NOWCASTING FROM SPACE

IMPACT OF TROPICAL CYCLONES ON FIJI'S AGRICULTURE

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ABSTRACT

The standard approach to 'nowcast' disaster impacts, which relies on risk models, does not typically account for the compounding impact of various hazard phenomena (e.g., wind and rainfall associated with tropical storms). The alternative, traditionally, has been a team of experts sent to the affected areas to conduct a ground survey, but this is time-consuming, difficult, and costly. Satellite imagery may provide an easily available and accurate data source to gauge disasters' specific impacts, which is both cheap, fast, and can account for compound and cascading effects. If accurate enough, it can potentially replace components of ground surveys altogether. An approach that has been calibrated with remote sensing imagery can also be used as a component in a nowcasting tool, to assess the impact of a cyclone, based only on its known trajectory, and even before post-event satellite imagery is available. We use one example to investigate the feasibility of this approach for nowcasting, and for post-disaster damage assessment. We focus on Fiji and on its agriculture sector, and on tropical cyclones (TCs). We link remote sensing data with available household surveys and the agricultural census data to obtain an improved assessment of TC impacts. We show that remote sensing data, when combined with pre-event socioeconomic and demographic data, can be used for both nowcasting and post-disaster damage assessments.

Keywords: satellite, cyclone, damage, impact, disaster, nowcasting

JEL codes: Q54, Q1, C8

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I. INTRODUCTION

In the last decades, satellite-based Earth observation data have been increasingly used for various applications in different fields. One of these is disaster and emergency management. Emergency responders and disaster risk managers have started to explore the use of satellite imagery as a reliable and immediate source for disaster-impact information (Voigt et al. 2016). Recent technological advances in remote sensing have led to a massive increase in temporal, spatial, and spectral resolutions of these images. Furthermore, we have also seen improvements in data availability and accessibility, and advances in the processing methods that are required to effectively interpret these large amounts of data (Notti et al. 2018). These developments have led to an increasing application of satellite imagery for more effective disaster mitigation, preparedness, response, and recovery.

One such disaster management application that has advanced due to improvements in remote sensing is post-disaster damage assessment. Traditionally, in a post-disaster scenario, a team of experts is sent to the area to conduct a ground survey and assess damages—this is sometimes connected to a commissioned Post-Disaster Needs Assessment (PDNA) report. This process is time-consuming and costly, and possibly difficult because often the access to the affected area is difficult, dangerous, or restricted. Alternatively, governments and, especially, public and private insurance companies use risk models to quantify these damages. Risk models are frequently inaccurate and are generally unable to account for compound or cascading events,[1] as these are much more difficult to quantitatively model. In contrast, satellite imagery can function as an easily available, timely, and accurate data source to gauge the damage severity and the specific impacts caused by a disaster event (even a compound or cascading one). Indeed, one can also develop, with the assistance of remote sensing data, nowcasting tools to forecast the impact of the event when it is already happening (or immediately thereafter). While these can serve as effective complements to ground surveys, particularly for immediate assessment, if accurate enough, satellite imagery can even potentially replace ground survey efforts altogether.

Satellite data are currently used for post-disaster damage assessment of various types of disasters caused by natural hazards—tropical storms, floods, earthquakes, landslides, and tsunamis. When calibrated well, these data are selected appropriately in terms of their spectral, temporal, and spatial resolutions to obtain the desired information. However, these data are rarely matched with traditional socioeconomic information (e.g., census) to better gauge the determinants of impacts and improve our ability to nowcast them.

In this study, we use one example to investigate the feasibility of using remote sensing data for post-disaster damage assessment. We focus on the islands of Fiji, on its agriculture sector, and on tropical cyclones (the main disaster-inducing hazard in Fiji, and in much of the other Pacific island countries). The main crop grown in Fiji is sugarcane, representing 60% of the area harvested averaged over the period 2016–2020 (FAO).

We consider the effect of four recent tropical cyclones (TCs) on agriculture since reliable satellite pictures of high resolution and frequency are only available for recent events. They are

- TC Winston (15 February 2016),
- TCs Josie (2 April 2018) and Keni (10 April 2018), and

[1] Compound events refer to multiple disasters happening concurrently or consecutively, thereby reinforcing each other to create a more complex condition that amplifies the impact of individual disasters; whereas, cascading events happen when one hazard triggers another hazard in a series (IGES 2022).

- TC Harold (7–8 April 2020).

As a Category 5 cyclone (the most extreme category), TC Winston was one of the strongest tropical storms in recorded history and the strongest cyclone ever to make landfall in the Southern Hemisphere, with estimated wind speeds of up to 230 kilometers (km) per hour. After making landfall in Viti Levu, Fiji in February 2016, TC Winston caused massive destruction, damaged 32,000 houses, and left approximately 350,000 Fijians in need of humanitarian aid. The total economic losses were estimated at $1.38 billion, approximately one-third of Fiji's gross domestic product (Reliefweb 2016a, 2016b; Di Liberto 2016; WFP 2017; UNICEF).

In 2018, Category 1 TC Josie affected the central and western parts of Fiji and caused heavy flooding, mainly on the main island Viti Levu. The Category 3 TC Keni passed close to Viti Levu just 1 week later, causing repeated flooding. The two cyclones affected approximately 78,000 Fijians, with 12,000 people seeking emergency shelter at evacuation centres. The economic losses caused by these two events were estimated at $3 million (Reliefweb 2018, RNZ 2018).

The Category 5 TC Harold caused destruction in the Pacific island countries of, Fiji, Solomon Islands, Tonga, and Vanuatu in April 2020. It impacted the southern part of Fiji as a Category 4 event and affected more than 180,000 people, displaced around 10,000 people, and destroyed or damaged almost 4,000 homes. The estimated economic losses associated with the event were estimated to exceed $40 million (DFAT, Reliefweb 2020).

