Scientific Papers Series Management, Economic Engineering in Agriculture and Rural Development
Vol. 24, Issue 2, 2024
PRINT ISSN 2284-7995, E-ISSN 2285-3952

DEVELOPING A DIGITALTWIN MODEL FOR CORN, WHEAT AND RAPESEED YIELDS COMPUTATION

Catalin CHITU*, Ilinca IMBREA, Stefan BATRINA*, Florin IMBREA***

University of Life Sciences "King Michael I" from Timisoara, *Faculty of Agriculture, **Faculty of Engineering and Applied Sciences, 119, Calea Aradului, Timișoara, Romania,
E-mails: cata.chitu@gmail.com, ilinca_imbrea@usvt.ro, stefan.batrina@usvt.ro,; florin_imbrea@usvt.ro

Corresponding author: stefan.batrina@usvt.ro; ilinca_imbrea@usvt.ro

Abstract

Digital Twin is an emerging agritech technology that involves creating virtual representations of physical systems, which can be used for various purposes, such as optimizing crop management, predicting yield, and managing resources efficiently. The research is focusing to build a accurate digital twin model for crop growth, considering factors like evaporation (ET), growing degrees days (GDD), crop type, soil data, and agricultural practices. The model handles data streams related with geolocation, IOT historical sensor data and weather forecasts streams to simulate the crop risk and yield. Frequent updates based on real-time data enhance accuracy. Aside essential water management crop flow, the model is processing historical data related with nutrients like nitrogen (N), phosphorus (P), and potassium (K) elements are vital for plant growth and health, and their optimal balance can significantly impact corn yield. The research is extended on five locations in both Romania and Luxembourg handling wheat, corn and rapeseed crop simulation.

Key words: *digital twin, climate conditions, yield computation*

INTRODUCTION

Our planetary ecosystem changes from year to year, the climate is getting hotter and generating extreme weather conditions from heavy rainfall to major droughts. Water plays a key role in how plants and pests mitigate and adapt to the effects of climate change. Climate change is becoming a major threat to agriculture, livelihoods and food for millions of people in many parts of the world [5, 13, 17].

Monitoring and assessing crop conditions to support plant productivity is the basis for land use strategies on agricultural farms. The health and productivity of crops depend on the quality and properties of the soil, but also on the climatic evolution of the area. More detailed information about agricultural soil can reduce the potential use of doses of chemical fertilizers and pesticides, thereby improving groundwater, protecting the environment and human health. It also supports defining plant density more efficiently.

In agriculture, Digital Twin supports scientists to better simulate, and study yields factors and farmers to reduce crop resources and operations based on their region. Soil monitoring sensors, such as moisture, temperature, organic matter, and soil pollutant sensors, play critical roles in digital agriculture. Information on moisture can be used to assess water stress and irrigation efficiency. In addition, to support smart agriculture decision-making, digital data is essential, bringing spatial information as overall crop evolution.

A Digital Twin for Crop Yields is a virtual representation of a specific plot area or field, that incorporates real-time data and modelling to simulate weather, soil conditions and practices. The model is based on:

1. Data integration assign field sensors, such as air and soil moisture probes or satellites equipped with spectral image acquisition, continuously collect data on soil moisture levels in the field.
2. Modeling: The collected data is integrated into a digital model of the field. This pattern can include factors such as soil type, topography, weather patterns, crop activities timeline & resources used and historical data.
3. Real-time monitoring: The Digital twin model is continuously updated with new data, allowing real-time monitoring of crop

conditions. This helps farmers make data-driven decisions about irrigation & water management, fertilization and in field activities.

4. Predictive analytics: By analyzing historical and real-time data, Digital Twin model can predict future conditions. This allows farmers to plan activities more efficiently, conserving resources and reducing emissions.

5.Optimization as recommendation on optimal water and resources strategies based on crop type, variety type, growth stage and environmental conditions, thus improving crop yield and resource efficiency.

