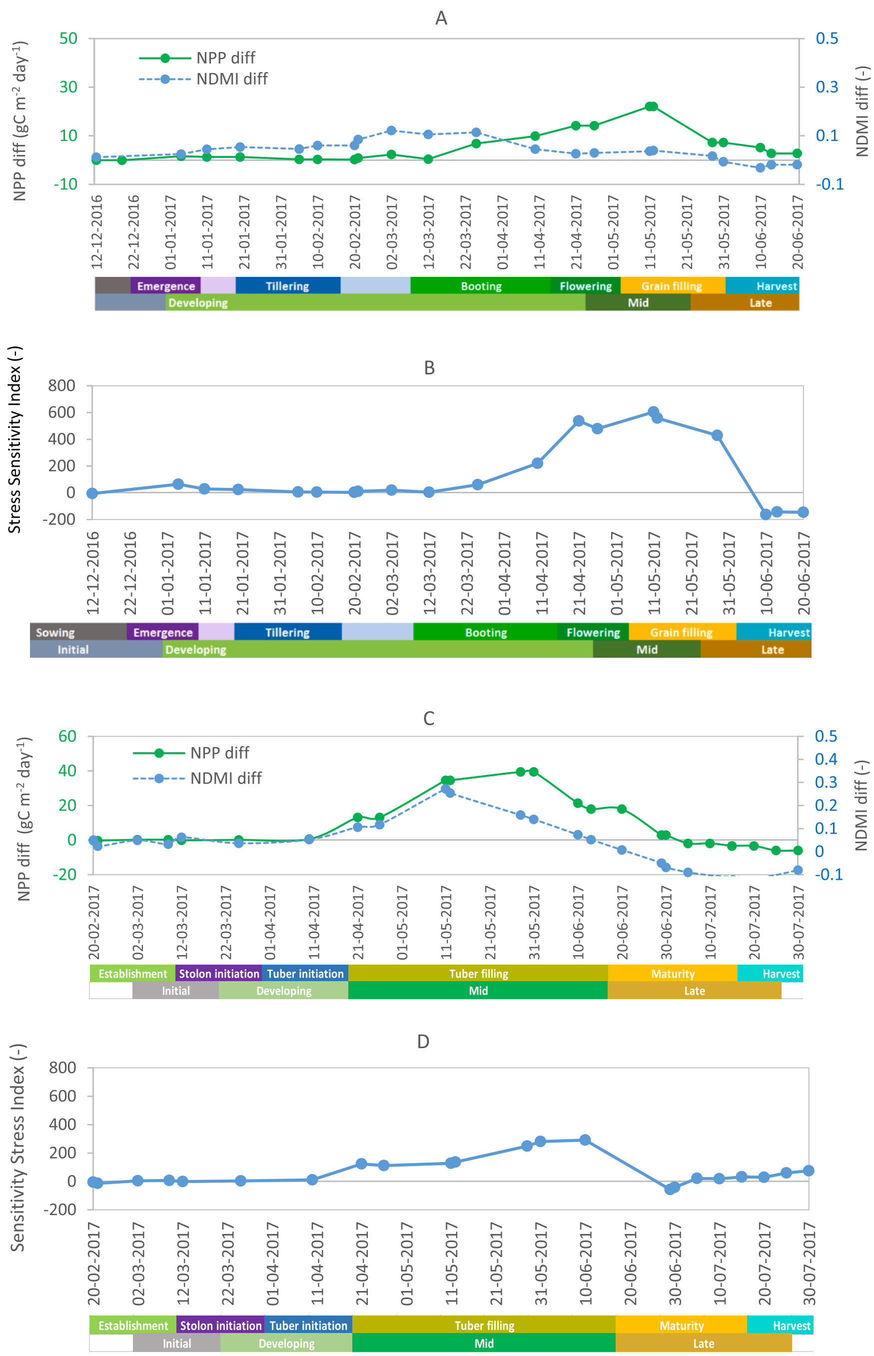

Fig. 9. NDMI and NPP difference graph for the wheat crop (A). Stress sensitivity index for various wheat growth stages (B). NDMI and NPP difference graph for the potato crop (C). Stress sensitivity index for various potato growth stages (D).

