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Agent-Based Modelling : An Approach to Integrate Emerging Tourism Interactions with the Environment

Tourism on the Verge

Student, Jillian

https://doi.org/10.1007/978-3-030-88389-8_23

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Agent-Based Modelling

An Approach to Integrate Emerging Tourism Interactions with the Environment

Jillian Student

> **Learning Objectives**
> - Illustrate the opportunities provided by agent-based modelling to study complexity, interactions, heterogeneity, nonlinearity, and uncertainty
> - Explain how to set up an agent-based model based on a research question
> - Appreciate the limits and challenges tourism researchers and practitioners face when applying agent-based modelling
> - Demonstrate how to apply agent-based modelling in a tourism context

1 Introduction and Theoretical Foundations

When people book a vacation, they want to experience a certain location, particular activities at affordable prices, desirable weather conditions, no queues or other hassles, etc., and they plan accordingly to make these wishes come true. This seems relatively straightforward. However, there are many factors beyond an individual's control and their booking decisions that can affect the vacation and the individual's satisfaction towards their vacation. For instance, other people at the attraction may block the view of the exhibit, prices may skyrocket, a hurricane may make activities unavailable and render the location dangerous, or a person may have to queue an unbearably long time to get on the gondola at a ski lift. These events range in their seriousness with regard to health and safety.

J. Student (✉)
Environmental Policy Group and the Wageningen Institute for Environment and Climate Research (WIMEK), Wageningen University and Research, Wageningen, The Netherlands
e-mail: jillian.student@wur.nl

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R. Egger (ed.), *Applied Data Science in Tourism*, Tourism on the Verge,
https://doi.org/10.1007/978-3-030-88389-8_23

In our current times, dramatic, unexpected changes to tourism have occurred due to the COVID-19 pandemic, where travelers contributed to the global spread of the virus (Neuburger & Egger, 2021). Consequently, local and global tourist movement was brought to a halt or, at least, extremely limited. In 2020, there were multiple attempts to reopen the borders to help tourism-dependent economies recover. However, the potential threat of the virus spreading remained. This desire for increased mobility while limiting the spread of the virus relies on human behaviour, creates uncertainties, and generates trade-offs for decision-makers. With little information, decision-makers need to decide how *much* to open or close their borders and deliberate on whether sweeping decisions or localised lockdowns would be more effective. In this respect, Assaf et al. (2021) highlight the importance of understanding changing consumer behaviour to be one of the key issues in post-pandemic research.

Agent-based modelling (ABM) can help researchers to understand how individual choices and actions lead to systemwide consequences. In this chapter, the acronym ABM is used to describe both "agent-based modelling" and an "agent-based model". In its basic form, ABM is a system containing agents, which can be individuals or entities, that make decisions autonomously by following simple rules and interact with each other and/or the spatial system (Bonabeau, 2002). For example, Dignum et al. (2020) applied ABM to include diverse human behaviours and explore the consequences of different policy interventions on the spread of the virus in order to complement the epidemiological models used in informing decision-makers during the pandemic. Figure 1 depicts a simple agent-based representation of infected and healthy individuals and their interactions in an abstract spatial setting.

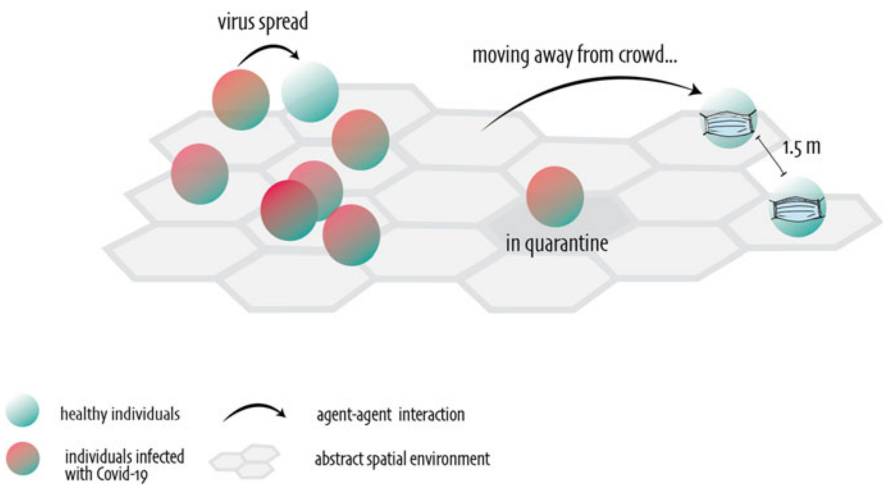

Fig. 1 Visualisation of interactions between agents who are infected with COVID-19 and those who are healthy in a simple spatial setting

Overall, this chapter aims to introduce ABM concepts and underline how ABM can improve the understanding of real-life tourism challenges. Moreover, this chapter provides tourism-related examples of this method and one in-depth practical demonstration.

1.1 Tourism as a Complex System

Complexity is a recognised characteristic of tourism due to the many levels of interactions, heterogeneity, nonlinearity, and the resulting uncertainty (Baggio, 2008; Baggio & Sainaghi, 2011; Boavida-Portugal et al., 2017; Johnson et al., 2016; Student et al., 2016b; 2020). In a similar vein, systems thinking is a holistic means to analysing interactions (e.g. Amelung et al., 2016). In Amelung et al. (2016), ABM is argued to be a tool that is particularly useful in systems thinking and integrating the socio-economic aspects of tourism with anthropogenic environmental change. Agent-based modelling (ABM) is a form of modelling that helps to understand the complexity of interactions and tries to make them transparent and interpretable. Furthermore, ABM studied systems are often classified as complex adaptive systems, which are systems characterised by nonlinear interactions and feedbacks, emergent properties, and where agents can adapt individually or at varying macro levels (Macal & North, 2010; van Dam et al., 2013). This next section unpacks the characteristics of interactions, heterogeneity, nonlinearity, uncertainty, and mobility further.

Interactions are actions that lead to responses or feedbacks, which, in the tourism system, are ongoing, can involve many individuals, and are part of a dynamic analysis (Student et al., 2020). Ongoing interactions lead to changes in both the individual agents and the system over time. To illustrate this with an example, interactions can be seen as direct exchanges between two individuals: with one individual, a tourist, purchasing an excursion (such as swimming with sea turtles) from the other individual, an excursion seller (see Fig. 2). Yet, interactions can also take place indirectly since one change can set off a chain reaction of other events through feedbacks. Placed in the context of a wider system, this one transaction of buying a sea turtle excursion can, in turn, motivate other companies to offer the same excursions in order to earn money, which would increase congestion of the sea turtle swimming areas due to more boats with tourists visiting at the same time. Figure 2 shows examples of direct interactions, while Fig. 3 shows how direct interactions such as excursion transactions indirectly affect the pollution level at the destination.

