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DOI:
10.1057/s10713-021-00063-6

Poverty and Hurricane Risk Exposure in Jamaica

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Abstract

This paper investigates the impact of hurricane risk exposure on poverty. To achieve this, we use a small area poverty mapping methodology to simulate our measure of poverty for households in Jamaica. Along with calculated hurricane wind exposure estimates that take account of the type of building material which matters for wind vulnerability, we calculate future risks for household poverty under different general circulation models under the RCP8.5 climate change scenario. We find that under most models, substantial increases in poverty are likely. The results are indicative of policy instruments needed to counteract the future risk of increases in poverty.

1 Introduction

Tropical cyclones are historically known to be very destructive given the costs they exact on affected geographical locations. Since the year 2000, costs have been estimated to exceed over $33 billion[1] where the Caribbean has borne roughly a third of this cost, amounting to $10 billion. Hurricanes, in particular, have been shown to negatively impact economic welfare, especially that of the most vulnerable households (Baez and Santos, 2007; Thomas et al., 2010; Anttila-Hughes and Hsiang, 2013; Karim and Noy, 2014; Arouri et al., 2015; Henry et al., 2019). Indeed, policymakers are keen to assist with the needs of households that are affected by such negative shocks. However, for proper design and implementation of welfare-protecting policies, it is important to have knowledge of the long-term risk involved in changes in hurricane behavior resulting from climate change. Although there is no definitive conclusion on the future of hurricanes as climate changes (Pielke Jr et al., 2005; Emanuel et al., 2008; Knutson et al., 2008; Knutson et al., 2010), the literature highlights two possible worrying outcomes for economies susceptible to these storms if faced with a warmer climate. First, despite an observed general decline in the frequency of hurricane strikes, the potential of a higher intensity is great (Emanuel et al., 2008). Second, based on other research, both the frequency and intensity of tropical storms will increase (Emanuel, 2005; Saunders and Lea, 2008). Given these possibilities, any policymaker's strategy to combat the welfare ill-effects of hurricanes should consider the future possibilities of these storm under different climate change scenarios. One may want to note that there is a degree of uncertainty regarding the impact of climate change policies for households. This uncertainty may be driven by households' attitude towards future climate change risk and other subjective beliefs that influence their behaviour (Harrison, 2011).

We study the future implications of hurricanes for poverty in Jamaica by analyzing what obtains under different climate change scenarios. Specifically, we compare expected poverty increases of Jamaican households for current (1981-

[1] Source: Emergency Events Database (EM-DAT)

2000) versus future (2081-2100) climate using five typical greenhouse gas (GHG) emissions projection scenarios. These are CCMS5, IPSL5, MICRO5, MPI5 & MRI5 for the climate representative concentration pathway (RCP) 8.5 GHG emission projection where RCP 8.5 is a high emissions pathway to which current emissions are closely aligned. For our measure of poverty, we make use of per capita consumption expenditure, the suitability of which has been demonstrated in the welfare literature. For example, by using household surveys for Jamaica and Nepal, Pradhan and Ravallion (2000) show that subjective poverty rates are closely aligned to actual poverty rates. These subjective poverty rates are based on a household survey in which participants indicate whether their consumption of food, clothing and housing were sufficient to satisfy their family's needs.

In this paper, to carry out our analysis we take a number of steps. First, we create a set of hurricanes under each climate setting, that is current and future, for each of the five climate models mentioned above. Second, we translate hurricanes into household poverty using an estimate derived from survey data[2] which we then use to infer the impact of hurricane damages. In other words, the estimated hurricane impact allows us to use the values of future hurricanes to calculate out the estimated impact on poverty. Third, to apply our derived estimate to census data, we use small area poverty estimation (Elbers et al., 2003) to obtain a local measure of poverty for all Jamaican households since survey data does not cover all geographical locations. Fourth, we calculate out the local maximum wind speeds (Holland, 1980) for each of the synthetic hurricanes generated in step 1 for each enumeration district in which households are located. Fifth, to obtain expected losses, we find the probability of each storm (Emanuel, 2011) which are used to calculate the annual implied impacts for household poverty under each climate change model.

Jamaica is particularly useful for a case study of this nature for a number of reasons. First, it is very vulnerable to hurricane shocks given its location, size and frequent storm experiences. For instance, since 1988, we identified 18 hurricanes,

[2]We use a similar approach to Henry et al. (2019) except that we allow for differences in the damage function according to household wall type.

the most damaging being hurricanes Gilbert and Ivan which struck in 1988 and 2004 respectively. Second, Jamaica is considered to be one of the most vulnerable countries in the Caribbean according to the environmental vulnerability index, which is based on 50 indicators including exposure to natural disasters, human health and climate change (Kaly et al., 2004). Its vulnerability is obvious from the destruction that these storms create. For example, the destruction caused hurricane Gilbert in 1988 amounted to US$4 billion in damages (Pan American Health Organization, 1988) while hurricanes Ivan in 2004 and Dean in 2007 generated US$139 million (Planning Institute of Jamaica, 2004) and roughly US$81 million (Planning Institute of Jamaica, 2007) respectively. Third, housing is an important component of the poverty which means that the type of building material used in house construction matters for a hurricane resilience (Agency for International Development, 1981). Based on the most recent (2011) Jamaican census, roughly 30% of households reside in homes that are not resistant to hurricane strikes. Given this background, the welfare of Jamaican households could be at risk considering the future of climate change.

We produce results for four hurricane return periods for each of the five climate change models on the RCP 8.5 high emissions pathway. Though our results vary according to each model, we observe, in general that compared to current climate, an increase in poverty will result from hurricanes across the spectrum of event years where this increase is likely to be substantial. However, households that build hurricane-resistant homes are likely to experience reductions in poverty.

The rest of this paper is organized as follows. Section 2 presents the data and descriptive statistics, which provides details on small area poverty estimates, household survey data, hurricane indexes and other climatic data. Section 3 outlines the estimation model, results and set the stage for poverty analysis. Section 4 engages the hurricane risk modelling and synthetic hurricane generation. Section 5 discusses the future outcomes for poverty and Section 6 concludes the paper.

2 Data

2.1 Small Area Poverty Estimates

Our objective is to use consumption expenditure data for all Jamaican households. Data that are comprehensive at a national level generally comes from the census. However, the Jamaican census does not collect consumption expenditure data. As a result, we simulated census consumption data for all households using small area poverty estimation methodology.

