Research Internship Abroad (BEPE/FAPESP)

Remote Sensing Anomaly Detection in Time-Series Imagery and Application Development in the Agricultural Context

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Brazil Advisor: Dr. Rubens Augusto Camargo Lamparelli
UK Supervisor: Dr. Jefersson Alex dos Santos
UK Co-Supervisor: Prof. Po Yang
Fellow: Fernando Kenzo Imami Fugihara

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Abstract

The use of plastic in agriculture has increased significantly in recent years, bringing both benefits and environmental challenges. While agricultural plastics improve crop yields and resource efficiency, they also lead to the accumulation of plastic waste in rural areas. Remote Sensing (RS) data, combined with advanced machine learning and computer vision techniques, provide an effective means to monitor plasticulture dynamics. Therefore, this research internship aims to explore RS anomaly detection (RSAD) techniques in time-series imagery and apply them to agricultural monitoring, particularly in detecting subtle cases that involve spectral changes such as material deterioration and pest-related disturbances Therefore, I'll join researchers at the University of Sheffield to learn RSAD techniques in the agriculture context and then explore whether they can be applied in plasticulture. In parallel, I'll collaborate with researchers at the University of Sheffield and contribute to the PEZEGO pest-management app. The internship will provide hands-on experience in scalable application design, app optimization, and model integration, which can enhance our ongoing application, GeoHuman. The University of Sheffield was chosen due to its internationally recognized expertise in application development, machine learning, computer vision, and remote sensing. This experience will strengthen our project in Brazil by improving the accuracy and scalability of agricultural monitoring systems. Upon my return, I will disseminate the knowledge gained through workshops and collaborative activities with my research group at UNICAMP to foster innovation and capacity building in remote sensing applications.

This report summarizes the activities and outcomes of the research internship conducted from December 01, 2025 to March 01, 2026. The internship focused on remote sensing anomaly detection in time-series imagery and the development of applications in the agricultural context. Key achievements include the implementation of novel algorithms for anomaly detection, analysis of time-series data.

1 Introduction

2 Methodology

2.1 Short Review of Methods (December, 1st - January, 1st)

In this project the focus is on detecting anomalies on the agricultural fields, in particular, the use of pest-net in the plasticulture fields, and the pest-attacks in the crops. Given this context, methods of anomaly detection in time-series imagery can be used to detected these devitations. Therefore, a short review of these RSAD methods was made to selected and therefore study how to approach this problems.

2.2 Sensors and Study Regions

We'll be using the Harmonized Sentinel-2 (S2) Level-2A surface reflectance images, accessed via Google Earth Engine (GEE) (Google 2023). The Copernicus Sentinel-2 mission features two polar-orbiting satellites (2A and 2B) in a sun-synchronous orbit at an altitude of 786 km, phased 180° apart, which enables a 5-day revisit at the equator under cloud-free conditions, extending to 2–3 days at mid-latitudes.

The study area is located in Mossoró, Rio Grande do Norte, Brazil, where previous field assessments and local expertise provide a solid foundation for this research. The region is particularly notable for its extensive use of plasticulture in melon cultivation, making it a relevant and representative site for analyzing agricultural land-cover dynamics. Additionally, pest-management practices, such as the use of pest nets, are commonly employed to protect melon crops. Field observations conducted by the research team also confirmed that plastic mulch is often reused across multiple cultivation cycles, resulting in areas with visibly deteriorated plastic materials. Figure 1 illustrates the landscape of the study region.