Soil temperature and water plays a key role in chemical processes of transformation of nitrogen forms in soil, especially nitrification, which relies on temperature can take from 8 to 42 days. Nitrification is a microbial process by which compounds with reduced nitrogen are oxidized to nitrites and nitrates. This stage of the nitrogen cycle includes two chemical reactions. As a first step, ammonia is converted to nitrite, followed by oxidation of nitrite to nitrate. This process is beneficial for microorganisms because they can obtain the energy needed for their growth through chemical reactions [9]. The microorganisms resulting from this process are known as nitrifying microorganisms. Influence of soil temperature on nitrification under moisture conditions, 60% of total soil capacity and pH 7.2 –7.5

The efficiency of fertilization is given by the ratio of the main elements in the soil. The optimal water content in the soil guarantees maximum fertilizing efficiency. The excess water in the soil also diminishes the efficiency of fertilizers due to the lack of oxygen required in the chemical processes that take place in the soil.

The concept

The purpose of developing on each site a well-defined productivity prediction model is to combine local climate evolution given by IOT sensors with weather forecasts and farming practices to mitigate the impact of climate change by making results available in an appropriate form for informed decision-making that impact the yield.

The studied Digital Twin yield engine consists of input and output data streams, algorithms, and data stream drifting hooks. A data stream is defined as array of elements, where each element consists of timestamp and value, information identifying when a certain event occurred (hour, day, week)

An input stream is processed by a specific algorithm or formula and has drifting hooks. An output data stream consists of feedback results. The concept of *drifting hook* was necessary to be used for inter-streams data dependencies and/or intermediate data mutation. Two types of hooks were used: the data driven hook (DDH) and time driven hook (TDH), both hooks conditionally may change the input and output of existing stream based on data or formula on specific input stream. For instance, a Seeding hook assigned to soil temperature and humidity streams consists of shifting the operation based on the right germinating temperature and humidity in the soil. There are several drifting hooks defined for a seasonal crop, most important are related with seeding, fertilization and watering, their configuration and auto-adaptation based on field location can have deep impact on the final yield.

Input streams are represented by (historical) sensor data streams (*GDD*), farmer operational and resources used data streams (OP_x) (as fertilizing time and quantities) and sensors data streams ($FSEN_x$), where SEN_x - are air T_{AIR} and H_{AIR} – (air temperature and humidity), R (rainfall quantity), T_{SOIL10} and H_{SOIL10} (soil temperature and moisture) at 10cm, E_{PAR} (Photosynthesis Active Energy), IND_{NVDI} (NVDI index)

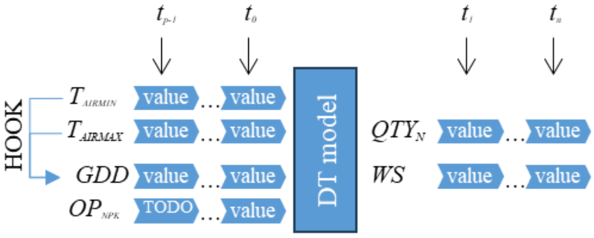


Fig. 1. Studied digital twin engine.
Source: original.

The concept of intermediate data stream (input or output) is necessary to generate data from existent streams as GDD - Growing degree days, *E* – evapotranspiration, or forecast $FSEN_x$ BBCH – crop state, or using conditional data set hooks like WS - water stress level (Figure 1).

A Digital Twin is not only process and virtually represent an entity's state, but in addition the output streams must provide a feedback mechanism [15] allowing the assertion of a decision-making, optimization, or simulation process by influencing an entity, either directly or indirectly. In our digital twin model, the feedback elements consist of drifting hooks adjustments for time and resources.

