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Research

Current and future climate change impacts on Indigenous lifestyle and cultural values in Ovalau, Fiji

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ABSTRACT. Many *iTaukei* (Indigenous Fijian) communities maintain traditional lifestyles that may be particularly vulnerable to climate change impacts because of a reliance on small-scale subsistence agriculture and fisheries, and the deep cultural connections between people, communities, and the environment. Quantitative analyses of climate impacts in the Pacific region are hampered by a lack of historical data measuring environmental change, resource productivity, or cultural values. Therefore, this study uses a structured elicitation method to estimate recent impacts based on the expert knowledge, experiences, and perceptions of local Indigenous communities from six villages on the island of Ovalau, Fiji. Workshops were conducted in the local language to elicit data for proportional decreases in agricultural production, fisheries, and water security. Impacts were also elicited for 10 measures relating to cultural values and practices, e.g., social cohesion and well-being, *veiwasei* (i.e., food sharing within villages), and *Vanua* (i.e., multi-dimensional cultural connections to land). Most participants identified reductions across almost all of the 13 elicited measures, often identifying decreases of over 50% for each measure within the last 20 years. These perceived changes to subsistence production and cultural values are combined with historical climate data for Ovalau in a Bayesian network modeling framework, to estimate potential loss under future climate scenarios. This work highlights a strong perception of recent climate loss and damage among Ovalau's communities and also demonstrates an innovative new approach for estimating historical climate impacts and predicting future changes based on the experiences, knowledge, and expertise of Indigenous communities.

Key Words: *climate risk; cultural heritage; food security; loss and damage; non-economic loss; Pasifika; sea level rise; water security*

INTRODUCTION

The Intergovernmental Panel on Climate Change highlights a range of impacts and projected risks for small islands because of climate change, including both natural systems (e.g., marine and coastal environments) and human systems. The latter includes impacts and risks to human infrastructure, health, agriculture/fisheries, water security, economies, and also cultural resources and heritage (Mycoo et al. 2022). Across the Fiji islands, a large proportion of *iTaukei* (Indigenous Fijian) peoples maintain traditional lifestyles, relying on small-scale subsistence farming and fisheries as a major food resource and source of income. These are at risk of degradation because of climate change, for example, decreasing fisheries production due to damage to critical coral and mangrove habitats, decreasing quality and availability of coastal land due to saltwater incursions from rising sea levels and storm surges, or potential increases in the prevalence of agricultural diseases and pests as local climatic conditions shift (Freeman et al. 2012, Wairiu et al. 2012, Taylor et al. 2016, Bakare et al. 2020, Mycoo et al. 2022).

Physical evidence of climate change has already been documented in the Pacific region, including rising sea levels, ocean warming, and increases in both air temperature and the frequency of temperature extremes (Kumar et al. 2014, Taylor et al. 2016, McGree et al. 2019, Marra et al. 2022, Mycoo et al. 2022). There is mixed evidence of changes to rainfall, where limited historical data, broad inter-decadal variability, and regional variation make it difficult to identify long-term regional trends across the Pacific (McGree et al. 2019, Brown et al. 2020). There is also mixed evidence for changes in the frequency or intensity of tropical cyclones (Marra et al. 2022, Mycoo et al. 2022). Nonetheless, physical changes in the climate are being experienced across the region, which is likely to have some impacts on *iTaukei* communities.

There is now increasing research attention given to understanding and characterizing the non-economic loss and damage related to climate change (see Serdeczny et al. 2016). This includes impacts on Pacific communities' subsistence lifestyles, including the availability of traditional food items, materials, and medicines (Handmer and Nalau 2019). Other forms of noneconomic impacts may include loss of cultural heritage and knowledge, physical and mental health effects, loss of biodiversity and ecosystem services, and impacts associated with climate-induced relocations (McNamara et al. 2021a, 2021b).

Climate may also have less tangible cultural and ontological impacts, including in the Pacific, where attachment to place and community is a significant component of Indigenous cultural identities (Adger et al. 2013, Raisele et al. 2025). Research with *iTaukei* communities showed how losses of traditional resources can lead to the erosion of associated cultural practices, traditions, and knowledge (Lykins et al. 2023). Participants also described how anticipated losses for future generations, including loss of cultural values and their land, are central to their own experiences of climate-related loss.

This demonstrates the importance of including the perspectives and social-ecological relationships of Indigenous communities when examining climate-related non-economic loss and damage. For example, the concept of *Vanua* relates to the interconnected

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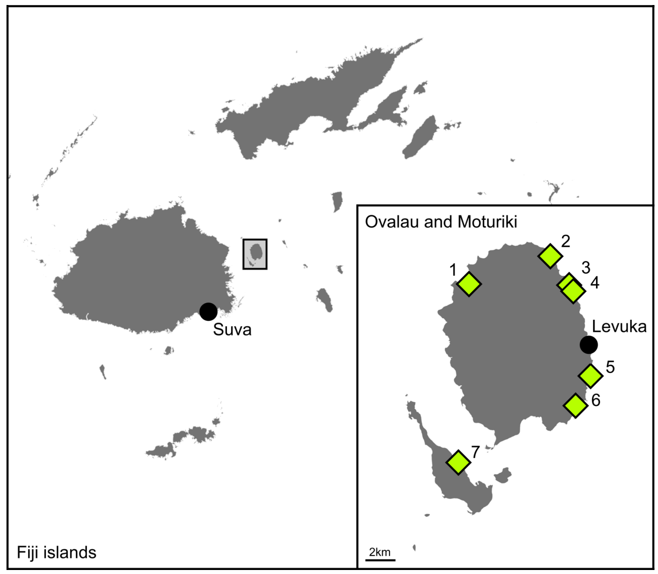
relationships between *iTaukei* people and land (Yee et al. 2022a). The broad concept can encompass spiritual connections to land, economic/livelihood connections, ancestral/family and social connections, stewardship over the environment and traditional roles associated with village communities (Yee et al. 2022b). The majority of land in Fiji is also owned and managed through customary law and family/clan units (i.e., *mataqali*; Charan et al. 2017). Consequently, concepts of land attachment like *Vanua*, as well as similar comparable concepts in other Pacific nations, are important for understanding how Pacific Island peoples may be impacted by climate change, in particular how environmental impacts or climate-induced relocations may have complex and far-reaching effects on Pacific communities (Gharbaoui and Blocher 2016, Oakes 2019, Piggott-McKellar et al. 2020, McNamara et al. 2021b, van Schie et al. 2024).

There is only a limited body of literature relating to the quantification and valuation of Indigenous cultural values (see Manero et al. 2022), and no established methodology that may be applied to measure climate-related loss and damage for cultural impacts in Pacific Island communities. Although a selection of studies have qualitatively assessed and characterized some cultural impacts of climate in the Pacific, only a limited number have attempted to semiquantitatively or quantitatively measure, model, and predict climate impacts on subsistence lifestyles (see one recent example: ACIAR 2021). Therefore, the overarching goal of this study is to develop a methodology to semi-quantitatively and quantitatively assess climate impacts on subsistence lifestyles and cultural values for Indigenous communities in the Pacific.

Climate impact studies in the region are often limited by a lack of historical empirical data, requiring the use of other sources of evidence to measure impacts (e.g., Nunn 2000). *Talanoa* is increasingly used as a form of direct engagement and qualitative data collection with Indigenous communities within Fiji (see for example: Janif et al. 2016, Martin et al. 2018, Yee et al. 2022a, Yee et al. 2022b, Raisele and Lagi 2023). This is a form of dialogue in some Pacific Island nations, which is characterized by inclusivity, mutual respect, and an openness to sharing opposing ideas and perspectives (Robinson and Robinson 2005), and has previously been incorporated into UN procedures for climate change (UNFCCC 2018). Furthermore, structured elicitation protocols (e.g., the IDEA protocol; Hemming et al. 2018) provide robust methods for estimating unknown quantities or parameters for which there may be limited/insufficient existing data, based on the knowledge of expert groups. This study therefore combines *Talanoa*-based community engagement and elicitation-based data collection methods to measure historical impacts due to climate, and then applies probabilistic modeling tools (i.e., Bayesian network, [BN models]; Pearl 1988, Hanea et al. 2006) to estimate potential losses under future climate scenarios the next decade.

The test case for this methodology is Ovalau Island (see Fig. 1). Ovalau is a mountainous island directly east of Viti Levu (i.e., the largest of Fiji's islands), and home to Fiji's historical capital and UNESCO World Heritage Site, Levuka. Ovalau has a largely Indigenous population with most villages concentrated around the coastal fringe of the island, and previous research has

Fig. 1. Ovalau and Moturiki within Fiji, and [inset], Ovalau and Moturiki Islands. Ovalau is approximately 10 x 15 km. Diamonds show the locations of villages participating in this study, (1) Rukuruku (-17.64201, 178.75568), (2) Nauouo (-17.625033, 178.808774), (3) Vatukalo (-17.64339, 178.82035), (4) Toki (-17.64675, 178.82361), (5) Naikorokoro (-17.70089, 178.83454), (6) Tokou (-17.72054, 178.82512), and (7) Nasesara (-17.75603, 178.74922). All were included in the initial *Talanoa* discussions, and all except Nasesara were included in data collection workshops.



described substantial coastal erosion on Ovalau, which is likely linked to sea level rise and the loss of mangrove habitats (Nunn 2000). Although we are not intending to undertake confirmatory hypothesis testing, we have some general expectations about impacts that may be observed, as follows:

1. *iTaukei* (Indigenous Fijian) communities on Ovalau have experienced impacts on their subsistence lifestyles (e.g., farming/fisheries production, and water security), and on their associated cultural values and practices (e.g., community/social well-being, traditional knowledge, connections to land, etc.) because of the effects of climate change.
2. Lifestyle and cultural impacts may be quantitatively or semi-quantitatively estimated, for example, as proportional changes to the productivity of traditional farming methods.
3. Lifestyle and cultural impacts are expected to be primarily negative.

These hypotheses/expectations are tested by establishing (i) whether cultural impacts can be identified and characterized; (ii) whether cultural impacts can be quantitatively or semiquantitatively estimated; and, (iii) whether measured impacts are primarily negative.

METHODS

Study design and overview

Community engagement and data collection were conducted in two phases. First, preliminary engagement (March 2024) included *Talanoa* sessions in seven villages on Ovalau and Moturiki, a small, low-lying island immediately south of Ovalau (Fig. 1). Villages were initially selected in consultation with staff from the Lomaiviti Provincial Office via local project facilitators.

Principal data collection was then completed in August 2024, with structured elicitation workshops conducted within six Ovalau communities in *Veitalanoa* sessions (i.e., focus group style *Talanaoa* discussions conducted in community language). Elicitation questions were formulated from information gathered during the preliminary engagement.

All data collection and analysis methods were pre-registered before principal data collection (27 June 2024), which can be accessed via the Open Science Framework (https://doi.org/10.17605/OSF.IO/WZTYS). Any departures from this protocol are described and justified below.

Preliminary community engagement and identifying impacts

Talanoa sessions

The purpose was to initiate engagement with local communities and participate in open-ended group *Talanoa* discussions regarding the local communities' experiences with climate-related impacts. Sessions were conducted in standard Fijian language (*Vosa Vakabau*) and English (facilitated by RL and a local guide). Following ceremonial introductions, researchers briefly described the purpose of the discussions, i.e., to understand how climate change is impacting local communities in any way that they feel is significant to them. We emphasized that our goal was to allow the community to freely discuss or raise any issues that they may be experiencing regarding climate impacts on their village, with minimal prompting.

Discussions were conducted over 5 days, lasting 1–3 hours with approximately 10–25 people per village. These began with an open question about how the community uses their land, then discussions were allowed to progress naturally, allowing the community to bring up issues freely. A broad topic list was also used to guide the conversation toward general subject areas, which included: land uses (e.g., agriculture, fishing, etc.); environment (e.g., changes in plants, rivers, animals, etc.); displacement/relocation (e.g., past experiences or future expectations); adaptation (i.e., changes made to anything they do that may be linked to climate impacts); and, submergence/inundation (e.g., experiences with coastal erosion or flooding). Discussions were then followed by free walks around villages where locals showed examples of physical climate impacts on their village.

Classification of lifestyle and cultural impacts

Based on extensive notes (collected via NM, AH) a preliminary list of impacts was formulated, including 5 general classes and 24 sub-classes (see the full list in Appendix 1). General classes were agriculture (e.g., yield losses, lost productivity), fisheries (e.g., reduced catches, increased production costs), water (e.g., reduced drinking water quality, damage to infrastructure from extreme events), human health (e.g., heat exposure, indirect health effects of reduced traditional food resources), and community/social well-being and cultural practices (e.g., ceremonial offerings, loss of traditional knowledge/skills).

These were cross-checked with key references classifying climate impacts in comparable contexts, i.e., "Observed Impacts and Projected Risks on Human Systems" for small islands (per Mycoo et al. 2022:2063), and an in-depth region-specific review of "non-economic loss and damage in the Pacific Islands" (per McNamara et al. 2021a), to define a subset of lifestyle and cultural value measures for primary data collection (see Appendix 2).

Data collection by structured elicitation

Veitalanoa workshops

The target sample size for elicitation was 20 participants per village, with a minimum total sample of 100 participants, and even samples of male/female and younger/older participants (i.e., ≤ 35 and > 35 years). This was based on the maximum number that could be included within the logistical constraints of the workshops, and based on our previous experience from the *Talanoa* sessions.

Workshops used an approach based on the IDEA elicitation protocol (Hemming et al. 2018). This follows an "Investigate," "Discuss," "Estimate," and "Aggregate" procedure, where an expert group (in this case the local Indigenous community) independently answer a set of questions. This is followed by a discussion based on their initial answers, after which they may adjust their answers if they misunderstood the question or changed their mind. For full details of workshop procedures, see Appendix 2. Briefly, participants were first guided through each question as a group (led by RL). Initial answers were then checked, and each participant was provided individual feedback and taken through their responses to ensure they were consistent with their knowledge, and to resolve any apparent inconsistencies or errors in their entries (by NM and AH, assisted by a local guide). Finally, participants were guided through a final run-through of each question as a group to give a final opportunity to adjust their responses. Each workshop lasted approximately 3–4 hours.

Questionnaire design

Questions about changes to lifestyle and cultural values were informed by climate change loss and damage literature (e.g., the *Handbook for assessing loss and damage in vulnerable communities*; Van der Geest and Schindler 2017), including studies that have used qualitative and semi-quantitative survey-based assessments of climate change-induced loss and damage in Pacific Island communities (e.g., Charan et al. 2017, Martin et al. 2018, ACIAR 2021, McNamara et al. 2021b).

Data were elicited for 13 lifestyle and cultural value measures as follows:

1. The amount and/or size of the food that you grow for your household (e.g., yaqona, cassava, vegetables).
2. The amount and/or size of the food caught from the sea for your household (e.g., fish or other seafood).
3. The quality or reliability of the drinking water supply for your household.
4. The proportion of traditional food in your diet compared to non-traditional food sources.