Estimates of the value of mortality and aggregated figures of economic damage these events inflicted (for all assets and sectors) at the regional level are available indirectly from the Fijian government through the United Nations Office for Disaster Risk Reduction (in DesInventar Sendai, https://www.desinventar.net/), and from a nongovernment source, Emergency Events Database (EM-DAT, https://www.emdat.be/). These are, of course, not specifically attempting to count losses in agriculture; and, indeed, in Tables 1 and 2, we show that these regional-level data from EM-DAT and DesInventar are not very tightly correlated with the remote sensing data we use to identify spatially detailed information on the damage the cyclones wrought to agriculture.

Our purpose, in this study, is to examine the possibility of combining remote sensing data with socioeconomic sources of information (household surveys and the census) to nowcast the damage from tropical cyclones on agriculture. We focus on Fiji and extract the change in the Enhanced Vegetation Index (details below) around four tropical cyclones that occurred in Fiji in recent years. We then aggregated these data spatially to the district level and match them with data we extract from the 2013-14 Household Income and Expenditure Survey (HIES) and the 2020 Fiji Agriculture Census (FAC).

By matching remote-sensing observations with socioeconomic, demographic, and agronomic data, we are able to better explain the identified changes in the vegetation index, and thus improve the nowcasting of impacts of the tropical cyclones on agriculture. In other words, we show that, in the case of Fiji's recent tropical cyclones, the remote sensing measurement we employed (the Enhanced Vegetation Index), when combined with pre-cyclone socioeconomic and demographic data, can be used for nowcasting damages (during the event and immediately thereafter). We conclude by describing, how, together with additional socioeconomic data, remote sensing can also be very useful for nowcasting post-disaster indirect losses (rather than the direct losses).

II. LITERATURE REVIEW

A. Optical Satellite Imagery for Disaster Damage Assessment

For disaster damage assessment, the most frequently used satellite sensors are optical, Synthetic Aperture Radar (SAR), and Light Detection and Ranging (LiDAR) sensors. Most optical satellite sensors gather surface reflectance data from the visible electromagnetic spectrum, as well as emissivity data from the infrared wavelengths to produce images. Optical imagery is relatively easier to interpret than SAR and LiDAR imagery, as the resulting imagery typically appears as a standard colored or black and white photograph and corresponds to how humans naturally view the world. The combination of visible and infrared wavelengths is particularly useful for the detection of water surfaces and vegetation-covered areas and is therefore well suited for flood mapping or estimating storm- or flood-induced vegetation impacts.

The applicability of optical satellite data for storm and flood damage assessment is partially limited because of its reliance on relatively cloud-free weather conditions for gathering the data and the fact that high precipitation is typically correlated with heavy cloud cover during the days surrounding the event (Rahman 2019). Furthermore, many sources of high-resolution satellite data (such as GeoEye, RapidEye, QuickBird, or WorldView) are not publicly available and their data can be very costly to acquire. Despite these limitations, researchers have repeatedly shown the efficacy of optical satellite imagery for immediate storm and flood damage assessments.

For rapid post-disaster impact assessment that can effectively assist emergency responders, there are high demands on both the temporal and spatial resolutions of the required satellite imagery. Imagery needs to be available quickly (Hodgson et al. 2010) and the spatial resolution requirements for reliable visual interpretation are also high. Where experts need to conduct damage assessment manually, and if accuracy is important, they require a high resolution at 1.5 meters per pixel (Battersby, Hodgson, and Wang 2012). Therefore, it is often necessary to obtain a combination of satellite sources to gather as much relevant data as is possible during the first few days after the disaster.

Furthermore, satellite images may not provide direct insights of disaster-inflicted damages because of the vertical viewing angles of satellite sensors. To assess disaster impacts, researchers often require the use of proxies to estimate specific damages. For example, a building's photographic texture or rubble and debris piles can be used to identify buildings that were damaged, or a building's shadow can be used to approximate building collapse (Ghaffarian, Kerle, and Filatova 2018).

Because of these difficulties, many damage assessment approaches also combine the remote sensing imagery with ancillary data such as satellite-derived Digital Elevation Models or Digital Terrain Models, soil or land use data, and other datasets that can be combined to derive more accurate disaster-related information. Many of these data types are freely accessible online from the United States Geological Survey, national sources, or other international organizations.[2] It is less common, in this literature, to combine these data with spatial economic and demographic data, such as those data that are collected in standard household living standards surveys, or the decadal census.

[2] See GeoSpatial Data Cloud (http://www.gscloud.cn/home#page1/1) and the United States Geological Survey (https://www.usgs.gov/).

B. General Damage Assessments

Flood and storm damage assessments based on satellite imagery vary in their use of specific remote sensing sources and the corresponding spatial and temporal resolutions of the imagery. Often, high spatial, temporal, and spectral resolution imagery would be most efficient, but not always available. There can also be trade-offs between the spatial and the temporal resolution of the data (Giraldo-Osorio and García-Galiano 2012, Fayne et al. 2017). With respect to the spatial resolution, damage assessments are conducted on a range of available resolutions, from low (>100 meters per pixel) to moderate (5–100 meters per pixel) and high resolutions (<5 meters per pixel). Summarized below are general hazard assessments of floods and storms, while the next subsection focuses on specific damage types such as vegetation, agriculture, or buildings and infrastructure.

Storms

With respect to general damage estimations of storms, and specifically tropical storms, researchers used moderate-resolution (Al-Amin Hoque et al. 2015; Al-Amin Hoque et al. 2016; Al-Amin Hoque et al. 2017; Phiri, Simwanda, and Nyirenda 2021) or high-resolution imagery (Barnes, Fritz, and Yoo 2007; Mas et al. 2015; Doshi, Basu, and Pang 2018). Studies by Al-Amin Hoque et al. (2015), Al-Amin Hoque et al. (2016), and Al-Amin Hoque et al. (2017) used moderate-resolution SPOT-5 imagery to analyze impacts of the 2007 Tropical Cyclone Sidr in Bangladesh. Phiri, Simwanda, and Nyirenda (2021) estimated the damages for the 2019 Cyclone Idai in Mozambique using Sentinel-2 images. Barnes, Fritz, and Yoo (2007) used high-resolution IKONOS imagery to estimate local damages of the 2005 Hurricane Katrina in the United States; and Mas et al. (2015) studied the 2013 Typhoon Haiyan in the Philippines using Google Earth imagery. Doshi, Basu, and Pang (2018) utilized freely available high-resolution satellite imagery datasets to analyze the 2017 Hurricane Harvey in the United States.