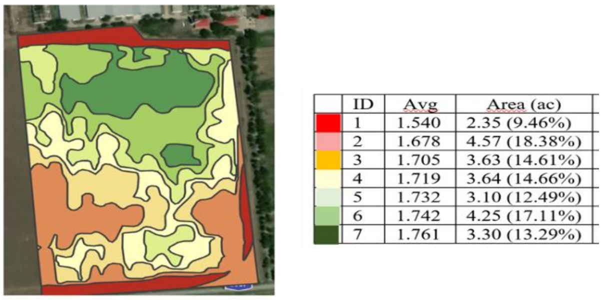
MATERIALS AND METHODS

The study was done in 5 locations distributed geographically across Europe: Luxembourg north and west, Romania West, East and South. Each location is equipped with agrometeorological weather station and soil sensors. The data used from 2018 January to 2023 July covering 5 years of seasonal crops focusing on wheat, corn, and rapeseed.

The sensor data streams were acquired hourly: air temperature, air humidity, rainfall, wind direction, wind speed, solar radiance, 10cm and 30 cm soil moistures and soil temperatures. The acquired data was correlated with field activities timeline as ploughing, sowing, fertilizing. The data was processed and structured over several seasons with weekly sensor data aggregation.

The model input is also spectral satellite information data as NVDI, EVI2, NIR as well terrain topographic shape that have impact on water drainage and retention, soil erosion and uniform fertility, sunlight exposure generating the field potential (FP) (Figure 2).

Regarding the varieties: in Romania as wheat variety were used Dropia (INCDA Fundulea) and Alhambra (Limagrain). In Luxembourg Faustus (Saaten) variety was used. Sown in dense rows at 12.5 cm between rows. Sowing in strips for carrying out maintenance work followed. For rapeseed the following varieties in Romania Madora (Saaten), in Luxembourg Ambasador (Limagrain).



	ID	Avg	Area (ac)
🟥	1	1.540	2.35 (9.46%)
🟥	2	1.678	4.57 (18.38%)
🟧	3	1.705	3.63 (14.61%)
🟨	4	1.719	3.64 (14.66%)
🟩	5	1.732	3.10 (12.49%)
🟩	6	1.742	4.25 (17.11%)
🟩	7	1.761	3.30 (13.29%)

Fig. 2. Field potential on studied East Romania plotbase on best NVDI Index on spring season over 5 years
Source: original.

Field elevation (%) has direct relation in nitrogen loss (N_{LOSS}) relying on precipitation / irrigation amount of water (mm)absorption and nitrogen washing (Figure 3).

Fig. 3. Field elevation east Romania
Source: Original.

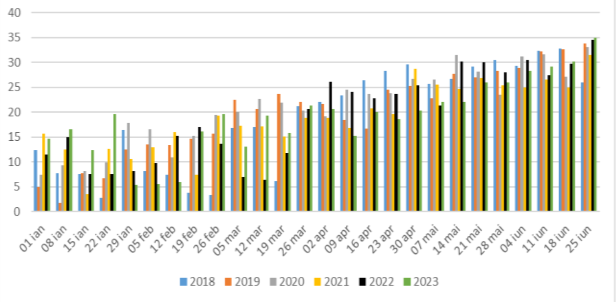


Fig. 4. 5 years T_{AIR} max comp. for spring-summer season East Romania (weekly set)
Source: Original.

For winter wheat period on red-brown soils, where conditions for nitrogen LOSS are met (when used in high doses), 1/3 of the nitrogen dose administered when preparing the germination bed, regardless of the preceding plant. In spring (starting in February/ March), the difference in the planned nitrogen dose is administered [1,18]. However, we consider model drifting hook for Nitrogen amount, depending on the amount of rainfall during autumn and winter and the condition of plants entering and leaving winter.

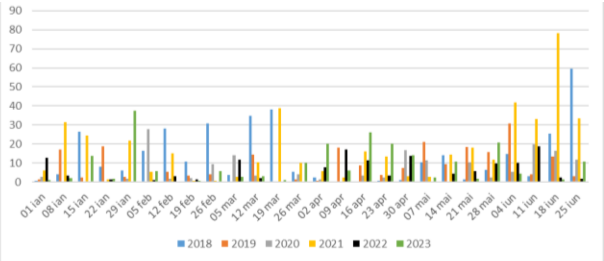


Fig. 5. 5 years rainfall (R) comp. for spring-summer season East Romania (weekly set)
Source: Original.

