Applying Different Remote Sensing Data to Determine Relative Biomass Estimations of Cereals for Precision Fertilization Task Generation

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Abstract. Recently, the area of passive remote sensing of agricultural fields has been developing fast. The prices of RPAS (remotely piloted aircraft system) equipment has gone down and new suitable sensors are coming into markets while simultaneously new and free relevant satellite data has become available. One of the most used applications for these methodologies is to calculate the relative biomass as a basis for additional nitrogen fertilization. In this work, we study the difference of biomass estimations based on Sentinel-2 imagery, tractor implemented commercial measurement system, a low-cost RPAS equipment with commercial software and a hyperspectral imaging system implemented in a professional RPAS system in fertilization planning. Our study revealed that while there was a 23 % spatial variation in our test field's yield, the relative biomass estimations for fertilization planning during the growing season varied 22 % on average although they were visually very alike.

Keywords: Sentinel-2, RPAS, variable rate application (VRA), fertilization

1 Introduction

The core idea of precision farming is to spatially and timely optimize the farming inputs to maximize the farming outcomes while reducing the environmental stress. Nitrogen fertilizers are one of the core inputs in plant production. An insufficient dosage of the nitrogen fertilizer for cereal crops can decrease the yield and quality of the yield. Excess of nitrogen causes a risk of a flattening of the growth causing yield losses. Also unused nitrogen in the soil leaches to the environment throughout the growing period and after.

Already developed precision nitrogen application methods for crops utilize an optical sensing of the growth status during the growing season to determine how much additional nitrogen is needed in different areas of a field. Sensing may take place from satellites, aircrafts, RPAS's (remotely piloted aircraft system), working machinery or handheld devices. Recently there has been a fast development in this area of passive remote sensing and the productization is in progress. The prices of

Proceedings of the 8th International Conference on Information and Communication Technologies in Agriculture, Food and Environment (HAICTA 2017), Chania, Greece, 21-24 September, 2017.

RPAS equipment have gone down and new sensor technologies are coming into markets. Also new, free and relevant satellite technology has become available for the environmental mapping. In Europe, the new Sentinel-2 satellites are providing useful data several times per week with up to 10 x 10 meter accuracy.

One of the most common applications for these methodologies in agriculture is to calculate relative biomass as a basis for additional nitrogen fertilization. Typically, these sensing systems compare a red and near infrared wavelengths by measuring a normalized difference vegetation index (NDVI) or its variants. Then an implemented decision support system (DSS) produces an estimate for the required nitrogen fertilization need. This DSS system requires calibration information about crop's remaining nitrogen needs and responsiveness according to the predicted yield potential (Raun et al., 2005, Lukina et al., 2001) being important factor for the nitrogen fertilization. Data from other sources are usually combined with remote sensing as inputs to decision support systems for determining nitrogen application rates (Shanahan et al. 2008; van Evert et al. 2012, Kaivosoja et al., 2013). Hyperspectral imaging for example was found to be a promising method for agricultural purposes (Bareth et al. 2015) and obtaining separate biomass and nitrogen content (Honkavaara et al. 2013, Pölönen et al. 2013) for additional fertilization need determination.

In practice, the basic NDVI maps indicate the amount of green mass in the field. However, the method is not able to differentiate situations of a low growth density with high nitrogen content from those of high growth density and a low nitrogen content. Thus, generating nitrogen fertilization plans based only on NDVI map might not be the best solution in all of the cases so many supporting optical methodologies has been developed. Pena-Yewtukhiw et al. (2015) found out that even the sensor output difference of 0.05 NDVI units could strongly affect the resulting nitrogen rate prescription, depending on the selected algorithms. Also image mosaics that are mandatory with RPAS sensing may create large radiometric errors that effect on spectral vegetation indices (Rasmussen et al. 2016).

Dong et al. (2015) presented 28 chlorophyll-related vegetation indices suitable to be applied with Sentinel-2 data and by simulation studies; they found out that incorporating red-edge reflectance (around 700nm) improved the estimates for assessing vegetation growth rate and predicting crop productivity. Also, Hunt et al. (2017) noted that assessing red-edge detection could make a difference in determining nitrogen applications to potato. In their study, they did not found RPAS beneficial to the WorldView-2 satellite data. The case is similar with the Sentinel-2 imagery in Europe since the resolution of the red edge is coarser.

