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Nowcasting from space: tropical cyclones' impacts on Fiji's agriculture

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Abstract

Ground-based disaster damage assessments typically take the form of a team of experts being sent to the affected areas to conduct a survey. This approach is time-consuming, difficult, and costly. An alternative to this is an assessment based on satellite data, which can provide faster, cheaper, and possibly accurate insights into disaster's specific impacts. An even timelier option of disaster 'nowcasting' is supposed to inform on impacts during or very shortly after the event. Typically, this has been done using risk models, but these usually do not account for compounding and cascading effects. We propose a novel nowcasting approach for tropical cyclones employing pre-existing socio-economic and demographic data and calibrated with satellite data. The method could be used to assess cyclone impacts based only on its known trajectory, and even before post-event satellite imagery is available. We investigate the feasibility of this approach focusing on Fiji and its agricultural sector. We link remote sensing data with available household surveys and the agricultural census data to identify potential correlates of vegetation damage from cyclones. If robust enough, these correlates could later be used for nowcasting cyclone impacts. We show that remote sensing data, when combined with pre-event socio-economic and demographic data, can be used for both nowcasting and post-disaster damage assessments.

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1 Introduction

In the last few decades, satellite-based Earth observation data have been increasingly used for applications in different fields due to the significant innovations of this technology. One of these applications is for disaster and emergency management (Voigt et al. 2016). Within this field, satellite data are currently being employed in all the four phases of emergency management: mitigation, preparedness, response, and recovery.

One specific application of these data is for post-disaster damage assessment. Traditionally, post-disaster damage (or needs) assessment has been done by experts on the ground through a structured surveys, which is time-consuming, costly, and associated with potential negative psychological impacts on the assessment team. Alternatively, governments and especially public and private insurance companies employ risk models to quantify damages, but their results are often not accurate, as the models do not account for compounding or cascading effects. 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 (including compounded or cascading effects). Satellite data are now being used for damage assessments of many types of disasters induced by natural hazards—tropical storms, floods, landslides, earthquakes, and tsunamis.

Additionally, historical satellite data could also assist in creating tools to forecast disaster impacts during or shortly after an event (i.e., nowcasting), at a time when a standard damage assessment has not yet been done and impact information is very scarce. Our purpose, in this paper, is to develop a method for nowcasting agricultural damages from tropical storms employing remote sensing and socio-economic data. By combining historical satellite, cyclone path and socio-economic data (household surveys and the agricultural census), we aim to identify potential correlates of vegetation damage from tropical cyclones (TCs). If robust enough, these correlates may later be combined with the current cyclone path data to produce preliminary estimates of remote sensing measurements (before post-event satellite imagery is available) and assess the degree and spatial distribution of agricultural damage. Secondly, we describe a potential method for estimating cyclone-induced agricultural income losses based on the historical relationship between post-event remote sensing data and agricultural income trends.

In this paper, we focus on Fiji, a Pacific island country. For Fiji and many other countries in the region, TCs are the main disaster-inducing hazard. Between 1950 and 2004 these events accounted for 76% of the reported disasters in the region (Bettencourt et al. 2006). TCs are associated with intense winds, extreme and prolonged precipitation, storm surges, flooding and landslides (Terry 2007). They lead to deaths, injuries and disease, displacement and loss of livelihoods, disruptions to essential and other infrastructure, and negative impacts on many sectors such as agriculture, housing, transport, primary industries, and tourism (Doocy et al. 2013; Esler 2016). Fiji, the most populated country in the South Pacific, has particularly high exposure to cyclone impacts and suffers significant losses due to these events (Peduzzi et al. 2012; Noy 2016).

Since reliable satellite pictures of adequate resolution and frequency are only available for recent events, we consider the effect of four recent TCs on Fiji's agricultural sector. They are TC Winston (February 15, 2016), TCs Josie and Keni (April 2 and 10, 2018) and TC Harold (April 7, 2020). These events caused massive social and economic losses in Fiji, especially in the case of TC Winston, which was one of the strongest tropical storms in recorded history. The cyclone resulted in economic losses of approximately USD 1.4 billion—one third of Fiji's GDP, and affected more than half of the country's population

(NOAA, 2021a; WFP 2017). We combine the satellite and cyclone path data on these TCs with socio-economic data to attempt to identify any significant socio-economic, demographic, or agronomic correlates of cyclone-induced vegetation damage, which could then be utilized to nowcast future cyclone vegetation damages.

2 Literature review

2.1 Optical satellite imagery for disaster damage assessment

For disaster damage assessment, the most frequently used satellite sensors are: (1) optical, (2) synthetic aperture radar, and (3) light detection and ranging sensors. For optical sensors, the used combination of visible and infrared wavelengths is particularly useful for the detection of water surfaces and vegetation-covered areas, which makes it well suited for flood mapping or estimating vegetation impacts.

The utilization of optical satellite data for assessments of storm and flood damage is constrained by its reliance on cloud-free conditions, and the fact that the occurrence of these extreme events is often correlated with extensive cloud cover in the days surrounding the event (Rahman 2019). Secondly, many sources of high-resolution satellite imagery may be costly to acquire or not publicly available. 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 imagery (Battersby et al. 2012; Hodgson et al. 2010). This often requires the use of different satellite sources to gather as much relevant data as is possible during the first few days after the disaster.

Most damage assessment approaches combine the remote sensing imagery with ancillary data (e.g., satellite-derived digital elevation or terrain models, soil data or land use data) to derive more accurate disaster-related information. Many of these data types are freely accessible online from the US Geological Survey, national sources, or other international organisations. It is uncommon, in this literature, to combine the remote sensing data with socio-economic and demographic data, such as the data collected in standard household living standards surveys, or the decadal census.

2.2 General damage assessments

Damage assessments of floods and storms based on optical satellite data employ various satellite sources with different spatial and temporal resolutions. Spatial resolutions are typically categorized as low (> 100 m/px), moderate (5–100 m/px) or high (< 5 m/px). General damage estimations of tropical storms typically employ moderate resolution (Al-Amin Hoque et al. 2015, 2016, 2017; Phiri et al. 2020) or high-resolution imagery (Barnes et al. 2007; Doshi et al. 2018; Mas et al. 2015). Flood mapping and impact assessments on a large scale mainly make use of publicly available low resolution optical sensors, most commonly the Moderate Resolution Imaging Spectroradiometer (MODIS) (e.g., Arvind et al. 2016; Ban et al. 2017; Coltin et al. 2016; Lin et al. 2017, 2019; Memon et al. 2015). The benefits of MODIS are high spatial coverage and temporal resolution along with free availability. However, the low spatial resolution limits the assessments to relatively less detailed impact estimations. Flood mapping and damage assessments based on moderate resolution imagery employ data from Landsat (Du et al. 2020; Gianinetto et al. 2005; Hutanu et al. 2018; Li et al. 2016; Ma et al. 2011; Sivanpillai et al. 2020), Sentinel-2 (Kordelas

et al. 2018) or HC-CCD (Feng et al. 2015) sensors. Flood mapping employing high resolution satellite imagery, which may also provide insight into damages inflicted on individual structures, utilizes satellite sources such as SPOT-5 (Lamovec et al. 2013a), RapidEye (Lamovec et al. 2013b) or Worldview2 (Malinowski et al. 2015; Scarsi et al. 2014).

