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Towards thresholds of disaster management performance under demographic change: exploring functional relationships using agent-based modeling

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Abstract. Effective disaster management is a core feature for the protection of communities against natural disasters such as floods. Disaster management organizations (DMOs) are expected to contribute to ensuring this protection. However, what happens when their resources to cope with a flood are at stake or the intensity and frequency of the event exceeds their capacities? Many cities in the Free State of Saxony, Germany, were strongly hit by several floods in the last years and are additionally challenged by demographic change, with an ageing society and out-migration leading to population shrinkage in many parts of Saxony. Disaster management, which is mostly volunteer-based in Germany, is particularly affected by this change, leading to a loss of members. We propose an agent-based simulation model that acts as a "virtual lab" to explore the impact of various changes on disaster management performance. Using different scenarios we examine the impact of changes in personal resources of DMOs, their access to operation relevant information, flood characteristics as well as differences between geographic regions. A loss of DMOs and associated manpower caused by demographic change has the most profound impact on the performance. Especially in rural, upstream regions population decline in combination with very short lead times can put disaster management performance at risk.

1 Introduction

When floods hit a community, disaster management and emergency services have to act as quickly and effectively as possible to safeguard people and property. However, effective disaster management depends on several conditions, e.g., the availability of resources for protection, the number of helpers and their skills, the existence of plans for emergency and evacuation (Kirschenbaum, 2002) and the effectiveness of communication and coordination (Comfort et al., 2004; O'Sullivan et al., 2012; Kreibich et al., 2016). Another crucial aspect is time: if lead time (i.e., time between warning of an imminent flood and its occurrence; Werner et al., 2005) is too short or the time needed to put all necessary measures into place – the coping time (i.e., effective response time) – is too long, disaster management might be unable to provide the necessary support and protection. Although disaster management has developed practical and well-tested routines over many years of service, these routines might come under pressure under changing context conditions such as increasing flood intensities, limited resources or changes in organizational structures (Kuhlicke et al., 2013). Worldwide disaster statistics show a strong increase in extreme events. Especially, weather-related events such as floods, storms and droughts have been occurring more frequently in the last decades (IPCC, 2012; Schuster, 2013). Likewise, an increase in disaster-related losses has been observed. However, the causes for this increase are controversially discussed. Many studies show that anthropogenic changes are main drivers for

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an increase in disaster losses (Barredo, 2007, 2009; Bouwer, 2011), especially due to increases in exposure caused, for example, by a rising number of properties in flood-prone areas (Fuchs et al., 2015; Jongman et al., 2014). In just 11 years the Free State of Saxony, Germany, has experienced three extreme flood events (2002, 2010 and 2013), of which two (2002, 2013) have exceeded the statistical return rate of 1 in 100 years and caused damages of several billion Euros (Mechler and Weichselgartner, 2003; DKKV, 2015, p. 32). Besides this, a large proportion of the flood-prone area in this region is currently undergoing major demographic transitions with an ageing society, out-migration and low birth rates leading to significant population shrinkage (BBSR, 2014). This shrinkage comes along with an economic decline, cutbacks in municipal finances, demolition of houses and loss of urban functions, e.g., in the area of infrastructure. However, this shrinkage does not take place uniformly: as Schulz (2012) is able to show in her case study on the Free State of Saxony, there is hardly any correlation between shrinkage and the demolition of the built environment, which often takes place in outer districts, and the reduction of exposure to flood risk on the other hand side. Additionally, Kuhlicke et al. (2012) show that for those shrinking cities we can observe a decline in adaptive and coping capacity, as the provision of essential public and private services (e.g., flood protection) is not possible anymore due to budget constraints. Therefore, in most cases shrinkage leads to no significant reduction of the communities' vulnerability to floods. This also affects disaster management as, on the one hand, disaster management organizations (DMOs) are more often confronted with extreme events and need to provide higher degrees of support and protection. On the other hand, they need to fulfil their services with shrinking resources, not only in monetary terms but especially in terms of manpower (Steinführer et al., 2014). Disaster management in Germany is largely on an organized but still voluntary basis (*Ehrenamt*) and is especially affected by a loss of members. This trend is strongest in the East German federal states, where, for example, voluntary fire brigades (*Freiwillige Feuerwehr*) have suffered a decline in numbers of active members of about 20 000 (9 %) between 1997 and 2007 (Albrecht et al., 2010). Additionally, the functioning of DMOs might be negatively affected by changes in the employment situation of their members: even if in theory the operational units are still fully equipped, the actual operational readiness is often impeded by larger distances between workplace and hometown and a lower willingness of employers to grant their employees a release from their work (Metzmann, 2006). This can lead to understaffing of DMO units during a disaster event.

