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EVALUATION OF FAO’S WATER PRODUCTIVITY PORTAL (WaPOR) YIELD OVER THE BEQAA VALLEY, LEBANON

by
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ABSTRACT
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With the increasing pressure of agriculture on water and land, achieving high water productivity is essential. Models such as FAO's Water Productivity Portal (WaPOR) aim to estimate water productivity by providing yield and evapotranspiration. In this study, the aim was to validate the yield product of WaPOR in the Beqaa Valley, Lebanon. The study was focused in two main fields. Yield of Potato and wheat, planted during 2017-2018, was validated in one field. In addition, the yields of barley, vetch, barley/vetch mixed fields and vetch/oat mixed fields, planted during 2012-2019,were validated in the other field by comparison against farmer reported yields. Statistical Indicators such as percentage relative error (RE), Root Mean Square Error (RMSE),R^2, correlation (r), and bias were used for this validation.
Wheat yield showed better results at a resolution of 30 m than that at a 100 m where recorded RE% of 1.14% < 20%, R^2 of 0.38, RMSE of 0.71 ton/ha, r of 0.61 and a bias of 0.68 ton/ha versus an RE%|-12.43%| <20%, R^2 of 0.38, RMSE of 1.2 ton/ha, r of 0.62, and a bias of 0.73 ton/ha respectively. For the other crops, level consistency could not be tested for since not all crops where equally identified at the different levels. Potato yield was considerably accurate at a 100m resolution with RE% of 19.55%<20%, an R^2 of 0.22 and RMSE of 9.31 ton/ha, r of 0.47, and a bias of 2.39 ton/ha. As for barley,vetch,barley/vetch and vetch/oat mixed fields results were considered to be poor with a RE% > 20% for all crops at both levels 2 and 3. This inaccuracy in crop yield estimations was attributed to inaccuracy in farmer reported yields which was detected in both fields, the standardized LUE max, harvest Index and moisture content.

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ABBREVIATIONS

AGBP	Above-ground biomass Production
DMP	Dry Matter Productivity
EC	Eddy Covariance Flux
EOS	End of Season
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation
GPP	Gross Primary Productivity
HI	Harvest Index
L1	Level 1 (250 m resolution)
L2	Level 2 (100 m resolution)
L3	Level 3 (30 m resolution)
LUE	Light Use Efficiency
NDVI	Normalized Difference Vegetation Index
NIR	Near-Infrared Reflectance
NPP	Net Primary Production
RMSE	Root Mean Square Error
RS	Remote sensing
r	Correlation
R^2	Coefficient of Determination
RMSE	Root Mean Square Error
SOS	Start of Season
TBP	Total Biomass Production
V1	WaPOR version 1.1
V2	WaPOR version 2.1

Vis	Vegetation Indices
WaPOR	The FAO portal to monitor Water Productivity through Open access of Remotely sensed derived data

CHAPTER I

INTRODUCTION

A. Background

With population growth, climate change, and economic growth worldwide, agricultural management is becoming of higher importance to ensure food security. By 2030, the global population is estimated to reach between 8.4 and 8.6 billion as reported by the United Nations Department of Economics and Social Affairs (FAO, 2017).

Hence, food demand is estimated to increase by 60 % as early as 2025 (FAO, 2017; OECD et al., 2012). Since agriculture is the primary source of food globally (Agriculture, food and water, 2003), the challenge of reaching up to the continuously increasing food demands by agriculture remains a food security challenge (Glotter et al., 2016). Nevertheless, the increase in agricultural production has a direct effect on the availability of land and water. According to FAO (2014), irrigated agriculture is among the most water-intensive sectors using up to 70% of water worldwide. Today, agricultural lands are estimated to take up to 11% of the globe's land surface, which represents approximately 36% of all land suitable for agriculture (OECD., 2019).

Optimizing water use depending on crop requirements can help achieve sustainable water resources management (Khan & Walker, 2015). Therefore, agronomic research aims at finding agricultural management strategies that increase agricultural production in a way that is sustainable to both land and water resources (Duda, 2017).

To track down agricultural production, evaluate management practices, and draw out future projections, agricultural models are developed to ensure sustainable agricultural practices (Jones et al., 2017b) .Often, understanding crop yield and the different interactions between soil, water, and the atmosphere helps to achieve sustainable development (Khan & Walker, 2015). Various factors could be tracked down using agricultural models, including biomass, evapotranspiration, and water productivity. Tracking biomass and primary productivity is essential to understand energy flows in ecosystems (Pan et al., 2014).

B. Research Problem and Objectives

1. Problem Statement

FAO's Water Productivity Portal (WaPOR) is the only open-access data portal providing remote-sensing based water productivity in Africa and the MENA region. It is the first portal to provide, at a continental level, comprehensive datasets combining biomass and AETI information near real time covering the period between 2009 to date,especially for the African continent (Delft, 2019). In order to evaluate water productivity, both AETI and NPP require evaluation and validation. At levels 2 (100m) and 3 (30m) , WaPOR covers the Beqaa Valley for the years 2009 forward. However, validation in the Beqaa was only done for grapes during 2015 and for wheat and potato during 2016-2018 at level 3 but not for level 2.

2. Research Objectives

The objective of this work is to validate the yield of an agricultural model namely WaPOR, which is a portal of Water Productivity through Open access of remotely sensed derived data. WaPOR was developed in order to estimate crop water productivity, an agricultural performance indicator, at different levels and providing different layers. In this study, the Net Primary Production and Above Ground Biomass

Production was validated by comparing values to observed crop yields for wheat and potatoes in Skaff during the 2017-2018 seasons and for barley, vetch, barley/vetch and vetch/oat mixed fields in AREC between 2012 and 2019 in the semi-Arid Beqaa Valley in Lebanon.

3. Research Questions

- Is the WaPOR NPP for wheat, potato, barley, and vetch valid in comparison to field yield in the Beqaa Valley in Lebanon?
- What are possible causes of inaccuracy in WaPOR's modeled yield estimations?

WaPOR yield calculated based on AGBP and NPP for wheat and potato for the years 2017-2018 do fall within the acceptable range of the Reported yield at levels 2 and 3 for wheat and level 2 of potato . Nevertheless, WaPOR yield calculated based on AGBP and NPP for barley, vetch, barley/vetch and vetch/oat mixed fields in Beqaa for the years 2012-2019 do not fall within the reported yield acceptable range for these fields. Inaccuracies could be stemming out from inaccurate farmer reported yields, or inaccurate parameters used such as Light Use Efficiency, harvest Index and moisture content.

CHAPTER II

LITERATURE REVIEW

A. Models

Agricultural Models were first developed in the 1950's through the 1970's (Jones et al., 2017a). Models have different applications including the simulation of geophysical, atmospheric, and oceanic processes (Willmott et al., 1985), the quantification of crop physiological and phenological processes (Zhang et al., 2018), the evaluation of different agricultural management strategies (Choruma et al., 2019), the evaluation of the implications of these practices on the environment (Zhang et al., 2018), and the estimation of futuristic food production (Glotter et al., 2016). Crop growth models facilitate decision making (Di Paola et al., 2016) for farmers and landowners where they provide a more comprehensive view of the state of agriculture in the land leading to refining the application of fertilizers, optimizing water usage (Choruma et al., 2019; Di Paola et al., 2016), and formulating policies even at national and subnational scales (Glotter et al., 2016).

Crop models can have different uses and are applied at different scales. Examples of crop models that are used at farm level include: The Agricultural Production Systems Simulator (APSIM), Environmental Policy Integrated Climate (EPIC), Dynamic Land Ecosystem Model (DLEM), Decision Support System for Agro technology Transfer (DSSAT), YIIELDSTAT, and CROPWAT. Other models, such as the Hadley Centre Atmosphere Model are used at a global level (Zhang et al., 2018). It is important to note that, spatial and temporal factors are taken into consideration in different models. Also, models might depend on different differential equations over time or various locations because of differences in weather, soil conditions, and crop management from the time of plantation to harvest (Khan & Walker, 2015). One crop model named APSIM consists of biophysical and crop management modules in the aim to reach accurate crop yield estimations while considering different economic and ecological outcomes of agricultural management practices (Keating et al., 2003). Besides, different management practices are integrated in order to predict consequences of certain farming practices on soil resources on the long term (Keating et al., 2003), and their association with climate risk (Holzworth et al., 2014). EPIC also simulates chemical processes that occur within the plant under different agricultural management practices. Even though EPIC was mainly developed to study soil erosion in the USA, it was also used in various geographical locations (Choruma et al., 2019). Another crop model, DLEM, aims to estimate the effects of environmental factors and stressors on agricultural yield and production. DLEM 2.0 takes into consideration multi-soil layer processes, coupled carbon, water, and nitrogen cycles; and many GHG emissions and simulates agricultural yield accordingly (Zhang et al., 2018). YIELDSTAT is another model developed to detect the spatial distribution of crops and crop yields for various crops in Germany, taking into account different factors that affect crop growth, such as weather variations and soil types (Mirschel et al., 2014). Not only were crop models used to detect crop yield and land productivity, other models such as CROPWAT provide crop evapotranspiration based on soil, climate, and crop information. It helps agronomists calculate water requirements, irrigation scheduling and total water withdrawal for irrigation based on the provided crop evapotranspiration (Khan & Walker, 2015).

Even though models based on remote sensing were developed in the 1980's (Running et al., 1989), most studies using models tackling environmental factors did not have enough ground observations, which made distinguishing whether errors resulted from the climate inputs or troubles with the model itself problematic (Glotter et al., 2016).

Zhang et al. (2018) identified gaps in existing models such as the absence of long-term data on the large-scale, the disregard of some environmental factors, and the lack of a holistic model that combines the various land ecosystem models. In addition, micronutrients, pests, and diseases cannot be simulated by most crop models (Ahmad et al., 2018). Therefore, new models should consider these gaps.

B. Remote-Sensing

Remote Sensing is a technology that depends on the sampling of reflected and emitted electromagnetic radiation from Earth's surface. It uses images from satellites and airplanes to understand features present on the surface of the Earth (Horning et al., 2010). Remote sensing techniques have been used in the systematic monitoring and estimation of water productivity (FAO, 2018) and crop yield since the 1980's (Kern et al., 2018) to identify gaps and propose appropriate solutions .

Different remote sensing biophysical parameters such as Leaf Area Index (LAI) and Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) act as significant indicators for plant status and productivity, and hence are used in crop yield estimations (Kern et al., 2018). Other remote-sensing parameters such as the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) can be used to monitor vegetation stress (Friedl et al., 2002). Several studies have showed that the assimilation of remotely-sensed data into crop models can lead to accurate crop yield estimation (Sivarajan, 2011), where Kern et al. (2018) showed that incorporating weather data with remote sensing vegetation indices helped improve crop yield predictions in models. Also, Al-Gaadi et al. (2016) showed that these advancements have been beneficial to monitor crop growth, health, and yield development in near real-time joined with actual meteorological conditions (Baruth et al., 2008).

C. Net Primary Production

Net Primary Production (NPP) is one of the most commonly modeled variables due to its significance in determining multiple factors such as water use, water productivity, crop response to weather conditions (Jones et al., 2017a), and the functioning of the ecosystem. Theoretically, NPP quantifies the conversion of carbon into plant biomass during photosynthesis (Pan et al., 2014; Running et al., 2004).

Nevertheless, part of the carbon captured by plants is spared for plant use and not converted into biomass. Based on that, Running et al. (2004) defined NPP as the sum of daily net photosynthesis minus the cost of growth and maintenance of living cells in permanent woody tissue. Since NPP is directly correlated with carbon, it gives us insight into the carbon intake by plants, which is later made partially available as food, fuel, and feed (Pan et al., 2015).

NPP can be monitored either using ground-based field measurements, satellite-based observations, or modeling (Pan et al., 2014). NPP models could either be statistical, parameter-based, or process-based (Hua et al., 2014). Statistical models calculate NPP based on a simple relationship between vegetation and climate factors whereas process-based models depend on multi-layer databases of climate, soil, and vegetation types (Churkina et al., 2003; Hua et al., 2014). Early on, scientists depended on ground observations of canopy heights on small scales to quantify production. Then, NPP's first model was put together by Lieth and Whittaker (1975). In the 1980's, NPP was modeled as the product of actual Evapotranspiration using meteorological data

(Running et al., 2004). Modeling NPP is crucial since it helps us simulate production over a large area, which is not possible using regular ground-based monitoring (Xiaobin et al., 2016). NPP models help us understand and quantify the effects of different environmental factors such as Climatic variability, precipitation, atmospheric CO2 concentrations, changes in land cover and nitrogen deposition in the determination of NPP (Pan et al., 2015). Nevertheless, ground and satellite based observations remain essential for the validation and calibration of models (Pan et al., 2014). Since, net primary production data are required on vast spaces and very accurately, satellites are considered a good way to derive NPP (Running et al., 1989).

Several models aim to simulate NPP using remote sensing based on the theory of light use efficiency, known as Production Efficiency models (PEM). This theory states that there is a constant relationship between photosynthetic carbon uptake and radiation receipt at the canopy level (McCallum et al., 2009). PEMs depend on two sources of input: meteorological data and satellite-derived data. PEM's use these data in a two-step equation for the calculation of NPP. The first formula calculates gross primary production (GPP) from which autotrophic respiration (Ra) is subtracted to calculate NPP (McCallum et al., 2009). Ra encompasses three factors in this equation summed as autotrophic respiration: growth respiration, maintenance respiration, and respiratory cost of ion uptake. GPP is calculated as a function of photosynthetically active radiation (PAR), a fraction of absorbed PAR (FPAR), Light use efficiency (LUE), and other scalars that include temperature and vapor pressure deficits (McCallum et al., 2009).

One of the process-based, Production Efficiency models is Carnegie-Ames-Stanford-Approach (CASA). CASA estimates terrestrial NPP based on satellite observations separately calculating NPP without calculating GPP (McCallum et al., 2009). According to CASA, NPP is the product of two factors mainly: absorbed photosynthetically active radiation (APAR) and a light use efficiency factor (ε). In this equation, APAR is calculated as a function of total solar radiation per pixel per month (Rs), the absorbed fraction of photosynthetically active radiation of vegetation (FPAR), maximum light use efficiency (ε*) which varies with the type of vegetation, stress factor temperatures (T(ε1),T(ε2)), and finally, water stress factor W(ε) (Xiaobin et al., 2016). APAR can be affected by the type of plant, plant size, and climatic conditions (Running et al., 2004). In the WaPOR model, NPP is the GPP without autotrophic respiration, Net Ecosystem Production (NEP) is NPP minus soil respiration, and Net Biome Production (NBP) is NEP minus the loses due to anthropogenic removals and disturbances (FAO, 2020).