Moreover, the increased sales of excursions could contribute to the sea turtles' weight gain as more tourists and operators feed them so as to attract the turtles to the tourists. In the described context, the buying of sea turtle excursions collectively and indirectly influences sea turtles' diet and weight. However, the relationship between a tourist buying a swimming excursion does not necessarily have a linear relationship with the increased weight of sea turtles. Some operators could decide that they

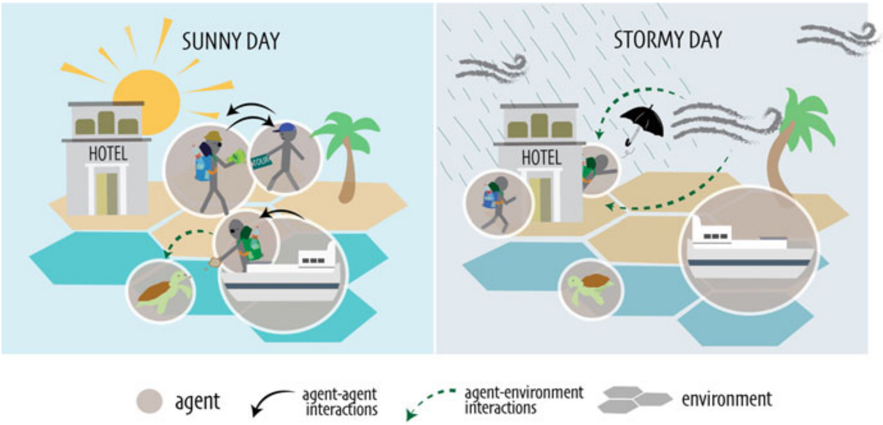

Fig. 2 Visualisation of two states of a tourism destination ABM with a sea turtle attraction – agents, environment, agents and environmental characteristics, different interactions (agent-agent, agent-environment), and changes to the system can be noted

do not feed the turtles or only visit sea turtle swimming areas during off-peak periods. Conversely, sea turtles could have a consistent weight and health up until a certain number of excursion boats with tourists and food arrive. Above this threshold, sea turtle weight could exponentially increase, and health decrease, because of excess food, the stress of being surrounded by boats, and limited access to natural food sources due to the interference of tourists. This would create a positive feedback of sea turtles accepting food provided by tourism operators and tourists.

Nonlinear relationships or feedbacks makes it more challenging to plan what kind of activities and services to offer and what kind of changes to prepare for (Baggio & Sainaghi, 2011; Johnson et al., 2016; Levin et al., 2013; Student et al., 2020). For example, governments and researchers want to better understand how tourism will develop in the Antarctic (Student et al., 2016a), but, currently, tourism is self-regulated in the Antarctic through the member organisation International Association Antarctica Tour Operators (IAATO). Membership is voluntary. As such, the ABM explored the implications of new operators entering the Antarctic cruise tourism without the same long-term commitment of established tourism operators. Moreover, it looked at different motivations for collaboration with IAATO (commitment to the environment and importance of public image) to explore possible tipping points of tourism operators' ability to self-regulate.

Heterogeneity is another important characteristic of tourism that contributes to complexity as there is a considerable difference between tourists and other integrated stakeholders (Johnson et al., 2016). There are even differences within stakeholder types. Some examples within the tourist type include differences in terms of their activities, destination preferences, willingness to try new things, contribution to waste, and spending capacity. Moreover, as in the previous example, heterogeneity impacts linearity of feedbacks, i.e., since different tourism operators have distinct

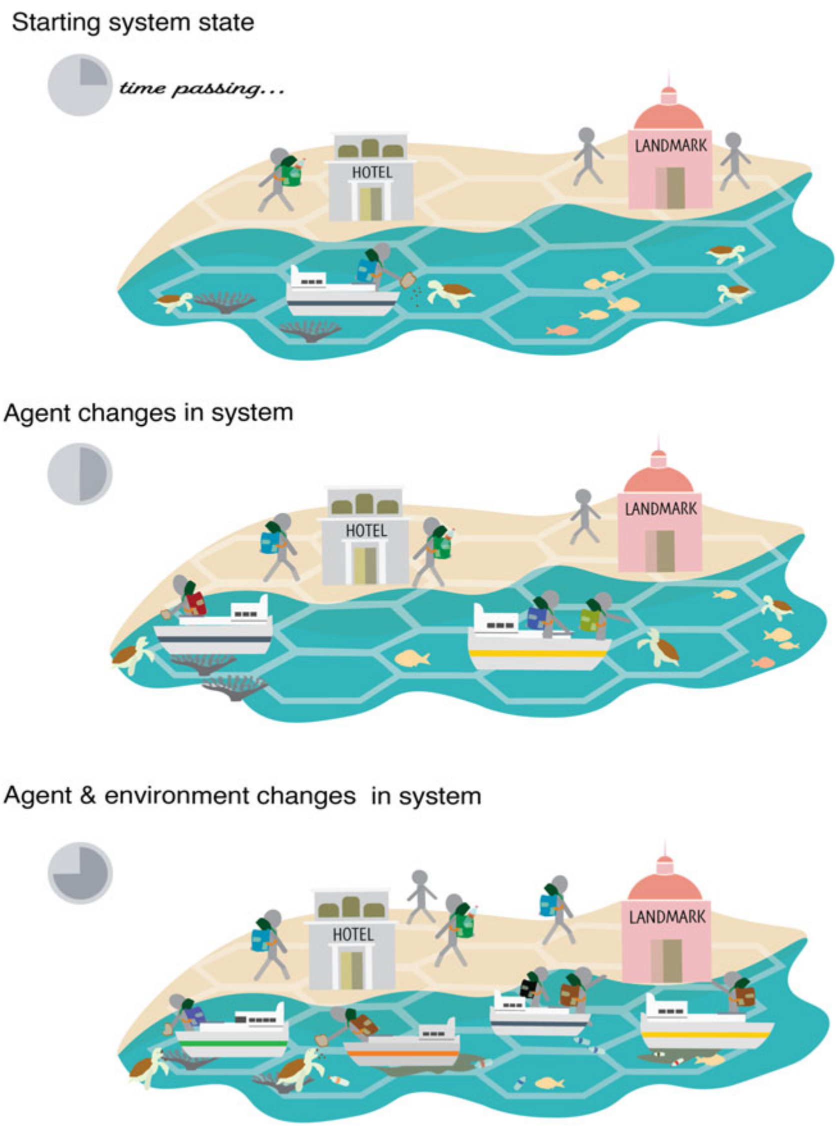

Fig. 3 Visualisation of the changing state of a tourism destination ABM with sea turtles and growing tourism over time

strategies, the pressure on the sea turtles and their weight may be mitigated by those who decide not to overfeed or, in contrast, those who do feed more because operators are competing for the attention of a limited number of sea turtles. ABM is capable of simulating agents, interactions, and spatial heterogeneity, which ultimately helps to capture the real system and the emerging changes (Bonabeau, 2002; Macal, 2016; Student et al., 2020).

Tourism is also characterised by a high degree of movement with regard to people and goods. Environmental mobility is a concept that focuses on movements of people, entities, and environmental factors as well as their associated impacts (e.g. Boas et al., 2018; Urry, 2000). Mobilities further contribute to tourism complexity in contexts such as understanding consumer demand (Gössling et al., 2012), overtourism (Milano et al., 2019), mitigating CO_2 emissions (Peeters & Dubois, 2010), crisis recovery (Assaf et al., 2021), and destination or event planning (Lew & McKercher, 2006). Tourism activities occur at a destination, but tourists tend to come from outside of the destination and are not limited to one location at the destination. At the same time, food and materials to build infrastructure are often imported to the destination to support tourism activities such as skiing, safaris, beach visits, and cultural events. Figure 3 illustrates sea turtle movement with the tourists and tourism operators following their movement. These factors limit decision-makers' control and create uncertainty. Moreover, movement and interactions are difficult to express in models that lack a spatial context. ABM, however, can include the movement of individual agents (humans or other entities) over time in the analysis of individual changes, patterns, or macro-level changes (Heppenstall et al., 2012).

