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RESEARCH ARTICLE

Household vulnerability on the frontline of climate change: the Pacific atoll nation of Tuvalu

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Abstract This paper investigates the vulnerability of households to climatic disasters in the low-lying atoll nation of Tuvalu. Small Island Developing States, particularly the atoll nations, are the most vulnerable to climatic change, and in particular to sea-level rise and its associated risks. Using the most recent household surveys available, we construct poverty and hardship profiles for households on the different islands of Tuvalu, and combine these with geographic and topographic information to assess the exposure differentials among different groups using spatial econometric models. Besides the observation that poor households are more vulnerable to negative shocks because they lack the resources to respond, we also find that they are also more likely to reside in areas highly exposed to disasters (closer to the coasts and at lower elevation) and have less ability to migrate (between and within the islands).

Keywords Vulnerability · Exposure · Poverty · Hardship · Tuvalu

JEL Classification C31 · I3 · Q54 · Q56

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1 Introduction

The Pacific Island Countries (PICs), particularly low-lying islands, are confronted with a range of economic challenges because of their smallness, remoteness and limited resources. These attributes increase their populations' vulnerability to economic shocks, and have hampered the islands' capabilities to match rising global living standards. Unfortunately for households in these small atoll islands, many of the same geographical features that raise vulnerability to economic shocks also contribute to heightened exposure and vulnerability to climatic shocks. These countries, in particular, have seen their circumstances change with the rise in sea levels, and the increase in damage caused by climatic hazards (in particular for the Pacific island countries, cyclones). For the islands' poorest people, these dual economic and climatic threats pose an even greater challenge.

Even though poverty has been well researched globally, less attention has been given to Small Island Developing States (SIDS), and specifically to the PICs. This is surprising as the low-lying atoll island nations in the Pacific—Tuvalu, Kiribati and the Republic of the Marshall Islands—lie at the frontlines of climate change. The World Bank (2014) acknowledges that, "although the aggregate or macroeconomic impacts of negative shocks have been relatively well studied, much less is known about the impacts on household well-being, in large part because of data limitations". This paper aims to fill that gap by focusing on hardship and vulnerability facing households in the context of low-lying SIDS.

In this paper, we consider the case of Tuvalu, and in particular, the conditions of the population which are likely to relate to rising hardship resulting from climate change. To date, there have been few previous empirical studies on hardship and vulnerability in Tuvalu, or on any other atoll country. Since disaster risk is the confluence of the hazard itself, exposure to the hazard, and the vulnerability of the exposed population, it is paramount to examine the current state of exposure and vulnerability in the affected countries. This is our intent in this paper.

Specifically, we aim to explain how and which households in Tuvalu are particularly exposed and vulnerable to climatic shocks. Knowing these factors will assist in devising policies that reduce vulnerability and contribute to more effective disaster risk management (DRM), a crucial and potentially the most important component of climate change adaptation. Using detailed expenditure survey data encompassing one-third of the nation's population, the study is able to take a micro-perspective of the household, presenting empirical evidence of hardship and vulnerability to shocks that complements the macroeconomic analysis done elsewhere (e.g. Noy 2015, 2016; Cabezon et al. 2015). The work sheds further light on how households are facing and coping with disasters currently.

The paper proceeds as follows. The next section discusses the context of Tuvalu, Sect. 3 provides a short survey of the relevant literature on the measurement of poverty and hardship, Sect. 4 discusses Tuvalu's exposure to disasters, Sect. 5 outlines the empirical methodology, Sect. 6 describes the data, Sect. 7 explains the empirical results, while conclusions are presented in Sect. 8.

2 Background

The increasing frequency and intensity of disasters in the Pacific is well documented, and has contributed to the high (proportional) loss of human, natural, financial, social and physical capital in the region (Noy 2016; World Bank 2016). Tuvalu is a small low-lying country in the equatorial South Pacific.[1] It has a population of about 11,000 people, scattered across nine low-lying atolls. It is surrounded by an exclusive economic zone of 900,000 square kilometres (km^2) with a landmass of 25.9 km^2 that rarely exceeds 5 m above sea level. Population density is highest in the capital Funafuti, which accounts for more than half of the population of Tuvalu. Tuvalu has a dual economy consisting of a small cash economy and a subsistence economy focussed on its traditional sectors of fishing and small-scale agriculture (ADB 2007). Government revenue largely comes from issuing fishing licenses to foreign fishing vessels, '.tv' internet domain revenues, remittances, and foreign aid (directly funding the budget, and through funding distributed to the Tuvalu Trust Fund). Families in the capital Funafuti are more dependent on cash income than those living in the outer islands. People migrate from the outer islands to the capital Funafuti in search of job opportunities, better access to health facilities, and better education. Food and non-food items are mostly imported except for fish and a limited supply of a very narrow range of fruits and vegetables. Most of the people currently residing in the capital are originally from the outer islands, and have limited access to land and property ownership on Funafuti, hence, the reason for the high dependency on cash income in the capital.[2]

Most development and settlement in atoll islands occurs close to the coast, which is vulnerable to storms, floods and sea-level rise (World Bank 2016). As a low-lying coral atoll, the high spring tide (King tide) floods properties situated in low-lying areas (including inner parts of the capital Funafuti) as the water rises through the coral ground, destroying household plantations. People typically adapt by raising gardens above the ground and cementing around and under crops to prevent intrusion of seawater. However, these precautions are not fully adequate, and the combination of high tides and storms continue to pose considerable threat to households living at low elevation and near the coastline. Adding to the problem is the fact that the sea-level rise at Funafuti is three times above the global average between 1950 and 2009 (Becker et al. 2012), and this trend will likely worsen over time (Yamano et al. 2007). Appendix 4 shows the increasing trend of sea levels in Tuvalu.

[1] See the map of Tuvalu in Appendix 1.

[2] According to the 2012 Census, only 17.7% of the people living on Funafuti are local Funafuti people, while the rest are without land ownership, and are renting houses from the locals. Based on the 2012 Census, 84.5% of rental houses in Tuvalu are on Funafuti.

3 Poverty and hardship

There is a broad literature on poverty and vulnerability, but very limited focus on SIDS, especially low-lying islands like Tuvalu. Jha et al. (2009) measure the extent of vulnerability as expected poverty using cross-sectional data from a household survey in Fiji and find that vulnerability is largely a rural phenomenon. Similarly, Jha and Dang (2010) use cross-sectional data from the 1996 Household Survey for Papua New Guinea (PNG) to assess household vulnerability to poverty in PNG. These papers on Fiji and PNG do not focus on geographical and climatic factors, and the geographical settings, resource base and economic characteristics of these volcanic Pacific islands are different from low-lying atoll island countries such as Tuvalu.

We focus on poverty and exposure since they are vital indicators of how vulnerable, resilient and responsive households are to crises. According to Haughton and Khandker (2009), vulnerability is defined as the risk of falling into poverty in the future, even if the person is not necessarily poor at present; it is often associated with the effects of "shocks" from disasters and economic crises. Dercon (2005) outlines, for Sub-Saharan Africa, the links between risk and vulnerability to poverty thus highlighting the vital role played by them in determining people's livelihoods and opportunities to escape poverty.[3]

Abject poverty in Tuvalu is rare or non-existent, partly because of cultural and community traditions.[4] Help and support are common from families, communities, religious groups and friends. Poverty, as a term, is, therefore, not frequently used in many of the PICs that have similar circumstances and cultural practices.[5] We compare poverty levels from the three household surveys from different years to examine how poverty levels have changed over time. We follow Ravallion (1998) and Haughton and Khandker (2009) in defining and measuring poverty. Hence, we define poverty incidence as the percentage of households who fall below the food consumption level. Hardship is similarly defined for households whose expenditures fall below the benchmark food and non-food consumption levels. The vulnerability to poverty incidence refers to the percentage of households who are above the hardship threshold, but are vulnerable to falling under it as a result of negative shocks (measured

[3] Recent papers on Asian and African poverty and vulnerability are Dasgupta and Baschieri (2010), Dutta et al. (2011), and Échevin (2014); a recent comprehensive survey of this literature is by Hallegatte et al. (2015).

[4] Abject poverty was first coined by the United Nations (UN) in 1995 referring to the form of severe deprivation of basic needs and services that is faced by many individuals or households particularly in some least developed countries (LDC). Specifically, this form of poverty is characterized by a severe lack of food access, safe drinking water, basic sanitation, healthcare access, shelter, educational resources and access to information. Although Tuvalu is classified as an LDC by UN standards, the presence of 'abject poverty' there is rare.

[5] Abbott and Pollard (2004) emphasize that 'hardship' is a more acceptable terminology. The World Bank (2014) also argues that "the label of poverty is considered culturally inappropriate because it is viewed as implying a failure of traditional, community-based safety nets". Below we used hardship and poverty interchangeably, to mean "living with less than expected to meet both required food consumption and non-food essentials".

as 110% of the hardship level).[6] In addition, we also include the non-resilience incidence which refers to the percentage of households who are still vulnerable to negative shocks and could potentially fall into poverty. This non-resilience threshold is determined as those households living below 10 USD (purchasing power parity) per person per day, a measure that is believed to be necessary to achieve the degree of economic stability and resilience to shocks (see World Bank 2013).[7] Therefore, we identify four thresholds: poverty (food), hardship (food and non-food), vulnerability (10% above hardship), and non-resilience (10 USD).

