Improving yield prediction accuracy using energy balance trial, on-the-go and remote sensing procedure

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Abstract. *Our long term experience in the ~23.5 ha research field since 2001 shows that decision support requires complex databases from each management zone within that field (eg. soil physical and chemical parameters, technological, phenological and meteorological data). In the absence of PA sustainable biomass production cannot be achieved. The size of management zones will be ever smaller. Consequently, the on the go and remote sensing data collection should be preferred. The paper presents the results of ECa and near-surface hyperspectral measurements. For the increase in accuracy of yield prediction of DS models the energy input-output analysis in the management zones can also be used.*

Keywords: *energy input-output in management zones, accuracy of maize yield prediction, increasing of database*

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Introduction

General approach:

According to John Neumann*: "The sciences do not try to explain, they hardly even try to interpret, they mainly make models."* The world – including agriculture - has reached the stage where without models neither ecological (sustainable) nor economic expectations can be fulfilled. At the same time, we are part of the paradigm shift: when new technology is introduced, the very first evaluation criterion is sustainability, which is followed by economic analysis. In applied biological sciences (medical, ecological, agricultural), it is often the case that the required biological background is not able to follow the technological development and steps. That means, the novelty in practice is applied only with some delay. This is what we see in the precision site specific plant production technologies. The technological development requires a new philosophical approach and new knowledge background (math, physics, technical, engineering and IT). The most fascinating discovery is that the biological knowledge we had earlier has to be converted to a different system and previously ignored factors have to be included in the plant production systems. This statement is also true for the technical and IT developments: today, the question is not the VRA application or the accuracy of the autonomous guidance in the tractors. The question is more likely how the on-the-go systems are going to provide the data and information for us, i.e. how quickly, how accurately and how frequently. Moreover, using these databases we can check and redefine yield predictions of decision support models in the vegetation period.

Accuracy of the decision support systems

Various decision support systems are available for decision making, some are working well in one location, but useless in others. In the recent work, we have applied DSSAT system, as this is applicable worldwide (Hoogenboom et al., 2010).

The yield prediction function of the model in a field level provides accurate and reliable information (Fig. 1a). At the same time, applying yield prediction function in a smaller treatment unit level (management zone), the predicted and the measured values in yield resulted in notable differences. This means that the field level prediction covers the positive and negative differences in the treatment unit level. Consequently, yield prediction can be given in a field level in our investigated field; however, treatment unit level prediction has to be corrected. This correction can be approached from measure-theoretical point of view. In the following, we provide some examples to support our statement.

Thorp et al. (2007) draws attention to the fact that if we want to apply environmental friendly plant production technologies, the agricultural fields have to be divided into smaller "technical" units in the case of modeling. The smaller units will be different in size-, however, they have to be homogenous, therefore, the accuracy of the simulations will improve (Graeff et al., 2012).

The model was developed and validated in various precision agriculture related circumstances. The DSSAT software was adapted for soybeans and winter wheat (Ceres-Wheat) in the Netherlands, Central America and Africa, where the model was investigated for the response to spatial differences in the soil (Booltink et al., 2001). Basso et al. (2001) has also investigated the Soybean model of the software, and has found ~0.5 t predicted yield differences, which was due to the variability in the soil. In this work, yield prediction was corrected by remote sensing based NDVI (Normalised Difference Vegetation Index) values.

Saseendran et al. (2005) and Li et al. (2015) applied the model for small plot experiments. Megyes (2001) used the Hungarian data of the long-term experiments and evaluated them by using Ceres-Maize 3.5 version. He concluded that in the case of meteorological anomalies, the model incorrectly estimates the quantity of biomass and also the yield. Paz et al. (1999) investigated the N fertilizer application between 60 and 220 kg/ha and found the optimum fertilizer amount between 141-160 kg/ha in a 16 ha field divided into 500 m^2 units. The model has estimated the yield by +/- 14% differences in a field level over the three year period-, however, the largest difference was 6 tons. Zhu et al. (2011) emphasizes - during investigation of DSSAT and APSIM - that without adaptation of plant-physiological models in PA, a sustainable agro-ecological system cannot be realized.