5. Your personal feelings of well-being and happiness (e.g., stress, etc.).
6. The amount of food sharing (*veiwasei*) between households in the village.
7. The size and/or quantity of ceremonial food offerings in the village (e.g., how many or how large are the cassava, taro, or fish that are offered for village celebrations, church functions, etc.).
8. The sense of cohesion and well-being within your household (e.g., because of conflict within the home, etc.).
9. The level of social cohesion and well-being in the village overall.
10. The amount of time that people spend in the village because of outside work (e.g., to work in the fish factory, in Australian Pacific worker schemes, in Suva, etc.).
11. The availability of traditional plants (e.g., pandanus leaves, traditional medicinal plants used for Fijian medicine).
12. The reliability or usefulness of traditional indicators used in the village (e.g., breadfruit tree bearing fruit in clusters of four, bees nesting underground, etc.).
13. The strength of your connection to the land itself (*Vanua*).

Changes in each measure were first assessed using categorical checkbox responses to assess community perceptions and knowledge of the overall directional changes in subsistence lifestyles and cultural values over the last 10 and 20 years (e.g., decreased, increased, no change). If a participant identified a categorical decrease in any value, scale responses were used to elicit quantitative data regarding proportional changes over both 10 and 20 years as a visual analogue scale/continuous rating scale from 0 to 100% loss (Chyung et al. 2018).

Causal ranking questions were also included for a subset of measures (i.e., 1, 3, 11, 12), for participants to rank their perceptions of the most important climate change and non-climate change factors driving perceived changes (e.g., ranking the top 1, 2, and 3 most important factors; for factors such as extreme heat, sea level rise, etc.). Potential causal factors included in questionnaires were based on those raised during the *Talanoa* discussions, and cross-referenced with major reports that have identified potential physical climate changes being experienced in the Pacific region (Taylor et al. 2016, Marra et al. 2022, Mycoo et al. 2022). Participants could include three additional factors under "other," which were then translated after the workshops. Causal factors for all other values were incorporated directly into the elicitation questions, and participants were asked to identify changes as a result of those specific factors only. For example, changes in food caught from the sea (i.e., measure 2), were directly elicited as a result of "ocean warming and effects on the marine environment (e.g., damage to coral reefs)," changes in most cultural values (i.e., measures 4–10) were elicited as a result of "less traditional food being grown or caught," while changes to land connection/*Vanua* were elicited as a result of "coastal erosion/inundation (e.g., from sea level rise, flooding, storm surges, extreme weather events, and any damage to village houses or cultural heritage sites)."

Minimal demographic questions were also included to categorize participant's age (18–25, 26–35, ..., and 66+), gender (male, female, other), the number of people in their household (1, 2, ..., 15+), and how long they have lived in their village (0–9, 10–19, ..., 100+). Finally, an additional question explored community experiences and expectations about past and future climate-related relocations. This included sub-questions relating to personal experiences with displacement in the past, expectations about potential future relations, the costs of past and potential future relocations, and an open-ended qualitative response question. Summary response data for relocations are available in Appendix 7.

The design and language used for questions were reviewed by local co-author and climate education expert, RL, and the full questionnaire was piloted with local community members from Ovalau to ensure that the language used reflected local understandings of climate change impacts and cultural values. RL also facilitated elicitation workshops in the local language, and local guides assisted participants to ensure the structure and format of questions were correctly interpreted. In addition to verbal instructions, a large A0 poster was displayed throughout the workshops to give further guidance on how to complete the questionnaire. During the first session, some participants had difficulty understanding the format of scale response questions, so two additional instructional diagrams were prepared and also displayed alongside the posters for subsequent workshops. RL also guided the translation of all text responses (i.e., for causal ranking questions and open-ended questions) to ensure the correct interpretation of qualitative responses.

For an example of the format of questions, see Appendix 2. PDFs for all questionnaires and instructional materials in both English and *Vosa Vakabau* can be accessed via the Open Science Framework (https://doi.org/10.17605/OSF.IO/4SCJYM).

Statistical analyses and modeling

Summary response data and subgroup analysis

All responses were initially analyzed per question, and summary measures were provided for each value. Qualitative response data (i.e., increase, decrease, no change responses) were assessed in terms of the proportion of respondents who have chosen a certain category.

Causal ranking response data were aggregated as a weighted score. A proportion of respondents also preferred to enter their rankings as checkmarks (e.g., ticks or crosses), which have also been incorporated into analyses. This used a simple weighting (i.e., 1st = 3 points, 2nd = 2, 3rd = 1), while ticks were scored 2 points to avoid biasing weights toward or against participants who preferred to enter scores as checkmarks. Where participants ranked a top 3, but also ticked or numbered additional causes (e.g., as 4th or 5th ranked), these additional rankings/marks were not scored. Although in cases where four causes were marked and there was no way to distinguish the top 3, all four marks were included to avoid excluding those entries entirely. A small number of responses were also excluded where the entries could not be interpreted.

Chi-squared (χ^2) tests were used to assess if the proportion of participants identifying decreases for each value differed between (i) female and male participants, and (ii) older (36+ years old) and younger (35 years old and under) participants. Data processing, summary data extraction, and subgroup analysis were conducted in the R statistical environment (v4.2.3, R Core Team 2025).

Bayesian network modeling

We used a simple BN model to represent the influence of environmental variables on lifestyle and cultural values, and predict the magnitude of potential decreases over the next decade under future climate scenarios. BNs are directed acyclic graphs that provide a visualization of complicated relationships among variables (e.g., Pearl 1988). The nodes correspond to random variables, and the arcs from "parent" to "child" nodes represent direct qualitative dependence relationships. BNs may be quantified by estimating a marginal distribution for variables represented by each node, and specifying a correlation structure for each arc (e.g., Hanea et al. 2006). The quantitative information can be either taken from existing data, elicitation, or a combination of both (e.g., Hanea et al. 2022). BNs can then be used to update multivariate distributions with new information (observations or measurements), referred to as "inference". For example, we can "condition" the model on future values of environmental variables under projected climate scenarios, and propagate the influence of these changes through the other nodes.

A preliminary BN model structure was designed based on the initial *Talanoa* (for details, see Appendix 3). The final BN model was refined from the initial design based on the structure of the elicitation questions, on information provided during the elicitation workshops (e.g., ranking data), and the availability of empirical data (see Fig. 2). For a detailed description of the design and quantification of the final BN used for inference, see Appendix 3.

Briefly, environmental variables included as nodes in the BN were either ranked highly by participants (i.e., *ExtremeHeat*, *SLR*, and *ExtremeRainIntensity*) or incorporated into elicitation questions explicitly as causes of resource decline (i.e., *OceanWarming*). *Pests* and *Cyclones* were also included, but because of data limitations, these variables were assigned a uniform distribution and not used for inference. A node representing seasonal predictability was initially incorporated (*SeasonalPredict*). This had extreme heat and rain intensity as parent nodes because seasonal predictability was very often equated with intense rain events and extreme heat during *Talanoa* discussions, and these two variables were considered sufficient to reflect the community understanding of season predictability. This assumption translated into excluding the *SeasonPredict* variable from the final BN used in analysis and making its two parents the direct parents of *SeasonPredict*'s children (see the expanded model in Appendix 3).

Effects of environmental variables on subsistence resource availability were represented with arcs to the nodes *TraditionalVegAvailability*, *DrinkingWaterAvailability*, *CatchRates*, *TradPlantsAvail*, and *TradIndicators*. Seven nodes represented elicited cultural value measures (e.g., *PersonalWellbeing*, *CeremonialOfferings*, etc.), with one additional node representing *TraditionalKnowledge* as a secondary cultural value. The proportion of traditional food in diets was elicited but not modeled as a distinct cultural value/practice.

Arcs that link to *TraditionalVegAvailability*, *DrinkingWaterAvailability*, *TradPlantsAvail*, and *TradIndicators* were determined from ranking data. Arcs associated with the remaining lifestyle and cultural values nodes were pre-determined based on the structure of elicitation questions (e.g., *CatchRates* was linked to *OceanWarming*, *Connection2Land* to *SLR*, and other elicited cultural variables were linked to nodes representing subsistence farming and fishing production). The secondary cultural node, *TradKnowledge*, was linked to *TradIndicators*, *TradPlantAvail* and *TimeSpentWithFamily* as parent nodes.

It is worth noting that there are no arcs between (nor common parents of) environmental variables. Even though these are very likely correlated on a large timescale, their decadal correlation structure is hard to estimate or make assumptions about. We circumvent this modeling difficulty in the inference stage by conditioning the model on joint values of these variables.

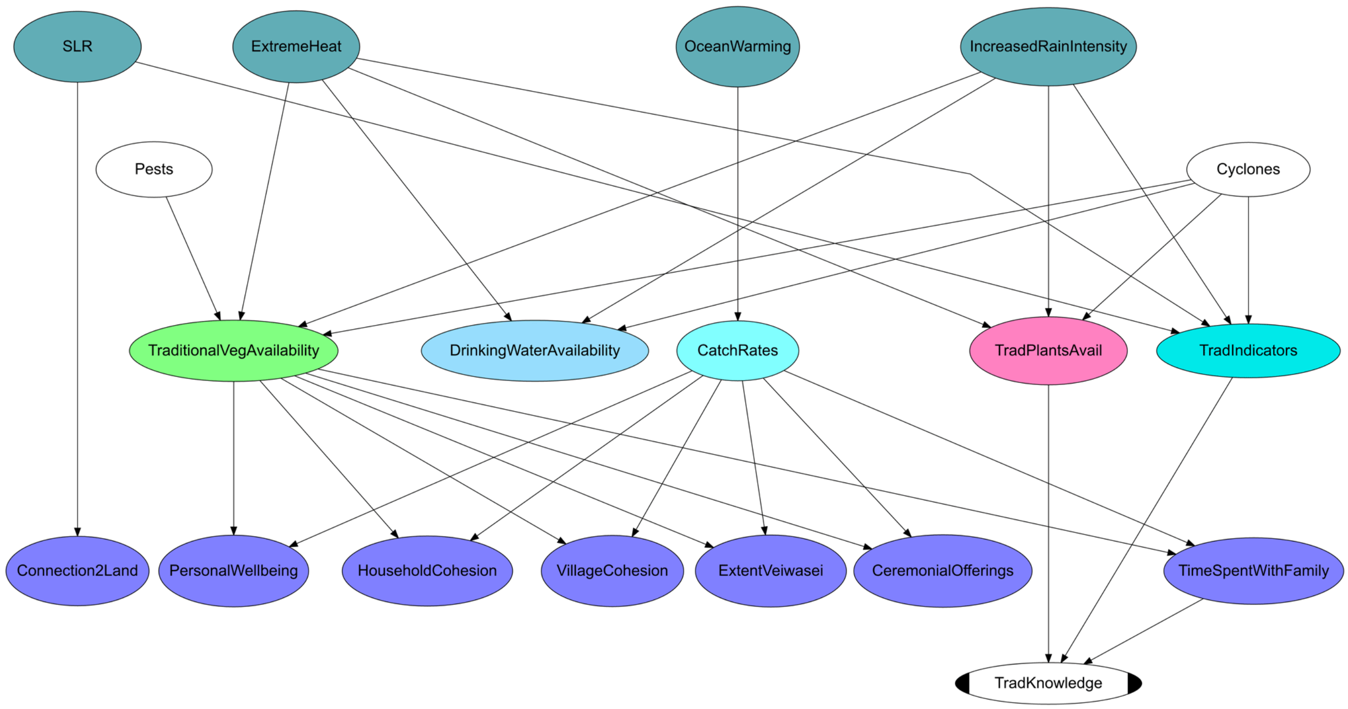
Nodes representing elicited lifestyle and cultural values were quantified using scale response data for percentage decreases in each measure, by fitting Beta distributions on the corresponding samples. Because scale responses were only elicited from the segment of the population that identified decreases in each measure, this BN can be characterized as modeling the current and future decreases in lifestyle and cultural values for the subset of the population that is experiencing/perceiving that loss only. Nonetheless, based on qualitative response data, this represents a large proportion of the community.

Arcs were quantified as both unconditional and conditional Spearman's rank correlations. We considered both a high and medium correlation model, where correlations are proportional to the weighted ranking scores for *TraditionalVegAvailability*, *DrinkingWaterAvailability*, *TradPlantsAvail* and *TradIndicators*, with the first ranking correlation equal to 0.8 for the high correlation model or 0.6 for the medium correlation model. *TraditionalVegAvailability* and *CatchRates*, considered to be equally correlated with each child (i.e., *PersonalWellbeing*, *HouseholdCohesion*, *VillageCohesion*, *ExtentVeiwasei*, *CeremonialOfferings*, *TimeSpentWithFamily*, approximately equal to a rank correlation of 0.6 in both dependence models. Finally, *TradKnowledge* was quantified as a linear combination of its parent nodes (see further details in Appendix 3).

Environmental nodes were quantified based on recent historical changes and future projections taken from local hydrological data and established climate models. These included the Pacific Sea Level and Geodetic Monitoring Project (BOM 2024), NASA's IPCC AR6 Sea Level Projection Tool (Fox-Kemper et al. 2021, Garner et al. 2021, Kopp et al. 2023), Bio-ORACLE (v3.0; Tyberghein et al. 2012, Assis et al. 2024), and the World Bank, Climate Change Knowledge Portal ("CCKP"; World Bank 2024).

This focused on four key variables for which data and future projections could be readily obtained, i.e., mean sea level (m), mean sea surface temperature (°C), average maximum daily air temperature (°C), and maximum 1-day rainfall per month (mm). These were used as proxies for climate-related factors that were described during *Talanoa* and correspond to both elicited causal factors in the questionnaire and BN nodes. For example, mean sea level was used as a proxy for the effects of "sea level rise (coastal flooding, saltwater intrusion)" in the questionnaire, and the BN node *SLR*. Historical change in each variable was calculated monthly between 2014 and 2024 to parameterize environmental nodes using distributions of estimated percentage decadal change.

Fig. 2. The simplified final Bayesian network model structure used for inference. Nodes represent environmental variables (e.g., SLR, ExtremeHeat, etc.), variables representing subsistence resource production and resource availability (e.g., TradVegAvailability, CatchRates, etc.), and other lifestyle and cultural measures (e.g., HouseholdCohesion, CeremonialOfferings, etc.). Arcs between nodes represent direct qualitative dependence relationships between parent and child nodes.



To estimate the potential change under climate scenarios, point estimates for the four key environmental variables were estimated 10 years into the future (i.e., 2034) under a moderate emissions/optimistic pathway, i.e., Shared Socioeconomic Pathway (SSP) 2-4.5, and a high emissions/pessimistic pathway, i.e., SSP 5-8.5. These point estimates were then used to condition BN models and estimate future distributions for lifestyle and cultural nodes. For specific estimates of past and future environmental change and details of climate data sources and processing steps, see Appendix 4.

