Spring wheat yield prediction with empirical regression models using different biomass parameters

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Abstract. Transition to smart agriculture demands tools for non-invasive monitoring of cultivated plants biomass. One of the most widespread and informative biomass indicators is leaf area index (LAI). LICOR 2200C has become de facto standard in modern ecological research for non-invasive LAI estimation. In this paper, on the example of spring wheat crops of the RSAU-MTAA experimental field, the efficiency of yield and biomass parameters prediction using data from AccuPAR LP-80 and LI-COR LAI 2200C was compared. LAI data from both devices obtained at different phenological phases of spring wheat were used as predictor for spring wheat yield models. Comparing the generated models show superiority of AccuPAR LP-80 in yield prediction while LI-COR LAI 2200C shown better result in overall biomass prediction.

1 Introduction

The progressive increase in average annual temperatures observed in recent decades is changing the agroclimatic potential for agriculture in Russia and the world [1,2]. In the conditions of economic and environmental risks typical for the agricultural sector, agricultural holdings need to monitor the parameters of their activities and conduct operational diagnostics. Building a model of a certain process, considering the profitability of production, is performed taking into account modeling, planning and forecasting, which are considered effective management methods [2].

The impact on agricultural production of biological and economic factors, the laws of development of which are not deterministic, can complicate the prediction of yield. The use of insufficiently effective methods for predicting the agroclimatic conditions of crop cultivation can negatively affect the reliability of forecasts performed [3].

Forecasting is based on the accumulated experience, that is, it is a complex process, during which it is necessary to solve many different tasks [2,3].

Against the background of constant changes in market demand and supply of various fertilizers and plant protection products, their zonal differentiation relative to agroclimatic conditions and soil types, it is necessary to develop decision-making systems that can optimally adapt agricultural facilities and agricultural technologies to the given conditions. It is necessary to take into account the large amount of data that requires modern computing equipment to process. In such conditions, the number of possible solutions is very large, and choosing the best one without a comprehensive and comprehensive analysis can lead to errors [2].

The main attention in the context of changes in agrometeorological resources is paid to operational information on the impact of weather conditions on the state and formation of productivity of agrocenoses. In many countries of the world, including the Russian Federation, gross grain collections are the basis of food security, so special attention should be paid to forecasts of grain yields. The application of measures to minimize damage and in favorable harvest years, the determination of possible grain export volumes helps to organize the preparation of forecasts. The effectiveness of yield forecasts decreases in some years and does not satisfy employees in the agro-industrial sector, so with such large fluctuations in yield, the task of forecasting is quite difficult. Forecasts are an important link in the decision support system of agricultural holdings, so the requirements for their accuracy and advance are increasing [2].

Currently, two approaches are used to forecast crop yields: based on empirical regression models and biophysical models of vegetation growth. Empirical models relate crop yields to meteorological data and biomass characteristics and do not require a large number of input parameters. However, the effectiveness of such models largely depends on the availability and quality of data [4].

Crop models allows to obtain biophysical parameters of crops: yield, biomass, water content, etc. Examples of such models are World Food Studies (WOFOST), implemented within the framework of the European Crop Growth Monitoring System (CGMS), EPIC (Erosion Productivity Impact Calculator) and CERES (Crop Environment Resource Synthesis). The main difficulty in applying such models is that they require numerous input

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parameters to run the model, including information about soil type, crop varieties, meteorological data, and agricultural technology. Such models are reliable, but their application requires appropriate adaptation and calibration considering the agricultural specifics of a particular region [4].

Most classical models of agroecosystem production use LAI as one of the main parameters. The practical utility and growing need for modeling and predicting yields using dynamic models has led to a growing demand for reliable information on leaf area. First, the leaf surface index is used to determine the density of vegetation cover and biomass, monitor the growth and death of vegetation cover, predict yield, and calculate the total evaporation of moisture.

The aim of the study was to evaluate the production process of spring wheat using the leaf surface index (LAI) and projective cover (PC), for subsequent modeling of crop yield.