Floods

Flood mapping and impact assessments on a large scale were predominantly conducted on publicly available low-resolution optical sensors such as the Visible Infrared Imaging Radiometer Suite (Li et al. 2018, Goldberg et al. 2018) or, more frequently, the Moderate Resolution Imaging Spectroradiometer (MODIS) (Brakenridge and Anderson 2006; Irimescu et al. 2009; Sun, Yu, and Goldberg 2011; Sun et al. 2012; Haq et al. 2012; Zhang et al. 2012; Li et al. 2013; Senthilnath et al. 2013; Kwak, Park, and Fukami 2014; Nigro et al. 2014; Memon et al. 2015; Arvind et al. 2016; Coltin et al. 2016; Ban et al. 2017; Lin et al. 2017; Lin et al. 2019). Several older studies applied data from the predecessor to MODIS, the advanced very high-resolution radiometer (Barton and Bathols 1989; Ali, Quadir, and Huh 1989; Sheng, Gong, and Xiao 2001; Jain et al. 2006). Benefits of these satellite sensors are high spatial coverage and temporal resolution, along with free availability. However, the low spatial resolution limits these studies to less detailed or accurate impact estimations.

Freely available Landsat data were utilized in flood mapping and damage assessments by Gianinetto, Villa, and Lechi (2006); Ma et al. (2011); Li, Xu, and Chen (2016); Hutanu, Urzica, and Enea (2018); Sivanpillai et al. (2021); and Musiyam et al. (2020). Kordelas et al. (2018) used Sentinel-2 data, while Feng et al. (2015) used HJ-CCD data. Du et al. (2021) developed a flood mapping method for data-sparse regions, combining Landsat, Google Earth Engine, and satellite-based soil moisture data.

High-resolution satellite images can provide more detailed information on specific flood damages inflicted on individual structures (Klemas 2015). Researchers conducted flood damage assessments based on high-resolution satellite sources such as SPOT-5 (Lamovec et al. 2013), RapidEye (Lamovec, Mikos, and Ostir 2013), Worldview2 (Scarsi et al. 2014; Malinowski et al. 2015), KOMPSAT-2 (Byun, Han, and Chae 2015), ASTER (Franci 2015), SPOT-6 (Franci et al. 2017), or Planet Lab imagery (Peng et al. 2019). In many flood assessments, researchers combined satellite imagery with ancillary geographic information system (GIS) data (Brakenridge and Anderson 2006, Dotel et al. 2020, Irimescu et al. 2009, Haq et al. 2012, Ma et al. 2011, Franci 2015) such as modelled or measured elevation (Gianinetto, Villa, and Lechi 2006; Lamovec et al. 2013; Lamovec, Mikos, and Ostir 2013; Malinowski et al. 2015; Franci et al. 2017).

C. Specific Impacts: Vegetation and Crop Damage

Apart from hazard assessments and flood mapping of general storm- or flood-affected areas, some studies focused specifically on analyzing and quantifying damages to certain features of interest such as vegetation, forests, agricultural production, or buildings and infrastructure. We do the same in this study.

Impacts of storms on vegetation were a focus of a few studies. MODIS data were used to estimate tropical storm damages to forests (Wang et al. 2010; Rossi, Rogan, and Schneider 2013) and coastal vegetation (Wang and D'Sa 2010; Lu, Wu, and Di 2020). A combination of MODIS and Landsat data was used to assess damages and recovery of the Philippines' mangroves by Long et al. (2016).

Researchers also utilized Landsat or Sentinel-2 imagery to assess tropical storm impacts on coastal vegetation (Rodgers, Murrah, and Cooke 2009; Konda et al. 2018; Charrua et al. 2021), forests (Negrón-Juárez et al. 2010, Zhang et al. 2013b), mangroves (Bhowmik and Cabral 2011, Bhowmik and Cabral 2013), and tropical vegetation (Hu and Smith 2018).

High-resolution imagery from satellites such as Formosat-2, RapidEye, ZY-3, or Worldview2 was used to estimate typhoon-induced vegetation and forest damages (Wang and Xu 2018, Furukawa et al. 2020), windstorm damages to maritime pine forests (Chehata et al. 2014), and windblown forest impacts (McInerney et al. 2016).

While most of the studies focused on a particular disaster event, Mandal and Hosaka (2020) followed a different approach and assessed long-run (29 years) impacts of cyclones on mangrove forests of India and Bangladesh based on Landsat and Google Earth imagery. Lu, Wu, and Di (2020) used MODIS data to estimate typhoon-induced vegetation damages in the southeast coastal region of the People's Republic of China over a period of 18 years.

Most closely related to our analysis, another set of studies focused on estimating storm and flood impacts on agriculture. Satellite-based flood crop loss assessments were typically conducted based on flood intensity, crop condition, or a combination of these two methods (Rahman and Di 2020). Flood-intensity-based studies, which rely on optical satellite imagery, used MODIS (Kwak et al. 2015; Kwak, Arifuzzanman, and Iwami 2015; Haq et al. 2012; Memon et al. 2015) or higher-resolution IKONOS images (Van der Sande, De Jong, and De Roo 2003). Within this approach, crop damages were mostly estimated using stage-damage curves based on satellite-derived criteria such as flood extent or duration.

Flood crop loss studies based on crop condition typically used MODIS, or the moderate-resolution Sentinel-2 and Landsat imagery, and satellite-derived spectral indexes to estimate crop condition (Pantaleoni, Engel, and Johannsen 2007; Shrestha et al. 2013; Yu et al. 2013; Shrestha et al. 2017; Ahmed et al. 2017; Son et al. 2013; Kotera et al. 2016; Di et al. 2013; Zhang et al. 2013a; Di, Guo, and Lin 2018; Rahman et al. 2021). These approaches involved comparing pre- and post-flood values of these indexes, estimating regressions using these indexes, and associating them with crop yields or other measures. This is the approach we take in this study.