The flexibility of BNs allowed the combination of qualitative and quantitative modeling as well as the parametrization using both objective field data and subjective expert/participant data. The community priors were used as elicited (without credibility-based differential weighting) because no data were available to be integrated with the community's insights. Complete uncertainty was expressed using uniform (maximum entropy) distributions (where neither field nor elicited data were available). A formal sensitivity analysis of the model's structure was not conducted. Instead, insights were gained through iterative processes and responses to the questionnaire. Similarly, conducting a formal sensitivity analysis for the BN parameters can be challenging when dealing with multiple correlated outputs. Although a semi-formal analysis highlighted the significant role of the dependence structure, leading us to model two different strengths of multivariate dependence.

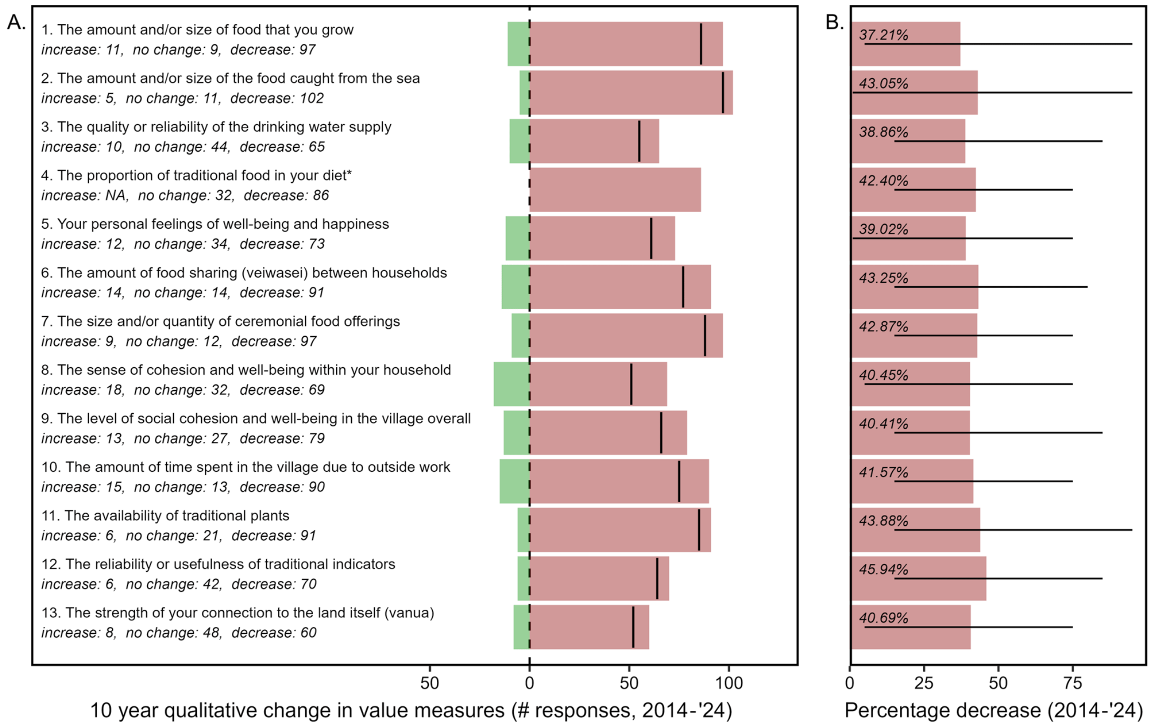
Finally, separate from BN modeling, the rates of decrease were also estimated by fitting a non-linear curve to the relative values for each elicited measure at 3 points in time (2004, 2014, and now). This was included to provide additional context for any future changes predicted by BN inference. Our questions covered percentage changes relative to 10 and 20 years ago, respectively; therefore, the value of each measure may be estimated relative to the current state, without consideration of causal factors. The spread in these answers was represented by a mean/median and an upper and lower bound corresponding to the 5th and the 95th percentiles of the distribution of answers. As such, at the three points in time, we can either fit a distribution or create a credible interval around the central tendency, which will represent the uncertainty of each variable. This allowed us to estimate the relative values for each measure 10 years in the future, if the perceived trends were to continue.

BN models were implemented in UniNet (version 3.5.9 Beta, https://lighttwist-software.com/uninet/). Additional pre-processing steps for the BN modeling and the non-linear curve fitting were conducted in Matlab (version 9.11.0.1769968, R2021b, https://www.mathworks.com/).

Ethics statement

Data collection methods were approved by the University of Melbourne's Human Research Ethics Committee (as of 27 June 2024; reference no. 2024-29726-51933-1). Participants were provided with a plain language statement and consent form

Fig. 3. Ten year summary response data. (A) The number of participants that identified increases (green, left-side) and decreases (red, right-side) between 2014 and 2024. Black vertical lines represent the net difference. No net difference is shown for measure 4 (*) because this response could not be "increase" based on the structure of the question. (B) Mean percentage decreases elicited for participants identifying a decrease for each value. Black horizontal lines show the range (min–max) of responses.



translated into *Vosa Vakabau* at the start of elicitation workshops, and were free to withdraw from participating in workshops at any time. All engagement with local communities was conducted in cooperation with the Lomaiviti Provincial Office (Ministry of iTaukei Affairs, Fiji), facilitated by the Fijian Environmental Law Association (FELA, Suva, Fiji), to ensure that all work was conducted in line with community expectations and cultural practices. Local Fijian collaborators and guides were also instrumental in facilitating community engagement, designing data collection methods, and interpreting responses and results.

RESULTS

Six workshops were completed (5–8 August 2024), with 125 participants. Three withdrew during the workshops and their responses were excluded. Six additional participants did not return for the feedback round, of which three were excluded from the analysis because their questionnaires contained serious inconsistencies and errors that could not be resolved. Therefore, responses from 119 participants were used for summary analysis of qualitative response data.

To summarize scale response data for use in BN modeling, we used a refined subset of response data. Each questionnaire was reviewed for inconsistencies and entry errors that may show a misunderstanding of the format of scale response questions that were not resolved during feedback sessions. Of 119 questionnaires, 13 (10.9%) were excluded as having several or widespread inconsistencies and mistakes. Twenty-year scale response data were also excluded for an additional 28 participants who may not have direct knowledge of those more distant changes, including those aged 25 and below, and people who had lived in the village for less than 10 years.

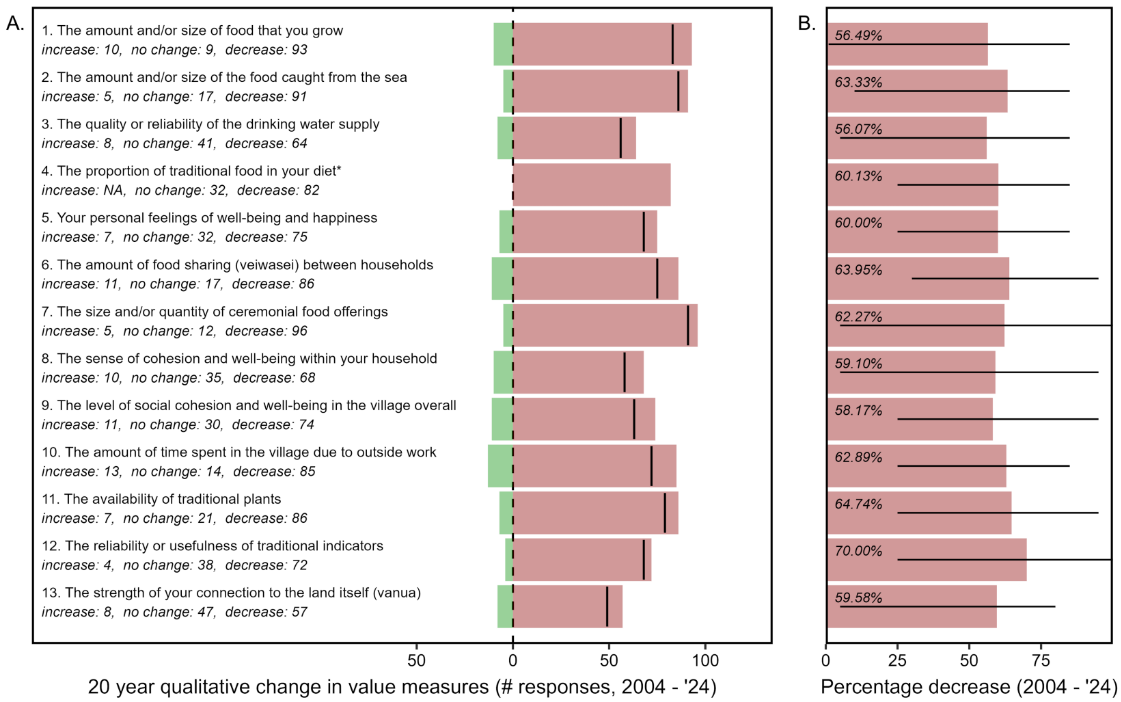
The demographic composition included similar numbers of female (54, 45.4%) and male (65, 54.6%) participants, with fewer younger (35 and under; 35, 29.4%) than older participants (84, 70.6%). Summary demographic data are available in Appendix 5.

Summary response data and subgroup analysis

The majority of responses identified decreases across almost all lifestyles and cultural values measures over the last 10 (Fig. 3.A) and 20 years (Fig. 4.A). The one exception was for the connection to land (measure 13) over the last 20 years, where a plurality of responses identified a decrease, but a substantial proportion also selected no change.

There was some variation in the number of participants selecting a decrease for each measure. Values where the highest number of participants identified decreases were for fisheries (measure 2), farming (measure 1), and ceremonial food offerings (measure 7). Fewer participants identified negative impacts on drinking water supply, social cohesion and well-being within households, and connection to the land (measures 3, 8, 13). Similar proportions of participants also identified decreases over both 10- and 20-year periods.

Fig. 4. Twenty year summary response data. (A) The number of participants that identified increases (green, left-side) and decreases (red, right-side) between 2004 and 2024. Black vertical lines represent the net difference. No net difference is shown for measure 4 (*) because this response could not be "increase" based on the structure of the question. (B) Mean percentage decreases elicited for participants identifying a decrease for each value. Black horizontal lines show the range (min–max) of responses.



Within the subset of participants that identified decreases for each value, the average percentage decrease was between 37.21 and 45.94% over the previous 10 years, and between 56.07 and 70.00% over the previous 20 years (see Fig. 3.B and 4.B). Note that these results are based on the refined subset of data focusing on the most reliable responses.

Causal rankings highlighted extreme heat as the most important factor in relation to farming impacts, although all other potential factors listed as options were rated as important causes by a substantial proportion of participants (Table 1). Only a small number of responses identified other potential causes for this value, such as fire/burning (*vakamakama*).

For impacts on drinking water, heavy rain was the highest-ranked factor (Table 1). Extreme heat was not included on the initial list of options for this value, but several responses included heat as an important factor under "other." Entries under "other" relating to dry weather (*draki mamaca*) and lack of rain *na lailai ni uca*) were included under seasonal predictability because these are assumed to be related to worsening dry seasons or periodic droughts. The remaining entries were grouped under "other," which included factors such as landslides (*sisi na qele*), fire/burning (*vakamakama*), and the cutting down of trees.

Extreme heat was the highest ranked causal factor for both impacts on traditional plant availability and for traditional indicators (Table 1). For traditional plants, a range of additional causal factors were also identified, including that these plants were no longer being planted/cultivated (e.g., *sega ni tei*, *sa sega ni teivaki tale*). Also, fire/burning was again identified as an important factor by several participants. For decreases in the reliability/usefulness of traditional indicators, participants also highlighted that knowledge is being lost, not being taught, translated, or passed down as another factor.

There were very few differences between subgroups. Over the last 10 years, fewer women identified decreases in the amount/size of food being caught from the sea than male participants (77% vs 94%, $\chi^2 = 5.438$, $P = 0.020$). There were no significant gender differences in the proportions identifying 10-year decreases for any other measure, or over 20 years for any measure. For older and younger participants, there were also no significant differences in their perception of decreases in each value over both the last 10 or 20 years (see full results in Appendix 5).

Bayesian network modeling

An example of the BN, with nodes quantified with a high correlation structure under SSP 5-8.5 is shown in Fig. 5.A, and the same BN conditionalized on projected environmental variables for 2034 is shown in Fig. 5.B. Note that conditioning on all four variables at the same time has the same effect as assuming a correlation structure between them (i.e., where when one changes, the other one changes as well).

This example represents a pessimistic climate scenario, assuming both high emissions and a strong dependence structure between variables, and is shown such that the changes in the distributions

Table 1. Summary causal rankings for decreases in four measures, i.e., the amount/size of food grown (#1), the quality/reliability of the water supply (#3), the availability of traditional plants (#11), and the reliability/usefulness of traditional indicators (#12). Also, in brackets, weighted scores for each cause based on questionnaire responses (i.e., 1st rank = 3 points, 2nd = 3, 3rd = 1, tick/check mark = 2). The highest ranking causal factor for each measure is shown in bold.

	Farming	Drinking water	Trad. plants	Trad. indicators
Extreme heat	**1st (180)**	6th (14)	**1st (140)**	**1st (89)**
Seasonal predictability	2nd (100)	2nd (97)	3rd (65)	2nd (86)
Tropical cyclones	4th (63)	3rd (70)	2nd (90)	5th (48)
Heavy rain	5th (55)	**1st (99)**	5th (51)	4th (51)
Sea level rise	6th (45)	4th (40)	7th (46)	3rd (57)
New pests and diseases	3rd (76)	NA	6th (51)	7th (26)
Other	7th (8)	5th (35)	4th (53)	6th (43)

of all child nodes are more clearly visible. Changes under both SSP 2-4.5 and a medium correlation structure are estimated in the same way, and conditional distributions for lifestyle and cultural values nodes under each of these combinations of scenarios are shown in Table 2 and Table 3. The conditional distributions are based on the distributions for historical changes in each value measure (i.e., 2014–2024), as shown in Fig. 3.B. These estimates show marginal decreases from 2024 to 2034 in all lifestyle and cultural measures, excluding *CatchRates* under 2-4.5, where the projected change is near zero. Increases in *Connection2Land* are projected under all scenarios, and high uncertainty accompanies all the value measures estimated for 2034. These estimates from the BN modeling represent only the subset of the Ovalau population that reported decreases in each value.

For further context, the projected estimates based on non-linear curve fitting are shown in Table 4. This represents the median estimate for each lifestyle and cultural value measure in 2034 relative to a 2024 baseline, if perceived temporal trends were to continue. Fit curves are shown in Appendix 6. These also appear to project decreases in most value measures, with the exception of *TradIndicators*, although with extremely high uncertainty represented by their lower and upper bounds. The estimated marginal decreases from 2024 to 2034 appear to generally be higher in magnitude than those estimated via BN models.

DISCUSSION

Veitalanoa workshops directly elicited the experiences and perceptions of Ovalau communities, where a large proportion of participants identified decreases in key components of their subsistence lifestyles within just the last two decades. The results are consistent with a widespread perception of negative impacts on the resources produced through traditional farming and fishing on Ovalau, and subsequent decreases in a range of cultural values due to corresponding decreases in the availability of traditional resources. Furthermore, climatic variables such as extreme heat, heavy rain events, and sea level rise appear to be important causal factors driving the loss and damage that communities have experienced.