2 Material and method

The study was conducted in 2022 at the experimental fields of the Russian State Agrarian University in the north of Moscow.

The microrelief of field is a relatively flat, with alternating between small elevations and extensive depressions, as shown in Fig. 1.

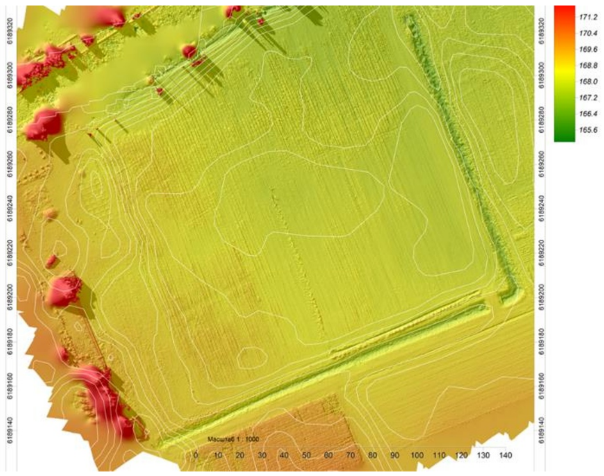

Fig. 1. Digital surface model of experimental field.

The soil cover is mainly represented by arable medium loamy sod-podzolic soil, cultivated since XVII century [5]. Investigated academical field is under crop rotation and in 2022 was used for spring wheat planting (*Triticum aestivum L.* breed Darya). Sowing was in first week of June 2022 and harvest was on 1 of August.

Before seeding field was separated into 81 squares. In each square sampling mark was randomly placed and georeferenced. Georeferencing was performed with a Stonex S9 RTK GPS pair with RMSE less than 4 cm, since precision of common GPS navigator is not suitable for precise field work [6]. All measurements were done in triplicate within a half-meter radius from sampling mark, Fig. 2.

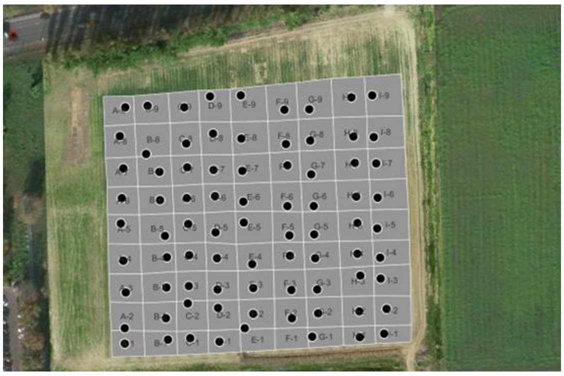

Fig. 2. Field sampling scheme.

Monitoring was performed on weekly basis starting from 16 of June. Every visit wheat phenology phase according to Zadoks scale [7], heights, number of stems, and plant biomass were estimated.

Plants heights were assessed using a measuring tape: from emerging to booting phenology phases from the soil surface to the top of the upper leaf; at the onset of earing to the top of the ear.

Photos for the subsequent calculation of crops PC were taken with an RGB camera with a resolution of 14 megapixel from a height of 1.2 m.

LAI was measured using an AccuPAR LP-80 and a LI-Cor LAI 2200C. Sensors were placed above the surface of the vegetation cover and below, below the level of the assimilation organs of plants, recording data considering spatial and temporal characteristics. AccuPAR model LP-80 uses photosynthetically active radiation (PAR) to measure light absorption in plant crowns and calculate the LAI. AccuPAR calculates LAI based on measurements of fractional radiation (with photosynthetically active radiation (PAR) measured above and beneath plant canopy), zenith angle, and leaf area distribution for a particular crop. LI-Cor LAI-2200C measures the leaf area using an optical sensor that detects the scattered radiation of the sky at five zenith angles, projecting a hemispherical image onto five detectors located in concentric rings [8].

