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RESEARCH ARTICLE

Simulating emerging coastal tourism vulnerabilities: an agent-based modelling approach

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ABSTRACT

Coastal tourism destinations face a range of climate-related changes. Prevailing challenges include understanding emerging changes and future uncertainties. A dynamic vulnerability approach is a promising way to analyse emerging socio-ecological vulnerabilities. This research presents an innovative coupling of the human-environment system in the agent-based model *Coasting*, and is applied to Curaçao's coastal tourism. We observe how operator numbers and environmental attractiveness, proxies for socio-ecological vulnerabilities, change over time. Global sensitivity analysis highlights the main interacting factors behind socio-ecological vulnerabilities. Scenario discovery explores the main drivers contributing to undesirable vulnerabilities. The model's findings provide key insights on which factors tourism destinations need to focus on to prevent socio-ecological vulnerabilities.

Introduction

Coastal tourism is exposed to a wide range of climate-related drivers of change, including sea-level rise (SLR), ocean acidification, coral bleaching, increased frequency of storms, and drought (Hall, 2018; Nurse et al., 2014; Rhiney, 2015; Scott et al., 2012). The Caribbean is a region that is both highly exposed to these climate-related drivers, and dependent on coastal tourism for employment and GDP (e.g. Cambers, 2009; Hall, 2018; WTTC, 2018). However, the rates and types of climate change vary among these islands. The IPCC has high confidence that "small islands do not have uniform climate risk profiles", that both physical (environmental) and human attributes and responses contribute to the diversity of climate change impacts, and recognises that this diversity of response "has not always been adequately integrated in adaptation planning" (Nurse et al., 2014 p. 1616). This diversity breeds uncertainty about the vulnerabilities a coastal destination is facing. It also requires translating climate change issues to the context of a tourism destination, which is lacking in the literature (Rhiney, 2015). Becken (2013) charted the development of tourism-related climate change research; her review indicates a gap in the context of coastal tourism and regional gaps for developing countries. Scott et al.'s (2016) review of the latest IPCC reports shows limited progress in integrated assessments and in small-island regions where coastal tourism often takes place. Fang et al.'s (2018) more recent review support this persistent regional knowledge gap. Environmental changes evolve over time and occupy different spatial areas within the destination, further creating uncertainties of who and what will become vulnerable under which conditions is important in the coastal tourism context. To deal with this complexity and

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uncertainty (Amelung et al., 2016; Baggio, 2008), we apply a dynamic vulnerability approach to analyse these emerging vulnerabilities in a coastal destination, and consider adaptation strategies (Student et al., 2016; Student et al., 2020).

A dynamic vulnerability approach includes five principles for conceptualising emerging vulnerabilities in a coastal system: agency, heterogeneity, feedbacks, uncertainty, and iteration; it also puts forward five methodological tools for implementing the approach (Student et al., 2020). Many coastal destinations are vulnerable to climate change. However, context is important for understanding emerging vulnerabilities. We apply this analysis of dynamic vulnerability to the Caribbean coastal tourism destination of Curaçao, which is situated in a highly vulnerable region (Rhiney, 2015; UNWTO-UNEP-WMO, 2008). Curaçao is a small island developing state. Small island developing states are particularly vulnerable to climate change due to limited capacities, resources, and alternatives (Nurse et al., 2014). Curaçao has been an independent state within the Kingdom of the Netherlands since 2010, and there is limited data and research related to climate change and tourism. Curaçao's tourism masterplan for 2015–2020 does not include environmental challenges nor climate change (CTB (Curaçao Tourist Board), 2015). Thus, although it is known that Curaçao is dependent on tourism in a region vulnerable to climate change, climate change is not directly considered in coastal tourism planning. This research can contribute to improving understanding at the destination level in a geographical region where there is a knowledge gap (Becken, 2013). There are many potential environmental threats identified for Curaçao and the Caribbean region, e.g. sea-level rise, hurricanes, coral bleaching. However, proactive, rather than reactive, responses to these challenges require new tools to explore the future (e.g. Cinner et al., 2018; Rhiney, 2015; Student et al., 2016; Student et al., 2020). A virtual laboratory can help test future vulnerability outcomes in coastal destinations such as Curaçao, improve our understanding of emerging socio-ecological vulnerabilities, and contribute to improving adaptation strategies. Student et al. (2020) propose computational modelling, specifically agent-based modelling, as part of a dynamic vulnerability approach to experiment with human and environmental heterogeneities, different levels of uncertainty, and test implications of different socio-ecological feedbacks.

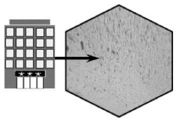
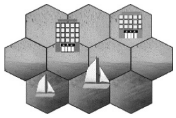
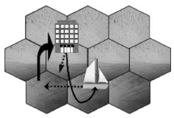
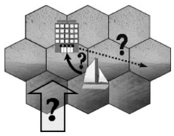
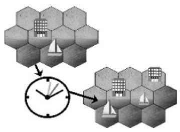
Agent-based modelling (ABM) is a promising method for multiple reasons. Baggio (2008) suggests that interactions, feedbacks, and iterations contribute to tourism system complexity. However, Bramwell et al. (2017) surmise that the tools applied to tourism sustainability research have been limited, and call for a more diverse range of methodologies. The tourism field has traditionally employed linear causality modelling techniques, which are insufficient for capturing system complexity (Baggio, 2008). Amelung et al. (2016) call for more exploratory and transdisciplinary methods "rather than disciplinary and predictive tools" to analyse changes in systems. ABM is comprised of three main elements: agents (e.g. humans), relationships (or interactions), and the environment (Macal and North, 2010); it is a form of computational modelling that integrates agents with the environmental system in a simulated spatial and temporal setting. ABM is a recognised tool for studying dynamic socio-ecological systems (Lippe et al., 2019). Recent applications of ABM in tourism include: the dynamics of changing destination choice preference (Alvarez and Brida, 2019), crisis management in China (Zhai et al., 2019), and the growth of Airbnb and rental housing regulations (Vinogradov et al., 2020). Some researchers recommend agent-based modelling (ABM) as part of an interactive process to facilitate better system understanding (Amelung et al., 2016; Le Page et al., 2017; Nicholls et al., 2017; Ruankaew et al., 2010; Student et al., 2020). ABM permits bottom-up modelling, including the heterogeneities of different actors and the environment in complex systems (Macal and North, 2010; Student et al., 2020), to investigate how destination level vulnerabilities emerge.

As little is known about the factors affecting socio-ecological vulnerabilities in coastal tourism destinations, we want to explore the interactions among people and their environment under varying conditions using ABM. Turner et al. (2003) identify two types of environmental change: slow emerging stressors and quick onset shocks. We look at globally-derived changes of sea-level rise (stressor) and new sudden events (shocks). We include locally-derived environmental pressures aggregated as pollution. These serve as proxies of the environmental challenges affecting stakeholders and the coastal system. Tourism operators are identified as being more vulnerable than tourists, as they have limited capacities, fewer alternatives, and are directly connected to the destination (Kaján and Saarinen, 2013; UNWTO-UNEP-WMO, 2008). The term *tourism operator* refers to the people operating coastal tourism-related businesses, not to be confused with tour operators, which offer package tours to tourists. Coastal tourism operators include beach hoteliers, beach operators (cafes, restaurants, beach activities), dive operators, boat operators, and nearshore operators (e.g. stand-up paddling, kayaking, surfing, glass bottom boats).

By exploring factors influencing socio-ecological vulnerabilities, we gain insights into adaptation strategies. Adaptation is "not an isolated phenomenon; the process requires cooperation at social, political and spatial levels" (Csete and Szécsi, 2015 p. 480). Collaborative action is considered important in small island developing states; the IPCC (2014 p. 106) states that "community-based adaptation has been shown to generate larger benefits when delivered in conjunction with other development activities". Thus, we want to understand individual and collaborative actions in a dynamic system and consider the trade-offs between looking after one's own resources and working on issues that are larger than individual abilities. Interactions among heterogeneous operators and the environment under climate change conditions lead to deep uncertainties (e.g. Lempert et al., 2003). However, decision-makers face limits on time and capacity. As such, they require insights on the main factors to concentrate on in order to avoid undesirable future situations. We explore these uncertainties in our model to provide key insights for decision-makers to focus on.

This research explores which human and environmental interactions lead to the emergence of social and ecological vulnerabilities in the coastal destination of Curaçao, and uses innovative analyses to better understand emerging socio-ecological vulnerabilities. This study offers three types of analysis to better describe these emerging vulnerabilities: vulnerability over time; main contributing and interacting factors that affect human and environmental vulnerabilities; and an analysis of the most influential factors leading to undesirable situations.