Figure 1 shows that the poverty incidence has increased by less than 2% from 2004/2005 to 2010 at all levels of national, urban and rural. Hardship incidence has also increased by around 2% from 2004/2005 to 2010 for the urban population, but decreased by 2.22% for the rural one. The 1994 hardship incidences from Abbott and Pollard (2004) are higher at all three levels. Poverty incidence is usually higher in the urban area when compared with the rural one.[8] Some possible reasons leading to a higher urban poverty incidence are the overcrowding in the urban households and high wage unemployment.[9]

Except for the non-resilience measure, we do not observe dramatic increases in poverty, hardship and vulnerability in the 5 years separating the two surveys. Worryingly, however, we observe higher incidence of all the lower threshold measures (poverty, hardship and vulnerability) in the urban areas relative to rural ones. As the urban population is increasing faster than the rural one (mostly because of rural–urban migration), this may indicate a trend decrease in well-being. However, the non-resilience incidence is higher in the rural areas, and has increased significantly, between 2005 and 2010, exclusively in the rural area by 10%, while it decreased in the urban setting. These tabulations demonstrate that more severe poverty is found in the urban region, but that the well-being in the rural areas is also potentially fragile as households do not have sufficient resources to cushion against

[6] In practice, this includes all those below a threshold that is 10% higher than the Basic Needs Poverty Line (BNPL). The BNPL was calculated based on Ravallion (1998), and in line with Tuvalu Statistics Office's policy. The hardship threshold is the sum of the food threshold and the non-food threshold. The food component was calculated from a basket of essential basic food items that is estimated to be equivalent to the widely used nutritional requirement for good health of 2100 calories per person per day suggested by the Food and Agricultural Organisation (FAO) of the United Nations. The non-food threshold is the average non-food expenditure by households in the lowest 3 deciles. The non-food threshold is calculated differently for rural and urban (Funafuti) areas as the non-food expenditure, especially housing, is quite different between the regions. Expenditure is derived as the sum of food expenditure and non-food expenditure.

[7] USD refers to United States Dollars while AUD refers to Australian Dollars. The AUD is the legal tender in Tuvalu.

[8] This is also reported by Abbott and Pollard (2004) but unlike the case for Fiji reported in Jha et al. (2009).

[9] Other possibilities can be traced to the availability of more employment in the rural sector from the island council, clinics, island development projects, and small-scale businesses (after the collapse of the Tuvalu Cooperative Society). Informal work allocation in the outer islands is also more equally distributed amongst families and may not rely on educational qualification as much as in the urban area of Funafuti.

disaster shocks (such as cyclone Pam that hit many of the outer islands in March 2015).

We note that it is possible that the correlations we identify in our estimated regressions, described below, do not provide any information about causality as there might be endogeneity in our estimates. Income may determine some of the values that are identified in the independent variables. For example, it might be that poorer households end up locating in specific locations because they are poor, and not that these locations are associated with their poverty. In Tuvalu, however, where much of the land is customarily owned, and there are few market transactions in land ownership, this reverse causality is likely to be less of a concern. Nevertheless, in as much as endogeneity might be biasing our results, we are still faced with the limitations of the data available to us.

Appendix 5 displays maps of hardship incidences in the islands for different villages; we are able to construct these maps as households have been geo-located in the surveys. It is evident that households close to central areas have lower hardship incidences. We also observe that in the capital Funafuti, hardship incidence is much higher for those households living in the narrow parts of the island to the North and South and further away from the central area. Tuvalu's main atoll Funafuti is just 12.5 km long and no more than 800 m wide.[10]

4 Exposure to natural disasters

Many households in low-lying islands are geographically exposed to climatic disasters, and in this section we quantify this exposure in Tuvalu. Figure 2 analyses the vulnerability of households to disasters for all the islands.[11] The islands were divided into three groups, i.e. the Northern Islands (Nanumea, Nanumaga and Niutao), the Central Islands (Nui, Nukufetau, Vaitupu and Funafuti) and the Southern Islands (Nukulaelae and Niulakita). In terms of vulnerability and exposure to climatic disasters, for each island we measured the proximity to hazard locations in reference to households living within 100 m in land width (i.e. narrow parts of the island), households living within 100 m of the east coast, households living within 100 m of the coastline, households living less than 5 m of elevation, households living in non-concrete houses, and households who have less than 16,000 l of water storage capacity.[12]

The Northern Islands have higher exposure indices (compared to the Central and Southern Islands). The Central Islands have the highest percentage of households residing in narrow parts of the islands which are prone to disasters. On the capital Funafuti, 13% of households reside in narrow parts of the island which are exposed

[10] Authors' calculations from digitized maps.

[11] Niulakita, the smallest island, was excluded from the household survey.

[12] The assumed 16,000 l of water capacity storage threshold used is the median of household water storage available for all households surveyed in the 2010 HIES. This is assumed to be sufficient if water is used efficiently.

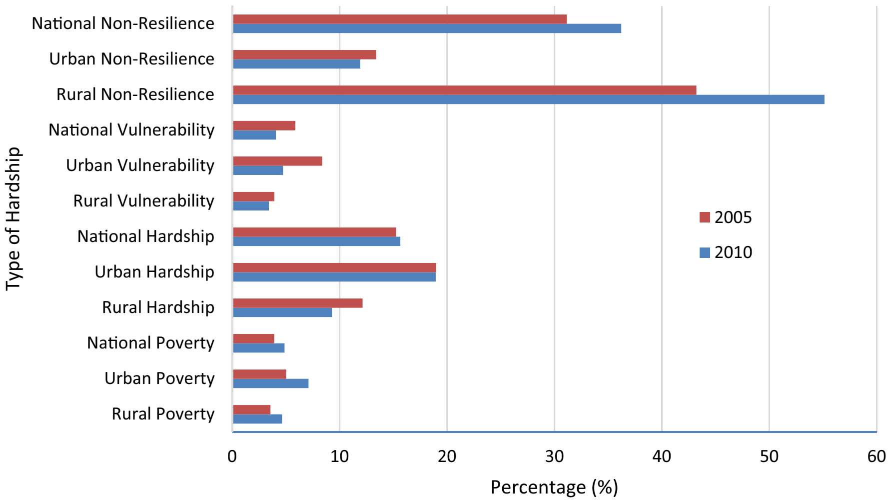

Fig. 1 Incidence of poverty and hardship in Tuvalu. Source: Authors' calculations, on data from 2004/2005 and 2010 Household Income and Expenditure Survey (HIES)

to storms, while 9.3% of households live beside pits and ponds which are prone to flooding during King tides.[13] While no surveyed households in the Northern and Southern Islands reside fewer than 50 m to the east coastline, it is not uncommon in the Central Islands, particularly Funafuti, with 17.2% of households living within 50 m of the coast. Many of the households in Nukulaelae (27.3% of households), Nui (16.2% of households), and Funafuti (12.5%) reside at low elevation compared to the other islands.[14]

Regarding house structures, 44.7% of households have concrete houses which are better able to withstand strong winds and storm surges. However, regarding vulnerability to droughts, Nanumea and Nui have the lowest water storage capacity.[15] Figure 3 displays exposure in terms of elevation and proximity to coastlines by income classification (hardship/non-hardship). In general, while we observe some

[13] Borrow pits (we will refer to it as "pits" onward) were created by digging/borrowing of soil from parts of the island of Fongafale (Funafuti), by the American military during World War II, to construct the airplane runway. We used 20 m to the pits as an indication of those living beside pits, based on the assumption that during King tides, a house within that range will most likely be flooded. This problem has been mostly solved in 2015 by the Tuvalu Borrow Pits Remediation (BPR) project funded under the New Zealand Aid Programme, where ten borrow pits on Fongafale island were filled with sand except for Tafua pond to the northeastern side of the airstrip, which is a natural pond. It is yet to be seen if we will observe any future flooding in these filled up pits.

[14] This was obvious since Nui and Nukulaelae were flooded during the 2015 Cyclone Pam. However, the three islands Nanumaga, Niutao and Vaitupu which have higher elevation did not experience flooding during Cyclone Pam, but only storm surge and coastal intrusion of sea waves from the western side. All islands build their harbour and houses on the western side of the island away from easterly winds, but a cyclone that strikes from the west side will badly hit most islands without lagoons and islets on the west as shields.

[15] Nanumea has a few wells that enable access to brackish freshwater lens (Johnston et al. 2012).

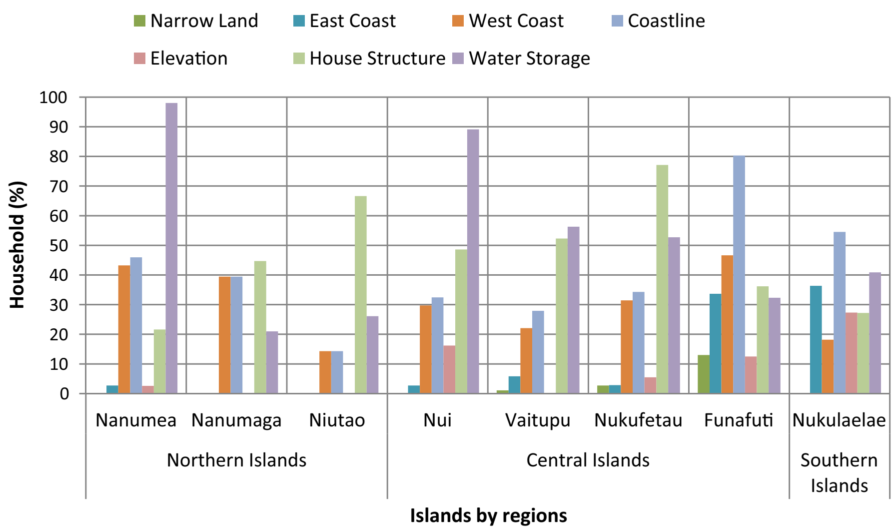

Fig. 2 Household vulnerability and exposure indicators to disasters by island. Source: Author's calculations from 2010 Household Income and Expenditure Survey (HIES) data

differences across the two groups: the non-hardship group is somewhat more likely to live closer to the coast, but also in higher elevation. However, these differences are not consistent across islands and do not represent a statistically significant difference across these samples.

5 Estimation methods

Olivia et al. (2009) argued that ignoring spatial dependencies across households, when using household survey data to estimate poverty levels, may lead to misleading estimates. Gibson and McKenzie (2007) further argue for the importance of using precise geo-location systems (e.g. GPS) to determine locations and distances between households. Their work suggests that distance from households to numerous geographic features like roads, markets, schools, and health clinics might be important in understanding poverty. Olivia et al. (2011) also outlined the importance of identifying environmental factors that influence poverty. Theoretical links are discussed in World Bank (2007) while Jalan and Ravallion (1998, 2002) provide empirical evidence linking the poor to geographical variables. Gibson and Rozelle (2002) used a probit estimation to show that poverty in Papua New Guinea (PNG) is primarily rural and is associated with communities with poor access to services, markets, and transportation.