Data was organized and statistically processed using R: A Language and Environment for Statistical Computing [9]. All graphs were produced utilizing ggplot2 R package [10]

3 Results and discussion

Due to high spatial heterogeneity of the field soil the high variance of wheat LAI were observed for all phenological phases caused by the high heterogeneity of the state of crops in the field, and not by the low accuracy of measurements. The values obtained by AccuPAR LP-80 are characterized by lower average errors, but also lower variance [6].

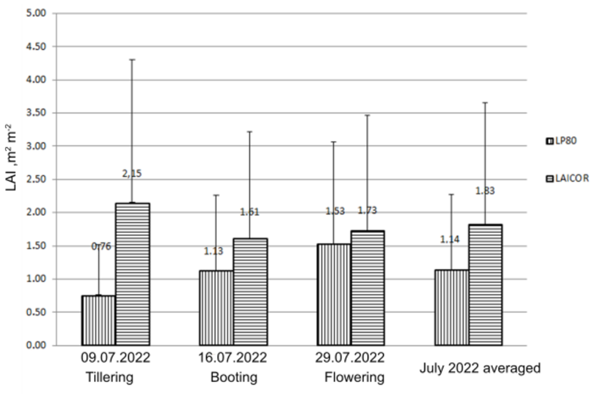

Fig. 3. LAI temporal dynamics and spatial variance according to LAI 2200C and AccuPAR LP-80, whiskers represent 95% conf. İnterval.

- Data from both devices have a statistically significant linear relationship as shown in Fig. 4 (R^2= 0.46), despite the obvious difference between the index values obtained by the devices [8].

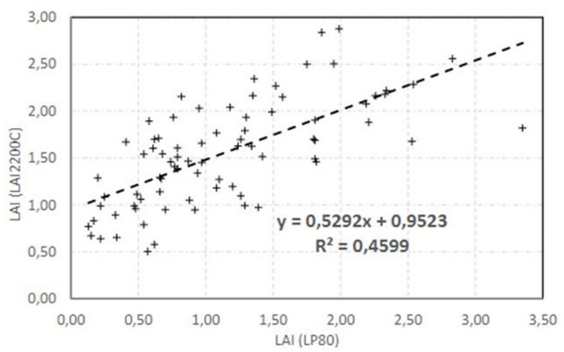

Fig. 4. Scatter plot and linear relation of LAI values obtained with the LAI 2200C and AccuPAR LP-80 .

Therefore, the LP-80 values can be used to estimate the real value of LAI (1):

$$LAI2000 = 0{,}53 * LAI80 + 0{,}95 \quad (1)$$

* LAI2000 – LAI measured with LAI-2200C,

* LAI80 – LAI measured with the LP-80.

The temporal dynamics of the leaf area index was recorded using AccuPAR LP-80 and LAI-2200C for different phenological stages presented on Fig. 5.

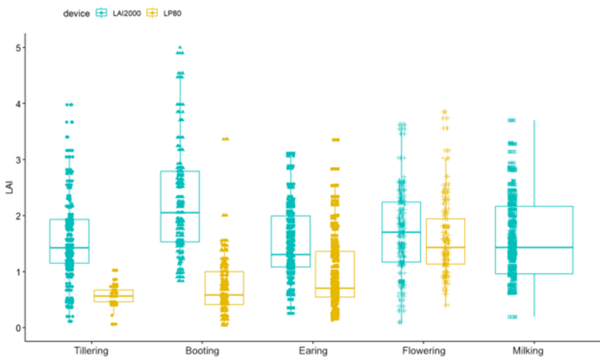

Fig. 5. Comparison of spring wheat crops LAI dynamics by phenophases for LAI 2000C (blue dots) and LP-80 (yellow dots).