This study demonstrates a valuable approach to assessing lifestyle and cultural impacts of climate change, an area where pre-existing data are largely unavailable. Empirical data describing climate impacts in the Pacific are often lacking, and although there is increasing availability of data supporting the physical effects of climate change, changes in highly variable or extreme events such as cyclones remain uncertain (Marra et al. 2022, Mycoo et al. 2022). Similarly, rainfall, seasonality, and associated patterns in the El Nino-Southern Oscillation are strongly influenced by inter-annual and inter-decadal variation, limiting the ability of researchers to estimate historical and future change for the South Pacific region (Brown et al. 2020, Marra et al. 2022). New pest and disease impacts are one particular environmental factor that participants frequently highlighted, and increased pest prevalence and damage may be an indirect effect of climate change with large potential impacts on agricultural production in *iTaukei* communities (Wairiu et al. 2012, Taylor et al. 2016, Bakare et al. 2020). There is a strong theoretical basis for expecting pest and disease impacts to increase under climate change (see, for example, Chakraborty and Newton 2011, Bebber et al. 2013, Skendžić et al. 2021). Still, the lack of available empirical data monitoring these impacts limits the ability of these factors to be incorporated into quantitative analyses.

Previous research has attempted to assess the historical impacts of coastal erosion for Ovalau, combining historical evidence (e.g., photos) and oral histories gathered directly from local communities (Nunn 2000). This identified coastal erosion impacts in the vast majority of villages, and quantitatively estimated lateral inundation levels up to an extreme of 125 m within the preceding 65 years at one location. Although sea level rise and loss of mangrove habitats were highlighted as potential causes, directly modeling these effects was not possible using the available empirical evidence. From an empirical perspective, modeling the climate impacts on the lifestyle and cultural values of Indigenous communities provides an even greater challenge.

A growing body of literature uses non-market valuation approaches in the context of Indigenous culture, primarily to assess direct or indirect use value concerning environmental assets and ecosystem services, or physical cultural assets like heritage sites or cultural artifacts (see Romão and Paupério 2021, Manero et al. 2022). These approaches were employed in a companion study to predict both market and non-market/ecosystem service losses associated with future sea level rise and storm surge impacts for Ovalau (Kompas et al., *unpublished manuscript*). This is especially relevant for Fiji, given the direct physical impacts on coastal ecosystems that support subsistence lifestyles, and coastal inundation leading to damage of physical heritage sites and the relocation of whole communities (Charan et al. 2017, McMichael et al. 2019, Piggott-McKellar et al. 2019). Also, impacts due to heat stress on agricultural and labor productivity may be severe given the importance of subsistence farming (see Kompas et al. 2018). Nonetheless, cultural barriers to relocation, voluntary immobility of Indigenous communities, and concepts of place attachment, place belongingness, or *Vanua* highlight the complexity of connections between *iTaukei* communities and the physical impacts of climate change (Nunn et al. 2020, Singh et al. 2020, Yee et al. 2022a). This complexity demands approaches that characterize and quantify the impacts of climate on *iTaukei*

Fig. 5. (A) A quantified simplified version of the Bayesian network (BN) model under the Shared Socioeconomic Pathway (SSP) 5-8.5, high correlation scenario, and (B) the high dependence SSP 5-8.5 BN conditional on the predicted values of the climate variables. Conditional means for each node in (B) are also shown in Table 3, under both high and medium dependence scenarios (estimates under SSP 2-4.5 are also given in Table 2).

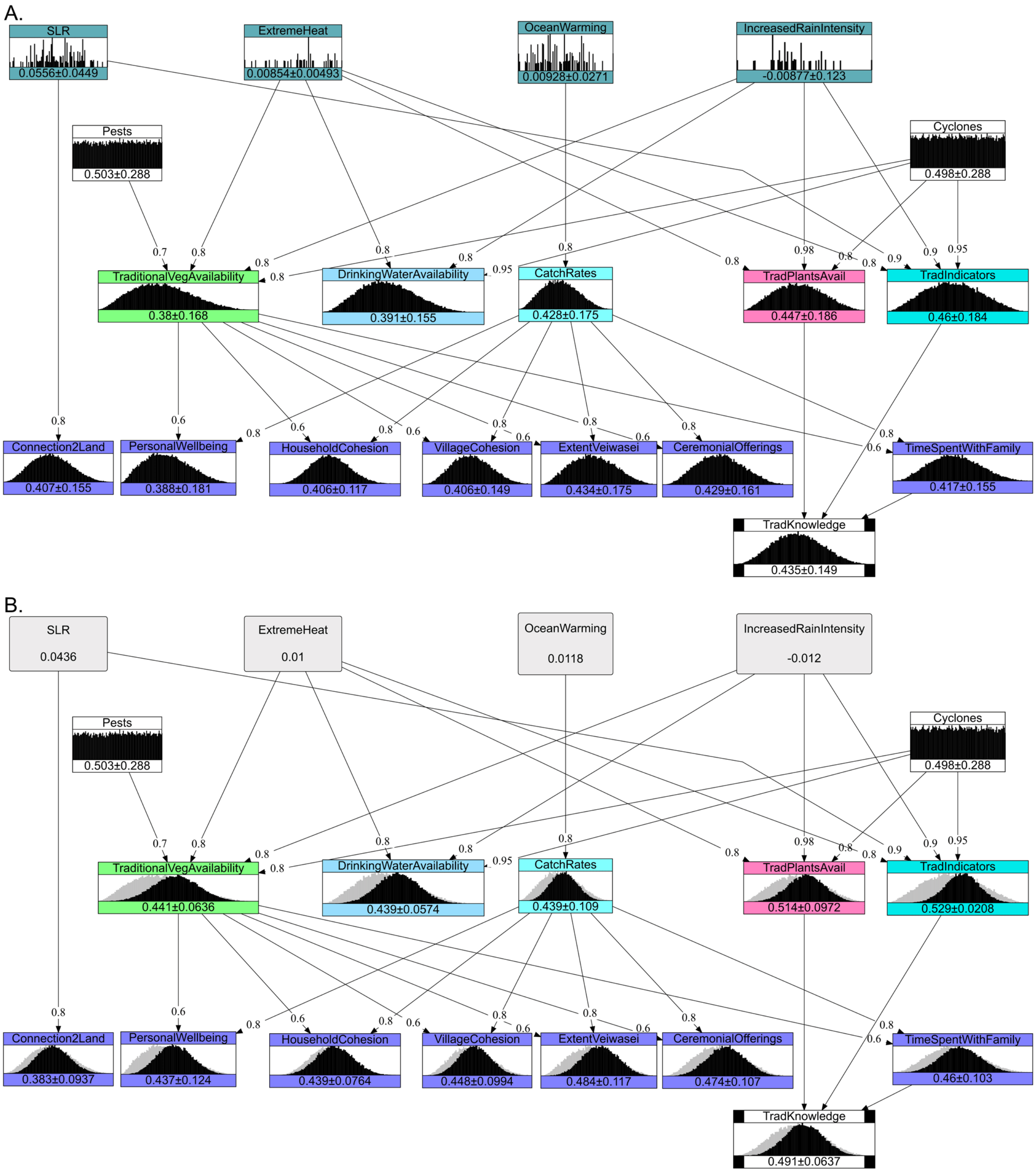


Table 2. Estimated conditional means for percentage decreases in lifestyle and cultural values estimated from the Bayesian network model under Shared Socioeconomic Pathway 2-4.5. Values in brackets represent conditional standard deviations from the conditional mean percentage decreases shown. Delta values represent the additional marginal decrease from the estimated mean for 2034, relative to the historical estimated decrease (i.e., from 2014 to 2024).

	2-4.5/med	Δ	2-4.5/high	Δ
TraditionalVegAvailability	41.8% (12.8)	-6%	42.6% (6.3)	-7%
DrinkingWaterAvailability	42.5% (11.7)	-6%	43.3% (5.7)	-7%
CatchRates	43.1% (14.3)	0%	43% (10.9)	0%
TradPlantsAvailability	48.8% (14.9)	-7%	49.7% (9.7)	-9%
TradIndicators	50% (11.6)	-7%	50.4% (2.1)	-8%
PersonalWellbeing	41.6% (15.4)	-5%	42.1% (12.3)	-6%
HouseholdCohesion	42.5% (9.7)	-3%	42.9% (7.6)	-4%
VillageCohesion	43% (12.6)	-4%	43.5% (9.9)	-5%
ExtentVeiwasei	46.3% (14.7)	-4%	46.9% (11.7)	-6%
CeremonialOfferings	45.5% (13.5)	-4%	46% (10.7)	-5%
TimeSpentWithFamily	44.2% (13)	-4%	44.7% (10.2)	-5%
Connection2Land	37.1% (12.3)	6%	35.9% (9.2)	8%
TradKnowledge	46.8% (8.3)	-7%	47.4% (6.4)	-8%

Table 3. Estimated conditional means for percentage decreases in lifestyle and cultural values estimated from the Bayesian network model under Shared Socioeconomic Pathway 5-8.5. Values in brackets represent conditional standard deviations from the conditional mean percentage decreases shown. Delta values represent the additional marginal decrease from the estimated mean for 2034, relative to the historical estimated decrease (i.e., from 2014 to 2024).

	5-8.5/med	Δ	5-8.5/high	Δ
TraditionalVegAvailability	42.3% (12.8)	-7%	44.1% (6.4)	-10%
DrinkingWaterAvailability	42.6% (11.7)	-6%	43.9% (5.7)	-8%
CatchRates	44.2% (14.3)	-2%	43.9% (10.9)	-2%
TradPlantsAvailability	49.3% (14.9)	-8%	51.4% (9.7)	-12%
TradIndicators	51.1% (11.6)	-10%	52.9% (2.1)	-13%
PersonalWellbeing	42.6% (15.5)	-6%	43.7% (12.4)	-8%
HouseholdCohesion	43.1% (9.8)	-4%	43.9% (7.6)	-6%
VillageCohesion	43.8% (12.6)	-6%	44.8% (9.9)	-7%
ExtentVeiwasei	47.2% (14.8)	-6%	48.4% (11.7)	-8%
CeremonialOfferings	46.3% (13.5)	-6%	47.4% (10.7)	-8%
TimeSpentWithFamily	45% (13)	-6%	46% (10.3)	-7%
Connection2Land	39% (12.4)	3%	38.3% (9.4)	4%
TradKnowledge	47.6% (8.4)	-8%	49.1% (6.4)	-11%

cultural values that incorporate their personal and communal perspectives and experiences, so that cultural aspects of climate-related loss and damage can be better understood and mitigated.

Several recent studies have sought to characterize and describe these cultural aspects of climate-induced loss and damage in the Pacific. The results here are similar to the qualitative findings of Lykins et al. (2023), which highlighted how losses in traditional resources (e.g., fisheries and farming) may lead to cultural impacts now and into the future. Yee et al. (2022a, 2022b) also describe in detail several interrelated aspects of *iTaukei* cultural values relating to *Vanua* and land attachment in the context of climate impacts, including numerous spiritual, social, ancestral, legal, and economic factors. Lagi (2015, 2017) also describes aspects of traditional cultural knowledge and practices specific to Ovalau's communities and their connection to land. These studies highlight *Vanua* as an aspect of culture that may be impacted by climate change, but that also may be a potential source of resilience and adaptability under future climate change. Notably, BN modeling here suggests that this cultural value measure may be expected to increase under future climate scenarios, although there is high uncertainty in all future estimates and a strong negative temporal trend in this measure from 2004 to 2024. Studies are increasingly seeking to capture impacts on these cultural aspects using qualitative and semi-quantitative methods such as structured interviews, *Talanoa*, and surveys (e.g., McNamara and Prasad 2014, Nunn et al. 2016, McNamara et al. 2021a, 2021b, Raisele and Lagi 2023, van Schie et al. 2024, Raisele et al. 2025).

By combining *Talanoa*, *Veitalanoa*, and structured elicitation, this study builds on this previous work. Structured expert elicitation is particularly valuable in contexts where there are inadequate or insufficient data to support quantitative analysis, and where the knowledge of topic experts is often used in data-limited contexts such as risk analysis (Ioannou et al. 2022, Bau et al. 2024). Importantly, elicitations may be subject to several biases that can influence the reliability of estimates (see Sutherland and Burgman 2015, Bau et al. 2024), and the design of studies and interpretations of results should take careful consideration of potential sources of bias that may influence the elicited data. Potential sources of bias in workshops may include group effects (i.e., where individuals' responses may be influenced by social pressures or particularly influential people, such as the village leaders), anchoring effects (e.g., where verbal or visual instructions or contextual information may bias participants toward a specific response), or motivational biases (e.g., if participants perceive personal gains by responding in a certain way). These are each partially addressed by participants initially completing questionnaire responses independently (i.e., limiting group effects), by providing individual feedback to ensure that responses reflect their personal experience and the real magnitude of changes experienced (i.e., limiting anchoring effects), and by clearly introducing ourselves as independent researchers undertaking an independent scientific research project (i.e., mitigating motivational biases). It may be perceived that ongoing work that is being conducted on Ovalau concerning climate change impacts (by the Environmental Defender's Office, EDO Ltd, Sydney, Australia, and the Fiji Environmental Law Association, FELA, Suva, Fiji) may be a source of motivational bias that may influence participants' responses within workshops. Nonetheless, our interactions with local communities during *Talanoa*, village walking tours, and elicitation workshops are fully consistent with a broad perception held by a large proportion of the community of serious recent losses linked to climate change.

A substantial proportion of participants perceived decreases over the last 10 and 20 years in each lifestyle and cultural value. As the classes of values were derived from the communities themselves, this is not unexpected. Nonetheless, this does confirm that the qualitative descriptions of climate impacts described during *Talanoa* reflect widespread perceptions and experiences of climate-related loss and damage in the community. The magnitudes of perceived loss were large, with average decreases across the elicited values of approximately 42% and 60% over the last 10 and 20 years. The percentage changes were also relatively

Table 4. Median 2034 estimates for lifestyle and cultural value measures relative to 2024, estimated via non-linear curve fitting. Values in square brackets represent lower and upper bounds for fitted curves in 2034. Delta values represent the marginal decrease from the 2034 to 2024 estimates.

	2034 Median	Δ
TraditionalVegAvailability	83% [5, 271]	-17 %
DrinkingWaterAvailability	61% [-34, 338]	-39 %
CatchRates	94% [-102, 127]	-6 %
TradPlantsAvailability	88% [-87, 421]	-12 %
TradIndicators	155% [-92, 1755]	55 %
PersonalWellbeing	61% [-8, 318]	-39 %
HouseholdCohesion	36% [-67, 467]	-64 %
VillageCohesion	61% [-28, 338]	-39 %
ExtentVeiwasei	88% [-75, 421]	-12 %
CeremonialOfferings	40% [-99, 313]	-60 %
TimeSpentWithFamily	40% [-73, 220]	-60 %
Connection2Land	22% [-106, 155]	-78 %

consistent across impact classes. Instead, there was some apparent variation in the proportions of participants identifying/experiencing decreases, increases, or no change in each value, with decreases in agricultural production, fisheries, food sharing, and ceremonial food offerings to most often identified value classes impacted. There were surprisingly few gender or age differences in these responses, which may suggest a strong community consensus. Gender differences were limited to recent changes in fisheries production, where female participants were less likely to identify a decrease. This likely reflects their more direct knowledge of changes to fishing production because fishing was generally described as a women-led activity in villages. Regarding age differences, Martin et al. (2018) previously showed differences between age groups in Yadua Island, Fiji, in their perceptions of change and attitudes toward adaptation and relocation, with older participants more likely to support relocation. However, this contrasts with other studies where older community members appeared more reluctant to relocate (e.g., Charan et al. 2017). Although we did not assess differences between age groups concerning relocation, older and younger participants responded similarly across all elicited values, including their connection to land.