Table 6
Crop yield response to water stress.

Crop type	Initial-stage	Developing-stage/boosting	mid-stage/ grain filling	late-stage	Source
Wheat	0.01	0.31	0.28	0.10	Zhang and Oweis (1999)
Potatoes	0.60	0.33	0.70	0.20	Steduto et al. (2012)

The results show that the changes in NDMI and NPP of potatoes are more prominent than in wheat. This implies that the potato leaf welt sooner than the wheat in response to the water stress. Such information can be very useful for choosing stress-tolerant cultivars such as wheat in areas where water stress occurs.

The results also reveal that farmers associated with the hot spots have lost substantial wheat yield during the flowering and grain filling stages and potato yield during the tuber filling stage. These growth stages were also identified as the most stress sensitivity periods for their corresponding crops therefore water stress during the most sensitive growth periods is suggested to be prevented. This indicates, a need for better irrigation scheduling, improved moisture conservation or wiser water allocation along the crop growth period.

3.3.2. Irrigation heterogeneity

Fig. 10-A-C show that irrigation heterogeneity (CV_{ET}) negatively correlates with the yield of all three crops, whereas CV_{ET} does not significantly correlate with the WP. This exposes that only the yield of the crops is negatively affected by irrigation heterogeneity. This confirms findings by Abd El-Wahed et al. (2016). Currently, 65% of the farmers use sprinkler irrigation systems with only 65% efficiency due to the windy nature of the Valley (Jaafar et al., 2017). The reduction in CV_{ET} and subsequent increase in the potato yield can be realized by changing the sprinkler irrigation system to the drip irrigation system. The farmers who have switched to drip irrigation systems have already increased their potato yield in the Valley (United States Agency for International Development USAID (2014)).

The CV_{ET} indicates variations in ET which is assumed to be due to irrigation application. This could be caused due to variable application of non-water inputs and variability in soil properties (Gil et al., 2019). Also, partial infection of a crop-field with diseases could lead to variability in ET. Furthermore, a farmer may grow various varieties of the same crop in a field. The chances of these contributing factors to variability are higher in the larger crop fields than the smaller. Therefore, the users must be aware of the other potential contributors to CV_{ET} to better inform decisions.

3.3.3. Salinity stress

The results in Fig. 10-D show that salinity has neither affected wheat yield nor WP, as represented by a non-significant and weak correlation. Likewise, potato WP and yield is not affected by salinity, demonstrated by weak correlations (Fig. 10-E). FAO and International Atomic Energy Agency (IAEA) (2018) also state that the soil salinity of rain-fed, flood irrigation and alternative drip and sprinkler irrigation practices is very low (0.7–1.7 dS/m) in the Valley. However, monoculture and localized irrigation practices have increased soil salinity up to 9 dS/m at 20 cm soil depth in the Northern parts of the Valley.

Furthermore, the indices used for soil salinity analysis in this study are only capable to detect topsoil salinity based on surface soil reflectance. But, for irrigated agriculture, only topsoil salinity assessment is not sufficient and root zone salinity analysis, from where crops take up water, is of vital importance. Therefore, it is suggested to complement these results with root zone salinity analysis as recommended by Scudiero et al. (2016).

3.3.4. Nitrogen stress

Fig. 11 demonstrates that leaf nitrogen content (SR_{RE3}) of bright spots is higher than the hot spots in all three crop types. So, farmers associated with bright spots have applied more nitrogen than the hot spot farmers. Fig. 11-A shows that the difference between SR_{RE3} of the bright and hot spots of the wheat crop is very small. This indicates that wheat bright spot farmers have applied slightly more nitrogen than the hot spots farmers, realising that nitrogen treatment has a limited impact on wheat yield (Karam et al., 2009). On the other hand, the SR_{RE3} of potatoes bright spots is prominently higher than the hot spots. This indicates that potatoes bright spot farmers have applied more nitrogen, knowing that the potato yield can be significantly improved with increase nitrogen application (Xing et al., 2016). Similarly, nitrogen doses significantly increase grape yield in the Mediterranean climate (Ozdemir et al., 2010), therefore, bright spot farmers have applied more nitrogen to obtain better table grapes yield as reflected in Fig. 11-C.

