FROM DRONE TO SATELLITE – DOES IT WORK? #9398

M. Söderström and K. Persson
Swedish University of Agricultural Sciences (SLU), Skara, Sweden
e-mail: mats.soderstrom@slu.se; Tel: +46-51167244

ABSTRACT

In order to assess the possibilities to transfer crop property prediction models generated from data collected with drone-mounted multispectral cameras to satellite image-based decision support systems, data from two multispectral drone cameras – a five-band camera (Micasense Rededge, AgEagle, USA), and a nine-band camera (MAIA, Eoptis, Italy) mounted on the same drone – were compared with surface reflectance data from the Sentinel-2 satellites. Data were collected in cereal crops in south Sweden during 2020-2022 at 30 different locations and dates. The time difference between the Sentinel-2 images and the corresponding drone flights was maximum two days. Comparisons were made both for individual bands and for a range of vegetation indices (VIs). Results calculated as average reflectance for each flight and location showed that individual bands of the drone cameras were often well correlated with the Sentinel-2 bands, but with an offset from the 1:1 line (as indicated by low Nash-Sutcliffe modeling efficiency E). For many VIs, the bias was much lower (e.g., for NDVI, R^2 was 0.90 and 0.96, and E was 0.69 and 0.93, for MAIA and Micasense Rededge respectively). Hence, models based on these drone sensors may be possible to apply on satellite image data but may require some adjustments to correct for systematic differences, depending on bands or indices used.

INTRODUCTION

Drones (unmanned aerial vehicles, UAVs) equipped with multispectral cameras can efficiently collect detailed crop canopy reflectance data in small-plot field trails (e.g., Prey and Schmidthalder, 2019), thereby reducing costs for manual field work. Additionally, this provides possibilities for the development of crop status prediction models based on spectral data, that may be of relevance in practical precision agriculture, e.g., for optimising nitrogen (N) input (Piikki et al., 2022) or protein concentration (Wolters et al., 2022). To make such models widely available, one option is to apply them in decision support systems (DSS) based on satellite images data (such as CropSAT.com (Dataväxt, Sweden); Söderström et al., 2017). If such a transfer of models should be successful, there must be a consistent and established relationship between crop reflectance registered by the drone camera and the satellite sensor. In earlier research, comparisons between data from drone sensors and Sentinel-2 data (e.g., Bukowiecki et al., 2021; Matese et al., 2015; Rasmussen et al. 2020) have shown variable results, partly depending on different strategies in the data collection, and how data was compared.

In this study the aim was to compare reflectance data (both individual bands and a selection of vegetation indices (VIs)) from two drone sensors with Sentinel-2 satellite data. Data was collected over a period of three years in different locations south Sweden, and the difference in time between drone and satellite acquisition was not more than two days. Based on this criterion, we tried to establish consistent sensor relationships. Ultimately, we assess whether transfer of prediction models developed by the drone sensor data to satellite images used in agricultural DSSs is possible.

MATERIALS AND METHODS

Two drone cameras were used: a nine-band sensor (MAIA, Eoptis, Italy), and a five-band sensor (Micasense Rededge-3, AgEagle, USA). Both were mounted on the same drone (a custom-made octocopter (Explorian 8, Pitchup, Sweden). The bands of these cameras cover the visible to near infrared (NIR) portion of the electromagnetic spectrum, bandwidths are shown in Fig. 1. Sentinel-2 has bands with the same specification as those of MAIA. Drone flights were carried out over small areas (1-4 ha in size) which included small-plot field trials in wheat, oats, and barley, with at least 80% image overlap, at 80-m height above ground, and with a speed of 5 m s^{-1}. Further details of flights and data processing are found in e.g. Piikki et al. (2022). Orthomosaics were generated with the Solvi.ag web application (Solvi, Sweden). Two methods were used for calculation reflectance for the drone sensors. For MAIA, 50 cm × 50 cm target panels (MosaicMill, Finland) with different reflectance characteristics were placed in the field. These were used to recalculate digital numbers in the orthomosaic to reflectance. For Micasense Rededge, a provided small target panel was photographed before and after the flight and used for deriving reflectance.