2.3 Specific impacts: vegetation and crop damage

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

Satellite-based assessments of storm-induced vegetation damage focus on various vegetation types such as forests (Cortés-Ramos et al. 2020; Chehata et al. 2014; Furukawa et al. 2020; McInerney et al. 2016; Negrón-Juárez et al. 2010; Rossi et al. 2013; Wang et al. 2010; Wang and Xu 2018; Zhang et al. 2013a), coastal vegetation (Charrua et al. 2021; Konda et al. 2018; Lu et al. 2020; Rodgers et al. 2009; Wang and D'Sa 2010) or mangroves specifically (Bhowmik and Cabral 2011, 2013; Long et al. 2016; Mandal and Hosaka 2020).

Even more closely related to our approach, another set of studies focuses on estimating storm and flood impacts on agriculture. Satellite-based storm and flood crop loss assessments are typically conducted based on flood intensity (Haq et al. 2012; Kwak et al. 2015a, 2015b; Van der Sande et al. 2003), crop condition (e.g., Di et al. 2013, 2018; Kotera et al. 2016; Rahman et al. 2020; Zhang et al. 2013b) or a combination of these two methods (Chen et al. 2017, 2019; Dao and Liou 2015; Gu et al. 2015). Flood-intensity-based studies typically estimate crop damages using stage-damage curves based on satellite-derived criteria such as flood extent or duration. Studies based on crop condition usually involve comparing pre- and post-flood values of satellite-derived spectral indices and apply regressions using these indices, associating them with crop yields or other measures (Rahman and Di 2020). This is similar to the approach we take here, as is described in detail in Sect. 3.

For the purposes of estimating crop condition in this paper, we employ the index differencing technique. This frequently used method belongs in the group of pre-classification change detection methods, which generally use an automated algorithm to detect differences in images between two discrete points in time, accounting for changes in pixel values (Deer 1995). In addition to being straightforward, this method has the advantage of reducing the impact of topographic effects and illumination (Lu et al. 2004). Index differencing techniques commonly employ vegetation indices such as the disaster vegetation damage index (DVDI), the normalized difference vegetation index (NDVI) or the enhanced vegetation index (EVI), with the EVI having an improved sensitivity over high biomass regions such as forests, and less sensitivity to atmospheric noise (Brun and Barros 2013).

While combining remote sensing data with socio-economic datasets is not entirely novel in disaster response and recovery (see for example Ghaffarian et al. 2021), it is typically not employed for post-disaster damage assessments. This is the case for macro-economic, or aggregated datasets, such as those we use here. In this case, the economic data are 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 spatially-detailed 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 geo-located, it can in principle be feasible to

Table 1 Correlation analysis at the regional level—EMDAT

Variables	Sentinel		MODIS	
	EVIch	EVIdiff	EVIch	EVIdiff
Disaster magnitude value	0.132	0.346	− 0.209	− 0.272
Total deaths	0.138	0.340	− 0.199	− 0.261
Number of injured people	0.142	0.331	− 0.188	− 0.248
Number of affected people	0.131	0.346	− 0.210	− 0.273
Total number of affected people	0.131	0.346	− 0.210	− 0.273
Economic damages	0.139	0.337	− 0.195	− 0.256

match these with remote sensing data that is of sufficient resolution. One of the main impediments for this kind of approach, however, is a justified concern about privacy. Regarding the analysis used in this paper, this concern was irrelevant as the household-level data are geolocated only to the district-level.

3 Data and methodology

3.1 Satellite sources

In this paper, we employ optical satellite data from Sentinel-2 and MODIS. Sentinel-2 is an Earth observation mission from the Copernicus Programme acquiring imagery over land and coasts with two twin satellites—Sentinel-2A and Sentinel-2B (ESA 2021). The imagery from the Sentinel-2 mission is characterized by moderate spatial (10, 20 and 60 m) and high temporal (5 days) resolution. We mask grid cells labelled as 'No data', 'Saturated or defective' as well as cloudy pixels ('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. This results in areas with missing data.

A different satellite source, MODIS, is used to supplement the missing Sentinel data. MODIS is obtained from instruments onboard the Earth Observing System Terra and Aqua platforms. Vegetation Indices data (MOD13Q1) Version 6 (LP DAAC 2021) from MODIS are provided every 16 days at a 250 m resolution. Cloudy and lower-quality pixels are also masked.

3.2 Vegetation damage

To estimate vegetation damage, we use satellite-derived vegetation indices. While vegetation indices are not greatly correlated with standard disaster loss measures such as disaster mortality, morbidity, or total economic losses (see Tables 1 and 2), they act as a useful proxy for vegetation or agricultural damages. In this paper, we use the *EVI*, which is more suitable to be used for the dense vegetation of the islands than other vegetation indices. Following Huete et al. (1997), the *EVI* is calculated as:

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

Table 2 Correlation analysis at the regional level—Desinventar

Variables	Sentinel		MODIS	
	EVIch	EVIdiff	EVIch	EVIdiff
Total deaths	0.043	0.136	− 0.156	− 0.190
Number of injuries	0.059	0.135	− 0.155	− 0.195
Number of missing people	− 0.051	0.094	− 0.110	− 0.104
Destroyed houses	0.061	0.135	− 0.155	− 0.195
Damaged houses	− 0.110	0.012	− 0.021	0.016
Directly affected people	− 0.113	0.007	− 0.015	0.025
Evacuated people	− 0.010	0.122	− 0.140	− 0.152
Total losses	0.062	0.134	− 0.155	− 0.195
Local losses	0.062	0.134	− 0.155	− 0.195
Hospitals	0.062	0.134	− 0.155	− 0.195

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

The impact of TCs on vegetation is estimated using vegetation image differencing between the pre- and post-TC *EVI* values using map algebra at the grid cell level. The closest available images within two months before and after each tropical cyclone are selected.[1] The calculated *EVI* change is regarded as cyclone-induced vegetation cover damage. We use indicators for both absolute (*EVIdiff*) and relative (*EVIch)* *EVI* change. These are calculated as:

$$EVIdiff = EVI_{postTC} − EVI_{preTC} \tag{2}$$

$$EVIch = \frac{EVI_{postTC} − EVI_{preTC}}{EVI_{preTC}} \tag{3}$$

whereby EVI_{postTC} and EVI_{preTC} correspond to post- and pre-TC landfall reading from the EVI, respectively. 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.

3.3 Socio-economic and cyclone path data

The socio-economic and demographic data, from which we attempt to identify vegetation damage correlates, are sourced from two primary sources: 2013–14 Household Income and Expenditure Survey (HIES) and 2020 Fiji Agriculture Census (FAC).

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

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[1] TCs Josie and Keni occurred only several days apart and images from the time between the two TCs were not available in many locations. Therefore, we calculate the EVI difference for this set of events using pre-Josie and post-Keni values (as if both were one single storm event).

at the district level (Tikina Cokavata). The respective districts were assigned to households based on the household ID numbers.

FAC is organised at a subdistrict (Tikina Vou) level. The data from a total of over 71,000 households capture detailed economic and demographic information related to the agricultural sector in rural and peri-urban areas where most agricultural activities are concentrated. Grouping up subdistricts into respective districts was done based on the administrative associations as defined in House of Chiefs (n. d.), 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.

Regarding the variables indicating the ratio of agricultural land used for specific crops, we were unable to access district-level data on sugarcane, which is the main crop grown in Fiji and represents approximately 60% of area harvested averaged over the period 2016- 2020 (FAO 2021). Using the available dataset on non-sugarcane crops, out of 75 crop types, only the crop types that cover at least 2% of the area used for non-sugarcane crops were selected: banana, cassava, coconuts, taro, rice and yaqona. These 6 crop types account for more than 85% of the non-sugarcane cropland. Similarly, for the land tenure variables, only the land tenure types which accounted for at least 5% of the total farmland area were selected: land under freehold, traditionally owned land, land under lease from state, and native lease. These four land tenure types together account for 98% of farm land.