D. Crop Yield Remote-Sensing Based Modeling

Many studies have aimed to estimate potato yield since it's considered the fourth major staple crop globally (Haverkort & MacKerron, 2012). A study performed by Bala et al. (2007) aimed to estimate the yield of potato in Munshigonj, Bangladesh, for 2006.

Normalized Difference Vegetation Index (NDVI) and Leaf Area Index (LAI) were calculated using 8 -Tera MODIS images and then analyzed spatially using ArcGIS 9.0. Regression analysis showed a good correlation between potato yield data and 16-day average NDVI data when the image is taken during an active time of plant growth (Bala et al., 2007). Potato yields were also estimated in another study by Al-Gaadi et al. (2016) in three 30-ha irrigated fields in the Eastern Region of Saudi Arabia. NDVI and

SAVI were calculated based on Landsat-8 and Sentinel-2-satellite images. The regression analysis showed difference in estimated yield predictions between the two sensors, with better estimated results by Sentinel-2-satellite images.

Wheat yield was also studied by many models. A study by Fahad et al. (2019) estimated the yield of wheat using the CERES-Wheat model in Faisalabad. Estimation of the wheat yield depended on remotely-sensed soil moisture. Then, the modeled yield was validated and compared to observed yield in 25 random farms. A close association appeared between the estimated yield (2979 kg/ha) and the reported observed yield (1500-3593 kg/ha) (Fahad et al., 2019). Another model known as WOFOST, the World Food Studies simulation model, was used in order to estimate wheat yield in China by Yuping et al. (2008). WOFOST and SAIL models were coupled through LAI to simulate soil adjusted vegetation index (SAVI) derived from MODIS images. Yield data were compared to those extracted from WOFOST with no remote-sensing data. This study showed that combining remote-sensing data for yield estimation decreased the relative error of maximum LAI from 31.6 % to 15.8%, and the relative error of above-ground dry matter weight at maturity from 24.4% to 15.3%, showing the importance of combining remote-sensed data in models (Yuping et al., 2008).

E. WaPOR Model

WaPOR is a portal of Water Productivity through Open access of remotely sensed derived data. This portal came as an output of a project titled: ‘Using Remote Sensing Support of solutions to reduce agricultural water productivity gaps. This project was funded by the government of the Netherlands, and developed by FAO and other project partners: FRAME consortium, IHE Delft and IWMI in 2017(FAO and IHE Delft, 2019). In order to monitor land and water productivity, identify gaps, and propose the appropriate solutions, this portal was developed as a contributor to achieving a sustainable increase in agricultural production. FAO’s WaPOR provides access to spatial data layers related to water and land use for agricultural production in addition to several time series analyses and area statistics (FAO, 2018). WaPOR was launched as WaPOR 1.1, and later a modified WaPOR 2.1 was added and is currently available.

The WaPOR model covers a time period of almost 12 years between 2009 until today, covering the whole of Africa and the Near East Region (FAO, 2018).It provides real- time accurate estimation which is very important for consequent decision-making (Ahmad et al., 2018). WaPOR is available at three different spatial resolution levels: level 1(L1) is a continental layer at a 250m resolution, level 2 (L2) is a national layer at a 100m resolution, and level 3 (L3) is a subnational layer at a 30m resolution. In specific, level 1 covers all of Africa and the Near East, while level 2 covers certain countries including Morocco, Tunisia, Egypt, Ghana, Kenya, South Sudan, Mali, Benin, Ethiopia, Rwanda, Burundi, Mozambique, Uganda, West Bank and Gaza Strip, Yemen, Jordan, Syrian Arab Republic and Lebanon, and level 3covers Irrigation schemes and rain-fed areas in Egypt, Ethiopia (2 areas), Mali and Lebanon (FAO, 2018).

Originally derived from freely available remote sensing satellite data, common standardized input was produced and used in WaPOR in the form of intermediate data that ensures consistency between the different data components produced as the final outputs (FAO, 2018). Layers in the WaPOR model are represented within different thematic areas which are: climate, water, land, and water productivity (WP). Two major components are included in the Climate Theme; namely precipitation (PCP) and Reference Evapotranspiration (RET). The Water Theme includes the components:

Actual Evapotranspiration and Interception (AETI), Transpiration (T), Evaporation (E), and Interception (I). The land Theme includes: Above ground biomass production (AGBP), Land cover classification (LCC), Phenology, and net primary production (NPP). Finally, the water productivity thematic area includes two components: Gross WP and Net Water productivity (Net WP). All mentioned layers are produced at the 3 different resolutions except Reference evapotranspiration and precipitation which are only available at level 1, and Phenology is only available at levels 2 and 3. At different levels, layers are available as either annual, seasonal, monthly, decadal, or daily data. To develop the afore-mentioned layers, satellite sensors, meteorological data and static data sources were used at different levels. In this study, we focused on NPP provided by WaPOR at the national and sub-national levels.

F. WaPOR NPP Validation

Different Earth Observation data validation techniques were used to validate WaPOR NPP including; rule- or model-based physical consistency evaluation, cross validation using inter-product comparison to reference datasets, internal validation of spatial and temporal consistency, direct validation against measured in-situ data and observations, and evaluation of the consistency of data components among the three spatial resolution levels (Delft, 2019; Mannaerts et al., 2020).

Two quality assessment reports aimed to validate WaPOR's water productivity product (Delft, 2019; Mannaerts et al., 2020) by evaluating and validating both NPP and ET. It was reported by Mannaerts et al. (2020) that WaPOR NPP was validated at level 1 (250 m) using cross or inter-product validation on an annual scale against the average of MODIS Terra and Aqua NPP products, against IBIS model, against annual

MODIS/Terra 8-day L4 Global 500m Net Primary Productivity (GPP-MOD17) (Mu et al., 2011), and against Dekadal geostationary Meteostat GPP (GPP-MSG) product from the EUMETSAT LandSAF (LSASAF) which also uses (Monteith, 1972). It was reported by Delft (2019) that WaPOR's initial comparison against MODIS was done against the average of MODIS Terra and Aqua NPP products in 2011. This comparison showed an underestimation of WaPOR in the eastern part of Southern Africa and eastern Madagascar and an overestimation in the Central African Republic. NPP's comparison against IBIS model by the Center of Sustainability and the Global Environment of the University of Wisconsin and showed a very similar trend with the WaPOR NPP with a lower spatial resolution as reported by Delft (2019). Even though the comparison against MODIS was done at level 1, average values were not for the entire continent but only averages of available data between 2009-2014. In this comparison, WaPOR showed higher high and lower low NPP, with a correlation that slightly improved across 2009 to 2014 as reported by (Mannaerts et al., 2020). This comparison showed existing variations between WaPOR and MODIS products in different land and climatic zones, and lower agreement between the two models for irrigated crops than rainfed crops. Upon further investigation, variations seemed to be correlated with land cover more than climate. Finally, it was suggested that the WaPOR NPP is within the adequate range at the continental, basin, land class scale and climate class, considering proven MOD17 underestimations. Hence, WaPOR NPP was generally overestimated in comparison to the MODIS NPP in arid and tropical climate classes whereas they were highly correlated in grasslands, shrublands, and croplands. The other comparison against MSG showed very good agreement where no significant bias was recorded for any of the dekads compared for the spatial NPP patterns. Some differences recorded were attributed to the land cover classification, model parameterization of both products such as LUE assumptions. Spatial comparison was also followed by a temporal comparison against MSG NPP over the African Continent for all its 3 climatic classes. In its temporal comparison, similarity between the two models was recorded to be positive. Nevertheless, it was noted that WaPOR NPP was higher in wetter climates and lower in more arid climates. NPP at L2 (100m) and L3 (30m) were tested for level consistency against L1 NPP and validated directly to in-situ data as reported in WaPOR's second quality assessment report (Mannaerts et al., 2020).

Several direct validations against in-situ ground observations were done in both quality assessment reports (Delft, 2019; Mannaerts et al., 2020). Validation against in-situ ground data included comparing WaPOR NPP to decadal and monthly Eddy Covariance flux tower data at 14 locations. WaPOR NPP was also compared against field surveys and farmer reported data at level 3 for sugarcane, grapes, bananas, and rice in Wonji, Fayoum, Kpong, and the Beqaa Valley using point observations (Delft, 2019). More in-situ observations were done at levels 1 and 3 in both the Litani Basin of the Beqaa Valley in Lebanon and the upper Awash river Basin in Ethiopia in the period between 2016-2018 (Mannaerts et al., 2020). In the validation against EC, it was shown that areas that showed high agreement between WaPOR NPP and EC NPP also showed a high correlation between the NPP-EC and the WaPOR NDVI, whereas in sites where WaPOR NPP was overestimated this correlation was less or non-existent which definitely affects WaPOR NPP. Nevertheless, seasonality was well captured in all fields. For further validation, MOD17A2 NCEP II GPP 8-day, 1km product was compared to EC at the sites showing low agreement with WaPOR. As with WaPOR, NPP during high vegetation peaks was underestimated by MOD17A2 by a similar magnitude to WaPOR. Nevertheless, low vegetation period was captured better by MOD17A2.

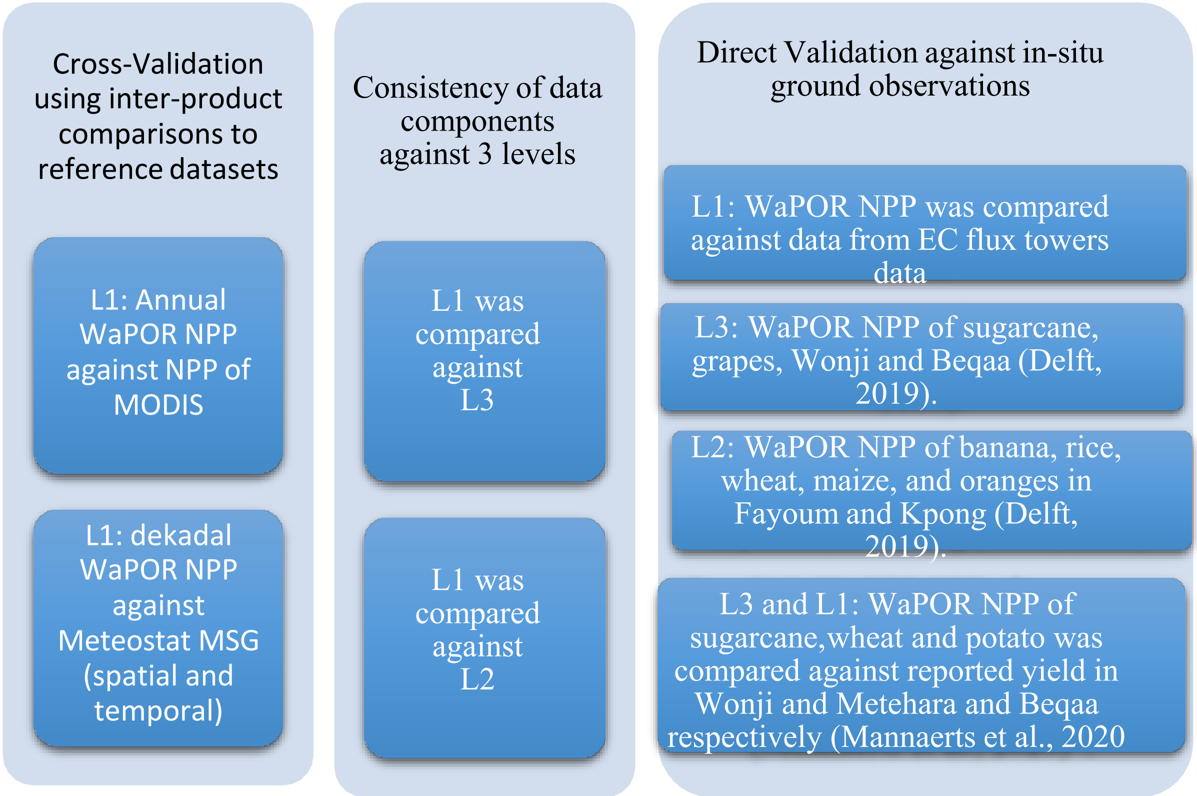

Figure 1 WaPOR NPP Validations at level 1, 2 and 3

As for its comparison against in-situ data, WaPOR yield of sugarcane, grapes, bananas, rice, maize, oranges, and wheat in Wonji, Lebanon, Kpong and Egypt (Delft, 2019) and that of potato, wheat, and sugarcane in Lebanon and Ethiopia (Mannaerts et al., 2020) was validated against ground data. In this validation, WaPOR sugarcane yield (100 tones/ha) in the Wonji Irrigation scheme located in the Awash Basin in Ethiopia was proven to be within the FAO reported ranges (50-150 tones/ha), the ranges given by Steduto et al. (2012) (70 tones/ha) and the ranges observed by Yilma (2017) (100 ton/ha) as reported by Delft (2019). Another assessment of the sugarcane yield was reported in the Wonji and Metehara Irrigation Schemes in the Awash Basin in Ethiopia for the years 2009 to 2016 and for 2012,2014, and 2016 respectively by Mannaerts et al. (2020). WaPOR derived AGBP was recorded to be (150.6 ton/ha) at L3 and (141.1 ton/ha) at L1 in Wonji lying slightly higher and slightly lower than AGBP reported by farmers in Wonji (147.3 ton/ha). As for Metehara, the WaPOR AGBP was reported to be (92.9 ton/ha) at L3 and (76.5 ton/ha) at L1 lower than the reported AGBP (173.5 ton/ha). Results were considered " highly promising" (Mannaerts et al., 2020) and would only require adjustment of parameters such as moisture content to decrease error. Three yield validations were located in the Beqaa Valley, Lebanon. WaPOR average grapes yield obtained using shapefiles during 2015 (7.6 tones/ha) was compared against reported yield by Alvarez Carrion (2018) (7.5 tones/ha). WaPOR yield of potato and wheat using shapefiles were also validated in the Beqaa Valley and compared against farmer reported yield at both levels 1 and 3. Mannaerts et al. (2020) reported WaPOR mean potato yield to be (32.2 ton/ha) at L3 and (35.8 ton/ha) at L1 while the mean yield reported by the farmers was higher recording (39.5 ton/ha). As for wheat, WaPOR mean wheat yield was recorded to be (1.1 ton/ha) at L3 and (1.0 ton/ha) at L1 lower than the mean reported yield reported by farmers (1.32 ton/ha) as reported by Mannaerts et al. (2020). Delft (2019) report more WaPOR yield validations at L3 including that of banana and rice in Kpong Irrigation Scheme in Ghana for 2015. WaPOR yield of banana (37.6 ton/ha) was lower than the reported yield by (GIDA, 2010) (40 ton/ha) but was considered to compare well as was that of rice in both its main and minor season was within the average range reported in the literature by (4-5 ton/ha) (GIDA, 2010). Finally, WaPOR NPP of wheat,, maize and oranges in 2015 was validated in the Fayoum irrigation Scheme in Egypt which is known for its non-uniform water distribution (Delft, 2019). WaPOR average yield for wheat (5.3 to/ha), maize (3.1 ton/ha), and oranges (17.7 ton/ha) were considered close to the literature values reported by (Salvadore, 2019) (5 ton/ha), (4.4 ton/ha) and (20 ton/ha) respectively. According to the performed validations by (Mannaerts et al., 2020) , WaPOR NPP and NDVI showed very high agreement.