The small area poverty mapping methodology in general is used to acquire estimates for areas of a population for which data are lacking. Such estimates are generated by models that make use of survey data which are then tied to external data such as from a population census (Elbers et al., 2003). The idea of this methodology is to use the ability of the population census or other national sources of information which are representative of small areas to generate data for poverty estimation from household surveys that do not cover all geographical locations (Molina and Rao, 2015). The usefulness of this method has been seen in the case of Ecuador, where small area poverty estimates were used by the government there after the 2016 earthquake to determine where to channel resources to help rebuild the country (Nguyen et al., 2017). A major application has been seen in the United States (US), where estimates using the Current Population Survey (CPS), administrative and census data were used to allocate financial aid to children of school age living under poverty (Molina and Rao, 2015).

In this study, we "borrow the strength" of the 2011 Jamaican Population Census (JPC), that is, its large sample size or representativeness, to generate consumption expenditure estimates for all small areas that are not covered in the Jamaica Survey of Living Conditions (JSLC).[3] In essence, the poverty indicator, which is consumption expenditure, is not collected by the census. Although this

[3]Data for the JPC and the JSLC are both collected by the Statistical Institute of Jamaica (STATIN) but are distributed by the Sir Arthur Lewis Institute for Social and Economic Studies at the University of the West Indies, Jamaica.

information is collected by the survey, it does not capture small geographical areas in Jamaica. So we use welfare indicators [4] in the household survey that are common to the population census to estimate a reliable indicator for welfare for all households from all areas in the country. We use the small area estimation command in STATA introduced by Nguyen et al. (2017) which includes reliance on the Elbers et al. (2003) methodology, a common approach in the small methods estimation literature. The estimation takes two stages. The first stage estimates a welfare model using household log consumption expenditure per capita and the welfare-influencing household characteristics inclusive of household size, building materials used to construct dwellings, and the share of children in the household. The second stage involves the use of Monte Carlo simulations. Thus, the first stage's parameter estimates obtained and applied to the data from the census to generate reliable consumption expenditure per capita estimates for all areas in Jamaica. Figure 1 presents the distribution of these estimates across Jamaica.

2.2 Household Data

We use the unbalanced panel of 9,553 households created by Henry et al. (2019) which includes their measure of welfare, deflated total consumption expenditure per capita, the share of children in each household and the household size, which is calculated as the number of persons living in the household. These data are from the JSLC, which is an annual survey carried out by STATIN, collecting information on areas such as health, education, consumption and social protection. Importantly, the survey collects data on the material that is used to build the walls of the homes that households reside in. In this regard, we note that households live in buildings whose walls are made of one of the following: wood, stone, brick, concrete nog, block and steel and wattle and adobe. These walls vary in terms of their vulnerability to hurricanes as identified by the Agency for International Development, 1981.

[4] These indicators include household size, share of children in the household and building material of household walls.

2.3 Hurricane Wind Damage Estimates

We construct a hurricane wind damage index similar to Henry et al. (2019). This index is seen as a more comprehensive measure of destruction since it takes into account the physical characteristics of storm events which produce spatial damages at affected localities (see for example, Strobl (2009), Spencer and Polachek (2015), Ishizawa and Miranda (2019)). One drawback of this approach in proxying potential damage at the household level is that, even though it allows for considerable spatial heterogeneity in exposure across households according to their location, it does not take account of household specific differences in vulnerability due to the type of dwelling they reside in. We thus construct an index that incorporates both the physical location of households as well as its building wind exposure vulnerability. Essentially, we are extending the approach by Henry et al. (2019) but allowing for differences in the damage function according to household wall type. Thus, for a set of households, i=1,. . . , I, that are located in regions, j=1,. . . ., J, and hurricanes, k=1,. . . , K, with lifetime s=1,. . . ,S, we define hurricane destruction for each household as:

$$H_{i,j,t} = \sum_{k=1}^{K} \sum_{s=1}^{S} (W_{i,j,k,s,t})^3 \tag{1}$$

$$W_{i,k,j,s,t} \geq W^{*}_{ij} \tag{2}$$

W represents the wind speed, s is the lifetime of storm k and W* is the specific threshold for wind damage. There are a few important details that must be noted. First, in line with the literature, wind speed is specified to the cubic power because the power of dissipation for hurricanes is cubic (Emanuel, 2011). Second, the summation of the values of W over the lifetime of a storm accounts for the duration of exposure. Third, the summation of the cubic value of the W across storms allows for the possibility of having more than one damaging storm occurring in a year. Importantly, one should also note that, in contrast to the previous literature, here we take account of differences in damages in the function in equation 1 across building wall types[5] as differences in the threshold above which damages are induced. To calculate W, we make use of the wind field modelling methodology by Boose et al. (2004) which is a version of Holland (1980)'s equation. [6][7] For W*, we use the information collected by the JSLC on the outer walls of households. Walls made of wattle and daub, concrete nog, or wood are vulnerable to hurricanes while those made of stone or block and steel are less vulnerable (Agency for International Development (1981)). The latter we refer to as weakly vulnerable and the former as strongly vulnerable.

2.4 Wind Damage Specific Thresholds

We next estimate the threshold W* separately for both weakly and strongly vulnerable housing types. To this end, we use information on the damages caused by Hurricane Gilbert in 1988. More specifically, the 1989 JSLC collected information regarding the damages incurred after the storm.[8] Households were asked whether there was any damage to their dwelling due to the hurricane and, if yes, whether (a) the house was totally destroyed, (b) the roof and structure was severely damaged, (c) the roof was totally destroyed, (d) there was major roof damage, (e) there was minor roof damage, or (f) there was other roof damage. To use this information to derive a building specific W*, we first created an ordered damage variable where no damage took on the value of 0, and then linearly increased its value starting from damage category (f) down to category (a), providing a maximum of 8 different ordered values. Subsequently, we estimated an ordered probit model where we regressed the damage indicator on the estimated H from (1) given a value of W*, while controlling for the number of rooms, the number

[5]The importance of taking account of building types is demonstrated in Figure 2 where we see the percentage distribution of households with weak walls across Jamaica.

[6]See Henry et al. (2019) for the exact details.

