Optimizing Agricultural Insurance Assessments: A Remote Sensing Framework for Evaluating Flood-Induced Damage

Upendra K.D.H.
Sri Lanka Survey Department
heshaniupendra@gmail.com

1. Introduction

Flooding has become a frequent disaster due to climate change, with its occurrence projected to increase in the future. The impact of floods on food production creates significant issues, including food shortages, economic hardship for farmers and broader socio-economic crises. In developing countries, where farming communities are among the poorest, the effects of floods can be devastating. The land in flood-prone areas often reflects the wealth and status of farmers, making them particularly vulnerable.

To prevent bankruptcy and financial ruin from such events, governments and other authorities have introduced farming loans and agro-insurance schemes. However, one major challenge in implementing these programs is accurately assessing the damage caused by floods. Floods affect crops in various ways, depending on the crop type, growth stage and location. Even within the same area the impact can vary due to cropping patterns and other factors.

Therefore, a reliable method for evaluating flood damage is essential. During floods the conditions are complex, and officials may be occupied with urgent humanitarian tasks. Hence, making field surveys and on-site data collection can be both risky and impractical. Farmers may be unable to access their fields and large-scale investigations can be costly, time-consuming, and lacking transparency.

While remote sensing methods are available for damage assessment (Tapia-Silva et al., 2011), the technical limitations faced by officials handling these assessments are a significant barrier. Outsourcing to third-party experts is often expensive, resource-intensive and slow. Google Earth Engine (GEE) offers an accessible solution providing free access to remote sensing data that can be easily handled by non-experts without the need for extensive software or hardware resources. This study proposes a GEE-based framework for flood damage assessment utilizing current freely available remote sensing resources.

The study proposes a framework to assess crop damage after floods using fusion of both optical and radar satellite data (Nguyen et al., 2020). While multi spectral optical images offer precise vegetation monitoring, they are often disrupted during rainy seasons due to cloud cover. Radar imagery which can penetrate clouds and detect water surfaces is ideal for flood assessment but has lower spectral resolution, making it more effective for structural changes than spectral ones (Shastry et al., 2023). Therefore, the study suggests a fused approach combining optical and radar data to evaluate flood damage more effectively (Clermont et al., 2023, Miao et al., 2023).

2. MATERIALS AND METHODS

The proposed framework was tested in a well-known flood-prone area in Sri Lanka where previous flooding events have occurred.

The proposed process begins when a farmer submits a damage claim by providing the geographical coordinates of their field. The first step is to check whether the location is in a flood-prone area or has a history of flooding using remote sensing images. Next, it determines if the location experienced flooding during the claimed period and for how long that flooded affected.

The system then examines the vegetation healthiness or greens pattern of the area to detect changes following the flood event. Historical patterns are used to evaluate the normal crop growth cycle and significant deviations after the flood provide evidence of flood damage.

The remote sensing-based framework includes:

1. Detecting flooded areas using radar data.
2. Evaluating vegetation patterns at the requested location using optical data.

2.1 Data Sources

The primary data sources for the framework include Sentinel-1, Landsat 8/9, and MODIS. Sentinel-1 is a radar-based sensor that provides VV and VH polarized images with a spatial resolution of 10 meters and a temporal resolution of 12 days since 2013. It is particularly useful for identifying flood-inundated areas as water surfaces tend to reflect lower radar values due to their smoothness. Landsat 8 and 9 are optical multispectral sensors offering a 30-meter spatial resolution and a 16-day revisit period. A key product of Landsat data is the Normalized Difference Vegetation Index (NDVI), which helps measure vegetation health by analyzing the difference between near-infrared and red-light reflectance. This index is widely used for monitoring vegetation growth, drought conditions and ecosystem health over time. However, cloud cover during rainy seasons can pose a limitation. To address this, the dataset T1_L2_8DAY_NDVI provides 8-day NDVI composites from Landsat Tier 1 Level-2 data, enabling continuous vegetation monitoring despite cloud interruptions. Lastly, MODIS, a sensor on the Terra satellite, offers daily images at a 250-meter spatial resolution. Its 16-day composite product helps mitigate cloud cover challenges and is useful for observing long-term vegetation patterns. The MOD13Q1 dataset, part of MODIS, provides vegetation indices like NDVI and Enhanced Vegetation Index (EVI) every 16 days at a 250-meter resolution, making it valuable for comprehensive vegetation monitoring and environmental assessments.