Robustness analysis depends on the online available data and the will of partners to share their data (Delft, 2019). When testing for level consistency between L1 and L2, high consistency was noted for NPP especially before 2014 after which consistency decreased due to the use of (PROBA-V) as an additional satellite source. In comparison, the consistency between L1 and L3 was lower than that between L1 and L2 in the irrigation schemes tested. These results showed inconsistency in water productivity between L1 and L3 on a plot to plot basis for the years 2009-2018 but better consistency for a single plot showing good temporal consistency and low spatial consistency as Mannaerts et al. (2020) concludes.

Table 1 WaPOR Yield Validation against In-situ Ground Data

Crop Type	Location	Level	Year	Modeled yield (ton/ha)	Reported yield (ton/ha)
Sugar Cane	Wonji Irrigation Scheme-Ethiopia	3	2015	100 ton/ha	FAO range: 50-150ton/ha
					70 ton/ha (Steduto,2012)
					100 ton/ha (Yilma,2017)
		1	2009-2016	141.3 ton/ha	147.3 ton/ha farmer reported yield (Mannaerts et al., 2020)
		3		150.6 ton/ha	
	Metehara Irrigation Scheme-Ethiopia	1	2012-2014-2016	76.5 ton/ha	173.5 ton/ha farmer reported yield (Mannaerts et al., 2020)
		3		92.9 ton/ha	
Grapes	Beqaa Valley-Lebanon	3	2015	7.6 ton/ha	7.5 ton/ha (Alvarez-Carrion,2018)
Potato		1	2016-2018	35.8 ton/ha	39.5 ton/ha farmer reported yield (Mannaerts et al., 2020)
		3		32.2 ton/ha	
Wheat		1		1 ton/ha	1.32 ton/ha farmer reported yield (Mannaerts et al., 2020)
		3		1.1 ton/ha	
	Fayoum-Egypt	3	2015	5 ton/ha	5.3 ton/ha (Salvadore, 2019)
Oranges				20 ton/ha	17.7 ton/ha (Salvadore, 2019)
Maize			2016	3.1 ton/ha	4.4 ton/ha (Salvadore, 2019)
Rice	Kpong Irrigation Scheme - Ghana	3	2015	main season: 4.2 ton/ha minor season: 4.0 ton/ha	4-5 ton/ha (GIDA,2010)
Banana				37.6 ton/ha	40 ton/ha (GIDA,2010)

CHAPTER III

METHODOLOGY

A. Study Site

This study was conducted in the fertile semi-arid Beqaa Valley of Lebanon. Lebanon is a relatively small country in the Middle East with a total area of 10,452 km², 64% of which is agricultural land (FAOSTAT, 2010). One of Lebanon's main agricultural areas according to CDR (2005) is the Beqaa Valley, with a total agricultural area of 118,000 ha (Jaafar & Ahmad, 2020) holding 39% of the total cultivated areas in Lebanon (FAOSTAT,2010). In the Beqaa, potatoes, grains, fruits and vegetables are the main agricultural crops. Since Lebanon is attributed with a Mediterranean moderate climate, the winter season mainly has more rain than the summer season. This study focused on potato: Solanum tuberosum, a water-efficient winter crop which constitutes almost half of the vegetable production in Lebanon. In addition, the study focused also on wheat: Triticum aestivum, barley: Hordeum vulgare, vetch: Vicia Sativa, and oat: Avena Sativa, all all of which can tolerate poor soils and lower temperatures. Even though Lebanon is characterized with a moderate Mediterranean climate, variations in temperature and precipitation patterns are detected between different regions. The Beqaa valley lies between two mountains (which is why it is recorded to have the lowest rainfall average 200 to 450 millimeters of annual rainfall). This study was conducted in two fields: AREC of the American University of Beirut (figure 2), and Skaff farm (figure 4) in the West of Beqaa (figure 3).

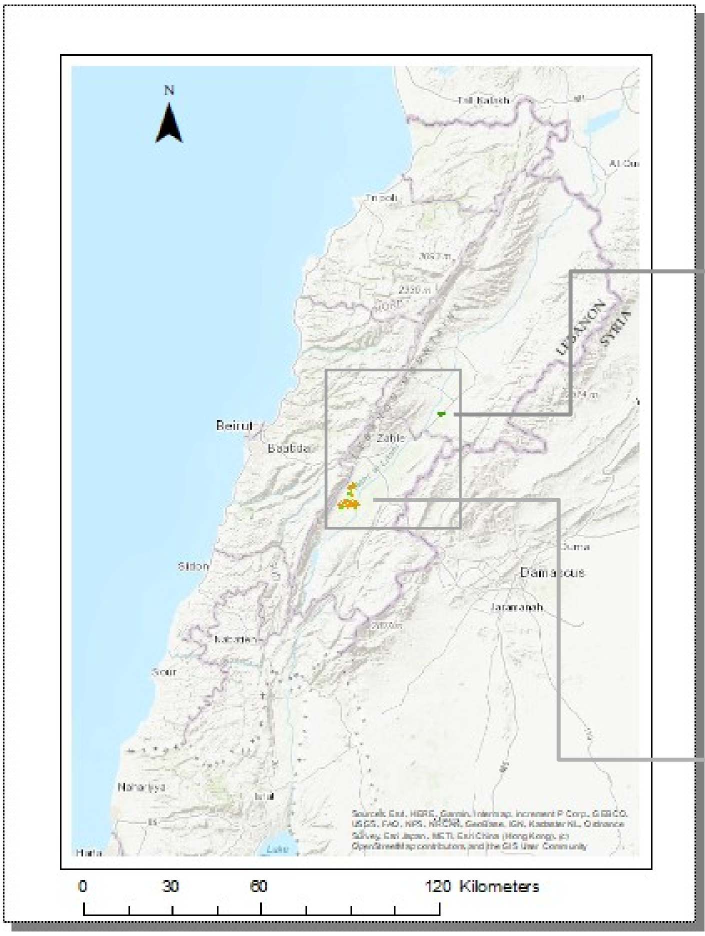

Figure 3 Study Site in The Beqaa Valley, Lebanon

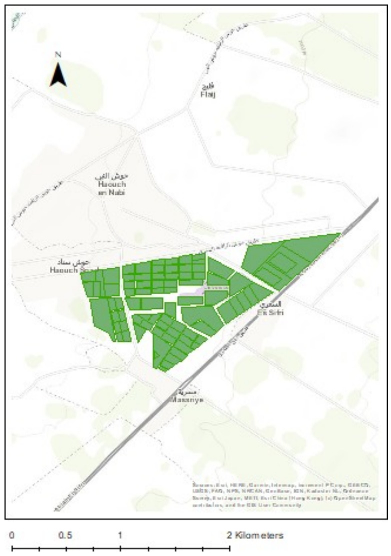

Figure 2 AREC Fields for 2012-2019

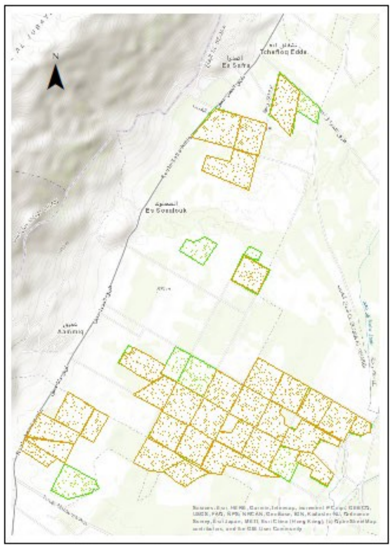

Figure 4 Skaff Fields for 2017-2018

As shown in figure (5), the studied crops at level 2 using point coordinates in AREC included 21 barley fields with an average area of 1.41 ha, 52 barley/vetch fields with an average area of 1.18 ha, 1 vetch field with an average area of 1.05 ha, and 5 vetch/oat mixed fields with an average area of 1.45 ha .Only shapefiles were used for the studied crop in Skaff (Jaafar & Mourad, 2021). As for the studied crops at level 2 using shapefiles (figure 5) , 15 barley fields with an average area of 1.84 ha were studied, 18 barley/vetch mixed fields with an average area of 1.96 ha, 1 vetch fields with an average area of 1.05 ha, 4 vetch/oat mixed fields with an average area of 1.59 ha in AREC. Aa for the crops studied in Skaff, 31 potato fields with an average area of 23 ha, and 20 wheat fields with an average area of 23.8 ha were studied. Finally, as shown in figure 6, the studied crops at level 3 using shapefiles included 29 barley fields with an average area of 1.47 ha,62 barley/vetch mixed fields with an average area of 1.19 ha, 1 vetch field with an average area of 1.05 ha, 5 vetch/oat mixed fields with an average area of 1.45 ha in AREC. As for Skaff, the other studied area in the West Beqaa Valley,31 potato fields with an average area of 23 ha and 20 wheat fields with an average area of 23.8 ha were studied (Jaafar & Mourad, 2021).

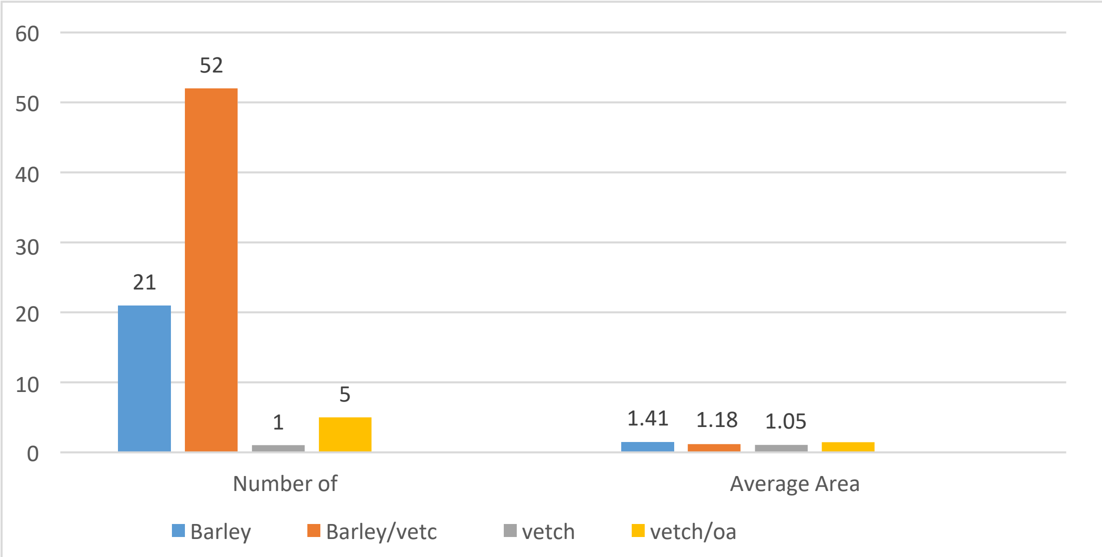

Figure 5 Studied Crop types at level 2 using point coordinates, the count of fields and their average areas

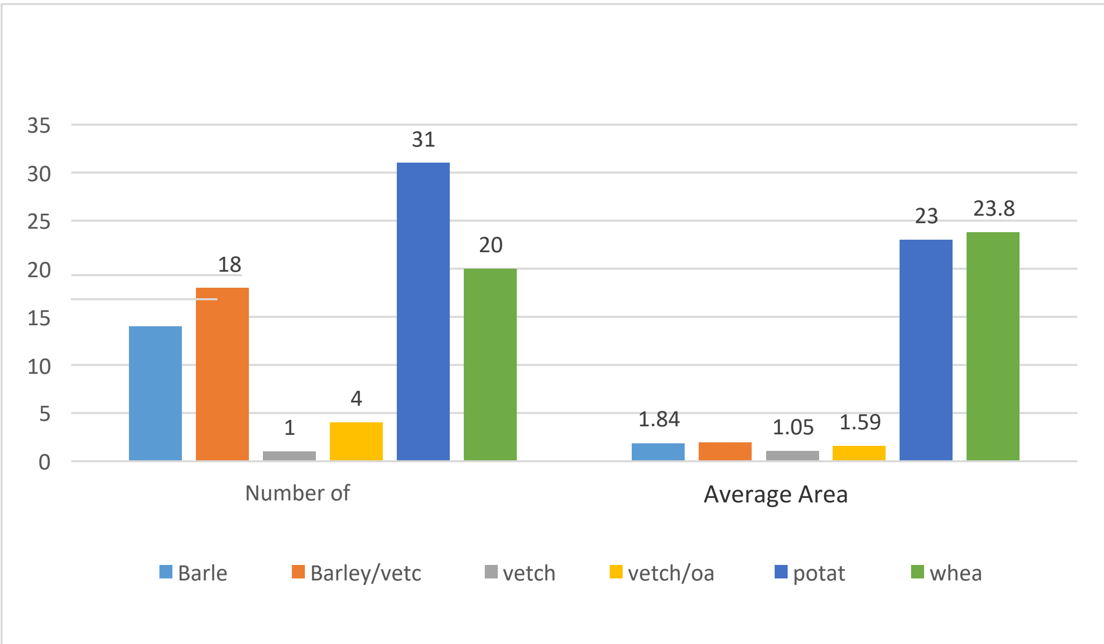

Figure 6 Studied crop types at level 2 using shapefiles, the count of fields and their average areas

