

Estimating Farmers' Creditworthiness under a Changing Climate [†]

Gregory Mygdakos ¹, Panagiotis Tournavitis ² and Emanuel Lekakis ^{1,*} ¹ AgroApps PC, Koritsas 34, 55133 Thessaloniki, Greece; mygdakos@agroapps.gr² Cooperative Bank of Karditsa LLC, Kolokotroni 1, 43100 Karditsa, Greece; ptournavitis@bankofkarditsa.com

* Correspondence: mlekakis@agroapps.gr; Tel.: +30-6978897754

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Abstract: CreditScore combines the predictive power of crop growth models with future climatic scenarios, satellite images, and market data to form a comprehensive profile for each farmer-borrower, based on the future yields of their crops, with the ultimate goal of assessing long-term risks affecting yields which are related to climate change. The objective of this study is to present the tools and datasets that are employed operationally by CreditScore for future yield and profitability assessments. A modeling approach built on a fusion of satellite-derived vegetation indices, agro-meteorological indicators, and crop phenology is tested and evaluated in terms of data intensiveness for the prediction of wheat and cotton yields. AquaCrop, a process-based model, provided high to moderate accuracies by fully relying on freely available datasets as sources of input data. The findings introduce a promising framework that can support the financial institutions in evaluating potential customers' agribusinesses prior to and throughout the lending process.

Keywords: CreditScore; yield estimation; financial institutions; bank lending; loan

1. Introduction

In agriculture, where large down payments are required in conjunction with a lump sum payment at harvest, credit and access to credit for agricultural supplies and equipment are crucial to the sustainability and performance of farming enterprises. The volatility and uncertainty of agricultural income caused by climate change and the anarchic market situation places producers in the “High Risk Borrowers” category [1,2]. It is estimated that at European level, only one-sixth of farmers currently have access to credit, while simultaneously, young farmers face significant difficulties in accessing bank lending [3,4]. Therefore, with the majority of farmers having neither the guarantee nor the credit history to secure credit approval [2], there is a need to find alternative methods of assessing their creditworthiness.

CreditScore aspires to fill this gap, providing the right means for banking institutions to assess the real credit risk of potential borrowers and to exploit this potentially profitable sector. CreditScore strengthens the position of banks, which previously did not have access to information about farmers, by enabling them to assess their future solvency. In this way, every farmer, smallholder, or young farmer will be able to access financial products, which until now, banks have been unable to offer or they were offered at very high costs, making them unattractive. The objective of this study is to present the tools and datasets that are employed by CreditScore for future yield assessments. A process-based crop growth model was evaluated in estimating the yield of wheat and cotton.

2. Materials and Methods

CreditScore supports financial institutions in evaluating potential customers prior to and during the lending process. During evaluation, information concerning a farmer's financial details (past income, active mortgage payments, etc.), the requested capital, and



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complementary data, with regards to their holdings and cultivation plan, are taken into account for scoring their creditworthiness. The complementary data concern the number and location of parcels and whether these are the farmer’s own capital or rent, the future crop plan per parcel, and possible subsidies. When registering a parcel in CreditScore, input data are retrieved automatically and are spatially aligned to allow for the estimation of yields. These are meteorological- (future climate based on the RCP scenarios) and soil (SoilGrids)-based. CreditScore employs the crop growth model AquaCrop to assess future yields.

To evaluate the performance of AquaCrop, wheat and cotton yield data were provided by the Cooperative Bank of Karditsa LLC, obtained from 15 farmers-borrowers. The data were fully anonymized and included the growing seasons (2019/20 and 2020/21 for wheat, 2021 for cotton), sowing dates, and yields for 87 wheat and 68 cotton parcels in the Thessaly region. The size of the parcels ranged from 0.1 to 13.4 ha. Gridded meteorological data for the growing seasons were derived from the ERA5-Land and ERA5 re-analysis, (Copernicus CDS). Daily weather data included T_{min} , T_{max} , ET_o , and precipitation. Soil data were retrieved from the SoilGrids database, up to a soil profile of 2 m, for each parcel. Sentinel-2 satellite images were acquired during the growing seasons. NDVI, GreenWDRVI, LAI, and Canopy Cover (CCRS) were assessed for pixels falling within each parcel. Using the representative CCRS curves, the CGC and CDC (canopy growth and decline coefficient) were calibrated for cotton and wheat. These parameters are provided in Table 1. A range of the average per parcel NDVI time series during the growing seasons is displayed in Figure 1. The simulations were executed for every parcel, and the yields obtained were compared to the actual yields provided by the farmers. The model efficiency (ME), the coefficient of determination (R^2), the root-mean-square error (RMSE), the normalized RMSE (nRMSE), the bias, and the Willmott’s index of agreement (d) were selected as performance evaluation metrics.