As illustrated in the previous paragraphs, many tourism-related research questions have to consider interactions, nonlinear feedbacks, heterogeneity, uncertainty, and mobility in complex systems (Baggio & Sainaghi, 2011; Johnson et al., 2016; Student et al., 2020). These system characteristics have far-reaching consequences, such as the spread of COVID-19 during the pandemic. However, these tourism system characteristics are difficult to simulate when applying many modelling approaches (Johnson et al., 2016). For instance, simple linear or reductionist models can obscure crucial interactions that lead to inconsistent system-level change (Levin et al., 2013). Although aggregating heterogeneities does give information on general trends, it does not easily show what happens to whom or to specific parts of the system and how they can adapt. Therefore, agent-based modelling (ABM) is a possible integrative solution for researchers wanting to study these challenges in complex adaptive systems.

1.2 ABM Benefits

ABM lends itself to complex adaptive systems research as it helps conceptualise and investigate complexity, interactions, heterogeneity, nonlinearity, movement, and emergence of unexpected phenomena from individual interactions in a spatial setting measured across a simulated time frame (see, for example, Bonabeau, 2002; Heppenstall et al., 2012; Levin et al., 2013; van Dam et al., 2013). In tourism contexts, this method is not only beneficial for capturing heterogeneous interacting agents (e.g. tourists from different areas, tourism operators providing different activities, etc.), but it can also incorporate nonlinear relations and complexity aspects useful for investigating human-environmental systems (Amelung et al., 2016; Balbi

& Giupponi, 2010; Boavida-Portugal et al., 2017; Macal & North, 2010; Müller et al., 2014; Student et al., 2020). In addition, ABM helps capture agency, such as actions, reactions, and interactions, that are missing or more difficult to capture in many other types of descriptive system models (Bonabeau, 2002; Heppenstall & Crooks, 2019; Macal, 2016). Moreover, the ABM approach is very flexible in defining and constructing use cases, which, in turn, makes it well-suited for interdisciplinary and transdisciplinary research topics (Amelung et al., 2016; Macal, 2016; Student et al., 2020).

A few of the commonly stated benefits of ABM include the following (Amelung et al., 2016; Bonabeau, 2002; Étienne et al., 2011; Macal, 2016; Macal & North, 2010; Nicholls et al., 2017):

1. Bottom-up approach, which can be more intuitive to model
2. Study of emergence (aggregating patterns stemming from individual interactions)
3. Ability to test different scientific theories
4. Flexible research approach that can be combined with participatory methods such as serious gaming
5. Supports decision-making processes by exploring multiple future scenarios

An overview provided by Nicholls et al. (2017) details potential applications of agent-based modelling in the context of tourism. More specifically, they highlight its use for (1) testing tourism theories and/or social theories applied in a tourism context, (2) simulating visitor flows for destinations or events, (3) experimenting with potential changes to destinations over time, and (4) supporting decision-making for marketing and planning. The following sections describe the conceptual background of this modelling approach, its main features, and its applications in tourism. In addition to these benefits, ABM can help simulate not only visitor flow, but also the movement of tourism operators, environmental factors, such as the sea turtles mentioned in the previous examples, and goods in a spatial setting. It can include randomness in the system set-up, the order of procedures, and possible outcomes of interactions. As such, ABM can support decision-making for marketing, general destination management, and planning under conditions of uncertainty. Since tourism is a challenging phenomenon to study in a lab environment, ABM offers a suitable space to experiment with different social and environmental challenges without harming people and the environment.

1.3 Background of ABM

ABM is rooted in systems thinking, complexity studies, complex adaptive systems, and ecological and societal adaptation, being a form of modelling that integrates human–environment interactions in the context of a system (e.g. van Dam et al., 2013). In itself, it is technically not new and evolved from other modelling processes such as cellular automata (Macal & North, 2010). However, unlike cellular automata, ABM distinguishes itself in that agents can move and carry their individual information with them. This is particularly interesting for tourism because movement, as discussed in the previous section, is an integral characteristic of tourism.

Since the 1970s, the application of ABM has spread to multiple fields, such as ecology, economics, and the social sciences, and has been applied to policy-oriented topics to support decision-making (see, for example, Macal, 2016; van Dam et al., 2013). As ABM can study phenomena emerging from individual interactions and decisions (Heppenstall et al., 2012; Macal, 2016; Student et al., 2020; van Dam et al., 2013) and is not limited to studying aggregates but, rather, is designed from the bottom up (e.g. Bonabeau, 2002; Macal, 2016), this sets it apart from other forms of simulation. In addition, this also means that it includes information about individual parts of a system, taking an agent perspective and including social processes, and how they interact with the natural environment (Macal, 2016).

A classic, early example of ABM concepts and its ability to look at individual decisions and how patterns emerge is the Schelling model (Schelling, 1971). This model investigated how residential preferences influenced the formation of racially segregated neighbourhoods. By applying very simple rules for the households (either to remain in their location or move), Schelling looked at how differences in household preferences influenced the general locations of the two distinct household types. As such, this simple model showed the power of ABM because it revealed to what extent small differences in individual preferences can lead to unexpected macro-level trends, such as segregation.

In the context of tourism, modelling different preferences can be relevant to many research/practical questions including destination preference (Boavida-Portugal et al., 2017) and the willingness of tourism operators to collaborate, act alone, or avoid action in the face of environmental challenges (Student et al., 2020b). ABM applications first emerged in tourism in the 2000s (e.g. Chhetri & Arrowsmith, 2008; O'Connor et al., 2005; Yin, 2007), and by the 2010s, these had continued to increase and appear in more academic tourism journals (e.g. Alvarez & Brida, 2019; Balbi et al., 2013; Boavida-Portugal et al., 2017; Johnson & Sieber, 2010, 2011; Li et al., 2015; Pirotta et al., 2014; Pizzitutti et al., 2014; Pons et al., 2012, 2014; Soboll & Dingeldey, 2012; Soboll & Schmude, 2011; Student et al., 2016a; Zhai et al., 2019). As time continues to pass, the number and types of ABM applications also continue to expand; thus, the following section aims to describe ABM's basic components in order to help new ABM researchers further develop this approach within the tourism domain.

1.4 Key ABM Features

The main features of agent-based models are agents, variable types, and the concept of ongoing interactions in a spatial setting over time. There are three main types of variables: agent, environmental, and system-level, which can either be static (stay the same throughout the simulation) or dynamic (change through interactions and successive events) (e.g. Heppenstall et al., 2012; Macal & North, 2010; van Dam et al., 2013). An example of a static feature of an agent could be that the agent is classified as a tourist throughout the simulation, while an example of a dynamic feature could be the agent's spending capacity. Figure 2 depicts the agent, the agent's surrounding environment, and the interactions amongst agents and between agent and the environment.

1.4.1 Agents

Naturally, there are different definitions of agents (e.g. Macal, 2016); however, in a tourism context, agents can be thought of as individuals or entities who are distinguishable, having their own outward features and internal rules for making decisions and interacting with other agents and/or their surrounding environment. Agents, and in some cases the environment, can possess memory and can learn, change strategies, and have changing adaptive capacities, which can be influenced by successive events (Bonabeau, 2002). The ability to study agents that have memory and can learn is useful for studying complex adaptive systems. Moreover, ABM does not need to assume perfect knowledge for agents as agents often have limited knowledge about other agents and the wider simulated system, i.e., they know more about those in close proximity, of the same type, or with whom they have previously encountered or worked with (e.g. Macal, 2016; van Dam et al., 2013).