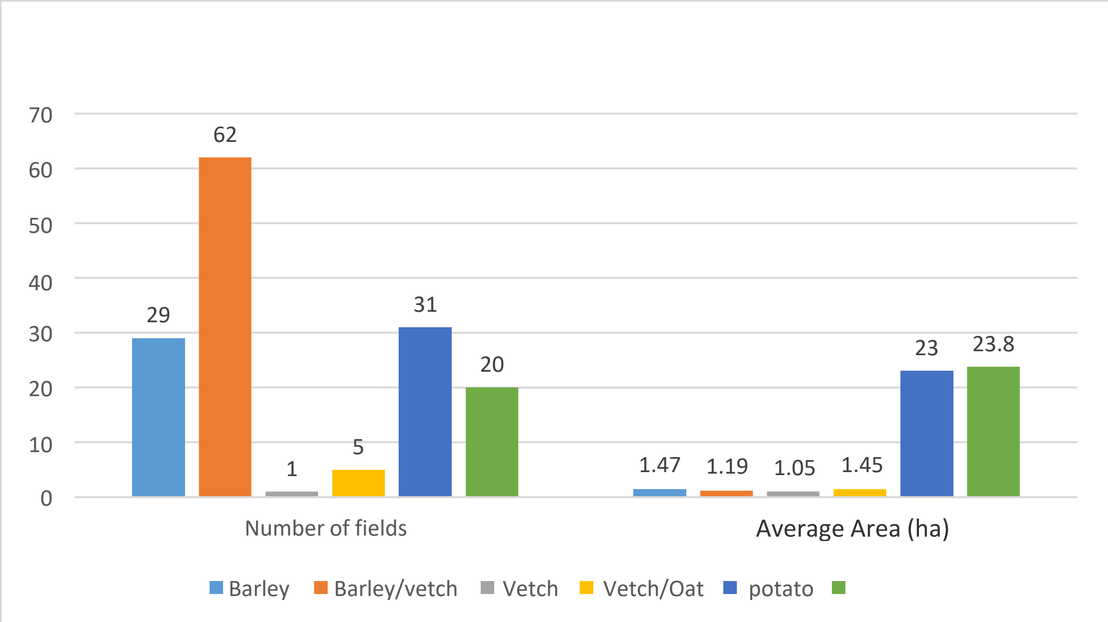

Figure 7 Studied crop types at level 3 using shapefiles, the count of fields and their average areas

B. Data Sources

Values were downloaded from WaPOR 2.1 available via (https://wapor.apps.fao.org/home/WAPOR_2/1). For the fields in AREC, Decadal NPP was downloaded from WaPOR v 2.1 using point time series at level 2 and area raster download from 2012 through 2019 at levels 2 and 3. In order to extract the NPP values for each field, Arc GIS 10.6 was used. NPP was extracted for Skaff farm at levels 2 and 3 using Raster download for the years 2017-2018. Ground-based observations were collected from farmers of every land. At level 3, soil moisture stress is determined by Landsat-5 and 7 and the Modern-Era Retrospective analysis for Research and Applications incorporated with the Geostationary Operational Environmental Satellite (MERRA/GEOS-5). Land cover and fAPAR are also calculated by Landsat 5 and 7 whereas precipitation is determined using CHIRPS V2. Finally, solar radiation is determined using MSG, MERRA/GEOS-5 sensor and SRTM data products. Other weather data such as temperature and humidity are determined by MERRA/GEOS-5 (FAO, 2019). As for level 2, soil moisture stress is determined by MODIS, land cover by WaPOR LCC product, and fAPAR using PROBA-V only. Similar to level 3, solar radiation is determined by SRTM, precipitation by CHIRPS V2 and weather data by MERRA/GEOS-5 (FAO, 2018).

C. WaPOR Model Method

According to the WaPOR Level 3 Methodology for WaPOR V1 (FAO, 2018), WaPOR depends on two external sources in order to calculate NPP: Satellite imagery and meteorological data. WaPOR's NPP is derived from a method retrieved from Veroustraete et al. (2002) along with its practical implementation retrieved from Eerens H (2004). This method was improved within the Copernicus Global Land Component framework. Therefore, WaPOR based its NPP calculations on the final output of the mentioned methodologies, and finally basing on an equation by (Monteith, 1972). Monteith (1972) is considered the first to propose the presence of a conservative linear relationship between the rate of NPP and the rate of solar energy absorption by foliage, known as the conversion efficiency of absorbed radiation into dry matter (McCallum et al., 2009). The equation is as follows (eq.1):

$$NPP = Sc \times Rs \times \varepsilon p \times fAPAR \times SM \times \varepsilon LUE \times \varepsilon T \times \varepsilon\, CO2 \times \varepsilon AR \times \varepsilon RES \quad (1)$$

Where: Sc stands for the Scaling factor from DMP (Dry mass productivity) to NPP, Rs stands for the Total shortwave incoming radiation in the form of solar energy (expressed in $Wm^{-2}d^{-1}$), εp stands for the Fraction of PAR with fAPAR as the PAR-fraction absorbed (PA) by green vegetation [JPA/JP], $SSSS$ stands for the Soil moisture stress reduction factor, εlue stands for Light use efficiency (DMP=Dry Matter

Production) at optimum [Kg DM/GJPA], εT stands for the Normalized temperature effect, ε CO2 stands for Normalized CO2 fertilization effect, ε AR stands for the Fraction kept after autotrophic respiration, and ε RES stands for the fraction kept after residual effects (including soil moisture stress).

In the WaPOR model, 1 $gC/m^2/day$ of NPP is considered equal to 22.222 kg DM/ha/day of DMP. εp is taken as a constant at 0.48 [JP/JT]. In addition, fAPAR is estimated by using a direct relationship between the NDVI and a global fAPAR product where values range between 0 and 1. It is based on 3 factors: Latitudinal position, day of the year and topographical features which help determine the angle of incidence of the sun at specific locations. In addition, Transmissivity is calculated to avoid including scattered wavelengths that do not reach the Earth's surface. Solar Radiation (Rs) is the amount of solar radiation that reaches land surface depending on local topography, location, date, and other atmospheric conditions

As for SM, Soil Moisture is usually released from vegetation in the form of evaporation and transpiration. A stress factor calculates if soil moisture is reduced due to a shortage using the following equation adapted from the American Society of Civil Engineers (ASCE, 1996).

$$SM = Ksf \times Se - \left(\frac{\sin(2\pi \times \mathrm{Se})}{2\pi}\right) \qquad (2)$$

In this equation (eq. 2), Ksf represents the tenacity factor for drought-sensitive plants,and Se represents soil moisture content. Se is calculated using three factors: Land Surface temperature (obtained from infrared imagery), vegetation cover (NDVI), and soil moisture content. It is calculated using the following equation (eq.3):

$$Se = \frac{b}{(a + b)} \quad (3)$$

In this equation (eq. 3):

$$a = LST - Tmin \quad (4)$$

And

$$b = (1 - Fc) \times (Ts.max - Tc.max) + Tc.max - LST \quad (5)$$

LST (eq. 4) is derived from thermal satellite imagery and NDVI is used in the derivation of the vegetation cover (Fc). NDVI is used in WaPOR to determine the partitioning of the soil radiation (Rn) into Rn soil and Rn canopy, along with the interception, ground heat flux, and the minimum stomatal resistance (Mannaerts et al., 2020)

Since the land cover is available for the years 2009-2015, LUE values are accurate. Nevertheless, a LUE correction factor is needed for the years 2016 onwards due to the lack of the land cover. At level 3, crops are not identified. Therefore, a generic cropland value of 2.49 is used. Nevertheless, this value 2.49 was later adjusted to 2.7 to avoid double counting of moisture content.

As for εT, it is derived using the following equation used from (Veroustraete et al., 2002).

$$p\ (Tatm) = \frac{e^{\left(C1-\Delta Ha.\frac{P}{RgT}\right)}}{1 + e^{\left(\frac{\Delta ST-\Delta Hd,P}{RgT}\right.}} \quad (6)$$

In this equation (eq. 6), C1 is a Constant, ΔHa.P is the Activation energy in (J/ mol), Rg is the Gas constant in J/ (K. mol), T is the Air temperature (K), ΔS is the Entropy of the denaturation equilibrium of CO_2 in (J/k.mol), and ΔHd.P is the Deactivation energy in (J / mol).

The CO_2 concentration is assumed to be constant over the globe, as well as within a year for the calculation of ε$CCCC2$. In addition, εAR is calculated for NPP using the following equation (eq. 7) (Veroustraete et al., 2002).

$$\varepsilon AR = \frac{7.825 - 1.145Ta}{100} \tag{4}$$

In this equation (eq. 7), Ta represents the atmospheric temperature.

Finally, ε RES is added in the above equation (eq. 1) to emphasize the fact that some potentially important factors, such as the effect of droughts, nutrient deficiencies, pests, plant diseases, and soil moisture stress influence NPP. Evidently, the calculation of NPP requires data from intermediate data sources such as weather data providing maximum and minimum temperature, soil moisture stress, decadal input from fAPAR, and solar radiation, and from indirect sources such as Land cover classification.

D. Yield Estimation

After extracting the decadal Net primary production (NPP) values from WaPOR 2.1 at level 3 (30 m) for the Skaff fields, NPP values were converted to yield. Two major crops are planted in Skaff; mainly potato during the summer and wheat during the winter season. Therefore, the actual planting and harvest dates of every field for the start and end of growing season were used. Decadal NPP for potatoes for the different fields was extracted between March and August 2017, and between March and September 2018. For wheat, we extracted decadal NPP considering a crop growing period between November 2017 and September 2018. The studied crops in AREC were barley and vetch which were planted in the same field or in separate fields and oat/vetch mixed fields. Decadal NPP values were extracted from WaPOR 2.1 as raster images, and therefore a conversion factor of 0.001 was used to get the accurate numbers as noted in the online WaPOR database. Then, the decadal NPP values were converted to seasonal Above Ground Biomass Production (AGBP) according to the WaPOR version 1 methodology for level 3. For the conversion, the following equation (eq. 8) was adopted from the WaPOR 1.0 Methodology at level 3 (FAO, 2019).

$$\text{AGBP s} = \sum \text{Nd (i)} \times \text{DMP (i)} \times \text{AOT} \tag{8}$$

In this equation (eq. 8), DMP refers to Dry Matter production in Kg DM/ha/day, Nd refers to the corresponding number of days in every decade which was calculated using the start and end of season determined by the farmers for each crop, considering the varying number of days per dekad. All dekads within the season period are then summed into a total NPP. In addition, AOT is the fraction between above and total biomass. In order to calculate DMP (i), NPP (i) is converted to DMP (i) using a constant scaling factor of 0.45 gC/gDM (Ajtay et al., 1979). Therefore, NPP (i) was multiplied by a factor of 22.222 (1 gC/m²/day (NPP) = 22.222 kg DM/ha/day (DMP)), since dry matter is more suitable for yield comparison. For potato, the mentioned formula was used as is considering AOT to be a standard of 0.65 shoot to root ratio. Nevertheless, AOT was taken as 1 for wheat grains, since grains grow entirely above ground. For barley, oat, vetch, and wheat planted in AREC, AOT is also considered to be 1.

The Dekadal AGBP are then summed into a Total AGBP for the entire crop growth period. Then, the third Step was to convert the total AGBP to yield using the following equation (eq. 9) from (Das et al., 1993).

$$Y = \frac{\mathrm{TBP} \times \mathrm{HI} \times \mathrm{C4}}{(1 - \mathrm{mc})} \tag{9}$$

In this equation (eq. 9) for yield (Y), TBP refers to total Biomass Production, HI refers to the harvest Index, C4 refers to the conversion factor of C4 crops in (eq. 9), and mc is the crop moisture content. Nevertheless, all crops studied were C3 crops and the conversion factor was not used in the yield calculation. The Total Biomass Production (TBP) was calculated from the AGBP by multiplying it with the shoot-to-root ratio of 0.65 for potatoes. The above ground biomass production includes the total weight of flowers, branches, stems, flowers and grains but not the weight of roots and tubers entirely above ground. The Harvest Index (HI) was calculated as 0.75 for potatoes, and 0.4 for wheat based on Jaafar and Mourad (2021). For the AREC crops, HI for barley, the oat/vetch mixed fields and barley/vetch mixed fields was used as 0.49, yet the HI for vetch was considered as 0.38 (Rao, 2011). The crop moisture content (mc) was considered as 0.75 for potato and 0.15 for wheat based on our own observations and testing. As for the AREC crops, mc was considered as 0.11 for vetch (Samarah et al., 2009), oat/vetch, barley, and barley/vetch fields (Unkovich et al., 2010a).

Table 2 Harvest Index and Moisture Content of studied Crops

Crops	**Harvest Index (HI)**	**Crop Moisture Content (MC)**
Barley	0.49	0.11
Vetch	0.38	0.11
Barley/vetch	0.49	0.11
Vetch/oat	0.49	0.11
Potato	0.75	0.75
Wheat	0.4	0.15

E. Accuracy Assessment

The major Earth Observation data validation technique used in this study is direct validation against measured in-situ data and observations. Accuracy as defined by Blatchford et al. (2019) is “the closeness of a measurement, observation, or estimate to a true value.” In our NPP validation, yield assessment of WaPOR NPP was performed for each crop group during the 2017-2018 growing seasons in Skaff and during the 2012 to 2019 growing seasons in AREC. This analysis aimed to evaluate the accuracy of WaPOR’s NPP layer as part of the validation of the water productivity layer of WaPOR. Statistical Analysis was performed based on the following indicators in this assessment: RMSE (Root Mean Square Error) (eq.10), RE (Relative Error) (eq. 11-12) , R2 (coefficient of determination) (eq. 13), r (correlation) (eq. 14) and bias (eq. 15). Since RMSE is not able to calculate the average magnitude of the mean absolute difference between observed and Reported yield, it has been used predominantly with other statistical methods such as the absolute difference (da), correlation (r), or the coefficient of determination (R2) in most research aiming to validate crop models (Cao et al., 2012). Therefore, the analysis RMSE was integrated with R2 ,RE (%), r, and Bias. The used statistical indicators were calculated according to the following equations (eq. 10,11,12,13,14,15):

Root Mean Square Error (RMSE)

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}(\textbf{Estimated yield} - \textbf{measured yield})^2}{\boldsymbol{n}}} \tag{10}$$

Relative Error (RE):

$$\text{RE}(\%) = \frac{|\,\textit{Absolute Error}|}{\textit{Measured Yield}} \times 100 \tag{11}$$

$$\text{Absolute Error} = \text{Modeled Yield} - \text{Measured Yield} \tag{12}$$