Several studies combined the two above-mentioned approaches and used both flood intensity and crop condition to estimate crop damages based on MODIS (Singh et al. 2019, Chen et al. 2019, Dao and Liou 2015) and HJ-CCD imagery (Gu et al. 2015, Chen et al. 2017). For tropical storm crop damage assessments, researchers used MODIS (Blanc and Strobl 2016; Omori et al. 2021; Cortés-Ramos, Farfán, and Herrera-Cervantes 2020), Landsat (Goto et al. 2015; Chejarla et al. 2017; Cortés-Ramos, Farfán, and Herrera-Cervantes 2020), SPOT-5 (Chen, Lin, and Chang 2015; Chen and Lin 2018), and high-resolution RapidEye (Capellades, Reigber, and Kunze 2009) imagery.

Blanc and Strobl (2016) used a combination of MODIS-derived spectral indexes and typhoon-intensity data to develop a method for fast typhoon rice field damage assessment. Omori et al. (2021) estimated cyclone damages to paddy fields also using MODIS data. A combination of MODIS and moderate-resolution Landsat data was used by Cortés-Ramos, Farfán, and Herrera-Cervantes (2020) to estimate cyclone damages to dry forests.

Also utilizing Landsat imagery, Goto et al. (2015) assessed typhoon-induced salinity damage to crops in Japan, and Chejarla et al. (2017) estimated cyclone economic loss for crops comparing vegetation biomass before and after the event. Moderate-resolution SPOT-5 data were used by Chen, Lin, and Chang (2015) and Chen and Lin (2018) to assess typhoon impacts on agricultural lands and attempted to distinguish between damage caused by the wind and the heavy rainfall.

With respect to these assessments of storm or flood-induced vegetation and crop impacts in general, researchers often use a vegetation index differencing method—calculating the change in a vegetation index. This is what we do here, as is described in detail in Section III.

Processing methods

Various processing methods for storm and flood impact assessments based on optical satellite imagery are being used. These range from manual methods such as visual interpretation, which rely on the skill and knowledge of experts to observe and identify damaged regions or objects manually, to more automated techniques such as change detection, data mining methods, and approaches involving machine learning. The selection of the processing method for a specific damage assessment typically depends on the type and availability of data (pre- and post-event data, only post-event data, training datasets for machine learning algorithms, etc.), scale of the study (regional, local, or specific sector damages), and other factors.

Visual interpretation relies on the skill and knowledge of experts to identify impacted regions and/or features manually without any automated algorithm identifying them. The disadvantage of this method is the time and skill needed to analyze large amounts of data. Some researchers, nevertheless, do apply visual interpretation methods on optical satellite imagery for damage assessments of tropical storms (Mas et al. 2015, Perante 2016), or incorporate visual methods for the post-classification editing of the imagery (Haq et al. 2012), or removal of falsely identified cloud shadows (Memon et al. 2015).

Al-Amin Hoque et al. (2017) noted that standard visual interpretation techniques are relatively slower than automatic change detection methods. Fayne et al. (2017) described various optical and physical processing methods for satellite-based flood mapping, such as band thresholding, spectral indexes, or physically based models with ancillary data.

Change detection

Change detection is an automated algorithm to detect differences in images between two discrete points in time. Deer (1995) distinguished two main methods: (i) post-classification comparisons, which involve comparing separately classified images; and (ii) simultaneous analyses of multitemporal data, which involve accounting for changes in pixel values. Lu et al. (2004) provided an overview of 31 change detection approaches for remote sensing data, such as image differencing, principal component analysis, unsupervised change detection, and artificial neural networks.

A handful of studies analyzed the efficacy of different change detection methods for tropical storm damage assessments. Wang and Xu (2010) evaluated change detection methods for hurricane-induced forest damage estimation and concluded that the post-classification comparison algorithm shows the best accuracy, similar to the finding of Al-Amin Hoque et al. (2017). Furukawa et al. (2020) also focused on storm-inflicted forest damages and estimated high accuracy for all three analyzed change detection techniques: the normalized difference vegetation index, spectral angle mapper, and support vector machine.

Several studies used a combination of object-based image analysis and post-classification change detection to estimate tropical storm impacts (Al-Amin Hoque et al. 2016; Al-Amin Hoque et al. 2015; Al-Amin Hoque et al. 2017; Phiri, Simwanda, and Nyirenda 2021). Ramlal, Davis, and De Bellott (2018) assessed hurricane-induced building damages with both pixel-based image differencing and object-based image analysis methods. Adriano et al. (2021) applied a phase-based change detection method to estimate the damaged areas for the 2013 Haiyan typhoon.

A commonly used preclassification change detection method is vegetation index differencing, which is applied to estimate vegetation and crop damage induced by tropical storms or flood events in studies such as Rossi, Rogan, and Schneider (2013); Rahman et al. (2021); Hu and Smith (2018); Rodgers, Murrah, and Cooke (2009); Wang et al. (2010); Lee et al. (2008), and others. This method has the advantage, in addition to being straightforward, of reducing the impact of topographic effects and illumination (Lu et al. 2004).

The vegetation index most commonly used with the index differencing technique to estimate the impact of tropical storms is the normalized difference vegetation index (NDVI) (Ramsey, Chappell, and Baldwin 1997; Rodgers, Murrah, and Cooke 2009; Ayala-Silva and Twumasi 2004; Lee et al. 2008). However, the enhanced vegetation index (EVI), which is a modified version of the NDVI, has an improved sensitivity over high biomass regions such as forests, and less sensitivity to atmospheric noise. EVI was therefore preferred to NDVI to study the effect of TCs (Brun and Barros 2013), and it was also used in various other vegetation and crop damage assessments such as Son et al. (2013), Kotera et al. (2016), or Wang and D’Sa (2010).

New change detection methods are being continuously developed to improve upon current approaches and to enhance the efficiency of change detection for disaster damage assessment. For example, Byun, Han, and Chae (2015) introduced an unsupervised change detection method for flood detection based on image fusion.