The modeller needs to determine who (which agents) should be included in the system, their key characteristics, and what rules govern their actions. Further questions to consider are with whom and what they interact with directly. Do they interact directly with other agents and the environment? It is also important to consider whether the agents simply react or if they adapt their behaviours during the simulation, i.e., learn from previous interactions and change their strategy or alter the decision rules. One of the benefits of ABM is that the agents are not limited to "if this, then do this" rules as they can be derived from mathematical algorithms, behaviour theories, empirical data, statistics, rules of logic, and/or incorporated randomness (Macal & North, 2010).

1.4.2 Environment

In ABM, the agent is typically connected to a spatial environment (depicted in Figs. 1, 2, and 3). The environment can be an abstract concept like in Fig. 1 and show location relative to others, or it can have features that represent a particular setting such as a landmark or destination, as depicted in Fig. 2. Alternatively, the spatial environment can be spatially realistic and derived from GIS maps. The different parts of the environment depend on what needs to be represented and the level of detail required, and, like agents, the environment can also record changes or have a memory (Bonabeau, 2002). How the spatial environment is set up can limit agents' interactions and their access to information (Macal & North, 2010). For example, in Fig. 1, the spatial environment indicates how close agents are to each other, and the agent's range of sight may only be to that of its neighbouring cell. One further example, in Fig. 3, involves the fact that only certain boats are close enough for the tourists to see and feed the sea turtles. Another important consideration to take into account is the simulated environment's spatial boundaries and what these boundaries represent (Macal, 2016; van Dam et al., 2013). Boundaries can be explicit limits to the agents' movement, or they can be open for agents entering and exiting the system. Alternatively, they can also wrap around in torus geometries, i.e., an agent going beyond the right border re-enters the system from the left border.

1.4.3 System-level

System-level variables are settings that apply to the whole system and can be accessed by both the agents and the environment for different model mechanisms. Some examples of system-level variables could be transportation costs, visitation number quotas, the temperature, and the rate of sea-level rise.

1.4.4 Interactions

Interactions are the links between agents, the environment, and the system, which shape the model mechanisms and are ongoing throughout the simulated time (Bonabeau, 2002). In ABM, the range of interactions can vary; for example, they can be localised and spatially close by to other agents who/that are spatially close or agents with specific characteristics (e.g. the sale of an excursion to a specific tourist with an interest in sea turtles). However, interactions can also include everyone in the system, such as the effect of weather conditions on tourism activities depicted in Fig. 2. Another key feature of interactions is how they change both the agents and the environment over time. In the example of buying a sea turtle excursion, the exchange of funds for a ticket is between two agents: one agent, the tourism business, will receive money, while the other agent, the tourist, will receive a ticket. The accumulation of multiple individual interactions affects the system over time, which is illustrated in Fig. 3. Here, the interactions of multiple people joining the excursions to visit sea turtles increases congestion in the waters surrounding the sea turtles, eventually contributing to more waste ending up in the water and the waters becoming more polluted.

The mechanisms of agent–agent and agent–environment interactions do not have to be deterministic algorithms, rather, they can include randomness (Heppenstall et al., 2012; Student et al., 2020b). This helps simulate the stochasticity and uncertainty present in the real world. In the ticket-buying example, an agent has decision rules that determine the excursion choice. This could indicate that agents usually buy tickets from the cheapest seller, for instance. However, occasionally, an agent may buy a ticket from the seller closest to their current location because of convenience. Figure 3 illustrates changes over time, both at the individual level (e.g. local agents not going to landmarks, the location of individual boat excursion operators) and the system-level (e.g. increasingly congested and polluted waters). This figure also shows how some of the operators' location choice does not match with the sea turtles' presence in the water, representing the randomness and uncertainty of movement.

1.5 Challenges When Applying ABM

Although ABM can be a useful method for tourism and other research domains, it is still considered more of a niche method when compared to other modelling approaches. General challenges with ABM include deciding on the amount/level of details to incorporate, drawing the environment's boundaries, considering time for model scheduling, model verification, and validation, in addition to other tourism research-related challenges.

As agent-based modelling deals with complexity, it makes it challenging to keep the model simple, and it can be tempting to include more details than necessary. Figure 1 depicts a simpler ABM simulation than Figs. 2 and 3 in terms of agents' characteristics, spatial environment, and interactions. Yet, the detail provided in Figs. 2 and 3 may not be relevant or necessary to answer the question of the effects of agent mobility, location, and mask-wearing on the percentage of the population that is healthy. It is true that representing behaviour and decision-making often include parts of mechanisms that are not observable; nonetheless, having more details requires more processing power and increases the chance of making errors. As such, Heppenstall and Crooks (2019) summarise some of the current challenges related to ABM in the spatial sciences, for instance, the availability and quality of data as well as translating vast amounts of geo-referenced data to specific agent behaviours. This "dance" between empirical data details and theoretical abstraction creates challenges in model development and analysis.

In the same vein, drawing the boundaries around a system, and a tourism system in particular, is challenging since boundaries are often ill-defined, even when looking at a tourism destination or venue, due to tourism-related agents' in and outbound movements. This necessitates a decision on what should be included in the model, what is considered external, who and/or what can enter or exit the modelled system, and what this means for tourism mobility.

Temporal boundaries also require specification. While in real life, events happen concurrently, in agent-based modelling, the timing or scheduling of events or agent actions needs to be itemised (Heppenstall et al., 2012; van Dam et al., 2013). This is not a trivial task as the order in which things occur can have a large effect on the outcome. For example, if all agents first go to the ticket office and then go on the excursion, there will be a queue, and a certain number would get tickets and then join the same excursion. Alternatively, the model could be scheduled in a way that agent "A" first completes both steps before Agent "B" does. In this case, agent "A" would first go to the ticket and encounter no one else and then go on an excursion alone before agent "B" goes to the ticket office to get a ticket and go on a separate excursion. The latter case seems less plausible in this instance, but, for other modelling queries, scheduling based on all agents completing a step might be necessary to mirror concurrent decisions.

Incongruent time scales further complicate this issue of scheduling. A model defines discrete time steps in which the schedule of events or agent actions occurs (van Dam et al., 2013). However, many scientific domains study time at different scales, and the rate of change for a phenomenon being studied determines the relevant time scale. In tourism, this is complicated as questions often draw on insights from multiple scientific domains. Figure 2, for instance, includes the weather, which can change rapidly, while, in addition, arrival numbers change daily, and decisions can be made instantaneously or can be deliberated over time. On this note, the timing of different model interactions needs to be calibrated to the selected time step.

The previously mentioned challenges complicate the verification and validation processes as well. Some parts of an agent-based model can be challenging to verify, depending on the availability of observable data (e.g. Macal, 2016). Similarly, verification and validation are particularly difficult as ABM has various forms based on the modelling goal, such as theory testing vs. exploration or prediction (e.g. Ligmann-Zielinska et al., 2020; van Dam et al., 2013). One consideration when it comes to validation is whether empirical data can even be used to compare model behaviours with model mechanisms and outcomes (Heppenstall et al., 2012). If empirical data is unavailable, then experts can help validate parts of the model (e.g. Bonabeau, 2002). Lastly, another challenge relates to communicating the model's mechanisms and results with stakeholders (Johnson et al., 2016). Acceptance of the model and their findings is not guaranteed, and transparency and trust in ABM processes and analysis are ongoing dilemmas (e.g. Heppenstall & Crooks, 2019; Macal, 2016; van Dam et al., 2013).

