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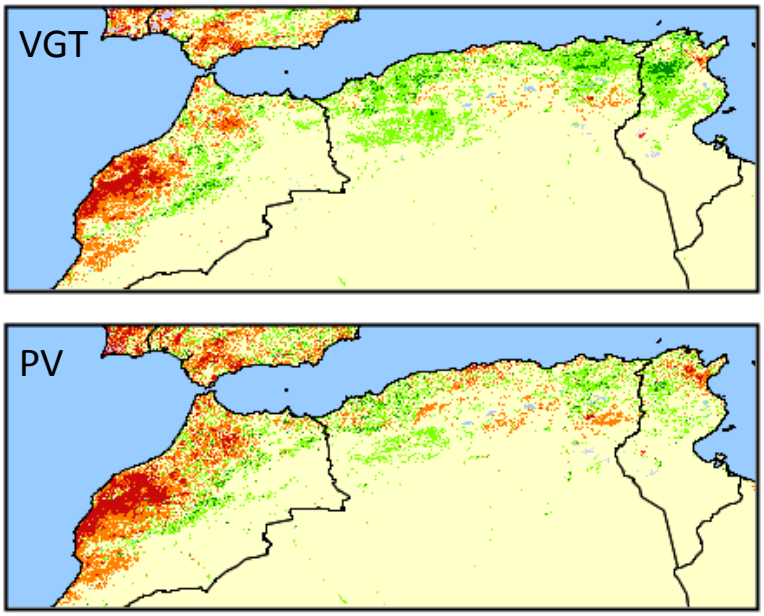

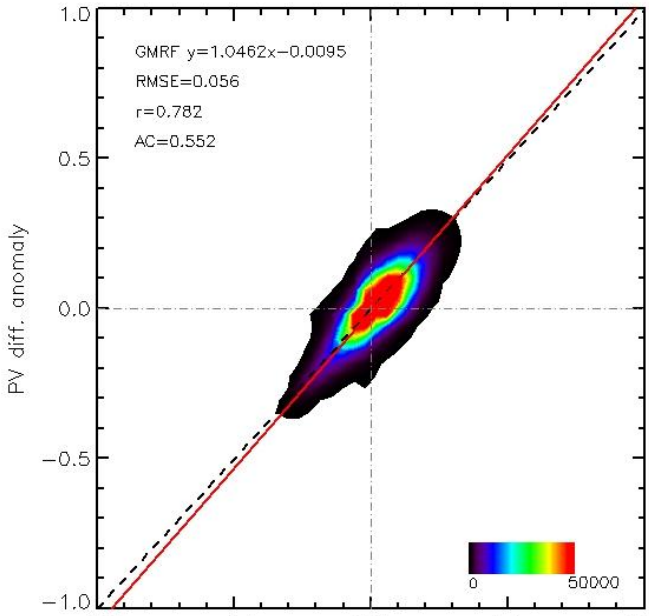

Testing VGT data continuity between SPOT and PROBA-V missions for operational yield forecasting in North African countries

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Abstract

The SPOT-VEGETATION mission operationally provided 15 years of remote sensing indicators of vegetation status. The mission reached its end-of-life in May 2014 and was timely replaced by the PROBA-V mission, aiming to ensure, among other objectives, the seamless continuity of provision of VGT-like products, including Normalized Difference Vegetation Index (NDVI).
Exploiting the period of overlap when both instruments were functioning (November 2013 –May 2014), this study compared NDVI data provided by the SPOT-VGT and the PROBA-V instruments from the point of view of the user interested in operational crop monitoring and yield forecasting. The comparison is performed for the three North Africa country of Morocco, Algeria and Tunisia. All such countries, through different agencies and institutional arrangements, had in place an operational crop monitoring system that was based on 10-day composites of SPOT-VGT NDVI. In view of the operational crop monitoring season of 2015, when they will have to decide whether to continue their business-as-usual activities with the PROBA-V data (instead of SPOT-VGT), this study analysed the impact of the use of this new data source on the information being operationally derived and analysed for crop monitoring and yield forecasting: anomaly maps, temporal profiles and cereal yield figures (for barley, durum and soft wheat) estimated using semi-empirical regression models.

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1 Executive summary

The SPOT-VEGETATION mission operationally provided 15 years of remote sensing indicators of vegetation status. The mission reached its end-of-life in May 2014 and was timely replaced by the PROBA-V mission, aiming to ensure, among other objectives, the seamless continuity of provision of VGT-like products, including Normalized Difference Vegetation Index (NDVI).

Exploiting the period of overlap when both instruments were functioning (November 2013 –May 2014), this study compared NDVI data provided by the SPOT-VGT and the PROBA-V instruments from the point of view of the user interested in operational crop monitoring and yield forecasting. The comparison is performed for the three North Africa country of Morocco, Algeria and Tunisia. All three countries, through different agencies and institutional arrangements, had in place an operational crop monitoring system that was based on 10-day composites of SPOT-VGT NDVI. In view of the operational crop monitoring season of 2015, when they will have to decide whether to continue their business-as-usual activities with the PROBA-V data (instead of SPOT-VGT), this study analysed the impact of the use of this new data source on the information being operationally derived and analysed for crop monitoring and yield forecasting: anomaly maps, temporal profiles and cereal yield figures (for barley, durum and soft wheat) estimated using semi-empirical regression models.

The greatest discrepancies were found to be related to the anomalies maps whose scatter plot SPOT-VGT vs. PROBA-V showed that, albeit no major systematic differences are present, a considerable scatter due to unexplained unsystematic variability exists (Agreement Coefficient, AC = 0.55, AC_s = 0.98, AC_u = 0.56). When looking at the agreement between maps of anomaly classes typically used by the analysts to assess crop conditions, a serious mismatch was observed for a 20-30% of the crop area, depending on the dekad being analysed. This unsystematic variability appears to be strongly reduced when the NDVI extracted over cropland is averaged by administrative units to derive temporal profiles, showing a high agreement between data sources (AC = 0.94).

Results for yield estimation comparison indicate an overall high agreement between data sources and both the hypotheses that the model prediction and the RMSEs in yield estimation are different when using PROBA-V instead of SPOT-VGT are rejected in all cases for Morocco and Algeria. The Root Mean Square Error (RMSE) in yield estimation is generally slightly lower for VGT with the exception of two cereals in Morocco, where the use of PROBA-V outperforms SPOT-VGT. On the contrary in Tunisia, where the RMSE is lower for all the cereals using PROBA-V, the hypothesis of statistically significant RMSE cannot be rejected. This findings thus indicates that yield estimation performances in the three country are not affected (Morocco and Algeria) or improved (Tunisia) by the transition from SPOT-VGT to PROBA-V.

Finally, despite the same nominal spatial resolution, the different spatial quality of the two sensors (PROBA-V delivering a higher spatial detail) was found to have a major effect on yield estimation in an arid area characterized by sharp transition between cropland and the desert.

The detailed methodology used in the present study, as the involvement of final stakeholders, will be of further interest to assess the continuity with future missions such a Sentinel 3.

2 Introduction

Operational crop yield forecasting systems provide objective and independent early quantitative yield assessment that is used by national governments and agencies to take timely decisions on grain import/export and address food security issues related to adverse climatic events such as droughts. Remote sensing can significantly contribute to provide a timely and accurate picture of the agricultural sector, as it is suitable for gathering information over large areas with high revisit frequency (Atzberger, 2013).

Crop growth development is currently monitored using space observation of the Normalized Difference Vegetation Index (NDVI, Rouse et al., 1974) from the SPOT (Système Pour l'Observation de la Terre) VEGETATION instrument (hereafter referred to as VGT) in the North African countries of Morocco, Algeria and Tunisia. Anomaly maps and temporal profiles of NDVI averaged at the relevant administrative level are routinely used in these countries to detect anomalous crop development against what can be assumed to be the average or "normal" situation (usually the long term average of the NDVI temporal evolution, see Rembold et al., 2013). In addition, statistical models have been developed to forecast the yield of major grain crops using NDVI as independent variable and crop yield official statistics aggregated at the appropriate administrative level as dependent variable.

The VGT instruments (VGT1 and VGT2) have provided the user community with daily global observations of continental surfaces at a resolution of 1.15 km at nadir. The instruments VGT1 on SPOT-4 (launched in 1998) and VGT2 on SPOT-5 (launched in 2002) are similar optical sensors operating in the VNIR (Visible to Near InfraRed, three spectral bands) and SWIR (Short Wave InfraRed, one band) ranges.