Machine and deep learning

The significant advances in machine learning and deep learning computer algorithms in recent years have enabled researchers to utilize their functionalities for disaster damage assessments. Due to the interest and potential of this field of research, novel methods and approaches are rapidly being developed. Important aspects of using machine learning techniques with remote sensing data are the preparation of the data, the selection of a suitable machine learning algorithm, and the selection of optimal training samples (Lamovec et al. 2013). Zhu et al. (2017) reviewed deep learning methods for remote sensing data and describe various techniques.

A Convolutional Neural Network (CNN) approach is one of the most popular deep learning algorithms (Albawi, Mohammed, and Al-Zawi 2017). This type of deep learning has been increasingly applied to remote sensing in pursuit of automated methods to facilitate fast and reliable disaster damage estimations. Specifically, several studies assessed storm-induced building or infrastructure damages based on high-resolution imagery using the CNN approach and other artificial neural network algorithms. Radhika, Tamura, and Matsui (2015) applied a change detection method using an artificial neural network and a support vector machine. Cao and Choe (2018) used CNN-based image classification algorithms for the 2017 Hurricane Harvey in the United States. Doshi, Basu, and Pang (2018) utilized a similar approach but applied a more scalable general building and roads dataset. CNN-based image classification algorithms were also applied in two subsequent studies of hurricane building damages from Cao and Choe (2020a, 2020b). In their second study, the authors improved upon the previous work—introducing a mixed data approach and combining freely available satellite imagery with geolocation features data—and increased the estimation accuracy (Cao and Choe 2020b). Wheeler and Karimi (2020) estimated building-level damages for multiple types of disasters based on a CNN-based computer vision model. Adriano et al. (2021) developed a building damage dataset to estimate impacts of various disasters and introduced a CNN-based method for building damage assessment. Jack (2017) used deep learning algorithms to identify hurricane-damaged roads.

For flood detection and flood damage assessments, an evaluation of machine and deep learning methods based on satellite data was conducted by Lamovec et al. (2013) and Lamovec, Mikos, and Ostir (2013). Li, Xu, and Chen (2016) similarly attempted to improve urban flood detection accuracy using a neural network algorithm, and Rudner et al. (2018) created a CNN-based technique for rapid flood mapping and damage assessment using a fusion of available satellite datasets. Peng et al. (2019) proposed a related method to identify urban flood hazard zones based on pre- and post-flooding satellite images and tested the method on the 2017 Hurricane Harvey floods. Finally, a recent study by Dotel et al. (2020) applied the CNN to distinguish image features and identify affected regions for floods and hurricanes.

Considering the pace of progress in the realm of machine learning and deep learning computer algorithms and their high potential—almost all the papers cited above were published in the last 4 years—it is reasonable to expect that better and more efficient methods for satellite-based disaster damage assessments will continue to be developed in the very near future.

None of these papers, however, attempted to use the remote sensing data in conjunction with traditional economic datasets. This is the case for macroeconomic or aggregated datasets, such as those we use here. In this case, the economic data is aggregated spatially for administrative units within a country (e.g., districts, regions, provinces, and states) or aggregated to the country level (when more regional and less aggregated data are not available).

More challenging, but equally informative, can be the use of micro-level economic data, such as household surveys or administrative (unit record) data on firms' balance sheets and tax information. If these data are geolocated, it can in principle be feasible to match these with remote sensing data that are of sufficient resolution. One of the main impediments for this kind of approach, however, is a (justified) concern about privacy.

III. DATA AND METHODOLOGY

A. Satellite Imagery

The satellite imagery we use is derived from two sources, Sentinel-2 and MODIS. We use Sentinel-2, which is an Earth observation mission from the Copernicus Programme acquiring optical imagery over land and coasts with two twin satellites: Sentinel-2A and Sentinel-2B (European Space Agency). Data from the Sentinel-2 mission are characterized by a high spatial (10, 20, and 60 meters) and temporal (5 days) resolution. We mask grid cells labelled as "No data," "Saturated or defective," as well as a cloudy pixel—i.e., "Cloud (high or medium probability)." Note that Fiji is covered by different orbit tracks (R029, R072, and R129); therefore, the dates of available images differ between the tracks. We also set the parameters to download images with less than 50% of cloud coverage only.

A different data source, MODIS, is obtained from instruments onboard the Earth Observing System Terra and Aqua platforms. Vegetation indexes data (MOD13Q1) Version 6 (LP DAAC 2021) from MODIS are provided every 16 days at a 250-meter resolution. Cloudy and lower-quality pixels are masked there as well.

B. Damage Estimates

In the context of this study's first step, we estimate the effect of TCs using the EVI, which is more suitable to be used for the dense vegetation of the islands than other vegetation indexes. Following Huete, Liu, and van Leeuwen (1997), EVI is calculated as:

$$EVI = 2.5\frac{\rho_{NIR}-\rho_{red}}{\rho_{NIR}+6\rho_{red}-7.5\rho_{blue}+1} \quad (1)$$

using the near-infrared (*NIR*; 841–876 nanometers [nm]), red (620–670 nm), and blue (459–479 nm) spectral bands and ρ the top-of-the atmosphere reflectance.

The impact of TCs is estimated using the vegetation image differencing between the pre- and post-TCs' EVIs using map algebra at the grid-cell level. The difference in EVI, labelled henceforth *EVIdiff*, is regarded as vegetation cover damage caused by a hurricane. The difference in EVI is calculated by the following equation:

$$EVIdiff = EVI_{postTC} - EVI_{preTC} \quad (2)$$

where $\mathrm{EVI_{postTC}}$ and $\mathrm{EVI_{preTC}}$ correspond to post- and pre-TC landfall reading from the EVI, respectively. As cloud contamination can hinder the acquisition of images, the closest available images to landfall are selected within 2 months before and after each tropical cyclone that is investigated. Because TCs Keni and Josie happened only several days apart, we calculate the EVI difference using pre-Josie and post-Keni (as if both were one single storm event); in many locations, images were not available between the two TCs.

