**Title: Rising climate risk and loss and damage to coastal subsistence livelihoods**

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**Goal:** to assess climate risk and estimate adaptation gaps and potential damage and loss for subsistence-oriented households and coastal communities in the WIO

**Objectives:**

1. To estimate climate risk for subsistence-oriented households/communities in the WIO
2. Map damage and loss (Estimate the residual risk as a function of adaptation gap and present/future risk)
3. To evaluate the adaptative capacity and opportunities for scaling up adaptation and transformative pathways

**Abstract**

**Introduction**

Climate change is causing damage to tropical coastal agroecological systems and compromising their ability to sustain resource-dependent livelihoods and cultures (Adger et al., 2012). While efforts have been made to quantify and manage climate risks, it remains unclear what the future climate risks will be in the most vulnerable and at-risk regions; how communities will cope with the negative impacts of climate change on sectors supporting subsistence economies; and adaptation occurring in practice and its efficacy in moderating risks (Brown, 2018; Conway et al., 2019; Cinner et al., 2022). Understanding climate risks at a community level is imperative for quantifying residual risks, identifying adaptation gaps, damages, and losses, and guiding efforts to reduce adverse effects on human and natural systems (Rising et al., 2022).

Coastal agro-ecological systems, characterized by social ecological dynamics on the land-sea interphase, support millions of tropical coastal inhabitants through extraction activities (ref). Losses and damages on critical coastal habitats - seagrass, coral reefs and mangroves, coastal catchments on land, and essential ecosystem services that accrue to communities and national economies are happening now and the risks of future losses and damages will increase with climate change (ref). The frequent occurrence of climate extremes, for example, has caused the loss of coral reef and mangroves with socioeconomic consequences (**ref**). Consequently, rising climate risks are increasing maladaptive adaptation and widening adaptation gaps particularly for high resource dependent, coastal communities of low socio-economic status and exacerbating poverty amid few or non-existent government-led adaptation initiatives (Macusi et al., 2020). Damage and loss finance, a mechanism for compensating poor countries for the economic, social, cultural, and environmental losses caused by climate change (refs) deemed as urgent during COP27 UN climate negotiations (ref), could support communities adapt sustainable pathways of nature-based mitigation and adaptation. In this regard, the understanding of residual risk and adaptation gaps, along with cross-sectoral climate risk to integrated coastal systems, is crucial to evaluating damage and losses and providing an evidence base for informing policy choices associated with loss and damage finance (Serdeczny and Lissner, 2023).

Climate change risk is typically assessed based on one hazard or as a compounded risk (Zscheischler et al. 2018; Barnard et al., 2021). In tropical coastal regions, efforts to develop holistic risk assessment and mitigation strategies are undermined by sectoral governance arrangements, scientific research and uncoordinated policies across sectors (David et al., 2021). In addition, there are diverse frameworks and conceptualizations of climate risks, which depend on the systems and contexts being studied, academic territorialism, and lock-in to separate processes at the global level (ref). **For example, the IPCC framework concept of vulnerability is often used to assess risks based on climatic and non-climatic factors affecting climate change vulnerability, including adaptive capacity and estimating damages expected and attempting to reduce them**(Füssel et al., 2006). Under the Sendai framework, which focuses on disaster-related risks of displacement, economic losses, infrastructure damage and vulnerability and preparedness (**ref**), climate change is one hazard driver among many, where discrete anomalous meteorological events directly ascribed to the consequence of climate change, such as floods, storms, and droughts are considered (**ref**). To ensure more integrated and efficient management of climate risks in coastal areas, it is important to take a holistic and interdisciplinary perspective on climate risks, characterize the human and natural coastal systems and the dominant processes adequately, and adopt sustainable development goals as a unifying framework for disaster risk reduction and climate change adaptation mitigation (Cramer et al., 2018; Serrano et al., 2019; Salack et al., 2022).

**Here, we present a quantitative assessment of climate risk to subsistence oriented coastal communities in four countries in the Western Indian Ocean (WIO) [Kenya, Tanzania, Mozambique and Madagascar]. Climate risk is a function of hazard, the exposure of people and natural assets, and their vulnerability to that particular hazard (IPCC, 202x; Zscheischler et al., 2018). Moreover, we estimate the residual risk, adaptation gaps and the damage and loss to coastal agro-ecological systems and present policy options amenable to different communities at village level based on the residual risk. We first analysed climate impact on natural assets and ecosystems that are critical for coastal agro-ecological systems that support subsistence- livelihoods in many tropical coastal areas. These included mangroves, coral reefs and cropland on the coastal catchments. Climate change impact was estimated as a function of hazard and exposure. Hazards comprised 13 climate-derived proxies of acute and chronic stressors, including frequency and intensity of extreme temperatures and drought, and long-term trends in ocean pH, among others (Fig. Sx, Table Sx). Exposure was derived by estimating the spatial coverage of mangrove, seagrass, coral reef, and cropland (i.e., maize and rice) and four functional metrics at reef scales, including functional diversity (FDiv), functional evenness (FEve), and functional richness (FRic).**