That is also what current commercial solutions support. The tractor implemented YARA N-Sensor five spectrometer detects the wavelengths of 550nm, 650nm, 700nm, 710nm and 840nm (Varco, 2010). The gained economic benefits of this tractor implemented solution have been around 5 % (Nissen, 2012). Typically drone installed Parrot Sequoia multispectral camera measures the wavelengths of RGB, 550nm, 660nm, 735nm, 790nm. The most accurate wavelengths of Sentinel-2 satellite are 490nm, 560nm, 665nm, 842nm with 10 meter spatial resolution and 705nm, 740nm, 783nm, 865, 1610nm, 2190nm with 20 meter spatial resolution. In Finland, the average field size is less than 4 hectares which makes it difficult to exploit coarser data efficiently.

Many new technologies are coming available, but since the productization for agricultural purposes is continuously developing, the farmers are somewhat left alone on how to really apply them and how to get the best benefits out of them and which methods would be the most suitable for their purpose.

This paper has three research questions: 1) how much there is typically variation in a Finnish field, meaning that how much we should typically adjust the amount of fertilizers? 2) How much there is variation of relative biomass estimations based on different remote sensing data obtained for the same purpose? 3) What is the effect of the determined variations in contrast to experimental but logical precision fertilization application variations? The main goal is to demonstrate in real conditions, how much difference there are in biomass estimations in contrast to actual fertilization task variations.

2 Material and methods

The test area was about 20 ha cereal crop field in southern Finland in Vihti, sowed at 29 May 2016. The overview picture of the field during the 2016 crowing season is presented in a Fig. 1. The field was evenly treated although a 12 meter wide not treated stripe was left in the middle of the field to have a bare soil reference.

Fig. 1. A slant view of the test field showing the high biomass area in the left size and the not seeded stripe in the middle, (date 16.7.)

First, to have a concrete knowledge about variations in our field, we analyzed our combine harvester data to measure the yield variation in the selected test field and in the fields nearby. We analyzed the yield data of barley and wheat from the years 2015, 2014, 2013. In total, 20 harvestings with an average field plot size of 6.4 ha. Those fields were evenly threated (no precision farming) and the harvesting was done with Sampo Comia C4 combine harvester with Ceres 8000 yield monitor, which logged position and filtered yield data with 5 Hz interval. We filtered out less than 900kg/ha measurements and exceptionally high yield values from the yield data.

Next, we calculated a variance for each harvesting operation. To study the effect of combine harvester measurement system effect, we added a separate moving average of five for the logged data.

Next we studied different remote sensing data. Fig. 2. presents relative biomass maps based on different remote sensing technologies: a professional UAV (unmanned aerial vehicle) with FPI (Fabry Perot Interferometer)-hyperspectral camera, consumer level Phantom 4 UAV with RGB-camera, a tractor implemented Yara N-sensor and Sentinel-2 satellite image. More detailed descriptions of data processing of these data are presented by Näsi et al. (2017). These maps represented the starting point of this work. The middle part in the N-Sensor map (Fig. 2.) was not measured due to low amount of biomass.

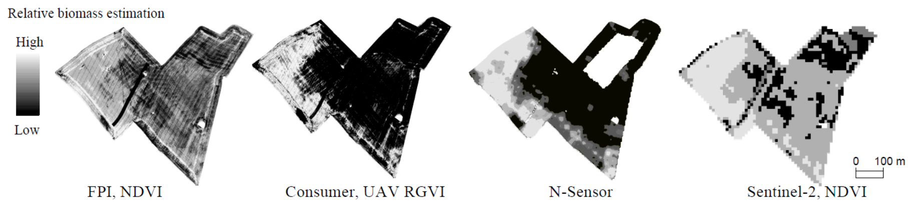

Fig. 2. Relative biomass estimations based on professional UAV with FPI-camera, consumer level Phantom 4 drone with RGB-camera, tractor implemented Yara N-sensor and Sentinel-2 satellite image.

Our next step was to use the different source data to produce precision nitrogen fertilization tasks without additional data. We used farmer knowledge to heuristically adjust the tasks in a similar manner. All remote sensing data that was used with our calculations are presented in the following list, including a name of data, measurement instrument and platform, classification type and imaging date in 2016.

- Tractor: Yara-N-sensor measurements, internal classification, driving, date 16.7.
- Satellite1: Sentinel-2 satellite, NDVI classification, image date 2.6.
- Satellite2: Sentinel-2 satellite, NDVI classification, image date 9.7.
- proUAV FPI (Fabry-Pérot interferometer) hyperspectral camera, NDVI classification, imaging date 4.7.
- rgbUAV1: Phantom 4, stock RGB camera, classification VARI Visible Atmospherically Resistant Index (G-R)/(G+R-B) (Gitelson et. al 2002) with DroneDeploy software, 16.7.
- rgbUAV1task: rgbUAV1 data classified with DroneDeploy, 16.7.
- rgbUAV2: 16.7. Phantom 4, stock RGB camera, VARI classification with DroneDeploy software, 16.7., constantly changing cloud cover
- Yield Map: Yield map based on combine harvester point data and surface fitting by using inverse distance weighting (5 m circle search distance and weighting power of 1), 23.9.