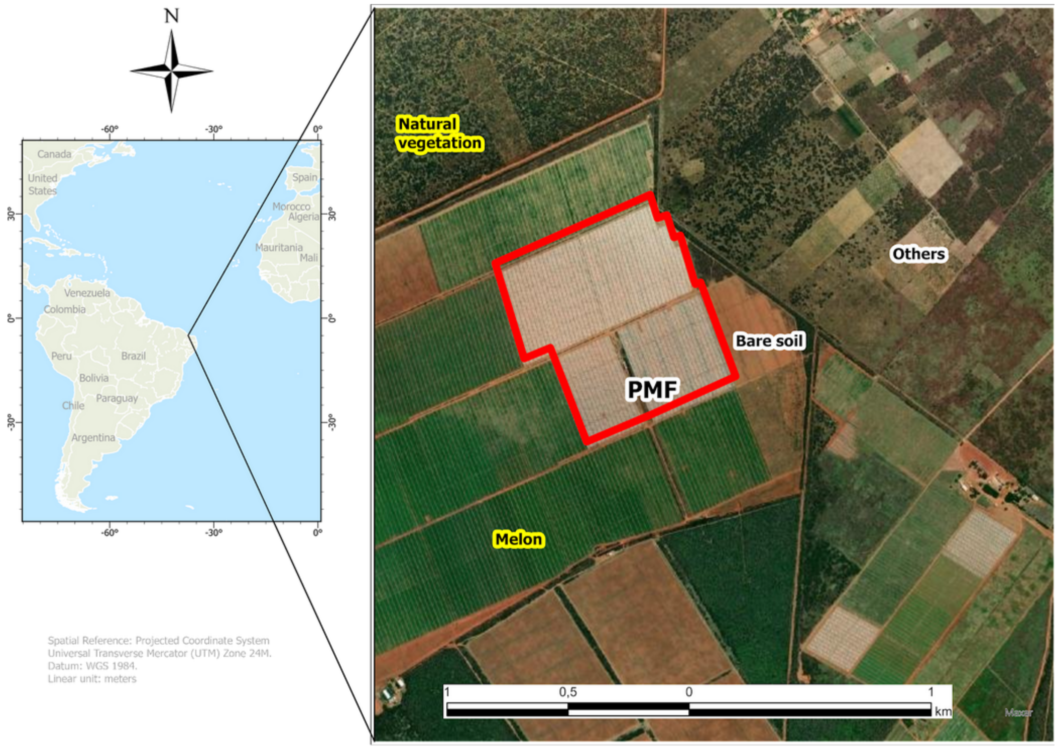

Figure 1: Mossoró region of study, Brazil, Rio Grande do Norte.

The second study area is located in Ejura, Ghana, West Africa. The region is characterized by a wide diversity of crops, including plantain, maize, yam, rice, beans, cassava, groundnuts, and watermelon. This agricultural diversity makes Ejura a suitable region for studying and detecting crop anomalies, such as pest attacks. In particular, the region is highly relevant due to the study conducted by Bilintoh et al. (2019), which investigated the impact of Armyworm infestations on crops with field validation. Furthermore, this study area aligns with the objectives of the ongoing Brazil–UK–Africa collaboration known as "SmartPest-Ghana: Exploring LLM-driven mobile solutions for climate-smart pest management in maize farming", funded by UK Research and Innovation (UKRI). This project represents a recently established short-term partnership between Brazilian and UK research groups and provides a strong contextual and scientific foundation for the selection of Ejura as a study area. Figure 2, presents the landscape of the Ejura study region.

Figure 2: Ejura region of study, Ghana, West Africa.

2.3 Time-Series, Geographical and Phenological Aspects

In this project, we'll be using time-series imagery from Sentinel-2 satallite. Where the atomic unit is a single pixel observed through time. In time-series, we have the univariate time-series (UTS) and the multivariate time-series (MTS).

A **UTS** is a series of data that is based on a single variable (such as NDVI) that changes over time, Therefore, the UTS X with t timestamps (**for a single pixel**) can be represented as an ordered sequence of data points in the following way (Zamanzadeh Darban et al., 2024):

$$X = (x_1, x_2, ..., x_t)$$

Where x_i represents the feature (NDVI) at timestamp $i \in T$ and $T = \{1, 2, \ldots, t\}$.

A **MTS** represents multiple variables that are dependent on time, each of which is influenced by both past values (*temporal* dependency) and other variables (dimensions) based on their correlation. The correlations between different variables are referred to as spatial dependencies in the literature.

Consider an MTS represented as a sequence of vectors over time, each vector at time i,

X_i, consisting of d dimensions:

$$X = (X_1, X_2, \ldots, X_t) = \Big((x_1^1, x_1^2, \ldots, x_1^d), (x_2^1, x_2^2, \ldots, x_2^d), \ldots, (x_t^1, x_t^2, \ldots, x_t^d)\Big) \tag{1}$$

Where $X_i = (x_i^1, x_i^2, \ldots, x_i^d)$ represents a data vector at time i, with each x_i^j indicating the observation at time i for the jth dimension, and $j = 1, 2, \ldots, d$, where d is the total number of dimensions.

2.3.1 Armyworm Life Cycle

When the pest begins and ends its life cycle. How long it lasts. Using two-week series considering that the pest lasts 3 months. Test different time windows.

Armyworm entire phenological cycle is from April to September of 2017 (Bilintoh et al., 2019).