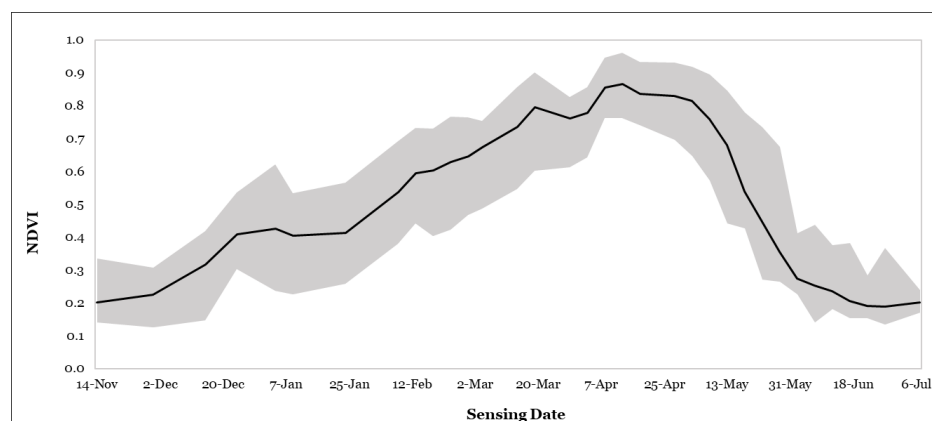


Figure 1. Reflected phenology, expressed as the NDVI, for the 2019/20 and 2020/21 seasons in wheat parcels.

Table 1. Calibrated parameters of AquaCrop.

Parameter	Unit	Wheat	Cotton
Soil surface covered by a seedling at 90% recover	cm ² /plant	1.50	6
Number of plants per hectare	Hm ⁻²	2,500,000	120,000
Maximum canopy cover (CC _x)	%	90	90
Calendar days: from sowing to emergence	d	13	14
Calendar days: from sowing to maximum root depth	d	93	98
Calendar days: from sowing to start senescence	d	178	144
Calendar days: from sowing to maturity	d	221	174
Calendar days: from sowing to flowering	d	150	64
Length of the flowering stage (days)	d	20	52

Table 1. *Cont.*

Parameter	Unit	Wheat	Cotton
Maximum effective rooting depth	m	0.3	1
Reference harvest index (HI ₀)	%	42	35
Water productivity (WP)	gm ⁻²	17	15
Canopy growth coefficient (CGC)	Fraction d ⁻¹	0.069	0.085
Canopy decline coefficient (CDC)	Fraction d ⁻¹	0.0605	0.0605
Irrigation		Rainfed	Schedule

3. Results and Discussion

AquaCrop was evaluated in order to investigate whether the model has the potential to provide safe yield results through a simplified approach, with respect to data intensiveness and data sources. For cotton, the model was implemented under an irrigation scheduling mode. This is the only way to simulate future yields for irrigated crops, and the results were evaluated under this mode. The calculated statistical metrics summarized in Table 2 show that a very good agreement was obtained by AquaCrop regarding the simulation of the wheat and cotton yields. These average to high prediction accuracies are similar to those found in the literature using detailed weather station data or soils’ physical properties derived from laboratory-analyzed samples as inputs [5,6].

Table 2. Statistical evaluation of AquaCrop results.

Statistical Metric	Units	Results for Wheat	Results for Cotton
Average estimates	kgha ⁻¹	3430	4950
Average measured	kgha ⁻¹	3450	4970
std estimates	kgha ⁻¹	1128	87
std measured	kgha ⁻¹	1233	541
Value range estimates	kgha ⁻¹	750–6220	4820–5030
Value range measured	kgha ⁻¹	1250–6700	4050–6370
ME	–	0.8	–0.1
RMSE	kgha ⁻¹	616	566
nRMSE	%	17.9	11.4
bias	kgha ⁻¹	1.3	–18.8
d	–	0.930	0.842
R ²	–	0.75	0.24

Many previous works supported that the use of calibration techniques based on remote sensing improves yield assessments from crop growth models [7,8]. The most logical pathway for a systematic calibration of AquaCrop is first and foremost to ensure a sound prediction of canopy cover. The key user-input parameters for this purpose are the coefficients defining the canopy development. In this study, the canopy cover data were derived from satellite images over the parcels and were used to safely simulate the future growth and yield of wheat and cotton crops for a particular area.

4. Conclusions

Apart from the identified significant contribution of remote sensing, the findings of this work also prove that gridded datasets on soil and environmental conditions can operationally be employed for yield prediction applications. The calibrated AquaCrop results, although obtained with a medium data input load and from publicly available datasets, were comparable with those reported in the literature for more detailed field experiments and treatments. It is challenging for simulation models to find relevance in real-world agriculture; however, the current work suggests that the combined simplicity and accuracy of AquaCrop make the model an indispensable tool within decision support systems. The investigated models and datasets are called upon to reduce the asymmetry of the available information and to cultivate trust and transparency between financial

institutions and borrowers, in order to pave the way for credit to farmers. Particularly through CreditScore, financial institutions are able to:

1. Have at their disposal a long-term yield forecast, based on the near-future climate, that takes into account the effects of climate change on future yields, using crop growth models;
2. Assess borrowers' creditworthiness (for single- and multi-year loans), thus contributing to the formulation of personalized banking products and the regulation of contract terms.

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