2024-03

SHAP-guided Explanations for the Machine Learning Classification of Irrigated Fields Using Satellite Imagery

Kopanja Marija, Pejak Branislav, Radulović Mirjana, Brdar Sanja

SHAP-guided Explanations for the Machine Learning Classification of Irrigated Fields Using Satellite Imagery

Marija Kopanja*[1], Branislav Pejak[1], Mirjana Radulović[1], Sanja Brdar[1]

[1]BioSense Institute, Novi Sad, Serbia

[*]Correspondence: marija.kopanja@biosense.rs

Abstract: Integration of machine learning (ML) models into real-world applications such as agriculture, demands explanations of the inner workings of such models. As ML models evolve and become more sophisticated, it becomes more challenging for humans to comprehend their decision-making processes. This lack of transparency presents a significant barrier to the widespread adoption of ML-driven models, especially in precision agriculture where the stakes are high. One of the applications in precision agriculture is the creation of ML-driven models for detecting irrigated fields. To provide explanations for the ML classifiers for detecting irrigated fields based on satellite imagery, we employ explainable AI (xAI), a paradigm that seeks to provide comprehension of the decision-making process hidden behind predictions given by the ML models. By using the SHAP method, we seek to unravel how the model decisions differ among several crops of interest (maize, soybean, and sugar beet) for the classification task of detecting irrigated fields. On the more fine-grained level, we seek to analyse the most decisive factors among fields covered with the same crop. Results indicate that the main factors (vegetation indices for different days during the season) that guide the decision of ML models differ among different crops. More importantly, the results show that some parts of the decision-making process of the ML models deviate from human reasoning. More sensible classification of irrigated fields is achieved for sugar beet, than in cases for soybean and maize. Analysis of the explanations why particular fields are classified as irrigated or not, confirmed conclusions obtained on the crop-specific explanations. Our results show that having syntheses of xAI and ML classification models for irrigated fields is a crucial component for building trust, mitigating biases, and enhancing the robustness of these models.

Keywords: Explainable artificial intelligence · SHAP · Remote sensing · Irrigation detection

1. Motivation

The ML classification models for detecting irrigated fields become more complex with the advancements in AI technology. Adopting the xAI methods can help in unraveling the decision-making processes of such models. By making the process transparent and understandable, the xAI methods can ensure unbiased and fair outcomes in the context of detecting irrigated fields. Regardless of who the end-users of such models are, they all need to have confidence in the decisions made by ML-driven models. In applications such as detecting irrigated fields, where the models can have indirect or direct influence on an end-user, there is a clear necessity for providing understandable explanations that all end-users can comprehend. On the one side, the domain experts by using the xAI tools can discover whether the model may be misled by some erroneous factors, enabling refinement and optimization of the ML algorithm thereby enhancing its robustness and performance. On the other hand, for farmers the integration of the xAI in the ML-driven systems can establish trust and therefore lead to broader and quicker adoption of the AI-based systems. In other words, the xAI tools can ensure that all stakeholders can see the full potential of these models.

Agricultural landscapes are widely diverse in terms of different crop types, soil types, and weather conditions. Therefore, it is challenging to create unbiased and robust ML-driven models for the classification of irrigated fields. Our research aims to demonstrate how the xAI methods can provide insights into the adaptability of the ML models to the mentioned variations, thereby enabling the opportunity for enhancing model's robustness and performance for particular crop depending on the soil type. The explanations obtained for different crops can show how the xAI can help in understanding main factors that guide the decision of complex ML models. It is also essential to ensure that these models are not biased towards influential factors characterized by large fields. Having robust and accurate ML models

Funded by: ANTARES project that has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement SGA-CSA No. 739570 under FPA No. 664387, https://doi.org/10.3030/739570 and Ministry of Education, Science and Technological Development of the Republic of Serbia, grant agreement 451-03-47/2023-01/200358.

for classification of both large and small irrigated fields would lead to the establishment of trustworthiness among farmers, regardless of their field's sizes.

Another motivation for integrating xAI into ML models for irrigation detection includes the understanding of the decision-making process behind classifying fields as irrigated within fields covered with the same crop. Having the xAI that is providing clear insights into why each field is classified as irrigated or non-irrigated, empowers stakeholders to make informed decisions about water management, enhancing the overall efficiency of irrigation systems and water consumption. The field-specific insights obtained by integrating xAI are important for other decisions that can impact yield and water resource utilization. This aspect is significant as agricultural practices are often subject to regulations governing water usage and environmental impact and having the xAI integrated in the ML-driven irrigation detection system, can facilitate compliance with regulations.

The synergy of SHAP and ML classifiers trained on satellite data is used in studies [1, 2] in a multi-class framework to enhance land cover mapping using ML-driven models. According to our knowledge, this is the first study that attempts to integrate xAI, specifically the SHAP method [3] with ML models based on satellite data for irrigation detection.

2. Research questions

In the context of irrigated field detection, the motivation for leveraging xAI into the ML-driven classification model is manifold. In our work, we seek to unravel both crop-specific and field-specified explanations for the ML classification model of irrigated fields.

