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Decision support system for crop damage estimation based on waterlogging detection using synergy of remote sensing and machine learning

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Decision support system for crop damage estimation based on waterlogging detection using the synergy of remote sensing and machine learning

Abstract: Agriculture, the backbone of the economy, faces numerous challenges, with waterlogging being a prominent threat to crop yield. Traditionally, detecting waterlogged areas in agricultural fields has relied on ground observation techniques, which are often time-consuming and prone to imprecision. Remote sensing technology has emerged as a pivotal tool in agricultural monitoring, offering extensive data on land surface conditions. In this paper, we propose a pixel-based decision support system that identifies waterlogged areas in agricultural fields, utilizing remote sensing data and machine learning. The model inputs include a range of crop types and parcel polygons that assist in delineating vegetation regions and identifying areas impacted by waterlogging. Employing Sentinel-2 satellite data, the machine learning model is trained with a dataset that spatially distinguishes these conditions. To further refine the model's ability to differentiate between vegetated and waterlogged areas, 20 vegetation indices are computed, thereby enhancing its accuracy. With this proposed method the model achieved a precision of 0.9. The fusion of this model with detailed crop classification and yield prediction maps facilitates a precise estimation of the damage caused by waterlogging.

Keywords: Waterlogging detection, machine learning, Sentinel-2, damage estimation.

1. Motivation

The motivation behind this research stems from the critical need for advanced tools and methodologies to address waterlogging issues in agricultural land. Waterlogging adversely affects crop health, leading to yield losses and economic setbacks for farmers. Traditional methods for waterlogging detection often lack precision and timely information. The objective of this study is to bridge this gap by integrating remote sensing and machine learning techniques to provide a more accurate and efficient solution for identifying and assessing waterlogged areas in agricultural fields.

In pursuit of the objective of enhancing waterlogging management in agricultural settings, we leverage the capabilities of Sentinel-2 satellite imagery for crop classification and damage estimation. The Sentinel-2 mission, operated by the European Space Agency (ESA), provides high-resolution, multispectral images that are invaluable for monitoring and analyzing various land features, including agricultural landscapes. Sentinel-2's multi-spectral sensors capture data in different bands of the electromagnetic spectrum, allowing us to discern subtle variations in vegetation health, moisture content, and overall crop conditions. This richness of information becomes particularly crucial when addressing waterlogging-related challenges, as it enables us to detect and differentiate between healthy crops and those affected by excessive water accumulation.

Machine learning algorithms play a pivotal role in processing and interpreting Sentinel-2 imagery for crop classification and damage estimation [1]. By training these algorithms on diverse datasets that encompass varying degrees of waterlogging stress which could be empowered to recognize patterns indicative of compromised crop health [2]. This approach not only facilitates accurate identification of waterlogged areas but also enables us to assess the extent of damage incurred by the crops.

The proposed method represents the integration of machine learning with Sentinel-2 imagery and offers a real-time monitoring solution. This timely information is invaluable for farmers, agricultural authorities, and policymakers, allowing them to make informed decisions promptly.

Whether it involves implementing drainage strategies, adjusting irrigation practices, or initiating crop recovery measures, this approach aims to provide actionable insights to mitigate the impact of waterlogging on crop yield and overall agricultural productivity.

2. Research questions

The specific problem addressed in this work revolves around the limitations of existing methodologies for waterlogging detection. Many approaches lack the precision required which is based at the field level. This paper investigates how the integration of crop types, Sentinel-2 images, and vegetation indices can enhance the accuracy of waterlogging detection. On the other hand, some works are related to the combination of field and remote sensing data, such as the approach provided by B Bukombe et al. (2023) [3], with dependencies of integration sensors in the field. In a study conducted by YW Yang et al. (2018) [4], the focus lies on employing hyperspectral data and machine learning techniques for the identification and categorization of waterlogging stress levels in oilseed rape crops. This research holds relevance for the swift estimation of crop damage. Y Wang (2019) [5], in a paper, introduces an approach that utilizes remote sensing data and machine learning methods to effectively distinguish waterlogged regions within crop fields. This method is pivotal for accurately estimating losses due to waterlogging in agricultural settings. In a more recent study by J Zhao et al. (2021) [6], a novel technique is developed for detecting waterlogging stress in cotton crops using hyperspectral imagery and convolutional neural networks. This research harnesses deep learning to identify early signs of waterlogging in cotton, thus facilitating yield estimation and loss assessment.