Spatial regression methods permit us to account for spatial effects or spatial dependence between observations, where spatial data were geo-coded for location. Generally, spatial dependence refers to a situation where values observed at one household location, say household i, depend on the values of neighbouring

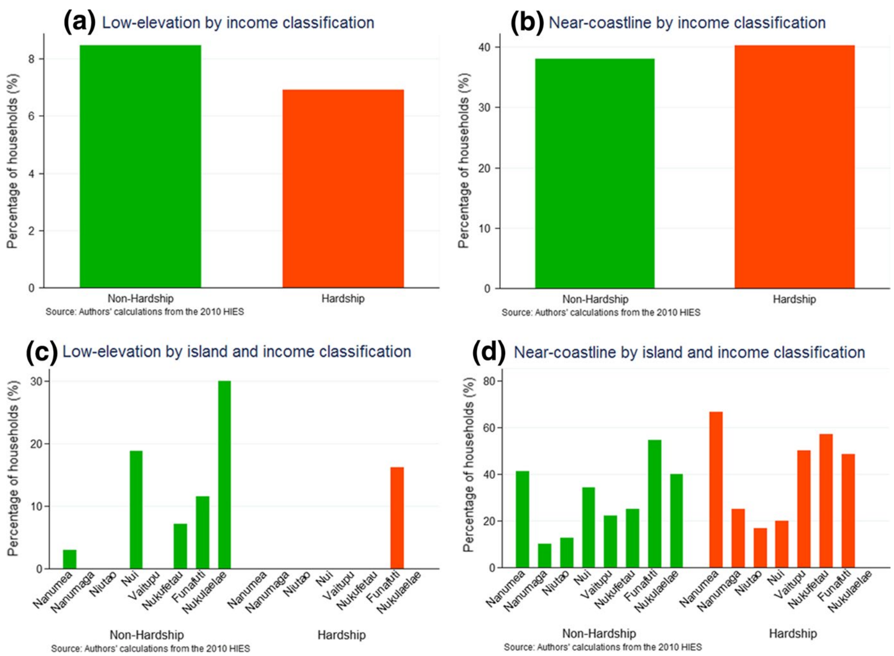

Fig. 3 Household exposure. Source: Authors' calculations from the 2010 HIES

households at nearby locations. Suppose we let households i and j represent neighbours, then the value taken by y_i depends on that of y_j. The spatial matrix identifies neighbours or spatially close households and their effects, and the need to account for the spatial dependence in the regression model.[16] Spatial models, similar to the one estimated here, have been used in other contexts in real estate economics, economic geography, and urban and regional science.

LeSage and Pace (2009) outline the two main motivations for estimation of spatial dependence. First, spillovers stemming from congestion effects may warrant estimation of spatial dependence models, as neighbours' outcomes directly impact one another. Second, spatial models may reduce estimation bias stemming from unobserved omitted variables which exhibit spatial dependence.[17] Following this literature,[18] we employed four spatial models (as described in the equations below) and

[16] ArcGIS was used for geo-coding of locations (households, schools, hospitals/clinics, etc.) creating a digitized map for all islands and islets in Tuvalu. These were then used in STATA for the empirical analysis.

[17] LeSage and Pace (2009) state that "omitted variables may easily arise in spatial modelling because unobservable factors such as location amenities, highway accessibility, or neighbourhood prestige may exert an influence on the dependent variable. It is unlikely that explanatory variables are readily available to capture these types of latent influences".

[18] See Anselin (1988), Elhorst (2014), Gibson and McKenzie (2007), Gibson and Rozelle (2002), Jalan and Ravallion (1998, 2002), LeSage and Pace (2009), and Olivia et al. (2011).

also include the standard Ordinary Least Squares (OLS) model for comparison.[19] The standard OLS model or the non-spatial linear regression model takes the form

$$Y_i = \alpha_i \iota_N + X_i\beta_i + \varepsilon_i, \tag{1}$$

where Y is the income that denotes an $N \times 1$ vector consisting of one observation on the dependent variable for the N units (households) in the sample ($i = 1,\ldots, N$), ι_N is an $N \times 1$ vector of ones associated with the constant term parameter to be estimated, X denotes an $N \times K$ matrix of exogenous explanatory variables, β is an associated $K \times 1$ vector with unknown parameters to be estimated, and $\varepsilon = (\varepsilon_1,\ldots, \varepsilon_N)^{\mathrm{T}}$ is a vector of disturbance terms, where ε_{i} is assumed to be independently and identically distributed for all with zero mean and variance σ^2.

We employ maximum likelihood estimation for the family of spatial regression models including Spatial Autoregressive Model (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM) and Spatial Autocorrelation Model (SAC). The SAR, SEM, SDM and SAC models take the specifications described in (2), (3), (4) and (5), respectively, below.

$$Y_i = \alpha_i \iota_N + \rho W Y_i + X_i\beta_i + \varepsilon_i \tag{2}$$

$$Y_i = \alpha_i \iota_N + X_i\beta_i + u_i, \quad \text{where } u_i = \lambda W u + \varepsilon_i. \tag{3}$$

$$Y_i = \alpha_i \iota_N + \rho W Y_i + X_i\beta_i + W X_i \gamma + \varepsilon_i \tag{4}$$

$$Y_i = \alpha_i \iota_N + \rho W_1 Y_i + X_i\beta_i + u_i, \quad \text{where } u_i = \lambda_i W_2 u_i + \varepsilon_i. \tag{5}$$

WY denotes the endogenous interaction effects among the dependent variable, and Wu the interaction effects among the disturbance term of the different units. The parameter ρ is the so-called spatial autoregressive coefficient, while λ is the spatial autocorrelation coefficient. There is no spatial dependence in the vector of cross-sectional observations Y if ρ takes the value of zero, thus yielding to the OLS model. W is a non-negative $N \times N$ matrix describing the spatial configuration or arrangement of the units in the sample. The spatial weight matrices will then be 'row-standardized' where the weights need to sum up to one on each row, or otherwise equal to zero if there are no neighbours.[20] The spatial weight matrix is defined as W with elements w_{ij} indicating whether observations i and j are spatially close, that is, $\mathrm{w}_{ij} = 1/d_{ij}$ for neighbours where d_{ij} is the distance between households i and j (inverse distance weights) and otherwise $w_{ij} = 0$. Beyond a certain distance, we assume that there are no spatial effects.

We also employ a binary outcome model (a probit) that is estimated with the dependent variable as the probability of a household experiencing hardship and an identical set of independent variables used in the non-spatial OLS regression.

[19] Elhorst (2014) shows the relationship between the different spatial dependence models for cross-section data.

[20] For our case, every household has at least one neighbour. Therefore, each row sums up to 1.

Following Gibson and Rozelle (2002) and Jha et al. (2009), the dependent variable in this case is a dummy defined as

$$\Pr\left(\mathrm{Pov}_i = 1|x_i\right) = F(X\beta), \tag{6}$$

where X is the vector of explanatory variables, β is the set of parameters reflecting the impact of changes in the probability. The F(Xβ) is the cumulative distribution function (CDF) of the standard normal distribution. This approach estimates the households' probability of being poor, but includes no spatial component. We estimate the limited dependent variable model as a robustness check and since this is a common methodology in the literature.

6 Data

We utilize the Household Income and Expenditure Survey (HIES) data collected by the Central Statistics Division (CSD) of the Tuvalu Government for the years 2004/2005 and 2010, which provide information on income and expenditures of households in Tuvalu. The 2010 HIES collected information from 541 households from all of the islands except for Niulakita[21] while the 2005 HIES has a sample of 459 households. The households surveyed were randomly selected. The surveys represent around 33% of the population of Tuvalu; this large sample was necessary for accuracy as a representative sample at the national level. The sample selection was spread proportionally across all the islands with a selection process that listed each dwelling on the islands by their geographical position and systematically skipped through the list to achieve the 33% randomly selected sample.

For spatial analysis purposes, we used the 490 households with available Global Position System (GPS) locations for the 2010 HIES. The survey includes both individual and household variables. For our model, the dependent variable used both income and expenditure as a measure of poverty and welfare. Additionally, we used a set of control variables of household characteristics and geographical measurements.

Income per capita was used as the measure of welfare for the non-spatial and spatial regressions while expenditure per capita was used to determine poverty lines where an acceptable minimum standard of that indicator was established (Pradhan and Ravallion 2000; Ravallion 1996a, b, 1998). We also used the binary indicator (poor and non-poor) as our dependent variable regressing on the same household characteristics used in the spatial and non-spatial regressions. Appendix 2 provides statistics about the dependent and independent variables and their sources.

[21] The smallest island in Tuvalu with only four households (based on the 2012 Census).