Table 1
Principles of the dynamic vulnerability approach implemented in the *Coasting* model.

Agency 	-Distribute resources based on individual preferences -Decide where to operate based on geospatial type preferences and presence of environmental resources -Determine whether to act, and whether to collaborate or act individually -Environmental resources (coral reef, mangroves, sea turtles, and reef fish) can reproduce and deteriorate -Move to another location (for mobile operators, sea turtles and reef fish)
Heterogeneity 	-Tourism operators: five operator types (hotels, beach, dive, boat, and nearshore), needed resource inputs required by type, mobility (mobile water-based versus immobile land-based), individually different input strategies (preferences), land-based versus water-based activities, different input strategy depending on whether possess sufficient or insufficient resources -Environmental resources: varying health levels, type, abundance, location, mobility (mobile vs immobile) -Environment: geospatial type, level of pollution, environmental degradation, biodiversity, types of environmental change (pollution, sea-level rise (SLR), sudden events) -Runs: different input parameters values (see MethodsX)
Feedback 	-Tourism operators: pollution limits returns, spending more on tourism increases profits, spending on environment can reduce pollution; if investments on the tourism product and environment are unbalanced, pollution levels change -SLR: decreases land area, bankrupts land-based businesses and associated water-based businesses if they become inundated -Sudden events: create environmental degradation -Pollution and environmental degradation: decrease health of environmental resources
Uncertainty 	-Tourism operators: will personal expenditures generate enough returns, will individual contributions help the environment -Collaboration: will others be willing to collaborate, will they be willing to invest enough -Pollution: where will it disperse to, will action alleviate it -Sudden event: where it will occur in the system, will it go away naturally, will actions reduce the environmental degradation caused -Environmental actions to SLR: will action be sufficient to deal with SLR
Iteration 	-Multiple runs with different settings -Within each run, every time step builds on the context of the previous round, operators' capacities, and environmental health -Explores a period representative of 30 years -ABM elements were adapted so that the model can be altered to simulate a different location and operator set-up

Methodology

Coasting agent-based modelling

The following sections explain the main features related to the human-environmental interactions in the agent-based model. Model specifics required for replication are available in the accompanying MethodsX. The model description is based on the Overview, Design concepts, and Details (ODD) protocol proposed by Grimm et al. (2010) and extended on by Müller et al. (2013).

The *Coasting* model, used to study emerging socio-ecological vulnerabilities in coastal tourism destinations, is based on a dynamic vulnerability approach developed in Barbados and Curaçao (Student et al., 2020). The *Coasting* model was developed in a way that it can be instantiated for other coastal destinations. This setting of this particular model instance focuses on the coastal destination of Curaçao and simulates the evolution of the coastal tourism sector and its environment 30 years into the future from the present date. The five principles of a dynamic vulnerability approach inform the set-up of the key human and environmental features, and socio-ecological interactions of the model; Table 1 shows how the model applies this conceptual lens.

Main features of the Coasting model

As we are assessing dynamic socio-ecological vulnerability, we focus on outputs related to tourism operators and the environment. Bankruptcy indicates that insufficient resources are available for sustainable tourism operations. The main output indicating socio-economic vulnerabilities is the number of tourism operators with enough resources to maintain their businesses at the end of the simulation. Each simulation session starts with 75 operators: 30 hotels, 10 beach operators, 20 dive operators, 5 boat operators, and 10 nearshore operators. This is a rough representation of Curaçao's coastal sector. No new operators are added during simulation runs to keep the number of parameters manageable and ease analysis of changes to tourism operator numbers over time.

The main output indicating changes to environmental vulnerability is environmental attractiveness. Environmental attractiveness is found in the literature as an important proxy for vulnerability. For example, Santos-Lacueva et al. (2017 p. 11) "define a destination's vulnerability to climate change as being a reduction in its attractiveness caused by climate change". Similarly, Hopkins et al. (2013 p. 449) state that "how climate change might affect demand and perceived attractiveness of destinations relative to their

Table 2
Main input parameters considered as part of the analysis.

Parameter name in *Coasting*	Explanation
tourism-returns	Ratio of tourism revenue earned compared to inputs in tourism product (e.g. 1:1, 2:1, 3:1)
revenue-limited?	Boolean, if true, limits the amounts operators can earn to consider capacity and infrastructure limitations; if false, ratio tourism-returns remains consistent
pollution-threshold	The amount of pollution that accumulates before an operator observes it (lower number indicates higher sensitivity)
cost-pollution	Cost to remove one unit of pollution from the environment
pollution-change	The amount (rate) of pollution added or removed from the system from operator actions
SLR-increase	The rate of sea-level rise (SLR) per year ranging from none to 50 mm
linear-SLR?	Boolean, if true, SLR assumes same continued yearly rate; if false, the SLR rate slowly increases
minimum-acceptable-elevation-above-sea-level	In figures: min-acceptable-elevation-above-SL Minimum elevation difference between sea level and land-based operators' infrastructure that operators find acceptable
increased-elevation	The increased coastal elevation through operator interventions on SLR
geospatial-weight	How much the geospatial type contributes to environmental attractiveness, the coastline has the largest value
biodiversity-weight	How much biodiversity contributes to environmental attractiveness
pollution-weight	How much anthropogenic pollution detracts from environmental attractiveness
environmental-degradation-weight	How much environmental degradation (from sudden events) detracts from environmental attractiveness
seed-for-random	Number generator; technical parameter for reproducibility of stochastic aspects of the model (during initialisation and further development of a run)

competitors" is used in tourism studies to determine relative vulnerability. Along with an average environmental attractiveness for the coastal destination, the model separates environmental attractiveness into three sub-categories: coastal (land and water in immediate contact), beach (land immediately connected to the initial coastal area), and nearshore (water area that is near to the coast and not considered deep sea). In the model, environmental attractiveness is made up of a base increased by geospatial type and biodiversity, and lowered by pollution and environmental degradation. As it is unknown how much these four factors determine environmental attractiveness, we implement the weights of these factors as uncertain input parameters. Table 2 displays the main parameters relevant to the analysis results (please see the MethodsX for the complete list of model parameters).

At each time step, the model performs the following procedures: (1) the local environment changes, (2) operators plan how to distribute their resources over their operational budget,(3) an environmental event may occur (slow increase sea level or sudden event), (4) operators decide whether they want to collaborate on environmental issue(s), (5) if not, they decide whether they want to act alone, (6) the environment responds to intervention, (7) the operators then collect their revenue from tourism minus any penalties for delays on maintenance, (8) pollution level is updated, (9) mobile water-based operator may move, (10) operators without enough earnings go bankrupt, (11) environmental resources (fish, turtles, reef, mangroves) update their health and if mobile, can move to another location (the MethodsX depicts a flowchart of the model steps). Fig. 1 shows the main human and environmental features included in *Coasting*.

Human (agent) inputs included in Coasting

Coastal tourism operators are represented by five types: hotel, beach vendor, dive operator, boat operator, and nearshore operator. The simulated tourism operator types differ in their mobility, resource input requirements, and resource allocation preferences (in both situations of excess and limited resources) (see the MethodsX for more details). There are four main allocations for their business: maintenance (upkeep of infrastructure and tools), the tourism product (bringing in and catering to tourists), short-term environmental actions (e.g. beach clean-up, educating on reef safety), and savings.

In ABM, entities can be considered "agents" if they express some form of agency—the ability to act independently (e.g. Macal &

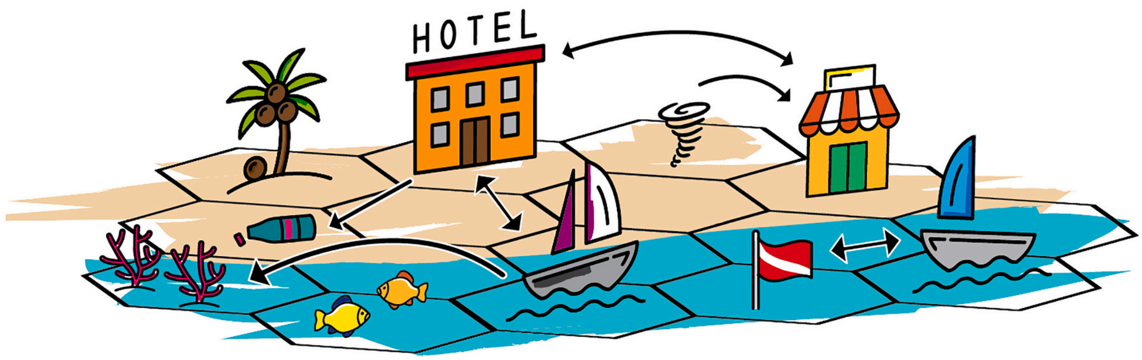


Fig. 1. *Coasting* model features: tourism operators, interaction between operators, diverse coastal environment features, effects of tourism on the environment (e.g. pollution, stress on reef), effects of the environment on tourism (e.g. storms and decreasing beach (right)).

