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Combined use of agro-climatic and very high-resolution remote sensing information for crop monitoring

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ABSTRACT

Accurate and real-time yield forecasting is one of the main pillars for decision making in farming and thus for farmers' profitability. Biomass has been traditionally predicted by multi- and hyperspectral vegetation indices from low- and medium-resolution platforms. This research work aimed to assess the accuracy of the combined use of agro-climatic information and very high-resolution products obtained with RGB cameras mounted on unmanned aerial vehicles (UAVs) for biomass predictions in maize (*Zea mays* L.). Two agro-climatic predictors, reference evapotranspiration (ETo) and growing degree days (GDDs), and twelve vegetation indices (VIs) derived from RGB bands were calculated for the entire growing cycle. The root mean squared error (RMSE) of the model that considers only GDD to estimate total dry biomass (TDB) was 692.7 $g\,m^{-2}$, which was reduced to 509.3 $g\,m^{-2}$ when introducing as predictor variables the VARI and GLI vegetation indices. Difficulties in the radiometric calibration of consumer grade RGB cameras together with sources of error such as the bidirectional reflectance distribution function and the blending algorithms in the photogrammetry processing could decrease the applicability of the obtained relationship and should be further evaluated. This study illustrated the advantage of the combined use of agro-climatic predictors (GDD) and green-based VIs derived from RGB consumer grade cameras for biomass predictions.

1. Introduction

Field maize (*Zea mays* L.) is one of the most harvested cereal crops worldwide for the food supply and animal feed. The total world harvested area is more than 184 million hectares (FAOSTAT, 2014). Maize is cultivated in both hemispheres and is the main pillar for food and feed security and smallholding maintenance in many countries. Accurate and real time yield estimation and forecasting is essential to develop national and international plans to guarantee food security (Zhou et al., 2017). Therefore, improving knowledge and methodologies to increase the accuracy of these predictions is essential in those countries where maize is a main source of food and feed.

The literature has widely reported that variables derived from climatic variables, such as temperature and photoperiod, are good predictors of biomass for maize (Bonhomme et al., 1989; Tollenaar et al., 1978). Thermal time, mainly based on growing degree days (GDD), i.e., accumulated degrees below and over a thermal threshold where there is no growth, has been traditionally used as an independent variable to describe accumulated biomass. The use of linear, polynomial and other non-linear functions, such as Gompertz or Weibull functions, to describe accumulated biomass for the entire growing cycle over the GDDs is well-known (Heggenstaller et al., 2008; Meade et al., 2013). The

Abbreviations: AI, aridity index; β, normalized blue; BCCH, *Biologische Bundesanstalt Bundessortenamt* and Chemical Industry scale; DTM, digital terrain model; ETc, crop evapotranspiration; ETo, reference evapotranspiration; EVI, enhance vegetation index; ExB, excess blue vegetation index; ExG, excess green vegetation index; ExGR, excess green minus excess red; ExR, excess red vegetation index; γ, normalized green; GCP, ground control point; GDD, growing degree days; GLI, green leaf index; GNSS-RTK, global navigation satellite system-real time kinematic; GPS, global position system; GRVI, green-red vegetation index; Ikaw, Kawashima index; LAI, leaf area index; NDVI, normalized difference vegetation index; NGRDI, normalized green red difference index; OSAVI, optimized soil-adjusted vegetation index; P, monthly total rainfall; ρ, normalized red; R, Pearson's correlation coefficient; R^2, coefficient of adjustment; R^2_{adj}, adjusted coefficient of determination; RDVI, renormalized difference vegetation index; RGB, red, green and blue; RGRI, red green ration index; RH, monthly means of mean relative humidity; RMSE, root mean squared error; RTK GPS, real time kinematic global position system; SAVI, soil adjusted vegetation index; SfM, Structure from Motion; SSE, sum of squared error; SWL, stepwise linear regression; TDB, total dry biomass; $TDB_{observed}$, total dry biomass observed; $TDB_{simulated}$, total dry biomass simulated; T_{MAX}, monthly means of mean daily maximum temperature; T_{MIN}, monthly means of mean daily minimum temperature; U_2, monthly means of mean daily wind speed; UAV, unmanned aerial vehicle; VARI, visible atmospherically resistance index; VI, vegetation index; WBI, water band index