Table 1 Comparing means of selected indicators

	2004/2005			2010		
	Rural	Urban	National	Rural	Urban	National
Household size	4.839 (2.4228)	6.301 (3.2771)	5.409 (2.8739)	4.721 (2.5089)	6.757 (3.6047)	5.420 (3.0839)
Depend				1.993 (1.4869)	2.408 (2.0828)	2.136 (1.724)
Age	52.157 (13.9806)	46.245 (12.8297)	49.851 (13.8336)	51.724 (12.3203)	47.461 (12.1625)	50.260 (12.4203)
Gender	0.782 (0.4135)	0.754 (0.4317)	0.771 (0.4204)	0.817 (0.3869)	0.763 (0.4263)	0.798 (0.4013)
Marital status	0.782 (0.4135)	0.849 (0.3588)	0.808 (0.3940)	0.817 (0.3869)	0.810 (0.3929)	0.815 (0.3886)
Ethnic	0.950 (0.2183)	0.960 (0.1943)	0.954 (0.2091)	0.965 (0.1816)	0.934 (0.2474)	0.955 (0.2068)
Literate				0.702 (0.4577)	0.928 (0.2575)	0.780 (0.4143)
Education years	7.689 (3.2736)	9.564 (5.4007)	8.420 (4.3246)	7.851 (3.3533)	10.526 (4.184)	8.770 (3.8708)
Work				0.275 (0.4474)	0.609 (0.4893)	0.390 (0.4883)
House owner				0.839 (0.3680)	0.526 (0.5007)	0.731 (0.4435)
Urban			0.389 (0.4882)			0.390 (0.4883)
Distance to the centre				256.016 (136.8334)	1.157 (1.4703)	168.437 (164.1853)
Distance to primary school				0.399 (0.4161)	0.959 (1.3881)	0.592 (0.9185)
Distance to the hospital/clinic				0.450 (0.4580)	1.261 (1.3193)	0.728 (0.9389)
Distance to the central government				256.1234 (136.8127)	1.348 (1.5264)	168.609 (164.1447)
Land width				2.1465 (2.2384)	0.347 (0.2125)	1.528 (2.0080)
Distance to the coast				0.201 (0.1570)	0.096 (0.0688)	0.165 (0.1423)
Distance to the borrow pits				68.811 (58.3149)	0.382 (0.4024)	45.305 (57.3436)
Elevation				10.659 (2.7163)	6.634 (1.5654)	9.277 (3.0559)
Rainfall				2382.575 (525.7113)	2765.869 (83.8429)	2514.235 (465.6705)
Density				858.487 (1080.921)	3349.086 (594.264)	1713.998 (1512.862)
Observations	280	179	459	323	169	492

Source: Authors' estimations from 2004/2005 and 2010 HIES data. Standard deviations in parentheses

7 Estimation results and discussions

Table 1 compares the means of selected variables and indicators for the years 2004/2005 and 2010. Household size on average is higher in the urban areas. Education levels of heads of households increased between the two surveys with more educated household heads in the urban area though the differences are not very large. Urban households have a higher number of dependents, depend more on cash income, live in areas of lower elevation, narrower land width, in higher density (i.e. more than three times compared to rural), and closer to coastlines. Although those in the urban area have less access to land, house ownership, fisheries and agricultural activities, they have better access to the economic opportunities present in the capital.

The diagnostic tests for spatial dependence of the spatial models were carried out using the Moran's I and Lagrange multiplier tests (see Table 2).[22] Moreover, the Moran's I test statistic indicates the strength of the spatial autocorrelation of the residuals while the simple Lagrange multiplier (LM) tests for missing spatially lagged dependent variable and the robust LM tests for error dependence in the possible presence of a missing lagged dependent variable. The diagnostic tests provide most support to the SDM specification; as they indicate the presence of spatial dependence for all levels. ρ is the spatial autoregressive coefficient while λ is the spatial autocorrelation coefficient. The values of R^2 indicate the goodness of fit of the model.

Table 2 shows the model estimation results explaining income with the independent (RHS) variables (i.e. household characteristics, distance and location characteristics of households, and geographic variables).[23] For comparison of models and approaches, we show results from the standard linear model (column 1), the four spatial models previously described (columns 2–5) and divide the sample into the urban and rural observations (columns 6–7) with the preferred SDM estimation method (Eq. 4).

The age of the household head (*age*), marital status of the household head (*maritalstat*), education level of the household head (*educ*), household head working in the formal sector (*formalwork*), living in the urban (*urban*), and the distant to the coast (*dcoast*) were all highly significant with positive correlations with income. Household size (*hholdsize*), house owner (*houseowner*) and elevation (*elevation*)

[22] The Moran's I test statistic is used to test if the data have spatial dependence. According to Olivia et al. (2009), the Moran's I for a row-standardized spatial matrix where e is a vector of OLS residuals and W is the spatial weight matrix, asymptotically normally distributed with an expected value of − 1/(N − 1) and its statistical significance can be evaluated from a standardized normal table. It is expressed as $I = e^{\mathrm{l}}We/e^{\mathrm{l}}e$. The Lagrange multiplier (LM) tests for SEM and SAR whether ($\lambda = 0$) and ($\rho = 0$). The robust LM tests were also developed by Anselin et al. (1996) to cater for the presence of both SEM and SAR (which is a weakness for the LM test as LM_λ and LM_ρ have power against the other alternative). Olivia et al. (2009) provides more detailed discussion of the tests.

[23] We classified Funafuti as the urban and outer islands as rural since Funafuti is the capital and where the central government, commerce, main hospital, seaport and airport are located.

Table 2 Estimation results—LHS income per person (2010)

	OLS (1)	SLM (2)	SEM (3)	SAC (4)	SDM (national) (5)	SDM (urban) (6)	SDM (rural) (7)
hholdsize	− 0.114*** (0.00978)	− 0.114*** (0.00971)	− 0.114*** (0.00971)	− 0.114*** (0.00970)	− 0.113*** (0.00964)	− 0.0935*** (0.0133)	− 0.125*** (0.0145)
Age	0.00741*** (0.00249)	0.00751*** (0.00247)	0.00752*** (0.00247)	0.00757*** (0.00247)	0.00811*** (0.00250)	0.0168*** (0.00427)	0.00917*** (0.00327)
Gender	0.0143 (0.0830)	0.0130 (0.0820)	0.0127 (0.0820)	0.00809 (0.0824)	0.00870 (0.0862)	− 0.108 (0.143)	− 0.214 (0.145)
maritalstat	0.149* (0.0886)	0.147* (0.0876)	0.147* (0.0876)	0.151* (0.0878)	0.151* (0.0909)	0.336** (0.134)	0.138 (0.142)
educ	0.0279*** (0.00830)	0.0284*** (0.00824)	0.0284*** (0.00824)	0.0282*** (0.00825)	0.0304*** (0.00884)	0.0745*** (0.0146)	0.0256* (0.0133)
formalwork	0.268*** (0.0662)	0.272*** (0.0656)	0.272*** (0.0656)	0.271*** (0.0655)	0.264*** (0.0664)	0.209** (0.0996)	0.308*** (0.0959)
houseowner	− 0.129* (0.0681)	− 0.136** (0.0681)	− 0.136** (0.0680)	− 0.131* (0.0684)	− 0.124* (0.0682)	− 0.101 (0.108)	− 0.468*** (0.101)
Urban	0.552*** (0.0811)	0.572*** (0.0856)	0.573*** (0.0850)	0.545*** (0.0937)	0.566*** (0.102)		
Elevation	− 0.0446*** (0.0113)	− 0.0449*** (0.0112)	− 0.0448*** (0.0112)	− 0.0426*** (0.0115)	− 0.0268* (0.0147)	0.00161 (0.0461)	− 0.0328* (0.0176)
dcoast	0.437** (0.214)	0.455** (0.213)	0.457** (0.213)	0.471** (0.214)	0.336 (0.238)	− 1.287 (0.966)	0.316 (0.236)
w1x_hholdsize					− 0.00568** (0.00224)	0.0119 (0.00726)	− 0.710** (0.308)
w1x_age					0.00138* (0.000759)	0.00171 (0.00134)	0.236*** (0.0515)
w1x_gender					0.00378 (0.0347)	− 0.237** (0.105)	− 4.112 (3.702)
w1x_maritalstat					0.0315 (0.0393)	0.00496 (0.0630)	2.985 (3.011)
w1x_educ					0.00267 (0.00319)	0.0266*** (0.00795)	− 0.0315 (0.296)
w1x_formalwork					− 0.0147 (0.0211)	− 0.0999*** (0.0368)	2.331 (1.793)
w1x_houseowner					0.00887 (0.0151)	0.00476 (0.0371)	− 5.899*** (1.876)
w1x_urban					0.0216 (0.0151)		

Table 2 (continued)

	OLS (1)	SLM (2)	SEM (3)	SAC (4)	SDM (national) (5)	SDM (urban) (6)	SDM (rural) (7)
w1x_elevation					− 0.000854 (0.000830)	− 0.000106 (0.0111)	0.0696 (0.0449)
w1x_dcoast					− 0.0255 (0.0313)	− 0.877** (0.362)	− 2.097 (1.601)
Constant	9.119*** (0.226)	9.143*** (0.227)	9.144*** (0.227)	9.160*** (0.229)	8.894*** (0.267)	7.870*** (0.543)	19.39*** (6.152)
Rho		− 0.0000622 (0.0000922)		0.000870 (0.000930)	− 0.00952* (0.00573)	− 0.0119 (0.00865)	− 1.510*** (0.466)
Sigma		0.607*** (0.0194)	0.607*** (0.0194)	0.606*** (0.0194)	0.594*** (0.0190)	0.534*** (0.0292)	0.592*** (0.0238)
Lambda			− 0.0000685 (0.0000963)	− 0.00111 (0.00126)			
N	490	490	490	490	490	169	321
R^2	0.393	0.393	0.389	0.287	0.387	0.418	0.329
Moran's I		0.0102*	0.0117**	0.3521***	0.3731***	− 0.0105	0.0278**

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Rho ρ is the spatial autoregressive coefficient while lambda is the spatial autocorrelation coefficient are also highly significant, but with negative correlations with income.[24] The R^2 for all models are 0.3–0.4, at most explaining 40% of the variation in income across households.

Our diagnostic tests support the use of the SDM model.[25] In terms of the geographic variables that will most likely be important when considering future changes in climatic conditions, we find that, *ceteris paribus,* poorer households locate in higher elevation areas in the outer islands, but in lower elevation in the main island of Funafuti (where we already observed the poor are on the narrower parts of the island). For the urban area, our econometric specification does not yield statistically significant results with respect to the geographic variables when the urban sample is exclusively estimated. However, the number of observations used in the regression is reduced dramatically, so this reflects, at least in part, the expected drop in statistical power. The coefficients for the spatial variables in columns (5–7) indicate the impact of neighbouring household characteristics on the estimated household observation. As such, for example, we note that nearby households with a head of household that is older will be correlated with increased income in the estimated household. Note that in this case, we are not suggesting this is a causal relationship, but just that the distribution of income is non-random, and has a spatial component.

As household expenditure is sometime used as a measure of well-being (or lack thereof), rather than income, we estimate the determinants of per capita expenditure using similar specifications to the one described for income (see Table 3). In the Tuvalu case, the difference between household income and household expenditure is not very large, so that the results obtained for income are largely preserved when we examine expenditure. Even the spatial relationships appear to be similar for the two quantities.