After 15 years of operational service, the VGT programme ended in May 2014 when the VGT2 instrument reached its end-of-life. Before this date, the PROBA-V (Project for On-Board Autonomy – Vegetation) satellite was launched in May 2013 by ESA, to assure the succession of the VGT instruments and as a "gap filler" between the SPOT-VGT programme and the future Sentinel 3 mission, foreseen to be launched in mid-2015. The PROBA-V mission instrument (called VGT-P and referred to as PV hereafter to avoid confusion) has spectral characteristics identical to VGT (i.e., blue, red, NIR and SWIR bands) and increased spatial resolutions (100 [200] m at nadir, 360 [600] m at the edge of the swath for VNIR [SWIR] bands). Radiometric performances in terms of Signal to Noise Ratio are also increased with respect to VGT (Dierckx and Benhadi, 2013). As VGT, PV has sun-synchronous orbit, but in contrast to the SPOT platforms, PROBA-V does not have the capability to maintain its orbit.

Global daily VNIR imagery at 300 m spatial resolution are obtained using the three camera characterizing the optical design of the instrument (one pointing nadir and the other two pointing at the right and left sides). Imagery at 100 m resolution are also produced using the central camera having a reduced swath of 517 km and thus preventing global daily coverage at this resolution. Despite the higher resolution in the VNIR, allowing PV to produce 300 m global imagery, products at 1 km are maintained to ensure the continuity of the 15-year time series of VGT (for further details see Sterckx et al., 2014; and Dierckx et al., 2014).

One kilometre products from both sensors are freely distributed to users under the framework of European Commission Copernicus programme (http://land.copernicus.eu/global/). The service provides a number of 1-km operational products (including NDVI, LAI, FAPAR, FCOVER) with specified characteristics in order to ensure a transparent data interoperability and a smooth service continuity for users of VGT data. After the commissioning phase, the PROBA-V mission has started delivering global images through this service since the end of October 2013, thus providing an overlap with VGT of about seven months.

Reference quality assessment of the new NDVI product from PV was performed by VITO (Flemish Technical and Research Institute, Belgium) and indicates that there is no significant systematic bias between VGT and PV NDVI (Swinnen and Diercks, 2014a). Some not negligible dispersion was observed when comparing the two datasets and most of the observed differences were attributed to the variation in illumination and observation geometry of the two set of paired observations. Differences were also found to be variable in time and this behaviour was attributed to the incorrect modelling of the sun-earth distance in the VGT processing (www.vgt.vito.be/pdf/Reflectance_communication_letter_V1.0.pdf).

The present study complements this producer quality assessment by analysing the effect of using PV NDVI instead of VGT NDVI for operational crop monitoring and yield forecasting activities, providing some kind of user or fitness for purpose assessments. The study makes use of paired observations from the two instruments collected during the overlap period when both satellite systems were active. This overlap period, ranging from end of October 2013 to end of May 2014, covers the time period used by North Africa countries to monitor crop development (January to May) to provide timely yield forecast of the major grain crops (barley, soft and durum wheat).

Instead of investigating the agreement between products as done in typical satellite product intercomparison studies (e.g., Meroni et al., 2013a) the purpose of this study is to verify that the information derived from PROBA-V can be used indeed in an operational and seamless way to replace that of SPOT-VGT and to assess, on a user perspective, the possible uncertainties linked to this shift of source.

This study focuses on the NDVI product used for national yield forecasting in the three North Africa countries and addresses two components of the operational use of remote sensing low spatial resolution products for crop monitoring: the qualitative analysis of vegetation index anomalies and temporal profiles, and the quantitative crop yield prediction by regression modelling.

The study has been accomplished in a timely manner before the 2015 yield forecasting season to allow the institutions of the three countries involved in the study to evaluate the effects of this data source shift on their monitoring and forecasting activities.

3 Data and study area

We used time series of 10-day (referred to as dekad) Maximum Value Composite (Holben, 1986) NDVI from the SPOT-VGT and PROBA-V missions. Both time series are computed from top of canopy reflectance processed by the Flemish Technical and Research Institute (VITO, Belgium). NDVI used in this study refers to version 0 and 2.1 for VGT and PV, respectively. Data are freely available from the Copernicus portal

(http://land.copernicus.eu/global/products/NDVI). Subsequent processing, i.e., computation of anomalies and use in statistical models to estimate crop yield, is based on raw NDVI data.

Different crop masks are used in the three countries to extract the cropland specific NDVI signal for the relevant administrative unit. In all the countries a so-called area fraction image is used to extract the mean NDVI over the administrative unit. This image describes the percentage of the coarse resolution satellite pixel that is covered by cropland in Algeria or more specifically cereals in Morocco and Tunisia. The area fraction image is static (i.e., does not change over time) and it is not crop specific (i.e., it indicates the presence of cropland or cereals). In Morocco the area fraction has been developed within the E-agri project (http://www.e-agri.info/), using two sources of data: (1) for most of agricultural lands, a land cover map based on SPOT 5 2.5m resolution satellite images provided by the Direction de la Stratégie et des Statistiques of the Ministère de l'Agriculture and (2) for the remaining area (about 10% of the total cropland area), the mask of Vancutsem et al. [13] compiled harmonizing different land cover/land use datasets. In Algeria this fractional cover is computed directly from GlobCover land cover classification [14] at 300 m resolution grouping the relevant cropland classes. Finally, in Tunisia, the area fraction is derived from the land cover/land use produced by the INFOTEL project (Inventaire des Forêts par Télédétection, CNCT, Tunisia) at a spatial scale of 1:25,000 (Infotel, 2010).

Yield official statistics for the three crops were provided by the national authorities of the various countries (Morocco: DSS-MAPM, Direction de la Stratégie et des Statistiques - Ministère de l'Agriculture et de la Pêche Maritime; Algeria: DSASI-MADR, Direction des Statistiques Agricoles et des Systèmes d'information-Ministère de l'Agriculture et du Développement Rural; Tunisia: DGEDA, Direction Générale des Etudes et de Développement Agricole - Ministere de l'Agriculture) at the administrative level of province, wilaya and governorate for Morocco, Algeria and Tunisia, respectively.

4 Methods

The purpose of the present study is to evaluate in an empirical way and on a user point of view the effective and seamless replacement of VGT by its successor, PV. Therefore, this evaluation is performed by comparing the derived products used by the analysts to formulate qualitatively (within-season anomaly maps, temporal profiles) and quantitatively (yield forecast figures) an evaluation about the ongoing crop season. The comparison exercise is carried out on the 2014 monitoring campaign exploiting the availability of NDVI computed from both instruments.

4.1 NDVI-derived information

4.1.1 Anomalies

Different types of NDVI anomalies are used for near real-time vegetation monitoring (Rembold et al., 2013): the simple difference between the current NDVI value with the long term average value (LTA), the percentage difference anomaly (difference/LTA * 100), the standardized Z-score (difference normalized by LTA standard deviation). Percentage and standardized anomalies can artificially show severe anomalies over deserts or over vegetated areas when vegetation cover is low. Therefore, here we used the first type of anomaly in order to avoid over-emphasizing small deviations on the arid areas widespread in the study area. The difference anomaly is defined by:

$NDVI\_Diff_i = NDVI_i - LTA\_NDVI_i$

where *i* is the dekad number and LTA_NDVI stands for the Long Term Average NDVI computed per dekad from the VGT archive 1999-2013.

Maps of anomalies obtained using VGT and PV, together with the map of their difference, were produced for the three countries (example in Figure 1). Note that when computing the difference between difference anomalies, the LTA cancels out, so that difference between anomalies is indeed simply difference between the two NDVI of the dekad considered.