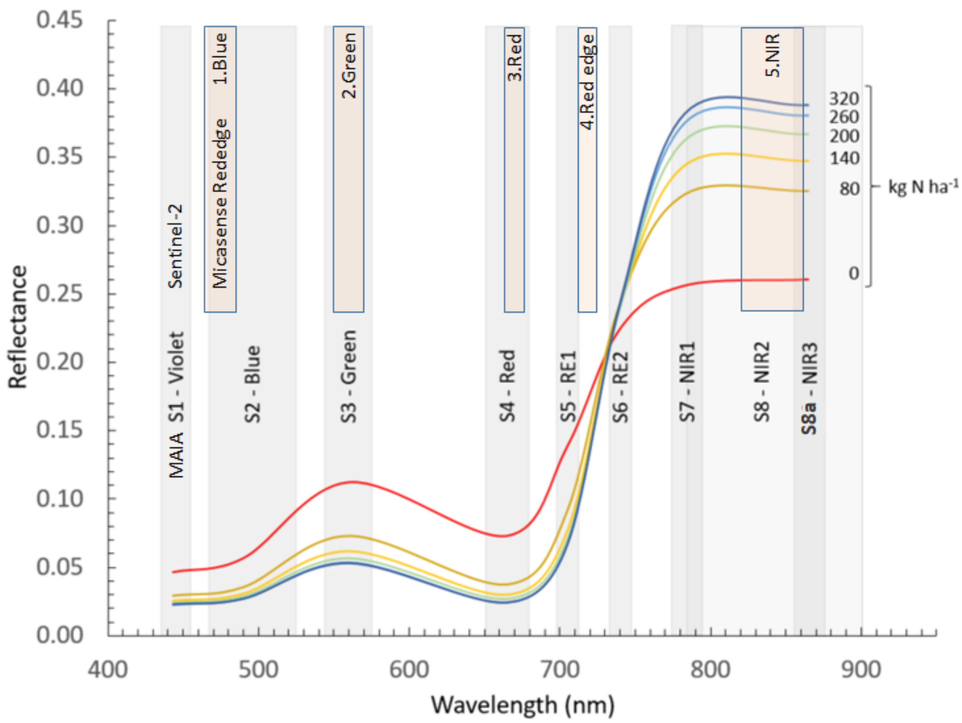

Fig. 1. Example spectral signatures of wheat in the spectral region 400-900 nm (visible to near infrared). Different curves represent data from after flowering in trial plots with different N rates applied. Shaded areas show the bands of different sensors (UAV: MAIA and Micasense Rededge; Satellite: Sentinel-2).

To georeference the drone mosaics, we used a national orthomosaic based on aerial photography provided by the Swedish Land Survey (Lantmäteriet, Sweden), which had a reported positional error of less than 20 cm. Only flights done within two days from an available Sentinel-2 image free from haze, clouds, and cloud shadows (as judged manually) were used. Thirty-two flights carried out over wheat, barley, and oats during the period 2020-2022 from start of the stem elongation period to end of flowering fulfilled these criteria.

Sentinel-2 L2A processed images (atmospherically corrected orthomosaics with ground reflectance) downloaded from European Space Agency's web site (https://scihub.copernicus.eu) were used. These were not further georeferenced but used as provided.

In this study, data extracted from the trial parcels (which was the initial aim of the projects within which the drone flights were carried out) were not used. Instead, average reflectance data for each band across all 20 m × 20 m areas coinciding with pixels of the Sentinel-2 satellite were calculated. Calculations were made for all individual bands (Fig. 1) and the VIs: NDVI (Rouse et al., 1973); MSAVI2 (Qi et al., 1994); NDRE (Barnes et al., 2000); NGRDI (Bannari et al., 1995); ChlI (Gitelson et al., 2003); and TGI (Hunt et al., 2013). In two cases, there were problems with the calculations of reflectance for the visible bands of the MAIA camera. These two flights were omitted. To derive general sensor-sensor relationships, and reducing impact of differences in e.g., georeferencing, averages of reflectance in bands and VIs for each flight was used in the analyses. Comparisons were analysed statistically with the determination coefficient R^2 of a linear regression line between reflectance data from the two sensors, as well as the modeling efficiency E (Nash and Sutcliffe, 1970; how well the data follows the 1:1-line). In a perfect relationship both R^2 and E are approaching 1.0. If the data are well correlated, but not close to the 1:1-line, the R^2 is high but E is low and can even be negative if the bias is large.