This study addresses the effect of the mentioned processes of change on disaster management performance, using two regions in Saxony as exemplary study sites. Although we selected the Free State of Saxony as an example region for our study, the just stated developments apply to other regions in Germany as well. Moreover, this region is very heterogeneous, so not every part is affected in the same magnitude of change. We will therefore also address the question of how disaster management performance is affected, depending on the local settings. To make this more explicit, we characterize each case site along two dimensions that affect the strength of impact of the floods on a community, namely the geographic (including hydrologic) and demographic settings.

Analyzing how change in a single aspect affects the functioning of DMOs might be possible with a pen and paper exercise. However, when changes occur in parallel and in different intensity, their combined effects are not as easily foreseeable anymore. We therefore develop and apply a simulation model to determine the impact of change on the performance of disaster management and estimate which conditions can lead to performance thresholds that put community protection at risk – for example, under which circumstances a certain lead time threshold might not be reached anymore.

Several modeling studies exist that address natural hazards and their influence on community functioning, ranging from pre-disaster to post-disaster assessments. The complexity of these models ranges from more simple or conceptual models to very complex models that are often used for prediction purposes. Models like the Life Safety Model (Lumbroso and Tagg, 2011) or MASSVAC (Hobeika and Jamei, 1985), for example, aim at predicting exact evacuation times for a specific disaster event or the expected loss of life. Dawson et al. (2011) developed a very detailed model of flood incident management to determine the risk of people being flooded under different hydrological and defense conditions and evacuation strategies. However, to achieve a good predictive power, these models require accurate input data. Other models are more conceptual or address specific issues of disaster management like information sharing between emergency personnel (Zagorecki et al., 2010) and the reliability of information in disaster relief operations (Kostoulas et al., 2008) post-disaster recovery (Nejat and Damnjanovic, 2012), with focus on housing recovery and how it relates to homeowners' decision making or to the recovery of critical services and community capital over time (Miles and Chang, 2006, 2011).

The model presented in this paper is not intended as a quantitative prediction tool but rather as an explorative tool in a "what if" manner, comparable to a flight simulator that is used to evaluate the performance and capacity of reaction of a pilot, both under normal and altered or extreme conditions, without putting pilots or passengers at risk. Likewise, disaster management organizations and other emergency services cannot exercise extreme events in real life; they can only plan for certain expectations (e.g., flood magnitude, resources needed) and develop action strategies in accordance with these expectations. When conditions change and these expectations fall short, the functioning of the organizations might not be guaranteed anymore. Our "flight simulator" approach is to develop a rather simple, stylized "virtual lab" (Seppelt et al., 2009) that allows us to quickly implement new ideas and test hypotheses to obtain a better mechanistic understanding of the system behavior. We therefore use a spatially explicit, agent-based modeling approach, as it allows us to incorporate, explicitly, the micro-level decision making of actors and observe their joint emergent behavior on a macro or system level (Holland, 1992) in their respective geographic context. Thus, agent-based models (ABMs) are suited to model the behavior of individual actors such as disaster management units that act independently to solve a common goal, i.e., protecting a community.

We apply the model to two exemplary case sites in Saxony – Leipzig, as an example for an urban area, and the Neisse region, representing a more rural region – and try to answer the following questions:

1. Which dimension of change has the most profound influence on the performance of disaster management?

2. Can we identify bottlenecks or critical thresholds for the capacities of disaster management to ensure protection?

3. How do these thresholds depend on the regional geographic and demographic setting?

2 Methods

In this section, we will first describe the model structure, i.e., entities, processes, model rules and data used. Second, we explain how we measure performance of disaster management in the model. We then present a characterization of the geographic and demographic settings. The section ends with a description of the scenarios that we used to demonstrate the functionality and robustness of the model.

2.1 Description of the agent-based model

The description of the model loosely follows the ODD+D protocol structure (Müller et al., 2013). A complete model description can be found in the supplemental material (Supplement A), which also includes technical implementation details and model assumptions (Supplement B).

2.1.1 Overview

Purpose

The purpose of the model is to analyze the performance of disaster management and understand how it is affected by change (e.g., demographic, climatic or technological). The model is designed for both scientists and stakeholders, as an exploratory tool to understand the functioning of disaster management under change and as a discussion tool to illustrate these results to experts, address possible shortcomings and highlight options for improvement.