Besides the data from 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 cyclone path) to 4 (furthest from cyclone path). More specifically, the distance from the cyclone was accounted for by establishing 4 zones with borders at 50, 100 and 200 km from the cyclone path, 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 2021b), and Reliefweb (2016). For the combined cyclone events of Josie and Keni, the lower cyclone distance value 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, along with their description and source. From the list of variables that were extracted from HIES and FAC, selected variables were removed from variable pairs that had a correlation coefficient higher than 0.7. The variables removed were: No savings account due to lack of access, number of females per agricultural household, ratio of agricultural land used for growing coconuts, native lease land ownership, average age, and imputed rent and wages [2].

3.4 Regression models

A linear regression model was applied to identify potential relationships between the demographic and socio-economic factors on one hand and cyclone-induced vegetation damage (approximated by the *EVI*) on the other. In principle, our aim is to identify the

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[2] 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.

Table 3 Independent variables

Variable	Description	Source
> 10 years of education	Ratio of farmers with at least 11 years of education	FAC
> 8 years of education	Ratio of farmers with at least 9 years of education	FAC
Agricultural education	Ratio of farmers who attended agricultural education	FAC
Agricultural income	Average household agricultural income	HIES
Agricultural use < 10 years	Ratio of land which has been in agricultural use for less than 10 years	FAC
Banana	Ratio of agricultural land used for growing bananas	FAC
Business income	Average household business income	HIES
Cassava	Ratio of agricultural land used for growing cassava	FAC
Taro	Ratio of agricultural land used for growing taro	FAC
Distance	Distance from the cyclone path (1 = less than 50 km, 2 = 50–100 km, 3 = 100–200 km, 4 = more than 200 km)	IBTrACS; Reliefweb (2016)
Farmers with difficulties	Ratio of farmers with functional difficulties (such as seeing, hearing or movement difficulties)	FAC
Female farmers	Ratio of female farmers	FAC
Household crop income	Average household crop income	FAC
Household size	Average agricultural household size	FAC
Irrigated farm area	Ratio of irrigated agricultural land	FAC
Land under freehold	Ratio of agricultural land under freehold land tenure	FAC
Land under lease from state	Ratio of agricultural land under lease from state land tenure	FAC
Married	Ratio of married farmers	FAC
Mobile phone ownership	Ratio of farmers who own a mobile phone	FAC
No savings account (money)	Ratio of farmers who do not own a savings account due to a lack of money	FAC
No savings account (money/access)	Ratio of farmers who do not own a savings account due to a lack of money or access	FAC
Other income	Average household other income	HIES
Permanent crop area	Ratio of agricultural land used to grow permanent crops	FAC
Rice	Ratio of agricultural land used for growing rice	FAC
Savings account ownership	Ratio of farmers who own a savings account	FAC

Table 3 (continued)

Variable	Description	Source
Selfemployed	Ratio of self-employed farmers	FAC
Tertiary education	Ratio of farmers with tertiary education	FAC
Average income	Average household income	HIES
Average transfer	Average household transfer (remittances and government transfers)	HIES
Traditionally owned land	Ratio of agricultural land traditionally owned	FAC
Yaqona	Ratio of agricultural land used for growing yaqona	FAC

correlates of vegetation damage from cyclones. We are not necessarily aiming to identify any causal mechanism from these independent control variables on the dependent variables (the variants of the *EVI* measure – see below) in our models.

We estimate the following equation:

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

whereby EVI_{cd}^x, the dependent variable, is calculated as one of the four variants of the EVI change around the time of the respective cyclone (*c*) in district (*d*). The EVI variants include: (1) absolute EVI change, *EVIdiff* (Eq. 2); (2) relative EVI change, *EVIch* (Eq. 3); (3) the same as (1) but including the condition that the *EVIdiff* < 0; and (4) the same as (2) 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 change values in certain districts to be positive despite the cyclone occurrence.

As for the independent variables (described in detail in Sect. 3.3), $HIES_d$ 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) [3]. $DIST_{cd}$ 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, and Josie and Keni); Winston; Josie and Keni; and Winston + Josie/Keni (all events except Harold).

Cyclone Harold is the only cyclone within the dataset that is associated with a positive average EVI value (when combining both Sentinel and MODIS data). This would, on its own, suggest that the overall condition of Fiji's vegetation improved after cyclone Harold's occurrence.[4] Due to this, we include the category 'Winston + Josie/Keni', which excludes the TC Harold observations. We present the regression results for TC Harold separately in Table 13 in the Appendix.[5]

From the full set of independent variables extracted from 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 and removed. Then, the regression was run again removing the least statistically significant independent variable. This process was repeated until all the independent variables were statistically significant at the 10% level of significance. This method was used to identify potentially significant variables separately for each of the total of 16 regression models reported below (four EVI categories and four cyclone grouping categories).

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[3] We note that FAC was collected after the TCs hit Fiji. Ideally, pre-cyclone data should be used. 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.

[4] We discuss TC Harold in more detail in Sect. 5.

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

The regression models applied in the first table within each of the four EVI categories (Tables 4, 6, 8 and 10) and within each cyclone type (table columns 1–4) contain only variables that were identified as statistically significant at the 10% level of significance for the specific regression for each specification. The second table within each EVI category (Tables 5, 7, 9, 11) shows a single regression model (a selection of independent variables) applied across all four types of cyclone grouping categories. Here, all variables that proved statistically significant for at least one cyclone event were included. Table 14 presents the summary statistics of all variables.

3.5 Data and method for agricultural income analysis

With sufficient data, one could apply statistical analysis to the historical relationship between post-cyclone satellite data (e.g., vegetation indices such as the EVI) and agricultural income trends. The insights could then be used to estimate cyclone-induced agricultural income losses using satellite data following a cyclone event. As we were not able to access annual district- or subdistrict-level agricultural income data, we are limited to an analysis on the national level, which is based on a very limited number of observations. Therefore, we only discuss the basic pattern and the correlation between the EVI change and the agricultural income change during the cyclone years.

The data for the annual agricultural income of Fiji were obtained from the Reserve Bank of Fiji, which contains Fiji's agricultural gross value added at constant basic prices of 2014. The data for the years 2015–2019 are from the Fiji Bureau of Statistics; the data for 2020 are based on the Macroeconomic Committee's estimates as of July 2021.

A list of variables used for agricultural income analysis is presented in Table 15. The country-level weighted average of *EVIdiff* and *EVIch* was calculated from district-level *EVIdiff* and *EVIch* values using household crop income values from FAC as weights, to account for varying contribution of the districts to the country's total agricultural income. Because 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).

4 Results

4.1 Regression results

We present the regression results for absolute EVI change (*EVIdiff*) in Tables 4, 5, 6 and 7 and the results for relative EVI change (*EVIch)* in Tables 8, 9,10 and 11. Out of the total of 29 variables originally identified to be potentially significant, only 5 variables come out as repeatedly significant[6] in the *EVIdiff* specification with a full set of observations and only

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[6] We consider a variable repeatedly statistically significant if it is significant at the 10% level in at least 3 out of 4 specifications, significant at the 5% level in at least 2 specifications and significant at the 1% level in at least 1 specification.