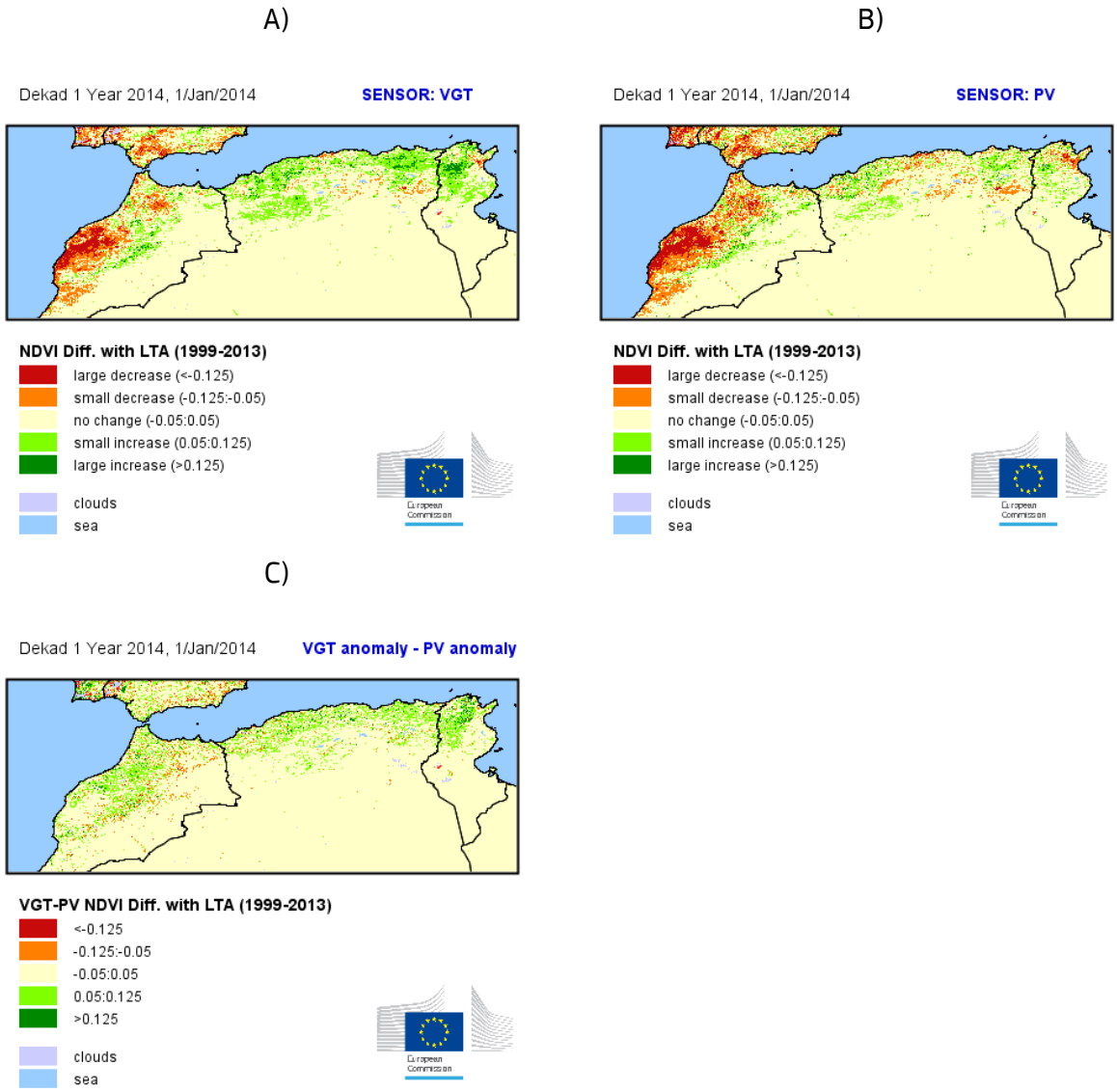


Figure 1: Example of graphical output used to qualitatively inspect the anomalies. A) and B) are difference anomaly maps as derived from VGT and PV, respectively; C) represents the difference between the two anomalies, thus VGT anomaly – PV anomaly.

For the graphical representation of the anomalies we employed the legend typically employed in crop monitoring bulletins classifying anomaly values into five categories (Table 1).

NDVI difference	Label	Colour
< - 0.125	large decrease	
- 0.125 : -0.05	small decrease	

-0.05 : 0.05	no change	
0.05 : 0.125	small increase	
> 0.125	large increase	

Table 1: Classification of the difference anomaly values

4.1.2 Temporal profiles

Temporal profiles show the temporal evolution of the NDVI averaged over a given spatial unit (usually some administrative unit) considering only the pixels belonging to the cropland land cover class. They are used by the crop monitoring analyst to qualitatively evaluate current vegetation development against the "normal" one, represented by the LTA curve. Differently from anomaly maps that represent only a snapshot of the vegetation development at a given time, profiles allow the analyst to visualize the overall development of the crop season from the beginning to the time of analysis.

Here the profiles were extracted at GAUL (Global Administrative Units Layer of the Food and Agriculture Organization of the United Nations) administrative level 1 using the JRC crop mask of Vancutsem et al., 2013 (examples of profile in Figure 2). These profiles shows, for the period November 2013 – May 2014, the temporal evolution of VGT and PV NDVI together with the long term average computed from the VGT archive 1999-2013.

A) B)

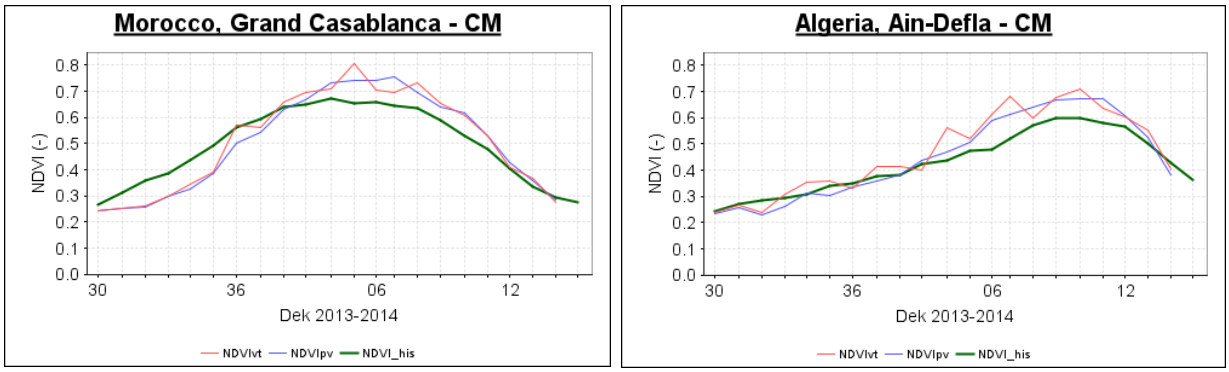


Figure 2: Example of graphical output used to qualitatively inspect the profiles at administrative unit level. GAUL 1 level extraction for Grand Casablanca (a) and Ain-Defla (b) districts in Morocco and Algeria, respectively.

4.1.3 Yield estimates

Each of the three countries uses its own model set up (dekad or dekads used as predictor, yield computed using sown or harvested area, crop mask, etc.). However, the focus of this analysis is not on the definition of model nor on the specific accuracy in yield estimation. The aim of this part of the exercise is to compare the yield predictions for the year 2014 at the relevant administrative unit level used operationally in each country as obtained by the same statistical model using either VGT or PV NDVI as input. Therefore, the important point is that the model configuration is the one used in forecast operations and, once calibrated with VGT data, it is used without modification with both VGT and PV NDVI as input.

In order to homogenise and make comparable the results obtained by the different countries we adopted the following protocol:

1) the model coefficients are tuned using official statistics and VGT NDVI for the period 1999-2013;

2) the model is applied to year 2014 using the VGT and PV data, resulting in two sets of yield estimation in full prediction mode;
3) the model is applied to years 2009-2013 using VGT data, resulting in one set of yield estimates for each year in fitting.

Step three has been considered to provide a characterization of the magnitude of the RMSE one can expect in each country.

All models rely on some form of linear regression between official yield statistics at some administrative unit and one or more dekadal unit level average of NDVI during the growing season. Pixel level NDVI values are aggregated to unit level mean making use of crop masks (e.g., Balaghi et al., 2008; Meroni et al., 2013b). A summary of the various model used by the different countries is provided later in this section.

When applying such kind of statistical models in each administrative unit of a country it may happen that the accuracy is reduced for some units having a very limited extent of croplands. This does not usually represent a problem as the level of production of such units is very limited and only marginally relevant to the national figure.

In order to exclude that the results of the comparison are masked out by the possible presence of less accurate model estimates over such administrative units, we calculated all the agreement statistics twice: once on the full set of administrative units and once on a subset composed by the most important units representing the 90% production. This latter set is obtained by ordering the units according to their mean production level over a period of 10 years (2003-2012), and retaining only those summing up to 90% of the total national production. Results of this further analysis do not indicate any significant difference between the two sets and are therefore not shown in the following.