Consequently, the models applied in the field level are not applicable if we take the criteria of sustainability into consideration. At the same time, we have to note that in the case of data collection in the treatment unit level, the number of point samples and laboratory analysis are too high, therefore, this threatens the profitability of the production.

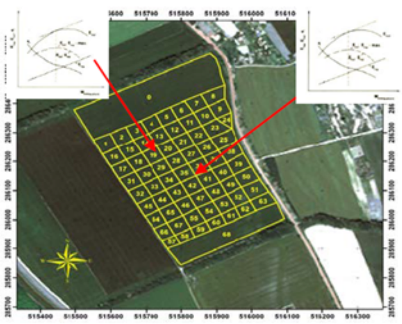
Theoretical accuracy improvement of decision support models*:*

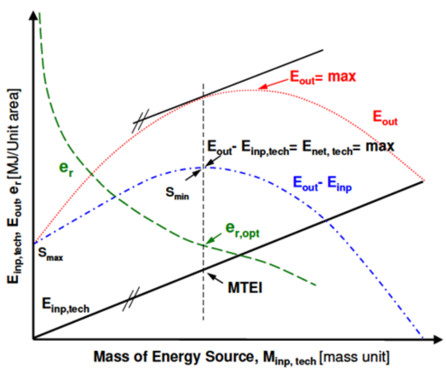
Energy balance models

Generally, we can state that biological systems are reacting to the input and treatment differences in a quadratic function. The same happens in plant density variations in the case of repeated soil treatments, as well as in the case of fertilizer applications (URL[1]).

Analysis of the energy balance of plant production started in the early 80’s (Pimentel, 1980), and the optimization of the energy balance was published by Neményi (1983). At this time, there was no possibility to apply the calculations for the precision plant production technologies, meaning that the calculations were carried out in the field level or in a larger area. The most up-to-date plant physiological models provide the possibility to optimize the energy balance in the management zone level (i.e. to optimize the net energy) **(**Fig. 1a). At the same time, it is important to mention that in given circumstances, indirect energy input is 50-70% higher than direct energy input (Neményi and Milics, 2010), therefore, this fact has to be taken into consideration. So far, our experiments showed that the fertilizer input optimization can be modified based on the energy balance functions by the net energy calculations. The authors expressed that in the model a yield, as well as an energy balance prediction function is calculated. From this function, total energy input has to be subtracted, resulting in the net energy-yield function: E_{out}-E_{inp}=E_{net}.

The amount of fertilizer has to be calculated for the maximum value of this function:Maximum Technological Energy Input (Fig. 1b). The importance of this value is that it provides information about the potential yield.





a, *b,*

Figure 1. Theoretical demonstration of Maximal Technological Energy Input (MTEIP) (b: Neményi, 1983; Neményi, 2009; Neményi and Milics, 2009; Neményi and Milics, 2010; a: Kovács et al., 2014)
Where: $E_{inp,techn}$=*technologic energy input;* E_{out}=*energy of produced biomass;* $e_r = E_{out}/E_{inp,techn}$; $E_{out} - E_{inptechn} = E_{net,techn}$

Measurements for improving decision support model accuracy

There are various ways to improve the accuracy of the databases of the decision support models. One of the many possibilities is the improvement of the different maps, such as grain moisture map (Csiba et al., 2013). EC_a measurements and near surface hyperspectral data collection also provide valuable information about the soil parameters. The accuracy improvement of the decision support models require information during the vegetation period, therefore, multispectral imaging at this time can help the accuracy improvement.

Materials and methods

Location of the study field

Measurements were carried out in the 23.52 ha experimental study field of Department of Biosystems and Food Engineering, Faculty of Agricultural and Food Sciences, Széchenyi István University in the vicinity of Mosonmagyaróvár, Hungary [N47°54’20.00”; E17°15’10.00”]. The research field is agricultural land - alluvial plain of the Leitha River - on which precision agriculture has been applied since 2001. The field is divided into 0.25 ha treatment units (66) according to the requirement of precision agricultural technology (Fig.1 a). The clay content is changing between 7.9–21%, sand content: 13.1-57.8%. Depending on the precise position, loam, silty loam and sandy loam appear on the field.