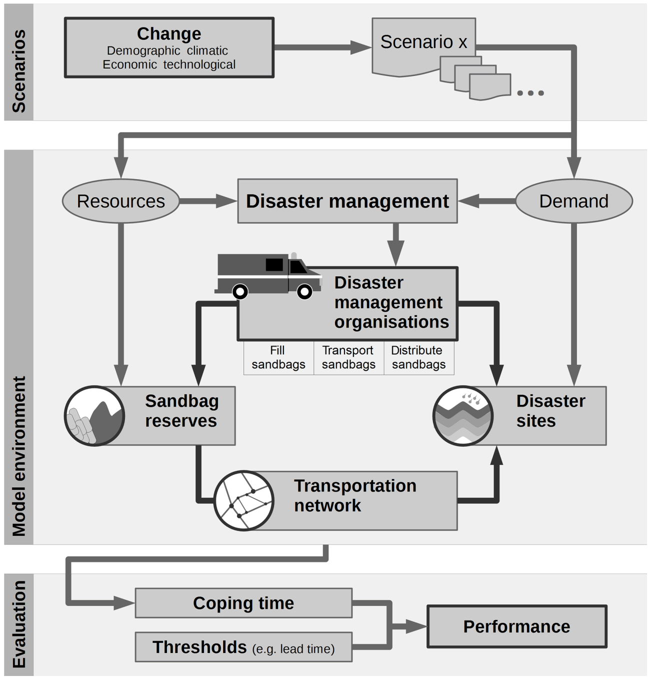

Figure 1. Conceptual diagram of the model. The model environment shows the entities and their relationships that are simulated in the model. The influence of change is incorporated via scenarios that allow us to change resources (e.g., available DMO units), demand (e.g., required amount of protection) and other boundary conditions. The performance of disaster management for each scenario is subsequently evaluated with respect to critical time thresholds (e.g., lead time).

Entities, state variables and scales

There are three main entities in the model: DMOs, disaster sites and sandbag reserves. We have selected the case of sandbag logistics as an exemplary task that is conceptually simple, yet crucial for the flood protection of a community. DMO agents represent a group of members or distinct units of a disaster management organization that can work independently and autonomously to perform certain tasks that are assigned to them. Each agent is characterized by certain properties, e.g., group size, and is associated with a transportation vehicle that is characterized by a given sandbag transportation capacity (ranging from small trucks to lowloaders). Disaster sites and sandbag reserves are stationary entities with which DMO agents interact, e.g., via filling and distributing sandbags. Space is explicitly included, the spatial setting of rivers, flood-prone areas and the street network are based on GIS data. Time is modeled in discrete intervals with one unit (tick) representing 1 min. There is no fixed time horizon; a model run stops after all tasks are finished. A conceptual diagram of the model is shown in Fig. 1.

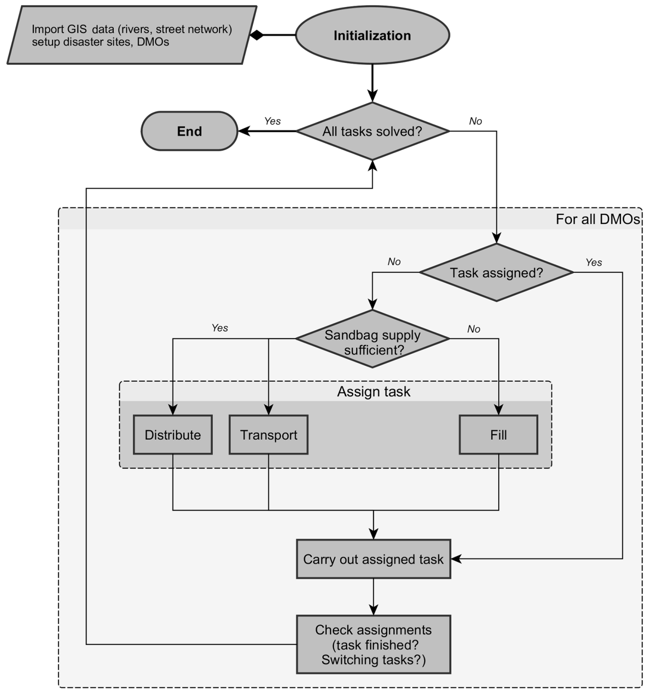

Figure 2. Model flow chart showing the general temporal sequence of processes. Processes in the dashed box are carried out in each time step for each DMO (disaster management organization) agent.

Process overview and scheduling

At the beginning of each simulation, each DMO agent is assigned a task. In the current model version, it is either to fill sandbags, transport sandbags or distribute sandbags. DMO agents will identify their nearest target site, which can either be a disaster site or a sandbag reserve (using the A* search algorithm; Hart et al., 1968; Goldberg and Werneck, 2005), move there and perform the required tasks. Agents can switch between tasks when necessary, for example, when more helpers are needed for either filling or distributing sandbags. The simulation stops when the required number of sandbags is present and distributed at all disaster sites. A flow chart of the general sequence of model processes is displayed in Fig. 2.