Model drifting hook uses the following factors: 1. The rainfall (R) accumulated during the winter period and are (2) temperature of soil (T_{SOIL})when it is warmer there is microbiological activity, (3) crop rotation (CR_L) (4) degree soil fertility (S_F).

East Romania is well known for drought and Luxembourg for a lot of rains. The model took into consideration the infield fertilizing operation applied and climate history. From data stream, the T_{airmax} is going down yearly with 10% which concludes a drastic weather change, but the same stream shows that spring season was drifted with 4 weeks ahead. (Figure 4). This doesn't correspond anymore with classical plan for seeding and fertilizing. The research shows also environmental trends, as T_{AIR}, R, T_{SOIL10}, HSOIL$_{10}$ show a 3-week drift and repetitive similitude at *2* years (Figure 5).

The model focuses on appropriate fertilization schema, important to achieve bigger yields with minimum nitrogen based on environmental evolution [2, 15, 16]. The following nitrogen factors were defined: N_{TOTAL}, $N_{RATE/HA}$, NCROP$_{-UPTAKE}$, N_{LOSS}, $N_{SOIL-REMAINS}$ S_F

Applied nitrogen (N_{TOTAL} was calculated by classical crop formula (kg/ha),

$$N_{TOTAL} = (PROD_{TARGETED} - PROD_{DEFAULT}) \ x \ N_{RATE/HA}$$

$PROD_{DEFAULT}$ *is* the default production without any nitrogen application. The digital twin model takes as data stream the crops rotation (CR_L) information on the following crops [Corn, Rapeseed, Sunflower, Winter Wheat]. The algorithm considers each CR_L nitrogen remains information to calculate $N_{CROP-UPTAKE}$, N_{LOSS}, $N_{SOIL-REMAINS}$ for each crop. Luxembourg fields are mainly on hill side with an 8-15% elevation that has impact on N_{LOSS} coefficient. For most Luxembourg winter crops, fertilization is mostly done in spring (due to autumn heavy rains)

For 2018-2022 period on above locations were monitored environmental parameters T_{AIR} and H_{AIR}, R, T_{SOIL10} and H_{SOIL10} E_{PAR}, IND_{NVDI} aside fertilizers and substances applied, and production. As nitrogen uptake, the model considered as 70% nitrogen use efficiency (NUE) [10, 6]. For N_{LOSS} it was considered that after the wheat was harvested, 30–51% of the applied N fertilizer remained in the 0–80 cm soil profiles and 59–83% of soil residual N was retained in the 0–20 cm soil layers [3, 12, 18]. The model N_{LOSS} is daily calculated talking into account [4, 8, 18**]** for $N_{CROP-UPTAKE}$ based on NUE and Nitrogen surplus (Ns) but also sensors dataH_{SOIL10} and R together with field shape degrees, GDD and crop IND_{NVDI} for that season.

RESULTS AND DISCUSSIONS

Sensor and satellite-based determination of crop yield based on nitrogen management provides critical data in site-specific fertilization algorithms. Nitrogen consumption shall be processed as data-stream array input where each item can change the soil remaining nitrogen based on other conditional drifting hooks (as water, temperature etc) and primary and secondary production. The water and temperature are playing a crucial role in nitrogen uptake but also in straws decomposition that inject additional nitrogen.

Significant differences were observed among varieties for yield, $N_{CROP-UPTAKE}$ as components of NUE in forage, grain, straw, and grain + straw. Estimates of N_{LOSS} over this two-year period ranged from 4.0 to 27.9 kg·ha-1 [7]. According to Smith et al. 1967**,** the dry soil is slowing straw decomposition (N_{STRAW}) [14]. Rainfall / irrigation water is necessary to speed up the decomposition process that can take between 3 to 6 months [11]. For next crops, the model took $N_{SOIL-REMAINS}$ as progressive calculation based on available soil water (H_{SOIL10}) and crop exposure on climate.