Instrumentation

Veris Soil EC-3100

The soil EC_a was measured by a Veris Soil EC-3100 (Salina, KS, USA) instrument. The most important parts of the Veris-3100 meter are the Coulter-Electrode blades (6 pcs) with 430 mm diameters, which are electrically insulated from the frame. The device measures the bulk apparent electrical conductivity of the soil at depths of 0–0.3 m and 0–0.9 m at the same time. The collected EC_a data was over ten thousand in each measurement campaign (Nagy et al., 2013).

ASD FieldSpec 3 Max

For the hyperspectral measurements an ASD FieldSpec 3 Max handheld spectroradiometer was used (Szalay, 2014). The advantage of this instrument is that it can be used in field, as well as laboratory circumstances. Spectral range of the instrument is 350-2500 [nm]. Laboratory measurements were carried out in a light-isolated cabinet by using an ASD FieldSpec 3 Max portable spectroradiometer. The cabinet excludes all external light and minimizes any unfavourable internal reflections. Basically, there are two examination procedures: contactless measurement with external light source and contact measurement carried out with a sensor-head equipped with internal illumination. The advantage of the latter is more reliable measurements due to independence from atmospheric factors. The basis of both in-field and laboratory measurements is the so called white reference measurement that is recommended to be repeated every 15 (in-field), 45 (laboratory) minutes. All reflectance measurements are derived from a reference panel's calibrated reflectance features.

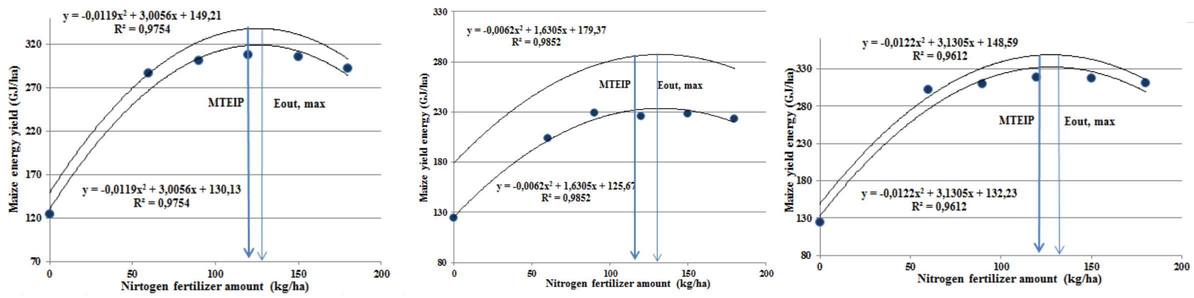
Airinov MultiSPEC 4c multispectral camera

For the multispectral measurements, an Airinov MultiSPEC 4c sensor was used. The integrated lux meter measures light intensity and colour. The sensor also records the geoposition and date of every picture. This enables us to correct the reflected light with the angle of sun's rays. The camera facilitates high speed mapping thanks to large overlap. The multiSPEC 4C sensor measures the reflected light from crops in 4 different spectral bands: green, red, red edge and NIR. Image resolution depends on the flight altitude, which can be adjusted depending on the result requirements.

Results

Energy balance

As can be seen in Fig. 2a, b and c sandy loam, loam and silt loam management zones result in different energy balance functions. Our experiments proved that - similarly to the literature - the model is predicting below the real values in dry circumstances, therefore, the resulted function has to be shifted until the coverage of the measured value. This shifted function will be used for calculating MTEIP (y=0.05n). This is valid for the prediction before sowing, as well as for the calculation of the head fertilizer amount based on the NDVI measurements. This also means that calculating with this function during the vegetation period, yield prediction can be improved in the management zone level.