Table 4 All *EVIdiff* – selected independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Distance	0.0458***	0.0899***	0.0433***	0.0422***
	(0.0058)	(0.0212)	(0.0102)	(0.0068)
Female farmers	0.1895*	0.3233*		0.3166***
	(0.0971)	(0.1740)		(0.1153)
Banana	− 0.2957***	− 0.6218***		− 0.5103***
	(0.0882)	(0.1586)		(0.1103)
Cassava	0.1111***	0.4136***		0.2439***
	(0.0327)	(0.0877)		(0.0535)
Taro	− 0.1332***			
	(0.0490)			
Average income	0.0027*	0.0092***		0.0066***
(in thousands of FJD)	(0.0016)	(0.0029)		(0.0021)
Average transfer	− 0.0103*	− 0.0190*	− 0.0126**	− 0.0221***
(in thousands of FJD)	(0.0055)	(0.0111)	(0.0052)	(0.0073)
Other income	− 0.0501**	− 0.0813*		− 0.0693**
(in thousands of FJD)	(0.0230)	(0.0418)		(0.0299)
>8 years of education		− 1.0667***		− 0.4451***
		(0.2346)		(0.1571)
No savings account (money/access)		− 0.2168**	− 0.1586**	
		(0.1074)	(0.0717)	
Permanent crop area		0.2058**		0.1388**
		(0.0862)		(0.0538)
Land under freehold		− 0.1779**		
		(0.0808)		
Yaqona		0.1743**		0.1189**
		(0.0697)		(0.0494)
Household size			0.0513**	
			(0.0211)	
>10 years of education			− 0.5711***	
			(0.1525)	
Self-employed			0.0942*	
			(0.0481)	
Irrigated farm area			− 0.1272**	
			(0.0495)	
Rice			− 0.2410**	
			(0.0962)	
Agricultural income				
(in thousands of FJD)				
Farmers with difficulties				0.4341*
				(0.2282)
Mobile phone ownership				0.1398*
				(0.0829)
N	183	60	62	122
adj. R-sq	0.349	0.591	0.508	0.446

Table 4 (continued)

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$

Table 5 All *EVIdiff* values – all independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Distance	0.0445***	0.0787***	0.0345*	0.0421***
	(0.0063)	(0.0269)	(0.0175)	(0.0070)
> 8 years of education	− 0.2041	− 0.9757**	− 0.1612	− 0.5573*
	(0.2640)	(0.4752)	(0.3355)	(0.3101)
Farmers with difficulties	0.1991	0.4991	0.1556	0.4289*
	(0.2185)	(0.4091)	(0.2715)	(0.2564)
Female farmers	0.2006*	0.3837*	0.2244	0.2998**
	(0.1202)	(0.2120)	(0.1508)	(0.1413)
Land under freehold	− 0.0357	− 0.1882*	0.0523	− 0.0576
	(0.0424)	(0.1005)	(0.0509)	(0.0522)
Rice	− 0.0664	0.0927	− 0.3073**	− 0.0959
	(0.1058)	(0.1929)	(0.1366)	(0.1249)
Banana	− 0.3202***	− 0.6722***	− 0.1801	− 0.4819***
	(0.1202)	(0.2303)	(0.1501)	(0.1412)
Cassava	0.1165	0.3767**	− 0.0063	0.1655*
	(0.0834)	(0.1471)	(0.1033)	(0.0976)
Average income	0.0043**	0.0107***	0.0014	0.0065***
(in thousands of FJD)	(0.0020)	(0.0038)	(0.0026)	(0.0024)
Average transfer	− 0.0137**	− 0.0242*	− 0.0161**	− 0.0221***
(in thousands of FJD)	(0.0065)	(0.0142)	(0.0079)	(0.0079)
Other income	− 0.0576**	− 0.0848	− 0.0242	− 0.0629*
(in thousands of FJD)	(0.0291)	(0.0524)	(0.0363)	(0.0341)
N	183	60	62	122
adj. R-sq	0.323	0.541	0.452	0.425

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$. Variables that were included in all columns but were never statistically significant are not presented. These include household size, > 10 years of education, mobile phone ownership, no saving account, irrigated farm area, permanent crop area, Yaqona, Taro, and agricultural income

the selected variables (Table 4): *Distance, Banana, Cassava, Average Income,* and *Average transfer*.

The most consistent results are observed for the *Distance* variable, as it is significant at the 1% level of statistical significance across all specifications in Tables 4, 8 and 9.[7] This

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[7] We note that the distance variable was not found to be significant for the Josie/Keni event in the specifications using only negative EVIdiff values. These specifications include a significantly smaller number of observations.

Table 6 Negative *EVIdiff* – selected independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston+Josie/Keni
Distance	0.0413***	0.0985***		0.0379***
	(0.0052)	(0.0192)		(0.0063)
Household size	0.0283**		0.0437***	
	(0.0141)		(0.0139)	
Banana	− 0.1670**			− 0.3338***
	(0.0793)			(0.0941)
Cassava	0.1167***	− 0.3088**	0.0712**	0.1569***
	(0.0298)	(0.1286)	(0.0339)	(0.0438)
Taro	− 0.1226***	− 0.4305***	− 0.0912**	
	(0.0413)	(0.1107)	(0.0377)	
Household crop income	0.0014**	0.0025*		
(in thousands of FJD)	(0.0007)	(0.0014)		
>8 years of education		− 0.7859***		− 0.3879**
		(0.2728)		(0.1665)
Tertiary education		1.5789***		0.5166*
		(0.4970)		(0.2840)
Mobile phone ownership		− 0.4719**		
		(0.1777)		
Savings account ownership		0.5290***	− 0.1066*	
		(0.1384)	(0.0576)	
Female farmers		0.7470***	0.2102**	0.1910*
		(0.2336)	(0.0842)	(0.1022)
Irrigated farm area		− 0.1798**	− 0.0633**	
		(0.0713)	(0.0293)	
Traditionally owned land		− 0.2291***		− 0.0825**
		(0.0663)		(0.0393)
Land under freehold		− 0.4953***	0.1081***	− 0.0973*
		(0.1120)	(0.0293)	(0.0541)
Land under lease from state		− 0.5753**		− 0.3076**
		(0.2540)		(0.1337)
Yaqona		− 0.1381*		
		(0.0668)		
Rice		− 0.3561**	− 0.1897**	
		(0.1526)	(0.0845)	
Average income		0.0101**		0.0043*
(in thousands of FJD)		(0.0039)		(0.0024)
Average transfer		− 0.0232*		− 0.0122*
(in thousands of FJD)		(0.0119)		(0.0068)
>10 years of education			− 0.3993***	
			(0.1069)	
Agricultural education			0.9081***	
			(0.1970)	
Self-employed			0.0935**	
			(0.0351)	

Table 6 (continued)

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
No savings account (money/access)			− 0.2891***	
			(0.0492)	
No savings account (money)			0.2570***	
			(0.0864)	
Other income			− 0.0260*	− 0.0570**
(in thousands of FJD)			(0.0133)	(0.0250)
Farmers with difficulties				0.4255**
				(0.2027)
N	127	39	50	91
adj. R-sq	0.463	0.731	0.749	0.499

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$

is the only proxy we use for the intensity of the hazard, and the data suggest that a change in the EVI is a satisfactory proxy for damage from tropical cyclones. The coefficient is consistently positive; and this suggests that an increased distance from the cyclone path was associated with higher EVI change values (i.e., less vegetation damage, a better outcome), which is consistent with our basic hypothesis. Considering the consistency and high statistical significance of the variable, cyclone distance is the primary correlate of cyclone vegetation damage among the independent variables included in the regression models.