All the different tasks were planned in order to have three different fertilization levels: 20 kg/ha, 30 kg/ha and 40 kg/ha according to farmer's understanding of the additional fertilization need. Three levels were selected to be practical with present farm machinery: there are always some delays and inaccuracies with precision adjustments, so it is not practical to adjust the machinery continuously. These fertilization tasks were calculated as 1 m grid maps. Then we compared these maps to accurately located biomass samples taken during the growing season (Näsi et al. 2017). We used 18 samples out of total 36 samples having the most homogenous surroundings around them. Then we also calculated the correlation between biomass amount and nitrogen content from the vegetation samples to see their correlation.

To evaluate the effect of the usage of other data sources, we demonstrated possible task variations by applying previous yield maps, vegetation samples, farmer's know-how and commercial software for data. We selected four different cases which were as follows:

1. Previous yield maps and Sentinel-2 data 9.7. First, we evenly balanced and then summed three consecutive yield maps. Next we scaled the final map values by using farmer's heuristic knowledge. The parameters were: min 0.4, Max 1.6, Mean 1.07, Std. deviation 0.19. Then we used this to multiply the Sentinel-2 NDVI-map. Then we applied contouring method to generate four application rate levels, and finally farmer decided the actual fertilization amounts.
2. Consumer UAV with RGB-camera (Phantom 4), Dronedeploy vegetation classification (VARI) and farmer estimates for actual fertilization amounts.
3. NDVI classification from professional UAV with FPI camera. We used supervised K-means teaching based on vegetation samples (nitrogen content) including 36 samples from all around the field (Näsi et al. 2017) and categorized into four classes by the farmer (none-now-med-high. We used it to supervise proUAV data to four classes. Then actual fertilization amounts were decided according to farmer's knowledge.
4. Consumer UAV (Phantom 4) with RGB-camera, VARI calculated with DroneDeploy software, added with farmer teaching (polygons drawn by the farmer including wanted nitrogen input) by using K-means methodology. In this study, the farmer drew the wanted fertilization amounts on top of a plain RGB-map. Then these areas were used to teach the VARI raster map. Finally, the contouring method was applied as in other cases.

We used 0-10-20-30 kg/ha fertilization steps for these data, because these other data suggested lower fertilization rates and it would not have be reasonable to compare these with the first classification results.

3 Results

The average of the yield amount variances in our fields was 32.7 %. Our test field yield had a variance of 23.3 %, the histogram is presented in Fig. 3. By applying the moving average, the variance was lowered only by 0.5 percentage points. This is indicating at least a 30 % variance in yields on average in our test fields in Finland. The total yields of our fields were 4.6 t/ha on average and the average variance was 1.8 t/ha. During the summer 2016, our test field had an exceptionally low yield on average.

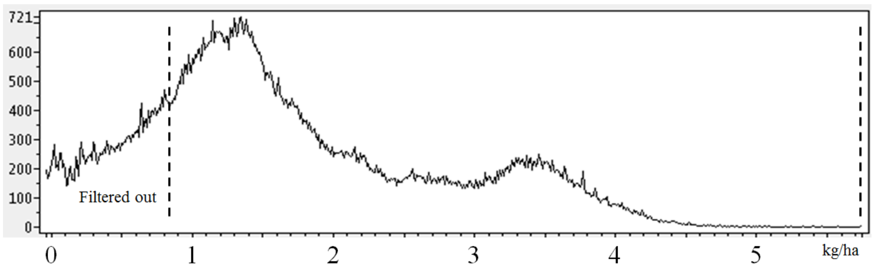

Fig. 3. Test fields yield histogram (yield amount and number of measurement points)

The different fertilization tasks based only on the remote sensing data are presented in a Fig. 4. Together with a relevant yield map that was harvested more than two months later. Table 1. compares these different maps by showing the average difference between application rates: if A=20kg/ha and B=30kg/ha, A compared with B is 10/20=0.5 different and B compared with A is 10/30=0.33 different. On average, the difference between calculated application rates was 22%.