North, 2010). In *Coasting*, agent types are tourism operators (human agents) and environmental agents (detailed in the following section). In the model, the simulated tourism operators have preferences of location (e.g. dive operators prefer coral reef areas with fish and/or sea turtles) and resource allocation (how to distribute their resources among four input categories: maintenance, tourism product, environment, and savings), and they interact with changes to the system. Our model explores how different tourism operator preferences for location and resource allocation interact spatially and temporally.

In response to environmental changes (detailed in the following sections), tourism operators can first choose to interact directly through collaborations. Tourism operators' networks are expressed as links between operators. Links are established either through model initialisation or as a result of collaborating on an environmental issue (pollution, sea-level rise, or sudden events). Links have strength; the strength can be positive (good past collaborations), neutral, or negative (unsuccessful or unhelpful past collaborations). The strength enables the simulated operators to remember whether, and to what extent, other operators in their network have helped them on previous environmental challenges. Links become more positive if others helped, and more negative when collaborations fall through or other operators free-ride. If the problem is not addressed through collaboration, tourism operators may act individually. The numbers of collaborative and individual actions are registered separately. Two alternative options to environmental action are doing nothing and, for mobile operators, moving away.

Environmental features included in Coasting

The environmental agents in *Coasting* are mangroves, fish, coral reef, and sea turtles. They have the following characteristics: some have mobility (fish and sea turtles), their health is affected by pollution and environmental degradation, they have a sensitivity to pollution and degradation, and they can multiply or die. These environmental resources contribute to biodiversity and influence some operators' (dive and boat operators) location selection.

The spatial coastal environment is characterised by key geospatial types (beach, coastline, nearshore waters, deep sea, and inland), biodiversity, elevation, pollution level, and environmental degradation. Biodiversity improves environmental attractiveness. The presence and abundance of environmental agents contribute to biodiversity. Elevation is important when considering sea-level rise and the dispersion of pollution (downhill on land, mixed along the coastline, and dispersed in nearshore waters). Pollution is a proxy for anthropogenic waste that includes chemical and physical waste. Pollution levels are calculated based on a balance between investments in tourism and environment. If they are in balance, no pollution is emitted. If there is more focus on the tourism product, then pollution is generated. If there are relatively more investments in the environment, pollution levels may be lowered. Environmental degradation relates to the damage caused to locations by climate change.

Environmental change inputs included in Coasting

Three types of environmental changes are included in this version of the *Coasting* model: locally-derived pollution; climate change related stressor of sea-level rise; and unspecified sudden events, which proxy environmental shocks. As mentioned in the previous section, pollution levels depend on the combined allocations in the tourism product and environment. To explore the emergence of vulnerabilities in relation to sea-level rise, the modelled system is exposed to different rates of sea-level rise, minimum acceptable height above sea level for land-based infrastructure, sea-level rise intervention costs, and the amount of elevation gained by an intervention. The unspecified sudden events represent the new emerging challenges that tourism destinations are confronted with, and stem from field observations. Sudden events can proxy the negative effects of heavy storms, coral bleaching events, inundations of sargassum seaweed, and outbreaks of diseases such as Chikungunya or Zika. Sudden events have a frequency of occurrence, chance of parts of the coastal space being affected, degree of environmental degradation caused by an event, natural duration before it may go away, amelioration costs, and a threshold for noticeability.

Data generation and analysis

Input data collection

Data collection for the agent-based model was based on mixed methods as part of a dynamic vulnerability approach described in Student et al. (2020): literature review, (semi-structured and simulation-guided) interviews, focus groups, and simulation game sessions. For example, the resource tourism operators' allocation preferences categories were identified in semi-structured interviews, verified in simulation guided-interviews, and experimented with during simulation sessions.

The *Coasting* model's human and environmental features described in the previous section mimic the *Coasting* simulation game. The set-up of coastal environmental features and tourism operator numbers and compilation are a rough representation of Curaçao. The main environmental features were identified and verified during interviews, field observations, and maps. The operator information is derived from interviews and field observations as well as tourism directories.

Two main considerations emerged when translating interview and simulation game data to the model: specifying human and environmental behaviour and incorporating ongoing interactions over a longer-time frame. Literature, interview, and simulation session data indicated key input parameters (e.g. threshold for observing pollution) and mechanisms (e.g. decisions for tourism operators' allocation preference), but not specific data points. In these cases, the model embraces uncertainties by exploring combinations of diverse input parameter values over multiple runs. Table 2 shows some of the explored parameters. Moreover, randomness was incorporated in the initialisation and model mechanisms to account for uncertainties.

Verification and validation

We verified the translation of the conceptual model and dynamic vulnerability approach designed in Student et al. (2020) into the

Coasting computational model by means of both agent tracking and multi-agent testing (van Dam et al., 2013). The mixed method design enabled verification of single agents' actions over time and the emergent behaviour of multiple agents. This was performed multiple times throughout the model construction and analysis.

Conventional validation of exploratory simulation models is difficult, as there is no data with which to compare model behaviour. We therefore restricted ourselves to evaluating the usefulness and credibility of the model through interviews with domain experts and problem stakeholders. We found that the model received significant interest as it could explore "what-if?" future scenarios, providing a fertile ground for discussion of how stakeholder interactions could shape (and be shaped by) future developments, and how those developments might arise. In this context, the simulation games reported in Student et al. (2020) were invaluable.

Software

The model was implemented in NetLogo 6.0.4. Global sensitivity analysis results are obtained using software packages developed by Herman and Usher (2017). Scenario discovery results are generated using the Exploratory Modelling and Analysis Workbench (Kwakkel, 2017) as well as software from Jaxa-Rozen and Kwakkel (2018).

Global sensitivity analysis

Global sensitivity analysis is used to test the uncertainty of the model outputs (67) to measured model inputs (34). The global sensitivity analysis results are derived from 700,000 runs using the Saltelli sampling method from the sensitivity analysis library (SALib) package in Python (Herman & Usher, 2017).

Scenario discovery

For exploring future scenarios of socio-ecological vulnerability, we use scenario discovery. Scenario discovery is a general analytic method for identifying decision-relevant or insightful scenarios in the outputs of complex system models (Lempert et al., 2006). It is based on the idea that the narratives used for scenario-based planning should not be specified in advance, but emerge from the complex interactions within the studied system (Bryant & Lempert, 2010). Scenario discovery can be seen as a computational back casting, and is a complementary model analysis technique to sensitivity analysis. For this research it is useful because decision-relevant input parameters are difficult to identify in advance. In scenario discovery, we set criteria or thresholds that indicate whether a run describes an acceptable or unacceptable future. From this, we can assess the most influential parameters that can lead to unacceptable futures.

In this case, we are interested in whether operator numbers decline below an acceptable threshold, and/or whether the environment declines beyond an acceptable threshold. Exactly what constitutes an unacceptable number of bankrupt operators or level of degradation by attractiveness varies from destination to destination, but extreme losses to the tourism sector or environment can be considered undesirable, and for Curaçao we look at extreme losses to both.

Experimental set-up

The main objective of this particular simulation of Curaçao is to analyse socio-ecological vulnerabilities. As such, the main model outputs that are explored in the results sections are operator numbers (by type), number of individual and collaborative actions over the simulation, and changes to average environmental attractiveness (see Table 3).

Vulnerability over time

Figs. 2 and 3 use kernel density estimation to indicate how operator numbers and environmental attractiveness change over time. Kernel density estimates are statistically inferred representations of the probability distribution curve—the shape—of some

Table 3
Main outputs of interest for *Coasting* simulation of Curaçao.

Output	Model name	Description
Socio-economic vulnerabilities		Number of [...]
	m-all-ops	all operators
	m-hotelops	hotels operators
	m-beachops	beach operators
	m-boatops	dive operators
	m-diveops	boat operators
	m-waterop	nearshore operators
Action outputs		Total number of [...]
	total-num-indiv-actions	individual actions
	total-num-collaborations	collaborative actions
Ecological vulnerabilities		Average per type [...]
	m-av-now-attr-beach	beach attractiveness
	m-av-now-attr-coast	coastal attractiveness
	m-av-now-attr-nearshore	nearshore attractiveness
	m-av-now-attr-area	overall environmental attractiveness

underlying data. They are the continuous equivalent of discrete histograms. In both figures, we plotted kernel density estimates at every time step for 4000 experiments on *Coasting*, with the probability density function being represented by the colour gradient: bright yellow indicates a large amount of data points (i.e. many of the simulation runs have roughly this value at this time step), dark blue the opposite. Plotting kernel density estimates over time can be useful for identifying overall trends across many simulation runs.