1.6 Tourism-related ABM

ABM continues to develop in many scientific fields, in spite of the challenges detailed in the previous section. Nevertheless, there are still relatively few ABM publications present in tourism journals. Johnson et al. (2016) identified three main challenges that tourism researchers and tourism practitioners face when considering the application of ABM:

1. The technical abilities of tourism researchers to translate the conceptual understanding of the problem into an agent-based model.
2. Communicating the model's mechanisms and findings with other tourism researchers and practitioners.
3. Having examples to build upon.

With regard to technical abilities, although ABM is also suitable for novice modellers (Macal, 2016), many researchers are unaware of where to start or have not undergone a formal training as part of their tourism studies (Johnson et al., 2016). The following sections of this chapter thus provide steps and references that can help inexperienced modellers to conceptualise and set up their projects. Furthermore, the resources at the end of the chapter provide the reader with online platforms and an in-depth description of the modelling process.

The second challenge of communicating ABM processes and results is difficult and often haphazard. However, there has been growing support to follow standardised forms in order to successfully communicate the model process, outcomes, and limitations with other researchers and stakeholders. Additionally, the model description is also becoming more standardised so that describing an ABM model's purpose, its conceptual framework, and its mechanisms comes with more ease (e.g. Grimm et al., 2020; Müller et al., 2013). When communicating a model's findings with practitioners and other stakeholders, it is vital to be clear about the model's purpose and explain, in terms of outputs, whether it is exploratory or predictive.

Examples help to accelerate the uptake of ABM; although ABM is still a relatively niche approach in tourism studies, there is a growing body of projects and publications in general as well as in the tourism context specifically. It is suggested to use existing examples from repositories and forums, similar to the one included at the end of this chapter. Nicholls et al. (2017) provide a summary of some earlier examples, and Table 1 gives an overview of some of the models developed for the tourism industry not included in Nicholls et al.'s (2017) summary.

Table 1 Examples of tourism-related agent-based models

Topic	Focus	Reference
Housing-market regulation and Airbnb growth	Tourism destination management	Vinogradov et al. (2020)
Destination choice	Tourist preferences	Alvarez and Brida (2019)
Destination preference change	Tourist preferences	Boavida-Portugal et al. (2017)
Recreation potential of nature areas	Tourism destination management	Chhetri and Arrowsmith (2008)
Tourism activities on Galapagos; scenarios of environmental change affecting markets	Tourism market/destination management	Pizzitutti et al. (2014)
User-generated content and strategic destination management	Destination management	Zhang et al. (2020)
Social media response to human-induced crises	Destination management	Zhai et al. (2019)
Evaluating the potential disturbance of tourism on dolphin activities and shark predation risk	Tourism–environment interactions	Pirotta et al. (2014)
Exploring emerging vulnerabilities in a coastal tourism setting	Tourism–environment interactions, destination management	Student et al. (2020b)
Individual visitors' multi-destination travel patterns and spill-over effect to other destinations	Visitor flow	Li et al. (2021)
Determinants of forest visitor spatial patterns	Visitor flow	Li et al. (2015)

2 Practical Demonstration

This section provides a step-by-step guide and presents some tools for applying ABM to tourism research as well as what to consider when communicating the agent-based model to others. In the **research case section**, an example of a tourism-focused agent-based model is described in detail. The basic steps, defining the model purpose, developing the model's conceptual set-up, writing the model description, determining model components, selecting the appropriate software, and analysing the mechanisms and outputs are discussed.

2.1 Defining the Model Purpose

First, it is important to check whether ABM is the right tool for the problem at hand. If there are sufficient aggregate variables or averages of the agents, then another modelling tool, such as systems dynamics modelling, may be more appropriate. Examples of such a case would include considering the number of arrivals as a function of adding or removing different flight routes from a destination. As mentioned in the introduction, ABM is a tool that helps deal with complexity, heterogeneity, nonlinearity, bottom-up and top-down emergence, and interactions between multiple (individual) agents and their environment. Moreover, in cases where studying the movement of people or entities in combination with decision-making is critical, ABM can provide more user-friendly ways of establishing movement rules for individuals as compared to mathematical equation-based modelling (e.g. Heppenstall et al., 2012; Macal & North, 2010). In addition, ABM can enrich GIS models when individual decision-making is important to consider.

Thus, to determine whether ABM is appropriate for researching the question at hand, the following questions can be used as a good starting point:

1. What is the question I am trying to answer with my model?
2. Does the model need to take individual agents, heterogeneity, and complex interactions into consideration?
3. Are mobility and the movement of people, information, or goods essential for answering the research question?
4. Are the desired outputs only at an aggregate level or are other types of outputs required (by type, at different moments in time, for parts of the system)?

2.2 Conceptual Model Set-up

If ABM is appropriate for answering the above-mentioned questions, then the modelling goal also needs to be taken into account:

1. Is the model based on empirical data and attempting to predict a specific output? Is it explorative with regard to a problem, a (theoretical) concept, or a situation?
2. What kind of output is needed to answer the modelling question?
3. What types of inputs are needed and for which of these is data available?

These questions help determine the level of precision required for the simulated agents, environment, and interactions. While exploratory and theory testing models may require little to no necessary empirical data, prediction models often require robust data for verification and validation.

2.3 Model Description

One good measure for conceptually and technically setting up the model is having a blueprint or model description. Although there are ongoing debates on which format is the most appropriate type of model description (Müller et al., 2014), one format that is often applied to agent-based models is the Overview, Design concepts and Details (ODD) protocol (Grimm et al., 2006, 2010, 2020). In an updated version, Müller et al. (2013) proposes the ODD + Decision-making protocol (ODD+D) to emphasise human decision-making. Either way, the ODD or ODD+D is a useful starting point to organise one's thoughts as the protocols help to clarify what the model's goal and mechanisms are. Moreover, a clear ODD (+D) increases model transparency, enables other researchers to reproduce the model, and is often required if the findings are submitted to a scientific journal.

2.4 Model Components

CoMSES OpenABM (see section **Further Readings & other Sources**) provides an extensive model library and is a great resource for education and research purposes and a platform to ask questions.

2.4.1 Agents

In relation to agents and their characteristics, some key questions to ask include:

1. Which tourism stakeholders will be included (e.g. tourism operators, tourists, airlines, etc.)? What level of heterogeneity is necessary (e.g. tourists with different spending power, operators offering different activities)? What types of other stakeholders are included (e.g. local communities, government bodies, the police)?
2. What kind of behaviours need to be included (e.g. the choice of location, decisions on whether to invest and what to invest in)?

3. What type of behavioural information is available? Which behaviour or decision rules need to draw upon theory, uncertainty (stochasticity), and/or assumptions? (Often times, some part of the decision-making needs a proxy based on theory, randomness, or assumptions).
4. Which characteristics are static and which are subject to change (e.g. an agent is a tourist throughout the simulation, but his/her preference of activity can change)?

2.4.2 Environment

Next, the tourism-relevant environmental features need to be defined.