The remaining nitrogen ($N_{\text{SOIL-REMAINS}}$) is reintroduced in the digital twin model flow as feedback to simulate next crop as following.

$$N_{\text{APPLIED}} = N_{\text{TOTAL}} – N_{\text{SOIL-REMAINS}}$$

$$N_{\text{SOIL-REMAINS}} = N_{\text{TOTAL PREV}} - N_{\text{LOSS-PREV}} – N_{\text{CROP-UPTAKE-PREV}} – (N_{\text{STRAWS-PREV}} + N_{\text{SOIL-REMAINS-PREV}})$$

Table 1 depicts the nitrogen usage for south Romania location (warmed & drought place with no irrigation). $\text{PROD}_{\text{DEFAULT}}$ = 1,800 kg/ha

Table 1. East Romania model outputs

Crop	Seeding	Harvesting	$\text{PROD}_{\text{TARGETED}}$	N_{total} (kg/ha)	$N_{\text{total-aplied}}$ (kg/ha)	Rainfall (liter)	GDD	$N_{\text{soil-remains}}$ (kg/ha)
Winter Wheat	Oct 2017	Jul 2018	6,000 kg	79.8 kg	79.8 kg	402	920 °C	16.0 kg
Rapeseed	Sep 2018	Jun 2019	3,500 kg	100.3 kg	84.3 kg	335	896 °C	20.1 kg
Sunflower	Mar 2020	Aug 2020	3,500 kg	102.0 kg	81.9 kg	225	1,589 °C	81.6 kg
Winter Wheat	Oct 2020	Jul 2021	6,500 kg	98.7 kg	17.1 kg	644	660 °C	30.6 kg
Corn	Apr 2022	Aug 2022	4,100 kg	48.3 kg	17.7 kg	215	1,629 °C	37.7 kg
Winter Wheat	Oct 2022	Jul 2023	7,500 kg	108.3 kg	70.6 kg	341	983 °C	29.2 kg

Source: Original data.

The red values correspond to crop loss due to lack of water. For instance, 2020 sunflower and 2022 corn crop require a minimum of 450L of water, and 30% in first BBCH development stages. The 2020 year was drought and lack of rainfall. The amount of N from straws were incorporated into the soil and model distribute the nitrogen from sunflower/corn decomposition over several months, to be used by next spring crop. Autumn 2020 spring 2021 winter period was abundant of rainfall (R), and soil temperature was below 5 deg. that helped with straw decomposition for spring. The $N_{\text{SOIL-REMAINS}}$ varies between 15% to 25%.

For Luxembourg west location, Table 2, water is more abundant having less risks on drought, but issues on temperature and cloudy area. Small GDD pushes the crops further in July/August and during winter temperature goes below -5 C. For instance, for rapeseed, a part of the leaf area produced might be destroyed by freezing, leading to important N losses of 2–3.5 % of the fallen leaves' dry weight [2,10]. The $N_{\text{SOIL-REMAINS}}$ goes up 29% due to higher applied rates.

Table 2. West Luxembourg model outputs

Crop	Seeding	Harvesting	$\text{PROD}_{\text{TARGETED}}$	N_{total} (kg/ha)	$N_{\text{total-aplied}}$ (kg/ha)	Rainfall (liter)	GDD	$N_{\text{soil-remains}}$ (kg/ha)
Winter Wheat	Oct 2017	Jul 2018	7,000 kg	98.8 kg	98.8 kg	299	2,014 °C	19.8 kg
Rapeseed	Sep 2018	Jun 2019	3,500 kg	100.3 kg	100.3 kg	295l	1,810 °C	20.1 kg
Corn Silo	Mar 2020	Aug 2020	12,000 kg	612.0 kg	612.0 kg	320	1,547 °C	489.6 kg
Winter Rye	Oct 2020	Jul 2021	3,500 kg	35.7 kg	-453.9 kg	422	1,646 °C	11.1 kg
Sunflower	Apr 2022	Aug 2022	3,600 kg	37.8 kg	26.7 kg	239	1,520 °C	29.5 kg
Rapeseed	Oct 2022	Jul 2023	3,800 kg	38.0 kg	8.5 kg	216	1,078 °C	10.3 kg

Source: Original data.