**We estimated residual risk as a function of the potential impact, socioecological sensitivity, and adaptive capacity metrics. Sensitivity and adaptive capacity were based on socioeconomic survey of xxx households in 29 villages in four countries in a socioecological vulnerability assessment framework (Thiault et al., 2021; Cinner et al., 2013; 2016). Finally, we calculated damage and loss to the natural assets using estimates of the value of essential ecosystem services that would be lost as a function of impact (more details are provided in the Methods). Here, losses and damages refer to the potential losses of goods and services derived from natural assets in coastal agroecological systems that may result from the interactions of climate-related hazards, exposure and vulnerability (More details can be found in methods).**

**RESULTS**

**(a) Climate risk for subsistence-oriented communities in the WIO**

We quantified social-ecological risk using social exposure (climate change impacts on ecological systems) and social vulnerability (i.e., sensitivity and adaptive capacity) at the village level (Fig 1). There is substantial variability in risk across countries, with risk scores averaging xx (SD = xx) and xx (SD = xx) for the highest and lowest emission scenarios, respectively. The highest risk score was found in Tanzania (0.78) for Mjini Kiuyu under SSP3-7.0. The lowest risk score (0.24) is for Cumbane in Mozambique under SSP2-4.5 (Fig. 1C).

Under the high emissions scenario, xx% of coastal communities assessed are at high risk, xx% at moderate risk and xx% at. Tsinjoarivo has high risk primarily because they are…

How does the impacts differ across the countries

The relative moderation of Vulnelerabity

**b) Residual risk and adaptation gap and damage and loss**

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**Fig. 2. Climate risk for coastal communities.** (A) the risk communities face with climate change despite potential impacts control mechanisms. (B) National averages (+/- standard deviation) of residual climate risk potential (MOZ = Mozambique [blue], KEN = Kenya [red], MDG = Madagascar [yellow], TZA = Tanzania [grey], and ALL = global average [cyan]).

* National level adaptation less effective in risk reduction,
* Low variability among countries in the region, even though GDP which is a major component varies among countries
* The CCVA based adaptation is variable across villages and countries, reinforcing the need for community level monitoring and assessment of the adaptation
* Overall RR patterns similar to the overall risk
* Clusters by country, but some villages deviate from country level ranges

NBS - EbA and EbM

* Strengthen national C and community adaptation.
* Climate scenarios – marginal differences between scenarios, increase mitigation, but also minimizing adaptation gap and damage and loss should be the priority.

Damage and loss results and discussion …-

**DISCUSSION**

Climate change is expected to cause widespread socio-ecological impacts. By integrating EEA with other knowledge relevant to decision-making around L&D, including vulnerability and exposure information (King et al. 2023), we show that …

**(b) Adaptative capacity communities and opportunities for scaling up adaptation and transformative pathways.**

**CAVEATS**

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**METHODS**

Social–environmental syntheses, including risk analyses, can help to identify opportunities for actionable solutions to address the potential impacts of climate hazards **(Ekstrom et al., 2015)**. This study assesses climate risk and estimates adaptation gaps for subsistence-oriented coastal communities in the WIO to inform local scale management. We define subsistence-oriented ….

**(1) Datasets**

(*i*) Socioeconomic survey

***Study communities*.** We undertook socio-economic surveys for **xx** households in 29subsistence-oriented coastal communities in four countries across the WIO region, including Kenya (*n* = 11 communities), Tanzania (*n* = 10), Madagascar (*n* = 7), and Mozambique (*n* = 4). Communities were purposefully selected for their dependency on mangroves, seagrass, and coral reefs as livelihood sources. Data were primarily obtained from key informant interviews, focus group discussions and cross-sectional field surveys. Surveys were conducted between **xx-xx in 20xx**.