We next examine household characteristics that make households more likely or less likely to be in poverty. We used a binary probit model with a hardship indicator, for all spatial aggregation levels (national, rural and urban), by regressing a binary dependent variable (poverty indicator, i.e. 1 if poor, else 0) with the same control variables we used for the linear income models. These specifications are estimated as some of the extant literature on poverty conducts these 'determinants of poverty' investigations, and we should like our findings to be comparable. The estimation results, in Table 4 column 1, show that households with higher household size (*hholdsize*), that reside on a higher elevation (*elevation*), and own a house (*houseowner*) are more likely to be poor. Nevertheless, households with higher household head's level of education (*educ*) and with formal work (*formalwork*) are less likely to be poor.

We also replicate the same regressions, after splitting the sample into urban and rural households (columns 2–3), to compare the differences in vulnerability and

[24] The elevation projected from the Digital Elevation Model (DEM) may differ marginally with land elevation. Variations between elevation and mean sea level (MSL) are explained in http://www.esri.com/news/arcuser/0703/geoid1of3.html. Note that the houseowner coefficient is only significant for the rural sample.

[25] Moran's I test is highly significant at 1% level, indicating spatial autocorrelation.

Table 3 Estimation results—LHS expenditure per person (2010)

	OLS	SLM	SEM	SAC	SDM (national)	SDM (urban)	SDM (rural)
hholdsize	− 0.0959*** (0.00967)	− 0.0951*** (0.00960)	− 0.0951*** (0.00960)	− 0.0951*** (0.00959)	− 0.0940*** (0.00956)	− 0.0835*** (0.0132)	− 0.101*** (0.0140)
Age	0.00538** (0.00246)	0.00551** (0.00244)	0.00552** (0.00244)	0.00558** (0.00244)	0.00618** (0.00246)	0.0166*** (0.00425)	0.00499 (0.00308)
Gender	− 0.0444 (0.0821)	− 0.0460 (0.0811)	− 0.0463 (0.0811)	− 0.0514 (0.0815)	− 0.0294 (0.0853)	− 0.135 (0.143)	− 0.282** (0.142)
maritalstat	0.181** (0.0876)	0.179** (0.0866)	0.179** (0.0866)	0.182** (0.0868)	0.164* (0.0898)	0.343** (0.134)	0.205 (0.139)
educ	0.0262*** (0.00821)	0.0268*** (0.00815)	0.0268*** (0.00815)	0.0266*** (0.00815)	0.0308*** (0.00875)	0.0697*** (0.0146)	0.0214* (0.0130)
formalwork	0.275*** (0.0654)	0.279*** (0.0648)	0.279*** (0.0648)	0.278*** (0.0648)	0.262*** (0.0657)	0.215** (0.0997)	0.320*** (0.0935)
houseowner	− 0.125* (0.0673)	− 0.134** (0.0673)	− 0.134** (0.0673)	− 0.129* (0.0677)	− 0.118* (0.0675)	− 0.100 (0.108)	− 0.403*** (0.0980)
Urban	0.368*** (0.0802)	0.393*** (0.0845)	0.392*** (0.0839)	0.364*** (0.0938)	0.386*** (0.101)		
Elevation	− 0.0460*** (0.0112)	− 0.0464*** (0.0111)	− 0.0463*** (0.0110)	− 0.0441*** (0.0114)	− 0.0267* (0.0145)	− 0.00221 (0.0461)	− 0.0349** (0.0172)
dcoast	0.463** (0.212)	0.486** (0.211)	0.487** (0.211)	0.501** (0.212)	0.389* (0.236)	− 1.001 (0.966)	0.355 (0.231)
w1x_hholdsize					− 0.00231 (0.00217)	0.0125* (0.00723)	− 0.596** (0.285)
w1x_age					0.00102 (0.000680)	0.00161 (0.00132)	0.151*** (0.0394)
w1x_gender					0.0222 (0.0345)	− 0.221** (0.105)	− 5.069 (3.615)
w1x_maritalstat					0.00873 (0.0386)	− 0.0102 (0.0630)	3.948 (2.953)
w1x_educ					0.00495 (0.00324)	0.0259*** (0.00789)	− 0.141 (0.288)
w1x_formalwork					− 0.0207 (0.0209)	− 0.105*** (0.0367)	3.015* (1.764)
w1x_houseowner					0.0140 (0.0149)	0.00761 (0.0370)	− 5.035*** (1.783)
w1x_urban					0.00888 (0.0135)		
w1x_elevation					− 0.00142* (0.000780)	− 0.000163 (0.0111)	− 0.0716 (0.0486)

Table 3 (continued)

	OLS	SLM	SEM	SAC	SDM (national)	SDM (urban)	SDM (rural)
w1x_dcoast					− 0.0157 (0.0310)	− 0.811** (0.362)	− 2.664* (1.574)
Constant	8.182*** (0.224)	8.211*** (0.224)	8.212*** (0.224)	8.231*** (0.227)	7.977*** (0.265)	6.835*** (0.544)	24.79*** (6.606)
Rho		− 0.0000878 (0.000103)		0.000994 (0.00104)	− 0.0121** (0.00606)	− 0.0131 (0.00921)	− 1.815*** (0.550)
Sigma		0.600*** (0.0192)	0.600*** (0.0192)	0.599*** (0.0191)	0.587*** (0.0188)	0.534*** (0.0292)	0.577*** (0.0235)
Lambda			− 0.0000933 (0.000106)	− 0.00129 (0.00144)			
N	490	490	490	490	490	169	321
R^2	0.327	0.328	0.322	0.214	0.343	0.385	0.272
Moran's I		0.0001	0.0021	0.3699***	0.0125**	0.0112**	0.0302**

Standard errors in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Rho ρ is the spatial autoregressive coefficient while lambda is the spatial autocorrelation coefficient

Table 4 Estimation results—LHS poverty binary indicator (2010)

	Probit			Spatial probit			
	National (1)	Urban (2)	Rural (3)	SLM (4)	SEM (5)	SAC (6)	SDM (7)
hholdsize	0.176*** (0.0264)	0.162*** (0.0386)	0.191*** (0.0390)	− 0.00000446 (0.0000952)	0.000124 (0.000399)	− 0.000106 (0.000374)	0.00176 (0.00352)
Age	− 0.00116 (0.00619)	− 0.00494 (0.0107)	0.00340 (0.00797)	0.000163*** (0.0000165)	0.000707*** (0.0000694)	0.000626*** (0.0000651)	0.00155* (0.000803)
Gender	0.0329 (0.222)	0.0943 (0.343)	− 0.0512 (0.327)	0.000112 (0.000820)	0.00103 (0.00347)	0.0000906 (0.00316)	− 0.0168 (0.0303)
maritalstat	− 0.141 (0.231)	− 0.432 (0.350)	0.0753 (0.343)	0.00331*** (0.000832)	0.0129*** (0.00351)	0.0138*** (0.00323)	0.0376 (0.0337)
educ	− 0.0517** (0.0222)	− 0.0786** (0.0339)	− 0.0263 (0.0311)	0.000333*** (0.0000769)	0.00143*** (0.000327)	0.00121*** (0.000301)	− 0.00693** (0.00342)
formalwork	− 0.654*** (0.189)	− 0.269 (0.279)	− 1.110*** (0.309)	− 0.000173 (0.000844)	0.000321 (0.00357)	− 0.000752 (0.00326)	0.0415 (0.0315)
houseowner	0.461** (0.194)	0.464* (0.267)	0.408 (0.309)	0.00313*** (0.000733)	0.0126*** (0.00311)	0.0124*** (0.00282)	0.0146 (0.0281)
Urban	0.264 (0.216)	0.0946 (0.566)	0.00669 (0.356)	0.00259*** (0.000882)	0.0122*** (0.00372)	0.00956*** (0.00340)	0.0735* (0.0423)
Elevation	0.0538* (0.0289)	− 0.00133 (0.0804)	0.0943** (0.0377)	0.000472*** (0.0000896)	0.00201*** (0.000382)	0.00195*** (0.000342)	− 0.00652 (0.00493)
dcoast	− 0.152 (0.558)	0.716 (2.134)	− 0.0899 (0.597)	− 0.00159 (0.00232)	− 0.00484 (0.00982)	− 0.00643 (0.00892)	0.286*** (0.0908)
w1x_hholdsize							0.00558*** (0.00110)
w1x_age							− 0.0000571 (0.000192)
w1x_gender							0.0268* (0.0152)
w1x_maritalstat							0.00821 (0.0144)

Table 4 (continued)

	Probit			Spatial probit			
	National (1)	Urban (2)	Rural (3)	SLM (4)	SEM (5)	SAC (6)	SDM (7)
w1x_educ							− 0.00865*** (0.00107)
w1x_formalwork							0.0339*** (0.00711)
w1x_houseowner							− 0.0140** (0.00558)
w1x_urban							0.00828* (0.00481)
w1x_elevation							0.000881*** (0.000282)
w1x_dcoast							0.0635*** (0.0120)
Constant	− 2.064*** (0.593)	− 1.032 (1.010)	− 3.040*** (0.855)	0.976	0.902	0.907	0.902*** (0.0975)
Rho				0.000134*** (0.0000389)		0.00105*** (0.000296)	− 0.0288*** (0.00546)
Sigma				0.00261*** (0.000195)	0.0111*** (0.000831)	0.0100*** (0.000753)	0.0864
Lambda					0.000599*** (0.000232)	− 0.000908* (0.000484)	
N	490	169	321	490	490	490	490
Moran's I				0.0121**	0.0121**	0.0293***	0.0518***

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

exposure. It generally shows very similar results with the national level, but with a few exceptions. The minor differences are mostly in statistical significance rather than qualitatively different. To further enable comparison, not only with previous research on the determinants of poverty, but also with our previous spatial results, we estimate the probit model with spatial effects (columns 4–7), with the last column estimating the model including the spatial relationships with neighbouring households. We observe that the spatial probit model appears to estimate the coefficients somewhat differently than in the non-spatial model. In this case, some of the coefficients appear to have counter-intuitive signs (education has a positive association with the poverty indicator, for example). Urban location is associated more with poverty, and we also observe a positive coefficient for the distance variable.[26]

Last, we used a panel of 130 households that we were able to identify in both the 2004/2005 and 2010 HIES to estimate income and poverty (total of 260 observations). We estimated this model using both fixed- and random-effects models and present these results in Appendix 3.[27] The results show that higher values of education (*educ*), higher distance to the coast (*dcoast*), migrating between islands (*b_islands*), household movements within islands (*w_islands*) and migrating to the urban (*urban_mig*) are associated with higher values of income. On the other hand, household size (*hhsize*) is associated with lower values of income.[28] Similar results were obtained from the panel data models estimating the binary poverty indicator (available upon request).

