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Examining limitations and future directions in climate change simulation models

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Abstract. Climate change refers to significant alterations in long-term climate conditions. If greenhouse gas emissions continue to rise, there is a high probability of exceeding the 1.5°C and 2° thresholds of global warming throughout the 21st century. This situation poses a serious threat to the agriculture sector and can lead to a decline in agricultural production and a reduction in product quality. Additionally, intensive farming practices can decrease the resilience of agriculture. This study aims to examine the effects of climate change on the agriculture sector, explain the concept of modeling and the parameters that can be measured, provide guidance on how modeling studies on alfalfa, and similar crops can be improved by identifying their shortcomings. The modeling method is used in many different fields by creating abstract representations of real-world objects or events via a mathematical equation, writing algorithm, or simulation. Parameters used in alfalfa modeling include yield, growth, carbon, water, nitrogen balance, climate effects, and other factors. However, these models have shortcomings such as the need for more comprehensive data collection and testing, the requirement for more parameter adjustments, the inability to address various crops and different growth cycles, the lack of simulation of crown and root roles in growth, sensitivity in measuring soil and input factors, limited testing and research, inaccuracies in automatic classification, the absence of growth and yield simulation models, and the lack of deep learning techniques. Addressing these shortcomings is crucial for achieving more reliable and effective results in the agricultural sector. Strengthening models and addressing these deficiencies have the potential to lead to more robust and sustainable solutions in agriculture.

1 Introduction

Climate change is defined as significant and long-term alterations in the average conditions and/or variability of the climate, regardless of the underlying causes. If substantial reductions in carbon dioxide and other greenhouse gas emissions do not occur shortly, global warming is projected to exceed the limits of 1.5°C and 2°C throughout the 21st century [11,1]. Climate change poses a substantial risk to the agriculture sector. Changing climate conditions increase the risk of reduced agricultural production and quality. Moreover, the excessive use of intensive farming practices diminishes the resilience of agricultural production [2].

The modeling method involves creating abstract representations of objects or events in the real world through mathematical equations, written algorithms, or simulations. Modeling is utilized in various fields, impacting numerous disciplines from scientific research to engineering, health sciences to economics. It plays a significant role in problem-solving, predictions, and future planning. Therefore, models effectively aid scientists in translating theoretical explanations and thoughts into tangible representations or in the development of new theories and ideas [25].

Modeling studies on alfalfa encompass factors such as yield, growth, carbon, water, hydrogen, nitrogen balance, quality, abiotic factors, ETC (evapotranspiration), root diseases, climate thresholds, and soil characteristics. However, these models may have limitations and inaccuracies due to restricted measurability, limited product diversity, complexity, and capacity constraints. Additionally, some models may lack yield and growth simulations, and there is a lack of research in deep learning. To address the shortcomings of the models, efforts should be made to enhance their capabilities and develop new modeling approaches that incorporate deep learning techniques. Additionally, there is a need to adapt deep learning techniques to modeling and conduct comprehensive studies in this regard. This study aims to elucidate the impact of climate change on agriculture and provide guidance on addressing the limitations in modeling studies on alfalfa.

2 Material and method

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In this study, articles related to modeling studies on alfalfa have been reviewed. A keyword-based search for these articles was conducted using the terms 'alfalfa' and 'model.' After gathering relevant studies, a detailed examination and analysis of these articles were carried out. Selected articles were individually analyzed with consideration of the following research questions:

- What are the limitations of existing modeling studies in alfalfa agriculture, and how can new modeling approaches be developed to address these limitations?
- What steps may be taken to improve the models used in alfalfa agriculture?

3 Results and discussion

3.1 Modeling approaches for measuring alfalfa growth and yield

The AquaCrop model is a simulation model that can be calibrated to simulate alfalfa yield, taking into account environmental (climate) and field management factors [21]. A calculation process in AquaCrop allows for the simulation of canopy development and crop production in areas invaded by weeds [27]. However, AquaCrop does not simulate the allocation of biomass among various plant organs [26].

The CSM-Cropgro-Pfm model takes advantage of the existing mechanical model, Cropgro-Pfm, to simulate its effects on alfalfa yield and growth. Adapting an existing mechanical model like Cropgro-Pfm has advantages because many processes are similar across models and are well-simulated. This allows for the utilization of modular sub-programs in Cropgro to simulate soil water balance, soil nitrogen balance, soil organic matter-residue dynamics, and pests [23]. To enhance the robustness of the model, further testing with more comprehensive datasets is required [16].

DNDC, (DeNitrification-DeComposition Simulation), is one of several advanced models which includes site-specific and regional modes using simulations and mathematical equations [14]. Process-based models like DNDC are particularly advantageous because they account for complex physiochemical and ecological processes in soil and soil-atmosphere interactions [6]. The DNDC model is highly sensitive to climate, soil, and crop inputs; therefore, errors can occur in some cases when auxiliary inputs are not accurately measured in the field [24].