***Sensitivity and adaptive capacity*.** Respondents rated 30 indicators linked to sensitivity (SS — livelihood, demography, cultural, and health) and adaptive capacity domains (AC — learning, assets, flexibility, agency, and organisation) (**Cinner et al., 2016, 2013; Thiault et al., 2021**). All indicators and domains were merged into aggregate indices of SS and AC using weights that indicate the relative importance of these indicators for communities. To achieve this, we first resale each indicator to a standardised score () using the Marine Community Monitoring (MACMON) guideline (**refs**). Weights were derived using Analytical Hierarchy Process (AHP). AHP is a multicriteria method that rates the performance of each variable against each alternative of the same hierarchical level (**Saaty, 1980**). Since AHP relies heavily on expert judgement, we solicit expert inputs through focus group discussions. Separate focal groups were designed for each country. Weights were organised hierarchically, whereby each indicator was assigned a weight relative to all other indicators within the same domain, and each domain was assigned a weight relative to all other domains. Separate weights were used to compute SS and AC for each target country (**Table S1**). We computed the **SS** and **AC** index (*I*) for each household *h* across all indicators and domains as:

|  |  |
| --- | --- |
|  | (1) |

where is the weight of domain *d*, is the weight of indicator *i* within domain *d*, is the subsidiary indicator domain *d*, and is the standardized score of indicator *i* within domain *d* for household *h*. from *d* = 1, 2, … *N* sums to 1.0, as does from *i* = 1,2, …, *dj*.

(*ii*) Climate data

*(a) Climate models*

This study analysed historical and future simulations of xx Global Climate Models (GCMs) from CMIP6. The data was obtained from the Earth System Grid Data Portal (https://aims2.llnl.gov/search), and information on the model datasets, development centers, and spatial resolution (Table **SX**). To maintain consistency and minimize bias, the study focused on the ensemble of the first realization (r1i1p1f1) of the historical and future runs for all models. The base period was set as 1981-2010, relative to the gridded observation datasets, despite the historical runs covering the period of 1850-2015. For future simulations, four scenarios were chosen, including SSP2-4.5 and SSP3-7.0, for near-future (2021-2050) and far-future (2071-2100) periods.

The GCMs' output on each native grid was re-gridded to a regular 0.25ᵒ × 0.25ᵒ horizontal grid using the climate data operators (CDO) remapbil function, which uses bilinear interpolation to map values from one grid onto another while preserving the original grid's area. This method ensured that the remapped data accurately represented the underlying climate processes.

*(b) Hazard metrics*

This study characterizes two broad climate hazards — i.e., abrupt and chronic, associated with changes in eight coastal systems across the WIO. We used extreme event metrics to present abrupt hazards (drought extremes, heat waves, and compounding extremes). Extreme climate events can be defined as the period in which climate notably exceeds a historical percentile threshold (**Meehl & Tebaldi, 2004**). Extreme events, such as drought and heatwaves, can increase crop switching, fallow periods and reduce subsistence, produce quality, agricultural income etc., ultimately resulting in severe macroeconomic implications (e.g., including commodity price surges) (**Davis et al., 2021**). Marine heatwaves (MHWs) cause coral bleaching, species migrations, and mass mortalities (**Eakin et al., 2019**). Compounding extremes, characterized by a combination of multiple drivers or hazards, significantly contribute to societal or environmental risk (**Zscheischler et al., 2018**). For example, compound drought–heatwave (CDHW) amplifies adverse impacts on socioeconomic sustainability and human well-being (**Yin et al., 2023**). CDHWs can exacerbate vegetation mortality and control ecosystem productivity, cascading into more proximal pressures impacting ecosystem services (**Yin et al., 2023**). Using the 90th percentile of the 30-year climatological series from 1981 to 2010, we defined extreme rainfall and heat wave events as the temperature and precipitation values of the wettest or hottest months, respectively, defined frequency of extreme rain events (**r90p**), rainfall intensity (**t90i**), heatwaves frequency (**ts90i** and **sst90i** for land and sea surfaces, respectively) and heat wave intensity (**ts90p** and **sst90p** for land and sea surfaces, respectively) as the temperature and precipitation values of the driest or hottest months, respectively. To represent drought events, we used the consecutive degree days (CDD). CDD represents the length of the longest period of consecutive dry days (i.e., days with rainfall <1 mm) in a year ending in that year. For the near and far future, we estimate the months where temperature and precipitation exceed the baseline threshold. We compute empirical frequencies of concurrent extreme drought and heatwave events. Heatwave events were calculated for land surface temperature (LT) and sea surface temperatures (SST).

In addition, chronic events were long-term changes in TAP, SST, pH, NPP, evapotranspiration, and TS. Ocean warming causes thermal stress that contributes to coral bleaching and may lead to infectious diseases (**Maynard et al., 2015**). Ocean acidification (i.e., reduced pH levels due to increased CO2) decreases corals' growth rates and structural integrity (Hoegh-Guldberg et al., 2007; Pandolfi et al., 2011).These metrics were calculated as the slope of the ordinary least-square (OLS) regression of projected monthly mean values for each variable (Δ[magnitude/yr]).

