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Strategy To Automatically Detect Agricultural Parcels With Abnormal Agronomic Development

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ABSTRACT

Using an unsupervised outlier identification method, this research investigates the detection of abnormal crop growth at the parcel level. Rapeseed and wheat fields in India are used for the experimental validation. The suggested approach may be broken down into four distinct phases: Using data from the Sentinel-1 and Sentinel-2 satellites, we perform four steps: (1) preprocessing; (2) extracting pixel-level features from the SAR and multispectral data; (3) computing parcel-level features using zonal statistics; and (4) detecting outliers.

KEYWORDS: unsupervised, identification, preprocessing, multispectral

INTRODUCTION

This research tackles an intriguing open problem in precision agriculture: how to automatically recognize crop plots with abnormal vegetation growth. Subsidy control and agricultural insurance are two possible uses. The Normalized Difference Vegetation Index (NDVI) is a satellite-based data series that may be used to locate potentially abnormal patches of plant life throughout the country. The goal of these methods is to forecast future NDVI values based on past measurements, hence allowing for anomaly detection. S1 and S2 data have been used in recent research that explored comparable methods. Using BFAST to identify irregularities in land usage.

First, the research takes the time to systematically describe the anomalous parcels that have been found. From here on out, parcels of farmland whose agronomic behavior deviates noticeably from the norm are labeled as anomalous (true positives). It is also regarded a genuine positive to find errors in the parcel data (such as incorrect crop types recorded or improperly drawn field borders). However, false positives are regarded to be noise or abnormalities that are irrelevant to crop monitoring (such as unseen clouds) since they are of little service to the end user.

LITERATURE REVIEW

David Christian Rose et.al (2018) Policymakers all across the globe are encouraging a technological revolution in the agricultural sector. Critics have argued that the social ramifications of smart technologies like AI, robots, and the Internet of Things are being overlooked, despite the fact that they might play a significant role in increasing both productivity and eco-efficiency. Studies have shown that some farmers are hesitant to adopt new smart technology because of safety concerns. Therefore, we urge policymakers, funders, technology firms, and academics to take into account the perspectives of both agricultural communities and broader society. Although two recent studies have offered helpful recommendations, the idea of responsible innovation in agriculture has not been generally discussed. Our proposal applies the four principles of responsible innovation anticipation, inclusivity, reflexivity, and responsiveness to the present agricultural revolution, therefore expanding the scope of these interventions. Our research suggests, however, that responsible innovation principles might need some honing to make them more widely applicable and robust in the face of rising agri-tech, and that frameworks need to be put to the test in the real world to determine whether they can actively affect innovation trajectories.

Marcos A. Lana et.al (2017) When it comes to alleviating poverty and feeding the continent's hungry, agriculture is Africa's best hope. Tanzania, like many other nations in sub-Saharan Africa, has vast untapped agricultural and natural resource potential. However, unpredictable and variable weather, particularly rainfall, is one of the most significant challenges confronting Tanzania's agricultural economy. Sowing the crop before the start of the rainy season is one way to deal with climatic unpredictability in semi-arid locations. The benefit is that the seeds are already in the ground and can start germinating as soon as the rains begin. In light of climate change, this paper set out to assess the potential of dry-soil planting for maize in Dodoma, a semi-arid region of Tanzania. This analysis made use of the DSSAT crop model and climate scenarios based on typical concentration routes. More than 80% of crops fail when planted between the first of November and the middle of December. The substantially lower chance of crop failure in the subsequent planting window we assessed, commencing on the 23rd of November, demonstrates that sowing prior to the start of the rainy season is a feasible adaptation strategy. The results also showed that areas prepared for dry-soil planting had sufficient quantities of maize grain, while not attaining the best possible yields. Farmers may mitigate the effects of low rainfall by increasing their chances of harvesting at least part of their fields via the practice of dry planting on several plots. We draw the conclusion that dry-soil planting is a reasonable and effective strategy, even under extreme weather conditions, for producing adequate yields of maize in Tanzania's semi-arid regions.

Rong-Kai Wang et.al (2014) The results demonstrate that germination of MdSIMYB1 transgenic tobacco seeds was unaffected by abscisic acid or NaCl treatment. At long last, we have some transgenic apple lines to try out. Increased tolerance to abiotic stress was seen in transgenic apple lines overexpressing MdSIMYB1, but tolerance was reduced in lines where MdSIMYB1 had been suppressed. Based on our findings, Stress tolerance in economically important crops may benefit from targeting MdSIMYB1.