2.2 Methodology

The framework operates using Google Earth Engine (GEE) and follows a series of systematic steps. First, the area of interest and the flood occurrence period are defined. This time range does not need to be exact; a broader date range can be provided to capture the event. Next, GEE retrieves available Sentinel-1 images for the specified period, allowing for spatial and temporal analysis of flood distribution.

In the third step, the temporal signature is extracted from Sentinel-1's VV band data, covering a year before and a year after the flood event. This data is plotted as a time series to observe changes over time. Similarly, Landsat NDVI data is extracted for the same time frame. However, due to cloud cover limitations, the images may not consistently reflect vegetation changes during this period.

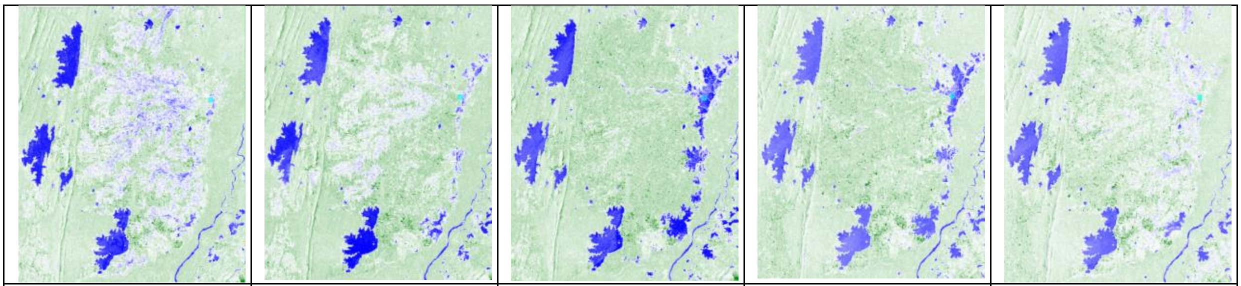
Additionally, MODIS 16-day composite NDVI is extracted to provide a smoother and more continuous time series. The final step involves assessing the influence of the flood by visually interpreting these time series plots, comparing variations in the data across the flood event and the surrounding periods.

3. Results and Discussion

The workflow is tested for several recent flooded location.

Figure 1: Overview of study area

Following shows the sample site where flood occurred in early January 2024 in Polonnaruwa district, Sri Lanka. Figure 1 shows the true color composite high resolution view of the study area.There was a huge flood in this area on January 1, 2024. Figure 2 depicts the sentinel-1 VV polarized images captured prior to, during, and following the flood.



2023-12-07	2023-12-19	2023-12-31	2024-01-12	2024-01-24

Figure 2: Spatial-temporal distribution of flood area captured in sentinel- 1 images.

Time series of sentinel-1 VV images are shown in figure 2. According to that there is flood appear on 2023-12-31 and 2024-01-12 images. There is slightly waterlog area in 2023-12-19 image. There are no temporal water patches in first and last images.

The study demonstrated how flood distribution can be tracked over time using Sentinel-1 radar images, which show low VV reflectance in flooded areas (Figure 3). Landsat NDVI data confirmed the difficulty of monitoring vegetation due to cloud cover (Figure 4), while MODIS provided a more consistent time series (Figure 5). Historical NDVI patterns before and after the flood can used to reveal the magnitude of crop damage.