Empirical yield modelling in the three countries

NDVI aggregation at the level of the administrative unit is achieved using area fraction images in all the three countries (described in Section II). In this way pixel level NDVI values are aggregated at the administrative unit level following the approach of Genovese et al. (2001), i.e., as the weighted average according to each pixel's area occupied by crops.

In Morocco yield modelling is performed at the province level. Operational yield forecast is made at the beginning of May, once the last dekadal observation of April for the current year (Y) is available. Simple to multiple linear regression models are tested using yield official statistics as dependent variable and remote sensing observations from 1999 to Y-1 as independent variables. The independent variables, up to a maximum of three, are selected among the following candidates: NDVI value of dekads from 36 (21-31 December) of the previous year (Y-1) to 12 (21-30 April) of the current year (Y), NDVI amplitude during this period, (i.e., $Max(NDVI_{36,Y-1}, .., NDVI_{12,Y}) - MIN(NDVI_{36,Y-1}, .., NDVI_{12,Y})$), NDVI difference between dekad 6 and 36 (of year Y-1), 12 and 6, and finally the year of harvest. This latter variable has the function of adjusting model prediction for the yield trend, where present. Model selection is performed according to the minimum Root Mean Square Error (RMSE) in cross-validation (jackknifing technique leaving one year out at a time) over the period 1999 to Y-1. Additional details about the methodology are in Balaghi et al., 2013.

Three basic models are used to relate NDVI to cereal yield for each *wilaya* in Algeria where cereals are grown: 1) a null model where NDVI is not used and instead yield is simply predicted as the average yield, where there is no evident relationship between interannual

variation in yield and interannual variation in NDVI; 2) a linear model relating NDVI to yield (*yield = a + b*NDVI*), selecting the dekad falling between dekad 1 (the first dekad of January) and dekad 15 (the last dekad of May) that maximises this linear fit between NDVI and yield in each *wilaya*; and 3) a linear model that also includes an additional term describing a technology trend (*yield = a + b*NDVI + c*year*) where such a trend is evident in the past yield statistics, again selecting the dekad that maximises the linear fit. The decision on which particular model to use for each *wilaya* is made after examining the relationship between past NDVI and past yield for that *wilaya*. In this way a different model is defined for each *wilaya*, and the dekad used to predict yield from NDVI can vary between *wilaya*. Observed NDVI during the appropriate dekad is then used to predict yield for each *wilaya*. This unit-level model was originally developed to forecast cereal production at the national level in both countries: unit-level predictions of yield are multiplied by reported areas for each unit to give unit-level forecasts of production, which are in turn summed to give the national level forecast for production. The model is simple (albeit with the freedom to select the dekad that best captures variation in yield), but has shown some skill in capturing the more complex relationship between NDVI and national level production.

The method currently applied in Tunisia is similar to model 2 of Algeria with the exception that the dekad used for prediction is selected maximizing the fit at the country level, therefore pooling all administrate units together (more details in Meroni et al., 2013b).

4.2 Comparison method

4.2.1 Comparison of qualitative information

A first evaluation of the agreement is performed analysing the scatterplot of the anomalies and profiles values provided by the two sensors. The agreement is quantified by standard statistics derived from the Geometric Mean Functional Relationship (GMFR) analysis. The GMFR linear model is preferable to ordinary least square linear regression for exploring the relationship between two datasets when both are subjected to error of equal or unknown intensity. To express the agreement between products we used the Agreement Coefficient (AC) proposed by Ji and Gallo (2006). AC is a non-dimensional, bounded (0-1 for no to perfect agreement) and symmetric (no preference to one dataset) indicator with distinguishable systematic and unsystematic agreement, AC_s and AC_u. The systematic component refers to the overall agreement of the data points with the 1:1 line while the unsystematic one takes into account the random component caused by noise or unknown factors. Any systematic difference can in principle be removed by regression analysis (Ji et al., 2008).

In order to stress the differences between anomalies from an analyst point of view, an additional measure of the agreement was quantitatively evaluated using the classes of Table 1 and by computing the occurrence of the concordance classes reported in Table 2.

Label	Condition
Unacceptable mismatch	sensors indicates anomaly with opposite sign ("increase" vs. "decrease", no matter the magnitude)
Serious mismatch	one sensor indicates "no change" and the other indicates "large" change (either "increase" or "decrease")

Mismatch	one sensor indicates “no change” and the other indicates “small” change (either “increase” or “decrease”)
Minor mismatch	both sensors have the same sign of the anomaly (“increase” or “decrease”) but different magnitude (“small” vs. “large”)
Agreement	both sensors indicate in the same class

Table 2: Classification of agreement of anomaly classes

Besides this numerical comparison, the analysts of the three countries were requested to visually inspect the maps and profiles to qualitatively evaluate, for its own country, the perceived magnitude of the differences between the anomalies and profiles computed with the different sensors.

4.2.2 Comparison of quantitative information

The agreement of model outputs is assessed by comparing the scatterplots of observed yield against model estimates using either VGT or PV and inspecting the scatterplot of modelled yield using VGT against that using PV. Statistics of linear Ordinary Least Square (OLS) regression analysis are used to evaluate numerically the agreement between estimates.

In addition we were also interested in statistically testing: *i)* if the model estimates made by using the two sensors are significantly different, and *ii)* if the RMSE provided by the models using VGT is significantly different than that of that using PV. For this purpose we used a paired sample *t*-test for point *i)* and Pitman-Morgan test of variance (Wilcox, 1990) for paired samples for point *ii)*.

4.3 Limits of the study

The validity of the conclusions about data continuity of the present study have some limitations due to two issues present in the VGT data used, both in its archive and in its near real time (NRT) data during the overlap period. First, it is known that VGT data are affected by an erroneous modelling of the Sun-Earth distance in the standardization of solar illumination (CTIV, 2012). This error introduces a seasonal effect on the estimated top of canopy reflectances with a maximum error occurring in July and estimated to be 7% of reflectance. Reprocessing of the VGT archive will be conducted during 2015 (VITO, personal communication) and it is expected to increase the agreement between VGT and PV NDVI. However, the magnitude of this increase is hard to be anticipated. Second, the overpass time of VGT2 was, due to the orbital drift occurring during the last period of operations, already beyond requirements for the entire overlapping period of the two sensors (Swinnen and Dierckx, 2014b). This resulted in an overpass lag time between the two sensors of about 45 minutes. Any impact of such lag related to the different illumination conditions at time of overpass of the two sensors will be captured in this intercomparison but is not representative for the entire period before the overall period when SPOT-VGT was not drifting. Unfortunately, the agreement in the absence of such effect cannot be evaluated.

Finally, it is recognized that, besides proving comparable performances during the test period of the 2014 growing season, the continuous monitoring of stability and quality of

PV data is a strategic activity to ensure that the performances assessed here are not degraded after the test period.

5 Results

5.1 Anomalies and profiles intercomparison

5.1.1 Statistic of agreement

In order to compute the relevant statistics and graphs described in this section, pixels were considered only if being classified as cropland according to the crop mask of Vancutsem et al. (2013).

The relation between the anomalies computed using PV and VGT is presented in Figure 3. The relationship appears to have a negligible bias (mean PV-VGT difference equals to 0.0076 NDVI units) but presents some relevant scatter. The agreement coefficient (AC) between the two datasets is 0.55 while its systematic (AC_s) and unsystematic (AC_u) components are equal to 0.98 and 0.56, respectively. The good systematic agreement is also shown by a GMFR line close to the 1:1 line (slope of the GMFR linear model is 1.0462 and the offset is -0.0095). The fairly low AC and AC_u indicate the presence of a substantial random or unexplained variability whereas the high AC_s and the GMFR linear model being close to the 1:1 line indicates no major systematic difference between the two data sources.