The results show that better performers (bright spots) are associated with higher nitrogen applications. However, it is difficult to explicitly identify nitrogen contribution to better performance in proportion to other improved irrigation and agronomic practices adapted by the bright spot farmers. It is also worth mentioning that the uptake of phosphorous and potassium is also encouraged by nitrogen (Bloom, 2015; Hemerly, 2016). Therefore, it is challenging to separate the direct and indirect influence of nitrogen application on crop yield. Thus, further correlation and comparative analysis between crop fields with different nitrogen applications and similar irrigation/agronomic practices can improve the results. Moreover, leaf nitrogen content (SR_{RE3}) is calculated as an index. For practical purposes, the index value has to be translated to the leaf nitrogen in percentage and then related to the applied amount of nitrogen. The further suggested study will also help quantify the optimum amount and timing of nitrogen application for each crop.

3.3.5. Effect of crop rotation on yield and WP

Table 7 summarizes the *t*-test results for crop rotation influence on yield and WP. The results show that the t score for wheat WP (3.48) has exceeded the critical value (1.96), thus rotation has a statistically significant impact on wheat WP. While the impact of rotation on wheat yield is not statistically significant, the t score (0.73) is lower than the critical value (1.96). However, wheat rotated with other crops has resulted in a 55 kg ha^{-1} increase in yield. This means that there is an increase in wheat yield, yet not statistically significant, as the *t*-test fails.

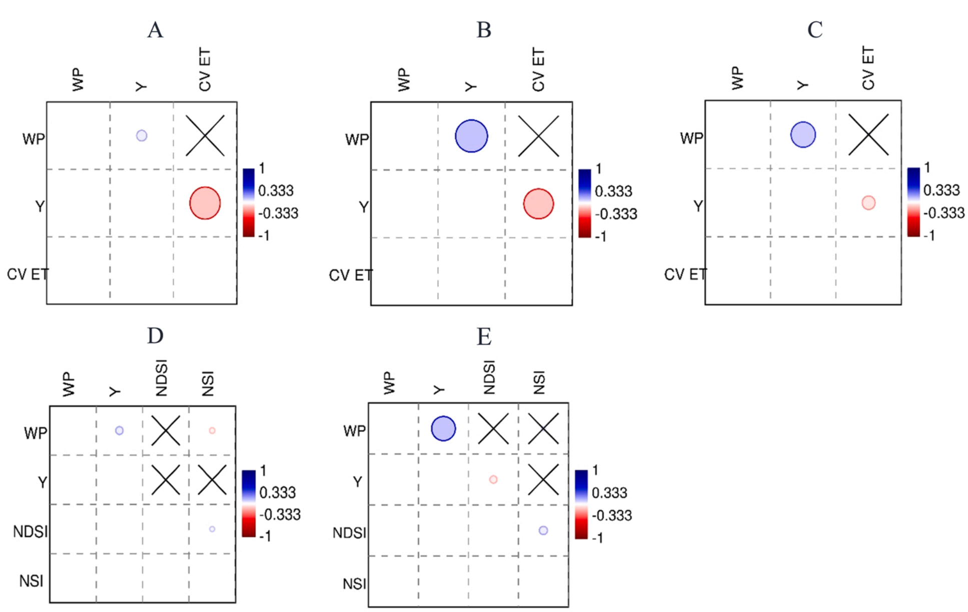

Fig. 10. The influence of CV_{ET} on yield and WP: wheat (A), potatoes (B) and table grapes (C). The effect of bare-soil salinity on water productivity and yield: wheat (D) and potatoes (E). The dark red and larger circle shows a higher negative correlation, whereas blue and larger circle shows a higher positive correlation. The legend represents the strength of correlation with 1 being the highest positive and − 1 highest negative. The non-significant correlations at $p > 0.05$ are marked with a cross. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)