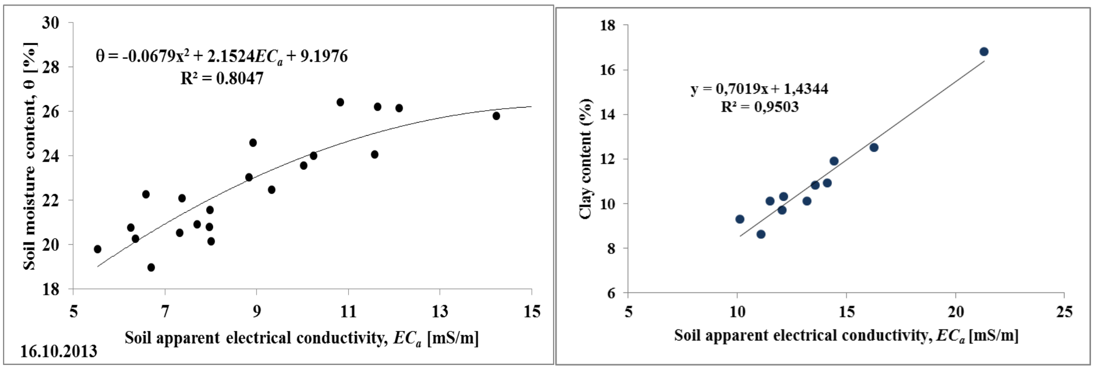
a, *b,* *c,*

Figure 2. MTEIP on sandy loam (a), loam (b) and silt loam (c) soils /Biomass (grain+straw) energy content: 15.5 MJ/kg;energy value of N fertilizer: 50 MJ/kg /

In the paper, we report the data collection methods (yield mapping, soil EC_a mapping and application of remotely sensed data as well as UAV based imaging) for extending our research field.

Soil apparent electrical conductivity *(EC_a)*

The management zones and treatment will be based on our earlier results (Nagy et al., 2013,; Milics et al., 2017), such as strong coefficient of regression between soil moisture map based on EC_a measurements (Fig.3 a) and clay content (Fig.3 b) of reference treatment units (R^2=0.95). Soil moisture map based on EC_a measurements was also compared to yield map showing correlation (R^2=0.81) between the two datasets.



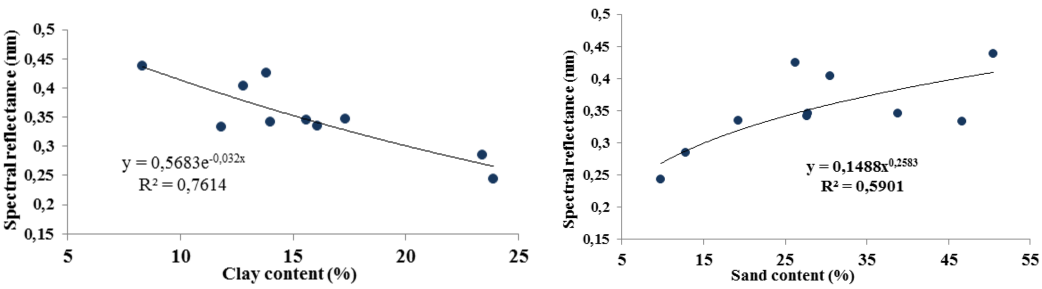
a, *b,*

Figure 3. Correlation function of the moisture content (a) and clay content (b) versus soil apparent electrical conductivity (EC_a)

Hyperspectral measurements

Hyperspectral (near field) measurements were recorded for soil physical and chemical parameters. Field hyperspectral measurements concerning clay content measurements resulted R^2=0.7614 in the reflectance values at 2200 nm. Relating the values to sand content the correlation was R^2=0.5901. We have concluded that in the case of surface smoothening with a soil roller, the correlation is increasing. Laboratory measurements on collected soil samples also increased the correlation between the investigated parameters (soil clay and sand content and reflectance value at 2200 nm, Fig.4 a and b).

At the 1600 and 2100 nm spectrum Zn (0.47) Mg (0.82, 0.85), a Cu (0.66, 0.61), a CaCO3 (0.47, 0.45) and OM (0.45) correlation was found.