Regarding the socio-economic variables, four variables are repeatedly statistically significant in the specification with only the selected variables (Table 4). From the FAC measures that describe the crop composition of each district, the noteworthy variables 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 vegetation damage from the cyclone [8], making the banana plant relatively more vulnerable to cyclone impact. The opposite was found for cassava – higher fraction of land used for the cassava plant is linked to less district-level vegetation damage (holding everything else constant). Interestingly, the coefficients for banana and cassava were found to be less significant or inconsistently estimated (for cassava) in some of the regressions specifications which use only the negative EVI values. Here, it was the coefficient for *Taro* which was found to be consistently negative and repeatedly significant in Tables 6 and 10. This suggests that the taro plant may be more vulnerable compared to other crops. However, its statistical insignificance in the regression models using all EVI change values limits us from including this variable among the more reliable agronomic vegetation damage correlates such as *Banana* or *Cassava*.

Apart from *Distance*, *Banana* and *Cassava*, the remaining two repeatedly statistically significant damage correlates in Tables 4 and 5 are average household income (positive coefficient) and average household transfer (negative coefficient). While these two variables

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[8] We remind the readers that by vegetation 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/year, from specific crops are not available, but we discuss this issue in more detail in Sect. 5.

Table 7 Negative *EVIdiff* – all independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Distance	0.0384***	0.1196**	0.0024	0.0380***
	(0.0057)	(0.0394)	(0.0143)	(0.0069)
Agricultural education	− 0.2650	− 1.0799	0.8260**	− 0.1899
	(0.3148)	(0.6671)	(0.2958)	(0.3934)
Self-employed	0.0008	0.0414	0.0869*	0.0120
	(0.0519)	(0.1314)	(0.0502)	(0.0625)
Farmers with difficulties	0.4139*	0.3575	0.1495	0.6643**
	(0.2297)	(0.5668)	(0.2042)	(0.2746)
No savings account (money/access)	− 0.0022	− 0.1990	− 0.2721***	− 0.0475
	(0.0822)	(0.2301)	(0.0835)	(0.1019)
No savings account (money)	0.0013	0.0431	0.2143*	− 0.0112
	(0.1280)	(0.3779)	(0.1220)	(0.1535)
Female farmers	0.0571	0.7060**	0.1885	0.2537
	(0.1407)	(0.2754)	(0.1206)	(0.1709)
Irrigated farm area	− 0.0283	− 0.2251*	− 0.0693*	− 0.0716
	(0.0461)	(0.1089)	(0.0404)	(0.0555)
Traditionally owned land	− 0.0898**	− 0.2513**	− 0.0475	− 0.1037*
	(0.0428)	(0.1037)	(0.0374)	(0.0524)
Land under freehold	− 0.0989*	− 0.4585***	0.0608	− 0.1091
	(0.0566)	(0.1379)	(0.0548)	(0.0690)
Land under lease from state	− 0.1995	− 0.6153	− 0.0943	− 0.3153*
	(0.1264)	(0.3691)	(0.1270)	(0.1817)
Yaqona	− 0.0509	− 0.2189	− 0.0029	− 0.0490
	(0.0513)	(0.1864)	(0.0511)	(0.0685)
Rice	− 0.0116	− 0.3177	− 0.2555*	− 0.0664
	(0.1083)	(0.2149)	(0.1279)	(0.1276)
Banana	− 0.2011*	− 0.0839	− 0.0407	− 0.3101**
	(0.1099)	(0.2650)	(0.1099)	(0.1411)
Cassava	0.1049	− 0.2452	0.0745	0.1205
	(0.0654)	(0.2255)	(0.0701)	(0.0935)
Taro	− 0.1457*	− 0.5942***	− 0.0609	− 0.1260
	(0.0802)	(0.1772)	(0.0842)	(0.0997)
Household crop income	0.0016*	0.0033*	− 0.0004	0.0006
(in thousands of FJD)	(0.0009)	(0.0017)	(0.0010)	(0.0012)
Average income	0.0021	0.0087	0.0001	0.0058*
(in thousands of FJD)	(0.0027)	(0.0060)	(0.0026)	(0.0034)
Average transfer	− 0.0123*	− 0.0264	− 0.0033	− 0.0168*
(in thousands of FJD)	(0.0070)	(0.0156)	(0.0061)	(0.0084)
Other income	− 0.0250	3.54e−08	− 0.0246	− 0.0499
(in thousands of FJD)	(0.0278)	(0.0761)	(0.0276)	(0.0357)
N	117	39	50	89
adj. R-sq	0.467	0.695	0.662	0.462

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$. Variables that were included in all columns but were never statistically significant are not presented. These include household size, > 8 and > 10 years of education, tertiary education, no saving account, Yaqona, Cassava, and other income from the HIES

Table 8 All *EVIch* – selected independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Distance	0.0761***	0.1440***	0.0915***	0.0735***
	(0.0101)	(0.0301)	(0.0157)	(0.0119)
Permanent crop area	0.1043**			
	(0.0500)			
Banana	− 0.4865***	− 0.8138***		-0.6357***
	(0.1534)	(0.2714)		(0.1816)
Cassava	0.2364***	0.6036***		0.2738***
	(0.0514)	(0.1156)		(0.0651)
Average transfer	− 0.0235***		− 0.0261**	− 0.0277**
(in thousands of FJD)	(0.0078)		(0.0098)	(0.0118)
> 8 years of education		− 1.6837***		− 0.7441***
		(0.3935)		(0.2643)
Female farmers		0.4936*		
		(0.2688)		
Yaqona		0.1813**		
		(0.0810)		
Average income		0.0120**		0.0072**
(in thousands of FJD)		(0.0048)		(0.0035)
Other income		− 0.1970***		− 0.0910*
(in thousands of FJD)		(0.0700)		(0.0487)
Mobile phone ownership			0.2723**	
			(0.1166)	
Agricultural use < 10 years			− 0.1960**	
			(0.0907)	
Irrigated farm area			− 0.2143**	
			(0.0910)	
Rice			− 0.4032**	
			(0.1720)	
Self-employed				
Agricultural income				
(in thousands of FJD)				
N	183	60	62	122
adj. R-sq	0.305	0.526	0.453	0.380

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$

are slightly less significant in the specifications with relative EVI change and negative EVI change values, the results generally indicate that districts with higher average income suffer less damage from tropical cyclones, *ceteris paribus*, and increased government transfers and international remittances are associated with more vegetation damage.