Lila Warszawski, et.al (2013) The Inter-Sectoral effect Model Intercomparison Project provides a framework for comparing sector-specific and scale-specific forecasts of climate change's effect. Integrating effect forecasts across sectors requires consistent climatic and socioeconomic input data. This work will allow for a quantitative synthesis of the effects of climate change at varying degrees of warming. This study gives a high-level overview of the worldwide impact models used in the first phase of the Inter-Sectoral Impact Model Intercomparison Project and describes the goals and structure of the project.

METHODS

Figure 1 depicts the four-step sequential technique central to the suggested method for identifying aberrant crop growth, which is unpacked in more depth below. Methods for describing and assessing the detection outcomes are also offered.

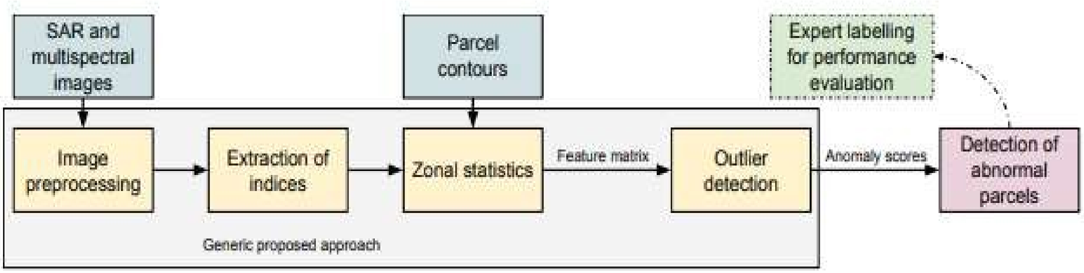

Figure 1. A flowchart describing the research process for identifying abnormal crop growth.

Image Preprocessing

The S2 images were preprocessed using the CNES PEPS platform with the help of the MAJA processing chain, which is accessible online. In terms of surface reflectance, this processing stage yields ortho-rectified results at level 2A. Images of the level-2A quality include both atmospheric correction and a cloud and shadow mask that may be used to filter out unwanted details. After resampling, the channels with a lower spatial resolution now have a resolution of 10 m. Data from parcels that were partially hidden by clouds at any given time was deleted from the database and analyzed using pixels that were not part of the cloud mask.

The Sentinel Application Platform was used in an offline processing to compile the S1 picture database. The approach described here was conceived after reading Filipponi's suggested procedure. Since the examined region is large and parcel characteristics are compared to one another, In order to account for local incidence angles, a Terrain-Flattening mechanism was put into place. The DEM was created using information gathered during the Shuttle Radar Topography Mission. Orthorectified pictures are produced through Range Doppler terrain correction. There were no appreciable changes in the outcomes when we tested a multi-temporal speckle filtering stage as well. Figure 2 shows the optimal process flow that yielded the greatest outcomes.

Figure 2. Sentinel-1 processing chain used in the Sentinel Application Platform (SNAP).

The importance of the multispectral and SAR image pixel-level properties derived in this work is explained in more detail below. Since unsupervised algorithms use all of the data at their disposal, it was shown that picking irrelevant characteristics might result in subpar detection performance. It is also crucial to choose characteristics with well-defined roles so that, after analysis and in real-world contexts, it is clear why an irregularity was detected.

Table 1. pixel-level characteristics calculated from S2 and S1.

Sensor Type	Indicator	Formula
Multispectral	NDVI	$(\mathrm{NIR}-\mathrm{RED})/(\mathrm{NIR}+\mathrm{RED})$
	$\mathrm{NDWI}_{\mathrm{SWIR}}$	$(\mathrm{NIR}-\mathrm{SWIR})/(\mathrm{NIR}+\mathrm{SWIR})$
	$\mathrm{NDWI}_{\mathrm{GREEN}}$	$(\mathrm{GREEN}-\mathrm{NIR})/(\mathrm{GREEN}+\mathrm{NIR})$
	MCARI/OSAVI	$((\mathrm{RE}-\mathrm{IR})-0.2\times(\mathrm{RE}-\mathrm{RED}))/\left((1+0.16)\times\frac{\mathrm{NIR}-\mathrm{RED}}{\mathrm{NIR}+\mathrm{RED}+0.16}\right)$
	GRVI	$(\mathrm{GREEN}-\mathrm{RED})/(\mathrm{GREEN}+\mathrm{RED})$
SAR	Cross-polarized backscattering coefficient VH	γ^0_{VH}
	Co-polarized backscattering coefficient VV	γ^0_{VV}