Coefficient of determination:

$$(R^2)\left[\frac{\text{n}(\Sigma\text{modeled yield}\times\text{measured yield})-(\sum\text{modeled yield})(\sum\text{measured yield})}{\sqrt{[\text{n}\Sigma(\text{measured yield})^2-(\Sigma\text{modeled yield})^2][\text{n}\Sigma(\text{modeled yield})^2-(\Sigma\text{modeled yield})^2]}}\right]^2 \tag{13}$$

Correlation (r):

$$\text{r} = \frac{\text{n}(\Sigma\text{modeled yield}\times\text{measured yield})-(\sum\text{modeled yield})(\sum\text{measured yield})}{\sqrt{[\text{n}\Sigma(\text{measured yield})^2-(\Sigma\text{modeled yield})^2][\text{n}\Sigma(\text{modeled yield})^2-(\Sigma\text{modeled yield})^2]}} \tag{14}$$

$$\mathbf{Bias} = \frac{[\sum(\textbf{measured yield} + \textbf{modeled yield})]}{\boldsymbol{n}} \tag{15}$$

CHAPTER IV

RESULTS

A. AREC

Accuracy of WaPOR NPP predictions for the 5 oat/vetch mixed fields showed lower Relative Error percentages (RE) at level 3 (L3) (24.82%) than those at level 2 (L2) using point coordinates (70.45%). RMSE was lower at L3 (1.94) than at L2 (3.44). Nevertheless, R2 was higher at L2 (0.18) than at L3 (0.13). Nevertheless, a positive bias at l3 recording (1.68 ton/ha) higher than that at L2 recording 1 ton/h. Only 4 oat/vetch mixed fields were identified at L2 using shapefiles and showed a high RE (41.2%), an RMSE of (2.03) and an R2 of (0.06). A positive bias of 1.9 ton/ha was recorded at L2. Correlation (r) could not be determined at any level due to the low number of fields. One vetch field was analyzed which also showed more accurate results at L3 according to both the RE(%) and RMSE. Results showed that the RE(%) at L3 (63.01%) were lower than those recorded at L2 calculated by point (78.86%) and those calculated using shape files (68.28%). Results of RMSE were also lower at L3 (3.27 ton/ha) than those at L2 using point coordinates (3.94) or using shape files (11.66). Positive Bias values were relatively close with the highest bias recorded at L3 as (6.73ton/ha), a lower value of (6.59 ton/ha) was recorded at L2 using shapefiles and the lowest value of 6.06 was recorded at L2 using point coordinates. Correlation (r) was also not determined due to the low number of fields of vetch.

Accuracy of WaPOR NPP Barley predictions for the 21 barley fields identified using point coordinates showed a RE (%) of (58.67%), a low R2 of (0.01) and an RMSE of (2.69 ton/ha). Low correlation was recorded as (0.08). Bias was recorded as

0.27 ton/ha. The NPP barley predictions at L2 using shape files were provided for 14 barley fields, and a RE(%) of (61.97%) was recorded, an R2 of (0.04) and an RMSE of (2.92 ton/ha). A positive low correlation of (0.2) was recorded and a positive bias of (0.41 ton/ha). At L3 WaPOR NPP was estimated for the highest number of barley fields (29), a RE(%) of (44.4%) was recorded, an R2 of (0.00) and an RMSE of (0.17 ton/ha). A positive low correlation of (0.04) was also recorded with a positive bias of (0.22 ton/ha). As for the barley/vetch fields, WaPOR NPP was calculated for 52 fields of barley/vetch at level 2 using point coordinates, a RE(%) of (55.52%) was recoded, an R2 of (0.08) and an RMSE of (3.07 ton/ha).A positive low correlation of (0.28) was recorded with a positive bias of (0.12 ton/ha). Estimations at L2 using shape files were calculated for 18 fields of barley/vetch and recorded a RE(%) of (37.19%), an R2 of (0.29) and an RMSE of (2.32 ton/ha). A medium correlation of (0.54) was recorded with a positive bias of (0.39 ton/ha).WaPOR NPP was estimated for 62 barley/vetch mixed fields at L3. RE(%), R2 and RMSE were recorded after the removal of two outliers to be (37.37%), (0.026) and (2.59 ton/ha) respectively. A low positive correlation of (0.24) was recorded with a positive bias of (0.12 ton/ha).

B. Skaff

Accuracy of WaPOR NPP predictions for the 31 potato fields was assessed against the actual yield reported by farmers in Skaff. An outlier was removed at L3 and therefore RE(%), R2 , and RMSE were recorded for 30 fields as (28.90%), (0.10) and (12.86 ton/ha) respectively. A close to moderate correlation was recorded as (0.47) with a positive bias of (2.39 ton/ha). As for L2, RE(%), R2 , and RMSE were also recorded to be (19.55%), (0.22), and (9.31 ton/ha). A weak positive correlation of (0.37) and a positive bias of (2.34 ton/ha) were recorded. Comparison between the two levels is not possible since the total number of fields is not the same between the two levels. As for wheat, the comparison of WaPOR NPP predictions against Reported wheat yields showed the lowest RE (1.14%) at L3 less than that shown at L2 (-12.43%). Analysis of the RMSE results showed lower and more accurate at level 3 (0.71) than those at level 2 (1.2). R2 analysis validated the previous results showing higher values at L3 (0.380) than those at L2 (0.376). Hence, the most accurate wheat yield estimations were found at L3 according to RE, RMSE, and R2. At both levels, the RE(%) of wheat was found to be below 20% signifying relatively accurate results (1.14%<20%) and (|-12.43|%<20%). At both L2 and L3, a positive moderate correlation was recorded as (0.61) and (0.62) respectively with a slightly higher correlation at L3. Bias was positive and higher at L2 than at L3 recording (2.39 ton/ha) and (2.34 ton/ha) respectively.

Table 3 Reported and Modeled Yield for studied crops and used Statistical Indicators

Crop	Number of fields	Level	Location	Year	Reported Yield (ton/ha)	Modeled Yield (ton/ha)	% Relative Error (% RE)	R^2	RMSE (ton/ ha)	r	Bias (ton/ ha)
Oat/ vetch	5	2 (By point)	AREC	2012 - 2019	4.8	1.42	70.45	0.18	3.44	-	1
Oat/ Vetch	4	2	AREC	2012 - 2019	4.8	2.82	41.2	0.06	2.03	-	1.90
Oat/ Vetch	5	3	AREC	2012 - 2019	4.8	3.61	24.82	0.13	1.94	-	1.68
Vetch	1	2 (by Point)	AREC	2012 - 2019	5	1.06	78.86	-	3.94	-	6.06
Vetch	1	2	AREC	2012 - 2019	5	1.59	68.28	-	11.66	-	6.59
Vetch	1	3	AREC	2012 - 2019	5	1.73	65.31	-	3.27	-	6.73
Barley	21	2 (By point)	AREC	2012 - 2019	4.08	1.68	58.67	0.01	2.69	0.08	0.27
Barley	14	2	AREC	2012 - 2019	4.19	1.59	61.97	0.04	2.92	0.2	0.41
Barley	29	3	AREC	2012 - 2019	4.09	2.28	44.4	0	0.17	0.04	0.22
Barley /vetch	52	2 (By point)	AREC	2012 - 2019	4.17	1.85	55.52	0.08	3.07	0.28	0.12
Barley /vetch	18	2	AREC	2012 - 2019	4.29	2.69	37.19	0.29	2.32	0.54	0.39
Barley /vetch	60	3	AREC	2012 - 2019	4.24	2.66	37.37	0.03	2.59	0.24	0.12
Wheat	20	2	Skaff	2017 - 2018	6.86	7.71	-12.43	0.38	1.2	0.61	0.73
Wheat	20	3	Skaff	2017 - 2018	6.86	6.78	1.14	0.38	0.71	0.62	0.68
Potato	31	2	Skaff	2017 - 2018	41.06	33.04	19.55	0.22	9.31	0.47	2.39
Potato	30	3	Skaff	2017 -	41.1	29.22	28.9	0.1	12.96	0.37	2.34

2018

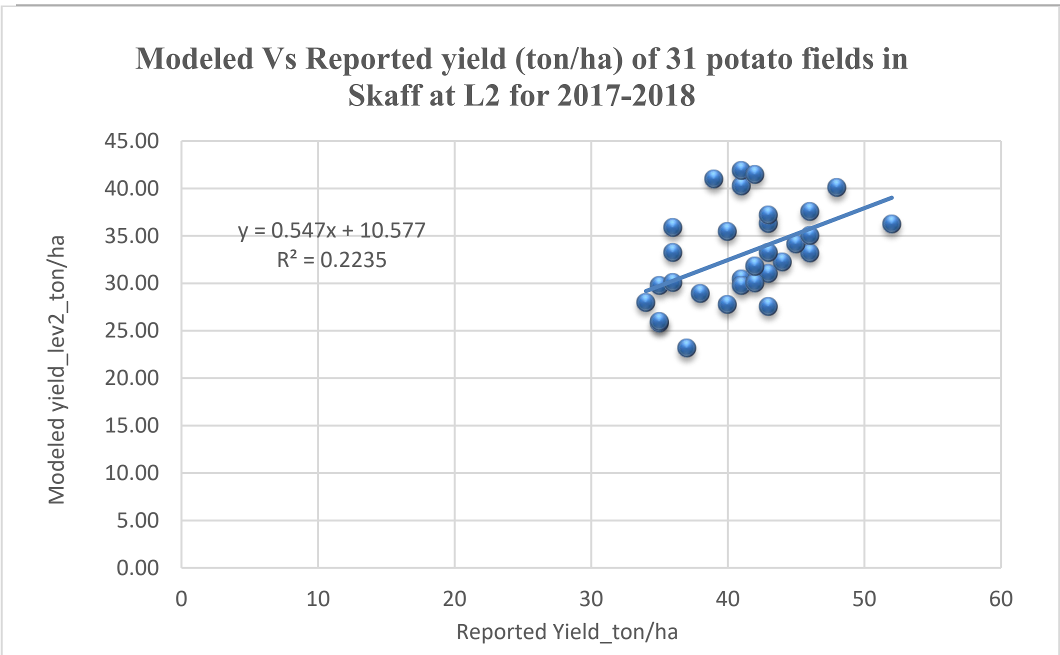

Figure 8 Modeled Vs Reported yield (ton/ha) of 31 potato fields in Skaff at L2 for 2017-2018

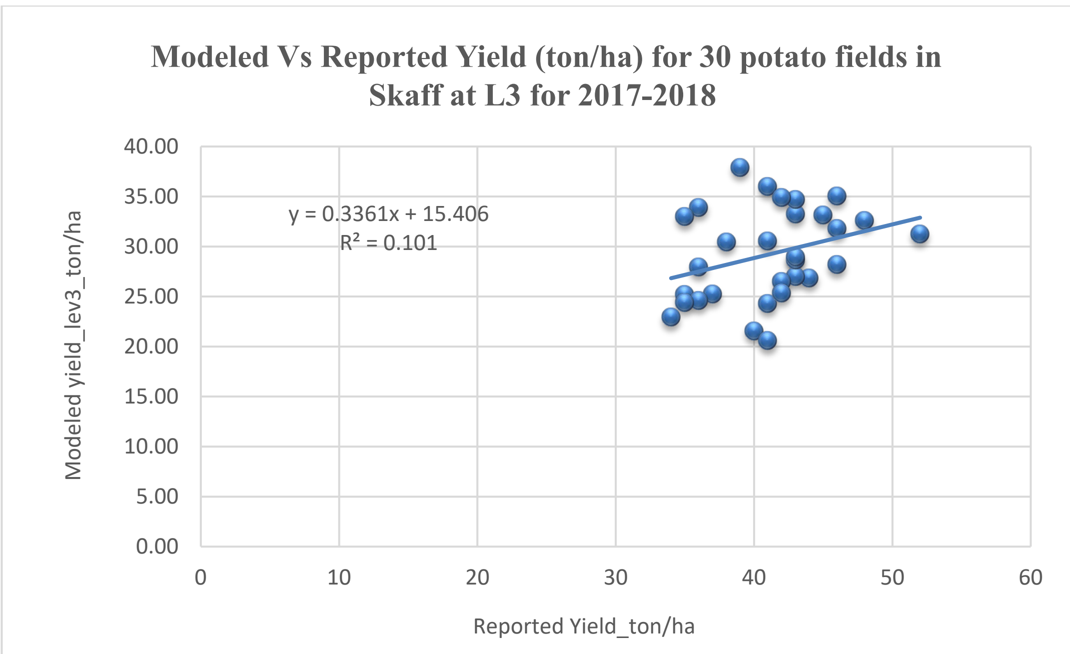

Figure 9 Modeled Vs Reported Potato Yield (ton/ha) for 30 potato fields in Skaff at L3 for 2017-2018

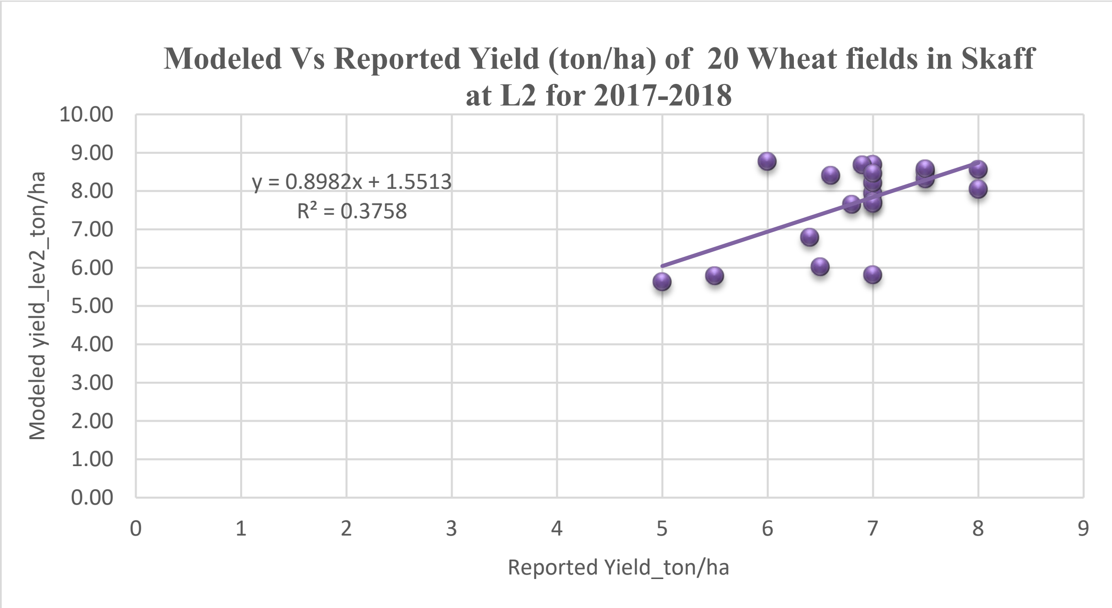

Figure 10 Modeled Vs Measured Wheat Yield (ton/ha) of 20 Wheat fields in Skaff at L2 for 2017-2018