Most of the other variables initially identified to be potentially significant are not robustly associated with post-cyclone EVI change. In the negative EVI change regressions with only the selected variables (Tables 6 and 10), *Household size* is significant and

Table 9 All *EVIch* values – all independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Distance	0.0750***	0.1553***	0.0944***	0.0735***
	(0.0106)	(0.0348)	(0.0213)	(0.0121)
> 8 years of education	− 0.2257	− 1.2493**	− 0.2603	− 0.6629*
	(0.3140)	(0.5643)	(0.4000)	(0.3716)
Mobile phone ownership	0.1032	0.1327	0.3176*	0.2548
	(0.1320)	(0.2393)	(0.1692)	(0.1573)
Female farmers	0.2491	0.6499**	0.3067	0.4333**
	(0.1792)	(0.3150)	(0.2416)	(0.2097)
Agricultural use < 10 years	− 0.0832	0.0042	− 0.2107*	− 0.1141
	(0.0959)	(0.1745)	(0.1237)	(0.1152)
Permanent crop area	0.1651*	0.2621	0.0655	0.1513
	(0.0880)	(0.1577)	(0.1161)	(0.1044)
Yaqona	0.1237	0.3324**	0.0664	0.1723*
	(0.0803)	(0.1419)	(0.1048)	(0.0949)
Rice	− 0.0481	0.1942	− 0.4736**	− 0.1059
	(0.1531)	(0.2646)	(0.2026)	(0.1810)
Banana	− 0.5319***	− 0.8800***	− 0.3853*	− 0.7200***
	(0.1723)	(0.3018)	(0.2184)	(0.2010)
Cassava	0.2852***	0.7331***	0.1058	0.3560***
	(0.0901)	(0.1617)	(0.1157)	(0.1060)
Average income	0.0070**	0.0143**	0.0053	0.0096**
(in thousands of FJD)	(0.0031)	(0.0055)	(0.0041)	(0.0037)
Average transfer	− 0.0234**	− 0.0241	− 0.0309**	− 0.0313**
(in thousands of FJD)	(0.0104)	(0.0202)	(0.0133)	(0.0126)
Other income	− 0.1010**	− 0.1330	− 0.0622	− 0.1050*
(in thousands of FJD)	(0.0486)	(0.0842)	(0.0628)	(0.0575)
N	183	60	62	122
adj. R-sq	0.305	0.507	0.426	0.381

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$. Variables that were included in all columns but were never statistically significant are not presented. These include self-employed, irrigated farm area, and agricultural income

consistently positive in 5 out of 8 specifications, indicating that the districts with bigger households were associated with less cyclone-induced vegetation damage. As this variable is related to *Average income*, it is not surprising that *Household size* is significant in the columns where *Average income* is not and vice versa in Table 6.

The negative *EVIdiff* regressions also show the variable measuring the irrigated farm area (as a share of the district's total farm area) to be significant and consistently negative for Winston and Josie/Keni (in the regressions focusing on a specific TC event—Tables 6 and 7). This suggests that irrigated agricultural land may be less resistant to cyclone impacts. One possible explanation could be that irrigated land is associated with higher levels of soil moisture, which could lead to more severe cyclone-induced flooding in flood-prone regions, as was shown for example in Rajeev and Mishra (2022). But other factors

Table 10 Negative *EVIch* – selected independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston+Josie/Keni
Distance	0.0687***	0.1378***		0.0640***
	(0.0081)	(0.0288)		(0.0095)
Household size	0.0405*		0.0561**	0.0581**
	(0.0219)		(0.0218)	(0.0272)
Banana	− 0.2317*			− 0.4118***
	(0.1235)			(0.1533)
Cassava	0.1611***	− 0.3400*		0.1729***
	(0.0464)	(0.1719)		(0.0602)
Taro	− 0.1890***	− 0.7470***	− 0.2352***	-0.2007***
	(0.0643)	(0.1804)	(0.0727)	(0.0743)
Household crop income	0.0021**	0.0042*		
(in thousands of FJD)	(0.0010)	(0.0021)		
>8 years of education		− 0.8894*		
		(0.4386)		
>10 years of education		1.4935***	-0.5094**	
		(0.4639)	(0.1902)	
Agricultural education		− 1.7946**	1.4420***	
		(0.7817)	(0.3060)	
Mobile phone ownership		− 0.8078***		
		(0.2593)		
Savings account ownership		0.6853***	-0.1793*	
		(0.1826)	(0.1035)	
Traditionally owned land		-0.1943**		
		(0.0784)		
Land under freehold		− 0.3897**	0.1776***	
		(0.1706)	(0.0463)	
Yaqona		− 0.3698***	− 0.1034*	
		(0.1146)	(0.0536)	
Self-employed			0.1293**	
			(0.0549)	
No savings account (money/access)			− 0.4516***	
			(0.0761)	
No savings account (money)			0.3813***	
			(0.1358)	
Female farmers			0.3644***	0.3316*
			(0.1308)	(0.1683)
Irrigated farm area			− 0.1419***	
			(0.0457)	
Permanent crop area			− 0.1051**	
			(0.0516)	
Rice			− 0.3953***	
			(0.1202)	
Other income			− 0.0474**	
(in thousands of FJD)			(0.0209)	

Table 10 (continued)

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Farmers with difficulties				0.5515**
				(0.2682)
Average transfer				− 0.0134*
(in thousands of FJD)				(0.0075)
N	127	43	50	91
adj. R-sq	0.468	0.595	0.755	0.512

Parentheses contain standard errors

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$

Table 11 Negative EVIch – all independent variables

Independent variable	All TCs	Winston	Josie/Keni	Winston + Josie/Keni
Distance	0.0649***	0.2035**	0.0097	0.0626***
	(0.0090)	(0.0769)	(0.0197)	(0.0107)
> 10 years of education	0.3457	1.6002	− 0.6392*	0.4220
	(0.4176)	(1.3931)	(0.3474)	(0.5041)
Agricultural education	− 0.4070	− 2.3084*	1.3298***	− 0.3740
	(0.5060)	(1.1079)	(0.4463)	(0.6149)
Mobile phone ownership	− 0.2605	− 1.1931*	0.0056	− 0.3050
	(0.1768)	(0.6320)	(0.1644)	(0.2306)
Savings account ownership	0.0794	0.8583*	-0.1406	0.1567
	(0.1682)	(0.4320)	(0.1575)	(0.2062)
No savings account (money/access)	0.0362	− 0.2118	− 0.4127***	0.0584
	(0.1244)	(0.4369)	(0.1291)	(0.1543)
No savings account (money)	0.0345	0.2177	0.3364*	0.0602
	(0.1989)	(0.6438)	(0.1727)	(0.2355)
Irrigated farm area	− 0.0031	− 0.2384	− 0.1243**	− 0.0625
	(0.0692)	(0.1620)	(0.0591)	(0.0836)
Traditionally owned land	− 0.0816	− 0.2437*	− 0.0339	− 0.0742
	(0.0592)	(0.1322)	(0.0506)	(0.0706)
Land under freehold	− 0.0960	− 0.4436*	0.1180	− 0.0743
	(0.0922)	(0.2428)	(0.0828)	(0.1123)
Rice	0.0014	− 0.2880	− 0.4375**	− 0.0869
	(0.1759)	(0.3508)	(0.1887)	(0.2071)
Taro	− 0.2798	− 1.0747**	− 0.1172	− 0.3633
	(0.1766)	(0.4132)	(0.1630)	(0.2337)
N	117	39	50	89
adj. R-sq	0.463	0.573	0.688	0.444

Parentheses contain standard errors

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$. Variables that were included in all columns but were never statistically significant are not presented. These include household size, > 8 years of education, self-employed, farmers with difficulties, female farmer, permanent crop area, yaqona, banana, cassava, household crop income, Average transfers, and other income

such as the location of irrigated land (potentially in more exposed places) or the use of irrigation for more vulnerable crops could play a role.

There are a few other examples of regularities among the different regression specifications. For example, in the negative *EVIdiff* models with only selected variables (Table 6), the ratio of female farmers is significant and consistently positive in 3 out of 4 specifications. In the models which include all variables (Table 7), the ratio of traditionally owned land is significant and consistently negative, except for TC Josie/Keni. This suggests that the more agricultural land is under traditional ownership, the more sensitive to cyclone impacts is the district. But while these results may be indicative, they are not robust enough to enable us to reach any firmer conclusions or to employ these correlates for nowcasting (see next sub-section).