*(c) Climate change scenarios*

To estimate climate impacts on local communities, we explored the most probable CMIP6 scenarios — SSP2-4.5 and SSP3-7.0 **(refs)**. Scenario SSP2-4.5 presents a middle-of-the-road, with medium challenges to mitigation and adaptation. Under SSP2-4.5, the social, economic, and technological trends do not deviate markedly from historical patterns. SSP3-7.0 follows approximately RCP7.0 global forcing with SSP3 socio-economic conditions. It represents medium to high end of the range of plausible future forcing pathways. This scenario includes a policy shift towards national and regional issues (IPCC, 2018).

*(d) Uncertainties estimation*

There are deep uncertainties in relation to important aspects of the physical climate response to climate forcing, and to vulnerability and exposure of socio-economic systems (**OECD, 2021**). We systematically applied several approaches to account for the uncertainties in projected data. First, several CMIP6 models are assessed, with the model ensemble size differing among scenarios depending on contributions from each model group. To reduce the inter-model variability, only one ensemble member per model is used for a given scenario. We typically use ensemble member “r1i1p1f1” from each CMIP6 model. Thus, we set the recommended external forcings employed by the various modelling groups. For both scenarios, we retrieve the monthly mean data for at least 10 GCM products made for the CMIP6 from the Earth System Grid Federation (ESGF) portal (Table **SX**). All models were re-gridded onto a 0.25 × 0.25ᵒ grid before conducting formal analyses.

*(iii) Exposure of agro-ecological systems*

We used mangrove cover, seagrass cover, coral cover, crop cover, functional diversity, functional evenness, and functional richness as models to examine the extent to which climate change might impact the services that agro-ecological systems deliver to coastal communities (Table **XX**).Justifications for their inclusion are supplied as Supplemental Information.We retrievedmangrove cover from XX (**REFX**). We collected spatial information on coral reefs and seagrass coverage distribution from Allen’s Coral Atlas (<https://allencoralatlas.org/>). To represent how climate-induced loss of distinctive species from assemblages likely create a shortfall in ecosystem functions, four functional metrics from Dagata and Maina (2022). The metrics were derived 367 Scleractinian coral (shallow habitat species) and 557 fish species. Phylogenetic diversity has derived based on Faith Index using only **97% (n = xx) and 63% (n = xx)** of corals and fish species, respectively, for which phylogenetic information is available. For trait diversity, D’agata and Maina (2022) computed selected functional coral traits, including xx, xx, and xx, among others. Functional richness, which represents the breadth of trait ranges, was calculates exclusively for each coral reef as the volume of the convex hall a species occupied.

To define the extent of reefs, seagrass, and mangrove exposure to chronic and abrupt hazards, we defined the Area of Occurrence (AOO) as the 0.25ᵒ × 0.25ᵒ grid cells that contain a minimum of 0.1% of the sum of all systems, and computing the metrics between baseline (1981-2010), near-future (2021-2050) and far future (2071-2100) periods across different climate change scenarios (see below).

**(2) Estimating risk**

(*i*) Gap analysis

To investigate climate change risk and adaptation gaps to socio-ecological systems across subsistence-oriented coastal communities across the WIO, we used a conceptual framework where residual risk (***RR***, i.e., the risk that remains despite adaptation [IPCC, 2023]) is a function of inherent risk (***IR***) minus impact controls potential (***C***), expressed as:

|  |  |
| --- | --- |
|  | (2) |

We modelinherent risk usingthe IPCC framework, whereriskis a function of exposure (***E***), hazards (***H***), and vulnerability (***V***).

|  |  |
| --- | --- |
| ) | (3) |

Given that vulnerability systems are those that are highly sensitive (***S***) [directly related] and are less likely to adaptive (***A***) [inversely related], we arranged equation 1 into equation 2.

|  |  |
| --- | --- |
|  | (4) |

(*ii*) Impacts (*I*) = Hazard\*Exposure

We built a model linking climate hazards and exposed systems to estimate climate change impacts on local communities. Because the compositions, skewness, mean-variance dependency, and extreme values of environmental datasets can notably influence model building, we transform any input feature *F(x)* to the quantiles of a standard normal distribution to facilitate direct comparisons of the elastic model across the WIO. This approach has proven robust to modelling and has been extensively used in environmental studies (**Saachi et al., 2021**). Following Saachi et al., we derived the cumulative distribution using a non-parametric density estimator.

|  |  |
| --- | --- |
|  | (5) |

The cumulative density functions were converted to a normalized scored using the quantile functions of the standard normal distributions. Outputs from step five were min-max rescaled between 0 and 1.