[7]An example of a wind field model is shown in Figure 3. As the figure shows, for hurricane Ivan which struck Jamaica in 2004, wind speeds varied across the country and thus calculating hurricane destruction based on the Equation 1 is important.

[8]Hurricane Gilbert was a category 5 storm that spent 8 hours moving directly over the island, destroying homes, hospitals, agriculture, schools and more. This storm generated US$4 billion in damage (Pan American Health Organization, 1988).

of rooms squared, and whether the building was a separate entity. This was done for each housing type – weakly and strongly vulnerable – separately across the range of the values of W* that correspond to the minimum wind speed at which a tropical storm (63 km/hr) is defined up to the maximum hurricane damage category (252 km/hr) of the Saffir-Simpson Scale (SSS) classification.[9] We depict the obtained t-statistics on H as well the r-squared for the range of values of W* for these two samples in Figures 4 to 7.

As can be seen, for the weakly vulnerable building sample, the r-squared and t-statistic on H for each W*, shown in 4 and 5, clearly fall after wind speeds above SSS 3, i.e., 178 km/hr. [10] We thus chose W* for weakly vulnerable buildings to be SSS 3. In contrast, the point at which the r-squared and t-statistic for the strongly vulnerable building types of the ordered probit regressions fall, as depicted in 6 and 7, is much lower than for the weakly vulnerable ones. More specifically, the maximum is reached around the cut-off point for a storm to be considered SSS 1 (119 km/hr) [11], and we thus chose W* to correspond to this cut-off value. The choice of these damage thresholds points allow us then to use equation 1 to calculate H for any household i located in any enumeration district j exposed to storm k. One should note that H can differ across households both in terms of building outer wall types as well as the fact that the time of interview may differ and thus whether any hurricane occurred before or after the interview.

2.5 Other Data

In line with Henry et al. (2019), we use rainfall and temperature data in our analysis. The use of these variables is motivated by Auffhammer et al. (2013)

[9] The Saffir Simpson Scale is commonly used to roughly categorize likely damages due to hurricanes.

[10] According to the National Hurricane Center (NHC), the Saffir Simpson Scale category 3 winds correspond to when "... well-built framed homes may incur major damage or removal of roof decking and gable ends, many trees will be snapped or uprooted, electricity and water will be unavailable for several days to weeks after the storm passes".

[11] Hurricane damages at Saffir Simpson Scale 1 according to the NHC correspond to "... well-constructed frame homes could have damage to roof, shingles, vinyl sliding and gutters; large branches of trees will snap and shallowly rooted trees may be toppled, extensive damage to power lines and poles likely to result in power outages that could last a few to several days".

who indicate the possibility of hurricanes being correlated with other weather phenomena. These weather events as noted by Henry et al. (2019) may also affect the economic welfare which in our case, is household poverty. These data are sourced from the Climatic Research Unit (CRU) TS v. 3.24 dataset which is housed by the University of East Anglia's CRU.

2.6 Descriptive Statistics

Table A.1 displays the summary statistics of the data used in our study. The average consumption expenditure per capita for the household survey and census are roughly J$16,000 and J$17,744 respectively. The average share of children living in each household is 0.20. Finally, the average value of the hurricane index is 0.37 [12], which is used to calculate out the impact of the mean hurricane strike on poverty. Finally, the average rainfall and temperature are roughly 181 millimeters and 26 °Celsius.

3 Method and Estimation

Using the JSLC data, we estimate the impact of hurricane strikes on the log of total consumption expenditure per capita. Our specification is as follows:

$$logC_{ijt} = \alpha + \beta_1 H_{ijt} + \beta_2 X_{ijt} + \delta_{it} + y_t + \phi_i + \mu_{ijt} \tag{3}$$

In equation 3, C is the measure for household poverty, that is, total consumption expenditure per capita, which we have for each household i located in enumeration district j for year t. H represents the hurricane destruction index that is specific to each household and is shown in equation 1. This index as mentioned before differs from that of Henry et al. (2019)'s since it varies according to the building material of household walls, which is very important in accounting for

[12] As with Henry et al. (2019).

household vulnerability. X is the vector containing rainfall, temperature and share of children.δ are interview month indicators, y are year dummies, and ϕ captures time invariant household specific unobservables. Finally, μ is the error term. As it relates to the calculation of standard errors, we follow the approach of Henry et al. (2019) who apply the work of Hsiang (2010) to model spatial dependence across households affected by hurricanes.

Table A.2 shows that the estimated impact of hurricanes on consumption expenditure per capita. As can be seen, we estimate a significantly negative coefficient on hurricane. Thus, hurricanes decrease consumption expenditure that implies an increase in poverty. Further analyzing the fixed effects results in Table A.2, we observe that the share of children in the household reduce consumption expenditure per capita, as would be expected. [13] With regard to the climatic variables, one may want to note that rainfall significantly reduces consumption, while there is no effect of temperature.

Now that we have the estimated impact of hurricanes on poverty from the household survey data, we apply it to our simulated census consumption expenditure values for all households across Jamaica to see what the future holds given a changing climate. But first let us discuss how to model hurricane risk and generate synthetic hurricanes for the future to which apply our estimate and damage function described above.

[13] From the perspective of household scale economies, a larger household results in lower expenditure per capita. Explanations supporting this point include the fact that households with more individuals engage in bulk buying which lowers the cost per person spent and can reduce the possible food wastages by utilizing leftovers (Robin, 1985; Deaton and Paxson, 1998). Additionally, since children consume less, one can expect a lowering of consumption expenditure per capita (Kim et al., 2009).

4 Risk Assessment

4.1 Hurricane Risk Modelling

Hurricane risk assessment models can be broadly divided into the traditional single site probability models and the more recent hurricane track modeling using statistical deterministic methods (Vickery et al., 2009). In traditional probabilistic models, location specific statistics of key hurricane parameters are first estimated using historical storm track data. An extreme value distribution is then selected and fitted typically to maximum wind speeds of a hurricane approaching a specific location of interest, allowing the calculation of probabilities of annual occurrence of storms of a given wind speed strength via Monte Carlo methods. Importantly, however, single site probability models are typically only valid for a specific location or a small region given that they use site specific tropical cyclone parameters. Also, since these models use historical hurricane tracks they assume that the intensity evolution of the hurricane is independent of the particular track taken. Moreover, since the historical data contain only a few very strong hurricane strikes, the estimated probabilities can be very sensitive to the tail of the assumed distribution, making direct inference fairly unreliable, particularly for regions that experience infrequent storms (Emanuel et al., 2008).