3. Methodology

In our proposed methodology, we leverage a diverse range of data sources to significantly enhance waterlogging detection in agricultural fields. At the point of this approach is the use of crop types as the foundational input layer, allowing us to establish parcel boundary polygons that provide the essential spatial context within agricultural areas. Within these delineated parcels, we briefly identify and extract waterlogged areas. To enrich our dataset further, we harness spatial vector data of these parcel boundaries to crop Sentinel-2 satellite images, from which we extract essential multispectral band feature values. We carefully select a specific period following substantial precipitation events, during which waterlogging typically occurs in agricultural parcels lacking adequate drainage networks. This strategy of timing ensures that we capture waterlogging instances at their developmental stage. Our machine learning model, predominantly based on Sentinel-2 satellite imagery, is then trained using this spatially enriched dataset. To enhance the model's ability to differentiate between vegetation and waterlogged regions, we calculate and incorporate 20 vegetation indices as additional inputs. Moreover, we employ the Corine layer to exclude non-arable land, thus refining the analysis to focus solely on agriculturally relevant areas. Moreover, we discard areas such as permanent water bodies, urban areas, and forests, which are not pertinent to our waterlogging assessment, employing the same layer for this purpose. This comprehensive approach harmoniously combines the strengths of remote sensing and machine learning. By assimilating multi-source data and spatial context, it offers a refined and nuanced understanding of waterlogging dynamics within agricultural landscapes. Ultimately, this methodology empowers the community to make more accurate and informed decisions regarding waterlogging management, thereby contributing to improved crop yield and agricultural sustainability.

4. Solution/Discussion

The provided solution involves the successful integration of crop classification, Sentinel-2 imagery, and vegetation indices to improve waterlogging detection accuracy. The machine-learning model trained on this combined dataset demonstrates enhanced performance in identifying waterlogged areas within agricultural fields. The calculated vegetation indices contribute to the model's discriminative power, allowing for more accurate differentiation between healthy vegetation and waterlogged regions. Additionally, our methodology facilitates the estimation of damage by generating detailed crop classification and yield maps for specific crop types. This paper contributes to the current state-of-the-art by presenting a holistic and effective approach to remote sensing and machine learning synergy for enhanced waterlogging detection in agricultural areas.

In summary, our research endeavors to harness the potential of Sentinel-2 satellite imagery and machine learning algorithms to revolutionize waterlogging management in agriculture. By advancing the accuracy and efficiency of crop classification and damage estimation, this study aspires to empower stakeholders with the tools they need to address waterlogging issues proactively and sustainably, ultimately contributing to the resilience and prosperity of the agricultural sector.

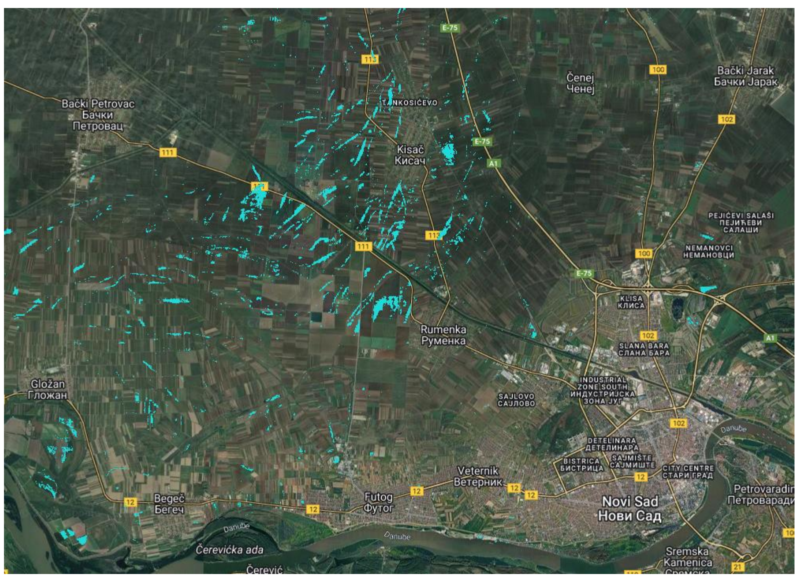

Figure 1: Output of the model where the blue
color represents waterlogged areas in the agriculture fields.

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