Previous research has already examined the pull of emigration in the atoll islands. Connell (2003) and Barnett (2005) find that climatic change is not the sole driver of ongoing population displacement in the Pacific. Based on interviews of a sample of the population on Funafuti in 2007, Mortreux and Barnett (2009) show that most respondents do not consider climate change as a main motive for emigration. However, emigration intentions may change following trigger events (like an extreme drought or a destructive cyclone)—see Noy (2016). Smith and McNamara (2015), while analysing the various factors that may determine emigration decisions, also suggest that migration from Tuvalu may become more common in several worst case climate scenarios.

[26] Note that the asymptotic theory of spatial models for limited dependent variables has only been developing recently, so we are uncertain about the robustness of these results (e.g., Qu and Lee 2012).

[27] The Hausman panel test indicated a strong preference for the fixed-effects (FE) model over random-effects (RE); while the Breusch–Pagan indicated the panel models are preferable to the OLS estimation. The FE model for N observations ($i = 1,\ldots,N$) and T time periods ($t = 1,\ldots,T$) is $y_{it} = \alpha_i + X_{it}+u_{it}$ where y_{it} is the dependent variable observed for individual i at time t, α_i is the unobserved time-invariant individual effect, X_{it} is the time-invariant $1 \times k$ regressor matrix, and u_{it} is the error term. However, we present all three specifications in the appendix for comparison.

[28] Note that there are no time-invariant variables on the right-hand side, e.g., variables such as "sex" and "ethnic" of the household head are not time-invariant variables as they change overtime in our data depending on who is the household head at a specified time. The identity of the household head present varies over time.

Table 5 Internal migration of households

Movement type	Households that moved	Non-poor households that moved	Households that moved to wider land width areas	Households that moved closer to the coast	Total number of households moved by region (actual and not in %)
	(% of households in source region)	(% of houses that moved from the source region)	(% of houses that moved from the source region)	(% of houses that moved from the source region)	
Outer islands to capital	14	70	20	90	10
Capital to outer islands	5	33	100	0	3
Between outer islands	11	100	75	50	8
Within the capital	19	91	72	54	11
Within outer islands	3	100	100	0	2
Total number of households by movement type (actual and not in %)	34	28	21	19	34

Source: Authors' calculations from the 2004/2005 and 2010 HIES data. The number of households used in the panel for the capital and outer islands are 57 and 73, respectively. The overall number of households is 130

A total of 26% of households migrated between islands where 82% are non-poor households.[29] Non-poor households dominate movements between islands except for movements of households from the capital island Funafuti to the outer islands where the poor represents 67%. Table 5 shows that most of the movements within islands happen with the capital Funafuti as either source or destination. It is evident that the poor and low-income households move less both between and within islands. The domination in movements by non-poor households is due to higher access to human and financial capital that is required for these moves.

There are more movements from the outer islands to the capital Funafuti and within the capital itself. Unlike the capital Funafuti, the fewer movements in the outer islands are due to the limited availability of rental houses. Some of the reasons for frequent movements of households on Funafuti are civil service employees moving between government houses or rented houses, civil servants on long-term training overseas availing their or rented houses to government or others, civil servants elevating in their work positions moving to higher level government or rental housing. Government houses on Funafuti are closer to the centre of the island—the wider part of the island in terms of land width. Household movements to the outer islands is mainly due to retiring civil servants, those who cannot find work in the capital, and professionals (teachers, nurses, police) who have to relocate for work from one island to another.[30] All outer islands have primary schools and clinics. The main secondary school is located on Vaitupu Island. It is evident that not only are the poor or low-income households more vulnerable and exposed to climatic disasters, they have less capacity for movements within and between islands. For statistics on movement between the islands, obtained from the surveys we used, see Table 5.

8 Conclusion

Hardship is a challenge that merits the attention of policy makers in the Pacific. Our findings indicate that poverty has increased in Tuvalu over the past decade, but other potential measures of hardship and vulnerability show a decrease over time. We do conclude that hardship levels are higher in the urban area (see Fig. 1) compared to the rural outer islands. The proportion of households who are potentially vulnerable

[29] Authors' calculations from data. These reflect the overall number of households that migrated between the islands and those who are non-poor.

[30] All outer islands have primary schools, clinics and police stations. The main boarding secondary school is located in the outer island on Vaitupu.

to falling into hardship if there is a shock is also higher in the urban area and is increasing.

Households on the urban region of Funafuti are also more exposed and vulnerable to disasters than most of the outer islands, because of their proximity and direction of exposure to the coast, and low elevation (see Fig. 3). We also find that not only are the poor more likely to reside in areas prone to disasters in both the rural islands and the capital, they also tend to migrate internally and externally less compared to non-poor households. This observation may end up being important in the future if migration becomes the only viable adaptation option to sea-level rise—as many observers foresee. As migration becomes more necessary, a further related concern is that those who will be most exposed and, therefore, the most desperate to migrate will have the least ability to do so. This may lead to 'trapped populations' that also lack the 'voice' to express their plight and mobilize assistance.[31]

More generally, the analysis that we provided here for Tuvalu could be applied to other Pacific Atoll nations (and atoll islands elsewhere). If the patterns of poverty and hardship elsewhere are closely associated with climate vulnerability as they are in Tuvalu, this is noteworthy on its own. The atoll islands are essentially the canary-in-the-coal-mine for our understanding of the impact of climate change on vulnerable populations. The observations we presented should then further inform discussions about the future of the atoll islands in the face of accelerating climatic changes and discussions about their future through, for example, the Warsaw International Mechanism for Loss and Damage (see Mechler and Schinko 2016).

Appendix 1

See Fig. 4.

Appendix 2

See Table 6.

Appendix 3

See Table 7.

[31] See Noy (2017) and Black and Collyer (2014) for relevant discussions about 'voice' and the risk of being 'trapped', respectively.

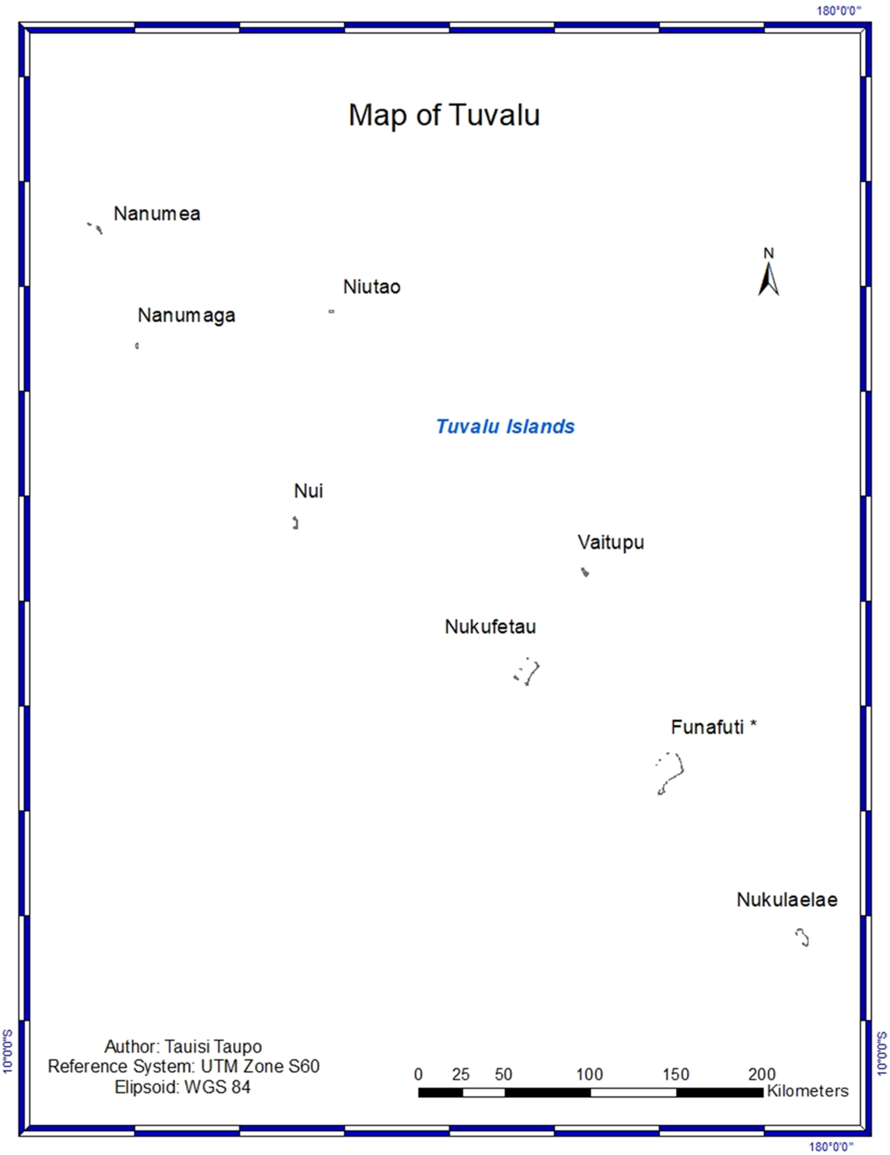

Fig. 4 Map of Tuvalu. Source: Authors' digitized maps

Table 6 Description of variables

No.	Variable	Description	Obs	Mean	Std. dev	Min	Max	Source
1	linc	Logarithm of income per person	490	9.1329	0.7795	7.2605	11.9135	Authors' calculations based on household data from the Central Statistics Division (CSD), Government of Tuvalu
2	hholdsize	Number of persons in the household	490	5.4265	3.0889	1	20	
4	age	Years of age of the household head	490	50.2551	12.4336	22	86	
5	gender	Gender of the household head. Dummy, takes the value of 1 if the household head is a male, otherwise 0	490	0.8	0.4004	0	1	
6	maritalstat	Marital status of the household head. Dummy, takes the value of 1 if the household head is married, otherwise 0	490	0.8142	0.3892	0	1	
7	ethnic	The ethnicity of the household head, whether is a Tuvaluan or not. Dummy, takes the value of 1 if the household head is from Tuvalu, otherwise 0	490	0.9551	0.2072	0	1	
8	lit	Household head potential to read and write in both English and Tuvaluan languages. Dummy, takes the value of 1 if the household head knows both Tuvalu and English, otherwise 0	490	0.7795	0.4149	0	1	
9	educ	Years of education of the household head	490	8.7673	3.8783	0	18	
10	formalwork	Dummy, 1 if the household head works in the formal sector, otherwise 0	490	0.3877	0.4877	0	1	
11	houseowner	Dummy, takes the value of 1 if the household head owns a house, otherwise 0	490	0.7326	0.4430	0	1	