To address some of the weaknesses of the single site models, Vickery et al. (2009) pioneered the hurricane track modeling method, which models the entire track of a given tropical cyclone from its formation over the sea to its final dissipation as it makes landfall using empirical global distributions of relative intensity in conjunction with climatological values of potential intensity to derive local intensity distributions. This allowed for the modeling of hurricane risk via generating synthetic tracks for large geographic areas, such as the entire coastline of the US. More recently, Emanuel et al. (2008) built on the approach of Vickery et al. (2009) in generating synthetic tracks, but instead used a random hurricane track model, together with a deterministic approach to model the hurricane intensity over the period of formation to dissipation. More precisely, hurricane tracks are generated from a random draw using a space time probability density function of tropical cyclone formation locations derived from the National Hurricane Centre's (NHC) data from 1970 onward (the year they consider the global satellite detection of tropical cyclones to be complete). Using information such as sea surface temperature and humidity together with historical storms, the model is able to trace the strengthening and weakening of hurricanes as they progress along the modeled tracks, but without using statistical models to model the changes in hurricane intensity as in traditional models. Once the synthetic tracks have been produced, a deterministic numerical simulation of hurricane intensity along each synthetic track is used to determine maximum wind speed and radius of maximum winds using the model developed by Emanuel et al. (2004). A filter is then applied to the tracks to select those coming within a specified distance of the location of interest. For each location of interest, the intensity model can then produce probabilities as a function of wind speed for that location.[14]

4.2 Synthetic Hurricane Tracks

In this paper we use the synthetic tracks generated with the Emanuel (2011) approach as a basis for the hurricane risk assessment. In this regard, Kerry Emanuel kindly implemented this methodology to generate for us a large set of synthetic tropical cyclone/storm tracks under five different climate models and for two different periods. More specifically, we have synthetic tracks generated using weather from each year of 1985-2000 period and each year the 2085-2100 period for the five different GCMs, namely MICRO5, CCSM4, IPSL5, MPI5, and MRI5. These tracks thus allow us to assess the change in impact of hurricanes on household consumption under the different climate change scenarios. For each of these storms, the model provides for every two hours of the storm's lifetime, the location of the eye, the maximum wind speed, the forward velocity, the central pressure, and the radius of maximum wind speed. Moreover, each storm is attributed to the

[14] The model was validated through comparisons with models which estimated maximum winds with the NHC best track data.

specific year's climate it was generated under. Finally, for each year, under each climate model, we have the average number of storms, similar to the ones in the set that are likely to arise.

We can calculate the local wind speed in each enumeration district for each storm for each point of its life cycle, given Boose et al. (2004)'s wind field model[15]. With our damage function and estimated impact from Section 3, using historical data we can then infer the impact of hurricane damages to a household's poverty due to each storm. Our next step is to generate a distribution of possible years of hurricanes from which we can calculate return period periods of annual poverty impacts. To do so, we assume that each year of weather in each of the ten storm track sets is equally likely to occur. To then generate a set of hurricane events specific to a year's climate, we randomly picked a year and used a Poisson distribution to randomly draw a number of storms of that year's set, according to the expected frequency of events of that year as given by the data. This was done 100,000 times. From this set we can calculate the distribution of implied annual impacts.

5 Poverty and Future Climate

The implied percentage changes in poverty impacts for damaging hurricanes under climate change for the five different climate model for different return periods are in Table A.3. As can be seen, there are likely to be considerable changes. Under the CCMS5 GCM, lower probability event-years are likely to experience decreased impacts on household poverty under both high frequency, but low impact, storms as well under low frequency, but high impact, storms years. For instance, if one considers an event year that is likely to re-occur every 50 years, under the weather, compared to current weather, the likely impact is about 38 per cent lower. In contrast, under the climate models IPSL5, MICRO5 and MPI5, the impact across lower and higher probability event-years is likely to increase by 100 per cent across the spectrum of event years. Finally, for the MRI5, our estimates

[15]See Henry et al. (2019) for model specifics).

predict that while high frequency, low impact damaging years are likely to be less damaging, years with low frequency but highly damaging storms are likely to be more substantial in their impact.

We also estimate the poverty impact for households with homes that are less susceptible to wind damage. Table A.4 shows the results from this estimation. As the table shows, households can expect substantial reduction in poverty regardless of the frequency of the storms. Under all GCM models, the impact is expected to be greater for the 20-year and 50-year return periods. However, unlike all other models that show an almost one hundred per cent reduction in poverty compared to current climate, the MPI5 model shows not more than an 84 per cent reduction in poverty for households with resistant walls. For low frequency event-years (100-year and 500-year), with the exception of IPSL5 GCM, all models show a decline in poverty less than one hundred per cent. Compared to all models, the MPI5 model predicts lower reductions overall across the spectrum of event-years.

6 Conclusion

This paper investigated the poverty impact of hurricane strikes in Jamaica under future climate change scenarios. To achieve this, we used hurricane damages that are calculated based on the location and vulnerability of households and the physical characteristics of the storm along with estimated impacts on poverty to understand the future risk of households in the case different climate change scenarios. We find that the future of household poverty can be very risky, which calls for design and implementation of policies to aid in buffering the expected impacts. The results also shows that households with homes that are built to be less vulnerable to hurricanes are likely to see substantial reductions in poverty. Its important to note that the design and implementation of climate change policies must take the preferences of households into account since they may have their own subjective beliefs and attitudes (Harrison, 2011) towards the poverty risk of weather impacts.

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1. Source: Emergency Events Database (EM-DAT).

2. We use a similar approach to Henry et al. (2019) except that we allow for differences in the damage function according to household wall type.

3. Data for the JPC and the JSLC are both collected by the Statistical Institute of Jamaica (STATIN) but are distributed by the Sir Arthur Lewis Institute for Social and Economic Studies at the University of the West Indies, Jamaica.

4. These indicators include household size, share of children in the household and building material of household walls.

5. The importance of taking account of building types is demonstrated in Figure 2 where we see the percentage distribution of households with weak walls across Jamaica.

6. See Henry et al. (2019) for the exact details.

7. An example of a wind field model is shown in Figure 3. As the figure shows, for hurricane Ivan which struck Jamaica in 2004, wind speeds varied across the country and thus calculating hurricane destruction based on the Equation 1 is important.