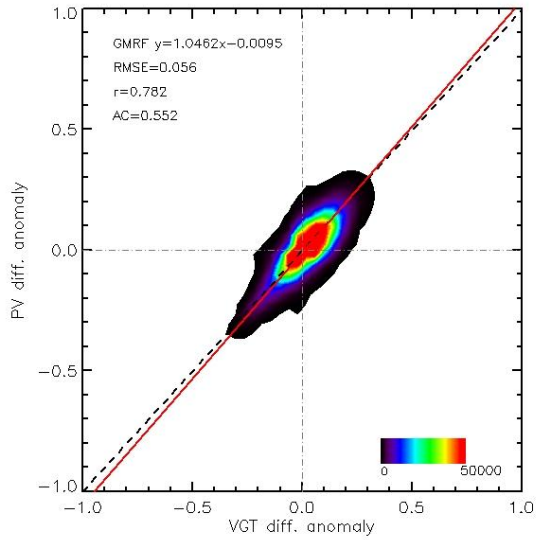


Figure 3: Density scatterplot PV vs. VGT difference anomalies, 15 dekads pooled together (from 01/01/2014 to 31/05/2014), n = 2,288,550. Continuous red dashed black lines refer to the GMFR regression and the 1:1 line, respectively.

The effect of this scatter is noticeable also when looking at the agreement between anomalies from the analyst's perspective: Figure 4 shows the temporal evolution of percentage of pixels in the various agreement classes as computed over all pixels belonging to the cropland land cover of three countries.

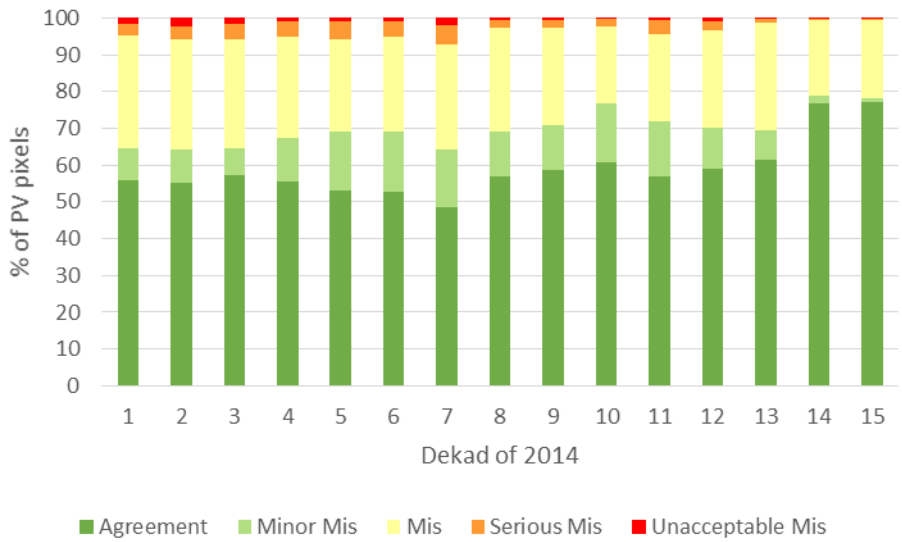


Figure 4: Statistics of agreement between VGT and PV absolute anomaly classes (n = 152,570) according to Table 2

The percentage of pixels showing perfect agreement plus minor mismatch does not exceed 80% and it is below 70% in the majority of the dekads. The total percentage of the two classes representing the lowest agreement (serious and unacceptable mismatch) is higher for the first half of the period and peaks at dekad 7 (7.3 %) and is minimum during the last two dekads (0.58 % for both).

The overall agreement between mean cropland land cover profiles extracted for GAUL 1 administrative level (Figure 5) is increased with respect to the pixel-level comparison of anomalies of Figure 3. Considering NDVI values instead of NDVI anomalies and averaging at this spatial level removes most of the unexplained scatter and results in an AC of 0.94. The bias is negligible (-8.4E-04) and slope and offset of the GMFR linear model are again very close to eth 1:1 line, i.e., 0.96 and 0.0189, respectively.

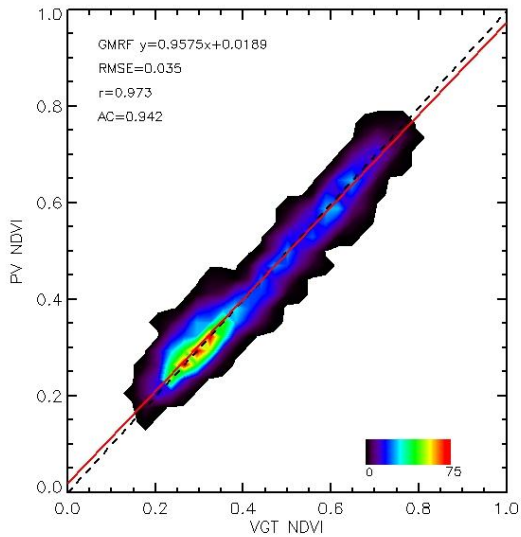


Figure 5: Density scatterplot PV vs. VGT average GAUL 1 NDVI for cropland land cover, all 81 GAUL 1 administrative units and 15 dekads pooled together (from 01/01/2014 to 31/05/2014), n = 1782. Continuous red and dashed black lines refer to the GMFR regression and the 1:1 line, respectively.

5.1.2 Visual inspection

Analysts from the three countries visually inspected the paired anomaly maps and the GAUL 1 administrative level profiles derived from the two sensors in order to qualitatively evaluate if they would draw the same conclusions when using PV instead of VGT in their business-as-usual evaluation of crop development. Asked to rank this agreement based on the anomaly maps from 0 (different conclusions about growth development using PV) to 5 (same conclusions), the Tunisian analyst assigned a score of 4.5 (high agreement) whereas the analysts of Morocco and Algeria assigned a score of 3, highlighting that they do perceive differences between data sources (overall mean for the three countries 3.5).

High constant agreement was reported by Tunisia, whereas analysts of Morocco and Algeria indicated that the agreement between anomaly maps is not constant over time, however no general consensus was reached about the specific dekads when the agreement was lower. Of the considered period, agreement was evaluated to be the lowest in the central part (dekads 5 to 8) and in agreement with Figure 4 for Morocco, at the beginning and end (dekads 2 to 4, 13 and 15) in Algeria.

When asked to rank on the same scale the accordance of the conclusions they would have drawn from the analysis of the GAUL 1 profiles, they assigned a mean score of 4, indicating that, when the spatial heterogeneity is averaged out to create the mean profiles, the agreement is perceived as higher. This effect may be related to the difference in actual spatial quality that will be discussed further in Section 5.2. The agreement between profiles was evaluated not to be constant over time in Morocco only.

5.2 Model outputs numerical intercomparison

5.2.1 Statistic of agreement

The graphics in the first and second column of Figure 6, Figure 7, and Figure 8 show the scatterplots of observed yield against model estimates using either VGT or PV whereas the graphics in the third column show the scatterplot of modelled yield using VGT against that using PV. A summary of the relevant statistics is reported in Table 3.