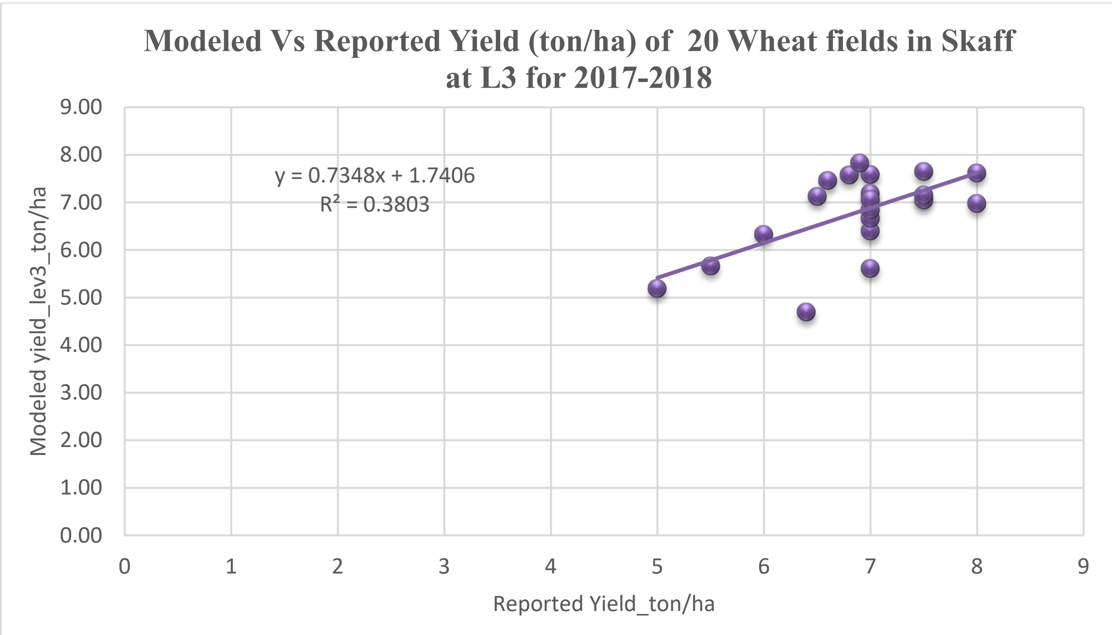

Figure 11 Modeled Vs Reported Wheat Yield (ton/ha) of 20 Wheat fields in Skaff at L3 for 2017-2018

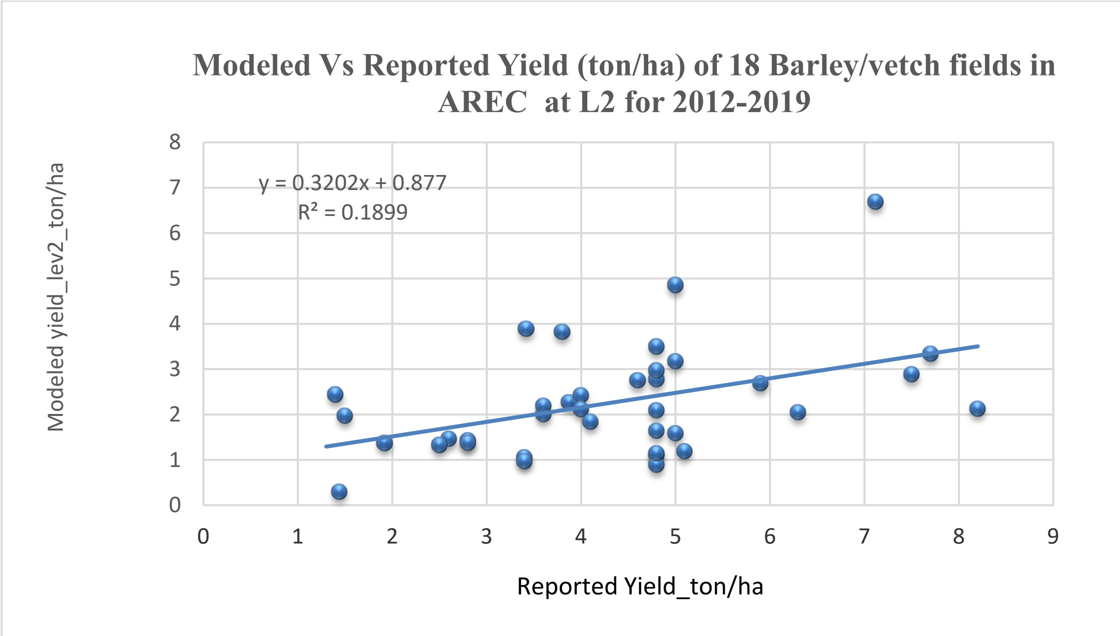

Figure 12 Modeled Vs Reported Yield (ton/ha) of 18 Barley/vetch fields in AREC at L2 for 2012-2019

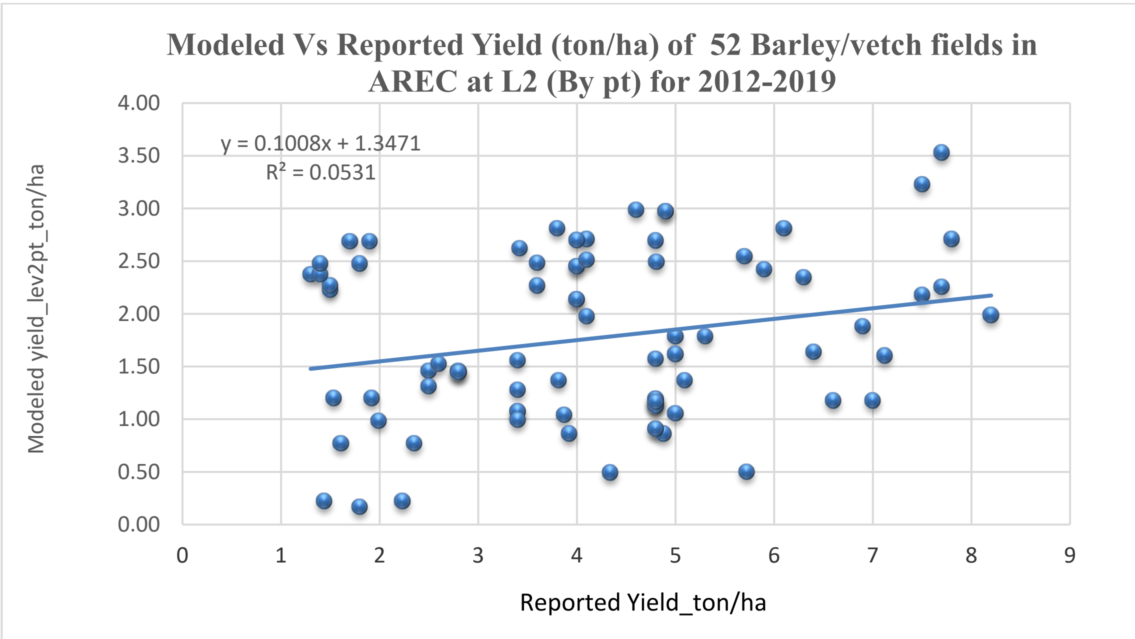

Figure 13 Modeled Vs Reported Yield (ton/ha) of 52 Barley/vetch Yield field in AREC at L2 (By pt) for 2012-2019

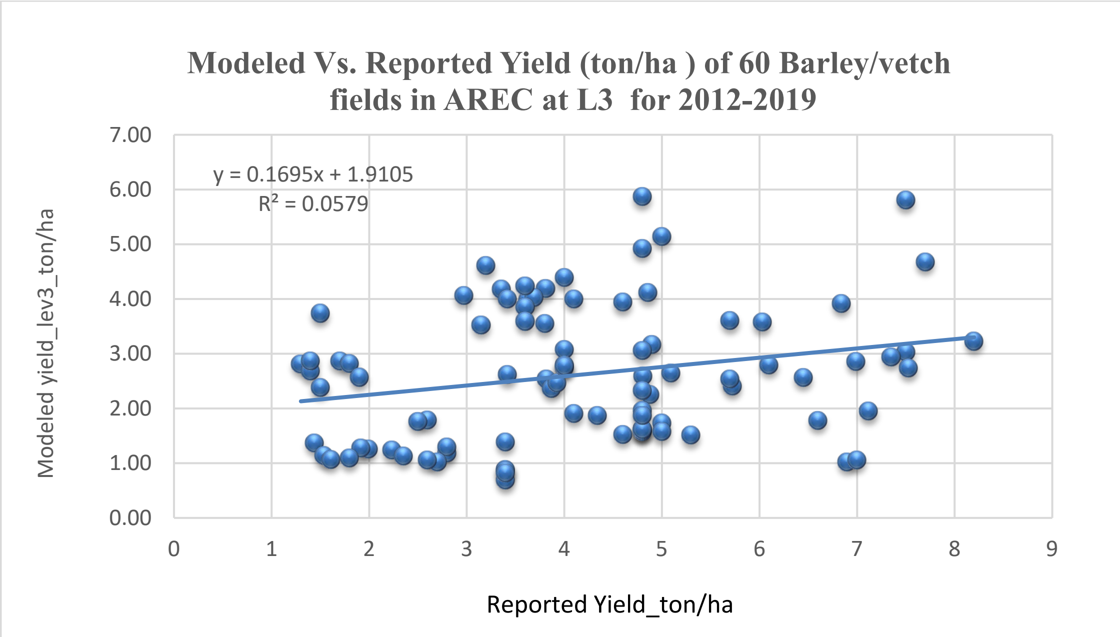

Figure 14 Modeled Vs. Reported Yield (ton/ha) of 60 Barley/vetch fields in AREC at L3

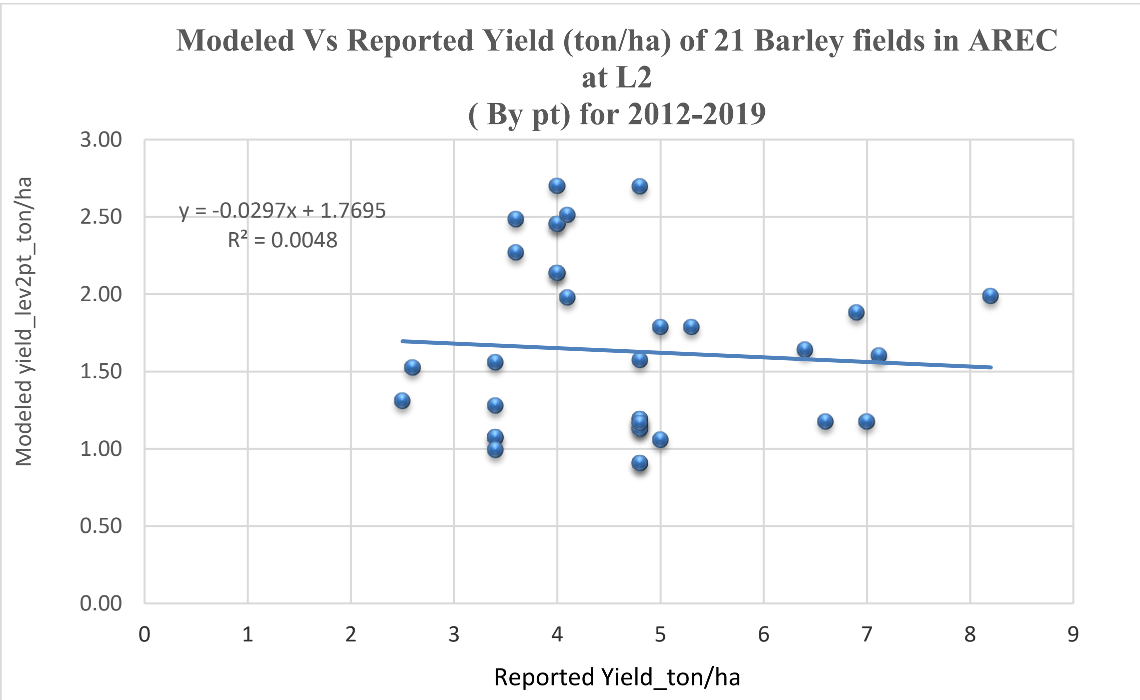

Figure 15 Modeled Vs Reported Yield (ton/ha) of 21 Barley fields in AREC at L2 (By pt) for 2012-2019

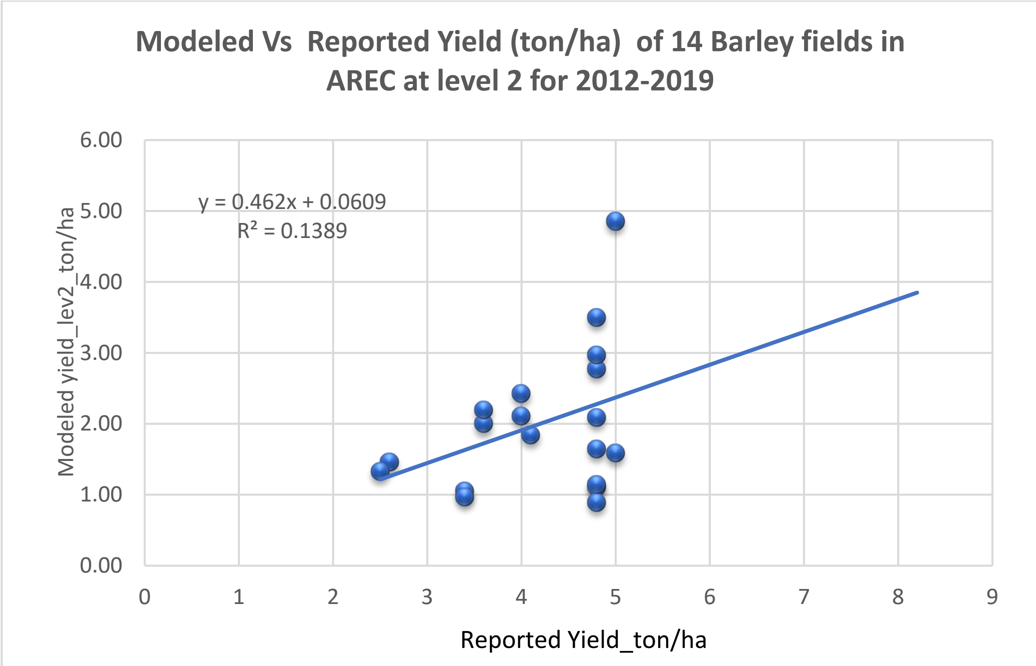

Figure 16 Modeled Vs Reported Yield (ton/ha) of 14 Barley fields at L2 for 2012-2019