Multispectral Vegetation Indices

There are a plethora of multispectral Vegetation Indices (VIs) available now (see, for example). Better quantitative and qualitative assessments of vegetation may be made thanks to a VI's ability to establish a connection between the obtained spectral information and the seen vegetation. In this study, we report on and discuss five different multispectral VIs, which may be found in Table 2. Raw S2 bands were also evaluated, but they did not outperform VIs in terms of detection accuracy and proved to be more difficult to understand.

Standard agronomic evaluations often use the normalized difference vegetation index (NDVI). There are two common metrics that both go by the name "Normal Difference Water Index" (NDWI). The second iteration utilizes the green band and NIR to track variations in water-related material. While both methods require distinct bands, they are conceptually comparable to the NDVI. Crop analysis may benefit more from the SWIR version of NDWI, however the GREEN version of NDWI may still be useful in some situations (such as for flooded parcels). To reduce the effect of ambient reflectance, MCARI/OSAVI makes use of the Optimized Soil Adjusted Vegetation Index (OSAVI). The Greenhouse Gas Vegetation Index (GRVI) "can be a site-independent single threshold for detection of the early phase of leaf green-up and the middle phase of autumn coloring".

Two recent reviews detail the many studies that have been conducted to find evidence of a connection between SAR pictures and vegetation. The literature makes extensive use of the backscattering coefficients. The polarization ratio 0 VH/0 VV, which has been utilized in other research, was also evaluated, although it did not significantly enhance results. In this article, we have used the backscattering coefficients shown in Table 1 to derive our findings.

DATA ANALYSIS

Abbreviations described in Table 2 are used in the figures to label the various feature combinations evaluated here.

Table 2. "S2: pixel-level features (parcel-level statistics), S1: pixel-level features (parcel-level statistics)".

Abbreviated Name	Features Used
S1: VV, VH (median)	Median of S1 features listed in Section 3.2
S2: all (median/IQR)	Median and IQR of all S2 features listed in Section 3.2
S2: all (median/IQR), S1: VV, VH (median)	Median and IQR of all the S2 features and median of the 2 S1 features VV and VH.

In this part, we show the results of an IF analysis performed on the whole rapeseed dataset. Due to the critical need of having access to data during the whole crop cycle, SAR data is used only for the outlier identification process. Then, the outcome of relying only on S2 traits is examined. Finally, a combined S1 and S2 feature set is employed to investigate the impact of sensor fusion.

Outlier detection with S1 features

Figure 3 (black curve) demonstrates the reliability of S1 data for crop anomaly identification, with an accuracy of 92.3% at a constant outlier ratio of 10%. S1 features provide somewhat greater accuracy than S2 features do for lower outlier ratios. Precision falls as the outlier ratio rises, but stays around 85% for an outlier ratio of 20%. These findings demonstrate that the IF algorithm is capable of generating useful outlier ratings, with the parcels that received the highest outlier scores being the most likely to represent genuine anomalies. The discovered parcels' distribution in the various anomaly categories is shown in Figure 3.21(a). Also often found are irregularities in databases. The percentage of found parcels is shown in Figure 3.21(b) for each classification, allowing for further examination of these data. Since this anomaly has such a profound effect on the characteristics at the parcel level, it is not surprising that all parcels in the category incorrect type are identified. More incorrectly shaped packages may be found when employing S1 features as opposed to S2 ones. The same may be said, to a lesser extent, for abundant yields and early flowering.