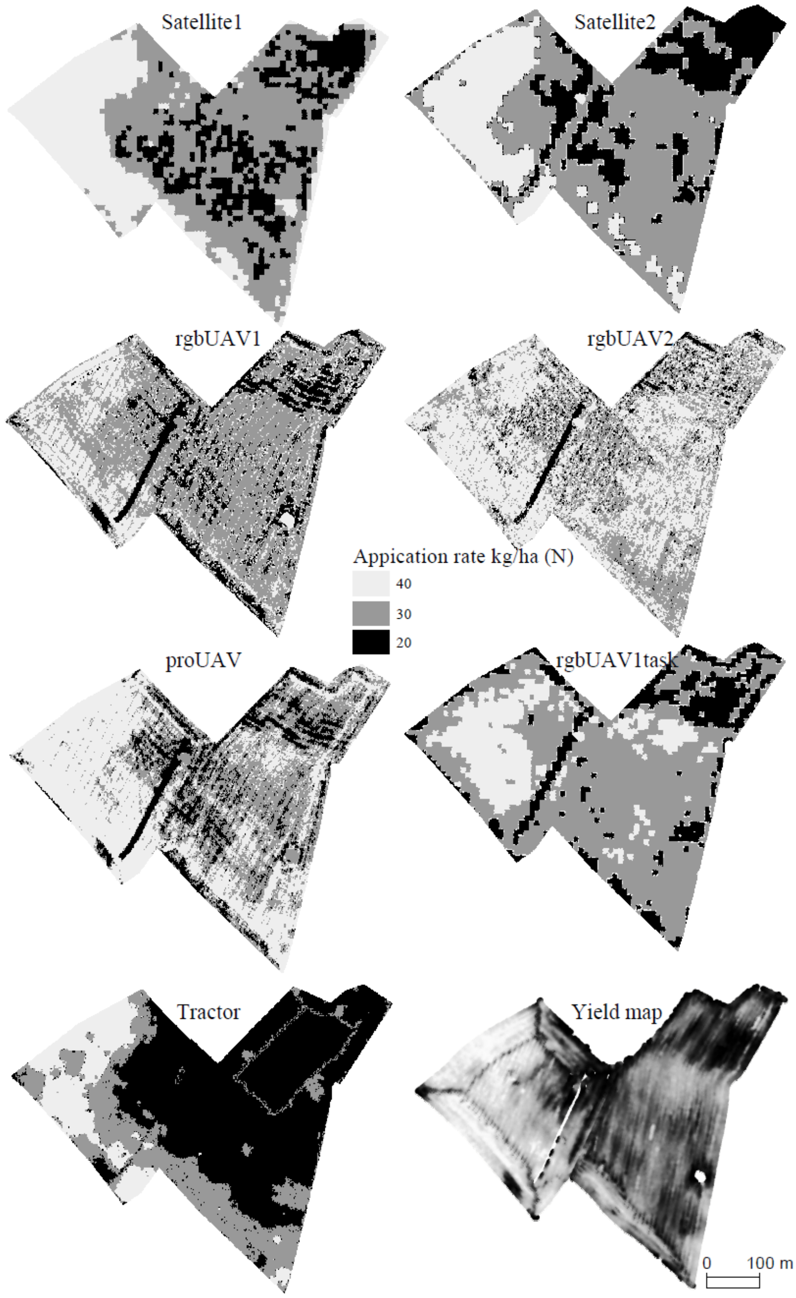

Fig. 4. Fertilization tasks based on remote sensing data and the final relative yield map

Table 1. Difference between calculated application rates

	rgb2	Sat2	Tractor	proU	rgb1t	rgb1	Sat1
rgbUAV2	0.00	0.17	0.41	0.18	0.21	0.22	0.29
Satellite2	0.18	0.00	0.39	0.20	0.21	0.19	0.26
Tractor	0.30	0.28	0.00	0.25	0.25	0.23	0.21
proUAV	0.17	0.19	0.33	0.00	0.17	0.17	0.28
rgbUAV1task	0.19	0.19	0.30	0.16	0.00	0.17	0.19
rgbUAV1	0.19	0.17	0.28	0.16	0.17	0.00	0.21
Satellite1	0.24	0.21	0.23	0.24	0.17	0.19	0.00

The correlations between biomass samples (18 spots) and calculated application rates with different methods are presented in Fig. 5. The tractor data had the highest correlation of 0.63. The correlation between biomass and nitrogen based on vegetation samples is also presented being -0.19.