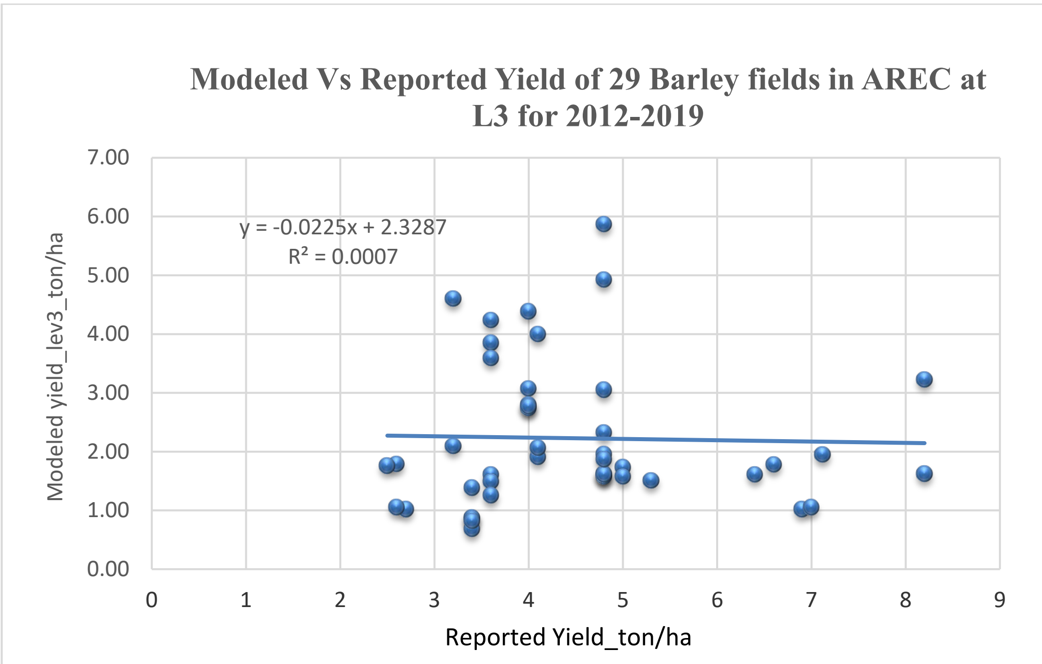

Figure 17 Modeled Vs Reported Yield (ton/ha) of 29 Barley fields in AREC at L3 for 2012-2019

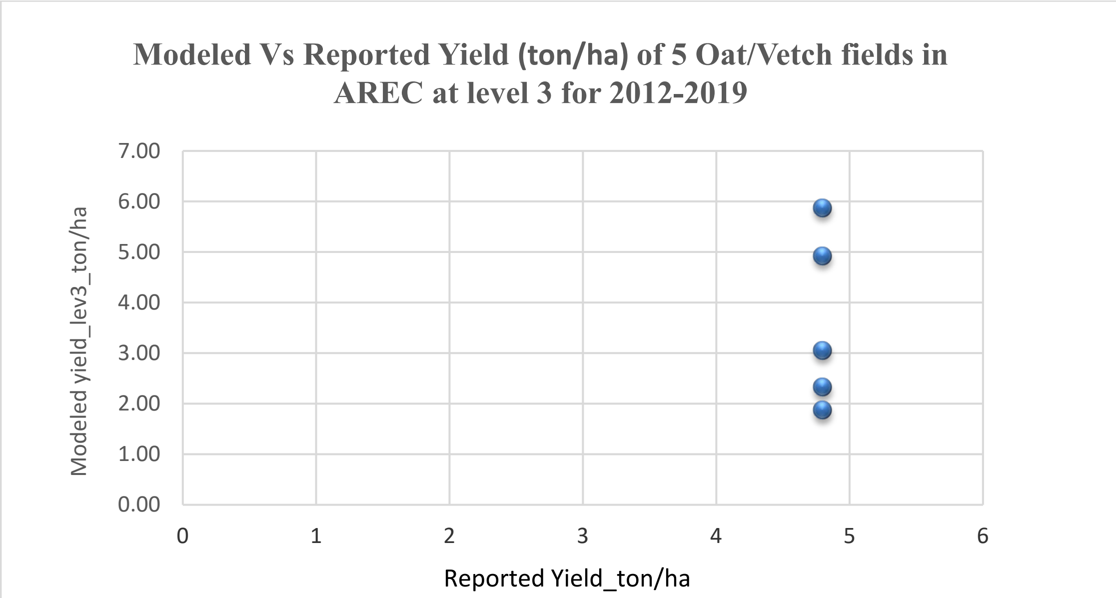

Figure 18 Modeled Vs Reported Yield (ton/ha) of 5 Oat/Vetch fields in AREC at level 3 for 2012-2019

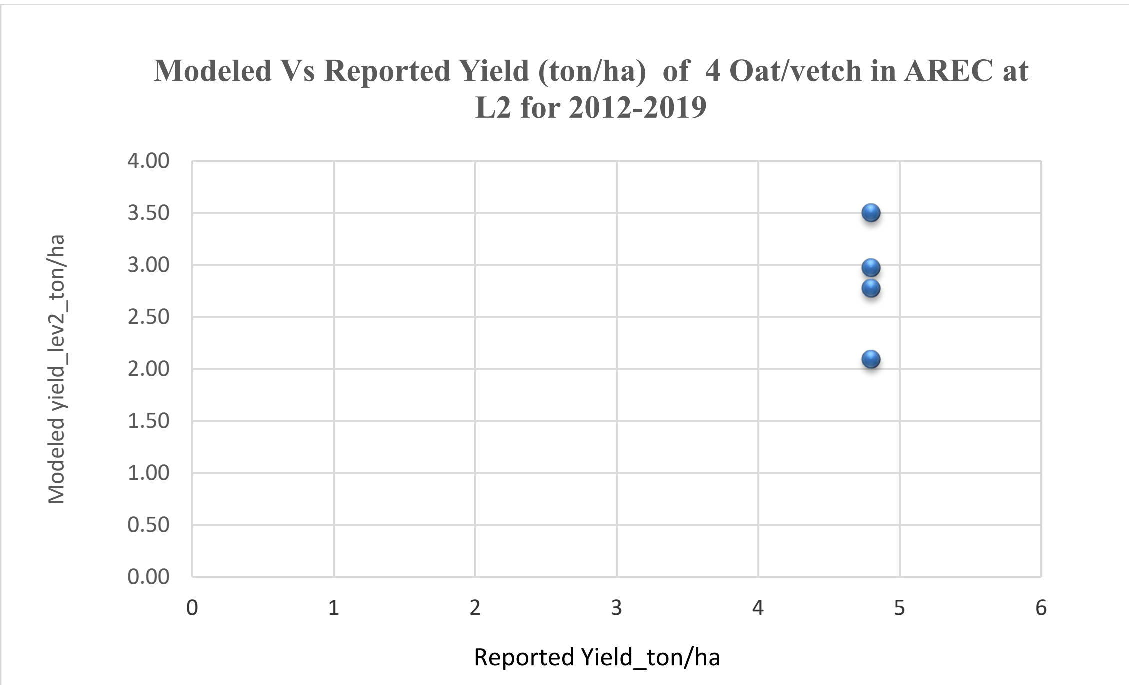

Figure 19 Modeled Vs Reported Yield (ton/ha) of 4 Oat/vetch in AREC at L2 for 2012-2019

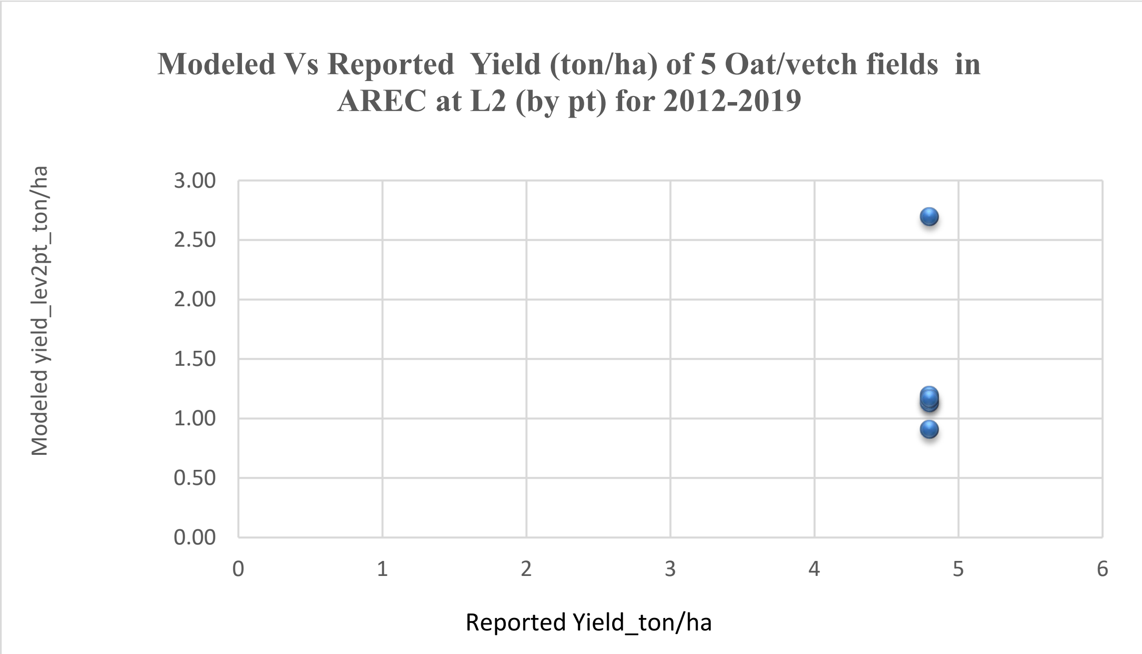

Figure 20 Modeled Vs Reported Yield (ton/ha) of 5 Oat/vetch fields in AREC at L2 for 2012-2019

CHAPTER V

DISCUSSION

A. Level Consistency

Level consistency could not be studied for the AREC crops since not all fields were equally identified at the different levels or when shapefiles or point coordinates were used at level 2 as shown in figures 1,2 and 3.WaPOR was not able to detect all selected fields and many fields showed no input and noticeable difference exists between the reported number of fields and the fields with detectable yield by WaPOR. In addition, for the year 2019, no NPP results appeared for the fields at both levels 2 and 3. As for potato and wheat, all fields were commonly identified at levels 2 and 3, which could be attributed to the higher field size of the Skaff fields(Jaafar & Mourad, 2021). Notably, wheat and potato fields in Skaff have a greater area than the AREC fields. Potato and wheat have average areas of 23 ha and 23.8 respectively whereas the average areas of the barley, vetch, barley/vetch mixed fields, and oat/vetch mixed fields are 1.84 ha, 1.96 ha, 1.05 ha and 1.59 ha respectively. Nevertheless, only 30 potato fields were analyzed at L3 due to the presence of an outlier, and therefore level consistency could not be tested for. Nevertheless, wheat yields for the 20 fields showed more accurate yields at L3 than those at L2.

B. Sources of Uncertainty

Even though remote-sensing has been widely used for different applications in agriculture, accuracy standards that set the quality standards of these datasets have not yet been established (Blatchford et al., 2019). NPP considers CO_2 that has been used by the plant but converted to biomass such as losses due to autotrophic respiration, conversion of basic products to higher-level photosynthetic products and the respiration required by the standing biomass. Nevertheless, contribution of soil respiration and the disturbance and anthropogenic removals are only counted within the net biome production (FAO, 2020) which could be behind some of the discrepancies in modeled NPP.

1. Reported Yield

Inaccuracies in yield estimations may be due to the inaccuracy of self-reported yields or model-estimated yields (Paliwal & Jain, 2020). In this study, measured crop yields in Skaff were based on farmer recall which has been considered to have higher accuracy than farmer predictive yields (Blatchford et al., 2019). However, measured yield in AREC was measured using whole-plot harvest, dried and weighed post-harvest. According to (Blatchford et al., 2019), lowest percentage relative error of yield was denoted for whole-plot harvests, with the relative error being considered in the expert error range category which refers to the maximum error derived from scientific literature as defined by AllenRG (2011). Nevertheless, farmer recall surveys recorded percentage relative errors up to (45%) in the typical error range; which as defined by AllenRG (2011) as the error associated with larger studies where scientific experts were not present during the collection of data. The farmer reported yield was based on one survey reported for each field and could not be compared to yields reported by other farmers to determine discrepancies. Nevertheless, Mannaerts et al. (2020) reported that farmers yield reports in the Beqaa Valley had very low precision for plot- by-plot comparison, where 3 different values were reported for potato tubers and the final comparison was done against the mean yield reported for both crops.

Uncertainties in model estimations of yield may be due to uncertainties in parameters, weather inputs, model structure and natural variability (Ramirez-Villegas et al., 2017). The increase in the number of crops occurring per pixel, decreases the accuracy of the model applied to 1.1 km pixels (Bastiaanssen & Ali, 2003). Moreover, variations in the sizes of fields of every crop could be behind some discrepancies in yield results(Mannaerts et al., 2020). In addition, as humidity increases as it is higher during the summer than winter season in the Beqaa, it is difficult to distinguish between natural vegetation and irrigated or agricultural areas by remote-sensing which might cause discrepancies which is why accurate land use maps are required (Delft, 2019). This was shown in WaPOR's second assessment report where WaPOR was not able to differentiate between potato and wheat fields in the Beqaa Valley where NPP values for both crops were within the expected range for C3 crops but with no distinction between those crops(Mannaerts et al., 2020).