2.1.2 Design concepts

The model has been developed in order to depict the case of flood protection and disaster management in Saxony. DMO agents have to make decisions about which disaster site should be handled in which order, based on their information access. Agents can switch between tasks, either when they completed their current subtask or when more helpers are needed for a different task. DMO agents have full knowledge about the spatial settings of the model. This means they know the location of all target sites (disasters and sandbags reserves). However, each DMO agent has a certain level of information access about the state of each site: full knowledge indicates that they have complete knowledge about the state of all disaster sites at all times, i.e., how many sandbags are needed at which site and when tasks at a certain site or all sites are completed. The second level, partial knowledge, implies that they can only acquire their knowledge through direct contact, i.e., when they are at a site; after having acquired knowledge, agents remember it from then onwards. Direct interaction between agents does not take place in the current model version. However, agents interact indirectly in several ways: they are aware of where resources are needed and where not; e.g., they know if a disaster site is successfully protected. In regards to heterogeneity, currently, within any single simulation, all DMO agents are homogeneous in their properties. Disaster sites are randomly distributed at the beginning of each simulation. The order in which DMO agents act in each time step is determined randomly by the Netlogo "ask" command. For each simulation, the time needed to fulfil all tasks – the coping time – is measured as the main indicator of performance. When the model is run interactively (using the graphical interface), several variables can be monitored during a simulation run, e.g., the current distribution of tasks onto the DMO agents or the degree to which tasks are fulfilled.

2.1.3 Details

Implementation details: the model is implemented in NetLogo. A screenshot of the model interface with a sample simulation run is shown in Fig. 3.

Flood characteristics and sandbag demand

The model only includes the location of rivers and flood-prone areas but does not employ a hydrologic model to simulate flood flow through the river. We translate flood intensity implicitly into a number of disaster sites and a total demand of sandbags that need to be distributed. Based on this total demand (e.g., 100 000 sandbags), the number of sandbags needed at each disaster site is calculated.

DMO movement and decision making

DMO agents have to decide (a) which task and (b) which target site to choose. In reality, DMOs rarely have the time to derive an optimal decision; they mostly rely on certain routines and past experiences (Kuhlicke 2010). In our model, DMO agents therefore employ simple heuristics in their decision making, based on their level of information access (partial or full knowledge) and their available resources (e.g., whether sandbag supply is sufficient or not). An example for a heuristic used by DMO agents is as follows: if sandbags are loaded onto the transport vehicle, locate the nearest target site X and calculate the route there. Then, move to the target site X. Finally, unload all sandbags and distribute sandbags.

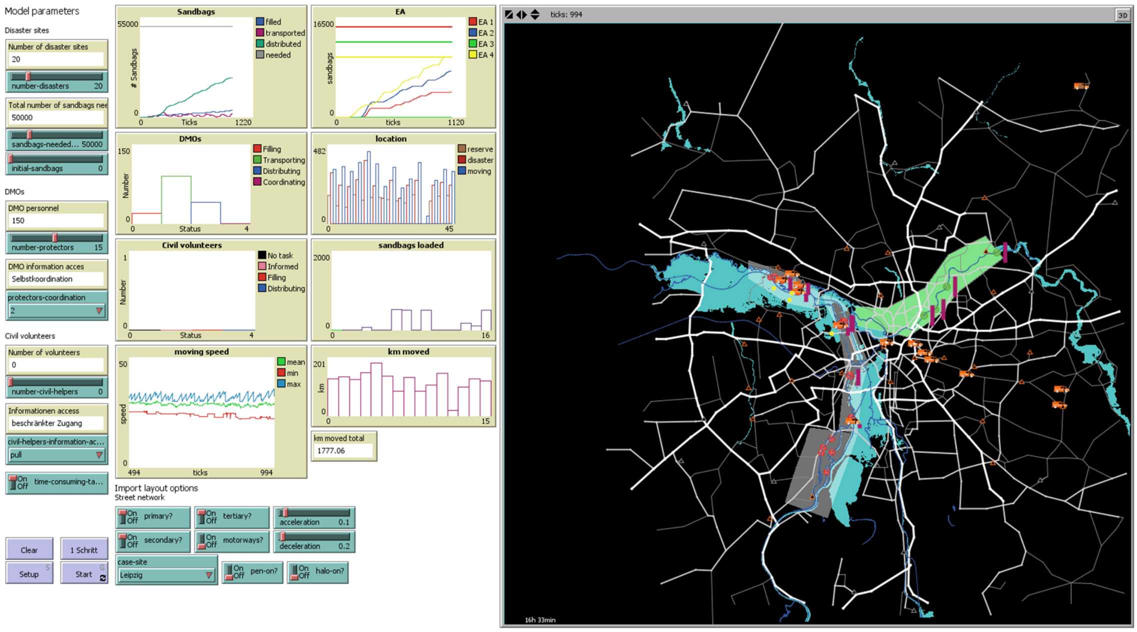

Figure 3. Screenshot of the NetLogo model interface. The map shows a snapshot of a running simulation, with DMO agents moving along the street network and disaster sites in various states of protection. The green shaded area depicts a river section that is already protected whereas in the grey shaded areas sandbags are still needed at various sites.