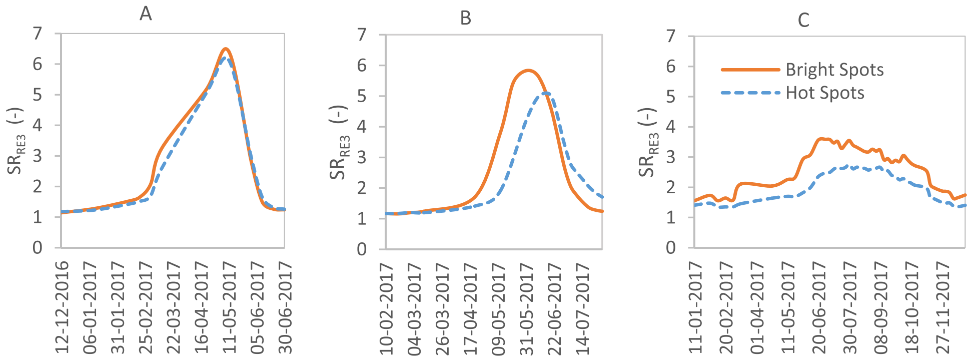

Fig. 11. average leaf nitrogen content of bright and hot spots: wheat (A), potatoes (B) and grapes (C).

Table 7
Summary of the *t*-test for the effect of crop rotation on yield and WP.

Effect of crop rotation on yield and WP							
Crop type		Yield (kg ha^{-1})			Water productivity (kg m^{-3})		
		Mono-cropping	Crop rotation	t-score	Mono-cropping	Crop rotation	t-score
Wheat	N	120	424	0.73 (1.96)	120	424	**3.48** (1.96)
	$\bar{x}$	2772	2827		0.64	0.66	
	σ	722	717		0.003	0.004	
Potatoes	N	25	316	0.59 (1.96)	25	316	0.06 (1.96)
	$\bar{x}$	25,479	26,188		5.39	5.41	
	σ	181	181		0.9	0.82	
	$\bar{x}$	12,919	14,056		1.55	1.49	
	σ	4381	3633		0.2	0.18	

The number of crop fields in the sample (N), the sample mean ($\bar{x}$), Standard deviation (σ). In parenthesis critical value of t at probability (p) equal to 0.05. The statistically significant results are shown in bold.

The t score for both potatoes WP and yield are lower than the critical value. This implies that the crop rotation has neither significantly influenced potatoes yield nor WP. Even though the results are not statistically significant (*t*-tests have not been passed), the farmers practising crop rotation harvest 709 kg ha^{-1} more potatoes than the farmers engaged in mono-cropping. Also, WP is slightly higher in the rotated crop fields.

Crop rotation increases crop yield because it improves soil structure and organic matter and controls pests (Nuñez et al., 2019). A study based on the data collected over the 20 years by Strauss (2017) has also revealed that wheat mono-cropping has the lowest yield than any other wheat crop succession. Our results also confirm that rotation has increased yield of both wheat and potatoes but not statistically significant. An improvement in the methodology might signify the results: if the yield figures of fully rotated crop fields are compared with the fully mono-cropped field. Currently, partially rotated crop fields are also included in the analysis (see section ↱2.3.3.5 for methodology). Moreover, other factors like irrigation practices and inputs application also affect WP and yield and thus may diminish the influence of crop rotation.

Furthermore, in this study, the crop rotation analysis is based on only two years of data. It can reflect the nutritional enrichment of the soil but not the breaking of the disease cycle. For the most appropriate cropping sequences and their impact on yield, it is recommended to analyse crop rotation data of four to five years (Mohler and Johnson, 2009).