1. What is the scale of the model (e.g. a venue, a destination, a country, a region)?
2. How is the environmental context characterised (e.g. geospatial type (such as coastline, beach, etc.) or location of attractions, the number of people a location can accommodate, pollution levels)?
3. What data is available?
4. What is the level of spatial specificity (e.g. abstract, reality-based, specified to a certain context)? If it is spatially explicit, are latitude and longitude values needed? (Refer to the section on **software** for literature and suggestions of possible software for GIS-specific simulations.)
5. What level of detail is necessary (e.g. how many characteristics are included, for instance, attractiveness, geospatial features, elevation, carrying capacity, pollution level, and so on)?
6. What types of heterogeneities are related to the questions that need answering (e.g. attractiveness, elevation, geospatial type)? Are the differences expressed in numerical values or in types?
7. Which characteristics of the spatial environment are static and which can change? What can influence these changes?

2.4.3 System-Level Variables

In addition to agents and the environmental variables specific to parts of the spatial setting, the model may have parameters that apply to the whole system. These global variables, as they are called, could include things like sea level, temperature, and exchange rates, and can be either static or dynamic.

1. Is the global variable static or dynamic?
2. If the variable is dynamic, what mechanisms influence the changes (i.e. are there external inputs or is it a result of emergence)?
3. Is there external data that initialises the global variable?
4. Is there data outside the model that is entered after initialisation? If so, how is the external data's timing determined?

2.4.4 Simulated Time

Time is an important consideration in ABM, and the modeller's question determines the total simulated time that they are interested in. The time step, sometimes referred to as ticks, is the smallest relevant time unit for model processes. The greater the difference between a time step and the total simulated time, the more time for interactions to occur. However, this also requires more processing power and leaves more room for errors. Therefore, the goal is to have the smallest *relevant* time unit, not the smallest possible time unit.

Another challenge is simulating interdependent events. In real life, complex interactions occur simultaneously in continuous real time, but, in a computer model, time steps are discrete and have to be explicitly determined (e.g. van Dam et al., 2013). This distinction requires careful attention when model scheduling in order to represent parallel processes, such as a group decision of whether to go on a sea turtle excursion. For tourism, the following points are relevant:

1. What is the total simulated time (e.g. xx days, xx months, xx years)?
2. What does each individual time step represent (e.g. a second, minute, day, week, months, years)?
3. Does the simulation run until a certain threshold has been reached (all visitors have been evacuated from the venue), or does it automatically end at a predetermined time?
4. How are the events ordered in a time step? Does an event occur in every time step?
5. What is the scheduling of events? Is there a specific order in which the interactions should occur? Which interactions need to be in parallel? Does the order in which an agent performs an action matter for the model outcomes? If so, does the order of the agent's actions follow a specific order, is it randomly determined, or determined by something else?

2.4.5 Interactions

Once an idea of who the key agents are and what environmental features need to be considered have been established, the mechanisms that determine how they interact and influence each other need to be developed. The ARDI (Actors, Resources, Dynamics, and Interactions) method is a series of questions that are useful for categorising the different states that the key agents and environmental features have, their potential actions, and the effects on the environment's and/or other agents' states (Étienne et al., 2011). An agent's or environment's state is the current condition of a particular variable. In the COVID-19 example from Fig. 1, a state would be whether an agent is infected or in quarantine. Categorising these system features in ARDI helps specify in what ways Agent "A" is connected to Agent "B", and how Agent "A"'s actions change Agent "B"'s state. For example, agents "A" and "B" have the variable "vacation satisfaction level"; Agent "A" buys the last ticket available for a tour, which prevents Agent "B" from joining. Since Agent "B" cannot join the excursion, the state of "B"'s vacation satisfaction level decreases. The following questions help specify interactions and provide context:

1. What are the direct interactions with other agents? With the environment? How do the interactions affect the state of agent and/or environment variables?
2. Are the agents mobile? If so, what conditions determine their movement?
3. In what ways does the spatial setting limit the extent of the interactions (actions localised, system-level)?
4. To what degree is randomness incorporated in the interactions?
5. Does the agent hold a memory of interactions? If so, is it perfect, does it deteriorate over time, or is it influenced by other factors? How does memory influence future interactions?

2.5 Software

Abar et al. (2017) provide a detailed overview of different software platforms for developing agent-based models, which include the following: information on the software's source code (e.g. *C++*, *Java*, *Python*, *Microsoft.net*), the coding language, the licence agreement (i.e. open, limited, or closed source), level of skill required, the visual interface, and typical types of model applications. The following questions can further help to determine the right software solution.

1. What level of experience does the researcher have with modelling?
2. What are the model's objectives?
3. What is the spatial and temporal scope needed to reach the model's objectives?
4. Is this specificity based on empirical data in relation to input data or the model's mechanisms?

Experience in (general) coding is a key determinant for which software is appropriate and whether external assistance in developing the model may be required. *NetLogo* programming software (Wilensky, 1999) is an entry-level open-source platform for model development and was used for the model described in the **research case section**. It is a relatively easy-to-use tool for those with limited coding experience and provides a graphical user interface, several modules, and code libraries.

In addition to modelling experience, which platform to select also depends on the type of research question and the kind of inputs and outputs needed. While *NetLogo* may be useful in many tourism-related studies, its scalability and ability to handle complex input files is limited compared to other software platforms. For example, if extensive GIS is required, another software tool such as *REPAST* or modelling space in *ArcGIS* may be more suitable.

Model development and analysis do not necessarily need to be performed using the same software. One platform might be needed to develop a model and another platform to perform the analysis of the outputs, as was the case for the tourism example presented in the next section. *NetLogo's* built-in analysis tool called *BehaviorSpace* has limited capabilities for sophisticated analysis of complex models. Therefore, the model presented in the next section was exploratory and developed in *NetLogo,* but the analysis itself was conducted in *Java* and *Python* using *PyNetLogo and the Exploratory Modelling and Analysis (EMA) Workbench. These analysis tools can perform many types of analyses and generate a variety of visualisations including interactive plots and multiplot graphs. NetLogo* can be integrated with *Java* and *Python* analyses.

2.6 Analysis

After defining the model's purpose, designing the conceptual model, and determining model components, modellers need to consider how they will verify or test if the code is doing what it is intended to (van Dam et al., 2013). Model processes need to be evaluated to check the extent to which the developed model can answer the modeller's question. Many analysis formats exist to address the various ABM process and output types (e.g. Hahn, 2013; Heppenstall et al., 2012; Herman & Usher, 2017; Kwakkel & Pruyt, 2013; Ligmann-Zielinska et al., 2020; Ngo & See, 2012; ten Broeke et al., 2016; Troitzsch, 2014; van Dam et al., 2013). Therefore, it is important to first consider what input types are needed and what output(s) is expected. Ideally, both the model process and outputs should be evaluated. However, due to the complexity involved, some processes cannot be validated with real-world behaviour and the modeller needs to determine whether or not the processes and/or results are plausible and convincing (Heppenstall et al., 2012; van Dam et al., 2013). As ABM often explores the uncertainty level of how interactions lead to observed outputs, sensitivity analysis (SA) is a popular analysis approach for both validating model processes and outputs. This section gives a short overview of considerations to take into account when verifying, validating, and analysing model processes and findings. For more details on specific considerations for various types of analysis, please refer to the references in the subsequent sections.