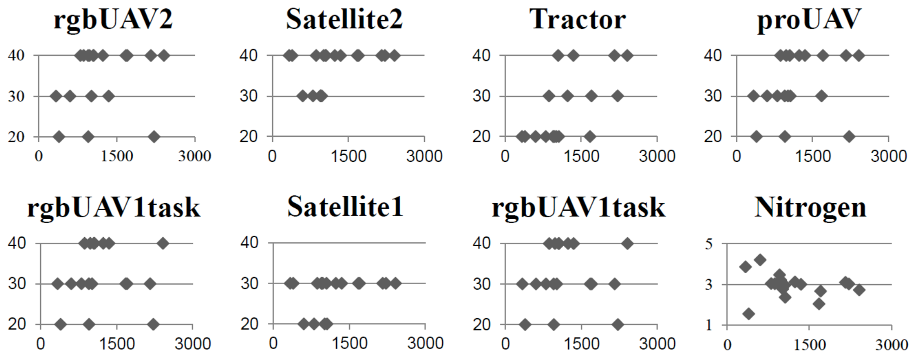

Fig. 5. Correlation between vegetation sample biomass and determined application rates

Next we present the demonstrative task maps, which combined other data to remote sensing, with the following early presented methodologies:

1. Previous yield maps and Sentinel-2 data
2. Consumer UAV with RGB-camera, Dronedeploy classification and farmer's nitrogen level estimates
3. NDVI classification from professional UAV with FPI camera, teaching with vegetation samples
4. Consumer UAV with RGB-camera, RGVI-index and farmer teaching

The nitrogen fertilization tasks were clearly deviating. The following Fig. 6. illustrates the different generated tasks.

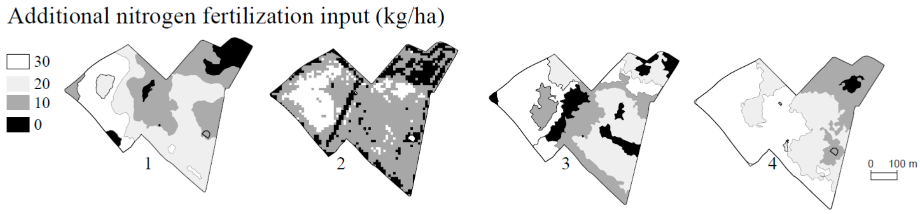

Fig. 6. Different fertilization tasks based on remote sensing and external data

4 Discussion and conclusions

Our test fields had the 30% yield variation in average so there is huge potential in precision farming activities. All the tested remote sensing methods managed to estimate the relative differences of biomass. The optimal timing for the additional fertilization would have been in the middle of July, and even the Sentinel-2 NDVI-map in early June estimated visually correctly the relative biomass. However, when developed into precision fertilization tasks, the relative biomass estimations produced a 22 % variation in an average, when the planned fertilization was 20kg/ha - 30kg/ha - 40kg/ha in all the cases, including the aim to produce similar looking maps. Similarly, Pena-Yewtukhiw et al. (2015) stated that even a slight difference in the single task generation parameter could produce a remarkable difference in the end. Also in our measurements, the correlations to the biomass samples were low.

When other parameters were used for task generations, the differences were large even when based on visual estimations. The main difference between images 2 and 4 in Fig. 6 is that in image 4, the farmer decided the effective area for the fertilizer, while in the image 2 the area was decided by the RGVI difference. The optimistic attitude of the farmer can be seen as the application rate is higher in the image 2 (Fig.4.).

The visual study of Fig. 4. shows that Sentinel-2 data from 2.6. and 9.7. are giving very similar information. This is indicating that these NDVI-level differences can be spotted even in a very early stage of growth.

The N-sensor values in Table 1. Were lower than others and were suggesting less fertilization. This was true according to our true vegetation samples and the yield map, there were mostly enough nitrogen resources for the plant. The N-sensor data (Tractor) had the highest correlation to the biomass samples. So without concrete relations, the RPAS and satellite data were exaggerating the nitrogen need.

When the hyperspectral imagery was used only for the biomass estimations as we did, there were no significant advantages seen. We assume that the usage of a multispectral camera would have similar results here. In both cases, additional estimations such as vegetation nitrogen content estimations would be essential.

As the main conclusion of this work, there is a large variation within cereal fields in Finland, the relative difference was easy to determine with different remote sensing methods, but there is huge step needed to use these biomass variations in a consistent way. Just picking up a drone or a free satellite image would possibly not give a sufficient knowledge for additional fertilization.

We should also note that the yield of our test field was low and the areal differences between crops were very similar during the entire growing season. These factors can be very different in different years when there is for example lack of water, so the very generalizing conclusions of the goodness of the relative biomass estimations cannot be drawn.

Acknowledgments. We acknowledge ESA (ESRIN/Contract No. 4000117401/16/I-NB), Tekes (1617/31/2016) and ICT-AGRI ERANET project Geowebagri II for funding the project. We are grateful to Paula Litkey and Milos Pandžića for their support in preprocessing of the Sentinel images.

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