Since the yield calculation is based on three major equations, large uncertainties might lie in the intermediates that convert GPP to yield. To start with, NPP is generated from GPP by subtracting a constant autotrophic plant respiration fraction for all crops(Mannaerts et al., 2020). In WaPOR, (Monteith, 1972) was used to calculate NPP (eq. 1). The scaling factor (SC), the fraction of photosynthetically active radiation (εp), light use efficiency (εlue), and the Normalized CO2 fertilization effect (εCO2) are all taken as constants in the calculation of NPP. The Scaling factor used to convert DMP to NPP is a constant where 1 g C/m2/day= 22.222 Kg DM/ha/day. Ep, the fraction of PAR received (0.4-0.7μm), is also used as a constant= 0.48 [JP/IT]. In addition, the

Normalized CO2 fertilization effect (εCO2) is an important factor in the calculation of NPP. Yet, εCO2 is used as a constant of 1 all over the globe all over the year. Increasing CO2 is taken into consideration using an increasing function over time. Even though LUE max and HI are essential factors in yield calculation, it is difficult in areas with small plot sizes and mixed cropping patterns (Blatchford et al., 2019).

2. Light Use Efficiency

Many remote-sensing models depend on the Normalized Difference Vegetation Index (NDVI) to drive LUE models. Nevertheless, these indices in different models are affected by several factors (Potter et al., 1993). Most remote-sensing models are based on the principle that there is a constant relationship between absorbed light and the carbon assimilation in plants, a ratio termed as Light Use Efficiency (LUE). Monteith (1977) incorporated LUE as LUE max which commonly accounts for the discrepancies caused by environmental stress considering optimal water conditions. Several factors affect LUE max of vegetation including: chlorophyll content, vegetation species, leaf age, light intensity, and growth stages at the leaf scale. In addition, leaf area index (LAI), solar zenith angle, leaf inclination angle, observation angle and canopy structure (Chen et al., 2008) , soil moisture and land cover (Blatchford et al., 2019) affect LUE max. In addition, the pixels mixed by different vegetation types increase the uncertainty of LUE as was recorded in the CASA model (Potter et al., 1993). Hence, LUE varies for different crops and is affected by climatic variations.

Several studies have identified the source of error in yield to the inaccuracy of LUE max. A study by(Wang et al., 2013) in China showed an underestimation of yield for both maize and orchard by MOD17. These values varied significantly upon the calibration and adjustment of LUE max and the relative error was reduced. A study by (Xin et al., 2015) suggested that parametrization of maximum LUE in the MOD17 model require readjustment in order to decrease uncertainties in cropland GPP in Midwestern US. According to Delft (2019), variations between MODIS and WaPOR NPP at L1 could be attributed to choices of parameters including LUE causing considerable variations in products. Hence, treating LUE as a constant for all crops, as is in most models is behind several discrepancies in production estimation (Xin et al., 2015; Yuan et al., 2016).

WaPOR considers a constant LUE value of 2.7 MJ/gr for all crops in the region it covers. This value was considered at optimal water availability conditions for cropland, since a soil moisture stress factor is already included in the calculation of NPP. Hence and to avoid double counting of soil moisture stress, this LUE correction factor was implemented in V2 after the standardized LUE was 2.49 MJ/gr for total biomass produced and C3 crops in WaPOR V1 (FAO and IHE Delft, 2019). Even though WaPOR V1 considered that different LUE max values exist for trees, savannah and pasture, these values were not provided in the methodology(FAO, 2020) and further explanation of information is required.

Since LUE max is affected by land cover, several scientists have worked on identifying LUE max specific for every crop. Several studies including that of Yuan et al. (2015) showed that C3 and C4 crops have different LUE max and thus result in significant errors in GPP and thus yield estimations. Typical Maximum Light Use Efficiency values range between 2.4 to 4.24 g C/MJ for C4 crops and 1.41 to 1.96 g C/MJ for C3 crops (Xin et al., 2015).As for WaPOR, the used LUE values were the same for C3 and C4 crops. Nevertheless, a correction factor to differentiate between C3 and C4 crops is incorporated in the calculation of the yield, where the yield of C4 crops is multiplied by 1.8 (FAO,2018).

Bastiaanssen and Ali (2003) identified a LUE range for barley, cotton, rice, sunflower, wheat, corn, maize, and sugarcane from the literature. According to this study's findings, the maximum LUE for barley ranged between 1.64 and 3.37 g/MJ and between 1.03 and 3.0 g/MJ for Wheat. Even though LUE max=2.7 lies within the reported range for both barley and wheat, LUE max differs for different crops and for different strains of the same crop. According to Mannaerts et al. (2020), a LUE correction factor was used to determine the yield of wheat, potato tubers and sugarcane AGBP during WaPOR yield validation. This correction factor is a fraction of actual LUE/ WaPOR LUE (2.7 gDM/MJ), which was determined as 0.93 for wheat, 0.96 for potato tubers and 2.15 for the sugarcane AGBP (table 4).

3. Above Ground Biomass Production

In order to calculate AGBP , the number of days per dekad, dry matter productivity and the fraction between above and total biomass production are incorporated as stated in (eq.7). According to equation (eq. 7) to calculate AGBP from NPP, the conversion factor from total to above ground biomass is incorporated as a constant of 0.65. Nevertheless, the ratio of above and below ground biomass production has been proven to vary across different landscapes which causes some variations to this ratio (Delft, 2019).It is important to note that in WaPOR V 1.0, AGBP considered crops as C3 not accounting to any variations in land use or crop types to determine actual AGBP with respect to the total biomass (Delft, 2019). For barley, vetch, oat and wheat AGBP=TBP and do not pose a problem.

4. Harvest index and Moisture Content

Since several factors affect the harvest index, it was reported to be behind the inaccuracy of estimated yields in different models. The Harvest Index (HI) varies in different environments (Prihar & Stewart, 1990) for every crop type and the different varieties (Delft,2019;Hay,1995). Harvest Index is also affected by nitrogen supply especially in wheat and barley (Unkovich et al., 2010b). In addition, the proportion of harvestable yield, lodging due to weakness in the stem, delay in sowing damages by insects and storms and extreme weather conditions, difference in temperature at the time of flowering, sampling time, and the extent of leaf drop (Unkovich et al., 2010b).
A study by (Yuan et al., 2016) compared GPP and Yield calculated after adding correction factors between remote-sensing model (EC-LUE model) and GPP from Eddy-Covariance flux towers (EC). GPP values had a good agreement with an R2 of 0.9, RMSE ranging between 0.02-0.11 ton/ha/day, and a RE= 0.5-88%. Nevertheless, yield values showed a lower agreement with an R2 = 0.61 and a Relative Error= 30-61%. In this study yield was reported to have a significantly poorer performance. Usually, GPP and NPP are validated at the image return period and often using EC towers with a point-to-pixel comparison. However, crop yield is validated at a seasonal or annual scale and compared to in-situ data at the field or plot scale (Blatchford et al., 2019). The study by (Yuan et al., 2016) attributed the significant reduction in certainty between GPP and Yield estimates to HI.

According to WaPOR Methodology (FAO, 2020), the harvest index of wheat, rice, maize and sugarcane at level 3 was adapted from Villalobos and Fereres (2016). In WaPOR, calculation of harvest Index considered soil moisture stress only at level 3, disregarding all other factors that affect Harvest index due to the complexity of incorporating all factors. Neither the WaPOR website nor methodology (V1 and V2) provide the used HI and MC values for all different crops or at level 2. Nevertheless, HI used by WaPOR for wheat and potato were 0.48 and 0.7 respectively. These values are very close to the measured values of 0.4 and 0.75 and hence, the low RE (%) for wheat at L3 (1.14%). The RE for potato at L3 (31.01%). Generally, WaPOR uses an HI range between 0.25 and 0.4 for all grain crops which include barley, vetch and oat. The harvest index was used from the literature for these crops is higher than the upper bound of the mentioned range. Nevertheless, WaPOR methodology V2 (2020) mentions that the reference HI can be 50% or slightly higher for modern high-yielding cultivars of grain crops.

Potato yield showed a relative error (RE) of 31.01% at level 3 and 19.55% at level 2. Accuracy is high at level 2 where RE= 19.55% < 20%. Higher relative error at level 3 might be a caused by several factors. One factor would be NPP values calculated during early and late stages of crop life. A study in Saudi Arabia by Al-Gaadi et al. (2016) showed that the vegetation cover is highly noised during early stages of crop growth and that potato leaves turn yellow during late stages of crop growth all of which reduce chlorophyll reflectance. Therefore, lower correlation of NPP values were attributed to these phases.

This study does not enable us to compare between results at level 2 (100m) and those found at level 3 (30m) except for wheat. For barley, oat/vetch, and barley/vetch fields, we noticed that the number of identified fields by WaPOR was not the same at the different levels. Even though the input was the same, yield results available at level 3 were more than those available at level 2. In addition, more fields were identified when fields were by point than when shapefiles were used at level 2, and the highest number of identified fields for most crops and yields was at level 3 for most AREC crop. As for potato and wheat, yield was studied at both levels 2 and 3 for the same number of fields; 20 and 31 respectively. For wheat, yield found at level 3 showed higher accuracy with a RE of only 1.14% and RMSE of 0.17 in comparison to those calculated at level 2 with a RE of -12.43% and an RMSE of 1.2. However, the estimated yield was lower at level 2 than at level 3 for wheat . It is important to note that wheat plantation was done in the winter where lower solar radiation, more clouding, and rain exists in the studied area which could be behind the minor difference in yield estimations. On the other hand, potato was planted during the summer where more solar radiation exists with less precipitation and less clouding.

As for the soil moisture content (SM) used by WaPOR for every crop, SM is considered as an intermediate data component that is not available by the portal (Mannaerts et al., 2020) and hence might be behind some discrepancies since the soil moisture values used cannot be validated against actual soil moisture (SM) in the fields of study. Soil Moisture Content was not validated at levels 2 and 3, and was only validated at L1 by direct validation to in-situ data and by internal or intra-product validation. NDVI and SR are also intermediate components that are incorporated in the determination of NPP and were validated at level 1 using internal or intra -product validation, in addition to the direct validation of NDVI to in-situ data (Mannaerts et al., 2020).

For the crops in Skaff, the moisture content (MC) for both potato and wheat was measured and thus was more accurate than those used for barley, vetch, barley/vetch, vetch/oat fields which were based on the literature.

Table 4 Parameters suggested by producer vs measured and WaPOR parameters for wheat and potato

Crops	Wheat	Potato
LUE max correction factor	0.93	0.96
LUE WaPOR	2.7	2.7
HI suggested by producer	0.37	0.8
Measured HI	0.4	0.75
WaPOR HI	0.48	0.75
MC suggested by producer	0.15	0.8
Measured MC	0.15	0.75
AGBF suggested by producer	0.86	0.2
Measured AGBF	1	0.65

As shown in table (4), in WaPOR's second quality assessment report by Mannaerts et al. (2020), the producer suggests a few crop specific parameters for wheat and potato yields validated in the Beqaa Valley including LUE max correction factor, HI, MC, and the above ground biomass fraction (AGBF). Upon the incorporation of these factors suggested by the producer, as suggested, minimum RMSE recorded was 1.22 ton/ha with a maximum of 12.21 ton/ha while the minimum R2 recorded was 0.12 with a maximum of 0.6 in the Beqaa. The correction factors suggested by the producer in Mannaerts et al. (2020) included a crop specific LUE max which was calculated by dividing the actual LUE by the WaPOR LUE. This correction factor was equal to 0.93 and 0.96 for wheat and potato respectively and was multiplied to the WaPOR LUE max (2.7 MJ/gr). According to the latest WaPOR methodology report (FAO, 2020),the WaPOR HI was based on Aqua Crop version 6.0 (Villalobos & Fereres, 2016). This report notes that HI used from the literature were chosen from the middle high-end HI values reported and could be within 50% or higher for high yielding grains. The harvest Index of wheat used at level 3 is HI=0.48. However, the HI suggested by the producer for wheat grown in the Beqaa (HI=0.37) was based on literature values and was less than the measured HI used for the analysis (HI=0.4). As for the potato tubers, the reference HI used by WaPOR (HI= 0.75) was equal to the measured HI. However, the producer suggested a value of HI=0.8 which is slightly more than the previous value for the validation done in Beqaa by (Mannaerts et al., 2020). The assessment by Mannaerts et al. (2020) showed a fluctuation in NDVI and MC along the course of the growing season where the MC is not constant all season long. For wheat, the SM was high for most of the season and only showed a minor dip between late February and early March aligned with the beginning of spring and irrigation after the wet Winter season. NDVI drops at the end of the season which is associated with tuber maturation for potato where leaves turn yellow and absorb less light and with the graining phase of wheat. Therefore, the suggested MC for wheat MC=0.15 was equal to the measurements, and that for potato tubers MC=0.8 which was slightly higher than the measured MC=0.75.

CHAPTER VI

CONCLUSION AND RECOMMENDATIONS

Since the importance of WaPOR lies in its ability to predict crop water productivity, validation and calibration is required to accurately estimate water productivity especially in semi-arid areas such as the Beqaa Valley which holds a great portion of the Lebanese agricultural sector. Hence, validation of yield and evapotranspiration is required.

In this validation of crop yield in the Beqaa Valley; the aim was to validate the yield of potato and wheat for the year 2017-2018 which showed generally good results RE<20% with R2 of 0.38 and an RMSE below 2 ton/ha at levels 2 and 3 for wheat and an RE< 20% with R2 between 0.22 and RMSE of 9.31 to/ha at level 2 for potato. In addition, the aim was to validate the yields of barley, vetch, barley/vetch mixed fields, and vetch/oat mixed fields between 2012 and 2019 at levels 2 and 3. At level 3, the highest number of fields was identified for all crops showing a % RE for barley, barley/vetch, and vetch/oat between 25-66%, R2 between 0.0-0.13, and an RMSE between 0.17-3 ton/ha. At level 2 using point coordinates, % RE ranged between 55 - 80% , an R2 between 0.01-0.18, RMSE between 2.69-3.94 for all crops and between 30-70%, an R2 between 0.04-0.3 and an RMSE between 2-11.66 ton/ha at level 2 using shapefiles when the number of identified fields was the lowest. Correlation was considered to be moderate or close to moderate for potato and wheat but low for all other studied crops. Bias was positive and high for all studied crops.

Validation of other layers or parameters between different models is required in some cases for better understanding of model accuracy. In other cases, such as the validation in the Fayoum fields reported by (Delft, 2019), Actual evapotranspiration and Interception (AETI) was also compared between MODIS and WaPOR to better understand discrepancies between the two models.

Future recommendations would include the validation against measured yield instead of farmer reported yield that is highly based on predictions, the investigation of more LCC specific parameters instead of some constant parameters such as AGBF and autotrophic plant respiration. In addition, more crop and land specific HI and MC could increase accuracy of NPP. Nevertheless, the effect of different parameters would require a sensitivity analysis for WaPOR. Future work would include the evaluation of crops considering accurately measured reported yield and land-specific measured parameters.

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