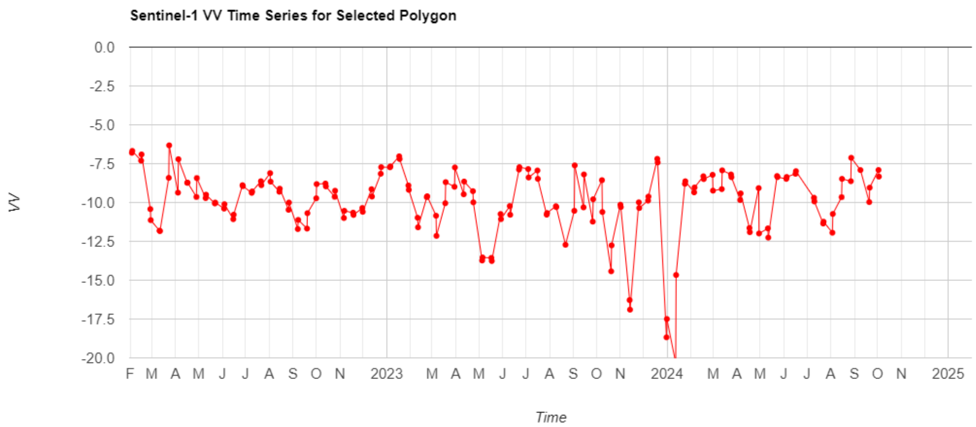


Figure 3: Sentinel-1 VV polarization time series plot of flood location

In this example, low VV reflectance values recorded on January 1, 2024, coincided with reports of flooding. Landsat NDVI data showed cloud interference, while MODIS NDVI indicated a lower peak than in previous years, consistent with flood-related damage.

Ground truthing confirmed crop loss due to the early January 2024 flood.

Figure 6 shows the Google Earth Engine interface derive to visualize the time series on web interface. There is an option to change the time duration and the interested area in interactive manner.