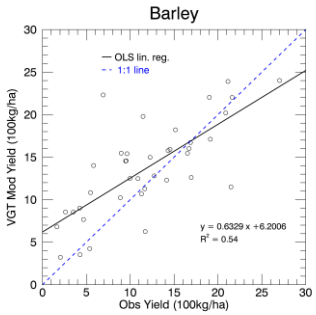
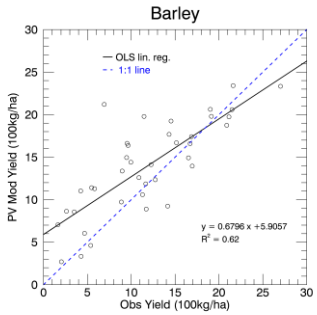
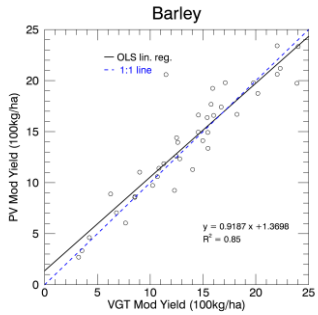
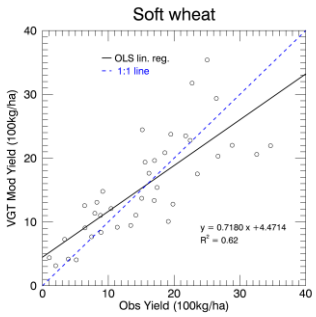
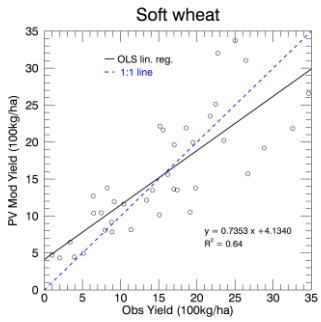
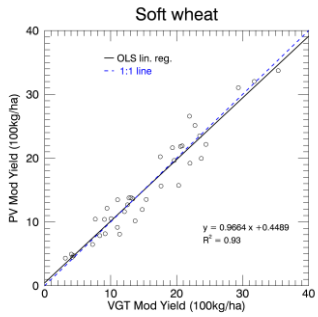
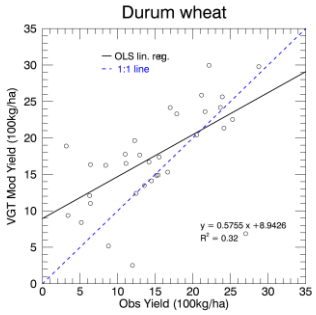
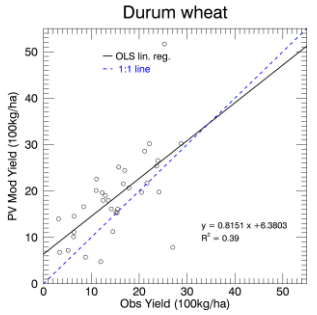
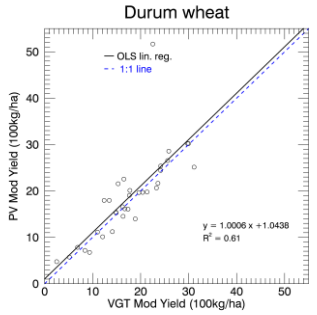
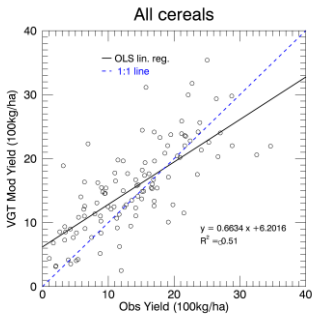
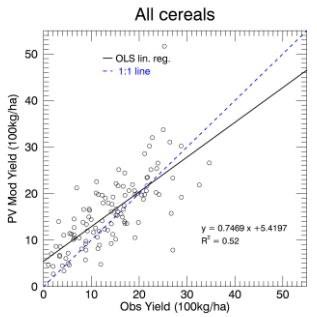
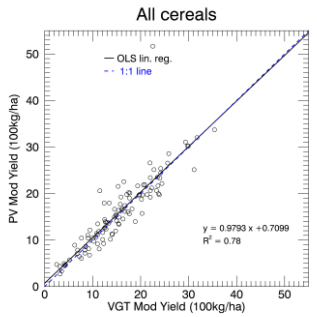
	Obs *vs.* VGT estimates	Obs *vs.* PV estimates	VGT *vs.* PV estimates
Barley			
Soft Wheat			
Durum Wheat			
All cereals			

Figure 6: Comparison of model performances using VGT and PV in the year 2014, Morocco

	Obs *vs.* VGT estimates	Obs *vs.* PV estimates	VGT *vs.* PV estimates

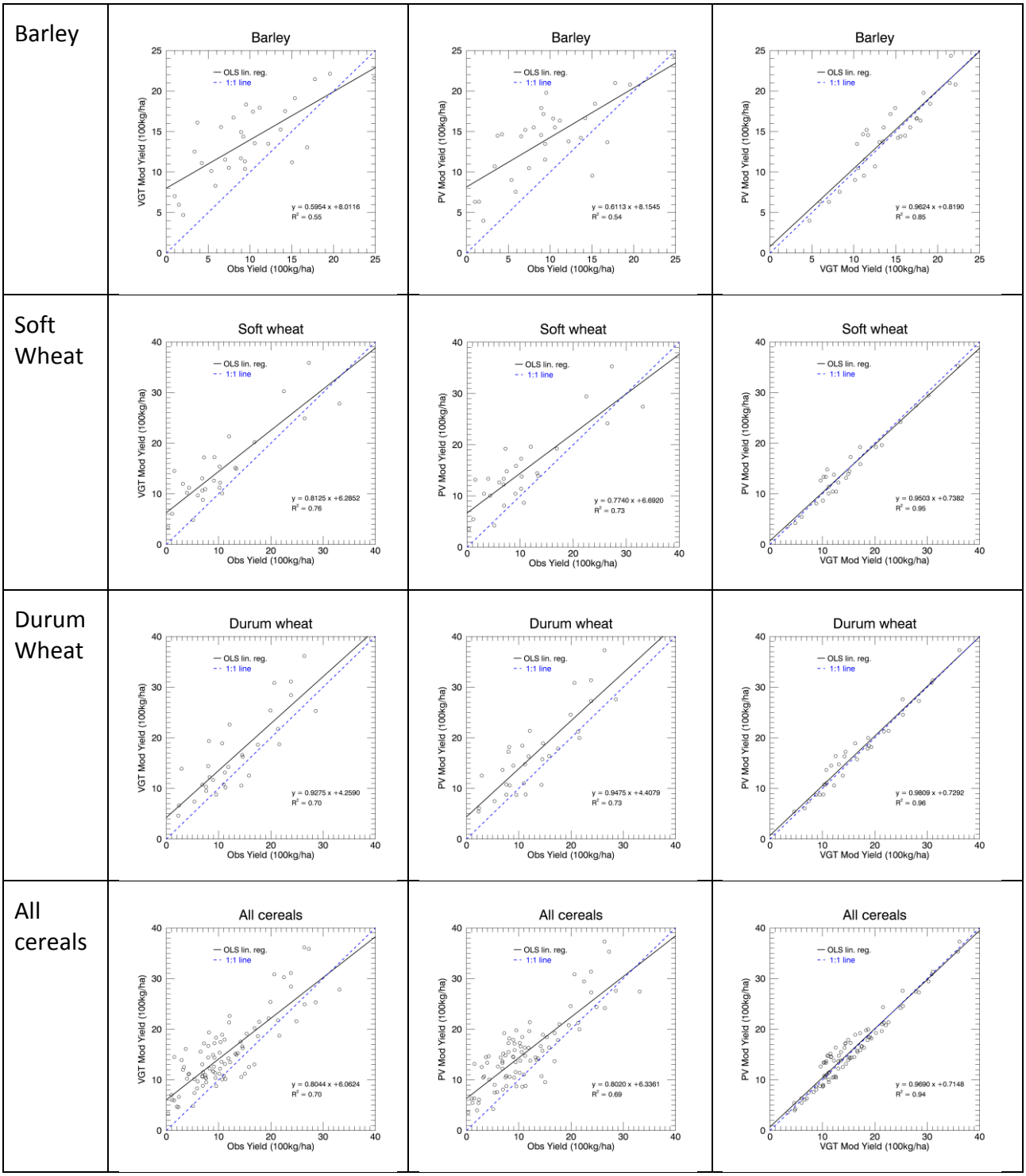


Figure 7: Comparison of model performances using VGT and PV in the year 2014, Algeria