Table 6 (continued)

No.	Variable	Description	Obs	Mean	Std. dev	Min	Max	Source
12	urban	The capital island Funafuti is referred to as urban while rural refers to all the outer islands. Dummy, takes the value of 1 when the household is in the urban, otherwise 0	490	0.3918	0.4886	0	1	Authors' calculations based on GPS locations of households using reference system UTM Zone S60 with ellipsoid WGS 84 and the Digital Elevation Model (DEM)
13	d_pri	Distant to the nearest primary school in km	490	0.5942	0.9198	0.0228	9.2590	
14	d_hosp	Distant to the nearest hospital and or clinic in km	490	0.7304	0.9405	0.0374	9.1691	
15	d_govt	Distant to the government and commercial area at the capital Funafuti in km	490	168.0857	163.9198	0.0483	466.3428	
16	dwide	Distant from lagoon coast to the sea coast in km	490	1.5295	2.0121	0.0656	8.2440	
17	dcoast	Distant to the nearest coastline in km	490	0.1653	0.1426	0.0087	0.9016	
18	d_pits	Distant to the nearest borrow pits and ponds in km	490	45.2424	57.3278	0.0023	128.602	
19	density	Population per kilometre square	490	1719.915	1513.103	151.4059	3476.629	
20	elevation	Elevation in metres	490	9.2718	3.0608	1.8976	17.3287	
21	b_islands	Dummy, 1 if household moved between islands	260	0.1307	0.3377	0	1	Additional variables for panel data. Authors' calculations based on GPS household locations and household data for 2004/2005 and 2010 from CSD
22	w_islands	Dummy, 1 if household moved within islands	260	0.0461	0.2102	0	1	
23	urban_mig	Dummy, 1 if household moved from outer islands to the capital	260	0.0653	0.2476	0	1	
24	migrate_oi	Dummy, 1 if household moved between outer islands	260	0.0423	0.2016	0	1	
25	rural_mig	Dummy, 1 if household moved from the capital to the outer islands	260	0.0230	0.1504	0	1	

Table 7 Panel data models estimating income

	Pooled OLS	Fixed effects	Random effects	Pooled OLS	Fixed effects	Random effects
educ	0.0541*** (0.0120)	0.0696*** (0.0263)	0.0544*** (0.0129)	0.0593*** (0.0119)	0.0587** (0.0255)	0.0590*** (0.0129)
hhsize	− 0.0611*** (0.0158)	− 0.0939*** (0.0287)	− 0.0676*** (0.0164)	− 0.0564*** (0.0161)	− 0.0965*** (0.0277)	− 0.0638*** (0.0167)
Sex	0.164 (0.112)	− 0.474** (0.236)	0.0822 (0.120)	0.145 (0.112)	− 0.333 (0.237)	0.0575 (0.121)
Age	0.000648 (0.00311)	− 0.00131 (0.00699)	0.000191 (0.00336)	0.000428 (0.00314)	− 0.00551 (0.00701)	− 0.000183 (0.00342)
Ethnic	0.186 (0.205)	0.00472 (0.614)	0.147 (0.226)	0.156 (0.208)	0.219 (0.593)	0.117 (0.231)
dcoast	0.000283 (0.000195)	0.000609** (0.000305)	0.000350* (0.000200)	0.000243 (0.000198)	0.000716** (0.000300)	0.000352* (0.000203)
dwide	− 0.00022*** (0.0000569)	− 0.000170 (0.000115)	− 0.00021*** (0.0000610)	− 0.00021*** (0.0000591)	0.0000808 (0.000148)	− 0.00018*** (0.0000651)
b_islands	0.199 (0.120)	0.419*** (0.145)	0.251** (0.115)			
w_islands	0.499*** (0.190)	0.139 (0.227)	0.426** (0.181)			
urban_mig				0.211 (0.171)	0.982*** (0.253)	0.347** (0.167)
migrate_oi				0.363* (0.196)	0.267 (0.226)	0.328* (0.186)
rural_mig				− 0.305 (0.268)	− 0.346 (0.372)	− 0.210 (0.258)
_cons	3.675*** (0.287)	4.393*** (0.639)	3.812*** (0.305)	3.682*** (0.289)	4.115*** (0.619)	3.809*** (0.308)
N	260	260	260	260	260	260
R^2	0.236	0.327	0.263	0.228	0.365	0.277

Standard errors in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Source: Authors' estimations from 2004/2005 and 2010 HIES data

Appendix 4

See Fig. 5.

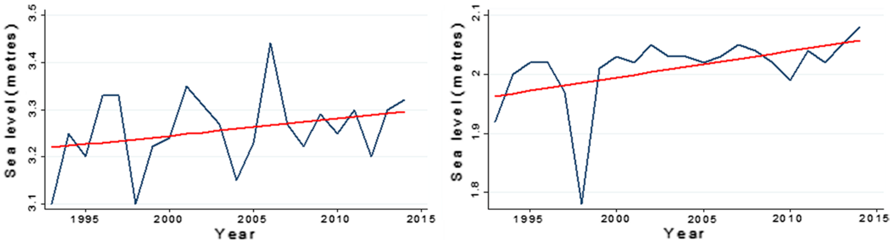

Fig. 5 Sea levels. The left panel shows the maximum sea levels on Funafuti (Tuvalu) from 1993 to 2014. Author's calculations, on data from the Tuvalu Meteorological Service (TMS). The floods cause sea water to come from the ground in the inner parts of Funafuti Island. From 1993 to 2002, the average number of times the sea level rose above 3 m is 8 per year, and 10 for 2003 to 2012. The right panel shows the mean sea level on Funafuti (Tuvalu) from 1993 to 2014

Appendix 5: Hardship maps

See Figs. 6 and 7.

Appendix 6: Elevation maps

See Figs. 8 and 9.

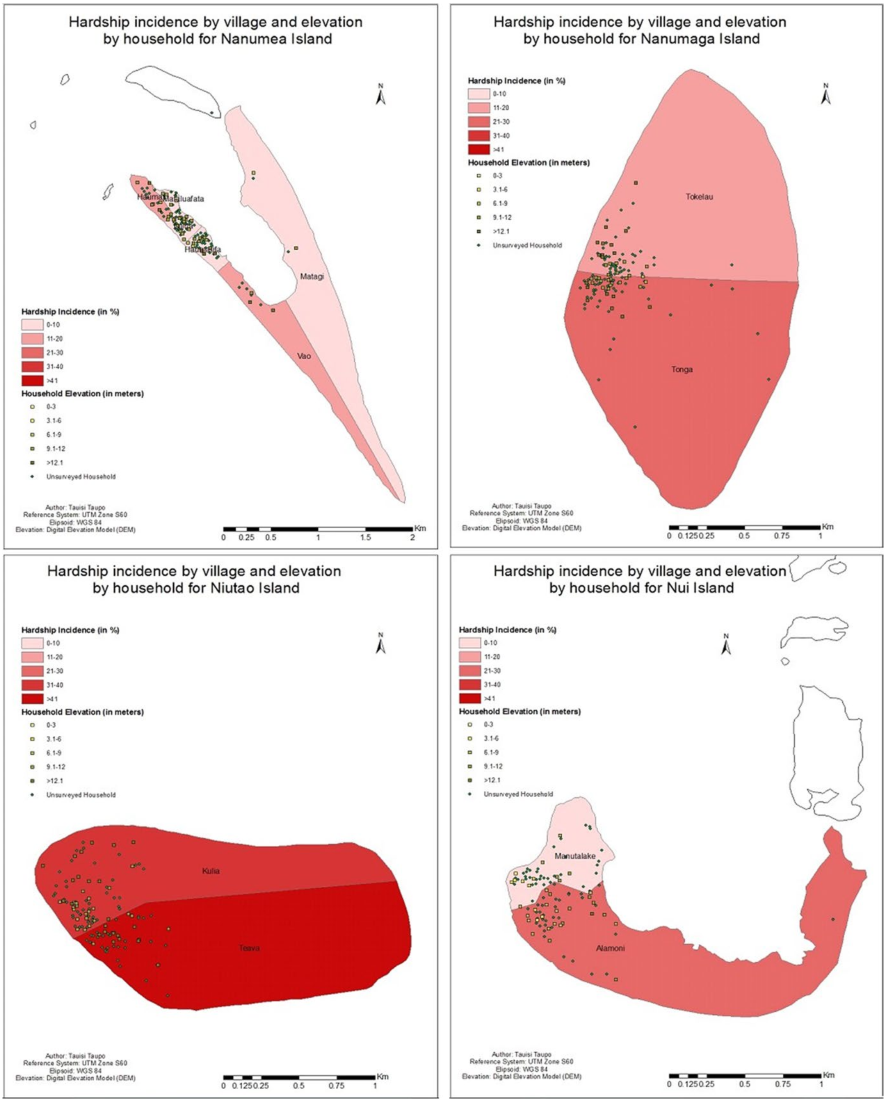

Fig. 6 Hardship incidence in the Northern Islands. Source: Authors' digitized maps