CONCLUSIONS

This research tries to elucidate the intricate dynamics between nitrogen management, environmental conditions, and crop yield, facilitated by the development and application of a digital twin model. Our findings underscore the pivotal roles of water and temperature in regulating nitrogen uptake and the subsequent decomposition of crop residues, which are essential processes for sustainable agricultural practices.

Through detailed analysis across different geographical locations and crop varieties, we have demonstrated significant variability in nitrogen use efficiency (NUE), nitrogen loss (NLOSS), and the impact of environmental factors on these processes. The comparative study of crop performance under varying conditions of drought and water abundance has provided insights into the critical need for precise nitrogen management and the importance of environmental considerations in agricultural planning and operations.

The digital twin model proved to be an invaluable tool in simulating the complex interactions between climate, soil, and crop growth conditions, offering a nuanced understanding of how to optimize nitrogen application, enhance crop yield, and minimize environmental impact. The model's ability to incorporate real-time and historical data enables predictive analytics that can guide decision-making processes, from field management to regional agricultural strategies.

The key conclusions drawn from this research are:

-**Optimized Nitrogen Management:** Effective nitrogen management, as revealed by the digital twin model, can significantly enhance crop yield while reducing the environmental footprint. The balance between nitrogen application and the crop's actual requirements—considering soil, weather, and crop variety—is crucial for maximizing NUE.

-**Environmental Impact on Crop Yield:** Environmental conditions, particularly water availability and temperature, have profound effects on nitrogen dynamics in the soil-crop system. These factors influence not only the immediate crop yield but also the sustainability of agricultural practices through their effect on nitrogen loss and soil nitrogen residuals.

-**Adaptive Agricultural Practices:** The study advocates for the adoption of adaptive agricultural practices, guided by digital twin technology and data analytics, to respond effectively to climate variability and changing environmental conditions. This adaptive approach can lead to more resilient and sustainable agriculture.

-**Future Directions:** There is a need for further research into the integration of digital twin models with other technological advancements in agriculture, such as precision farming tools and AI-driven predictive models, to enhance the efficiency and sustainability of crop production.

In conclusion, the deployment of digital twin technology in agriculture offers a promising pathway towards achieving high-efficiency, sustainable crop production systems. By harnessing the power of real-time data analytics and simulation, agricultural stakeholders can make informed decisions that balance productivity with environmental stewardship.

REFERENCES

[1]Al-Darby, A.M., Lowery, B., 1986, Evaluation of corn growth and productivity with three conservation tillage systems, Agronomy Journal, 1986, Vol. 78(5), 901-907.

[2]Campbell, C.A., Myers, R.J.K., Curtin, D., 1995, Managing nitrogen for sustainable crop production. Fertilizer Research 42, 277–296 https://doi.org/10.1007/BF00750521

[3]Chen, Z., Wang, H., Liu, X., Lu, D., Zhou, J., 2016, The fates of ^{15}N-labeled fertilizer in a wheat–soil system as influenced by fertilization practice in a loamy soil. Sci Rep 6, 34754 (2016). https://doi.org/10.1038/srep34754

[4]Faber, A., Jarosz, Z., Rutkowska, A., Jadczyszyn, T., 2021, Reduction of Nitrogen Losses in Winter Wheat Grown on Light Soils. Agronomy 2021, 11, 2337. https://doi.org/10.3390/agronomy11112337

[5]Gherasimescu, L., Batrina, S.L., Imbrea, I.M., Imbream F., 2023, The evolution of agricultural yields. A case study on Timiș County, Scientific Papers. Series A. Agronomy, 2023, Vol. LXVI, No. 1.