Analyzing the graph shown in Fig. 5, we can see that during the tillering and booting phenological phases, the LAI values obtained with AccuPAR LP-80 differ significantly from the data obtained with LAI-2200C. AccuPAR LP-80 values in the tillering phase reach a maximum of slightly more than 1 m^2 m^{-2}, while LAI-2200C data exceed them several times (reach almost 4 m^2 m^{-2}). AccuPAR LP-80 values in the tube exit phase are a maximum of 3.5 m^2 m^{-2}, and LICOR-2200C data reaches 5 m^2 m^{-2}. During the earing and flowering phases, the leaf surface index values do not vary much and are within the same range. During the milk ripeness phase, data were collected only from LAICOR-2200C, the maximum values of which did not exceed 3.8 m^2 m^{-2}.

We compared PC data obtained using the ImageJ software with the yield and with the measured height in the tillering-tube exit phases in order to understand how effectively yield and biomass can be predicted (Fig. 6).

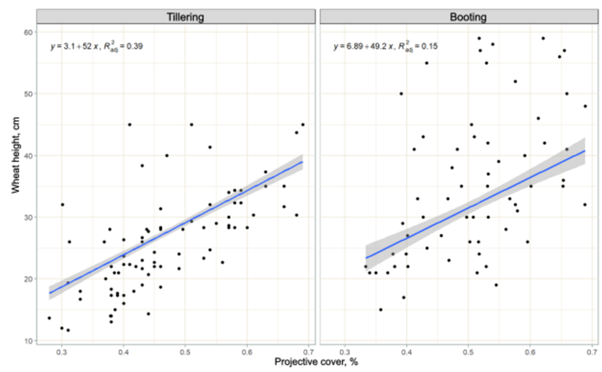

Fig. 6. Scatter plot and linear relation of wheat height and projective cover, for tillering and booting phenophases.

Based on the graph shown in Fig. 6, we can see that there is a relationship between the PC and the height in the tillering phase R^2 = 0.39, and a very weak linear relationship between this parameter is observed during the booting phase, with R^2 = 0.15. Hence, projective cover can be used for prediction of some biomass parameters (height) in the early stages of development.

There was no statistically significant dependence between PC in the tillering and booting phases and yield. Projective cover was not measured at later phases due to saturation of one after booting. Therefore, PC cannot be used for spring wheat yield prediction.

Evaluation of LAI obtained with AccuPAR LP-80 and LAI 2200C at different phenological phases as a predictor of spring wheat yield showed that AccuPAR LP-80 well predicts yield in the flowering phase, which is supported by the obtained correlation coefficient R2= 0.71 (strong linear relationship), Table 1. In the booting and earing phases, the data of the device did not have strong relationships with yield (R^2= 0.23 and R^2= 0.05, respectively).

Table 1. R^2 of spring wheat yield predicted with LAI values obtained with LAI 2200C and AccuPAR LP-80 at different phenological phases.

Phenophase	LAI 2200C	AccuPAR LP-80
Tillering	< 0.01	< 0.01
Booting	0.03	0.23
Flowering	0.32	**0.71**
Earing	0.04	0.05
Milking	0.11	< 0.01

Assessment of LAI obtained with LAI 2200C had the strongest relationship with yield, as well as with AccuPAR LP-80 in the phenological phase of flowering, while the absolute values were lower (R^2= 0.32). In other phases, LAI 2200C readings had no significant linear relationship with yield. As a result, LAI estimated by both devices had a significant linear relationship with yield only in the flowering phase, but the strength of the relationship in AccuPAR LP-80 data was higher.

4 Conclusion

The study showed that LICOR LAI 2200C can predict the yield during the flowering phase, but in general there is a weak relationship between LAI and yield, while AccuPAR LP-80 predicts the yield well during the flowering phase, and in other periods it is also less effective. The AccuPAR LP-80 ceptometer, despite its cheaper price segment than LICOR, is more suitable for measuring the LAI of low growing crops. While data obtained with LAI 2200C better predicted overall biomass, specially during the flowering phase (R^2= 0.35), in contrast to AccuPAR LP-80, which has a weak correlation between the tillering and earing phases.

Funding

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