8. Hurricane Gilbert was a category 5 storm that spent 8 hours moving directly over the island, destroying homes, hospitals, agriculture, schools and more. This storm generated 4 billion USD in damage (Pan American Health Organization, 1988).

9. The Saffir Simpson Scale is commonly used to roughly categorize likely damages due to hurricanes.

10. According to the National Hurricane Center (NHC), the Saffir Simpson Scale category 3 winds correspond to when ". . . well-built framed homes may incur major damage or removal of roof decking and gable ends, many trees will be snapped or uprooted, electricity and water will be unavailable for several days to weeks after the storm passes".

11. Hurricane damages at Saffir Simpson Scale 1 according to the NHC correspond to ". . . well-constructed frame homes could have damage to roof, shingles, vinyl sliding and gutters; large branches of trees will snap and shallowly rooted trees may be toppled, extensive damage to power lines and poles likely to result in power outages that could last a few to several days".

12. As with Henry et al. (2019).

13. From the perspective of household scale economies, a larger household results in lower expenditure per capita. Explanations supporting this point include the fact that households with more individuals engage in bulk buying which lowers the cost per person spent and can reduce the possible food wastages by utilizing leftovers (Robin, 1985; Deaton and Paxson, 1998). Additionally, since children consume less, one can expect a lowering of consumption expenditure per capita (Kim et al., 2009).