Interacting factors affecting vulnerabilities

The circle plots show how strongly model outcomes depend on parameter values of individual parameters and combinations of parameters. The inner (black) circles indicate the sensitivity of an outcome to an individual parameter (1st order sensitivity). The outer (white) circles indicate the sensitivity of an outcome to a parameter in conjunction with all other parameters (total sensitivity). The connecting lines indicate the sensitivity of an outcome to the combination of two parameters (2nd order sensitivity). All sizes of lines and circles are relative: the larger the circle or thicker the line, the larger the sensitivity.

For each of the three circle plot sets, we took the four most sensitive parameters for each output (e.g. each of the operator number types). Overall, this resulted in six unique input parameters. We present the same six parameters in all sub-figures of one figure to enable comparison among social vulnerabilities, environmental actions, and ecological vulnerabilities. To look at social vulnerabilities, we examined the sensitivities of operator numbers (Fig. 4). As both individual and collaborative action are required to deal with environmental challenges, Fig. 5 indicates which factors influence operators' environmental actions. To look at ecological vulnerabilities, we looked at the average attractiveness for the three main coastal areas: beach, coastal, and nearshore waters as well as the overall average for the destination (Fig. 6).

Discovering factors leading to undesirable futures

We identified two distinct system failures to be avoided, which are indicative of socio-economic and ecological vulnerability. The first scenario, *Economic Failure*, is characterised by a 75% decrease or more of businesses. The second scenario, *Ecological Failure*, describes a decrease in environmental attractiveness by 25% or more. See the MethodsX for more details on the individual *Economic* and *Ecological Failure* scenarios. We also considered a third scenario, *Combined Failure*, which is the combination of the two aforementioned conditions: a future in which both the economy collapses and the environment degrades unacceptably (see the results section). These thresholds describe worst case scenarios for Curaçao, and are context-dependent.

We use the machine learning algorithm called Patient Rule Induction Method (PRIM) (Friedman & Fisher, 1999; Kwakkel, 2017) to find the most relevant input parameter combinations. PRIM tries to fit an orthogonal box around the region of the input space in which inputs generating undesirable outputs lie. This box can then be considered a very simple surrogate model, and its dimensions indicate under which input conditions an undesirable output is likely to develop. The fitting of this box is governed by three distinct parameters. Coverage represents how many of the decision-relevant (i.e. unacceptable) futures are included in a PRIM box. This attribute should be maximised to reduce false negatives (decision-relevant input parameter sets outside the box). Density captures the ratio of decision-relevant to irrelevant futures in the boxes, which should also be maximised to avoid false positives (decision-irrelevant inputs inside the box). Interpretability describes which dimensions the box has been restricted to, i.e. the more parameter dimensions, the more influencing input parameters the output has. To ensure the induced box is analytically tractable and useful, this value should be minimised.

To evaluate these scenarios, we performed 4000 simulation experiments with 30 replications. Each experiment was performed with a unique set of input parameter values, while the replications of each experiment differed only in the random seed (stochastic influence). We computed the mean across the 30 replications for each experiment to reduce stochastic influence.

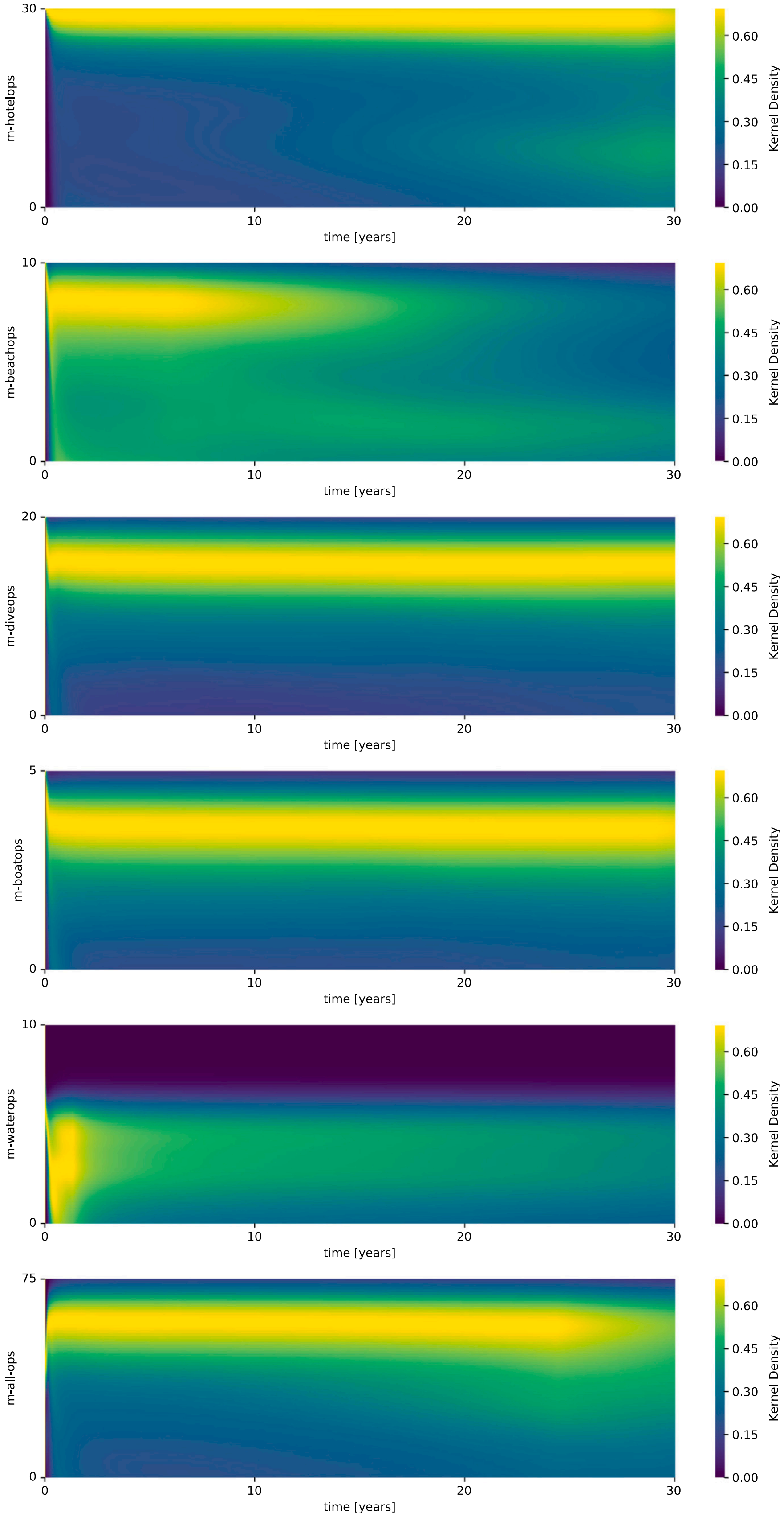
Results

The following three sections show: which main vulnerability patterns for operators and the environment are observed over time; the interactions among factors affecting vulnerabilities; and scenario discovery of the main factors contributing to vulnerability at the end of 30 simulated years.

Operator and environmental vulnerability over time

The following figures give an indication of how operator numbers and environmental attractiveness change over time. Fig. 2 shows the probabilities for operator numbers (i.e. how many are still in business) over the simulated time of 30 years. Unsurprisingly, as no new businesses form, the general trend for all operator numbers is a decrease. However, the time period and plausible range of decrease varies considerably by operator type. It further indicates different levels of operator success when exposed to the same wide range of environmental and social input parameters. Hotel operations (*m-hotelops*) stay uniformly high, although from 25 years of simulation time onwards, a second density peak appears at much lower operator numbers. For beach operators (*m-beachops*), we find that for the first ten years, most simulation runs show around 8 to 9 businesses in operation. Thereafter, the number of businesses starts diverging rapidly, with a second density peak emerging around 2 to 3 businesses in operation. These two secondary density peaks with far fewer operators in business indicate that under certain conditions, a drastic socioeconomic shift may occur. Dive and boat operations (*m-diveops* and *m-boatops*, respectively) show relatively stable numbers over all simulation runs, indicating they are less sensitive to model parameters than hotel or beachfront operations. Finally, nearshore operators (*m-waterops*) show a wide variety of behaviours across the simulation runs, although an early decrease in operator numbers seems common.