RESULTS AND DISCUSSION

Results from the analyses are shown in Table 1. Individual bands are often well correlated (relatively high R^2), notably the Micasense Rededge bands 1-4 and MAIA bands 2, 4 and 5 with an $R^2 > 0.70$, but in some cases, there is a bias, resulting in a low or negative E. Among the individual bands, only MAIA band 5 and Micasense Rededge bands 1 and 3 had an E > 0.50. For some of the tested VI's, this bias was removed, and both E and R^2 were high, e.g. the Micasense Rededge indices NDVI and NGRDI, and for MAIA, the indices MSAVI2, NDRE and ChlI. The index TGI (based on the visible bands) was only well correlated to the Micasense Rededge sensor (still with a very large bias).

The results indicate that for some of the best performing VIs, it should be possible to a apply a prediction model from drone sensor data that is based on one or more of these indices on Sentinel-2 satellite images, directly or with some linear adjustment. Especially simple indices based on ratios and quotients between two bands seem to be well correlated between the sensors and producing very similar values. The more complex TGI index did not work equally well.

When data from individual flights (the 20 m × 20 m pixels, on average 40 pixels per flight; n=1188 in total) were analysed (data not shown here), it is evident that the relationships vary between flights. The reasons for this can be many. With this type of dataset, which consists of orthomosaics of agricultural fields, but each of which includes small-plot field trials with small areas with considerable variation in reflectance, including areas of bare ground, it is likely that also minor variation in the position of the Sentinel-2 images will have a large impact on the relationship with data from the drone flight. The drone orthomosaics are very accurately positioned, whereas it is difficult to be sure of the correct position of the satellite image. Some other issues may be related to the radiometric corrections, both for the Sentinel-2 images and certainly for the drone images. In this case, drone flights were done in as uniform weather as possible, but still light conditions may fluctuate during a flight. Incoming light sensors were used on the drone, which can correct for this to some extent. In addition, flights were carried out with slightly varying solar altitude. On average it was 48° but ranging between 31° and 54°. Such varying conditions may impact on the results (e.g., de Souza et al., 2021). Still, the high R^2 and E for some indices on average, suggest that the procedures used generate useful drone sensor data. To minimize variation between flights, it is recommended to carefully follow a predetermined protocol in terms of flight height, speed, and image overlap, avoid data collection in varying weather conditions, and also use the same method for geometric and radiometric corrections (see further discussion in e.g., Maes and Steppe, 2019).

Table 1. Modeling efficiency (E) and coefficient of determination (R^2) between data (individual bands, see Fig. 1, and selected indices) from Sentinel-2 and two drone cameras. The table shows averages from 30 flights (2020-2022; date between drone flight and satellite image is max 2 days).

	MAIA			Micasense Rededge		
Band or index	Band(s) used	E	R^2	Band(s) used	E	R^2
Blue	2	-0.09	0.70	1	0.56	0.83
Green	3	-0.09	0.40	2	-0.36	0.86
Red	4	0.49	0.87	3	0.63	0.93
RE1	5	0.84	0.86	4	-2.09	0.88
RE2	6	0.39	0.59	-	-	-
NIR1	7	0.22	0.48	-	-	-
NIR2	8	-0.01	0.43	5	-2.68	0.40
NIR3	8a	-0.09	0.46	-	-	-
MSAVI2	4, 8	0.79	0.83	3, 5	-0.32	0.81
NDVI	4, 8	0.69	0.90	3, 5	0.93	0.96
NDRE	5, 8	0.83	0.90	4, 5	0.49	0.95
NGRDI	3, 8	0.29	0.55	2, 5	0.88	0.93
ChlI	6, 7	0.85	0.90	-	-	-
TGI	2, 3, 4	1.34	0.12	1, 2, 3	-10.15	0.78

CONCLUSIONS

As judged by the comparisons with the L2A calibrated Sentinel-2 satellite images, both drone cameras used in this study seemed to produce rather consistent orthomosaics. This was achieved with drone data collected over several seasons, during varying conditions and locations. In this study, average reflectance from different bands and indices were computed from this range of flights and was used in the comparisons. Individual bands were in most cases well correlated between drone sensor orthomosaics and satellite images, but with a bias. Simple indices of the normalized difference type (NDVI, NDRE etc.) showed smaller biases, and in some cases the computed index values were very similar from the different platforms. This indicates that models of various crop properties calculated based on drone data collected in field trials, may well be transferred to Sentinel-2 image based DSSs, possibly with some correction factor depending on the indices included in the model.

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