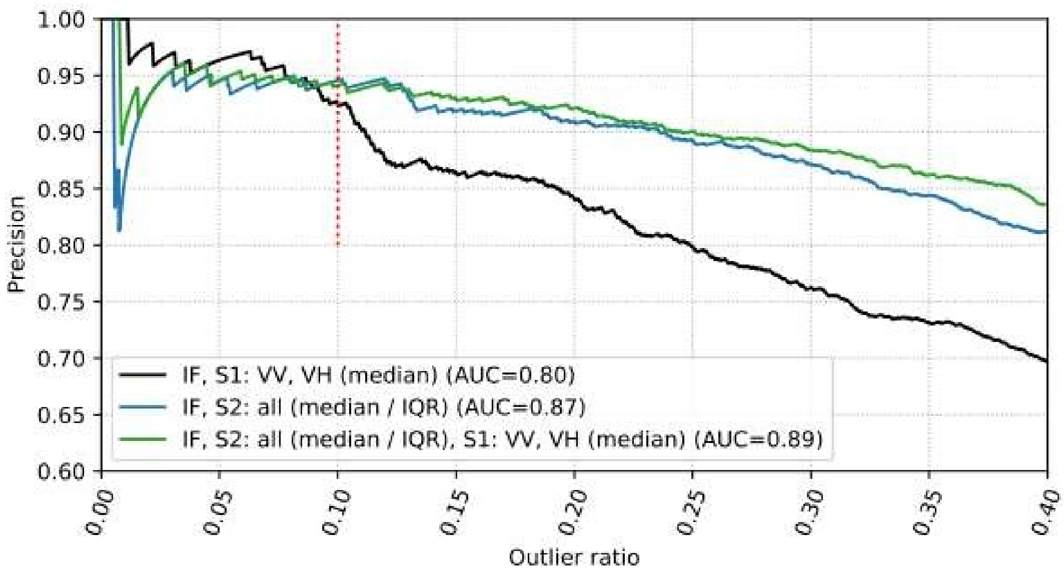

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Figure 3: Precision vs. outlier ratio using the IF algorithm on the rapeseed parcels.