For environmental attractiveness (Fig. 3), the wide spread kernel density of potential attractiveness values indicates response to



(caption on next page)

Fig. 2. Kernel density estimates for operator numbers over time across 4000 simulation runs. Bright colour bands highlight frequently occurring values and temporal dynamics.

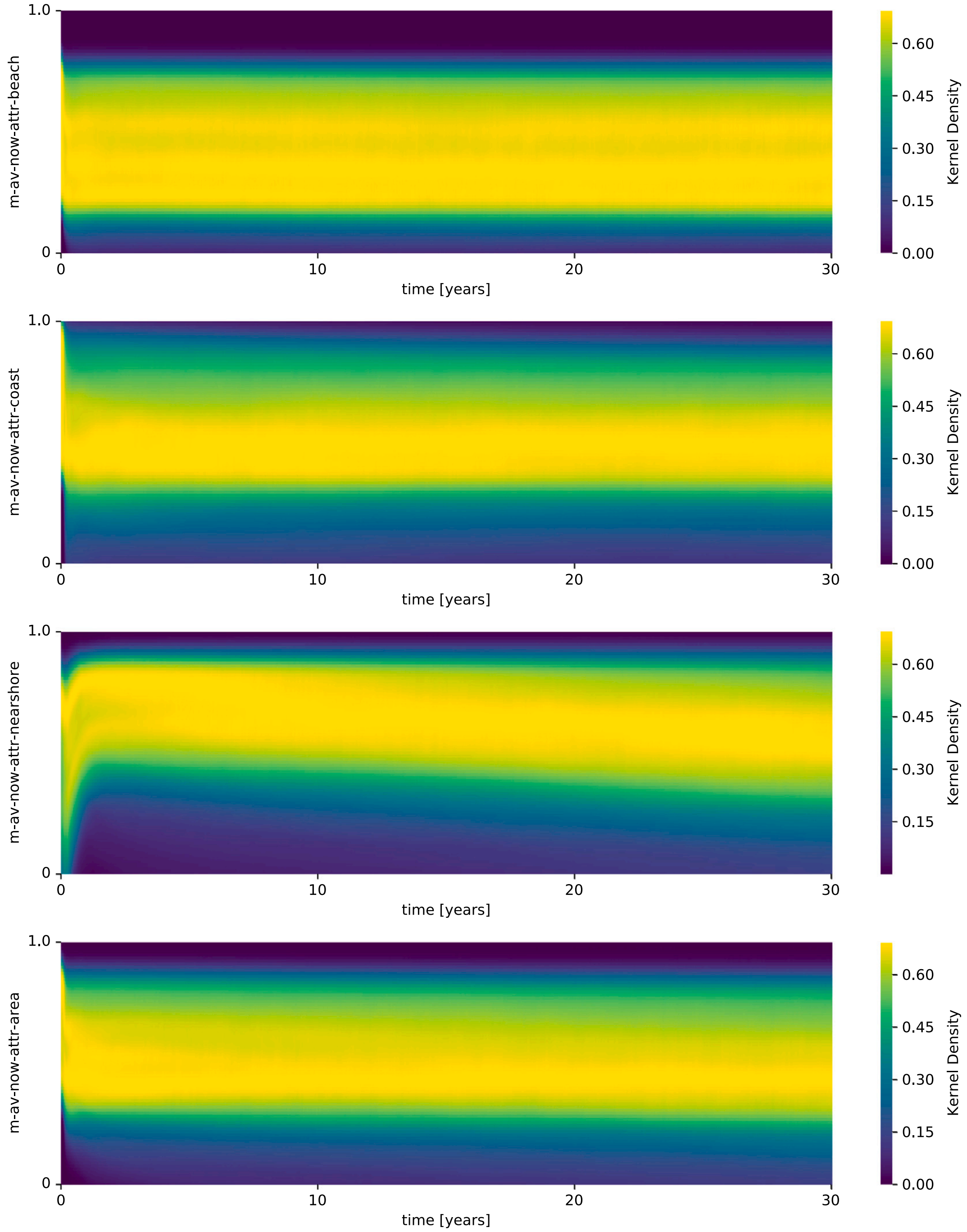


Fig. 3. Kernel density estimates for environmental attractiveness over time across 4000 simulation runs. Bright colour bands highlight frequently occurring values and temporal dynamics.

the wide-range of socio-ecological parameter combinations. In other words, the environmental attractiveness of different parts of the system (beach, coastal, nearshore areas) are highly dependent on the initialisation of the input parameters and changes in the system over time.

Interactions among factors leading to different levels of environmental and operator success

The previous section gave a global indication of how operator numbers and environmental attractiveness responded to all of the parameter combinations during the runs. But it does not indicate the main parameters that influence operator numbers and environmental attractiveness within the runs, nor does it show which of these input parameters interact with others. It also does not give any indication of which conditions (input parameters) induce operators to act (output). Fig. 4 indicates the influence of the most important parameters on different operator numbers. For example, the largest direct influence (1st order sensitivity) on beach operator numbers are *tourism-returns*, *SLR-increase* (rate of sea-level rise), and the minimum acceptable elevation of their infrastructure above sea level (*minimum-acceptable-elevation-above-sea-level*). Along with direct influences, interactions (2nd order sensitivity) between *tourism-returns* and *SLR-increase*, *tourism-returns* and *minimum-acceptable-elevation-above-sea-level*, and to a lesser extent *tourism-returns* and stochasticity (*seed-for-random*) affect beach operator numbers. Stochasticity on its own does not exert much influence, however in combination with other parameters it does exert influence on operator numbers (total sensitivity). For all five operator types, *tourism returns* are the main influence on operator numbers. However, the input parameter *tourism-returns* interacts differently with other parameters. For example, for land-based operators, i.e. hotel and beach operators, as well as nearshore operators, their sensitivity to rising sea levels (*minimum-acceptable-elevation-above-sea-level*) has a relatively strong interaction with *tourism-returns*.

As individual and collective actions are required to deal with environmental challenges, Fig. 5 indicates which factors influence their numbers. Surprisingly, the parameter *tourism-returns* (which contributes to the amount of available resources) is a more influential determinant of collaborative action while for individual action, the *pollution-threshold* (the amount of pollution present necessary to consider action) is more influential. Moreover, for individual action, there is less interaction among the factors, while for collaborative actions and the main factor of tourism-returns, we see more influence of other factors for generating collaborative actions.

As the weights determining environmental attractiveness are one of the tested parameters, we observe in Fig. 6 how the weights play a large role in the overall attractiveness, with *geospatial-weight* (i.e. nearshore waters, coastline, nearshore beach) consistently being the most important parameter. This value only changes in the simulation under conditions of sea-level rise: when beach becomes water, or when the land elevation is heightened to prevent loss of beach. Beach attractiveness, where immobile land-based tourism occurs, has second order sensitivities to pollution factors (threshold, weight, and change) as well as *tourism-returns*. This shows operators' activities have a strong influence on beach attractiveness.

Scenario discovery of socio-ecological vulnerabilities

Many experimental runs resulted in ecological, economic, or combined failures. Fig. 7 indicates the number of unacceptable outcomes that occurred. In dark blue, the number of purely economic failures is given—the majority of businesses go bankrupt, but the environment does not significantly degrade. In green, the purely ecological failures are shown—most businesses survive, but the environmental attractiveness degrades unacceptably. Turquoise represents both combined (ecological and economic) failures. It is evident that ecological and economic failure can occur independently of each other. However, the overlap indicates that there are some interactions between the two failure modes under certain conditions. Scenario discovery can help identify under which conditions these combined failures may occur. The analysis of purely ecological and economic failures is presented in the MethodsX.

Combined failure

For the scenario of combined economic and ecological failure, three parameters exert the strongest influence on this outcome: *pollution-change*, *pollution-weight*, and *tourism-returns* (Fig. 8). The red box of the scenario region indicates the parameter settings where there is the highest prevalence of runs that indicate an unacceptable future. The red boxes' coverage (how many of the decision-relevant futures are located within the box) is 64% and the density (ratio of decision-relevant to irrelevant futures in the boxes) is 67%. For example, in the top-right plot, the box indicates a high failure rate (yellow circles representing runs) when *pollution-change* is > 0.1 and *tourism-returns* are < 3. Outside of this box, many runs indicate desirable outcomes (purple); however, there are clusters of yellow when *tourism-returns* is > 3 and for *pollution-change* > 0.4 showing undesirable outcomes. The histograms in the diagonal indicate the acceptable and unacceptable future distributions for every parameter (x-axis).