If all tasks at site X are completed, mark site as finished; otherwise, remember the current state of the site.

The times needed for certain tasks, e.g., the filling or distribution of sandbags, is calculated based on estimates that serve as a calculation basis in disaster management. For example, one helper can fill about 80 sandbags h^{-1} (taken from *Taschenkarte Deichverteidigung*, THW, 2007). Likewise, estimates for traveling speeds of transport vehicles (minimum, maximum and average speed) are included in the model (a detailed table is available in the Supplement). DMO agents can move along the transportation network to their target sites. Here, the model uses the A* search algorithm (Hart et al., 1968; Goldberg and Werneck, 2005) to determine the shortest paths to target sites within the spatial environment of the model. The algorithm is an extension of the popular Dijkstra search algorithm (Dijkstra, 1959) but is significantly faster.

Initialization and input data: currently, there are two study sites implemented in the model, the city of Leipzig and the Neisse region. For both areas, spatial data for rivers, flood-prone areas and the street network are imported from pre-processed GIS data layers. River and street network data are pulled from OpenStreetMap (Geofabrik, 2014), including road categories and associated speed limits. Flood-prone areas are extracted from data of the Saxony State Office for Environment, Agriculture and Geology (Landesamt für Umwelt, Landwirtschaft und Geologie, LfULG, 2012). All data are initially simplified in ArcGIS to reduce complexity (e.g., reducing the number of nodes or approximating arcs with straight lines).

2.2 Measuring performance

The functioning and performance of disaster management, i.e., the provision of protection against the negative impacts of a flood, is a central part of making a community resilient, i.e., able to cope with a flood event and maintain its functioning (IPCC, 2014). To measure the performance of the disaster management and its capacity to cope with a single disaster event, we use the coping time t_{cope}. During a disaster operation, the degree to which protection measures are realized increases (Fig. 4a, black line) until all measures are put into place. We define this time span as the coping time t_{cope} (Fig. 4a, bold light grey line). Only if this time is below a certain threshold (in most cases the flood lead time t_{lead}, see Fig. 4a, bold dark grey line) is the communities' protection guaranteed. Depending on the available resources, the coping time t_{cope} can change, reflecting an increase or decrease in coping capacity. Additionally, the demand posed onto the organizations, e.g., in terms of the intensity of the flood, can change too. If available resources decrease and demand increases, it is less likely that coping time stays below a given threshold. For every scenario of change (detailed in Sect. 2.4) we can measure coping time t_{cope} and evaluate it with respect to the lead time t_{lead} (or other critical time) threshold. A lower coping capacity leads to a slower realization of protection measures, represented by a slower rise of the protec-

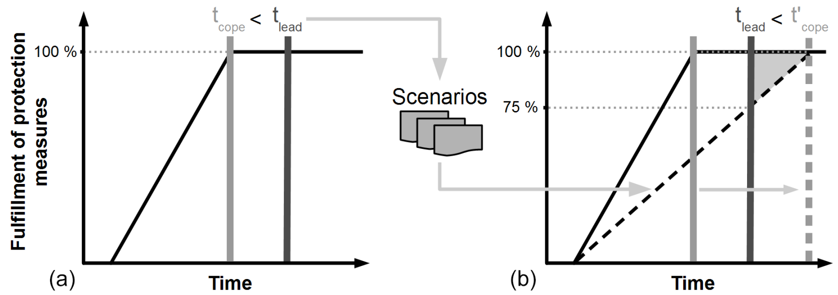

Figure 4. Measuring the performance of disaster management. Coping time t_{cope} refers to the time needed to put all protection measures into place (light grey lines). Whether coping time is above or below the lead time threshold t_{lead} (dark grey lines) determines whether community protection can be ensured or not. The black lines present the degree of fulfilment of protection measures.

Table 1. Characterization of geographic and demographic settings and comparison across the two study sites.