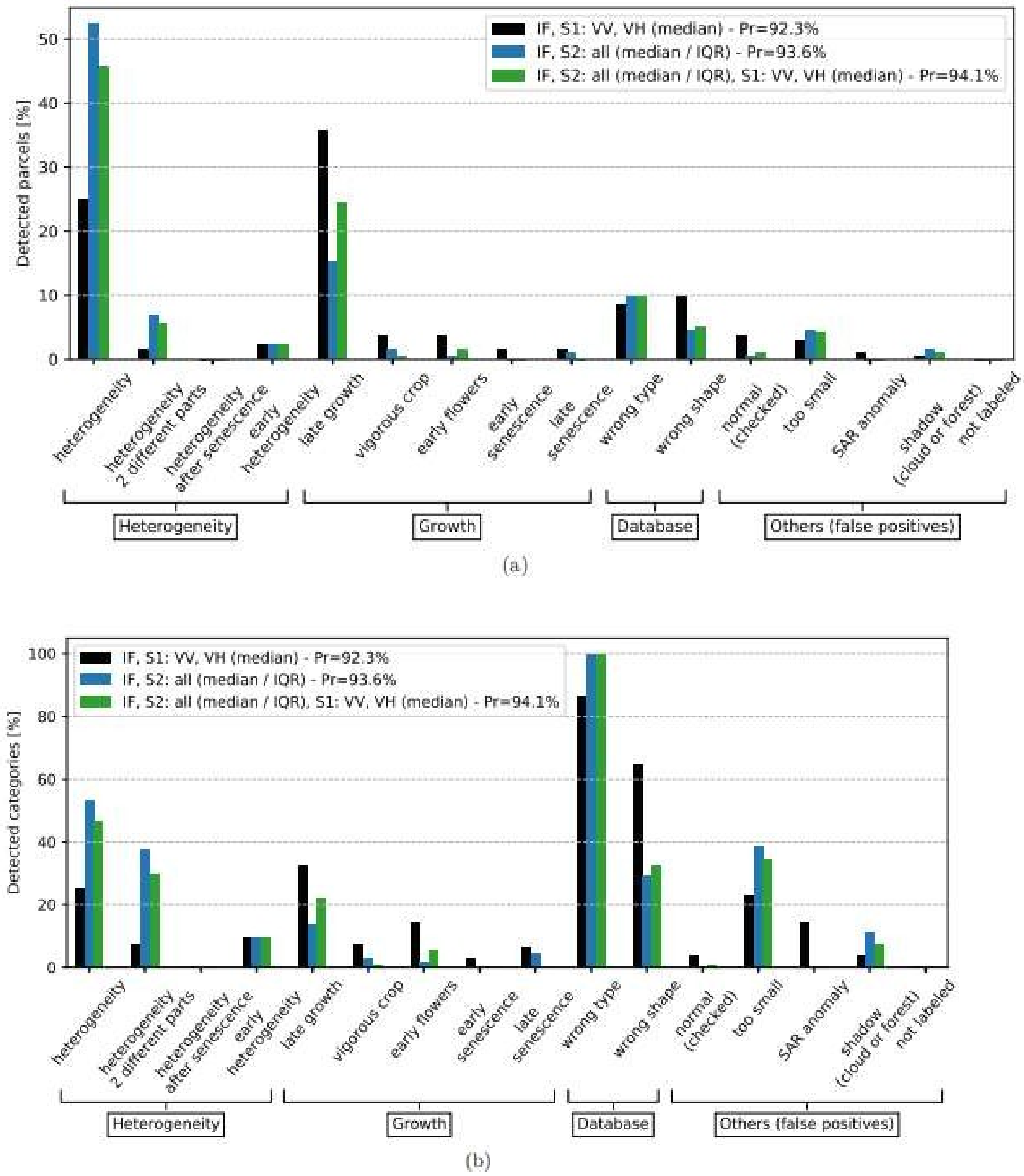

Figure 4: rapeseed parcels with an outlier ratio equal to 10% and the IF algorithm.

Outlier detection with S2 features

As illustrated in Figure 3 (blue curve), S2 time series are effective for outlier analysis despite having poorer temporal resolution than S1 time series. Using just S2 characteristics, the detection accuracy remains at above 90% even when the outlier ratio is set at 20%. The average accuracy for outlier ratios in the range [0, 0.5] is 87%, but it is only 80% when just S1 features are used. The bulk of important irregularities may be detected with only 13 S2 photos for a whole growth season. Figure 4(a) shows that S1 and S2 characteristics seem to recognize various kinds of outliers. The IF method discovers more heterogeneous (52% of the time) and fewer late growth (15%) parcels when S2 characteristics are included. This finding provides support for combining S1 and S2 traits, as will be explored later. Figure 4(b) demonstrates that

S2 features can identify 40% of the parcels impacted by two-part heterogeneity (whereas S1 features can only detect 10% of the parcels). Furthermore, as compared to when S1 features are used, S2 features are able to identify almost 40% more too-small shipments. This last finding has to be placed in context with the low percentage of discovered packages that fall into this category (less than 5 percent).

Outlier detection with S1 and S2 features

The potential of combining S1 and S2 for outlier detection in agricultural crops is one of the primary motivations for this study. This indicates that, compared to employing either S1 or S2 characteristics alone, For a certain outlier ratio, more significant abnormalities are identified. Positive implications include the IF algorithm's ability to use sensor-specific information. As can be seen in Figure 4(a), combining S1 and S2 characteristics is an effective way to take into consideration the value contributed by both sensors. In particular, more heterogeneous parcels and late growth anomalies are identified when S1 and S2 characteristics are combined rather than each used alone. As seen in Figure 4(b), these findings are reliable.

Using S1 and S2 traits together is the best combination of features found throughout the investigation. The strengths of both sensors are used in this setup for crop monitoring. To be more precise, the S1 sensor is insensitive to the hue of agricultural parcels, therefore the presence of certain heterogeneous parcels does not affect the characteristics derived from these photos. However, Because they are more sensitive to changes in vegetation, S1 time series are better at revealing the effects of anomalies on agricultural production. Given the abundance of S1 time series, it may be simpler to spot issues with late growth or senescence (as was indicated for the study of a wheat crop, for which only a small number of S2 photos were available during the senescence period). Analysis of a different kind of crop confirms these findings.

CONCLUSION

This paper investigated the use of S1 and S2 photos for outlier analysis at the parcel level as a novel anomaly detection tool for crop monitoring. There are primarily four stages to this procedure: Paper 2 describes the first step, which is multispectral and SAR image preprocessing; The second stage is to calculate the pixel features, and the third step is to calculate the zonal statistics at the parcel level for all the pixel features on each date. fourthly, using the retrieved characteristics and the Isolation Forest method, we look for odd agricultural patches. The suggested approach requires no training data and is completely unsupervised. This paper demonstrated that S1 and S2 characteristics work in tandem to identify anomalous produce shipments. It is recommended that median statistics be used for S1 features, and that these be computed at the parcel level using VV and VH backscattering coefficients.

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