Discussion

The *Coasting* model integrating human-environmental interactions is the first attempt known to the authors of modelling the coastal tourism system, including both locally-induced environmental problems and global challenges. The analysis of dynamic vulnerability is also new for tourism-climate studies. This study developed an agent-based model to research the emergence of socio-ecological vulnerabilities and is instantiated for Curaçao, which responds to Amelung et al.'s (2016) call for more transdisciplinary and exploratory tools, and multiple researchers' calls for destination-level approaches to improve our understanding of emerging vulnerabilities and potential adaptation strategies (e.g. Cinner et al., 2018; Nurse et al., 2014; Rhiney, 2015). This study shows the heterogeneity of socio-ecological vulnerability patterns (Figs. 2 and 3), which highlights the value of incorporating complexities rather than assuming linear causalities when assessing vulnerability. It identified some of the dynamic mechanisms related to coastal destination vulnerability in Curaçao. This helps address the prominent climate change challenge of relating “physical impacts and changes in the environment with their human implications such as socioeconomic impacts or human responses” (Pons et al., 2012 p.

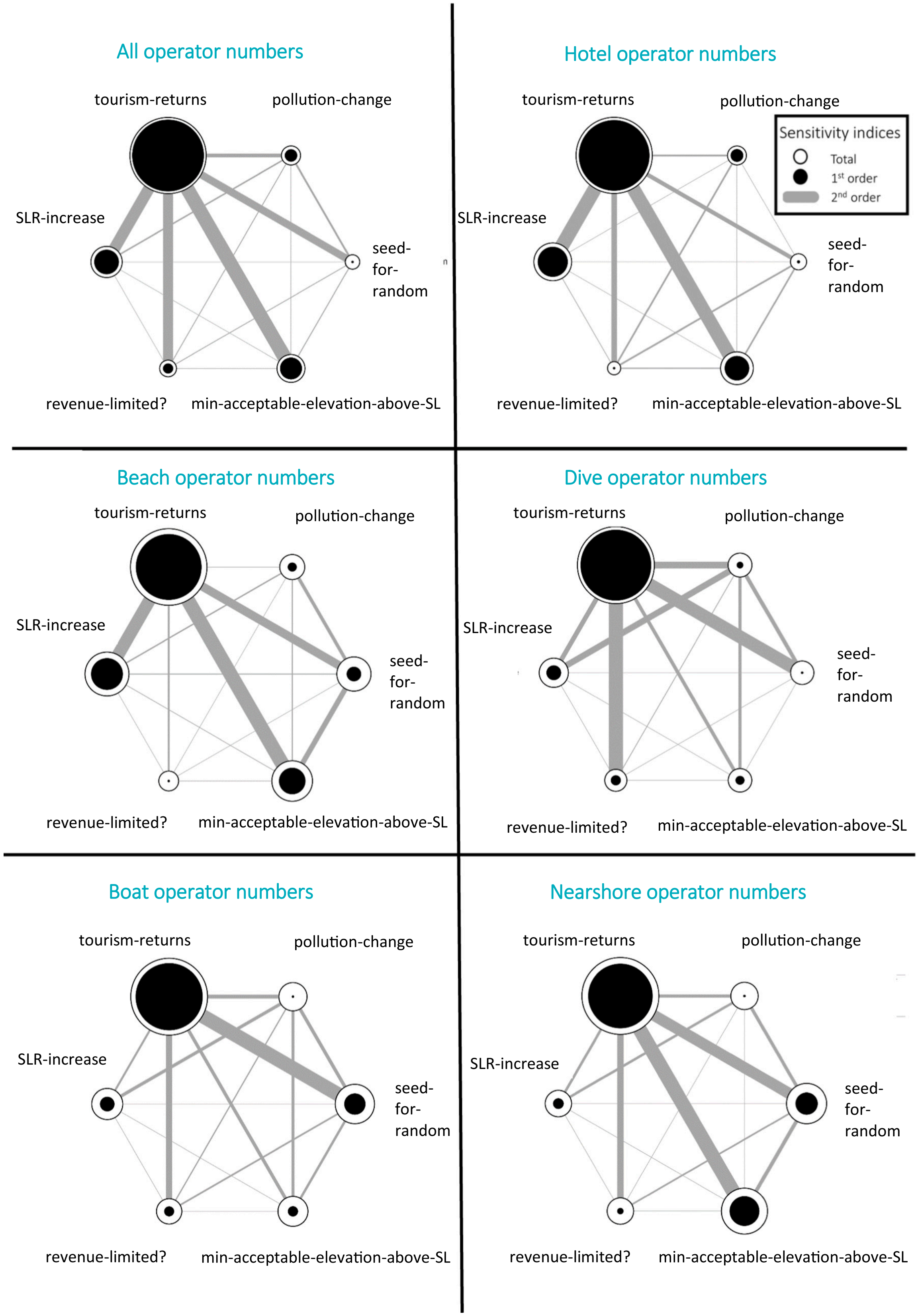


Fig. 4. First, second, and total order sensitivity indices for tourism operator numbers. Node and edge sizes indicate relative influence of the named input variable.

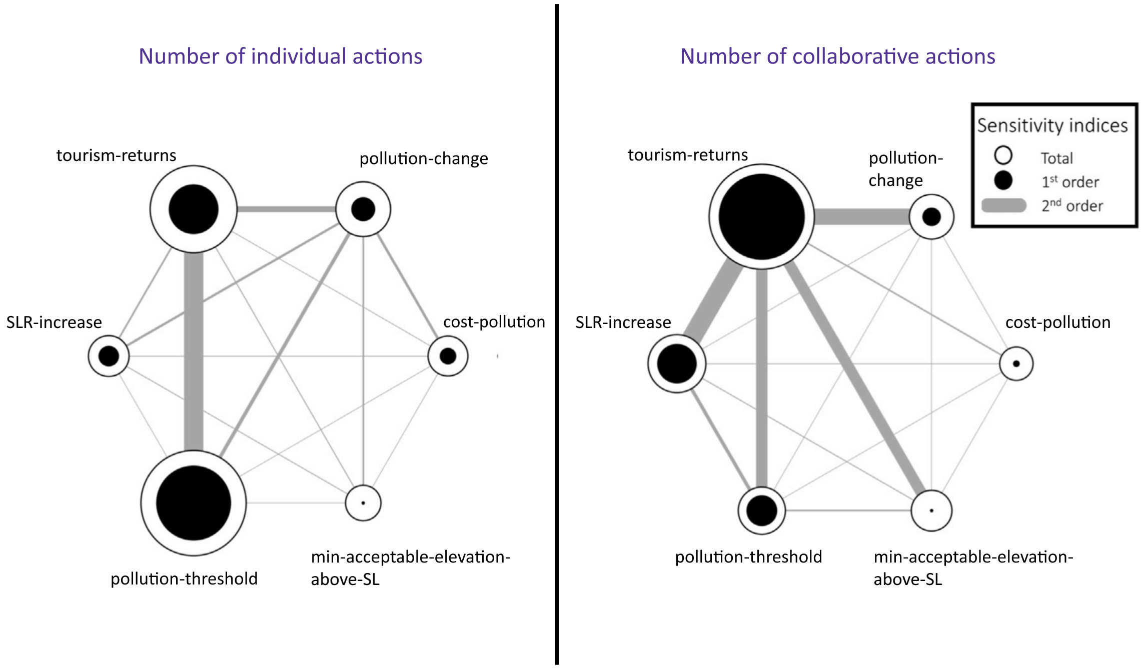


Fig. 5. First, second, and total order sensitivity indices for operator actions. Node and edge sizes indicate relative influence of the named input variable.

199) at a destination level, and highlights the utility of ABM for tourism planning and management (Nicholls et al., 2017). The *Coasting* model is part of a dynamic vulnerability approach, and helps analyse complex effects in the socio-ecological tourism system from the ground up, including unexpected interactions between the social and ecological components.

In addition, the findings suggest areas where decision-makers can focus on for developing adaptation strategies in Curaçao. *Tourism-returns* is the most predictive parameter for success according to multiple analyses of vulnerabilities. In the presented model applied to Curaçao, economic failure is largely driven by low tourism returns, i.e. the ratio of returns compared to the resource investments. This does not bode well for real tourism-based economies, where the "race to the bottom" on tourism returns is evident in price dumping on flights and accommodation fees, high competition among islands, and tax incentives to attract foreign tourism companies. In our model, there appears to be a sharp transition for *tourism-returns* (around *tourism-returns* = 3). This indicates there may be a tipping point regarding the health of the tourism sector. This tipping point can also be identified in Fig. 3, where secondary density peaks (values frequently observed) for hotel and beachfront operator numbers are observed towards the end of the simulation runs. This sensitivity and potential tipping point indicate that there is not much room for operators to adapt to impending combinations of environmental change. This finding is important for decision-makers in Curaçao, as it indicates their positioning of Curaçao in the market and accepting lower returns from tourism can lead to both economic and ecological decline.