14. The model was validated through comparisons with models which estimated maximum winds with the NHC best track data.

15. See Henry et al. (2019) for model specifics).

Appendix

A Tables and Figures

Figure 1: Consumption Per Capita Estimates: Jamaica

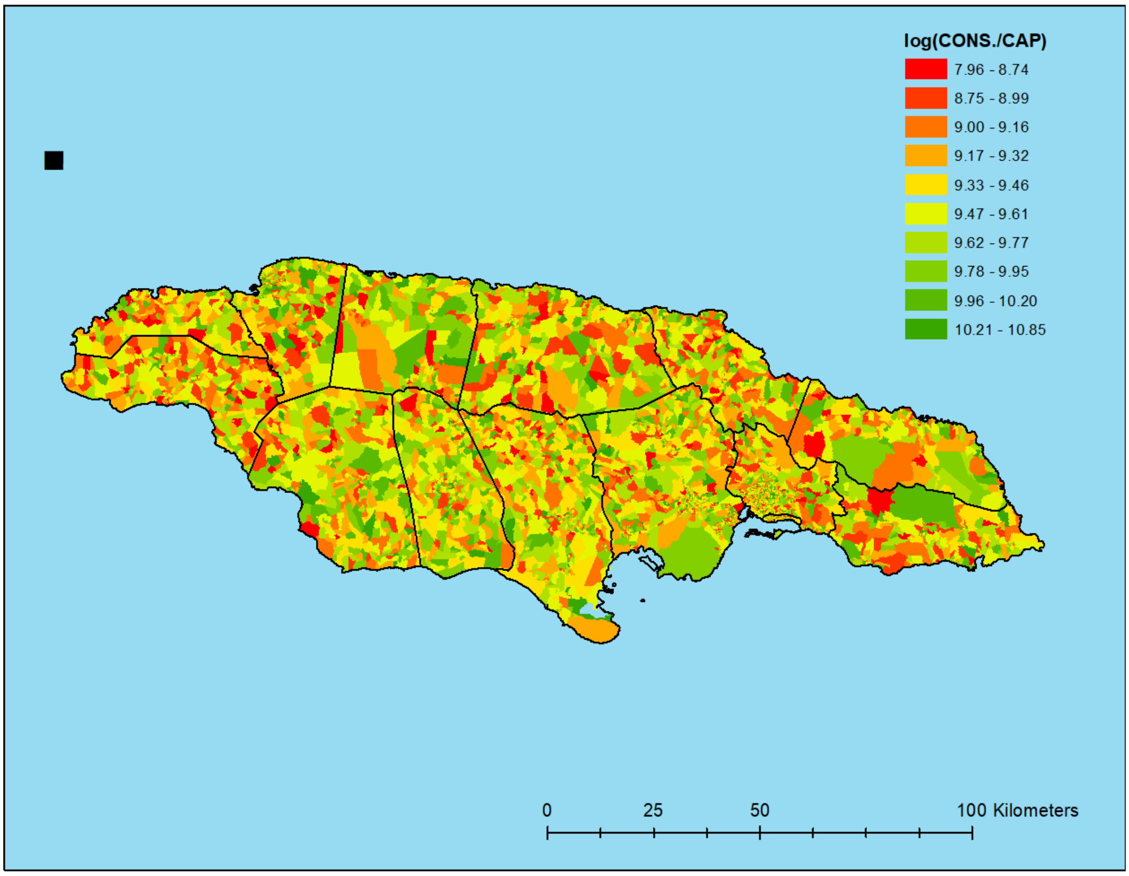


Figure 2: The Distribution of Building Wall Types Across Jamaica

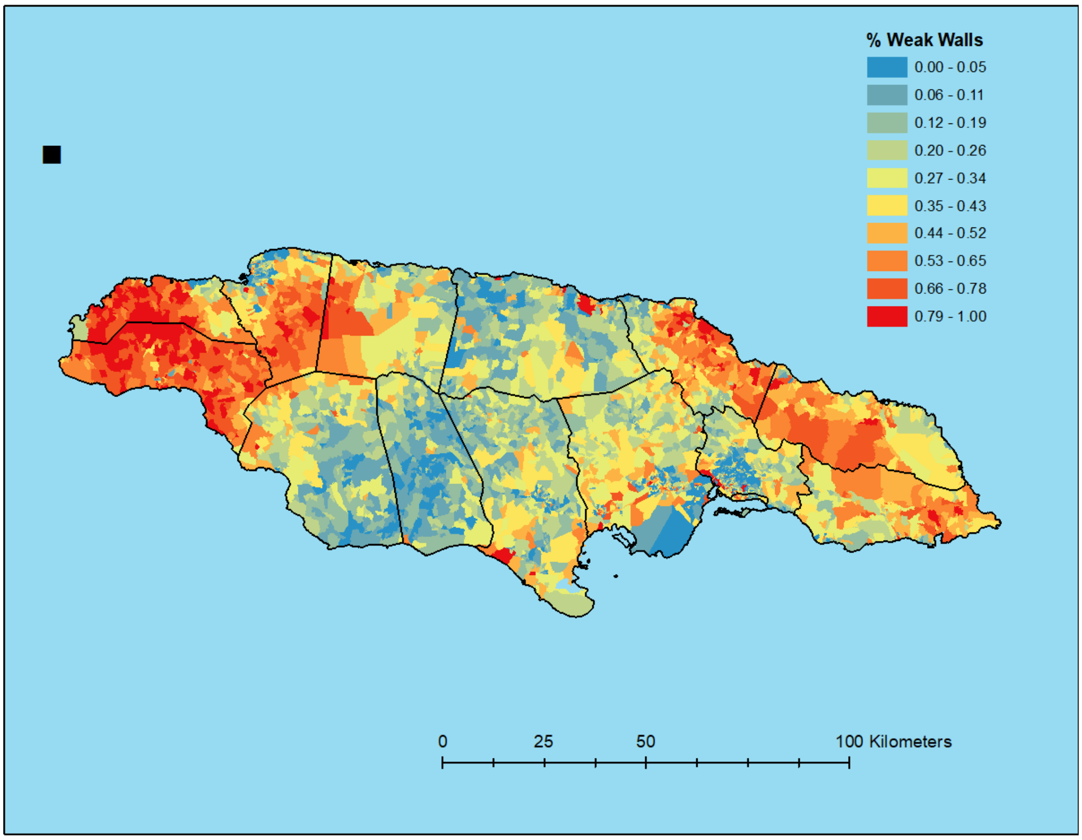


Figure 3: Wind Field Model Example: Hurricane Ivan (2004)

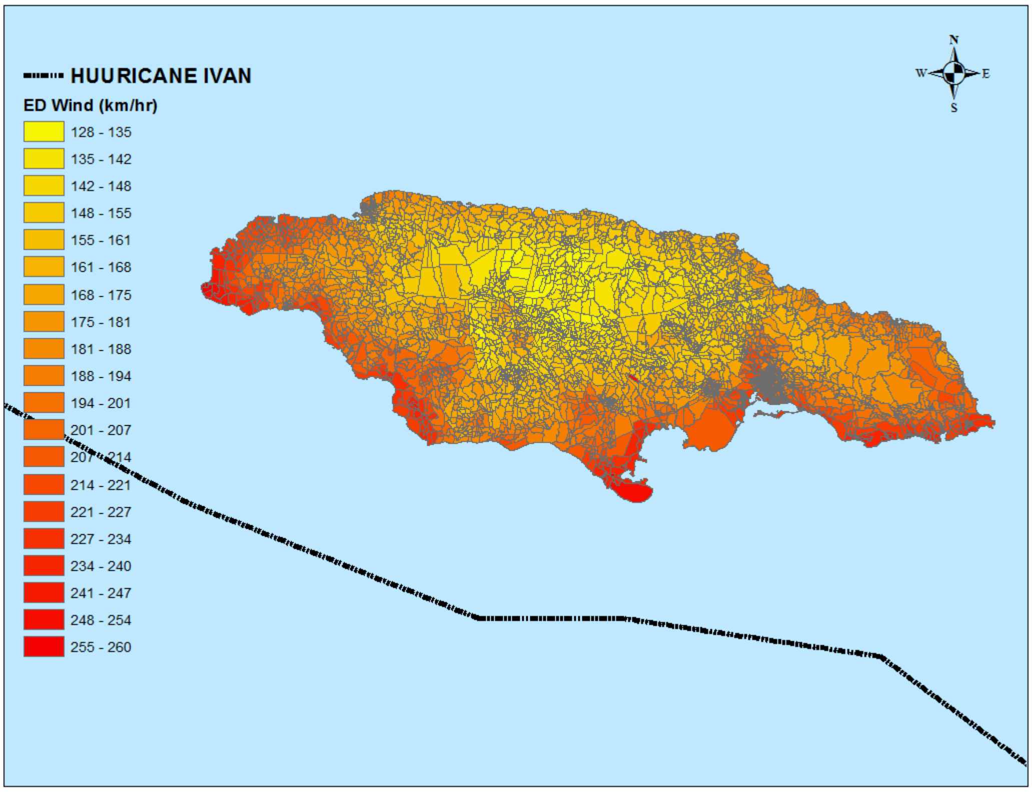
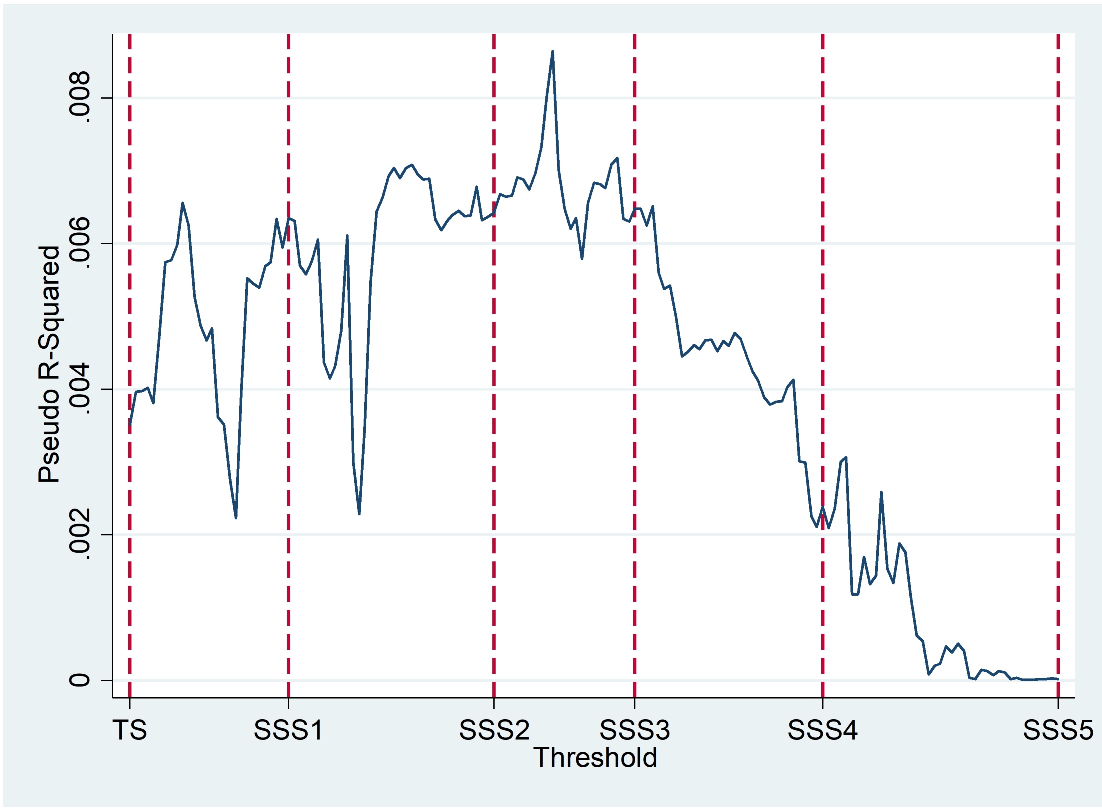
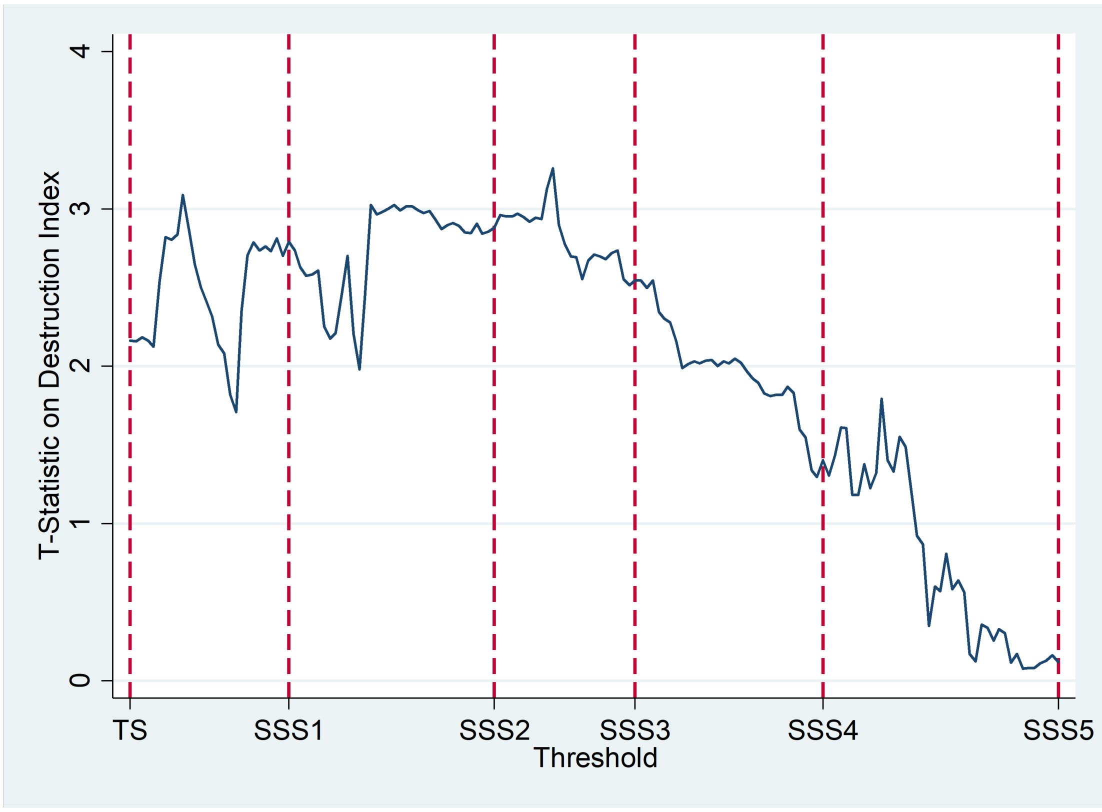