3.3.6. *Effect of soil type on yield and WP*

According to the USDA soil classification, nine soil classes were identified in the Valley (see Fig. 12). However, the figure shows that crops under study—wheat, potatoes, and grapes—are grown only on Xeralf and Xerolls soil classes. The number of crop fields distributed over each soil type is presented in Fig. 13. Xeralf and Xerolls are respectively loam and clay loam soils based on soil texture triangle. The hydrological

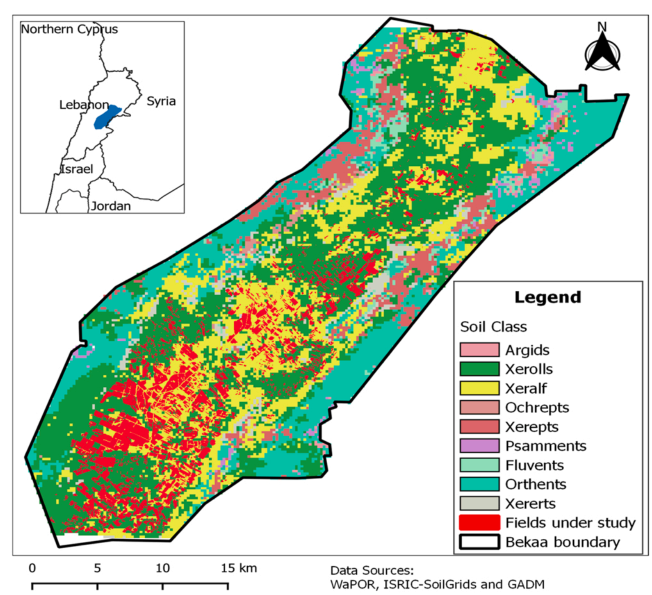

Fig. 12. Spatial distribution of wheat, potatoes and table grapes over the soil types.

properties of both soil classes are presented in Table 8.

To ensure the accuracy of the results, crop fields lying partially on both soil types were removed from the analysis. Thereafter, the *t*-tests were conducted to determine the statistical significance of the soil-type influence on yield and WP (Table 9). Results show that soil type significantly impacts wheat WP but not wheat yield ($p > 0.05$). Results also reveal that both yield and WP of potatoes are significantly

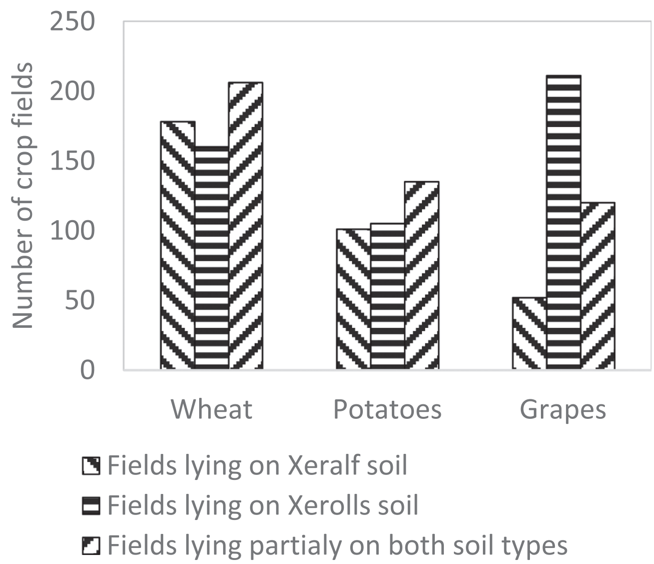

Fig. 13. Frequency distribution of crop fields over the soil types.

influenced by soil type. Although the values are close to the critical threshold for significance, soil type is not a statistically significant factor influencing yield and WP for grapes.

The influence of soil type can be ascribed to its hydrological properties. The plant available water (PAW) of the Xerolls (clay loam soil) = 200 mm m^{-1} is higher than the Xeralf (loam soil) = 167 mm m^{-1} (New Mexico State University, 2018). Therefore, in a water-scarce region, Bekaa Valley, the potatoes and grapes grown on the Xerolls soils have a higher yield than Xeralf. A proper irrigation scheduling can increase potatoes and grapes yield grown on Xeralf soils. For this purpose, the depth of irrigation is recommended to be reduced and frequency increased, as Xeralf soils cannot hold a larger quantity of water to support crop water demand for a longer time.