We used a BN model to represent a subset of the data (namely, the subset of the community with an identified and quantified experience of loss for 12 of the elicited values), because BNs seamlessly integrate human expertise and perceptions with rigorous statistical analysis within a robust framework. Where data are scarce, this approach allows human judgment to be systematically woven into the probabilistic model. The probabilistic framework then offers a structured method to update beliefs, make predictions, and explore "what-if" scenarios as new data emerges, thereby boosting the model's reliability. This synergy ensures optimal use of both empirical data and community insights, resulting in a dynamic and adaptable model.

The BN helps represent all the different aspects of the perceived and experienced loss and its causes, by first building a mental map of the flow of influence/causality between different factors/variables. This representation allows us to separate the uncertainty around each of these factors from their interdependencies. It also allows us to explore how a change in an environmental variable propagates through to and affects all potential resources, and through those, all cultural values discussed with the participants. Although painting a complete picture was important, it hindered a very informed parametrization of the model, which in turn limits its predictive power. The chosen correlation structure was assumed to be moderate, especially between resource availability nodes and the cultural value nodes, recognizing that other uncertain factors may influence and explain variability in the latter.

As a consequence, only moderate changes were predicted by the models when conditioning on values of the climate variables as predicted for the next decade. For example, the percentage decrease in vegetable availability that had a mean of 38% in the last decade, will reach a 44% decrease relative to 2014 under the SSP 5-8.5 scenario, and the uncertainty around this mean will shrink almost to a third (i.e., the standard deviation decreases from 17% to 6%). A similar magnitude of loss is predicted for the reliability of the traditional indicators (from 46% to 53%), although in this case, there is very little uncertainty about the loss (the standard deviation gets 9 times smaller, reaching 2%). These further losses predicted over the next decade in resources also translate into additional losses in terms of cultural values. The magnitude of the flow-on effect is, however, determined by the choice of the correlations, which we kept moderate.

Using the BN quantified for the current decade to inform the situation in the next decade assumes that the trajectory of all losses is similar between decades. The community's perceptions about the rate of change between decades, however, imply a much more rapid decline, at least when it comes to cultural values. The discrepancy, therefore, may come from two sources: one is the use of extra information elicited about differences between now and 20 years ago, and the other is due to declines in cultural values not being modeled as a consequence of the decline in resources, like in the BN. This may also be partly because changes estimated for the past 10 and 20 years may be linked to a wider range of potential causal variables (e.g., pests, cyclones, and a limited range of "other" causes identified by participants), where future predictions from the BN under future SSP scenarios are based only on a limited set of climate variables for which data are available, of which only sea level, extreme heat, and ocean warming show a clear positive signal of climate change within the next decade.

Despite using a conservative approach to future predictions, the results are consistent with the ongoing decreases in lifestyle and cultural values under future climate scenarios. Although there is substantial uncertainty as to the magnitude of future losses, this is to be expected given the limited empirical data available to model such changes and the complexity of climate impacts on communities and social systems. Additionally, this study demonstrates how traditional forms of dialogue can be combined with structured data collection to overcome some of the challenges of assessing and quantifying non-economic loss and damage, particularly in the context of cultural impacts in Indigenous communities. Because these methods continue to be developed, this type of approach may allow for the better integration of Indigenous cultural values into climate governance frameworks, including improving how social impacts and risks are characterized via the Intergovernmental Panel on Climate Change, and for mechanisms aimed at minimizing climate-related loss and damage in developing countries such as the Warsaw International Mechanism for Loss and Damage and the Santiago Network.

Author Contributions:

NPM: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft
AMH: Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Software, Validation, Visualization, Writing – original draft
RL: Investigation, Methodology, Writing – review & editing
TK: Conceptualization, Funding acquisition, Project administration, Supervision, Writing – review & editing

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Data Availability:

Fully anonymized datasets, analysis code, models, and outputs are all available at the Open Science Framework (https://doi.org/10.17605/OSF.IO/4SCJY).

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1. Preliminary Impact Classifications

1. Agriculture

1.1. Yield losses
1.2. Increased production costs (distance to farm, input costs)
1.3. Lost productivity (lost work time due to extreme heat)

2. Fisheries

2.1. Reduced catch rates
2.2. Increased production costs

3. Water

3.1. Reduction in water quality
3.2. Increased water supply costs
3.3. Loss of freshwater food resources
3.4. Direct damage from flooding/riverbank erosion

4. Human health

4.1. Heat exposure
4.2. Waterborne diseases
4.3. Mental health
4.4. Indirect effects due to reduced traditional food sources
4.5. Life expectancy

5. Community/social well-being and cultural practices

5.1. Sharing culture
5.2. Ceremonial offerings
5.3. Domestic violence
5.4. Loss of traditional knowledge/skills
5.5. Loss of traditional medicines
5.6. Traditional indicators
5.7. Cultural connections to land itself, place-belonging (i.e., textitVanua)
5.8. Physical cultural heritage
5.9. Relocation/ adaptation of village infrastructure
5.10. Flood and coastal erosion mitigation infrastructure

Impacts related to human health and physical infrastructure were only partially included in the structured elicitation, as purely health impacts were considered beyond this study's scope, and also, health costs may be more appropriately quantified directly using healthcare data. Physical infrastructure damages were captured under a companion paper focused on estimating damage and loss for those asset/value classes in monetary terms (Kompas et al., in review).

2. Methodological Details – Structured elicitation

2.1. Example elicitation questions

An example of the format, response variables and type of questions/sub-questions for question 1 is as follows:

- *1_a* For your household, how has the amount and/or size of the food that you grow changed (e.g., yaqona, cassava, vegetables), ... from 10 years ago to now? (response type: categorical; response variable: categories: decreased, increased no change)
- *1_b* For your household, how has the amount and/or size of the food that you grow changed (e.g., yaqona, cassava, vegetables), ... from 20 years ago to now? (response type: categorical; response variable: categories: decreased, increased no change)
- *1_c* If it has decreased, what are the most important causes? (response type: ranking; response variable: categories: sea level rise (coastal flooding, saltwater intrusion); more extreme heat; more heavy rain; tropical cyclones; less predictable seasons; new pests & diseases; other)
- *1_d* If it has decreased, how much has it decreased, ... from 10 years ago to now? (response type: numerical response scale (continuous); response variable: proportional loss (0-100%))
- *1_e* If it has decreased, how much has it decreased, ... from 20 years ago to now? (response type: numerical response scale (continuous); response variable: proportional loss (0-100%))

Categorical response questions (e.g., *1_a*, *1_b*) required a simple tick box response. Ranking questions (i.e., *1_c*) required numbered responses ranking the top three causes in boxes, as 1, 2, and 3 (or simply using ticks or crosses if the participant preferred). Scale responses required a cross/mark along a visual scale, as shown in Fig. 2.1.

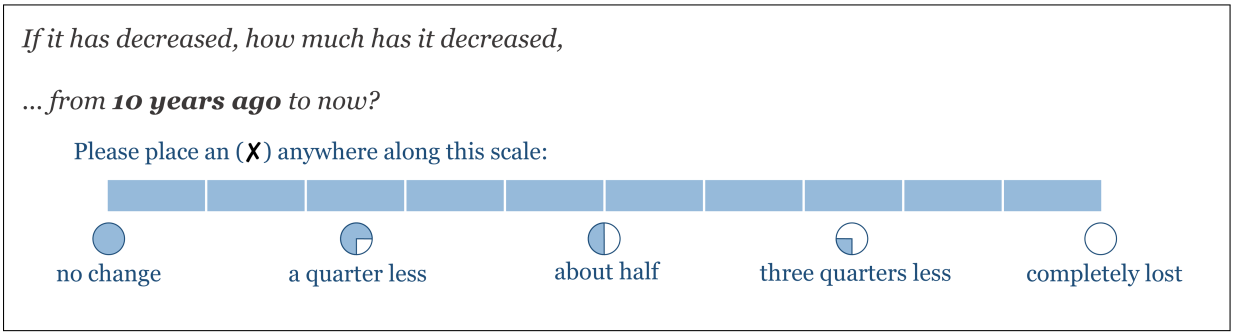

Figure 2.1: A visual analogue scale/ continuous rating scale for eliciting quantitative estimates for the magnitude of decreases in lifestyle and cultural values.

2.2. Elicitation workshop procedure

The elicitation process for Ovalau was as follows:

1. *Welcome & introductions (∼30 mins)*: Researchers (NM, AH, RL) re-introduced themselves and participated in welcome ceremonies.
2. *Instructions & initial responses (1h to 1.5 hours)*: Researchers (led by RL) provided instructions to the participants as a group for how to complete the questionnaire and guided them through each question, during which participants each completed their questionnaire independently.
3. *Break (∼30 mins)*: Participants then rested and enjoyed refreshments, while researchers (NM, AH) collated a quick feedback summary for each participant.
4. *Feedback and group discussion (1h to 1.5 hours)*: Participants were taken through their responses individually (i.e., by NM and AH, assisted by a local guide), to ensure that the direction and magnitude of changes identified in responses were consistent with their knowledge, and to resolve any apparent inconsistencies or errors in their entries. This was followed by a brief group discussion and a final run-through of each question, to give participants an opportunity to adjust their answers if they changed their minds or misunderstood any of the questions. Participants were provided with different coloured pens for their initial (red) and revised (black) responses so that the final responses could be distinguished.
5. *Conclusion & farewell ceremonies*.

Participants were generally not directly financially compensated for taking part. Instead, the village was engaged to provide refreshments (i.e., food and drink) for the participants and researchers during workshops. Researchers then compensated the community ∼$20 FJD per participant and member of the research team.

Initially, feedback was to be provided to the full group or smaller subgroups. Based on our initial assessment of responses in the first workshop, feedback was instead given one-on-one, as individual feedback appeared to be more effective at clarifying some common issues and misunderstandings of the questionnaire, for example, the direction of the scale, and the relationship between 10-year and 20-year changes.

3. Methodological Details – Bayesian network modelling

3.1. Preliminary (pre-workshop) BN model design

The preliminary pre-registered BN model for Ovalau (Fig. 3.1) was based on *Talanoa* discussions and represents the influence of environmental variables on resource availability. Environmental variables include those for which existing data are available from local hydrological and meteorological stations (i.e., ocean warming, sea level rise, extreme heat and extreme rainfall events), and which were highlighted in initial *Talanoa* discussions as potential causes of climate-related impacts. Coastal inundation is also included as a separate node influenced by both sea level and temperature.

The influence of environmental variables on resource availability was represented via effects on fishing and farming production, drinking water supply, and the availability of traditional plants and resources. Changes in cultural values were then primarily included as effects of changing resource availability.

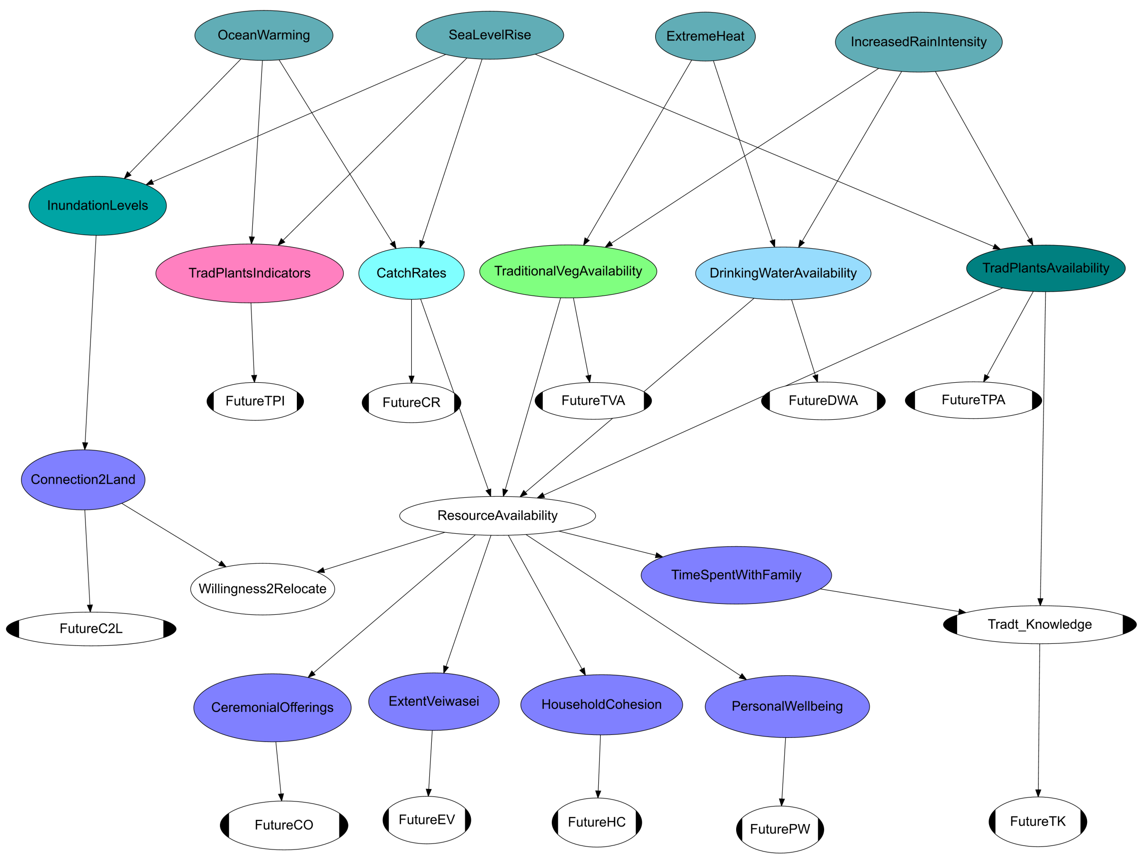

Figure 3.1: Preliminary BN model for subsistence lifestyles and cultural values for Ovalau, Fiji.

Two variables/nodes were included in the preliminary model for which we did not elicit data directly. The first is included to represent the traditional knowledge passed on to the next generation, as a measure of the loss of the inheritance value of cultural knowledge in communities. This was represented as being proportional to both the changes in time spent with the family and the availability of traditional plants (e.g., pandan leaves used in traditional mat weaving practices). Second, willingness to relocate was represented as being determined by both resource availability and the connection to land, although this was ultimately not included in the final model or analysed quantitatively in the BN framework. It was depicted in the BN for completeness of the conceptual model and to show the flow of influence between the variables.