The cumulative impacts of climate change (***I***) as calculated as the inverse variance-weighted sum of the impact estimates in each grid (*i*) as

|  |  |
| --- | --- |
|  | (6) |

For any given dimension, *X*, [i.e., climate hazard (***H***) or agro-ecological exposure (***E***)] on the *i*th grid, is estimated as

|  |  |
| --- | --- |
|  | (7) |

Wherethe mean and standard deviation of the standardised scores of climate hazards on the *i*th grid was estimated as

|  |  |
| --- | --- |
|  | (8) |

and

|  |  |
| --- | --- |
|  | (9) |

(*iv*) Linking impacts to villages

To assign impact metrics to coastal villages, we assumed that potential impact dissipated with distance from a village. Thus, we generated weights proportional to the inverse of the distance between the village point and the impact grid raised to a power value of *p* (**van Sickle et al., 2008**). Accordingly, as the distance between the village point and the impact grid increases, weights decrease rapidly. Based on the value of *p*, the rate at which the weights decrease varies. We used a *p* value of 1, such that at a village point, the predicted impact weight is 1 and decreases with distance away from the village point. This method is known as Inverse Distance Weighting (IDW) and is commonly applied to data interpolation. To calculate village level *IRv*, we applied the weights to the impact in the risk equation.

|  |  |
| --- | --- |
|  | (10) |

Where is the inverse distance weighted impacts estimated as

|  |  |
| --- | --- |
|  | (11) |

(*v*) Impact controls or effectiveness/potential to reduce risk (*C*)

After calculating the village level “inherent” risks, we were interested in understanding the gap after actions taken to alter the risk's impact or likelihood. To represent impact control potential (C), we use the Notre Dame-Global Adaptation Initiative (ND-GAIN), an index constructed from 45 indicators of vulnerability and readiness to respond to climate change. ND-GAIN represents a country’s readiness to mitigate climate change using nine indicators under three components: economic, governance and social readiness. Social AC encapsulates social inequality, ICT infrastructure, education, and innovation. Governance comprises political stability and non-violence, control of corruption, the rule of law, and regulatory quality. Economic AC refers to the ease of doing business in a country. AC ranges from 0–1, representing higher readiness to mitigate climate change. ND-GAIN index has been used to analyze vulnerability to climate change across 192 countries (Sarkodie & Strezov, 2019). It is strongly correlated with the gross domestic product (GDP) (Chaudhary et al., 2018) and the human development index (HDI) (Russo et al., 2019).

**(4) Estimating loss and damage**

Once we had estimated residual risks, we were interested in knowing how much monetary losses would accrue despite potential adaptation. We used economic valuation approach to estimate loss and damages (LD). Economic value approach has been widely applied to quantify monetary values ecosystem delivery (Constanza et al., 2010) and applying them in the context of our study allowed us to sufficiently report financial implications of climate related risks to governments (OECD, 2022). To achieve this, we estimated the current Total Economic Value (TEV) for the reefs, mangroves, and seagrass ecosystems for coastal protection, tourism, climate mitigation, and fisheries services delivered to coastal communities. Additionally, we value the food services for agriculture. Unit service values (coefficients) were derived from literature reviews. However, value coefficients are likely influenced by inflation, so we accounted for these disparities by converting estimates into US$ (2020 price levels).

**Table Sx.** Ecosystem value coefficients applied to estimating TEV for coastal communities in the WIO.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Ecosystem | Service values (2020 US$/ha/y) | | | | Total |
| Tourism | Food | Carbon  sequestration | Flood  protection |
| Mangroves | 2,979.89 | 13.00 | 1,920.19 |  | 4,913.08 |
| Seagrass | NA | 23.00 | 758.66 |  | 781.66 |
| Reefs | NA | 1,184.00 | NA |  | 1,184.00 |
| Cereal yield - KEN | NA | 322.54 | NA |  | 322.54 |
| Cereal yield - MOZ | NA | 218.66 | NA |  | 218.66 |
| Cereal yield - MDG | NA | 580.06 | NA |  | 580.06 |
| Cereal yield - TZA | NA | 357.99 | NA |  | 357.99 |