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response of maize to irrigation has been shown to be a greater determinant of yield and biomass formation than other actors involved, e.g., fertilization. Regarding this statement, Di Paolo and Rinaldi (2008) and Zwart and Bastiaanssen (2004) explored the yield response of maize to actual evapotranspiration and crop evapotranspiration rates under different environmental and management constrains, such as different nitrogen application rates. However, deeper knowledge is essential for detailed crop monitoring, especially in those areas where broad use and affordable technologies are required (Vergara-Díaz et al., 2016), e.g. when small farmers are the targets.

Remote sensing is a very useful tool for real-time decision support systems in agriculture. High- resolution (10 m or less) and medium-resolution (less than 100 m) remote sensing have evolved rapidly in the last years, overcoming previous constraints related to spatial and temporal resolutions, i.e., the Sentinel-2 constellation that delivers multispectral data from 10 to 60 m spatial resolution and 5 days temporal resolution, or the use of constellations of nanosatellites that can operate from 3 to 5 m resolution on a daily scale (Houborg and McCabe, 2016; Martín et al., 2011). Nevertheless, atmospheric effects or weather interference and the lack of information related to specific phenological events are still unsolved constraints in crop monitoring (Matese et al., 2015). In addition, these remote sensing images require exhaustive data processing algorithms and post-interpretation (Fonstad, 2012). Also, when small plots, complex terrain, and cloudy weather prevails, authors such as Zhou et al. (2017) recommended the use of high resolution platforms.

The high spatial (centimetric) and flexible resolution data offered by unmanned aerial vehicles (UAVs) are becoming a widely used tool for agronomic observation. UAVs have overcome satellite fixed revisit constrains allowing flight sampling under desired temporal resolutions. Although UAV platforms have noticeably improved flight endurance, the low payload capacity, ground coverage and the use of miniaturized sensors with inconsistent characterisation and calibration constrain their applicability. In order to solve these constrains we developed tools and methodologies such as: 1) developing software to perform accurate flight planning that optimizes the covered area per flight and the accuracy in the results (Hernández-López et al., 2013); 2) developing methodologies to avoid the use of targets and detect blur images that reduces the field work and post-processing time (Ribeiro-Gomes et al., 2016); 3) to perform accurate thermal cameras calibration to improve the quality in the measurement of crop temperature (Ribeiro-Gomes et al., 2017); 4) detecting sun glint and hotspot in images obtained with UAVs (Ortega-Terol et al., 2017); together with many procedures to extract useful information from high-resolution remote sensing information, primarily using RGB images (Ballesteros et al., 2018, 2015b; Córcoles et al., 2013). Thus, with these methodologies and many others developed by researchers all along the World, the applicability of UAVs in agriculture is becoming a reality.