2.3.2 Clustering Time Window

A pratical use of this research is to alert to the farmers about a possible pest attack in their crops. In order to this, we need a way to detect the pest infestation as quick as possible, for example, let's say that the

2.4 Time Series Basic Structure

There're four important structure concepts of time-series which are very important to understand time-series and its smoothing methods.

2.4.1 Stationary

A stationary time-series is a sequence of data where statistical properties of the series do not change over time. In other words, if the mean, variance and covariance of a time series remain constant over time, the series is said to be stationary.

2.4.2 Trend

It is the structure of the long-term increase or decrease of a time series. If there is a trend, it is very unlikely that the series will be stationary because the statistics of the periods (mean, standard deviation, etc.) will change in an increasing or decreasing trend.

2.4.3 Seasonality

Seasonality is when a time series repeats a certain behavior at certain intervals.

2.4.4 Cycle

It contains repetitive patterns similar to seasonality and these two issues can be confused with each other. Seasonality can be mapped to specific time periods. It overlaps with structures such as day, week, year, season. For example, markets do more business on weekends or a product gets more attention in winter, etc. The cyclicity takes place in a longer time, in a more uncertain structure, in a way that does not overlap with structures such as day, week, year, season. It occurs mostly for structural reasons, with cyclical changes. For example, it is shaped by the speeches of some people from the business world and the speeches of politicians. Although this i s not completely seasonal, it occurs in a certain period, but the period in which it will occur is not clear.

2.5 Time-series Smoothing

With Jefersson I've got contact with different time-series smoothing methods. Those are very useful to extract more information of the series and avoid some common mistakes when analysing the data smoothing techniques are kinds of data preprocessing techniques to remove noise from a data set. This allows important patterns to stand out.

For example, let's say we have two pixels with different time series responses, where one series in like a sine and the other like a cosine. If we decide to utilize in this series a clustering algorithm which is based on the distance between these values, the difference will be high, but in reality the distance is not that, but because the data is noisy it creates this misconception. Therefore, is really important to use time-series smoothing when utilizing time-series.

There are several time-series smoothing techniques such as Moving Average Smoothing, Weighted Average Smoothing, Single Exponential Smoothing (SES), Double Exponential

Smoothing (DES), Triple Exponential Smoothing (TES) among others. Their use depends on the time-series structure, as presented in Table 1.

Table 1: Smoothing Algorithm usecases in different time-series structures

Algorithm	**Level**	**Trend**	**Seasonality**	**Tuning Parameters**
Single HWES	Yes	No	No	α
Double HWES	Yes	Yes	No	α, β
Triple HWES	Yes	Yes	Yes	α, β, γ

Where the Level is the average value of the time-series. The variables used in those methods are presented in Table 2.

Table 2: Variables utilized in the smoothing models

Symbol	**Description**
X	Observation
S	Smoothed observation
B	Trend factor
C	Seasonal index
F	The forecast at m periods ahead
α	Data smoothing factor, $\alpha \in (0, 1)$
β	Trend smoothing factor, $\beta \in (0, 1)$
γ	Seasonal change smoothing factor, $\gamma \in (0, 1)$
ϕ	Damped smoothing factor, $\phi \in (0, 1)$
t	The index that denotes a time period

2.5.1 Moving Average and Weighted Average Smoothing

The future value of a time series is the average of its k previous values. Moving average trading is generally used in practice not for forecasting, but for capturing/observing a trend. However, while deriving features within the scope of machine learning, we are still generating features based on moving averages. Similar to a moving average. Weighted average carries the idea of giving more weight to later observations.

Although this methods are very useful, they cannot be used in our context because they do not consider trend and seasonality, which are present in our satelite time-series.

2.5.2 Single Exponential Smoothing (SES)

SES = Level (Unsuccessful if Trend and Seasonality).

It is successful only in stationary series. There should be no trends and seasonality. It can model the level(Level can be thought of as the average of the series.). The effects of the past are weighted on the assumption that ”the future is more related to the recent past”. SES is suitable for UTS without trend and seasonality, it is successful in stationary series.

$$S_0 = X_0$$

$$S_t = \alpha X_t + (1-\alpha)S_{t-1}$$

$$\{\, t > 0,\ 0 < \alpha < 1 \,\}$$

2.5.3 Double Exponential Smoothing (DES)

DES = Level (SES) + Trend

The basic approach is the same. In addition to SES, the trend is also taken into account. It is suitable for univariate time series with and without seasonality.