2.6.1 Verification

Verification is the process of testing the model logic to check that the model is doing what it is supposed to (Heppenstall et al., 2012). Yet, calibration is challenging in the ABM context due to a lack of empirical data to compare findings, and, in addition, it involves identifying the range of input values that are appropriate for the model's mechanisms (Ngo & See, 2012). Although ABM helps to explore complex systems, a more detailed model is more prone to technical errors and more computing power is required to analyse the data. Moreover, the random number generators used to integrate randomness into interactions makes every model run unique (Abdou et al., 2012). As a result, verification looks at anticipated result ranges instead of exact outcomes and requires more runs to test model behaviour. Hence, it is advisable to take a layering approach and to test out different mechanisms separately before adding them to the main model. In this way, it is easier to troubleshoot and to ensure that each mechanism is performing as it should. For example, in the turtle-feeding case from Figs. 2 and 3, the movement of pollution mechanism could first be developed autonomously to observe whether it moves according to the expected patterns.

2.6.2 Validation

Validating ABM is an ongoing challenge and the subject of ongoing debates regarding what it is and what it should show (Hahn, 2013; Heppenstall et al., 2012; Heppenstall & Crooks, 2019). While verification tests model logic, validation is applied to check whether the design fulfils its purpose (van Dam et al., 2013). In other words, validation ensures that a model is actually representing what it has originally been set out to represent (Hahn, 2013). There are many forms of validation, with some examples being empirical validation, statistical validation, conceptual validation, process validation, and output validation (Ngo & See, 2012). As such, validation of agent-based models requires validating agent behaviours and emergent phenomena in addition to system-level model outcomes (Hahn, 2013). When available, model processes and outcomes can be compared with empirical data; alternatively, model outputs can be validated through consultation with experts, simulating past events where data is available, literature validation, and/or by comparing outcomes with another model applying a different modelling technique (such as systems dynamics modelling) (van Dam et al., 2013).

SA evaluates the influence of one or more inputs on specified model outputs and indicates the strength of this link (Ligmann-Zielinska et al., 2020). Furthermore, it can be local or global: local SA focuses on the effects of small changes to one or a few inputs, while global SA explores changes to all inputs within a specified parameter (input space) and can look at variability derived from single inputs or interactions among inputs (Ligmann-Zielinska et al., 2020; Saltelli et al., 2008; Saltelli et al., 2004). ten Broeke et al. (2016) describe three types of sensitivity analysis in the context of ABM and the considerations for selection: one-factor-at-a-time, model-free output variance decomposition, and model-based output variance decomposition. Ligmann-Zielinska et al. (2020) further advise reflecting on the model's purpose in order to choose the appropriate sensitivity analysis and recommend global SA whenever possible. SALib (sensitivity analysis library), for instance, is a Python-based tool, which provides multiple types of global sensitivity analysis (Herman & Usher, 2017).

2.6.3 Analysing Findings

Findings analysis depends on the outputs of interest. The outputs could be agent or system-level change, patterns of movement, processes, value of outputs at the end of the simulated time, the changes to output values over time, the amount of time to reach a particular outcome, or the system or agents' characteristics when a defined equilibrium has been reached (see Heppenstall et al., 2012; van Dam et al., 2013). Statistical analysis can evaluate model findings, to which Troitzsch (2014) provides guidelines for appropriate conditions to apply such statistical analyses. Moreover, SA is a statistical analysis to explore emerging model behaviours and guide decision-making (Kwakkel & Pruyt, 2013; Student et al., 2020b; van Dam et al., 2013).

In many forms of sensitivity analysis, the inputs are defined and their influence on the various outputs is observed (see the validation subsection for more details). However, for scenario discovery, the opposite is done. Scenario discovery is a form of analysis similar to backcasting, where a threshold for one or more outputs is defined and the inputs are observed (Kwakkel & Pruyt, 2013; Steinmann et al., 2020). The threshold can be defined by modellers or decision-makers and indicates a situation that one either wants to attain or avoid. The analysis then determines which input variable combinations in which range have the most influence on exceeding this threshold. In this case, the *EMA Workbench* is a Python-based open-source toolbox used for scenario discovery analysis and other exploratory analyses (Kwakkel & Pruyt, 2013). Referring back to the transmission of the COVID-19 example depicted in Fig. 1, the threshold could be that less than 20% of the population becomes infected. The analysis could show that mask-wearing and social distancing are the most influential inputs for attaining the defined goal, when more than 65% of the simulated individuals wear masks and a social distance of 1.5 metres is maintained, or that other inputs are more influential for reaching the desired infection percentage of less than 20%. Defining the outputs instead of the inputs makes scenario discovery useful for decision-support under conditions of extreme uncertainty (Lempert, 2019). The decision-making goals are predefined, and the analysis reveals the factors that should be placed under focus in order to prevent an undesirable situation or attain the goal, rather than investing in factors that have little influence on the desired outcome (Kwakkel & Pruyt, 2013).

3 Research Case

This section provides a walkthrough of an agent-based model developed for the tourism domain. The agent-based model "*Coasting*" was developed as part of a dynamic vulnerability approach (Student et al., 2020) with the aim of assessing emerging socio-economic and ecological vulnerabilities in relation to climate change. *Coasting*, as the name implies, simulates a coastal tourism destination

Fig. 4 Visual description of main agents (tourism operators), environmental features, and interaction characteristics. Author image published in Student et al. (2020b)

context and is applied to the destination Curaçao (Student et al., 2020b). The image in Fig. 4 depicts some of the main agents, environment, and interactions featured in this model.

This model was first developed as a serious game with stakeholders (see Student et al., 2020), and parameters were determined based on literature and empirical insights from simulation game sessions with tourism stakeholders. Wherever information was unavailable, randomness was introduced and/or a large parameter range was explored to account for some of the uncertainty.

The actual model has many components, as can be observed in Table 2. Figure 5 depicts the interface at the set-up of a simulation run using *NetLogo* software. The model's description, which follows the ODD+D protocol format, is available in Student et al. (2020a). It includes details of the model design and mechanisms as well as the tools used for the analysis. The research question for this case was "*what are the main (interacting) factors leading to socio-economic and/or ecological vulnerabilities?"* The main output indicators of socio-economic vulnerability were tourism operators going bankrupt, as this indicated that their capacity to deal with changing economic and environmental factors was too great. Furthermore, the main system-level ecological indicator of vulnerability was the aggregated environmental attractiveness of three different parts of the coastal system. These three parts were the land-based area (where hotels and beach operators were based), the coastal area (the spaces directly bordering the distinction between water and land, depicted in light yellow and light blue, in Fig. 5), and the nearshore waters (where diving and boating activities took place). Pollution, biodiversity, and environmental degradation levels were the main dynamic characteristics of each spatial unit that contributed to each spot's attractiveness and that could change over time.