The relationship between the variables representing the current decadal changes and the corresponding future variables may be defined by these fitted curves and, in the BN model, are depicted as nodes with a special type of shape (i.e., ovals containing ”Future TPI”, ”FutureCR”, etc.).

3.2. Final model design and parameterisation

The structure of the BN model was refined from the preliminary BN (i.e., Fig. 3.1) based on the questionnaire responses, including both the elicited variables and rankings. Also, revisions from the initial pre-registered model are described below. The choices made regarding nodes and arcs (i.e., the qualitative part of the BN) were also driven in part by the questionnaire itself, as well as the availability of relevant data (e.g., empirical data for the parameterisation of environmental variables). The revised model is shown in Fig. 3.2, and the simplified version used for inference is shown in the main text (Fig. 2),

3.2.1. Qualitative structuring of the BN

Nodes: The climate variables included in the models were included as they were either ranked highly by participants (i.e., Extreme heat/ *ExtremeHeat*, Sea level rise/ *SLR*, Heavy rain/ *ExtremeRainIntensity*) or incorporated explicitly as causes of resource decline (i.e., Ocean warming/ *OceanWarming*).

Some environmental factors ranked highly by participants were increases in pests/diseases,

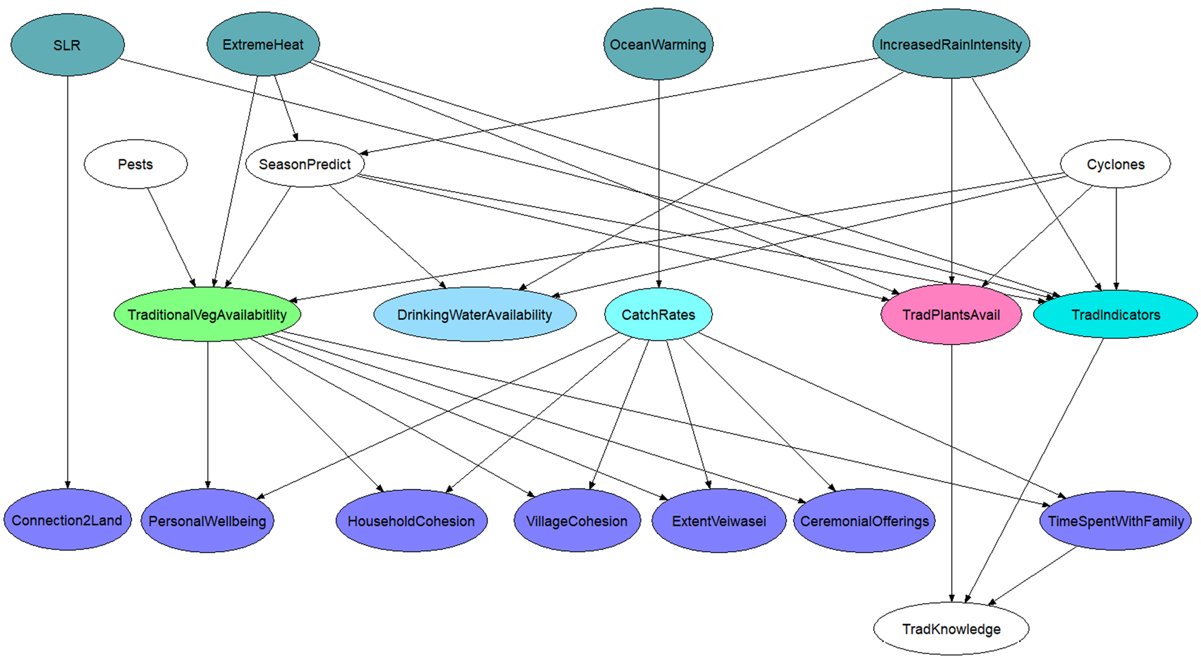

Figure 3.2: BN model for subsistence lifestyles and cultural values for Ovalau, Fiji, refined from the preliminary model based on the final questionnaire and the results of the causal ranking exercise.

the impacts of tropical cyclones, and changes in seasonal predictability. Therefore, these were included as nodes to represent the community's perception that they are the direct causes of the changes in those measures. Even though we could conjecture causal links between the modelled climate variables, pest/disease prevalence and cyclones' intensity, there isn't sufficient empirical evidence to model these links. As a simplification, the nodes *Pests* and *Cyclones* are added to the model as causes, but no parents are assigned to them.

Moreover, the relationship between seasonal predictability and climate for Fiji is not yet well understood, and there is also limited empirical evidence to directly quantify this. However, during our *Talanoa* discussions, intense rain events and extreme heat were often equated to seasonal predictability. Because of this, we chose to explain the changes in seasonal predictability (as perceived by the participants) in terms of the changes in the extreme heat and rain intensity and these two variables became the parents of *SeasonalPredict*.

The change in the climate/environmental variables affects the resource availability, and in the BN model, this is represented with arcs from the former to the latter, which are represented by the nodes *TraditionalVegAvailability*, *DrinkingWaterAvailability*, *CatchRates*, *TradPlantsAvail*, and *TradIndicators*.

The remaining nodes in Fig. 3.2 correspond to responses for seven elicited measures for lifestyle and cultural values (e.g., *PersonalWellbeing*, *CeremonialOfferings*, etc.), and an additional node representing a secondary cultural value/measure defined through the elicited values (i.e., *TraditionalKnowledge*). Change in the proportion of traditional food in diets was also elicited, but it was not modelled as a distinct cultural value/practice. The BN model from Fig. 3.2 represents only the current decadal changes, with no representation of future decadal changes (which were instead represented by functional nodes in Fig 3.1).

Arcs: The choice of arcs was guided by the choice of the modelled variables' parents. The parents of *TraditionalVegAvailability* were determined using the elicited causal ranking data for decreases in the amount and/or size of the food that is grown (see Table 5.2). We selected the four variables with the highest weighted score, rather than all chosen causes, both to simplify the model and based on the assumption that the four most influential variables will incorporate the influence of other variables. Moreover, these four variables account for at least 80% of the total points allocated to potential causes. The parents of *DrinkingWaterAvailability*, *TradPlantsAvail*, and *TradIndicators* were similarly determined using their corresponding ranking data (i.e., Tables 5.3, Table 5.4 and Table 5.5).

Through the formulation of question 2, the sole parent of the *CatchRates* is the node representing the increasing sea temperature (i.e., we directly elicited changes in catch rates as caused by changes in sea temperature, excluding changes due to other causes). Through the formulation of question 13, the parent of the *Connection2Land* is the node *SLR*, representing the sea level rise.

Through the formulation of questions 5 through 10, the parent set of the *PersonalWellbeing*, *HouseholdCohesion*, *VillageCohesion*, *ExtentVeiwasei*, *CeremonialOfferings*, *TimeSpentWithFamily* represents the decrease in resources. The preliminary model presented in Fig 3.1 considered resources to be crops/vegetables, fish, drinking water, and traditional plants. For simplicity, these resources were conceptually grouped into one node, *ResourceAvailability*, which could then act as a single parent. However, the final formulation of questions 5 – 10 only focused on the food they grow (i.e., vegetables/crops) and fish as the main subsistence resources, reducing the set of potential parents from 4 to 2. An extra node became unnecessary in this case, hence the *ResourceAvailability* node was not needed, and the set of parents simply contains the variables *TraditionalVegAvailability* and *CatchRates*.

Ranking responses strongly highlighted that an important causal factor for the decrease in the reliability of traditional indicators was knowledge not being passed down. Therefore, an arc was included to link *TradIndicators* as a parent for *TradKnowledge* (i.e., a variable included to estimate decreases in the traditional knowledge passed on), in addition to those causal factors included in the preliminary model (i.e., *TradPlantAvail* and *TimeSpentWithFamily*).

The willingness to relocate, initially thought of as a variable that will represent the distance people are willing to relocate (which we elicited in question 14), was directly influenced by their connection to land as well as the decrease in the available resources (see Fig. 3.1). This was eventually excluded from the model due to the difficulty of quantifying the dependence structure between these variables. More discussions with the community are necessary to properly understand these relationships.

3.2.2. Quantitative parameterisation of BN nodes & arcs

Nodes: Quantifying the BN involves assigning marginal distributions to the variables represented as nodes and assigning (conditional) correlations to the arcs. Local hydrological and meteorological data sources were used to represent the decadal change in mean sea level, sea surface temperature, maximum daily air temperature, and maximum 1-day rainfall per month between 2014 and 2024 (as detailed in Appendix 4). Sea level, sea temperature, and maximum daily air temperature variables in the BN are modelled as a percentage increase and are represented by the empirical distributions described in Appendix 4. Because the empirical distributions of the extreme heat and the rain intensity variables are obtained under two scenarios (Shared Socioeconomic Pathway “SSP” 2-4.5 and SSP 5-8.5), two different quantifications of the model are available.

Because modelling the changes in seasonal predictability (*SeasonPredict*) are equated with modelling the perceptions of the participants that seasonal predictability is closely related to changes in extreme heat and precipitation, we simplified the model by assuming that the variability in *SeasonPredict* is almost completely explained by changes in rain intensity and extreme heat. This assumption translated into excluding the *SeasonPredict* variable and making the other two the direct parents of *SeasonPredict*'s children.

Modelling the decadal change in the pest and disease prevalence and tropical cyclone impacts was not considered possible given the available data. However, because of the difficulty in attributing these changes to other quantified environmental variables, we had no means of excluding the nodes *Pests* and *Cyclones*. Instead, we assigned a uniform distribution that is meant to communicate the lack of knowledge and the large uncertainty around this variable. Although there is some evidence suggesting that pest/disease and cyclone impacts may be increasing in the Pacific, these variables are also not used in projections under future climate scenarios.

All the other variables depicted in Fig. 2, except *TradKnowledge*, were modelled using the data collected from the community. The values corresponding to a percentage decrease were modelled by fitting Beta distributions on the corresponding samples. The sample sizes per variable ranged from 52 to 92. All marginal distributions are shown as histograms with associated means and standard deviations displayed at the bottom of each histogram (see Fig. 5 for climate variables estimated with the SSP 5-8.5 scenario).

Arcs: For the correlation structure, we considered a high and a medium correlation model. In the high correlation model, the highest unconditional correlation between parent and child is quantified as 0.8, and in the medium correlation model, we use 0.6.

The correlations associated with the arcs in Fig. 5 are both unconditional and conditional (Spearman's) rank correlations. For each node, the set of parents is ordered, and the correlation on the arc between the child and its first parent is unconditional, while the correlations between the child and its next parents in the ordering are conditional on the subset of previous parents. For example, for the node *DrinkingWaterAvailability*, the set of parents is ordered as follows: *IncreasedRainIntensity*, *ExtremeHeat*, and *Cyclones* (based on the elicited information). As such, the correlation between *DrinkingWaterAvailability* and its first parent *IncreasedRainIntensity* is an unconditional correlation equal to 0.8 (and shown as such on the arc between these two variables), the correlation between *DrinkingWaterAvailability* and its second parent *ExtremeHeat* is a conditional correlation between these two variables, given the previous parent. The conditional rank correlation of 0.8 shown on the arc corresponds to an unconditional correlation of 0.4 estimated from the elicited data. The correlation between *DrinkingWaterAvailability* and its third parent *Cyclones* is a conditional correlation between these two variables, given the two previous parents.

The absence of arcs implies (conditional) independence statements between variables, which correspond to zero conditional correlations. For example, one can notice that there is no arc between *TraditionalVegAvailability* and *DrinkingWaterAvailability*, however, these nodes share common parents, indicating that their dependence is solely driven by their common causes/parents, and once these influences are known with certainty, these nodes become conditionally independent.

It is worth noting that there are no arcs between (nor any common parents of) the climate change variables. Even though they may be correlated on a large timescale, their decadal correlation structure is hard to estimate or make assumptions about. We circumvent this modelling difficulty in the inference stage by conditioning the model on joint values of these variables.

For each child node, the set of parents is ordered from the most to the least influential. The displayed correlation between the child and its first parent is an unconditional rank correlation; whereas the displayed correlations between the child and its next parents are the conditional rank correlations, given the previous parents (and in a way measure remaining variability and dependability, when the previous parents' influence is fixed). As previously mentioned, the parents of *TraditionalVegAvailability* are determined using the information from Table 5.2, by selecting the first four variables with the highest weighted score. However, since some of these were replaced by their parents in the model, the set of parents changed, and so did their weighted scores. The points previously attributed to the seasonal predictability are now attributed to the heat and rain variables. The most influential parents are now, in the order of their weighted scores, *ExtremeHeat*, *IncreasedRainIntensity*, *Pests*, and *Cyclones*.

We modelled the correlations to be proportional to the weighted scores, with the first/ highest correlation being equal to 0.8 (in the high correlation model) and 0.6 (in the medium correlation model). In the *TraditionalVegAvailability*'s case, its unconditional correlations with its parents are 0.8, 0.46, 0.23, and 0.18 in the high correlation model, and 0.6, 0.31, 0.21, and

0.14 in the medium correlation model. Fig. 5 represents the high correlation model. To achieve the unconditional 0.8, 0.46, 0.23, and 0.18, the arcs between *TraditionalVegAvailability* and its parents are assigned 0.8, 0.8, 0.7, and 0.8. The same reasoning and calculations as above are applied to the *DrinkingWaterAvailability*, *TradPlantsAvail* and *TradIndicators* nodes.

TraditionalVegAvailability and *CatchRates*, are the parents of *PersonalWellbeing*, *HouseholdCohesion*, *VillageCohesion*, *ExtentVeiwasei*, *CeremonialOfferings*, *TimeSpentWithFamily*. They are considered to be equally correlated with each child (and approximately equal to a rank correlation of 0.6 in both dependence models). No rank correlations were assigned to the arcs between *TradKnowledge* and its parents. Instead, a functional relationship is defined such that *TradKnowledge* is equal to the following:

$$0.5 \cdot TimeSpentWithFamily + 0.25 \cdot TradIndicators + 0.25 \cdot TradPlantsAvail$$

4. Methodological Details – Climate variables and future projections

Environmental variables parameterised in models include four key variables, i.e., mean sea level (m), mean sea surface temperature (°C), average maximum daily air temperature (°C), and maximum 1-day rainfall per month (mm).

These are used as proxies for climate-related factors that were described in preliminary *Talanoa* discussions. Each variable corresponds to both elicited causal factors in the questionnaire and nodes used in the BN modelling, as follows:

- "*sea level rise (coastal flooding, saltwater intrusion)*" (Node: *SLR*).
- "*ocean warming and effects on the marine environment (e.g., damage to coral reefs)*" (Node: *OceanWarming*).
- "*more extreme heat*" (Node: *ExtremeHeat*).
- "*more heavy rain*" (Node: *IncreasedRainIntensity*).

A combination of empirical data and modelled climate estimates were used to: (1) parameterise nodes in the BN model using distributions of estimated percentage change in each variable over the last decade; and, (2) provide estimates for projected future change in each of these variables 10 years into the future for use in BN inference. Climate model estimates are taken under SSP 2-4.5 and SSP 5-8.5.