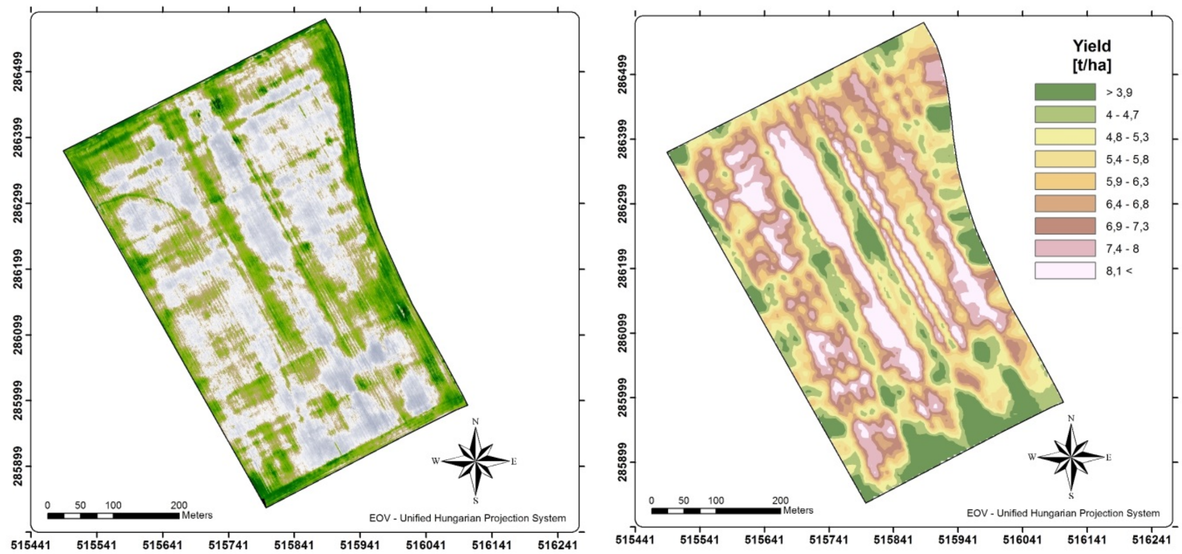
a, *b,*

Figure 4. Correlation function between clay (a)and sand (b) content (%) and hyperspectral reflectance on silt loam soil at 2200 nanometer (2015).

At smooth soil, the correlation was between hyperspectral and laboratory measurements.

NDVI mapping using multispectral sensing

With the advance of technology, more and more sensors and tools are available, such as UAV based remote sensing sensors. These sensors provide extended input data for the decision support models. Decision support models – in our case the DSSAT – are using long term meteorological databases. The accuracy of yield prediction therefore is still limited in such models. We assume that applying UAV based remote sensing data collection during the vegetation period can continuously correct the accuracy of yield prediction. According to our experience we have concluded that some technological advances such as UAV based imaginary (multiSPEC 4C) provide increased spatial resolution; however, these data can hardly be used in everyday practice. Multispectral UAV based data provides sufficient amount of reliable data with acceptable accuracy (r>0.7) for yield prediction, as well as a possibility for corrections within the vegetation period (Fig.5 a and b).



a, *b,*

Figure 5. NDVI map (UAV) in April (a) and winter wheat yield (b) maps (2016).

Discussion and conclusions

All the methods described in the paper can increase the accuracy of yield prediction in a larger field than the investigated area. Energy balance analysis of the improvement in accuracy of decision support models provides a novel and an until now unknown approach. Fig.2 a, b and c show that within the management zone where fertility is good, the MTEIP and the maximum yield are not far from each other. At the calculation of optimal nitrogen fertilizer amount, the former yield should also be taken into consideration.

The energy balance models can also increase the effecticiency of fertilizer of the models. According to the experience of the authors, the level of application of DS models has entered a new phase. The accuracy of the above mentioned sensoring methods is approaching the accuracy recorded in the laboratory. Therefore, the size of the management zones can even be smaller, while the DS models can increasingly contribute to the fulfilment of the requirements for sustainability. This paper draws attention to the importance of accuracy improvement by decision support models of predicted yield during the vegetation period. It also emphasises the role of the required data for the improvement such as NDVI index, thermovision or other image collecting methods during the vegetation period. Earlier measurements, such as soil apparent electrical conductivity (EC_a) or meteorological data during the vegetation period, can also be useful for the improvement of the accuracy of the yield prediction. Large and various data all adds up the information for the most reliable prediction, since only one of them (for instance NDVI) is not sufficient enough for nitrogen content, as it is also dependent on the water availability for the plants.

The more accurate is the data we can collect (on the go, remote sensing), the more accurate are the predictions of DS models.

Based on the above described methods, the most important directions for the future research on development of decision support models can be: improved accuracy of soil physical and chemical parameter measurements by means of hyperspectral reflectance measurement, development of the speed of data collection and analysis, improvement of reliable vegetation indices, and monitoring by means of UAV based imaging.

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