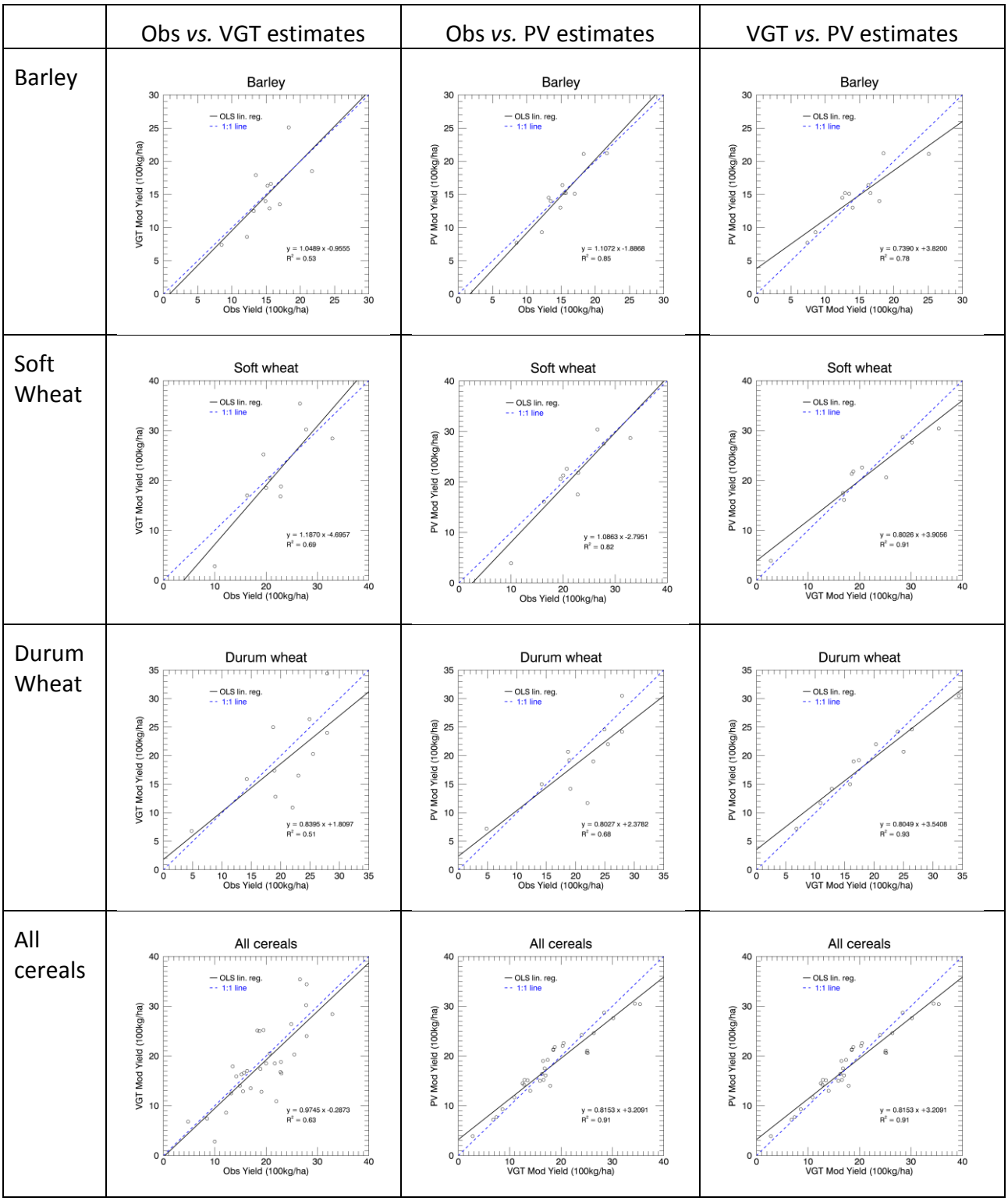


Figure 8: Comparison of model performances using VGT and PV in the year 2014, Tunisia

In Morocco and Algeria, the data source used does not appear to have a significant effect on the scatterplot observed vs. modelled yield (Figure 6 and Figure 7, first and second

columns) with the exception of durum wheat in Morocco (Figure 6). Here, the model estimate of Errachidia province appears as a clear outlier when using PV (modelled value = 51.67 100kg/ha against 25.27 observed and 22.54 modelled using VGT). This difference is due to an interaction between the spatial quality of the two sensors and the spatial fragmentation of the crop cover in this area as explained with more detail in Section 0. In Tunisia on the contrary, the observed vs. modelled scatterplots do highlight differences.

Country	Crop	No. admin. units	2014: VGT vs. PV yield estimates, regression statistics						2014: RMSE					2009-2013: RMSE using VGT, Mean (SD)
			Slope	Intercept	P	R^2	Mean diff. test	Paired sample t-test P	VGT	PV	difference (%)	RMSE test	Paired sample t-test P	
Morocco														
All administrative units														
	Barley	*39*	0.92	1.37	<0.0001	0.85	*n.s.*	0.46	4.71	4.41	-6.45	*n.s.*	0.17	4.88 (1.03)
	Durum wheat	*34*	1.00	1.04	<0.0001	0.61	*n.s.*	0.29	6.88	7.91	14.98	*n.s.*	0.47	6.69 (1.15)
	Soft wheat	*38*	0.97	0.45	<0.0001	0.93	*n.s.*	0.83	5.36	5.15	-3.80	*n.s.*	0.56	6.77 (1.80)
	All		0.98	0.71	<0.0001	0.78	*n.s.*	0.26	5.67	5.92	4.51	*n.s.*	0.65	6.23 (1.14)
Algeria														
All administrative units														
	Barley	*30*	0.96	0.82	<0.0001	0.85	*n.s.*	0.37	5.51	5.79	5.14	*n.s.*	0.78	2.45 (0.15)
	Durum wheat	*31*	0.98	0.73	<0.0001	0.96	*n.s.*	0.15	5.41	5.49	1.49	*n.s.*	0.38	2.10 (0.23)
	Soft wheat	*27*	0.95	0.74	<0.0001	0.95	*n.s.*	1.00	5.85	6.03	3.14	*n.s.*	0.41	2.24 (0.34)
	All		0.97	0.71	<0.0001	0.94	*n.s.*	0.17	5.58	5.76	3.27	*n.s.*	0.95	2.28 (0.14)
Tunisia														
All administrative units														
	Barley	*11*	0.74	3.82	<0.0005	0.78	*n.s.*	0.94	3.20	1.60	-50.00	<0.05	0.006	3.80 (1.76)
	Durum wheat	*11*	0.80	3.54	<0.0001	0.93	*n.s.*	0.79	5.57	4.15	-25.49	<0.05	0.011	5.76 (3.20)
	Soft wheat	*11*	0.80	3.91	<0.0001	0.91	*n.s.*	0.74	4.93	3.24	-34.28	<0.05	0.034	5.67 (2.37)
	All		0.82	3.21	<0.0001	0.91	*n.s.*	0.68	4.66	3.18	-31.76	<0.0001	0.00002	5.31 (2.04)

Table 3 Statistics of yield estimation performances using VGT and PV, per country and per crop.

Depending on the crop and the country being analysed, the model accuracy in terms of RMSE ranges from a minimum of 3.20 to a maximum of 6.88 100kg/ha when using VGT and from a minimum of 1.60 to a maximum of 7.91 100kg/ha when using PV.

Independently from the data source used, the model used in Algeria appears to generally overestimate yield in 2014 (Figure 7). In fact, 2014 was an anomalous year for this country. A relatively warm and wet winter in Algeria led to good vegetative growth, and unusually high NDVI through until spring. Models based on NDVI at this stage of the campaign then naturally led to high forecasts of yield and production. However, an absence of rainfall in Algeria from mid-April onwards (that would have only become evident in the NDVI signal at even later stages) then severely affected grain filling, which in turn led to much reduced yields and production. SPOT-VGT and PROBA-V both showed this high NDVI, and so both led to over-prediction.

Statistics of the scatterplot VGT vs. PV yield estimates (Table 3) indicate no major differences in PV estimates as compared to VGT for Morocco and Algeria. The regression line slope is close to one and the intercept is small and mostly positive, with a small positive bias indicating a small yield overestimation of PV compared to VGT. Given that we are here comparing the prediction of a model calibrated with VGT observation, it is not surprising that the RMSE is generally slightly lower for VGT. Nevertheless, it is noted that in Morocco the RMSE value achieved with PV is lower than the mean RMSE obtained in the previous five year (2009-2013). On the contrary, this is not the case in Algeria where the

RMSE of both VG and PV models for year 2014 is greater than that of the previous five year because of the peculiar conditions experienced in 2014 as commented above.

In Tunisia, scatterplot statistics indicate differences with respect to the other two countries. The regression line is not close to the 1:1 line and the slope and the intercept compensate each other (a slope lower than 1 and positive intercept). The RMSE is in all cases smaller when using PV, with a relative improvement with respect to VGT RMSE that reaches 50%.

The hypotheses of different model estimates and different RMSE are rejected in all cases for Morocco and Algeria, indicating that, given the observed variability in the data, it is not possible to statistically detect a difference between the yield estimates achieved using one or the other data source. On the contrary, in Tunisia, where the use of PV improves the estimation performances, the hypothesis that the RMSE is different cannot be rejected.

5.2.2 Effect of different spatial quality

Errachidia province, located in the south east of Morocco in the Saharan agro-ecological zone (Balaghi et al., 2013) is an arid area (mean annual rainfall being less than 150 mm) where irrigated agriculture and palm plantations are established in a desert landscape (Figure 9A and B).