Spectral indices derived from multi- and hyperspectral images have been traditionally used to monitor, analyse and map crops and vegetation (Bendig et al., 2014; Córcoles et al., 2013; Duan et al., 2017; Jannoura et al., 2015). Many authors have deeply explored the relationships between traditional spectral indices with different crop variables, such as the normalized difference vegetation index (NDVI), which has been widely studied to estimate crop growth status and yield for high- and medium-resolution platforms. Nevertheless, vegetation indices (VIs) are strongly dependent on the different spectral wavebands used in calculations, the spectral resolutions and the different equations used (Rasmussen et al., 2016). It is well-known that the NDVI is strongly correlated with the leaf area index (LAI), although it saturates when the canopy closes (Duan et al., 2017). Many studies have analysed the crop growth status based on the different patterns of the NDVI behaviour for maize and other cereals to discriminate and map weed patches (Martín et al., 2011), for field phenotyping (Zaman-Allah et al., 2015), for yield forecasts under drought conditions (Martyniak et al., 2007), under different conditions of nitrogen (Vergara-Díaz et al., 2016) or phosphorus fertilization (Gracia-Romero et al., 2017) and to determine water requirements (Toureiro et al., 2017). Although there are many multispectral, commercial cameras available for UAVs, knowledge about their performance and image processing is incomplete. However, conventional RGB cameras and photogrammetric settings and process to obtain the derived geomatic products are perfectly known and are easy to use. Currently, VIs based on wavelength in the visible spectrum are widely used, e.g., Gitelson et al. (2002) expended considerable efforts to describe the multispectral properties of the wheat canopy by comparing VIs, such as visible atmospherically resistant index (VARI), and mostly used the NDVI. Other authors, such as Rasmussen et al. (2016) and Zhou et al. (2017), assessed VIs derived from RGB cameras versus traditional multispectral VIs obtained from multispectral sensors mounted on UAVs for accurate crop monitoring. Synergies between indices derived from satellite imagery and meteorological parameters have been evaluated to predict cereals yield in recent times: e.g. Sarma et al. (2008) developed a statistical mode of agro-climatic model (annual rainfall, southern oscillation index, sea surface temperature, and GDD) combined with NDVI in predicting rice yield in India, Savin and Isaev (2010) used a model where inputs variables were NDVI derived from MODIS and temperature and incident solar radiation. Other authors, such as Vicente-Serrano and Cuadrat-Prats (2006) combined drought indices with NDVI retrieved from AVHHR to predict wheat and barley yield four months before harvesting. These studies highlighted the significance of meteorological variables based of temperature and GDD, precipitation, and solar radiation as predictive models. However, no reference has been found that combines the use of very high-resolution remote sensing obtained with UAVs with agro-climatic data to improve crop monitoring.

Accurate real time biomass estimation is crucial to improve crop management and thus farmers' profitability. Based on experience, consumer-grade RGB cameras can provide very reliable information about crop growth status, such as green canopy cover (GCC), LAI and plant height, among others, (Ballesteros et al., 2018, 2015b; Ballesteros et al., 2014). This research led to the assessment of the accuracy of the combined use of agro-climatic information and very high-resolution geomatic products obtained with UAVs to estimate maize biomass. Specific objectives were: 1) to evaluate the traditional used VIs about significance for maize biomass estimation; 2) to establish and evaluate models based on combining agro-climatic variables, reference evapotranspiration (ETo) and GDD, and the proposed VIs

2. Materials and methods

2.1. Study area

The study was carried out in Tarazona de La Mancha (Albacete, Spain) (Fig. 1) which is located in the hydrological unit (H.U.) 08.29., during the seasons 2010–2011 and 2011–2012. This H.U. is located in

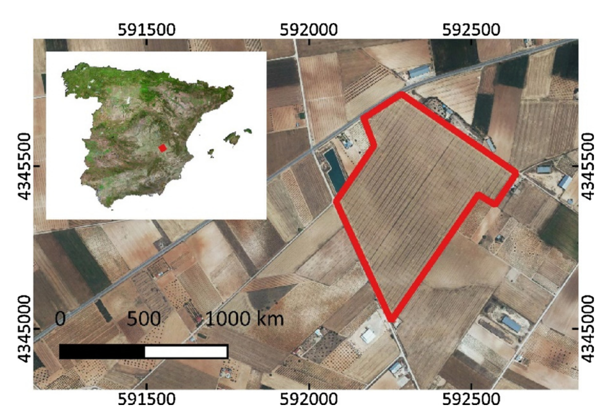

Fig. 1. Location of the commercial maize field in Southeastern Spain.