Figure 4: Pseudo-R-Squared for Ordered Probit Regressions for different W thresholds -Weakly Vulnerable Outer Wall Type Household Sample*



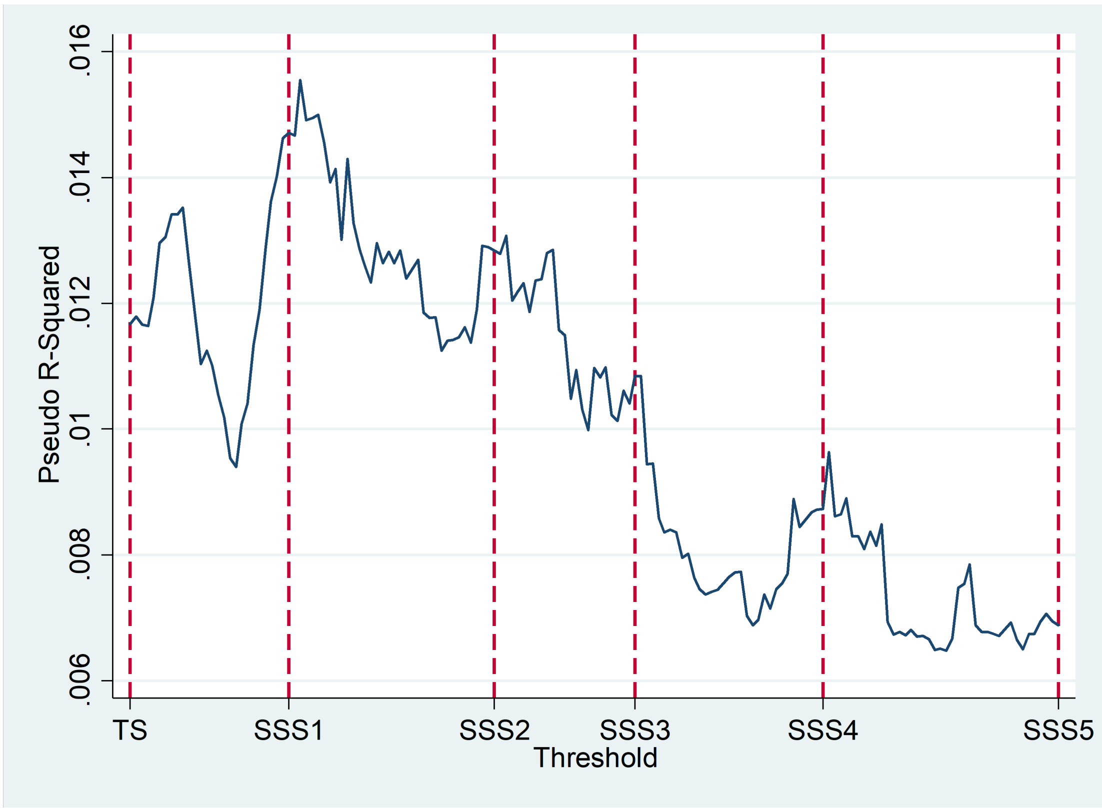
Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) Pseudo R-Squared corresponds to value obtained along different values of W* used to construct H.