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**APPENDICES**

Figure xx, Research framework

**Table S1.** AHP-based weights supplied to adaptive capacity and sensitivity calculations.

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
| Domain | | # | Type | Relative weights | | | |
|  | Indicators | KEN | TZA | MOZ | MDG |
| Livelihood | |  | **SS** | **.47** | **.60** | **.45** | **.32** |
|  | Employment status | 1 |  | .20 | .13 | .26 | .25 |
|  | % Catch from fishing sold | 2 |  | .12 | .34 | .28 | .26 |
|  | % Income from main activity | 3 |  | .46 | .34 | .31 | .30 |
|  | Time spent conducting activity | 4 |  | .13 | .20 | .15 | .19 |
| Demography | |  | **SS** | **.08** | **.16** | **.22** | **.24** |
|  | Gender | 5 |  | .34 | .06 | .22 | .22 |
|  | Years living in the village | 6 |  | .10 | .20 | .31 | .21 |
|  | % Children in the family members | 7 |  | .27 | .27 | .20 | .23 |
|  | Family dependency | 8 |  | .23 | .47 | .28 | .35 |
| Cultural | |  | **SS** | **.13** | **.09** | **.19** | **.17** |
|  | Appreciation of biodiversity | 9 |  | .59 | .25 | .41 | .31 |
|  | Identity and pride | 10 |  | .41 | .45 | .33 | .32 |
|  | Appreciation of lifestyle | 11 |  | - | .30 | .26 | .37 |
| Health | |  | **SS** | **.32** | **.15** | **.14** | **.27** |
|  | Age | 12 |  | .50 | .23 | .41 | .23 |
|  | Nutritional dependency | 13 |  | .37 | .50 | .28 | .50 |
|  | Sense of place | 14 |  | .13 | .27 | .31 | .28 |
| Learning | |  | **AC** | **.34** | **.13** | **.26** | **.25** |
|  | Level of education | 15 |  | .32 | .10 | .24 | .38 |
|  | Knowledge of values | 16 |  | .15 | .34 | .43 | .28 |
|  | Access to information | 17 |  | .53 | .56 | .33 | .34 |
| Assets | |  | **AC** | **.14** | **.18** | **.22** | **.20** |
|  | Material style of life | 18 |  | .50 | .26 | .28 | .33 |
|  | Community infrastructures | 19 |  | - | .32 | .39 | .43 |
|  | Access to credits | 20 |  | .50 | .42 | .33 | .24 |
| Flexibility | |  | **AC** | **.31** | **.33** | **.20** | **.21** |
|  | Livelihood multiplicity | 21 |  | .30 | .16 | .34 | .38 |
|  | Adapt to live without fishing | 22 |  | .36 | .48 | .18 | .22 |
|  | Gears | 23 |  | .16 | .21 | .25 | .21 |
|  | Spatial mobility | 24 |  | .10 | .14 | .23 | .20 |
| Agency | |  | **AC** | **.09** | **.12** | **.15** | **.15** |
|  | Perceived capacity to change | 25 |  | .42 | .41 | .30 | .36 |
|  | Recognition of causality | 26 |  | .10 | .15 | .31 | .31 |
|  | Level of participation | 27 |  | .45 | .44 | .40 | .33 |
| Organization | |  | **AC** | **.12** | **.24** | **.17** | **.18** |
|  | Trust in organization | 28 |  | .15 | .45 | .35 | .33 |
|  | Community cohesion | 29 |  | .34 | .22 | .40 | .34 |
|  | Linking social capital | 30 |  | .51 | .33 | .25 | .33 |

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Country | Villages | SS | AC | Hazard\*Exposure | | | | | |  | Risk | | | | | |
| SSP1-2.6 | | SSP2-4.5 | | SPP3-7.0 | | SSP1-2.6 | | SSP2-4.5 | | SSP3-7.0 | |
| **2050** | **2100** | **2050** | **2100** | **2050** | **2100** | **2050** | **2100** | **2050** | **2100** | **2050** | **2100** |
| Madagascar | Analanabe | 0.50 | 0.48 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Madagascar | Andranoboka | 0.57 | 0.45 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Madagascar | Antafiatambalaka | 0.53 | 0.48 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Madagascar | Besakoa | 0.56 | 0.47 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Madagascar | Lagnamena | 0.54 | 0.46 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Madagascar | Maromanjo | 0.59 | 0.44 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Madagascar | Tsinjoarivo | 0.56 | 0.41 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mozambique | Cumbane | 0.47 | 0.42 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mozambique | Farol | 0.53 | 0.49 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mozambique | Gazene | 0.57 | 0.49 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Mozambique | Mahilene | 0.45 | 0.39 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Boma Subutuni | 0.62 | 0.46 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Gando | 0.58 | 0.41 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Kangagani | 0.61 | 0.50 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Kwale | 0.61 | 0.48 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Mjini Kiuyu | 0.57 | 0.40 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Moa | 0.60 | 0.46 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Mtambwe | 0.66 | 0.47 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Mwandusi | 0.62 | 0.47 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Ndumbani | 0.56 | 0.47 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Tanzania | Selemu | 0.54 | 0.49 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Faza | 0.48 | 0.44 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Gazi | 0.45 | 0.47 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Kiwayu | 0.41 | 0.45 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Matondoni | 0.51 | 0.44 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Mida | 0.55 | 0.50 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Ndau | 0.46 | 0.43 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Uyombo | 0.50 | 0.49 |  |  |  |  |  |  |  |  |  |  |  |  |  |
| Kenya | Vanga | 0.56 | 0.46 |  |  |  |  |  |  |  |  |  |  |  |  |  |