Additionally, we calculate the relative (percent) change in vegetation due to TCs given by:

$$EVIch = \frac{EVI_{postTC}-EVI_{preTC}}{EVI_{preTC}} \quad (3)$$

For the district, rather than the grid-cell level, average district level *EVIdiff* and *EVIch* values are calculated as the average of the grid-level EVI values for all grid cells within each district, based on Fiji's administrative division.

C. Socioeconomic and Demographic Data

The socioeconomic and demographic data used for the linear regressions were gathered from two primary sources: 2013-14 Household Income and Expenditure Survey (HIES) and 2020 Fiji Agriculture Census (FAC).

The HIES contains household-level data for a sample of 6,020 households and is aimed to be representative per district. Household income values were averaged per district using weights included in the original HIES dataset to arrive at average household income values at the district (*Tikina Covata*) level. The respective districts were assigned to households based on the household ID numbers.

FAC is organized at a subdistrict (*Tikina Vou*) level. The data from a total of over 71,000 households capture detailed economic and demographic information relating to the agriculture sector in rural and peri-urban areas, where most agricultural activities are concentrated. Grouping subdistricts into respective districts was done based on the administrative associations as defined in the House of Chiefs (n.d.) list, and a combination of regional maps in FAC documentation. Average district values were calculated using a weighted average with the number of farmers, agricultural households, or their members used as weights for the respective indicators.

With respect to the variables indicating the ratio of agricultural land used for specific crops, only the crop types that covered at least 1% of the total area planted were selected. Similarly, for the land tenure variables, only the land tenure types that accounted for at least 5% of the total farmland area were selected.

Besides the data from the HIES and FAC, a "cyclone distance" variable was added to the regression model to account for the effect of cyclone proximity on vegetation damage. The value of this variable ranges from 1 (closest to the cyclone path) to 4 (furthest from the cyclone path). More specifically, distance from the cyclone was accounted for by establishing four zones, with borders at 50 km, 100 km, and 200 km from the cyclone path and with the value of 1 indicating that the majority (>50%) of the district area is closer than 50 km from the cyclone path. The values were calculated using cyclone trajectory maps from the International Best Track Archive for Climate Stewardship (IBTrACS; NOAA) and Reliefweb (2016a). For the combined cyclone events of Josie and Keni, the lower value of cyclone distance was selected from the two (implicitly assuming no cumulative damage).

A complete list of the independent variables used in the regression models is presented in Table 3 in the Appendix[3], along with their description and sources. From the list of variables that were extracted from the HIES and FAC, selected variables were removed from variable pairs that had a correlation coefficient higher than 0.7. The variables removed were (i) no savings account due to lack of access, (ii) number of females per agricultural household, (iii) ratio of agricultural land

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[3] The Appendix is available online at http://dx.doi.org/10.22617/WPS230007-2.

used for growing coconuts, (iv) native lease land ownership, (v) average age, and (vi) imputed rent and wages.[4]

D. Regression Models

A linear regression model was applied to identify potential relationships between demographic and socioeconomic factors on one hand, and cyclone-induced vegetation damage on the other, which is approximated by the EVI measures described earlier. In principle, our aim is to identify the correlates of significant damage from cyclones. We are not necessarily aiming to identify any causal mechanism from these independent control variables on the dependent variables in our models (the variants of the EVI measure; see below).

We estimate the following equation:

$$EVI_{cd}^{x} = \alpha + \beta_1 HIES_d + \beta_2 FAC_{sd \subset d} + \beta_3 DIST_{cd} + \varepsilon_{cd} \quad (4)$$

Whereby EVI_{cd}^{x}, the dependent variable, is calculated as variations of the EVI around the time of the respective cyclone (*c*) in district (*d*). Variants include (i) the absolute EVI change, *EVIdiff* (eq. 2); (ii) the relative EVI change, *EVIch* (eq. 3); (iii) the same as (i) but including the condition that the *EVIdiff*<0; and (iv) the same as (ii) but including the condition that *EVIch*>0. The latter two variations of the independent variable are used as an attempt to limit the effect of other potential influencing factors that may have caused the EVI values in certain districts to be positive despite the cyclone occurrence.

As for the independent variables (described in detail in section III-C, $HIES_d$ is the vector of district-level variables available from the Fiji household survey. $FAC_{sd \subset d}$ is the vector of subdistrict-level variables available from the agricultural census, aggregated to the district level (to match the level of aggregation in the household survey data).[5] $DIST_{cd}$ is the measured distance from the cyclone path, identified for each cyclone, for each district. The error term (ε_{cd}) is assumed to be independent and identically distributed.

For each of the four independent variables, we estimate a set of regressions for four distinct samples: all cyclones together (Harold, Winston, Josie, and Keni); Winston, Josie, and Keni; and all events except Harold.

TC Harold is the only cyclone within the dataset that is associated with a positive average EVI value (when combining both Sentinel and MODIS data), which would, on its own, suggest that the overall condition of Fiji's vegetation measured by EVI improved after TC Harold's occurrence. This further suggests that there might have been some measurement errors or other factors that affected the outcome associated with TC Harold. We are unable to explain this, and we therefore also estimated a sample that excluded only the observations on TC Harold.

[4] With respect to outliers, for the indicator "Average Income from Sale of Crops," two extreme values were removed for subdistricts Muaira and Vaturova as these were more than 20 times higher than the average. Therefore, the average crop income values for the respective districts did not account for these two subdistricts.

[5] We note that the FAC data was collected after the TCs hit Fiji. Ideally, we would have had access to a similar census done before cyclones. However, the census is not run frequently (the previous one was in 2009), and we were not granted access to it. In addition, land use is a slowly moving variable, and it is unlikely that the TCs themselves have led to such rapid land use changes to make the 2020 census irrelevant. We therefore use the 2020 census, in spite of its timing.