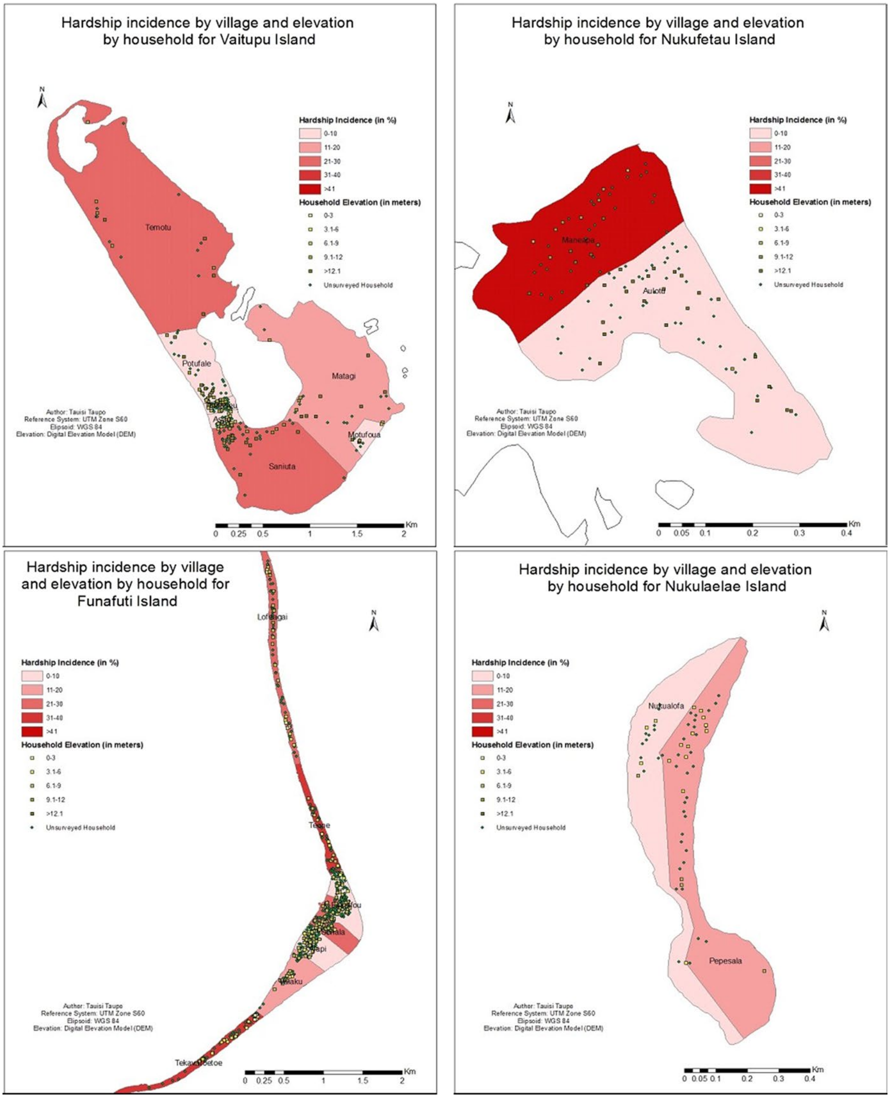

Fig. 7 Hardship incidence in the Southern Islands. Source: Authors' digitized maps

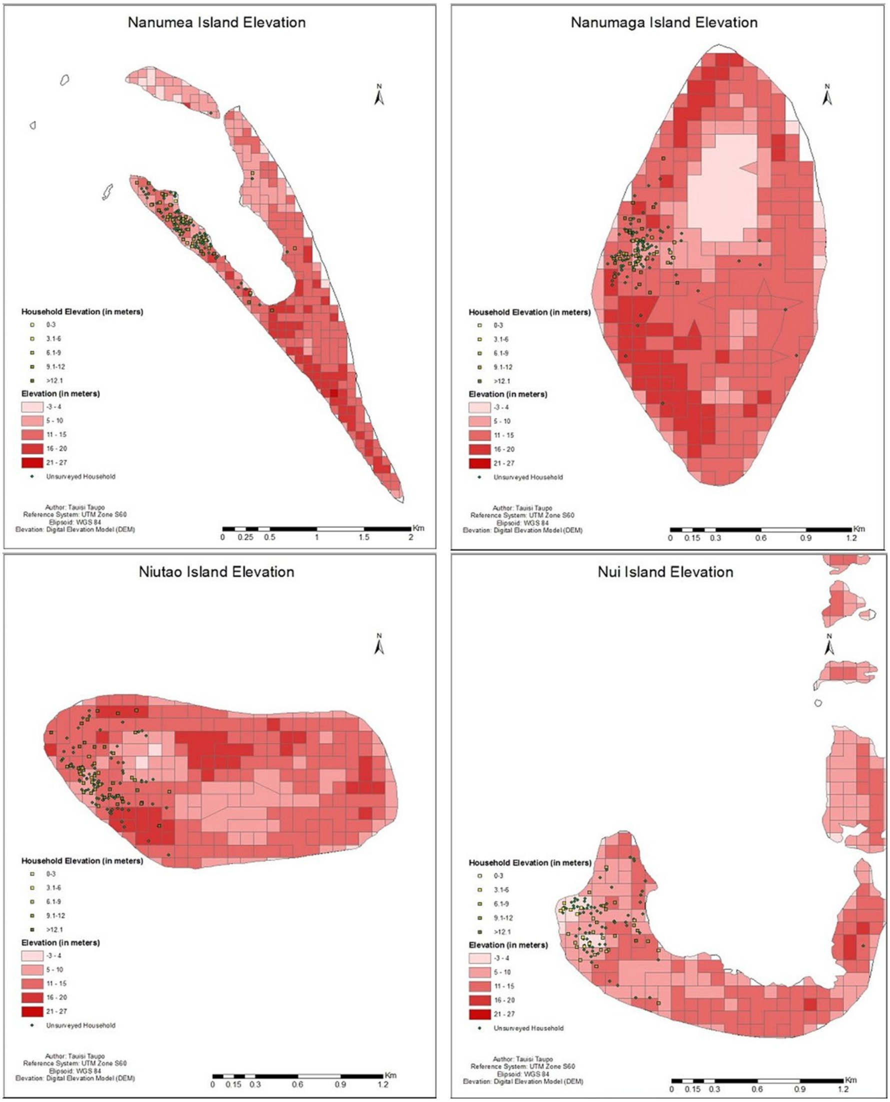

Fig. 8 Elevation in the Northern Islands. Source: Authors' digitized maps

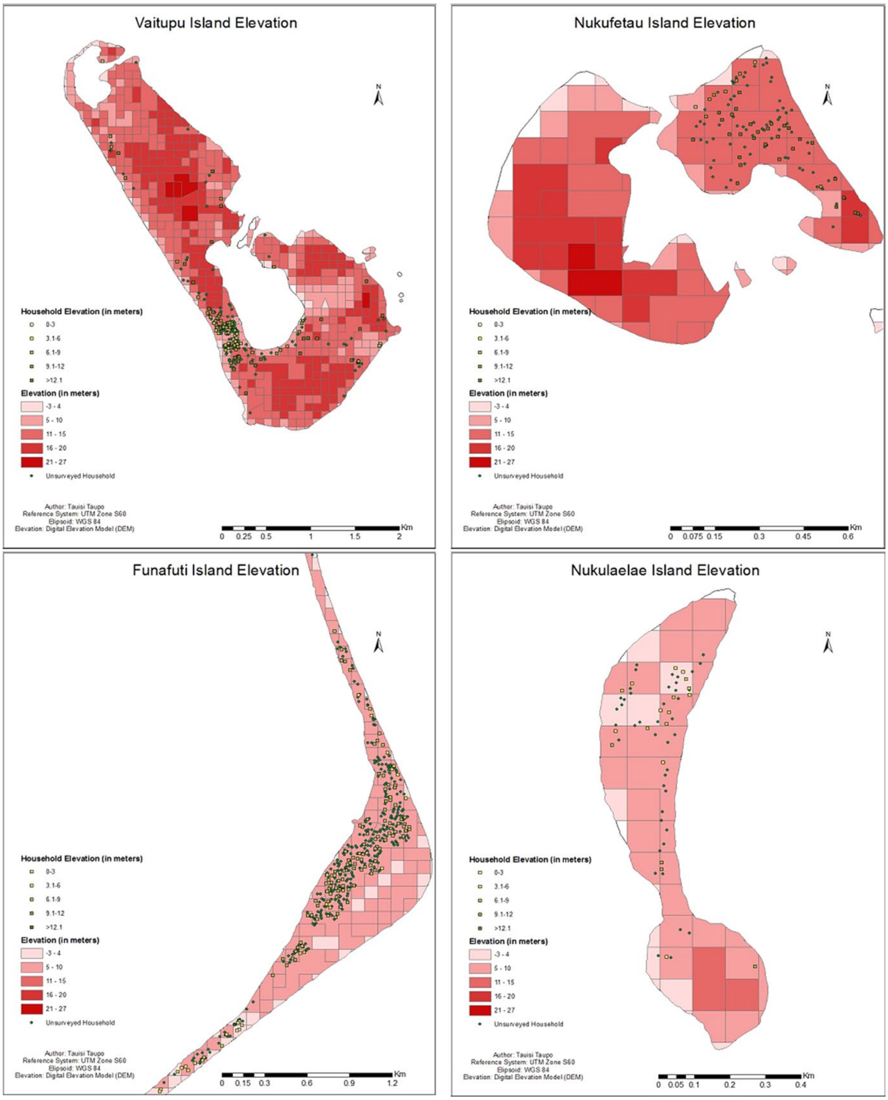

Fig. 9 Elevation in the Southern Islands. Source: Authors' digitized maps

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