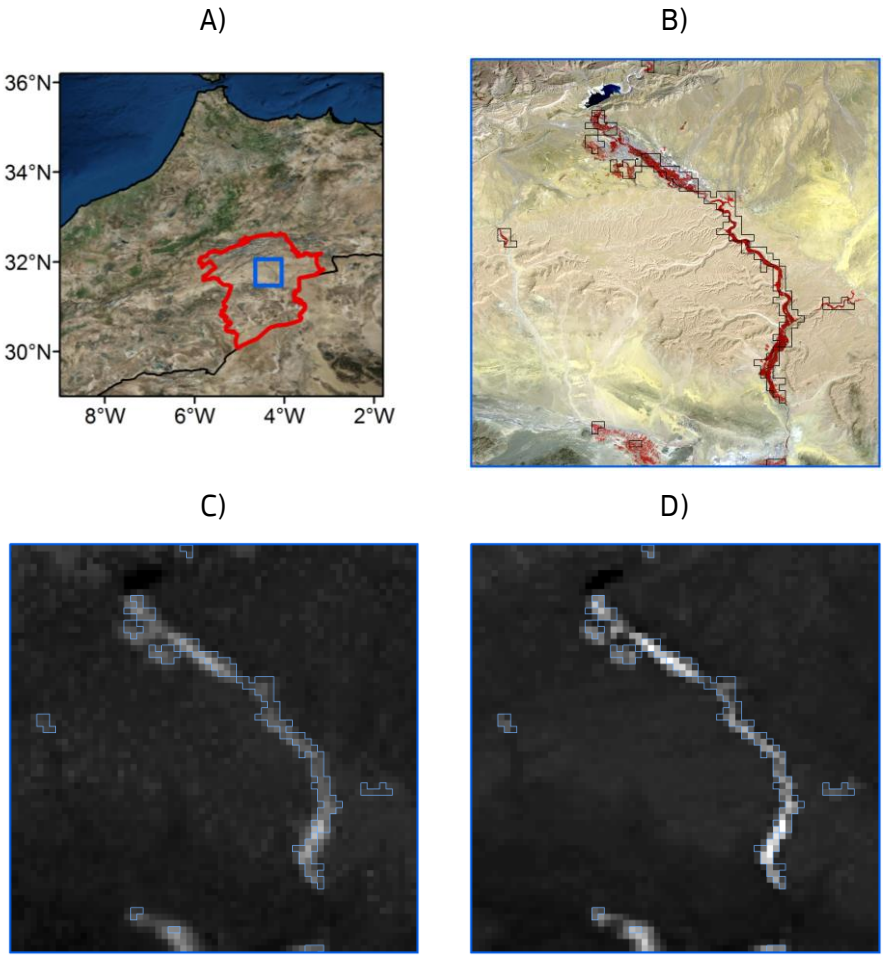


Figure 9: A) Location of Errachidia province (red polygon), true colour composite in the background (Source: Esri); B) Landsat 8 false colour composite (April 2014) geographically corresponding to the blue box in A); C) VGT NDVI dekad 3 2014; D) PV NDVI same dekad. Same liner stretching applied to C) and D). Polygons in B), C), and D) delineate the crop mask used to extract NDVI.

It's interesting to analyse the cause of the observed difference in yield estimation using PV instead of VGT in this province as it is related to the different spatial quality of the data provide by the two sensors. In fact, although the nominal resolution (the GSD, ground Sampling Distance) is the actually the same (1 km), the VGT images appears blurred compared to PV ones. The area over which the radiometric signal is integrated is a function of both GSD and the Point Spread Function (PSF, describing the relative contribution of the spatial domain as a function of distance from the pixel centre and characterising the resultant multi-directional blurring) and it is generally larger than the nominal pixel size as determined by the GSD (e.g., Tarnavsky et al. 2008). The PSFs of the two instruments are not directly comparable as the 1 km PV product is derived from the finer native resolution of 1/3 km using a stretched bi-cubic interpolation filter (Dierckx et al., 2014). Visual

inspection of the imagery suggests that the spatial quality of PV is superior to that of VGT. For instance, the sharp contrast between the vegetation and the desert visible in the Landsat 8 scene of Figure 9B is clearly more spatially smoothed in the VGT (Figure 9C) than in PV NDVI (Figure 9D). This in turn means that the NDVI value extracted over a crop mask delineating the cropland layer (with more or less success), will be more contaminated by the surrounding areas in the case of VGT. As the desert has a much lower NDVI signal, the VGT NDVI is lower than that of PV. This explains why, feeding a regression model tuned on the spatially blurred VGT NDVI with the less desert contaminated (and thus higher) PV NDVI value in 2014, results in the observed yield estimation overestimation. In fact, the model selected in this region to predict the yield in this region is a multiple linear regression making us of the NDVI of dekad 3, 6 and the variation between the NDVI of dekad 36 of the previous year and dekad 6. As an example Figure 9C and D show one of the independent variables used by the model, the NDVI of dekad 3. The mean value at province level for this variable is about a 25 % higher for PV (0.20 for VGT and 0.24 for PV).

The effect of the different spatial quality is in the case of this province quite severe as vegetation borders the land cover of the desert, characterized by contrasting NDVI values. However, this spatial effect is expected to play a role in any fragmented landscape.

6 Conclusions and recommendations

The SPOT-VGT mission provided 15 years of operational remote sensing indicators of vegetation status to the user community dealing with crop monitoring. The mission reached its end-of-life in May 2014 and was timely replaced by the PROBA-V mission, aiming to ensure, among other objectives, the seamless continuity of provision of VGT-like products, including NDVI.

Exploiting the period of overlap when both instruments were functioning (November 2013 –April 2014), this study compared NDVI data provided by the SPOT-VGT and the PROBA-V instruments from the point of view of the user interested in operational crop monitoring and yield forecasting. The study was motivated by the need of three North Africa country (Morocco, Algeria and Tunisia) to fully check the interoperability of the two data sources in view of the operational crop monitoring season of 2015, when the crop monitoring institutions of the three countries have to decide whether to continue their business-as-usual activities, carried out in the past with NDVI from the SPOT-VGT sensor, with the new PROBA-V data.

The study analysed the impact of the data differences on the products being operationally derived and analysed for crop monitoring and yield forecasting: anomaly maps, temporal profiles and yield figures estimated using semi-empirical regression models.

The greatest discrepancies were found to be related to the anomalies maps whose scatter plot VGT vs. PV showed that, albeit no major systematic differences are present, a considerable scatter due to unexplained unsystematic variability exists. When looking at the agreement between maps of anomaly classes typically used by the analysts to assess crop conditions, a mismatch was observed for a 20-30% of the crop area, depending on the dekad being analysed. This lack of perfect agreement was also picked up by the visual inspection of the various country analysts that reported an intermediate score when asked if they would have drawn the same conclusion about vegetation development when using one or the other data source.

Consistently, this unsystematic variability appears to be strongly reduced when the NDVI values (instead of NDVI anomalies) are extracted over cropland and averaged by administrative units to derive temporal profiles, showing a high agreement between data sources.

Results for yield estimation comparison indicate an overall high agreement between data sources and both the hypotheses that the model prediction and the RMSEs in yield estimation are different when using PV instead of VGT are rejected in Morocco and Algeria. This is not the case in Tunisia where the hypothesis of different RMSE could not be rejected. However, in this country the yield estimation performances using PV improve with respect to that of using VGT. As a result, the empirical findings of this study indicate that using PV does not deteriorate the yield estimation accuracy with respect to VGT.

Nevertheless it is recognized that, besides proving comparable performances during the test period of the 2014 growing season, the continuous monitoring of stability and quality of PV data is a strategic activity to ensure that the performances assessed here are not degraded after the test period. Recent analysis performed by Meroni and Rembold (2015) over the Horn of Africa after the overlap period (June to December) indeed showed relatively large discrepancies between NDVI anomalies derived from the Proba-V sensor and other comparable sensors (METOP and MODIS).

Finally, despite the same nominal spatial resolution, the different spatial quality of the two sensors (PV delivering a higher spatial detail) was found to have a major effect on yield estimation in an arid area characterized by sharp transition between cropland and desert. This effect is likely to be present in other areas and it is expected to have a significant impact in any fragmented landscape where the pixels laying on the borders of the cropland area represent a significant proportion of the total area. Improving the similarity of the spatial quality of the two sensors would be required to overcome such issue and ensure data continuity. A pragmatic approach of further degrading the PV spatial quality by some additional spatial filtering may be considered to achieve full spatial compatibility with VGT.

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