We observe that the specifications of individual cyclone events (columns 2 and 3) which use the sample of only negative EVI change observations contain more significant variables than the regressions that use a complete set of EVI change observations. The explanatory power of these models is also relatively higher, though the results of these regressions are statistically less robust because they use a smaller sample. As our aim is to identify a set of variables that will assist in nowcasting TC damage, we do not believe these can be reliably used.

4.2 Nowcasting regression equation

Based on the regression results, five variables were identified to be repeatedly statistically significant. These were: *Distance*, *Banana*, *Cassava*, *Average income,* and *Average transfers*.

Using the coefficients from the regression specification with all *EVIdiff* values with the highest explanatory power, which is the specification for TC Harold, we can derive the final regression equation for nowcasting of district-level EVI change values during or right after a cyclone event (Eq. 5). We discuss the application of the equation in more detail in Sect. 7.[9]

$$
\begin{aligned}
EVIdiff_d = {} & 0.451 + 0.0899 * TCDistance_d - 0.6218 * Banana_d \\
& + 0.4136 * Cassava_d + 0.0092 * Income_d - 0.0190 * Transfer_d
\end{aligned}
\tag{5}
$$

5 Discussion

We identify a statistically robust relationship between the distance from the cyclone path and EVI change. This is in line with the results of other studies who find a strong link between cyclone distance and satellite-based vegetation indices such as NDVI, EVI or DVDI (Ayala-Silva and Twumasi 2004; Charrua et al. 2021; Lu et al. 2020; Zhang et al. 2013a). In general, greater distance from the cyclone path expectedly entails less impact on vegetation and this impact can be measured by vegetation index change.

With respect to socio-economic correlates of damage, the most robust results were observed for the share of the banana and cassava crops on agricultural land, average

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[9] See also the nowcasting tool described in Noy et al. (2023).

household income and average household transfers. The finding that banana plants are relatively more vulnerable to the cyclone shock may be explained by the fact that banana plants are known to be highly sensitive to wind stress (Ravi and Vaganan 2016). Consequently, cyclone impacts may lead to significant adverse effects on banana production and exports, as was documented for example for Dominica in Mohan (2017). On the other hand, a higher fraction of land used for cassava was, in our sample, associated with less vegetation damage. Even though cassava is known to be sensitive to flooding (Benkeblia et al. 2018), as a root crop, it is generally considered more resilient to abiotic stresses (such as wind stress) than most over-ground crops (Hershey et al. 2012).

Some indicative results also point to the taro plant, conversely to cassava, being highly sensitive to cyclone impacts. As both taro and cassava are root crops, one might expect similar results for both. There may be several reasons explaining this disparity. Interestingly, McNamara and Prasad (2014) mention that some cyclone mitigation strategies used in Fiji include cutting down the cassava plant (but not taro) to lower its height and prevent wind damage.[10] However, different physical characteristics of the two plants and other factors may also play a role and cause them to respond to the cyclone shock differently. In general, these discussed agronomic correlates of cyclone vegetation damage and their later empirical verification could add to the literature discussing tropical storm impacts and agricultural land use such as in Philpott et al. (2008) or Uriarte et al. (2004).

Lower levels of average household income were linked to higher vegetation damage. Lower-income farmers are known to be more vulnerable to cyclone impacts due to the relatively lower ability to mitigate, cope with, or adapt to these shocks (Rakotobe et al. 2016). Equally, it is plausible to assume that regions that receive higher levels of government transfers and remittances pre-event are poorer and more vulnerable (which is why they received more support). Therefore, these results fit well with the findings with respect to income.

The results for the identified socio-economic vegetation damage correlates (*Banana*, *Cassava*, *Average income* and *Average transfer*) appear to be indicative of certain observable recurring vegetation damage patterns, but the statistical robustness of these correlates, given our available dataset, is not high enough for current nowcasting use as an algorithm for producing preliminary EVI change estimates for future cyclones. While most of these correlates were relatively robust in the specifications with all EVI change values, their significance was reduced in the specifications limited to a sample of districts where vegetation damage was observable on average (the negative EVI change specifications). Ideally, damage correlates which can be employed for nowcasting should be confirmed with more statistical robustness. Later studies with access to more detailed (spatially and temporally) data may further confirm, refute, or add to the cyclone damage correlates identified here. As such, at this point our contribution is focussed on describing and developing a procedure for constructing such a nowcasting tool, rather than providing an operational prototype.

Future efforts in identifying cyclone damage correlates may benefit from using a more accurate proxy for cyclone intensity than cyclone distance; in particular focusing on maximum sustained wind speed and local percipitation). Our current procedure does not distinguish between variations in cyclone magnitude. Including intensity measures could improve the accuracy of the projected damages and enable easier identification of socio-economic or

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[10] It is worth pointing out that such a practice, were it conducted on a large enough scale, could lead to an EVI decrease itself.

other damage correlates. However, as our purpose is to develop a tool that can be immediately implementable in post-disaster situations (possibly hours after the event), relying on models that require data (wind-speed, high-resolution precipitation), that may be very difficult to obtain in many post-cyclone cases, should be seen as a weakness of the modelling approach.

If statistically robust damage correlates are identified, the resulting nowcasting tool consisting of the final regression equation also needs to be validated against verified damage data before the method could be reliably applied for Disaster Risk Reduction and Management purposes. Such validation could be conducted with ground-based measurements of cyclone impacts at a detailed spatial level, with aggregate ground-based impact measurements for multiple TCs.

We note a substantial difference between the results for TC Harold and the other examined cyclones (including the sample that includes all cyclone events). The cyclone distance variable, which is the most reliably significant variable in the other regression specifications, is not significant in the case of TC Harold. Potentially, this discrepancy in the results may be linked to the unusual EVI change values associated with the event, as Harold was associated with a positive EVI change on average. This would, on its own, suggest that the vegetation condition improved on average post-cyclone. One possible explanation could be that the cyclone-induced rainfall improved vegetation growth, perhaps due to low antecedent soil moisture conditions. We know that TC Harold led to significant crop damage especially in the most affected areas and the initial damage assessments estimated the total agricultural damage at over USD 12 million (ADB, n.d.; PHT 2023), but we were unable to find any estimates of the overall vegetation damage to verify such claim or the accuracy of the EVI readings. Alternatively, there might have been measurement errors or other factors that affected the outcomes associated with TC Harold, which we cannot explain.

Undeniably, this seems to be a weakness of our model – it is not yet good enough to account for each TC's impact. Each cyclone has, to a certain extent, its own idiosyncratic pattern of damage. Afterall, damage, per the UNDRR terminology, is determined by an interaction of the hazard with exposure and vulnerability. Damage can therefore differ substantially between communities whose fields are differently exposed or vulnerable. Generally, a nowcasting effort is aimed at identifying 'expected' damage. The actual damage will inevitably deviate from this expected damage, and we are not yet able to explain why it deviates as it does in the case of Harold.

6 Agricultural income analysis

In this section, we attempt to assess the historical relationship between post-cyclone satellite data and agricultural income trends. More specifically, we compare the EVI change (*EVIdiff* and *EVIch*) observed for each of the tropical cyclones with the change in Fiji's annual agricultural income as measured by agricultural gross value added.

As Table 12 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, which decreased by 8.7% between 2015 and 2016. While the year 2018 still shows an overall negative EVI change related to TCs Josie and 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%

Table 12 Comparison of EVI with agricultural income change	Year	EVIdiff	EVIch	Agricultural income change
	2016 (TC Winston)	− 0.077	− 11.79%	− 8.72%
	2018 (TC Josie/Keni)	− 0.035	− 5.14%	5.55%
	2020 (TC Harold)	0.002	0.44%	2.98%
	EVI and agricultural income change correlation	0.79	0.80	

in absolute and relative terms, respectively. In the same year, the country's agricultural income increased by 3.0%.