3.4. Framework limitations

The above-mentioned research findings with regard to yield and WP figures estimation, crop response to water stress, variability in ET, salinity stress, nitrogen application, and influence of crop rotation and soil type on performances compare well with the available information from the field and knowledge in literature. However, we acknowledge the limitations of this framework.

This framework is mainly aimed at crop-field level analysis. Therefore, the spatial resolution of the remote sensing data in relation to crop-field (polygons) size is a key consideration concerning the accuracy of results. In this study, crop fields smaller than one hectare is removed from the analysis based on data with a 30 m resolution. For a coarser resolution (250 m) soil data analysis the crop fields lying on multiple soil types are not considered for analysis. Removal of such crop fields from analysis reduces data population and affects the significance of the results, therefore, users are recommended to consider data with reasonable spatial resolution in relation to crop-field size. In this study, after data cleaning, the population of the data remained sufficient for analysis due to a reasonable resolution of the data as compared to the size of crop fields in the Valley.

4. Conclusions

To translate open-source remote sensing data to actionable information by using a structured approach, a diagnostic framework has been developed. The realistic estimation of yield and ET figures with sufficient spatial resolution to capture crop-field level variability enabled crop fields' categorisation and their comparative analysis. The study revealed that four factors have negatively affected yield and WP in the Bekaa Valley (and they are): water stress at the critical crop growth stages; low within-farm irrigation uniformity; low nitrogen application; and improper irrigation schedule based on soil properties. It was also exposed that mono-cropping has reduced yield and WP, but the results are not statistically significant. Whereas topsoil salinity has neither influenced yield nor WP in the Valley. To improve Yield and WP in the

Table 8
Soil hydrological properties.

Soil layer depth (cm)	Xeralf				Xerolls			
	Sand[a]) (%)	Clay[a]) (%)	Soil type	PAW[b]) (mm m^{-1})	Sand (%)	Clay (%)	Soil type	PAW (mm m^{-1})
0	41	25	Loam	167	37	33	clay loam	200
5	42	25	Loam	167	38	31	clay loam	200
15	43	22	Loam	167	40	29	clay loam	200
30	45	21	Loam	167	42	27	clay loam	200
170	45	21	Loam	167	43	27	clay loam	200

PAW is plant available water.
Sources: a) Stokvis (2017)*; b)* New Mexico State University (2018).

Table 9
Summary of the *t*-test for the effect of soil type on yield and WP.

Crop type		Yield (kg ha^{-1})			Water productivity (kg m^{-3})		
		Xeralf soil	Xerolls soil	t-score	Xeralf soil	Xerolls soil	t-score
Wheat	N	178	160	0.70 (1.96)	178	160	**2.59** (1.96)
	$\bar{x}$	2862	2808		0.64	0.66	
	σ	739	667		0.063	0.063	
Potato	N	101	105	**2.05** (1.97)	101	105	**6.80** (1.97)
	$\bar{x}$	25,548	27,240		5.05	5.82	
	σ	195	178		0.78	0.82	
Table grapes	N	52	211	1.93 (1.96)	52	21	1.82 (1.96)
	$\bar{x}$	12,919	14,056		1.55	1.49	
	σ	4381	3633		0.2	0.18	

The number of crop fields in the sample (N), the sample mean ($\bar{x}$), Standard deviation (σ). In parenthesis critical value of t at probability (p) equal to 0.05. The statistically significant results are shown in bold.

Valley investments should target the above four factors. While we acknowledge the errors and caveats inherent to the use of remote sensing data, we are confident that the application of the diagnostic framework provides reliable and useful results, since the analyses focus on the comparative analyses and less on the absolute value.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Abdur Rahim Safi reports financial support was provided by Directorate General for International Cooperation (DGIS) of the Ministry of Foreign Affairs of the Netherlands.

Acknowledgements

This study was supported by the Water Productivity Improvement in Practice (Water-PIP) project, which is funded by the IHE Delft Partnership Programme for Water and Development (DUPC2) under the programmatic cooperation between the Directorate-General for International Cooperation (DGIS) of the Ministry of Foreign Affairs of the Netherlands and IHE Delft (DGIS Activity DME0121369).

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