The Gaussian Amplitude Growth model, commonly referred to as the Gauss Genlik model, is a widely used biological growth research model to examine environmental factors affecting alfalfa yield and growth [20]. There are limited studies that use the Gaussian function to simulate changes in the growth age (years) of perennial plant biomass [20]. The use of multi-year observations is still necessary [29].

3.2 Models used to assess alfalfa climate thresholds and climatic suitability

The MaxEnt (Maximum Entropy) model is an algorithm and simulation method used to model the climatic thresholds of Chinese alfalfa and measure climatic suitability. MaxEnt's excellent performance on small samples is consistent with previous studies indicating that productive methods perform better predictions than discriminative methods when training data is limited [17]. To optimize the performance of the Maxent model, further parameter tuning is required [19].

3.3 Modeling approaches for disease detection in alfalfa

WCSMO-CNN holds great importance in categorizing plant root diseases in alfalfa using algorithms to identify issues in the root regions of plants [12]. However, automated classification approaches may sometimes fail to accurately classify root diseases [28]. Such diseases can significantly hinder the healthy growth of plants, adversely affecting farmers' crops. To address this issue, deep learning methods have been designed to make root disease detection more effective [30,8,9].

3.4 Modeling approaches for simulating soil characteristics in alfalfa

The STICS modeling system works through simulation, aiming to model the effects of agricultural production (both in terms of quantity and quality) and the environment, including important components such as carbon, water, and hydrogen, as well as the management of climate, soil. This simulation model works at daily time intervals and can integrate the spatial and temporal variations of different crops [18]. However, the use of STICS is currently limited to specific crop systems and lacks representation of some important processes (e.g., ammonia volatilization, drought resistance, soil anoxia, etc.), so that requiring updates for broader application [4].

CropSyst is generally successful in simulating crop growth systems, as it can successfully perform simulations of alfalfa aboveground biomass and soil water content over three-year periods. However, the sleeping period of the model alfalfa plant inhibrist post-harvest regrowth and the effectiveness of petals and roots. Additionally, it neglects the impact of petals reserves in the automatic scheduling of cuttings. Therefore, there is a need to develop more comprehensive and detailed simulation models for the person interested in alfalfa cultivation [5],[16].

The SimET model stands out as an effective algorithm aimed at simulating plant evapotranspiration (ETc) and soil water balance [15]. This model offers the capability to rapidly and accurately predict the ETc and soil water dynamics of plants across multiple growth cycles, simplifying users' processes of data preparation, model simulation, and result analysis [22]. Furthermore, it provides a practical tool for quickly simulating multiple scenarios [3]. However, the existing software has some shortcomings that indicate areas for improvement, particularly in complex processes, limited measurability, lack of batch processing, and inclusion of only a single ETc model [15]. Eliminating these problems could enhance the potential of the SimET model and allow for more effective utilization in various application areas.

APSIM is a simulation model developed for simulating the biophysical processes of agricultural systems. Recently, the integration of a general forest module into APSIM has expanded the diversity of agricultural systems [10]. This model successfully relates water and nutrient processes with surface residue dynamics in soil [10]. However, APSIM currently offers limited capacity for pastures and has not sufficiently focused on animal production systems, particularly those involving meat, milk, and wool production [7]. It also has shortcomings for important crops like rice [7]. Therefore, there is a need to enhance the existing capabilities of APSIM and develop it to encompass various agricultural systems.

DSSAT is an agricultural simulation model that incorporates many essential parameters, including soil properties (such as layer thickness, depth, clay, silt, coarse, and organic carbon fractions). DSSAT has been updated with combining CROPGRO and other modules and created DSSAT-CSM which is a new crop system that can simulate different crops. However, there is no specific model within the DSSAT software package that provides growth and yield simulation for alfalfa, so it indicates a need for a more comprehensive simulation model for such crops [16].

4 Conclusion

Modeling involves a range of factors that address various aspects of agriculture, including yield, growth, carbon, water, hydrogen, nitrogen balance, product quality, abiotic factors, evapotranspiration (ETC), root diseases, climate change, and soil properties. However, these models may cause errors due to limited measurability, product limitations, complexity, and sensitive measurements. It has been observed that some models lack yield and growth simulations, and there is insufficient work in the field of deep learning. To address these shortcomings, new modeling approaches need to be developed, deep learning techniques should be integrated into modeling, and more extensive datasets should be used to conduct comprehensive studies. Models can be enhanced and made more functional by combining them with deep learning techniques, can lead to positive impacts on the sustainability of agriculture.