	Setting	Characteristics	Urban area Leipzig	Rural region Neisse
Geographic	Topography	Mountainous/hilly or flat land/lowland Elevation	Lowland	Lowland
	River location	Upstream/downstream	Downstream	Downstream
	Flood setting	Flash floods or plain floods Duration	Plain floods Usually long duration (up to several days)	Plain floods (flash floods from smaller tributaries) Usually long duration (up to several days)
Demographic	Size	Town size Number of inhabitants	Large city > 500 000	Small towns < 5000
	Population growth rate	Growing/shrinking	Significantly growing	Shrinking
	Migration	In- and out-migration trends	Influx of young people	Departure of young people, leading to an ageing society

tion measure fulfilment curve (Fig. 4b, black dashed line). If the coping time t_{cope} exceeds the lead time threshold t_{lead} (Fig. 4b, bold light grey dashed line), the community might be at risk as realized protection measures are below 100 % when t_{lead} is reached. Therefore, coping time t_{cope} reflects a measure of resistance with regard to a concrete flood event. In our analysis, we measure coping time t_{cope} in each simulation, where one simulation represents the realization of one disaster event based on the boundary conditions and resource and demand settings of the current scenario. If we consider disaster management as a social–ecological system by itself that is subject to change (demographic, climatic, technological), we can adopt a resilience perspective and analyze under which conditions the capacity of DMOs to cope with flood events (i.e., to have a coping time below a given threshold) can still be ensured. However, as in the definition given by the IPCC (2014), resilience comprises not only the "capacity [. . .] to cope with a hazardous event or trend [. . .], responding or reorganizing in ways that maintain their essential function" but also includes "the capacity for adaptation, learning and transformation" (IPCC, 2014, Annex II, p. 1772). Thus, in our analysis we also focus on steps of adaptation or reorganization that can improve coping time and might be necessary to maintain the functioning of DMOs.

2.3 Characterization of the geographic and demographic settings

The selected study region, the Free State of Saxony, is very heterogeneous in both its geographic (including hydrologic) and demographic situation. Therefore, the impact of change can be different, depending on the specific local settings of the community of interest. This in turn can have different effects on disaster management performance.

The geographic location of a community has strong implications for the occurrence of the flood – e.g., its lead time and the associated resources needed for flood protection. In the upper reaches, flash floods are more prominent occurring with relatively short lead times and high force and velocity, whereas downstream plain floods are more prominent often associated with longer lead time, lower low velocity, but much longer duration.

The population size and its growth or shrinking rate are indicators for the availability of manpower for disaster management. In small towns or rural areas, the number of helpers that are deployable is usually lower than in urban areas. Additionally, rural areas are often affected by both population decline and ageing, whereas opposite trends can be observed in urban regions.

To account for these differences, we characterize each case site along these two dimensions, as shown in Table 1. By taking these two dimensions as a basis, we can identify further combinations of settings that are relevant for the study region (e.g., rural and urban areas, towns along the upper or lower reaches of the rivers). Additionally, we can draw some inferences from these settings, such that urban areas usually have a dense transportation network that reduces travel times of disaster management, which is often the opposite in rural regions. When we compare disaster management performance with respect to change, we can then draw implications as well on these regional levels.

2.4 Scenario description

Change mainly affects two components of the system: disaster management and its capacities, e.g., via the number of available helpers or resources, and the disaster event, e.g., flood intensities that result in changed demand. We also structure our scenario analysis along these two dimensions, so that in scenario (1) we analyze how a given flood event can be handled under changing organizational settings. In scenario (2) we then investigate the effects of changes in the flood and demand settings. Table 2 shows a list of the change processes, their impacts on the system level and the affected model parameters with their range of variation. Furthermore, all analyses from scenarios (1) and (2) were carried out in scenario (3) for two different spatial settings: (a) the city of Leipzig in the north west of Saxony and (b) the rural Neisse region between Zittau and Görlitz in the east of Saxony, adjacent to the border to Poland (see also Table 1). These two sites have been selected as examples of an urban and a rural region that are affected differently by change, e.g., demographic change leading to either population growth or shrinkage. Additionally, this comparison serves as a test of robustness to see if the model is applicable to different spatial settings. For each parameter combination, 100 simulations have been run. The model results have been evaluated using the R Statistical Environment (R Core Team, 2014).

3 Results

3.1 The influence of the number of DMOs

For all conducted simulations, we measured the coping time t_{cope} as an indicator of how well disaster management can cope with a certain disaster event. At first, we take a closer look at the relationship between coping time t_{cope}, the number of DMO agents and their properties in scenario (1) while leaving the flood settings constant (Sects. 3.1 and 3.2). Here, we could observe a decline of coping time t_{cope} with increased number of organizations N_{DMO} (see Fig. 5). This general relationship held across all parameter combinations and became especially evident on a double logarithmic scale: coping time t_{cope} and number of disaster management organizations N_{DMO} are apparently linked by a power law relationship, i.e.,:

$$t_{\text{cope}} \propto 1 \big/ N_{\text{DMO}}. \tag{1}$$

The number of DMO agents N_{DMO} is therefore a main determinant of the coping time t_{cope}. Decreasing DMO numbers, e.g., due to demographic change, lead to increasing coping times. These coping times might exceed the flood lead time t_{lead}, depending on the flood characteristics and geographical location of the community at risk. In Fig. 5, we have superimposed three different lead time t_{lead} thresholds (72, 48 and 24 h) to illustrate this relationship: to achieve a coping time below a 72 h lead time threshold, at least 10 DMO agents were needed in this setting. However, when this lead time threshold was only 24 h, 33 DMO agents were needed to stay under this threshold.