As part of their adaptation strategies, decision-makers also need to consider how to encourage individual and collaborative actions (e.g. Nurse et al., 2014). Fig. 5 provides insights on which key factors influence individual and collaborative actions. Individual action depends on when (at what level of pollution) people notice change; this is more influential than how much it costs or what rate it increases at. Thus, heightening operators' understanding of the impact of pollution may help initiate more environmental actions. For collaborative action, the model indicates that having enough resources is a precursor to collaborating, in conjunction with other environmental thresholds and change rates. This means that decision-makers in Curaçao needs to consider both ecological challenges as well as operators' capacities to promote collaborative actions, which is a socio-economic challenge. If operators' have limited capacities, decision-makers providing economic support can increase collaboration.

Ecological failure is largely driven by the rate of pollution change. Pollution affects environmental attractiveness (through *pollution-weight*) and lowers tourism returns; however, no significant tipping point can be identified. The importance of pollution change rate and pollution weight gives both hope and warning. This finding indicates that actions to lower and prevent locally-induced waste are significant influences on ecological success (i.e. limited environmental vulnerability). In other words, local actions matter. At the same time, if the island does not address locally-induced pollution, it risks ecological and economic vulnerabilities, especially when other factors can also reduce operator capacities. This suggests that policies protecting the coastal environment from locally-induced pollution are a critical part of long-term climate change adaptation strategies. Surprisingly, sudden events did not have a significant influence on economic or ecological failure. This could be due to the larger role of pollution and sea-level rise; or possibly, their designed influence on the coastal system in the model was too conservative. This simulation indicates that the ongoing challenges of generating and dealing with waste along with sea-level rise have larger influences on the emergence of vulnerabilities than the sudden extreme events that receive much media coverage. In summary, although Curaçao is facing global climate change, local

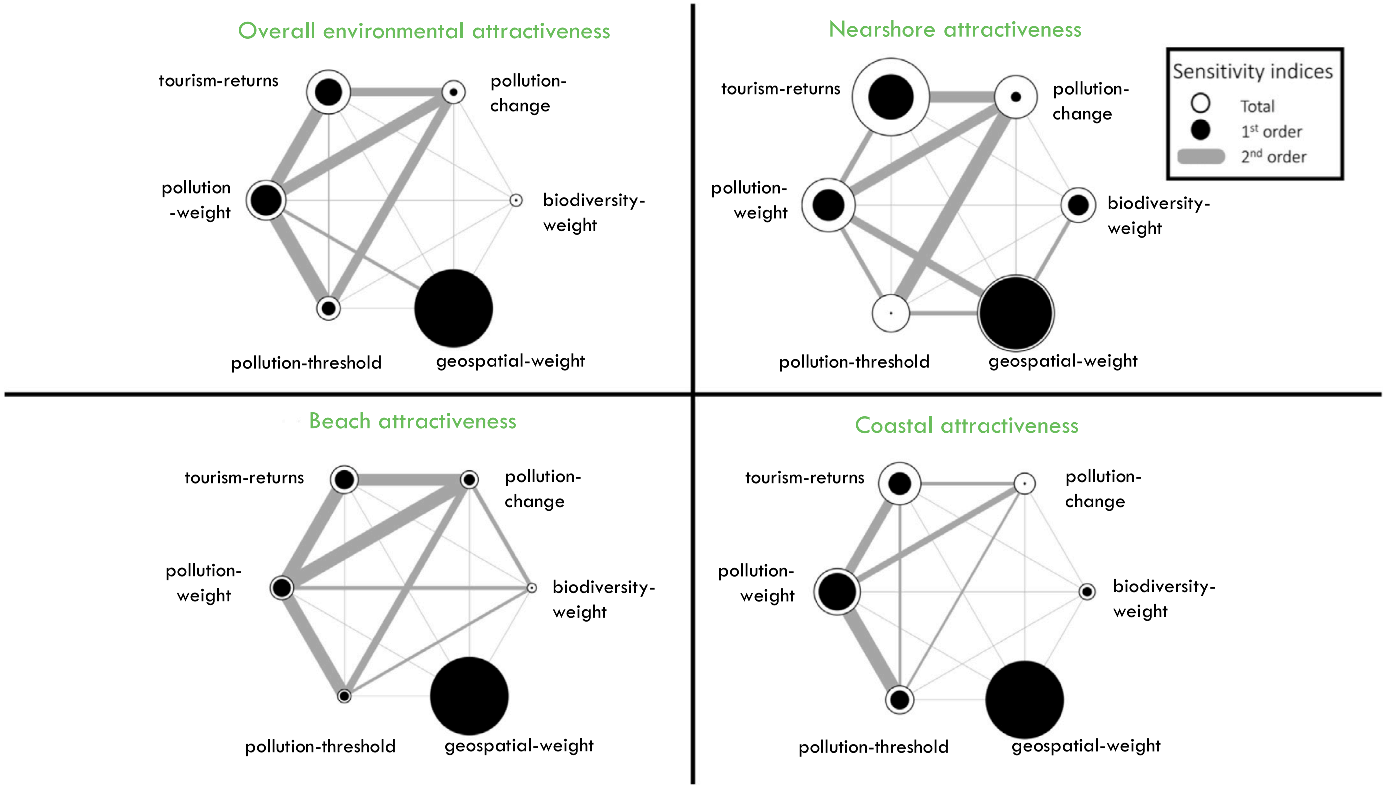


Fig. 6. First, second, and total order sensitivity indices for environmental attractiveness. Node and edge sizes indicate relative influence of the named input variable.

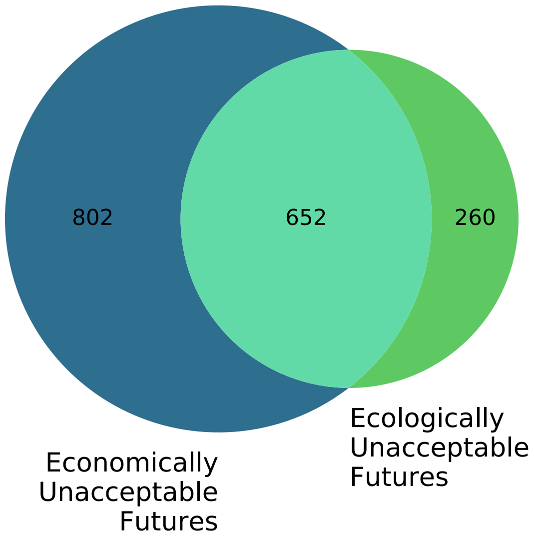


Fig. 7. Venn diagram of unacceptable economic and/or ecological futures (from 4000 experiments).