From the full set of independent variables extracted from the HIES and FAC, the variables used in the final regression models were selected by the following method. Initially, all available independent variables were included in the regression model, and the least statistically significant variable was identified based on its p-value. Then, we rerun the regression, removing the least statistically significant independent variable. This process was repeated until all the independent variables were statistically significant at a 10% level of significance. This method was used to identify statistically significant variables separately for each of the total of 16 regression models reported below (four EVI categories and four cyclone-grouping categories).

The regression models applied in the first table within each of the four EVI categories (Tables 4, 6, 8 and 10 in the Appendix) and within each cyclone type (table columns 1-4) contain only variables that were identified as statistically significant at a 10% level of significance for the regression of each specification. The second table within each category (Tables 5, 7, 9, 11 in the Appendix) shows a single regression model (a selection of independent variables) applied across all five types of cyclone events. Here, all variables that proved statistically significant for at least one cyclone event were included. The regression outputs for TC Harold by itself are in Table 12 in the Appendix,[6] while Table 13 presents the summary statistics of all variables.

E. Data and Method for Countrywide Analysis

Data for the annual agricultural income of Fiji were obtained from the Reserve Bank of Fiji (2021), which contains Fiji's agricultural gross value added at constant basic prices of 2014. Ideally, we would have liked to use annual district level agricultural income, but this data was not available. The data used for the years 2015–2019 are from the Fiji Bureau of Statistics; whereas, the data for 2020 are based on the Macroeconomic Committee's estimates as of July 2021.

A list of variables used for countrywide analysis is presented in Table 14 in the Appendix. The country-level weighted averages of *EVIdiff* and *EVIch* were calculated from district-level *EVIdiff* and *EVIch* values, using household crop income values from FAC as weights, to account for varying relevance of the district for the countrywide level of agricultural income. Since the only available district-level crop income data were for the year 2020 (during which TC Harold occurred), these values were also used as weights to calculate the weighted EVI averages for the years 2016 and 2018 (the years of the other two cyclone events).

In addition, since the national-level data only include a few observations, we could not pursue any statistical analysis. However, we discuss below the correlation between the change in agricultural income during the cyclone years, and the change in the EVI measures.

[6] Regression results for TC Harold when using negative *EVIdiff* and *EVIch* values are not reported due to the small number of observations (28).

IV. REGRESSION RESULTS

A. Absolute Enhanced Vegetation Index Change

Tables 4–7 in the Appendix show the regression results when *EVIdiff* is the dependent variable. Many of the variables do not seem very robustly associated with the difference in the EVI experienced post-cyclone. One variable that repeatedly comes out as significant at 1% of statistical significance, and maybe not surprisingly, is the distance from the TC path.[7] This is the only proxy we use for the intensity of the hazard, and the data seem to suggest that indeed a change in the EVI is therefore a satisfactory proxy for damage from TCs. The coefficient for the *Distance* variable is consistently positive (except for TC Harold), suggesting that an increased distance from the cyclone path was associated with higher *EVIdiff* values (i.e., less vegetation damage, a better outcome), which is consistent with our basic hypothesis.

Four other variables seem to consistently be statistically significant for the full set of observations (i.e., all districts, rather than just those in which the EVI decreased). From the FAC measures that describe the crop composition of each district, the variables that stand out are *Banana* (negative) and *Cassava* (positive).

The negative coefficient for banana suggests that a higher proportion of land cultivating banana, in an exposed district, is associated with more damage from the cyclone. Put differently, banana plants seem more vulnerable to the cyclone shock. The opposite is true for cassava; the more cassava a district has, the less damage from the cyclone it experiences (holding everything else constant).[8]

The total income and total transfer variables are also consistently statistically significant in Tables 4 and 5; although, *Income* is consistently positive and *Total transfer* is consistently negative. These results suggest that higher-income districts suffer less damage from tropical cyclones, other things being equal, and increased government transfers and remittances (from abroad) were associated with more damage to vegetation from tropical cyclones.

Beyond these five consistently identified associations with TC vegetation damage (*Distance, Banana, Cassava, Income,* and *Total transfer*), the coefficients for the *Dalo* crop share, similar to *Banana*, are consistently negative and significant for All TCs, but were not significant in the regression model that includes the same independent variables across the four cyclone categories (Table 5).

Next, we examine only those districts that experienced noticeable (remotely from space) damage from the TCs (the sample of observations with negative *EVIdiff* values). The results are shown in Tables 6 and 7 in the Appendix. The distance (from the cyclone path) is again consistently positive and statistically significant, except for the combined events of TCs Josie and Keni. This set of regressions includes a significantly smaller number of observations, so it might not be surprising that fewer variables are now statistically significant. *Banana* and *Dalo* still appear to be the crops

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[7] The only exception is in the case of TCs Josie and Keni, while using only negative EVI values.

[8] We remind the readers that, by "damage" here, we refer to a decrease in the EVI. It therefore might also be that banana plants experience more (remotely) visible damage, rather than genuine economic damage that manifests in reduced income from these crops. Unfortunately, data on income, by district and/or year, from specific crops are not available.

that are most vulnerable to cyclone damage; although, for banana, these results are slightly less consistent than what we had in Tables 4 and 5 for the full population of districts in Fiji.

Household size is now significant and consistently positive for All TCs and for TCs Josie and Keni in Table 6. When considering only observations with negative *EVIdiff*, the districts with bigger households were associated with less cyclone-induced vegetation damage. This variable is related to *Household income*, which is also positive and significant; hence, it is noteworthy that it is still statistically significant. *Cassava* is now statistically significant on at least 5% level of significance across all categories in Table 6.

The variable measuring the irrigated farm area (as a share of the district's total farm area), was significant and consistently negative for TC Winston and TCs Josie and Keni (in the regressions focusing on a specific TC event; Table 6, columns 2 and 3). This suggests that irrigated agricultural land may be less resistant to cyclone impacts, possibly because of its location or the crops using irrigation. The ratio of traditionally owned land is significant and consistently negative, except for TCs Josie and Keni, in the regression models including all variables (Table 7). This regression output also suggests that the more there is agricultural land under traditional ownership, the more sensitive to cyclone impacts is the district. The ratio of female farmers is now significant and consistently positive in TC Winston, in TCs Josie and Keni, and in TC Winston plus TCs Josie and Keni. These results, while indicative, are not robust enough to reach any firmer conclusions.