References

1. N. Alexandridis, B. Feit, J. Kihara, T. Luttermoser, W. May, C. Midega,..., M. Jonsson, Agriculture, Ecosystems & Environment, **352,** 108511 (2023)
2. A. Aydın, Tarım sektöründe sürdürülebilir kalkınma için ekosistem tabanlı uyum (etu) faaliyetleri. Çevre Şehir ve İklim Dergisi, **2**, 3, 132-157 (2023)
3. C. Bendtsen Pso: Parçacık Sürü Optimizasyonu, https://CRAN.R-project.org/package=pso, (2022)
4. N. Brisson, B. Mary, D. Ripoche, M.H. Jeuffroy, F. Ruget, B. Nicoullaud,..., R. Delécolle, STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parameterization applied to wheat and corn. Agronomie, **18**, (5-6), 311-346 (1998)
5. R. Confalonieri, L.A. Bechini, European Journal of Agronomy, **21**, 2, 223-237 (2004)
6. K. Cuddington, M.J. Fortin, L.R. Gerber, A. Hastings, A. Liebhold, M. O'connor, C. Ray, Ecosphere, **4**, 2, 1-12, (2013)
7. J.R. Donnelly, M. Freer, A.D. Moore, New Zealand Journal of Agricultural Research, **37**, 3, 269-275 (1994)
8. D.C. He, J.S. Zhan, L.H. Xie, Journal of Integrative Agriculture, **15**, 4, 705-715 (2016)
9. A. Henry, A.J. Cal, T.C. Batoto, R.O. Torres, R. Serraj, Journal of experimental botany, **63**, 13, 4751-4763 (2012)
10. N.I. Huth, V.O. Snow, B.A. Keating, Integrating a forest modelling capability into an agricultural production system modelling environment-current applications and future possibilities, (2001)
11. IPCC, Climate change widespread, rapid, and intensifying, Erişim Tarihi: 21.06.2023 Erişim adresi: IPCC, 2021, https://www.ipcc.ch/2021/08/09/ar6-wg1-20210809-pr/,(2021)
12. D.F.S.Jayapalan, J.P. Ananth, Concurrency and Computation: Practice and Experience, **35**, 3, e7504,20239 (2023)
13. R. Jiang, J.Y. Yang, C.F. Drury, W. He, W.N. Smith, B.B. Grant, ... W. Zhou, Science of the Total Environment, 759, 143433 (2 021)
14. C. Li, Y. Zhuang, M. Cao, P.M. Crill, Z.H. Dai, S. Frolking, X.K. Wang, Nutrient Cycling in Agroecosystems, **60**, 1-3, 159-170 (2001)
15. M. Liu, M. Yang, H. Yang, SimET: An open-source tool for estimating crop evapotranspiration and soil water balance for plants with multiple growth cycles. The Crop Journal, (2023)
16. W. Malik, K.J. Boote, G. Hoogenboom, J. Cavero, F. Dechmi, Agronomy Journal, **110**, 5, 1777-1790 (2018)
17. A. Ng, M. Jordan, Advances in neural information processing systems, **14** (2001)

18. J.B. Passioura, Agronomy Journal, **88**, 5, 690-694 (1996)
19. S.J. Phillips, M. Dudík, Ekografi , **31**, 2, 161-175 (2008)
20. R. Qin, J. Xu, M.T. Harrison, K. Liu, F.M. Li, G. Sun, F. Zhang, Field Crops Research, **298**, 108966 (2023)
21. Raes, D., Steduto, P., Hsiao, T. C., & Fereres, E. Aquacrop reference manual. FAO, Rome, Italy, 218, (2009)
22. R. Rosa, P. Paredes, İkili Ürün Katsayısı Yaklaşımını Kullanarak Su Dengesi Hesaplaması ve Sulama Planlaması için Yazılım Uygulaması, Tez, Lizbon Teknik Üniversitesi, Lizbon, Portekiz, (2011)
23. S.J. Rymph, K.J. Boote, A. Irmak, P. Mislevy, G.W. Evers, Adapting the CROPGRO model to predict growth and composition of tropical grasses: developing physiological parameters. In Proceedings (2004)
24. Z. Sa'adi, Z.M. Yaseen, M.K.I. Muhammad, Z. Iqbal, Environmental Science and Pollution Research, 1-15 (2004)
25. T. Schick, J. Dwivedi-Yu, R. Dessì, R. Raileanu, M. Lomeli, L. Zettlemoyer, ... T. Scialom, Toolformer: Language models can teach themselves to use tools. arXiv preprint arXiv:2302.04761 (2023)
26. D. Undersander, D. Cosgrove, E. Cullen, C. Grau, M.E. Rice, M. Renz,... & M. Sulc, Alfalfa management guide. American Society of Agronomy, Inc. Crop Science Society of America, Inc., Soil Science Society of America, Inc., Madison, WI,
27. H. Van Gaelen, N. Delbecque, B. Abrha, A. Tsegay, D. Raes, The Journal of Agricultural Science, **154**, 6, 1026-1039, (2016)
28. T. Wang, J.A. Thomasson, C. Yang, T. Isakeit, R.L. Nichols, Remote Sensing, **12**, 8, 1310, (2020)
29. Y. Yang, Y. Zong, R. Qin, H. Wei, Y. Ma, F. Zhang, Land Degradation & Development, **33**, 12, 2142-2154, (2022)
30. J.C. Zhao, J.F. Zhang, Y. Feng, J.X. Guo, *The study and application of the IOT technology in agriculture.* In 2010 3rd international conference on computer science and information technology (Vol. 2, pp. 462-465) (2010)