Historical and future projection data for each variable were obtained as follows:

- *Sea level*: Monthly mean sea level data were obtained from the Pacific Sea Level and Geodetic Monitoring Project for Suva (-18.1325, 178.4275; Nov 1997 – June 2024; BOM, 2024). Future projections were obtained through NASA's IPCC AR6 Sea Level Projection Tool (data accessed 21/Oct/2024; Fox-Kemper et al., 2021; Garner et al., 2021; Kopp et al., 2023), which provides decadal median sea level projections based on the 2021 IPCC 6th Assessment Report.
- *Sea temperature*: Monthly mean temperature data were also obtained from the Pacific Sea Level and Geodetic Monitoring Project for Suva (Nov 1997 – June 2024; BOM, 2024).

Future projections were obtained from Bio-ORACLE (v 3.0, accessed 22/Aug/2024; Tyberghein et al., 2012; Assis et al., 2024), which is a collection of spatial data layers based on a multi-model ensemble incorporating data from the Coupled Model Intercomparison Project (CMIP6). Decadal mean sea surface temperature projections were extracted for non-terrestrial raster cells that overlapped areas within 10 km North, South, East and West of Ovalau (i.e., approximately between latitudes -17.5277604 to -17.8394874; longitudes 178.641285 to 178.9326078).

- *Maximum air temperature/ Maximum 1-day rainfall*: Historical estimates and future projections were obtained from the World Bank, Climate Change Knowledge Portal ('CCKP', accessed 7/Nov/2024 World Bank, 2024). This provides spatially aggregated national and sub-national/regional historical estimates and future projections based on a multi-model ensemble incorporating CMIP6 data. Seasonal median estimates (i.e., Jan-Mar; Apr-Jun; Jul-Sep; Oct-Dec) estimates for Fiji were extracted from 1950 – 2100.

Historical change in each variable was calculated over the last 10 years (i.e., July 2014 – June 2024; see Table 4.1), where the absolute and percentage change at each time point was measured relative to the corresponding month/seasonal time point 10 years prior. Note, as some of the air temperature and rainfall data for the past decade were estimated via climate modelling, there are slight differences between the historical change estimated under both SSP 2-4.5 and SSP 5-8.5. Data showed average increases in three of the four variables assessed. The exception was maximum 1-day rainfall, which instead showed extremely high variation and slight decreases in the mean percentage change.

Table 4.1: Estimated decadal changes in climate variables for Ovalau, Fiji. Percentage change and mean differences are estimated from July 2014 to June 2024.

Variable	% Change (s.d.)	Mean Diff. (s.d.)	Source
Sea level	5.5% (4.49)	0.06m (0.05)	BOM, 2024
Sea temperature	0.91% (2.73)	0.23°C (0.74)	BOM, 2024
Max air temp. (SSP 2-4.5)	0.66% (0.45)	0.18°C (0.12)	World Bank CCKP
Max air temp. (SSP 5-8.5)	0.86% (0.5)	0.23°C (0.14)	World Bank CCKP
Max. 1-day rainfall (SSP 2-4.5)	-2.77% (12.43)	-1.45mm (6.42)	World Bank CCKP
Max. 1-day rainfall (SSP 5-8.5)	-0.98% (12.26)	-0.66mm (6.33)	World Bank CCKP

Point estimates for future projected decadal change in air temperature and rainfall are calculated using the same method as above, using the mean percentage change between monthly/ seasonal estimates from July 2024 – June 2034 (Table 4.2). Future projections for sea level and sea temperature are available as decadal estimates, therefore, future changes are estimated as the difference in the projected mean or median anomaly for the 2030s and the current decade. The percentage change is then calculated relative to the average sea level/temperature most recent 12-month period recorded through hydrological data.

Table 4.2: Projected future changes in climate variables for Ovalau, Fiji for the next 10 years. Percentage differences are estimated relative to 2014-2024 values. Actual projected changes are shown in brackets.

Variable	% Change (SSP 2-4.5)	% Change (SSP 5-8.5)	Source
Sea level	3.80% (0.05m)	4.36% (0.06m)	NASA IPCC AR6
Sea temperature	0.80% (0.22°C)	1.18% (0.32°C)	Bio-ORACLE 3.0
Max air temp	0.82% (0.22°C)	1.00% (0.27°C)	World Bank CCKP
Max. 1-day rainfall	0.94% (0.48mm)	-1.2% (-0.62mm)	World Bank CCKP

5. Further Results – Summary response data and subgroup analysis

The number of participants per village ranged from 15 in Toki to 24 in Vatukalo (see Table 5.1). There was a broad range of age groups represented within each village, with at least one member of each categorical age group (i.e., 18 – 25, 26 – 35, 36 – 45, 46 – 55, 56 – 65, and 66 +) in most villages. The exceptions were Nauouo with no 19 – 25 year old participants, and Rukuruku with no 66+ participants. There was also a relatively strong gender balance across all participants, with female participation ranging from 1/3rd in Toki, to 2/3^{rds} in Vatukalo.

Table 5.1: Demographic composition of workshop participants, including the total number of participants to successfully complete the questionnaire, the gender representation, and estimated mean age.

	Rukuruku	Nauouo	Vatukalo	Toki	Tokou	Naikorokoro
Site_ID	RUKU	NAUO	VATU	TOKI	TOKO	NAIK
Date	5/Aug	6/Aug	7/Aug	7/Aug	8/Aug	8/Aug
Participants	21	18	24	15	20	21
- Female	8 (38%)	7 (39%)	16 (67%)	5 (33%)	8 (40%)	10 (48%)
- Male	13 (62%)	11 (61%)	8 (33%)	10 (67%)	12 (60%)	11 (52%)
Mean_Age	41.12	52.17	43.58	44.10	47.10	44.88

Summary causal ranking data are shown below for decreases in four measures, i.e., the amount/size of food grown (measure 1; Table 5.2), the quality/reliability of the water supply (measure 3; Table 5.4), the availability of traditional plants (measure 11; Table 5.3), and the reliability/usefulness of traditional indicators (measure 12; Table 5.5). Weighted scores for each cause based on questionnaire responses (i.e., 1st rank = 3 points, 2nd = 3, 3rd = 1, tick/check mark = 2).

Outputs of subgroup analysis for the proportion of participants identifying decreases in each measure are shown below, including gender differences over the last 10 years (Table 5.6), 20 years (Table 5.7), and age group differences over 10 years (Table 5.8) and 20 years (Table 5.9).

Table 5.2: Causal rankings for decreases in the amount and/or size of the food that is grown. Entries from 99 participants were used in rankings for this value.

Cause	1st	2nd	3rd	X's	Weighted_Score
Extreme heat	34	16	4	21	180
Seasonal predictability	10	13	16	14	100
New pests and diseases	8	4	24	10	76
Tropical cyclones	7	13	4	6	63
Heavy rain	1	13	8	9	55
Sea level rise	7	4	4	6	45
Other	0	0	0	4	8

Table 5.3: Causal rankings for decreases in the quality or reliability of the drinking water supply. Entries from 68 participants were used in rankings for this value.

Cause	1st	2nd	3rd	X's	Weighted_Score
Heavy rain	13	11	8	15	99
Seasonal predictability	11	7	18	16	97
Tropical cyclones	5	15	3	11	70
Sea level rise	7	1	3	7	40
Other	3	1	2	11	35
Extreme heat	1	4	1	1	14

Table 5.4: Causal rankings for decreases in the availability of traditional plants. Entries from 89 participants were used in rankings for this value.

Cause	1st	2nd	3rd	X's	Weighted_Score
Extreme heat	21	19	3	18	140
Tropical cyclones	6	13	18	14	90
Seasonal predictability	8	6	11	9	65
Other	3	5	4	15	53
Heavy rain	4	9	7	7	51
New pests and diseases	8	2	9	7	51
Sea level rise	8	2	2	8	46

Table 5.5: Causal rankings for decreases in the reliability or usefulness of traditional indicators used in the village. Entries from 75 participants were used in rankings for this value.

Cause	1st	2nd	3rd	X's	Weighted_Score
Extreme heat	11	18	4	8	89
Seasonal predictability	16	3	10	11	86
Sea level rise	11	3	6	6	57
Heavy rain	0	14	9	7	51
Tropical cyclones	2	9	10	7	48
Other	5	3	2	10	43
New pests and diseases	5	1	5	2	26

Table 5.6: Proportions of male and female participants that identified decreases over the last 10 years (2014 - 2024). P-values for Chi-Squared estimates < 0.05 represent a significant difference in the proportions identifying a decrease for each value.

	Male	Female	χ^2 (P-value)
1. Food that you grow	55/64 (86%)	42/53 (79%)	0.505 (P = 0.477)
2. Food from the sea	61/65 (94%)	41/53 (77%)	**5.438 (P = 0.020*)**
3. Drinking water supply	41/65 (63%)	24/54 (44%)	3.414 (P = 0.065)
4. Traditional food proportion	48/65 (74%)	38/53 (72%)	0.003 (P = 0.958)
5. Personal well-being and happiness	42/65 (65%)	31/54 (57%)	0.378 (P = 0.539)
6. Food sharing (veiwasei)	49/65 (75%)	42/54 (78%)	0.008 (P = 0.929)
7. Ceremonial food offerings	52/65 (80%)	45/53 (85%)	0.203 (P = 0.652)
8. Household cohesion and well-being	41/65 (63%)	28/54 (52%)	1.100 (P = 0.294)
9. Village social cohesion and well-being	47/65 (72%)	32/54 (59%)	1.704 (P = 0.192)
10. Time spent in the village	53/65 (82%)	37/53 (70%)	1.618 (P = 0.203)
11. Traditional plants	50/64 (78%)	41/54 (76%)	0.004 (P = 0.949)
12. Traditional indicators	37/65 (57%)	33/53 (62%)	0.159 (P = 0.690)
13. Connection to the land (*Vanua*)	39/65 (60%)	21/51 (41%)	3.336 (P = 0.068)

Table 5.7: Proportions of male and female participants that identified decreases over the last 20 years (2004 - 2024). P-values for Chi-Squared estimates < 0.05 represent a significant difference in the proportions identifying a decrease for each value.

	Male	Female	χ^2 (P-value)
1. Food that you grow	53/61 (87%)	40/51 (78%)	0.873 (P = 0.350)
2. Food from the sea	53/61 (87%)	38/52 (73%)	2.590 (P = 0.108)
3. Drinking water supply	39/60 (65%)	25/53 (47%)	2.953 (P = 0.086)
4. Traditional food proportion	43/62 (69%)	39/52 (75%)	0.211 (P = 0.646)
5. Personal well-being and happiness	41/62 (66%)	34/52 (65%)	0.000 (P = 1.000)
6. Food sharing (veiwasei)	45/61 (74%)	41/53 (77%)	0.051 (P = 0.821)
7. Ceremonial food offerings	51/61 (84%)	45/52 (87%)	0.029 (P = 0.865)
8. Household cohesion and well-being	39/61 (64%)	29/52 (56%)	0.477 (P = 0.490)
9. Village social cohesion and well-being	45/62 (73%)	29/53 (55%)	3.234 (P = 0.072)
10. Time spent in the village	49/61 (80%)	36/51 (71%)	0.957 (P = 0.328)
11. Traditional plants	47/62 (76%)	39/52 (75%)	0.000 (P = 1.000)
12. Traditional indicators	37/62 (60%)	35/52 (67%)	0.418 (P = 0.518)
13. Connection to the land (*Vanua*)	35/62 (56%)	22/50 (44%)	1.255 (P = 0.263)

Table 5.8: Proportions of younger (35 years and under) and older (36 years and over) participants that identified decreases over the last 10 years (2014 - 2024). P-values for Chi-Squared estimates < 0.05 represent a significant difference in the proportions identifying a decrease for each value.

	Younger	Older	χ^2 (P-value)
1. Food that you grow	28/34 (82%)	69/83 (83%)	0.000 (P = 1.000)
2. Food from the sea	30/34 (88%)	72/84 (86%)	0.004 (P = 0.948)
3. Drinking water supply	18/35 (51%)	47/84 (56%)	0.062 (P = 0.803)
4. Traditional food proportion	27/35 (77%)	59/83 (71%)	0.202 (P = 0.653)
5. Personal well-being and happiness	18/35 (51%)	55/84 (65%)	1.506 (P = 0.220)
6. Food sharing (veiwasei)	26/35 (74%)	65/84 (77%)	0.016 (P = 0.900)
7. Ceremonial food offerings	28/35 (80%)	69/83 (83%)	0.020 (P = 0.886)
8. Household cohesion and well-being	21/35 (60%)	48/84 (57%)	0.007 (P = 0.933)
9. Village social cohesion and well-being	27/35 (77%)	52/84 (62%)	1.933 (P = 0.164)
10. Time spent in the village	26/34 (76%)	64/84 (76%)	0.000 (P = 1.000)
11. Traditional plants	28/34 (82%)	63/84 (75%)	0.383 (P = 0.536)
12. Traditional indicators	20/34 (59%)	50/84 (60%)	0.000 (P = 1.000)
13. Connection to the land (*Vanua*)	19/32 (59%)	41/84 (49%)	0.656 (P = 0.418)

Table 5.9: Proportions of younger (35 years and under) and older (36 years and over) participants that identified decreases over the last 20 years (2004 - 2024). P-values for Chi-Squared estimates < 0.05 represent a significant difference in the proportions identifying a decrease for each value.

	Younger	Older	χ^2 (P-value)
1. Food that you grow	25/30 (83%)	68/82 (83%)	0.000 (P = 1.000)
2. Food from the sea	28/32 (88%)	63/81 (78%)	0.832 (P = 0.362)
3. Drinking water supply	19/32 (59%)	45/81 (56%)	0.025 (P = 0.874)
4. Traditional food proportion	25/33 (76%)	57/81 (70%)	0.123 (P = 0.726)
5. Personal well-being and happiness	19/33 (58%)	56/81 (69%)	0.926 (P = 0.336)
6. Food sharing (veiwasei)	22/33 (67%)	64/81 (79%)	1.320 (P = 0.251)
7. Ceremonial food offerings	25/32 (78%)	71/81 (88%)	0.969 (P = 0.325)
8. Household cohesion and well-being	19/31 (61%)	49/82 (60%)	0.000 (P = 1.000)
9. Village social cohesion and well-being	23/33 (70%)	51/82 (62%)	0.297 (P = 0.586)
10. Time spent in the village	23/31 (74%)	62/81 (77%)	0.000 (P = 0.989)
11. Traditional plants	25/32 (78%)	61/82 (74%)	0.030 (P = 0.862)
12. Traditional indicators	21/32 (66%)	51/82 (62%)	0.016 (P = 0.900)
13. Connection to the land (*Vanua*)	19/30 (63%)	38/82 (46%)	1.903 (P = 0.168)

6. Further Results – BN modelling and trend analysis

Further details of the values used for parametrization BN models, and for future projections for lifestyle and cultural values are provided in the Open Science Framework repository for this study (osf.io/4scjy/; doi:10.17605/OSF.IO/4SCJY). This also includes Uninet (version 3.5.9 Beta, https://lighttwist-software.com/uninet/) modelling files, and Matlab (version 9.11.0.1769968, R2021b) scripts to support both BN modelling and non-linear curve fitting.