[6]Girma, K., Holtz, S., Tubaña, B., Solie, J., Raun, W., 2011, Nitrogen Accumulation in Shoots as A Function of Growth Stage of Corn and Winter Wheat, Journal of Plant Nutrition, 34: 2, 165-182.

[7]Kanampiu, F., K., Raun, W. R., Johnson, G. V., 1997, Effect of nitrogen rate on plant nitrogen loss in winter wheat varieties, Journal of Plant Nutrition, Vol. 20(2), 389-404, http://dx.doi.org/10.1080/01904169709365259

[8]Mailhol, J.-C., Albasha, R., Cheviron, B., Lopez J.M., Ruelle, P., Dejean, C., 2018, The PILOTE-N, 2018, model for improving water and nitrogen management practices: Application in a Mediterranean context, Agricultural Water Management, Vol. 204 C, 162-179, https://doi.org/10.1016/j.agwat.2018.04.015

[9]Malagoli, P., Laine, P., Rossato, L., Ourry, A., 2005, Dynamics of nitrogen uptake and mobilization in field-grown winter oilseed rape (*Brassica napus*) from stem extension to harvest: I. Global N flows between vegetative and reproductive tissues in relation to leaf fall and their residual N. Ann Bot. Apr. 95(5): 853-861, https://doi.org/10.1093/aob/mci091

[10]Mehrotra, O.N., Sinha, N.S., Srivastava, R.D.L., 1967, Studies on nutrition of Indian cereals. Plant Soil 26, 361–368. https://doi.org/10.1007/BF01880185

[11]Mühlbachová, G., Růžek, P., Kusá, H., Vavera, R., Káš, M., 2021, Winter Wheat Straw Decomposition under Different Nitrogen Fertilizers. Agriculture 2021, 11, 83. https://doi.org/10.3390/agriculture11020083

[12]Raun, W.R., Solie, J.B., Johnson, G.V., Stone, M.L., Mullen, R.W., Freman, K.W., 2002, Agronomy Journal Improving Nitrogen Use Efficiency for Cereal Production, Agronomy Journal 94(4), 2002, https://doi.org/10.2134/agronj2002.0815

[13]Sitnicki, M. W., Prykaziuk, N., Ludmila, H., Pimenowa, O., Imbrea, F., Șmuleac, L., Pașcalău, R., 2024, Regional Perspective of Using Cyber Insurance as a Tool for Protection of Agriculture 4.0. Agriculture, 14(2), 320.

[14]Smith, J. H., Douglas, C. L., 1967, Straw Decomposition. Current Information Series No.57, USDA.

[15]Tao, F., Cheng, J., Qi, Q., Zhang, M., Zhang, H., Sui, F., 2018, Digital twin-driven product design, manufacturing and service with big data. Int J Adv Manuf Technol 94, 3563–3576. https://doi.org/10.1007/s00170-017-0233-1

[16]Tripolskaja, L., Verbyliene, I., 2014, The effect of different forms of nitrogen fertilizers on nitrogen LOSS Zemdirbyste-Agriculture 101(3), 2014, https://doi.org/10.13080/z-a.2014.101.031

[17]Viets, G., 1962, Fertilizing And The Efficient Use Of Water, Advances in Agronomy (14), pp. 223-264, 1962, https://doi.org/10.1016/S0065-2113(08)60439-3

[18]Wright, D., Small, I., Mackowiak, C., Grabau, Z., Devkota, P., Paola-Moraes, S., Rowland, D.L., Marois, J.J., Rich, J.R., Mulvaney, M.J., 2022, Field corn production guide; https://edis.ifas.ufl.edu/publication/AG202, Accessed on 18.02.2024.