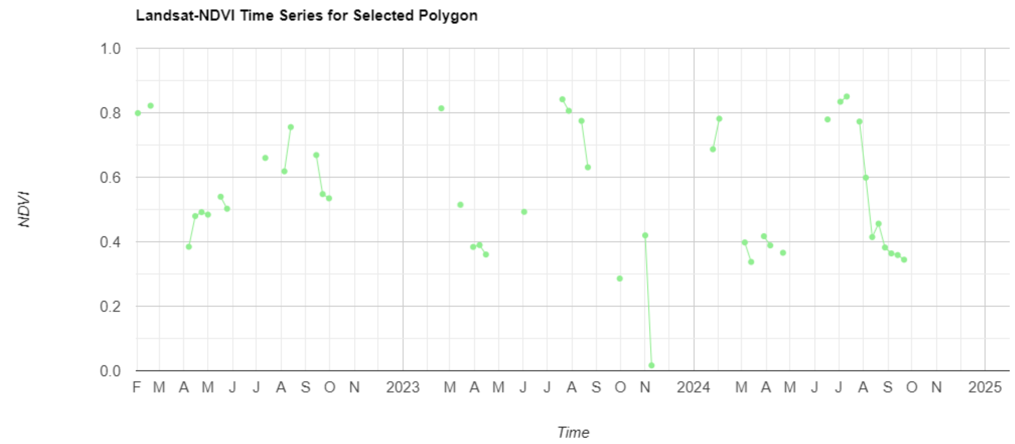


Figure 4: Landsat 8-day NDVI composite time series plot of flood location

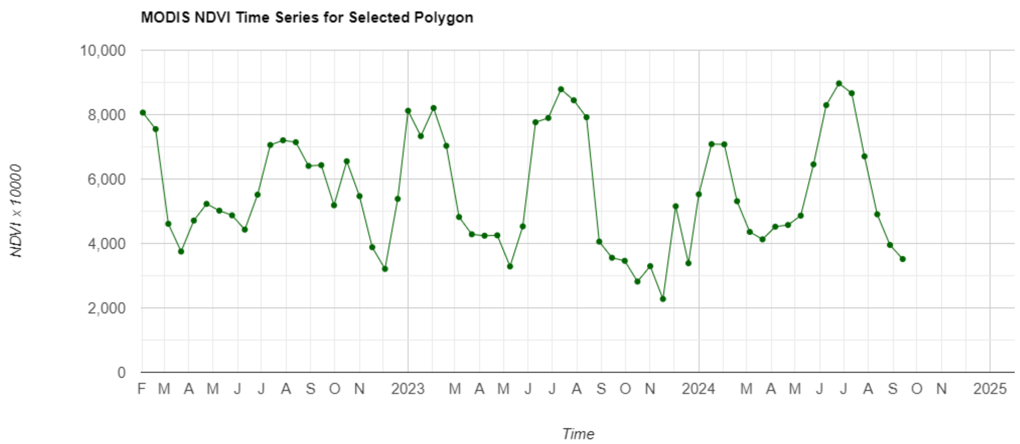


Figure 5: Modis 16-day NDVI composites time series plot of flood location

4. Conclusion and Recommendation

This study proposes a user-friendly, cost-effective framework for assessing flood-related crop damage using free remote sensing data. The framework successfully demonstrated the capability to detect flood damage. However, it does not account for minor-scale damage below the resolution of the available data. Additionally, the assessment is qualitative, based on visual graph interpretation rather than a precise quantitative measure.

As an improvement, the framework could incorporate cadastral boundaries, allowing for the generation of flood damage maps for larger areas more efficiently. Further enhancements could include integrating additional data layers such as topography, weather, and land cover to create a more consistent and user-friendly evaluation tool.

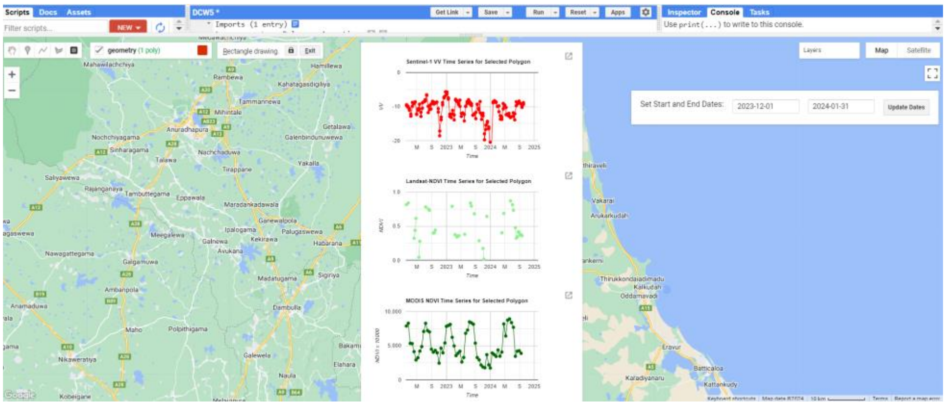


Figure 6: Derived Google Earth Engine tool

References

Tapia-Silva, F.-O., Itzerott, S., Foerster, S., Kuhlmann, B., & Kreibich, H. (2011). Estimation of flood losses to agricultural crops using remote sensing. *Physics and Chemistry of the Earth*, *36*(7–8), 253–265. https://doi.org/10.1016/j.pce.2011.06.004

Nguyen, N. B., Nguyen, N. H., Tran, D. T., Tran, P. T., Pham, T. G., & Nguyen, T. M. (2020). Assessing damages of agricultural land due to flooding in a lagoon region based on remote sensing and GIS: Case study of the Quang Dien district, Thua Thien Hue province, central Vietnam. *Journal of Vietnam Environment*, *12*(2), 100–107. https://doi.org/10.13141/jve.vol12.no2.pp100-107

Miao, S., Zhao, Y., Huang, J., Li, X., Wu, R., Su, W., Zeng, Y., Guan, H., Abd Elbasit, M. A. M., & Zhang, J. (2023). A comprehensive evaluation of flooding's effect on crops using satellite time series data. *Remote Sensing*, *15*(5), 1305. https://doi.org/10.3390/rs15051305

Clermont, M., Kinnard, C., Dubé-Richard, D., Campeau, S., Bordeleau, P.-A., de Grandpré, A., Ziyad, J., & Roy, A. (2023). Using remote sensing to assess how intensive agriculture impacts the turbidity of a fluvial lake floodplain. *Journal of Great Lakes Research*, *49*(6), 102240. https://doi.org/10.1016/j.jglr.2023.102240

Shastry, A., Carter, E., Coltin, B., Sleeter, R., McMichael, S., & Eggleston, J. (2023). Mapping floods from remote sensing data and quantifying the effects of surface obstruction by clouds and vegetation. *Remote Sensing of Environment*, *291*, 113556. https://doi.org/10.1016/j.rse.2023.113556