$$S_0 = X_0$$
$$B_0 = X_1 - X_0$$

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + B_{t-1})$$
$$B_t = \beta(S_t - S_{t-1}) + (1-\beta)B_{t-1}$$

$$\alpha, \beta \in (0,1)$$

2.5.4 Triple Exponential Smoothing (TES)

TES = SES + DES + Seasonality

It is the most advanced smoothing method. This method makes predictions by evaluating the effects of level, trend and seasonality dynamically. It can be used in UTS with trend and/or seasonality.

$$S_0,\ F_0 = X_0$$

$$B_0 = \frac{\sum_{i=0}^{L-1}\left(X_{L+i} - X_i\right)}{L^2}$$

$$S_t = \alpha\left(X_t - C_{t \bmod L}\right) + (1-\alpha)\left(S_{t-1} + \phi B_{t-1}\right)$$

$$B_t = \beta\left(S_t - S_{t-1}\right) + (1-\beta)\phi B_{t-1}$$

$$C_{t \bmod L} = \gamma\left(X_t - S_t\right) + (1-\gamma)C_{t \bmod L}$$

$$F_{t+m} = S_t + B_t \sum_{i=1}^{m} \phi^i + C_{t \bmod L}$$

$$\alpha, \beta, \gamma \in (0, 1)$$

2.5.5 Hyperparameter Optimization for TES

2.6 Anomaly Detection Models

2.6.1 Density Estimation

We're going to model a probability density function (pdf), which gives the probability of any given n feature vector. Assuming that $\vec{x}^{(i)}$ are independent from each other, we have that

$$p(\vec{x}) = p(x_1; \mu_1, \sigma_1^2)\, p(x_2; \mu_2, \sigma_2^2)\, p(x_3; \mu_3, \sigma_3^2)\ \cdots\ p(x_n; \mu_n, \sigma_n^2)$$

$$p(\vec{x}) = \prod_{j=1}^{n} p(x_j; \mu_j, \sigma_j^2)$$

For tractability, we assume conditional independence across timestamps, although temporal correlations are known to exist.

2.6.2 Algorithm

1. Choose n features x_i that you think might be indicative of anomalous examples. In our case, the pixel features that could be an indicative of anomalous are the NDVI and EVI, spectral indexes.

2. Fit parameters $\mu_1, \ldots, \mu_n, \sigma_1^2, \ldots, \sigma_n^2$:

$$\mu_j = \frac{1}{m} \sum_{i=1}^{m} x_j^{(i)}$$

$$\sigma_j^2 = \frac{1}{m} \sum_{i=1}^{m} \left(x_j^{(i)} - \mu_j\right)^2$$

$$\vec{\mu} = \frac{1}{m} \sum_{i=1}^{m} \vec{x}^{(i)}$$

3. Given new example $\vec{x}$, compute $p(\vec{x})$:

$$p(\vec{x}) = \prod_{j=1}^{n} p(x_j; \mu_j, \sigma_j^2) = \prod_{j=1}^{n} \frac{1}{\sqrt{2\pi}\,\sigma_j} \exp\left(-\frac{(x_j - \mu_j)^2}{2\sigma_j^2}\right)$$

$$\text{Anomaly if } p(\vec{x}) < \varepsilon$$

2.6.3 Algorithm 2

1. Choose n features x_i that you think might be indicative of anomalous examples. In our case, the pixel features that could be an indicative of anomalous are the NDVI and EVI, spectral indexes.

2. Group pixels exhibiting similar temporal behavior using an clustering. Let each pixel $\vec{x}^{(i)}$ be assigned to a cluster $c \in \{1, \ldots, K\}$.

3. For each cluster c, estimate the parameters of a Gaussian distribution independently for each feature:

$$\mu_j^{(c)} = \frac{1}{m_c} \sum_{i=1}^{m_c} x_j^{(i)}, \quad \sigma_j^{2(c)} = \frac{1}{m_c} \sum_{i=1}^{m_c} \left(x_j^{(i)} - \mu_j^{(c)} \right)^2$$

4. Given a new example $\vec{x}$ assigned to cluster c, compute its likelihood:

$$p(\vec{x} \mid c) = \prod_{j=1}^{n} p(x_j; \mu_j^{(c)}, \sigma_j^{2(c)}) = \prod_{j=1}^{n} \frac{1}{\sqrt{2\pi}\, \sigma_j^{(c)}} \exp\left(-\frac{(x_j - \mu_j^{(c)})^2}{2\sigma_j^{2(c)}} \right)$$

$$\text{Anomaly if } p(\vec{x} \mid c) < \varepsilon_c$$

3 Results and Discussion

4 Conclusion

References

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4.