|  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Risk space | Options space | Villages | | | | | | | | |  |
| **V1** | **V2** | **V3** | **V4** | **V5** | **V6** | **V7** | **V8** | **V9** |  |
| ***Acceptable*** | |  |  |  |  |  |  |  |  |  |  |
|  | Biosphere protection |  |  |  |  |  |  |  |  |  |  |
|  | Basic drinking water supply |  |  |  |  |  |  |  |  |  |  |
|  | Rural development |  |  |  |  |  |  |  |  |  |  |
|  | Employment creation |  |  |  |  |  |  |  |  |  |  |
|  | Agricultural development |  |  |  |  |  |  |  |  |  |  |
|  | Fishery development |  |  |  |  |  |  |  |  |  |  |
|  | Fishery research |  |  |  |  |  |  |  |  |  |  |
|  | Tourism policy and administrative management |  |  |  |  |  |  |  |  |  |  |
|  | Small and medium-sized enterprises development |  |  |  |  |  |  |  |  |  |  |
| ***Tolerable*** | |  |  |  |  |  |  |  |  |  |  |
| ***comprehensive risk management approaches*** | |  |  |  |  |  |  |  |  |  |  |
|  | Multisector aid for basic social services |  |  |  |  |  |  |  |  |  |  |
|  | Social protection and welfare services policy, planning and administration |  |  |  |  |  |  |  |  |  |  |
|  | Develop local-level management to increase ecological recovery potential and ecological sensitivity (e.g., marine protected areas, gear-based management). |  |  |  |  |  |  |  |  |  |  |
|  | Education and participation in research |  |  |  |  |  |  |  |  |  |  |
|  | Support for community initiatives/organizations |  |  |  |  |  |  |  |  |  |  |
|  | Poverty alleviation plans and pro-poor growth policies |  |  |  |  |  |  |  |  |  |  |
|  | Infrastructure development projects in rural areas |  |  |  |  |  |  |  |  |  |  |
|  | Microcredit schemes, support for community savings |  |  |  |  |  |  |  |  |  |  |
|  | Skills and capacity building |  |  |  |  |  |  |  |  |  |  |
|  | Promote the use of gears less likely to be negatively impacted by coral bleaching (e.g., hand lines) |  |  |  |  |  |  |  |  |  |  |
|  | Training, gear provision |  |  |  |  |  |  |  |  |  |  |
|  | Agricultural extension |  |  |  |  |  |  |  |  |  |  |
| ***Intolerable*** | |  |  |  |  |  |  |  |  |  |  |
|  | human mobility, including migration, displacement and planned relocation |  |  |  |  |  |  |  |  |  |  |
|  | enhanced co-operation and facilitation in relation to action and support including finance, technology and capacity building |  |  |  |  |  |  |  |  |  |  |

Table Sx: The CMIP6 Earth system models used in this study; their individual components used to represent ocean, land, and atmosphere.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| No. | Model | Variable ID | Resolution | Reference |
| 1 |  |  |  |  |
| 2 |  |  |  |  |
| 3 |  |  |  |  |

**Table xx**

|  |  |  |  |
| --- | --- | --- | --- |
| Variable | Category | Domain | Description |
| SST90p and LST90p | **Acute** | Hazard | Frequency of extreme temperature; the number of months with temperature exceeding the 90th percentile of the baseline (1981-2010) divided by 360 months (30 years \*12 months). Unit: **%** |
| SST90i and LST90i | **Acute** | Hazard | Intensity of extreme temperature; Arithmetic mean temperature across months with temperature exceeding the 90%tile of the baseline. Unit: **℃** |
| R10p | **Acute** | Hazard | Drought frequency: the number of months with precipitation below the 90th percentile of the baseline (1981-2010) divided by 360 months (30 years \*12 months). Unit: **%** |
| TAPi | **Acute** | Hazard | Drought intensity; total rainfall across months with precipitation below the 10%tile baseline threshold. Unit: **%** |
| CDD | **Acute** | Hazard | Cumulative degree days; |
| dpH, dSST, dLST, dTAP, dNPP, dEVAP | **Chronic** | Hazard | Increases in climate variable; a slope of a linear regression over the 30-year climatological period. Unit: **variable** |
| Mangroves | **-** | Exposure |  |
| Coral cover | **-** | Exposure |  |
| Crop cover | **-** | Exposure |  |
| Seagrass | **-** | Exposure |  |
| FRic | **-** | Exposure |  |
| FEve | **-** | Exposure |  |
| FDiv | **-** | Exposure |  |
| Nb\_sp | **-** | Exposure |  |