Table 2 "Coasting" model components

Modelling goal	Exploratory	Understanding emerging socio-ecological vulnerabilities in a coastal tourism setting.
Software	Model development:	NetLogo
	Analysis: Global sensitivity analysis Scenario discovery	Java, Python, SALib PyNetLogo, Exploratory Modelling and Analysis (EMA) Workbench
Agents	Coastal tourism operators	*Five operator types*: hoteliers, beach vendors (e.g. cafes and beach activities), nearshore operators (e.g. surfing, jet ski and kayak businesses), day excursion boat operators, and dive operators. *Example of characteristics:* location selection and preference, resources. *Heterogeneities:* inputs necessary for business, location preferences. *Static variable example:* operator type, whether mobile (yes, no). *Dynamic variable example*: level of resources, links with other operators, location if water-based operator.
	Marine life and coastal resources	*Four types*: sea turtles, coral reef, reef fish, and mangroves. *Heterogeneities:* location preference. *Static variable example:* operator type, whether mobile (yes, no), sea turtle yes, mangroves no. *Dynamic variable example*: health level.
Environment	Key features simulated represent a simple depiction of a coastal area in Curaçao	*Static variable examples:* geospatial characteristics (e.g. inshore, beach*, coastal waters, nearshore waters, deep sea). *static except in the case of sea-level rise *Dynamic variables:* attractiveness of each part of the location, elevation, pollution level, environmental degradation level.
Inputs	Example of some of the input	*Decision-influencing inputs:* resources gained, income penalty for not doing maintenance, positive association with others if collaboration goes through. *Environmental change inputs:* rate and height of sea-level rise, probability, impact, and duration of sudden event affecting a part of the spatial setting, costs of addressing impacts of either pollution, sea-level rise, or environmental degradation through a sudden event.
Outputs	Vulnerability indicators focus on a proxy indicating ecological and socio-economic vulnerabilities	*Ecological vulnerabilities*: environmental attractiveness of beach, coastal, nearshore waters, and destination. *Socio-economic vulnerabilities:* number of operators bankrupt throughout the

(continued)

Table 2 (continued)

Modelling goal	Exploratory	Understanding emerging socio-ecological vulnerabilities in a coastal tourism setting.
		scenario; this was aggregated as well as investigated for each operator type.
Analysis	Global sensitivity analysis Time analysis & scenario analysis	Completed at the end of the 30 years of simulated time. All time steps for ecological and socio-economic vulnerability indicators.
Special considerations	Model design	Designed to enable adaptation to other coastal tourism settings and add other environmental challenges.
	Data	Data collected at multiple time steps instead of only the final step.

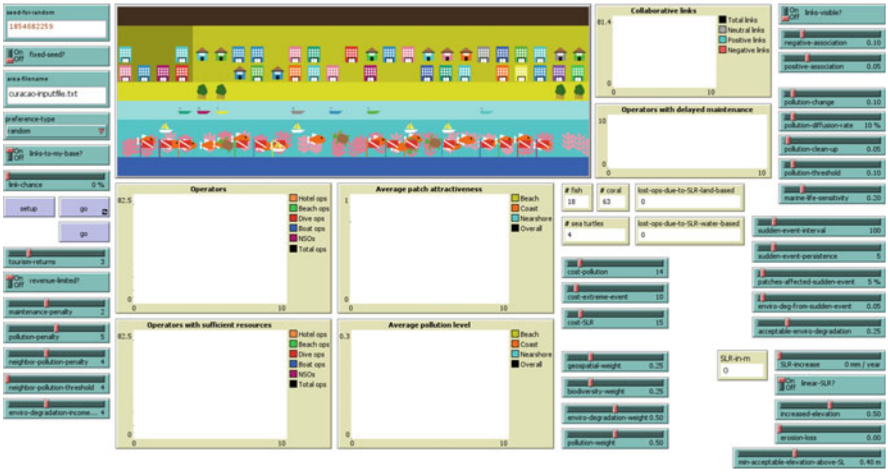

Fig. 5 Interface of "Coasting" simulation model set-up in NetLogo software

3.1 *Contribution of Method*

The *Coasting* game was developed first by applying the ARDI (Actors, Resources, Dynamics, and Interactions) method in order to generate a game that could be translated into a model (Étienne et al., 2011; Student et al., 2020).

3.2 *Analysis*

In this study, the goal was to look at how multiple human–environment interactions at a coastal tourism destination lead to vulnerability outputs. Specifically, the model

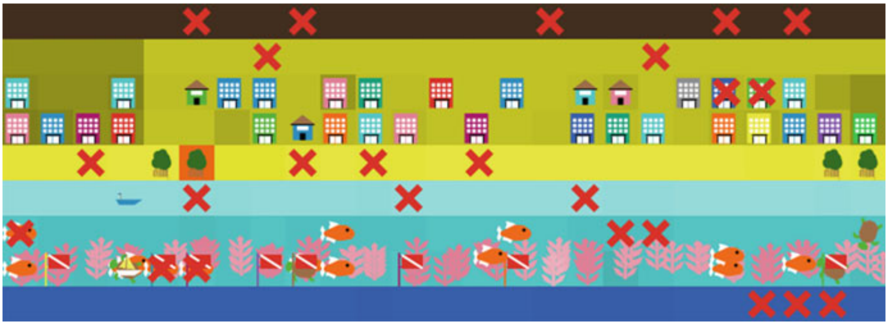

Fig. 6 View of "Coasting" simulation with areas affected by sudden events (red crosses), pollution (squares in a relatively darker shade), and land that has been artificially raised to mitigate sea-level rise (red square)

looked at the number of actions to address environmental challenges (individual and collaborative), socio-economic vulnerabilities (bankruptcy), and ecological vulnerabilities (decreased environmental attractiveness). This study was explorative and looked at a wide combination of inputs using global SA and scenario discovery so as to assess the different number of inputs across different ranges of interaction and see the cumulative effects these inputs have on socio-economic and ecological vulnerabilities. As such, this analysis diverged from other tourism-related agent-based models.

Figure 6 shows a simulation run of a scenario with conditions of sea-level rise and sudden events. The global SA looked at first order (direct sensitivity), second order (sensitivity resulting from two interacting variables) and total sensitivity for number of actions, number of operators that stay in business, and the level of environmental attractiveness. Moreover, scenario discovery was used to identify interacting parameters that led to undesirable vulnerabilities of business loss (a proxy for socio-economic vulnerability) and environmental attractiveness (a proxy for ecological vulnerability). The results indicated that the ratio of input to revenues and how much tourism contributed to pollution were the most influential factors in socio-economic and ecological vulnerability scenarios.

Service Section

Main Application Fields: ABM is applied to many scientific fields with main applications taking place in ecology, the social sciences, land use planning, and transport logistics. In the context of tourism, climate change (human-environment interactions), visitor flow, disaster planning, and tourist/operator decision-making support are the main types of application to date.

(continued)

Pros: The basic concepts of ABM, agents, a spatial setting, and interactions are easy to grasp. This form of modelling incorporates complexity, interactions, heterogeneity, nonlinear feedback, and uncertainty. Moreover, ABM can include movement of individual agents, which is of interest in many tourism-related studies.

Limitations and Pitfalls: There are several limitations to ABM. Although the basic ideas thereof are easy, modelling human decisions and other processes can be quite complicated and conceptually deep. Complex models can mask processing and input errors as well as require extensive processing power to analysis. Moreover, ABM's predictive ability is disputed and difficult to verify and validate because of the dearth of empirical data to verify and validate model processes and outputs.

Similar Methods and Methods to Combine with: ABM can be combined with many modelling approaches and analysis types. For instance, GIS is a common addition in cases where specified spatial details are important. On the other hand, systems dynamics modelling is a top-down approach to modelling the system, and ABM and systems dynamics models can be used on the same research questions to compare results. Artificial intelligence could also be applied to help provide richness and depth to simulating behaviours. Lastly, big data can be used in ABM to provide input parameters, improve predictive capabilities, and for verification and validation of model processes and results.

Code: The NetLogo Model for the Coasting Model (Student et al., 2020a) is accessible at: https://github.com/DataScience-in-Tourism/Chapter-23-Agent-based-Modeling

Acknowledgements Thanks to Emily Liang, creative science communicator at Wageningen University & Research's Environmental Policy Group, for designing Figs. 1, 2, and 3.

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