The resulting correlation coefficient between the EVI change and agricultural income change is relatively high at 0.8, but the limited number of observations restricts us from drawing any firm conclusions. While the correlation can be completely coincidental, we do believe that the severe damage wrought about by TC Winston (and in principle by other intense cyclones) is observable from space and that it may have implications for agricultural income in the affected regions. Vegetation damage is not the only determinant of cyclone agricultural impacts. Other effects may include damage to equipment, irrigation infrastructure or disruption of market access routes (Chikodzi et al. 2021). However, we suggest that the analysis of the relationship between vegetation damage and agricultural income trends holds promise and should be conducted with greater data abundance and in higher spatial detail (using at least district- or subdistrict-level data). As we were not able to do this due to data unavailability, we believe future research efforts in this area may prove helpful.

7 Next steps

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

- Once the TC path is known (this information is available immediately after the event), it is possible to provide preliminary estimates of district-level EVI change, based on the coefficients for cyclone distance and other damage correlates (we identified the share of the banana and cassava crops, average household income and transfers). As this information is not time-sensitive, it allows one to estimate the likelihood that the cyclone will entail significant vegetation damage and where that damage might be, based on the basic parameters of the event.
- Once remote sensing readings of the vegetation index after the cyclone are available, one can identify affected districts more precisely based on the EVI change, and attempt to re-direct 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 and in recovery and reconstruction.

- With additional spatially detailed data on agricultural production and income, one could potentially design a tool (as described in Sect. 6) that allows even more precise estimates of the economic impact on the agricultural sector more directly. We leave that for a time when the additional information required for this step will be, hopefully, forthcoming.

8 Conclusion

The aim of this research was to develop a data management process that will enable nowcasting of disaster impacts. While there is extensive literature that attempts to link hazard indicators (such as ground shaking) with remote sensing data, we attempt to model the agricultural damage from a tropical cyclone also using socio-economic and demographic exposure and vulnerability information.

This project was hampered by the unavailability of socio-economic and demographic data in sufficiently high spatial and temporal resolution, so the analysis had to be cross-sectional, and at the district level. Another limitation of the study is that due to the lack of data, we do not distinguish agricultural from non-agricultural land and analyse Fiji's vegetation cover more broadly. This may be obscuring some damage patterns which may apply to agricultural land specifically.

Apart from cyclone distance, the results for the socio-economic damage correlates identified here (mainly banana, cassava, income, and transfers) may not be robust enough to be presently used for nowcasting, considering the data limitations of the project. In essence, our aim was to demonstrate a method which can be applied to more detailed data to identify reliable vegetation damage correlates, which can be used to nowcast agricultural damages from tropical cyclones.

The use of nowcasting and timely disaster impact assessment can assist decision-making during disaster response and help adequately direct resources towards the most affected areas and potentially improve disaster outcomes in the South Pacific. The type of nowcasting proposed in this paper is currently not being employed by Disaster Risk Reduction agencies (multi-lateral or national), but we believe it holds a significant promise for application in the South Pacific and other regions which are exposed and vulnerable to tropical cyclones (and potentially other natural hazards). We suggest it would be beneficial for this type of nowcasting using remote sensing high spatial and high-frequency imaging that is now available, coupled with socio-demographic and economic data, to be further validated and consequently integrated in the Disaster Risk Reduction and Management efforts. This nowcasting may prove to be a useful complement to other nowcasting structural model-based approaches, such as those that have been used in initiatives such as the Pacific Catastrophe Risk Assessment and Financing Initiative (e.g. Begg et al. 2021).

Appendix

Tables 13, 14 and 15.

Table 13 TC Harold regression output – EVIdiff and EVIch

Independent variable	EVIdiff (selected variables)	EVIdiff (all variables)	EVIch (selected variables)	EVIch (all variables)
Self-employed	− 0.1167***	− 0.1352*	− 0.1982**	− 0.2479**
	(0.0436)	(0.0747)	(0.0847)	(0.1215)
Agricultural income	− 0.0126**	− 0.0099	− 0.0235**	− 0.0159
(in thousands of FJD)	(0.0048)	(0.0080)	(0.0094)	(0.0138)
Other income	− 0.1010***	− 0.0623	− 0.1940***	− 0.1180
(in thousands of FJD)	(0.0241)	(0.0439)	(0.0468)	(0.0781)
Permanent crop area		0.1360		0.2442*
		(0.1235)		(0.1431)
Agricultural use < 10 years				− 0.0120
				(0.1491)
N	61	61	61	61
adj. R-sq	0.259	0.056	0.241	0.127

Parentheses contain standard errors

***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$

Table 14 Summary statistics

Variable	Obs	Mean	Std	Min	Max
EVIdiff	199	− 0.04	0.09	− 0.33	0.20
EVIch	199	− 0.05	0.16	− 0.49	0.47
Distance	199	2.58	0.98	1.00	4.00
Female farmers	197	0.13	0.07	0.00	0.32
Banana	197	0.03	0.06	0.00	0.40
Cassava	197	0.20	0.20	0.01	0.85
Taro	197	0.11	0.13	0.00	0.58
> 8 years of education	197	0.86	0.06	0.66	0.96
No savings account (money/access)	197	0.22	0.14	0.03	0.72
Irrigated farm area	197	0.15	0.14	0.00	0.60
Land under freehold	197	0.11	0.16	0.00	0.95
Household size	197	4.21	0.40	2.78	5.24
> 10 years of education	197	0.32	0.06	0.11	0.43
Selfemployed	197	0.41	0.18	0.08	0.85
Rice	197	0.02	0.08	0.00	0.45
Tertiary education	197	0.07	0.03	0.00	0.13
Mobile phone ownership	197	0.59	0.12	0.19	0.82
Savings account ownership	197	0.45	0.15	0.13	0.69

Table 14 (continued)

Variable	Obs	Mean	Std	Min	Max
Traditionally owned land	197	0.68	0.28	0.01	1.00
Land under lease from state	197	0.05	0.09	0.00	0.38
Yaqona	197	0.31	0.28	0.00	0.84
Agricultural education	197	0.05	0.02	0.00	0.11
No savings account (money)	197	0.12	0.05	0.00	0.28
Permanent crop area	197	0.29	0.24	0.01	0.92
Agricultural use < 10 years	197	0.39	0.15	0.03	0.74
Married	197	0.73	0.04	0.65	0.84
Farmers with difficulties	197	0.07	0.04	0.01	0.18
Household crop income (FJD)	191	5282.80	7790.91	7.01	44,202.96
Average income (FJD)	184	16,314.59	6151.03	6382.47	42,989.52
Average transfer (FJD)	184	1716.48	1293.41	136.00	6729.21
Other income (FJD)	184	268.98	340.90	0.00	1198.31
Business income (FJD)	184	595.54	510.32	0.00	1978.73
Agricultural income (FJD)	184	3315.48	1840.77	350.48	9301.18

Table 15 Variables used in agricultural income analysis

Variable	Description	Source
Absolute EVI change	Weighted average of district *EVIdiff* values	Satellite imagery (Sentinel, MODIS)
Relative EVI change	Weighted average of district *EVIch* values	Satellite imagery (Sentinel, MODIS)
Agricultural income change	Relative change (%) of Fiji's agricultural gross value added compared to the previous year	Reserve Bank of Fiji

Declarations

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