Firstly, on the coarse-grained level are obtained the crop-specific explanations for ML models trained on irrigated and non-irrigated fields. Having the explanations obtained for different crop types can help us to comprehend the main factors that guide the decision of the ML model for different crops. By having domain experts included in analysis of the obtained results, we are fostering confidence in the accuracy and reliability of developed irrigated field detection models. Furthermore, by providing a crop-specific understanding of the model reasoning, the xAI provides valuable insights for refining and enhancing the ML model's robustness.

Another aspect of integrating the xAI into ML models for irrigation detection includes the understanding of the decision-making process behind classifying fields as irrigated within fields with the same crop. Therefore, on a more fine-grained level, SHAP is used to unravel the most decisive factors among fields covered with the same crop. Having explanations per field enables us to identify errors in the labeling data process, thereby allowing us to correct data and create a solid foundation for the training of ML models.

3. Methodology

In previous work [4, 5] the ML classification models are designed for the identification of irrigated fields by using Sentinel-2 satellite imagery data. The models are created for three different crops of interest: maize, soybean, and sugar beet in the Vojvodina region (Serbia). From the ML classification task perspective, the training phase of the ML models was challenging due to the uneven number of irrigated and non-irrigated fields. For tackling the imbalanced distribution of the target variable, are used ML models capable of handling such data. Namely, the Random Forest (RF) model is used with incorporated class weights into the learning process of each base decision tree model. In general, a single tree-model is considered as interpretable by its nature due to the possibility of nice tree structure visualization. However, having an ensemble model composed of many trees hinders the model's interpretability. The xAI methods can provide explanations of model decisions with a certain level of detail, making ensemble systems more understandable and transparent. In our work a post-hoc approach is used, where the explanations are provided after the ML models are trained. More precisely, the SHAP method [3] is applied for the RF model among different crops, thereby creating local explanations at the sample (pixel) level. To provide crop-specific explanations, the local explanations are aggregated per crop, while for field-specific explanations, field-based aggregation is used. The crop-specific and field-specific explanations are calculated as the mean absolute value for each feature on the pixels belonging to the same crop and field, respectively.

4. Discussion

Today successful integration of ML models into real-world applications requires the inclusion of the xAI methods to provide an understanding into the decision-making process. In the context of ML detection of irrigated fields, the inclusion becomes a prerequisite for the responsible, ethical, and effective implementation of precision agriculture. By providing explanations using SHAP method on the ML models for detecting irrigated fields, our work demonstrates that xAI methods can serve as a valuable tool, for understandable explanations of the driving forces of the model's decisions that are crop-specific and field-specific. Comprehending the most influential factors that drive decisions of the model on both levels enhances the transparency of the model. The results obtained show that for soybean and maize, the decision-making process of the ML models deviates from human reasoning indicating where further refinement of the ML model is needed. In contrast, a more reasonable classification of irrigated fields is achieved for sugar beet. Field-specific explanations revealed errors in the labeling data process, thereby allowing data corrections and the creation of more valid data for the training of ML models. Our study shows how xAI can help us validate the model's predictions and obtain valuable insights for further refinement of the ML models in order to provide more robust and accurate models for diverse agricultural landscapes. Besides, the xAI ensures that stakeholders can trust the model's decisions which is particularly important in agriculture where further human decisions can impact crop yield and water resource utilization. Therefore, integration of the xAI can be helpful for the widespread adoption of technology in precision agriculture.

References

[1] Chen H, Yang L, Wu Q. (2023) “Enhancing Land Cover Mapping and Monitoring: An Interactive and Explainable Machine Learning Approach Using Google Earth Engine.” *Remote Sensing*. 15(18):4585. https://doi.org/10.3390/rs15184585

[2] Benyamin Hosseiny, Abdulhakim M. Abdi, Sadegh Jamali, (2022) “Urban land use and land cover classification with interpretable machine learning – A case study using Sentinel-2 and auxiliary data”, *Remote Sensing Applications: Society and Environment*, Volume 28, ISSN 2352-9385, https://doi.org/10.1016/j.rsase.2022.100843.

[3] Lundberg, S.M. and Lee, S. (2017) “A Unified Approach to Interpreting Model Predictions.” *Advances in Neural Information Processing Systems 30.* pp. 4765–477. Curran Associates, Inc.

[4] Radulović, M., Brdar S., Pejak B., Lugonja P., Pajević N., Pavić D., and Crnojević V.. (2023). “Machine Learning-Based Detection of Irrigation in Vojvodina (Serbia) Using Sentinel-2 Data.” *GIScience & Remote Sensing* 60 (1). Taylor & Francis. doi:10.1080/15481603.2023.2262010.

[5] Radulović, M., Pejak, B., Pandžić, M., Brdar, S., Athanasiadis, I. N., Pajević, N., Kopanja, M., Lugonja, P., & Crnojević, V. (2023). “Earth Observation and Machine Learning for estimating the irrigation potential of municipalities in Vojvodina, Serbia.” In 39th International Symposium on Remote Sensing of Environment (ISRSE39): "From Human needs to SDGs" https://doi.org/10.5281/zenodo.7920674