This strong relationship between coping time t_{cope} and number of DMOs N_{DMO} can be explained by the link between transportation capacity of DMOs and the time needed per trip to a target site, i.e., one trip from a sandbag reserve to a disaster site (and back). This results in a total number of trips that is split upon the number of DMOs present, thus the power law relationship. Based on these observations, we can reformulate this relationship as follows:

$$t_{\text{cope}} = c \cdot \frac{1}{N_{\text{DMO}}^{(1-\varepsilon)}}, \tag{2}$$

$$\log t_{\text{cope}} = y_1 - (1-\varepsilon) \log N_{\text{DMO}}, \tag{3}$$

where ε and $y_1 = \log c$ are parameters that can be derived by fitting the relationship to the data extracted from the simulation runs. Once the fitting formulas are determined, they can be used for calculating the critical minimum coping time t_{crit} that results for a given number of DMOs or, vice versa, calculating the minimum number of DMOs needed $N_{\text{DMO}}^{\text{min}}$ to achieve a certain coping time below the flood lead time t_{lead}. Results for this are presented in Sect. 3.3.

3.2 Scenario 1: variation of DMO properties

The general power law relationship between the number of DMO agents and coping time that we showed in the previous section was found to be robust when we changed properties of the DMOs. This is evident from the results presented in Fig. 6 (on a double logarithmic scale) and the similarity of the fitted linear slope. However, quantitatively we observed

Table 2. Scenario overview, showing change processes, their impact and affected model parameters. All analyses carried out for scenarios (1) and (2) have been carried out for two different spatial settings in scenario (3). Flood lead times represent a flood characteristic; however they are mostly determined by geographical and hydrological settings as well as river morphology, not by climate change. Therefore, no process is associated to it.

Scenario		Process	Impact	Affected model parameters	Range of variation
Spatial heterogeneity	DMO properties	Demographic change	Population decline	Number of DMOs N_{DMO}	5–100
Spatial layout of rivers, flood-prone areas and the transportation network.		Technological change	Improvements in transportation	Capacity of DMOs (# sandbags/DMO unit)	250–2000
			Better information availability	DMO information access (knowledge of disaster sites)	Partial knowledge full knowledge
	Flood characteristics	Climate change	Increased flood intensity	Required total number of sandbags N_{Sandbags}	50 000–100 000
Two case sites: Leipzig, Neisse				Number of disaster sites N_{Disaster}	5–80
		–	Differences in lead times	Flood lead time threshold t_{lead} (h)	12–48

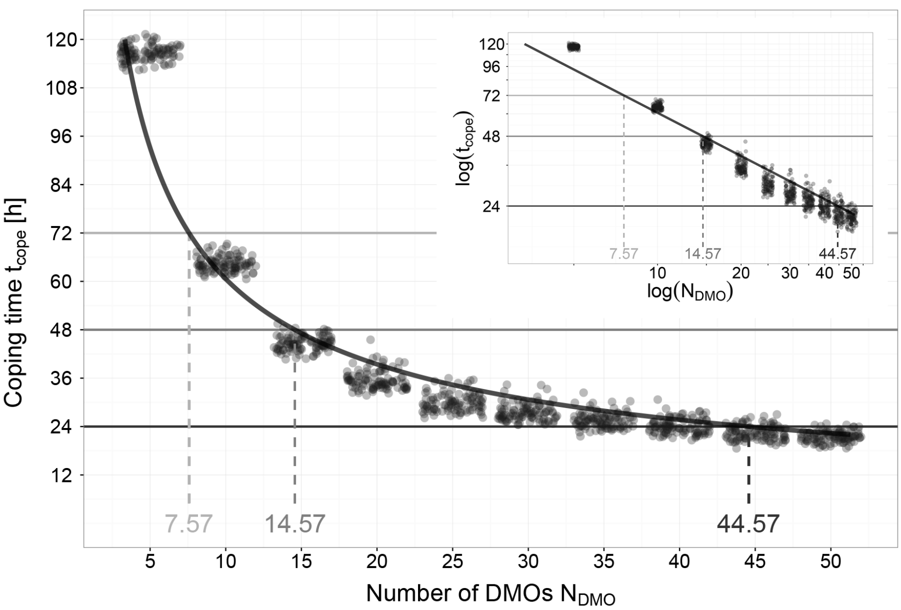

Figure 5. General qualitative relationship between coping time t_{cope} and number of DMOs N_{DMO}. Coping time decreases with increasing number of DMOs following a power law relationship (as depicted in the smaller inset plot, showing the same data on a log–log scale). Dots represent results of single simulations, where overlapping dots result in darker colors. Black curve shows the fitted power law and the intersection with the 24, 48 and 72 h threshold yields the minimum number of DMOs necessary to achieve that coping time. Results correspond to a flood setting of 40 disaster sites and a total demand of 50 000 sandbags.