This includes the following key files:

- *.../BN modelling/correlation_matrices.xlsx* – Full correlation matrices calculated for medium and high correlation BN models.
- *.../BN modelling/parameters.xlsx* – Input environmental parameter estimates, unconditional distribution parameters for historical change lifestyle and cultural values (2014 – 2024), and conditional distribution parameters for future change lifestyle and cultural values under both medium and high correlation BNs and SSP 2-4.5 and SSP 5-8.5.
- *.../outputs_visualisations/TrendAnalysis_BNEstimates.csv* – Conditional distribution parameters for future change lifestyle and cultural values extracted from the parameters.xlsx file, used for producing main text Tables 2 and 3.
- *.../outputs_visualisations/TrendAnalysis_CurveEstimates.csv* – 2034 projected values for lifestyle and cultural values determined through non-linear curve fitting, used for producing main text Table 4.

The non-linear curves fitted to each elicited lifestyle and cultural value are shown in Figs 6.1 and 6.2.

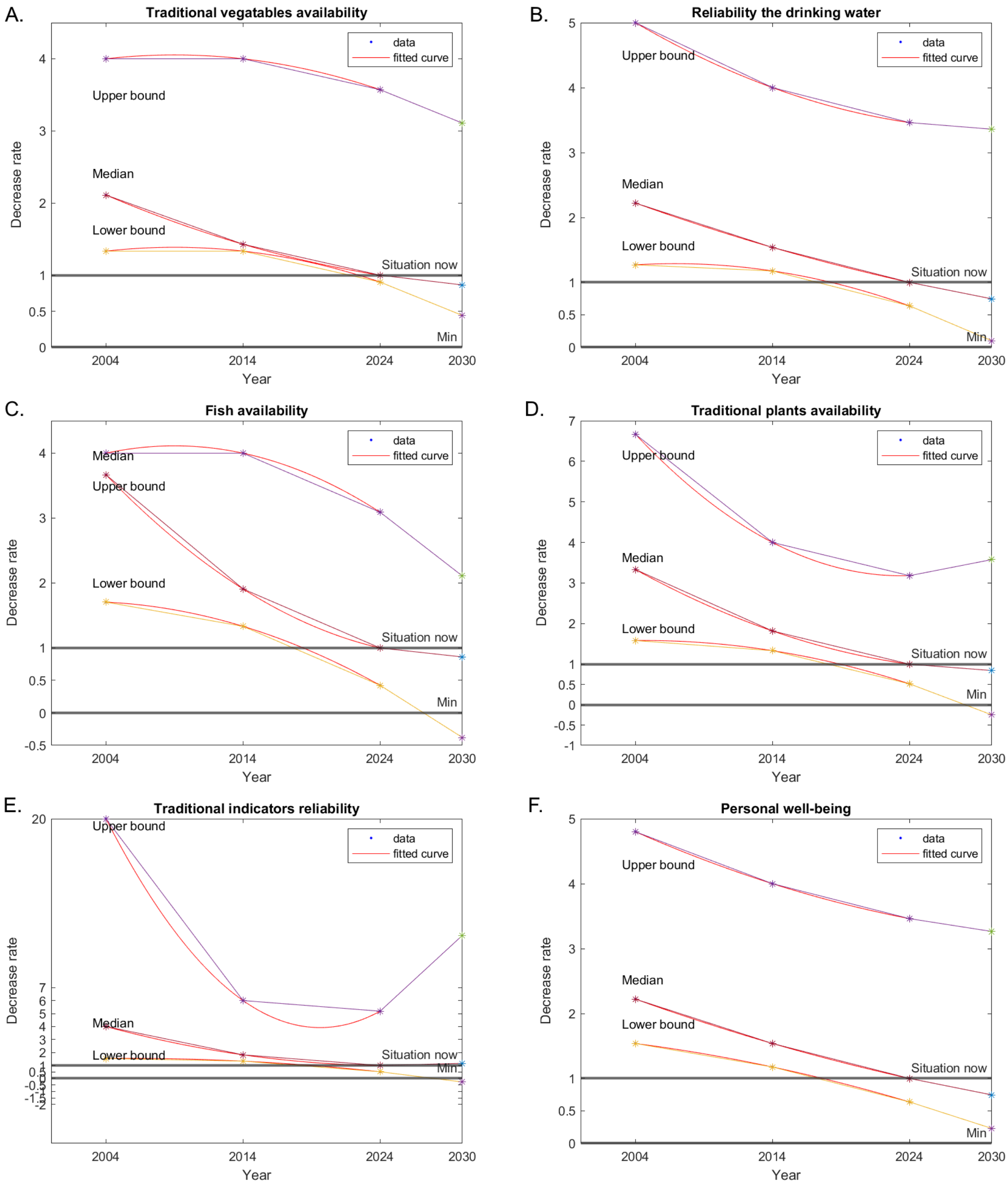

Figure 6.1: Non-linear trend curve fitting, for elicited lifestyle and cultural values used in BN modelling, including (A) *TraditionalVegAvailability*, (B) *DrinkingWaterAvailability*, (C) *CatchRates*, (D) *TradPlantsAvailability*, (E) *TradIndicators*, and (F) *PersonalWellbeing*.

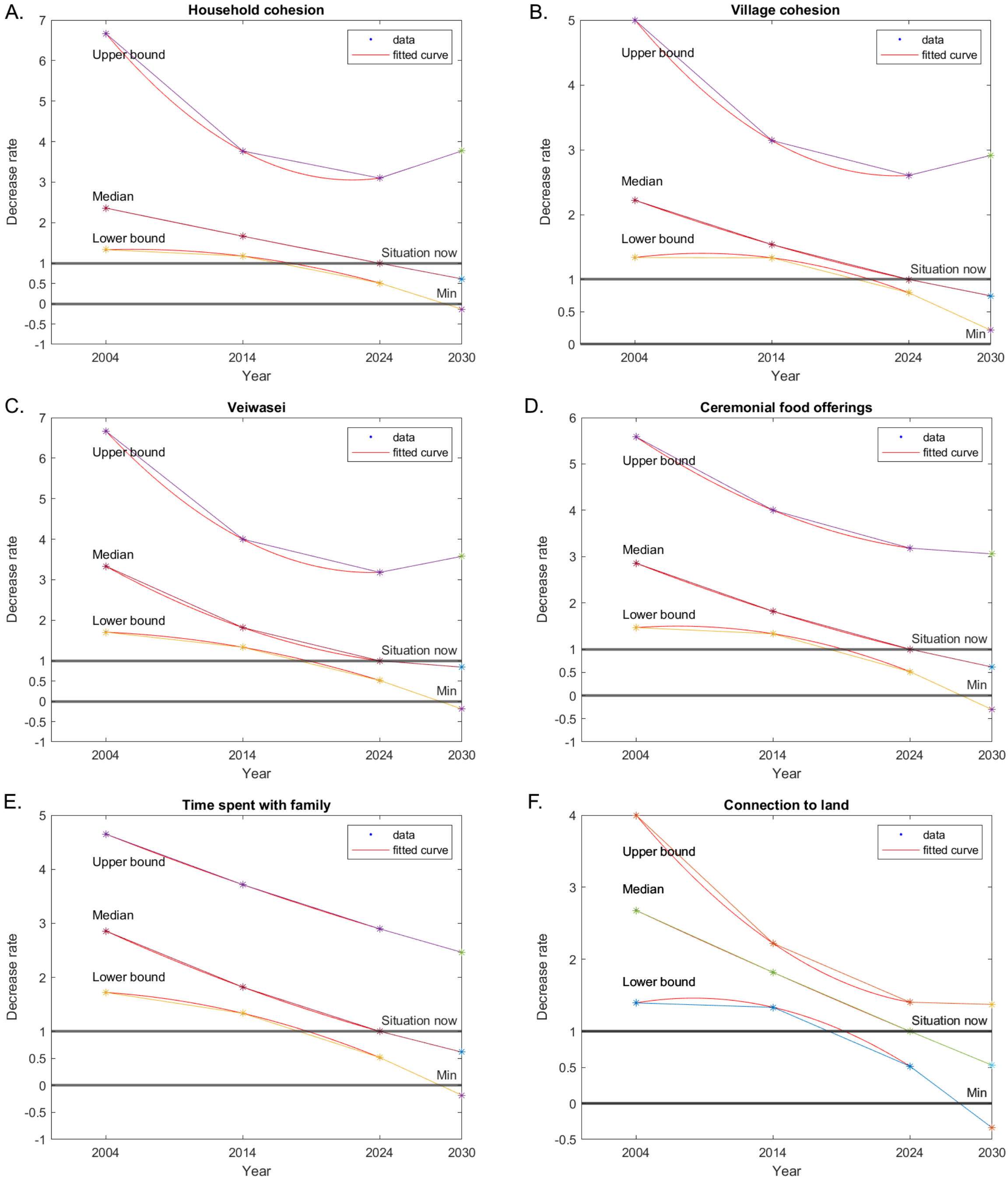

Figure 6.2: Non-linear trend curve fitting, for elicited lifestyle and cultural values used in BN modelling, including (A) *HouseholdCohesion*, (B) *VillageCohesion*, (C) *ExtentVeiwasei*, (D) *CeremonialOfferings*, (E) *TimeSpentWithFamily*, and (F) *Connection2Land*.

7. Further Results – Relocation (Question 14) response data

Responses to questions regarding relocations are summarised in Table 7.1 for past experiences, and in Table 7.2 for future expectations. Note, the wording of questions in the tables are shortened from the questionnaire versions for presentation purposes. The full text of the question relating to past experiences with relocations was "*Because of extreme weather events or coastal erosion/inundation, have you ever been displaced/had to relocate from your house or from your village in the past?*".

For future experiences, the question regarding the likelihood of future relocations identified extreme weather events or coastal erosion/inundation as specific causal factors, i.e., "*Because of extreme weather events or coastal erosion/inundation, how likely do you think it is that you or your village will be asked to relocate in the future (i.e., in the next 10 years)?*". The questions regarding expected costs of future relocations included a description of the types of costs that should be considered, i.e., "*How much money do you think it would cost to relocate your home and all your belongings, including building materials, labour and any other costs, ... 50 meters inland? ... 500 meters inland?*". Finally, the questions regarding willingness to move stated that the relocation costs described above would be paid for, i.e.,"*If all your relocation costs were fully paid for, how far inland would you be willing to relocate, ... with just you or your household alone?, ... together with your extended family/clan from your village?*"..

Almost a quarter of the participants stated that they had previous experiences with relocations due to extreme weather events or coastal erosion/inundation. The majority of these relocations had occurred within the last decade, likely a direct result of the impacts of 2016 Cyclone Winston on the communities. Most relocations were also for relatively short distances inland ($<$ 500 m).

A majority of participants also stated that it is likely or very likely that they will be asked to relocate due to extreme weather events or coastal erosion/inundation within the next 10 years. Also, most estimated the costs of relocation to be greater than $30,000 FJD for both a short distance (i.e., 50 m inland) and a longer distance move (i.e., 500 m inland). If the costs of relocation are fully paid for, many respondents stated they would not be willing to move at all, or only move relatively short distances inland (< 500 m). The proportions of respondents willing to move were similarly low if the relocation was with their household alone or with their extended family/clan.

Table 7.1: Response summary table for questions relating to the participant's experiences with past relocations. Note, the relocation question has been shortened from the version in the questionnaire.

Have you ever been displaced/had to relocate in the past?	Responses (%)
– no	92 (77.97%)
– yes	26 (22.03%)
If 'yes' ... when did you relocate?	
– less than 5 years ago	1 (3.85%)
– 5 to 10 years ago	17 (65.38%)
– 10 to 20 years ago	6 (23.08%)
– more than 20 years ago	2 (7.69%)
If 'yes' ... how far did you relocate?	
– less than 50 meters (only a small distance inland)	12 (46.15%)
– 50 to 500 meters (0.05 - 0.5 km; a little bit further inland)	11 (42.31%)
– 500 to 5000 meters (0.5 - 5 km; quite a bit further inland)	3 (11.54%)
– more than 5000 meters (over 5 km; a lot further inland)	0 (0.00%)
If 'yes' ... how much did it cost?	
– $0 - 5,000 FJD	3 (12.5%)
– $5,000 - 10,000 FJD	2 (8.33%)
– $10,000 - 15,000 FJD	1 (4.17%)
– $15,000 - 20,000 FJD	3 (12.5%)
– $20,000 - 25,000 FJD	4 (16.67%)
– $25,000 - 30,000 FJD	2 (8.33%)
– more than $30,000 FJD	9 (37.5%)

Table 7.2: Response summary table for questions relating to the participant's expectations about future relocations (i.e., question 14). Note, the questions have been shortened from the version in the questionnaire.

How likely is it that you or your village will be asked to relocate?	Responses (%)
– very likely	32 (28.07%)
– likely	43 (37.72%)
– neutral/ don't know	31 (27.19%)
– unlikely	4 (3.51%)
– very unlikely	4 (3.51%)
How much money do you think it would cost to relocate 50 meters inland?	
– $0 - 5,000 FJD	2 (1.77%)
– $5,000 - 10,000 FJD	1 (0.88%)
– $10,000 - 15,000 FJD	8 (7.08%)
– $15,000 - 20,000 FJD	9 (7.96%)
– $20,000 - 25,000 FJD	6 (5.31%)
– $25,000 - 30,000 FJD	27 (23.89%)
– more than $30,000 FJD	60 (53.1%)
How much money do you think it would cost to relocate 500 meters inland?	
– $0 - 5,000 FJD	1 (0.92%)
– $5,000 - 10,000 FJD	1 (0.92%)
– $10,000 - 15,000 FJD	3 (2.75%)
– $15,000 - 20,000 FJD	4 (3.67%)
– $20,000 - 25,000 FJD	5 (4.59%)
– $25,000 - 30,000 FJD	13 (11.93%)
– more than $30,000 FJD	82 (75.23%)
How far would you be willing to relocate, with you or your household alone?	
– not at all	37 (32.46%)
– less than 50 meters (only a small distance inland)	19 (16.67%)
– 50 to 500 meters (0.05 - 0.5 km; a little bit further inland)	40 (35.09%)
– 500 to 5000 meters (0.5 - 5 km; quite a bit further inland)	9 (7.89%)
– more than 5000 meters (over 5 km; a lot further inland)	9 (7.89%)
How far would you be willing to relocate, with your extended family/clan?	
– not at all	37 (32.74%)
– less than 50 meters (only a small distance inland)	16 (14.16%)
– 50 to 500 meters (0.05 - 0.5 km; a little bit further inland)	37 (32.74%)
– 500 to 5000 meters (0.5 - 5 km; quite a bit further inland)	13 (11.5%)
– more than 5000 meters (over 5 km; a lot further inland)	10 (8.85%)