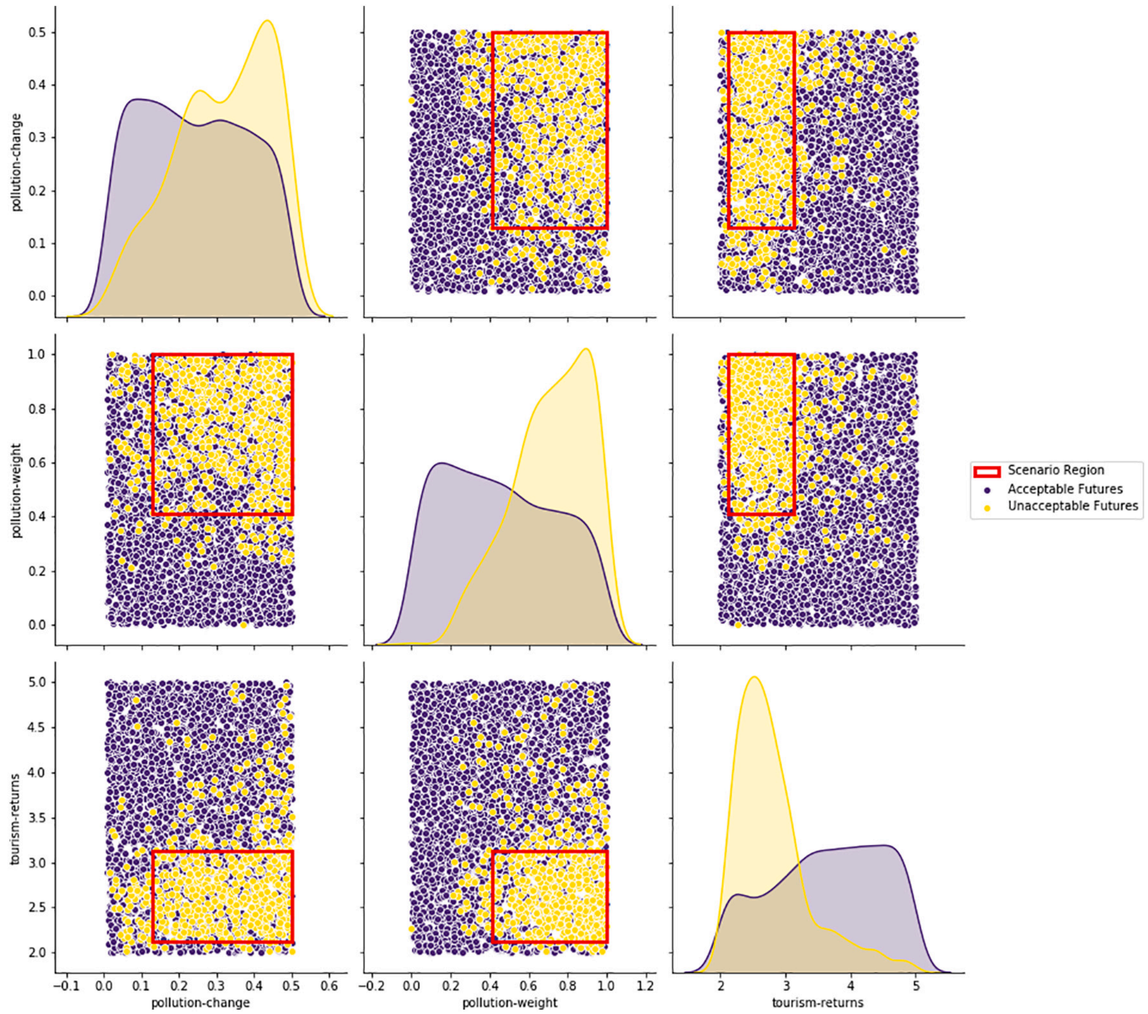


Fig. 8. Main factors and boundaries defining the scenario region of combined economic and ecological failure futures (threshold: 25% ecological loss and 75% economic loss). Kernel density estimates of the two output classes are on the diagonal.

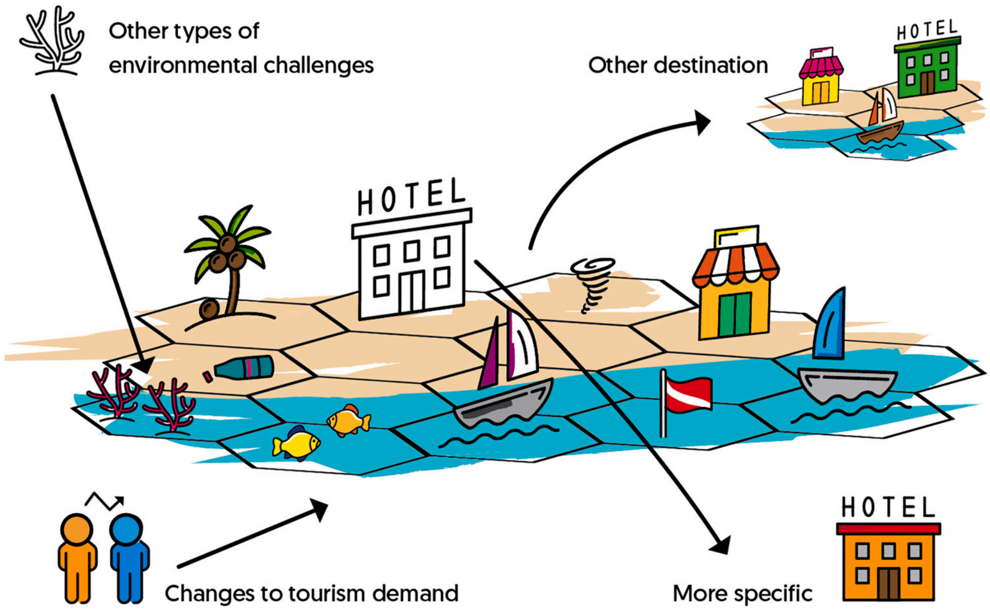


Fig. 9. Potential expansions of the *Coasting* model.

actions to limit pollution are critical for limiting socio-ecological vulnerabilities.

This research is an important point of departure for future research on emerging vulnerabilities in coastal tourism. While this model does indicate important patterns leading to socio-ecological vulnerabilities, this model should not be confused for being predictive in nature. Rather, *Coasting* is an exploration of potential vulnerabilities under known and anticipated environmental change. Researchers (e.g. Le Page & Perrotton, 2018) advocate for starting simple and adding complexity to the model in layers as different parts of the base are better understood. The scenario analysis in this version indicates extreme situations we want to avoid. A potential avenue for future studies is to define and explore socio-ecological outputs that we want to achieve with decision-makers. In the context of dynamic vulnerabilities, it could also be interesting to study how these scenarios might change over time (e.g. Steinmann et al., 2020). Necessarily, the *Coasting* model is a simplification of the system; some simplification is common when simulating complex systems (e.g. Rouan et al., 2010; Turner et al., 2003). But, *Coasting* has been designed in a way that it is a promising means for improved understanding of emerging vulnerabilities.

Future versions of this model can go in many directions to help decision-makers and researchers: looking at different case study areas, further specifying model mechanisms (for humans, the environment, policy-making, and/or the environmental challenges), including global and tourism demand scenarios, and including more types of environmental challenges. Fig. 9 indicates opportunities for further applications of the model. One of the low hanging fruits for *Coasting* is changing the initialisation of environmental space and tourism operator numbers to proxy other coastal destinations on small island developing states to explore what kind of vulnerabilities emerge there. In order to set up the model to explore a new destination, a general knowledge of the main environmental features (geospatial, environmental resources, and elevation) as well as the number and compilation of tourism operators are necessary. A second opportunity is to further specify different mechanisms and inputs. For example, this model does operationalise the effects of individual preferences for inputs in their own businesses or emerging relationships. This reflects the limited willingness of (local) respondents to contribute extra reserves to deal with environmental change (Cumberbatch et al., 2018). In future editions of this model, nuances of behavioural rules can be added. This especially applies to the individual trade-offs on where to expend resources, which were based on observations during simulation sessions. However, as there was no clear indication of how individuals dealt with trade-offs, preferences were randomly attributed to simulated operators during model initialisation.

A further means to expand this model is to explore the influence of changing tourism demand. The assumption of this model instance is that tourism demand is inelastic, but is mediated by maintenance delays, pollution, environmental degradation, and environmental attractiveness, which are recognised as having potential impacts on visitor preference/arrival numbers (e.g. Cumberbatch et al., 2018; Hopkins, 2015; Santos-Lacueva et al., 2017). Thus, the modelled potential returns are dependent on the local environmental conditions and maintenance delays, but not on changing international arrival scenarios. Future versions can consider changes to this ratio over time or among operators to reflect uncertainty to tourism arrivals (Cumberbatch et al., 2018; Gössling et al., 2012), tourism numbers affected by weather data information (Matthews et al., 2019), or tourist destination preference (Alvarez and Brida, 2019).

Conclusion

This research makes two significant contributions to dynamic vulnerability assessments, tourism research, and climate change impact studies: the flexible simulation of a coastal tourism destination, and the novel analysis techniques applied to analyse deep uncertainty in the tourism sector. In this paper, emerging vulnerabilities to tourism operators and the coastal environment of Curaçao were explored. The most prominent parameters increasing vulnerabilities were low tourism returns, increasing pollution levels, and how much pollution levels influence environmental attractiveness. Tourism returns and increasing pollution levels are prominent factors that Curaçao can consider in its adaptation strategies to both environmental and socio-economic challenges. However, neither the computer simulation nor the challenges of climate change are limited to the Curaçao destination. Thus, the ability to adjust the set-up mechanisms to those that simulate other destinations, or changes to other key parameters, are available for users. This type of modelling does not predict which type of future is more likely, but it does indicate what the patterns mean for emerging vulnerability and adaptation.

In addition to the model, the innovative mode of analysis is a contribution to dynamic vulnerability assessments and forward-looking scenarios under conditions of deep uncertainty for tourism studies. The model's time scale helps us look at different trends for operator numbers over time, and reveals how different operators are affected differently by the emerging challenges in the shared coastal system. We were also able to see which parameters interact to influence socio-ecological vulnerabilities, as well as individual and collaborative action. Scenario discovery enables us to consider what kind of future we want as a basis for scenario analysis, and determine decision-relevant factors to act on, simplifying decision-making. As such, scenario discovery can be applied more broadly to tourism and climate change impact research.

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