Figure 5: T-Statistic on H for Ordered Probit Regressions for different W thresholds -Weakly Vulnerable Outer Wall Type Household Sample*



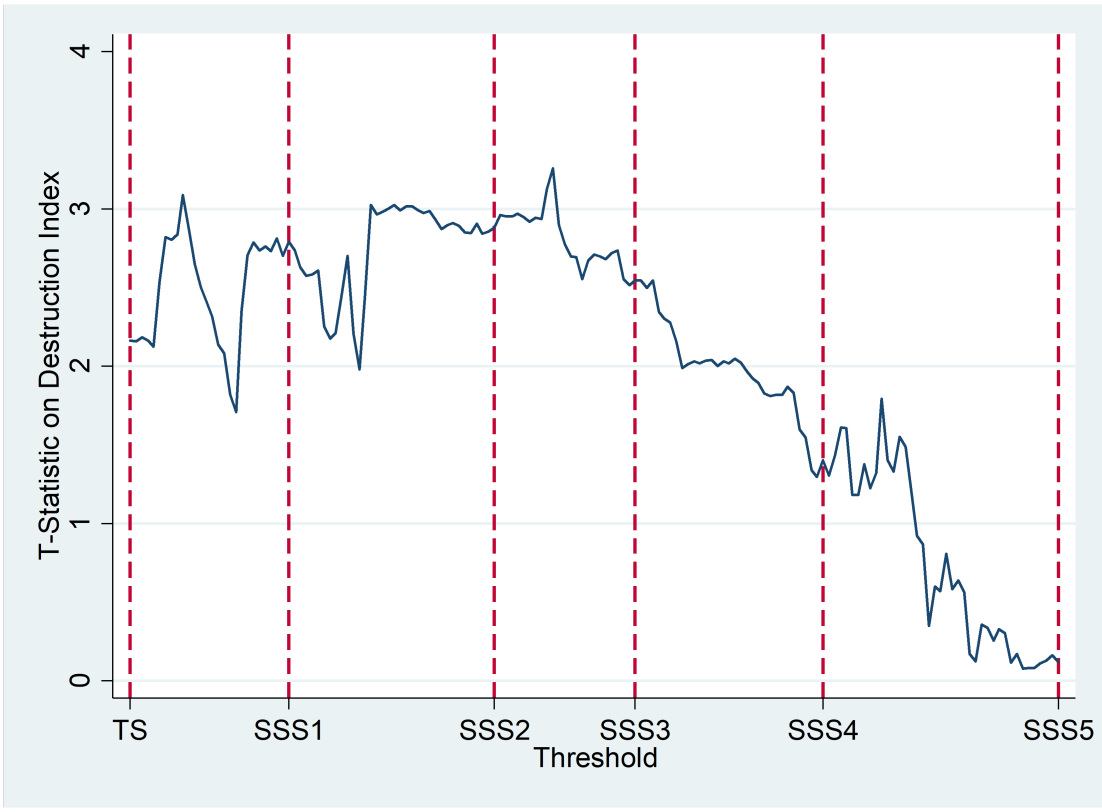
Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) T-Statistic corresponds to value obtained for H for different values of threshold W*.

Figure 6: Pseudo-R-Squared for Ordered Probit Regressions for different W thresholds -Strongly Vulnerable Outer Wall Type Household Sample*



Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) T-Statistic corresponds to value obtained for H for different values of threshold W*.

Figure 7: T-Statistic on H for Ordered Probit Regressions for different W thresholds -Weakly Vulnerable Outer Wall Type Household Sample*



Notes: (i) TS: Tropical Storm Classification; SSS1-SSS5: Saffir-Simpson Hurricane Classification; (ii) T-Statistic corresponds to value obtained for H for different values of threshold W*.

Table A.1: Descriptive Statistics

Variable	Mean	Std. Dev.
Consumption expenditure per capita:		
Household, JSLC	15776.97	17372.63
Census	17744	19539.05
Share of children	0.20	0.24
Hurricane	0.37	0.98
Rainfall	180.98	285.04
Temperature	25.5	1.03

Table A.2: The Impact of Hurricanes on Consumption Expenditure

Variable	Estimate	Std. Error
Hurricane	-0.0083***	(0.0020)
Share of children	-0.2207***	(0.0441)
Rain	-0.0004**	(0.0002)
Temperature	-0.0830	(0.0567)
Observations	22,934	
Number of households	9,546	
Household fixed effects	3.71***	
R-squared within	0.0900	

Notes: (i) The results are from household fixed effects estimation. (ii) Monthly and yearly time dummies are included. (iii) ***, ** - 1%, and 5% levels of significance respectively.

Table A.3: Climate Change in Annual Hurricane Impact (% pts.) on Poverty under 5 different GCMs and different Return Periods

GCM	CCMS5	IPSL5	MICRO5	MPI5	MRI5
20-year	-8.96	100.00	100.00	100.00	-87.77
50-year	-38.34	100.00	100.00	100.00	-50.88
100-year	-42.40	100.00	100.00	100.00	50.73
500-year	-48.31	100.00	100.00	100.00	89.91

Table A.4: Climate Change in Annual Hurricane Impact (% pts.) on Poverty under 5 different GCMs and different Return Periods for Households with Wind Resistant Walls

GCM	CCMS5	IPSL5	MICRO5	MPI5	MRI5
20-year	-100.00	-100.00	-99.99	-83.80	-100.00
50-year	-100.00	-100.00	-95.11	-81.48	-100.00
100-year	-99.99	-100.00	-73.64	-53.49	-99.24
500-year	-48.31	-100.00	-72.96	-52.29	-97.55

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