Chart, radar chart

Description automatically generated

**Fig. Sx.** Relative importance of adaptive capacity and sensitivity domains.

Chart, timeline

Description automatically generated

**Variables**

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| Proposed variables | | Class | System impacted | Scale | Rational |
| **1. Hazard** | |  |  |  |  |
|  | * *Compound hot-dry events (Extreme heatwaves vs drought events)* | Acute/Abrupt |  | Grid | Extreme events (e.g., drought, rainfall, temperature, etc.) can increase crop switching, increase fallow periods, and reduce subsistence, produce quality, agricultural income etc., ultimately resulting in severe macroeconomic implications (e.g., including commodity price surges) (Davis et al., 2021). Compound drought–heatwave (CDHW) amplify adverse impacts on socio-economic sustainability and human well-being. CDHWs can exacerbate vegetation mortality and control ecosystem productivity, which can cascade into more proximal pressures impacting on ecosystem services ( |
|  | * *pH* | Chronic |  | Grid | Ocean acidification (i.e., reduced pH levels due to increased CO2) decreases corals' growth rates and structural integrity (Yin et al. 2023). |
|  | * *SST* | Chronic |  | Grid | Ocean warming causes thermal stress that contributes to coral bleaching and may lead to infectious diseases (Maynard et al., 2015). |
|  | * *Evapotranspiration* | Chronic |  | Grid |  |
|  | * *Rainfall* | Chronic |  | Grid | Changes in precipitation lead to increased runoff of freshwater, sediments, and land-based pollutants, resulting in algal blooms and murky water, reducing light. |
|  | * *Temperature (mean)* | Chronic |  | Grid |  |
|  | * *NPP* | Chronic |  |  |  |
| **2. Exposure** | |  |  |  |  |
|  | **Ecosystems exposed:** |  |  |  |  |
|  | * Corals |  |  | Grid |  |
|  | **Human exposure:** |  |  |  |  |
|  | * Population |  |  | Grid | An additional 20–36% and 11–33% population are projected to face hunger by 2050 under a once-per-100-yr extreme climate event under high and low emission scenarios, respectively (Hasegawa et al., 2022). |
| **3. Vulnerability** | |  |  |  |  |
|  | **Adaptive capacity:** |  |  |  | The severity, frequency and duration of droughts are likely linked to the degree of exposure, susceptibility and coping capacity of the social-ecological system (Meza et al., 2019). |
|  | * Learning |  |  | Local |
|  | * Assets |  |  | Local |
|  | * Flexibility |  |  | Local |
|  | * Agency |  |  | Local |
|  | * Organisation |  |  | Local |
|  | **Sensitivity:** |  |  |  |  |
|  | * Livelihood |  |  | Local |  |
|  | * Demographics |  |  | Local |  |
|  | * Cultural |  |  | Local |  |
|  | * Health |  |  | Local |  |

**#Regridding climate datasets**

One of the most widely used models is the Coupled Model Intercomparison Project (CMIP), used to study the Earth's climate system. The latest version of the CMIP model is CMIP6, which includes a high-resolution ocean component. However, the raw data from the CMIP6 model is not always at a high enough resolution for certain research purposes. This report will describe a methodology for regarding CMIP6 ocean data to a higher resolution using the Climate Data Operators (CDO) tool. The CDO tool is a command-line tool that can be used to manipulate climate data. It includes a wide range of commands, including the ability to re-grid data.

The regridding of CMIP6 ocean data to high resolution using CDO involves the following steps:

1. Data preparation: The CMIP6 ocean data are downloaded from the Earth System Grid Federation (ESGF) data portal and checked for completeness and consistency. The data can be downloaded in netCDF format, a widely used format for climate data. Once the data is downloaded, it can be re-gridded using the CDO tool.
2. Remapping: The CMIP6 ocean data is remapped to a high-resolution grid using the CDO remapdis command. The remapping is done using the nearest neighbor interpolation method, which preserves the values of the original grid cells. To re-grid the downloaded SST data, the "**remapcon**" command is used which allows to re-grid the SST data to a new high-resolution grid. The following is an example command for regridding the data to a high-resolution grid: cdo **remapcon,grid.txt** infile.nc outfile.nc In this command, "grid.txt" is the file containing the high-resolution grid, "infile.nc" is the input file, and "outfile.nc" is the output file.
3. Output: The final output is a high-resolution version of the CMIP6 ocean data that can be used for further analysis and modelling.