B. Relative Enhanced Vegetation Index Change

The regression models involving a relative EVI percentage change (*EVIch*) as the dependent variable (rather than the absolute EVI change) showed, to a certain extent, similar outcomes as the *EVIdiff* regressions. The most consistently significant variable is *Distance* and has positive coefficients. The *Banana* and *Cassava* variables, similar to the *EVIdiff* regressions, are significant except for the regressions for TCs Josie and Keni. The values of their coefficients also indicate that these crops are, again, associated with more vegetation damage in the case of bananas, and less damage for cassava.

The *Total transfer* variable is significant for All TCs, for TCs Josie and Keni, and for TC Winston plus TCs Josie and Keni in Tables 8 and 9 in the Appendix. Similar to the *EVIdiff* regressions, the coefficient values here are consistently negative and pointing at the same conclusion—that increased government transfers and remittances were associated with larger vegetation damage.

Noticeably, there are a few more variables that are statistically significant in some specifications, especially in the case of TC Winston (by far the strongest TC to hit Fiji in the last decade, and possibly the strongest TC ever recorded in the South Pacific). These include education, the yaqona crop, total income, and other income. However, since our aim is to identify a set of variables that will assist in nowcasting TC damage, we do not believe these can be consistently and reliably used.

In the last set of regressions (Tables 10 and 11 in the Appendix), we again use the percentage change in EVI as the dependent variable but restrict the sample to those observations for which the change was negative (i.e., there was observed decrease in the EVI). As we have seen above, the results become less statistically robust since the sample decreases, but the explanatory power of the model is quite high. The main consistently and reliably positive coefficient is still the distance from the cyclone path. Interestingly, in the specification of only the selected independent variables

(Table 10), the *Dalo* variable is consistently negative and significant at a 1% level of significance, suggesting a higher vulnerability to cyclone damage.

There is less consistency in any of the other variables, and we note that the regressions for TC Winston and for TCs Josie and Keni show the highest number of statistically significant associations with the EVI change variable.

In Table 11, where we include all statistically significant variables that came up through the algorithm, we find very little that is statistically and robustly significant (except for the distance variable).

V. COUNTRYWIDE ANALYSIS

When examining countrywide data, we can compare the EVI change (*EVIdiff* or *EVIch*) identified for each of the TCs with the change in Fiji's annual agricultural income as measured by agricultural gross value added. As Table 15 in the Appendix shows, the year 2016, which is associated with the largest decrease (both absolute and relative) in EVI values, is also associated with the worst outcome in terms of agricultural income that decreased by 8.7% between 2015 and 2016. While the year 2018 still shows an overall negative EVI change related to TC Josie and TC Keni, Fiji's annual agricultural income increased by 5.6%, which is the highest agricultural income increase among the three observed years. The year 2020 is the only year that shows an increase in EVI values despite TC Harold's occurrence, by 0.002 and 0.44% in absolute and relative terms, respectively. In the same year, the country's agricultural income increased by 3.0%.

This pattern can, of course, be completely coincidental. But we do believe that the destruction wrought by TC Winston is easily identifiable from space and, in principle, so should other intense cyclones. Ideally, if we were granted access to the district-level estimations of agricultural income, from which the aggregate figure is possibly derived, we would have been able to better examine the reliability of our proposed indicator.

Finally, we would like to suggest a possible algorithm for estimating the predicted change in agricultural income following a tropical cyclone.

- Once the TC path is known (this information is posted immediately after the event), it is possible to provide a preliminary estimate of the district-level change in the EVI, based on the coefficients for the variables we identified: distance from the path of the cyclone, banana and cassava (as grown in each district), income, and transfers. While this information is not time-sensitive, it allows one to estimate the likelihood that the cyclone will entail significant damage to agricultural production based on the basic parameters of the event.
- Once remote sensing readings of the cyclone are available, one can try to identify affected districts more closely, and attempt to redirect assistance toward them (when that is relevant). This, together with the information about general vulnerability (e.g., the share of banana plantations in the district) can assist in disaster risk reduction planning.
- With additional geolocated observations about local agricultural production, one could potentially design a tool that allows even more precise estimates of the economic impact on the agriculture sector more directly. We leave that for a time when the additional information is forthcoming.

VI. NEXT STEPS

The aim of this project was to develop a tool that will enable nowcasting of disaster impacts. While there is an extensive literature that attempts to link hazard indicators (such as ground shaking) with remote sensing data, we attempt to model the agricultural economic damage from a tropical cyclone also using socioeconomic and demographic information. Typically, only remote sensing geospatial data are used. This project was hampered by the unavailability of socioeconomic and demographic information in sufficiently high spatial and temporal resolution, so the analysis had to be cross-sectional, and at the district level. In essence, the aim of that was to show a prototype tool that can be used with more detailed data (spatially and temporally) to nowcast disaster impacts, in general, and agricultural damages from tropical cyclones, in particular.

This type of nowcasting is not yet done by disaster risk management agencies (multilateral or national), but we believe it holds significant promise in such cases as tropical cyclone impacts in the South Pacific. Using remote sensing high-spatial and high-frequency imaging that is now available, coupled with information from sociodemographic and economic data, should be superior to nowcasting modelling approaches that have been used in initiatives such as the Pacific Catastrophe Risk Assessment and Financing Initiative.

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Nowcasting from Space

Impact of Tropical Cyclones on Fiji's Agriculture

Satellite imagery can be a source of easily available, fast, affordable, and accurate data for assessing disaster impacts. This study investigates the feasibility of using remote sensing data for post-disaster damage assessment. It focuses on Fiji, its agriculture sector, and the tropical cyclones that wreaked havoc on the country in recent years. Findings of the study show that remote sensing data, when combined with pre-event socioeconomic and demographic information, can better explain the identified changes in the vegetation index, thereby improving both nowcasting and post-disaster damage assessments of tropical cyclones on agriculture.

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