large differences in the coping time when we varied (a) the capacity and (b) the information access of the DMO agents, for a given flood demand setting. With a larger capacity (panels a–d), more sandbags can be transported in one round, i.e., one trip from sandbag reserve to disaster site and back, which effectively reduces the number of rounds that are needed to achieve protection at one site. For a given number of DMOs, this reduced the coping time t_{cope}. However, increasing the capacity also had its limits. The largest reduction of coping time was achieved for the doubling of the capacity from 250 to 500 sandbags (Fig. 6a, b), whereas the subsequent capacity increases to 1000 and 2000 sandbags only achieved a smaller reduction (Fig. 6c, d). This suggests that there is a marginal utility where the costs involved in improving the capacity of

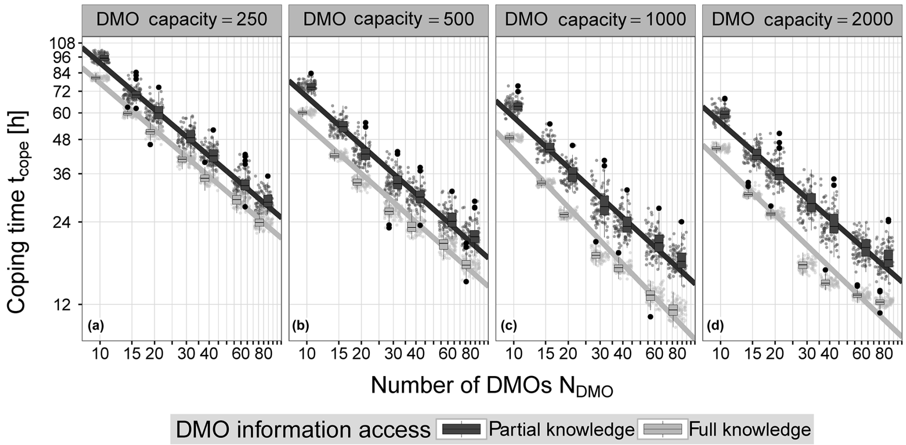

Figure 6. The distribution of coping time depending on DMO properties: (i) DMO transportation capacity (panels **a**–**d**), (ii) the number of DMOs (x axis) and (iii) their information access (dark grey/light grey). Dots represent results of single simulations, where overlapping dots result in darker colors and superimposed box plots show the distribution of the results. Thick line shows the fitted power law. Results are presented on a double logarithmic scale. Results correspond to a flood setting of 80 disaster sites and a total demand of 50 000 sandbags.

a single DMO agent are not worth the obtained performance increase. Increasing the number of DMO agents was more effective; especially for high numbers of DMOs, an increase in capacity resulted in almost no reduction in coping time (e.g., $N_{\mathrm{DMO}} = 80$ and an increase in capacity from 1000 to 2000 sandbags).

The way that DMOs have access to information about disaster sites also influenced the coping time. With only partial knowledge, DMOs recognize the (demand) state of a disaster site only when they visit it. This potentially leads to unnecessary trips to sites. With full knowledge, DMOs know the state of all disaster sites at all times, so they avoid such unnecessary trips. Coping time t_{cope} was therefore always lower when DMOs had better information access. We could even observe cases where better information access had the same effect as doubling the number of DMO agents, e.g., for $N_{\mathrm{DMO}} = 40$ and a transportation capacity of 500 sandbags (Fig. 6b), the average coping time for DMOs with full knowledge was equal to the coping time of 80 DMO units with the same capacity but only partial knowledge. For a DMO capacity of 1000 and 2000 sandbags (Fig. 6c, d), the slope of the power law fit for DMOs with full knowledge is steeper than for those with only partial knowledge. This indicates that the combination of full information access and high transportation capacity is more effective (i.e., leads to higher reduction in coping time) than just a higher capacity alone. However, results were not significantly different to prove that point, based on the current simulation results.

3.3 Scenario 2: variation of the flood characteristics

Changed flood settings can be translated in a higher demand for resources or manpower or in shorter lead times. Here, we first tested the performance of DMOs for different levels of demand in terms of (a) the number of disaster sites and (b) the total number of sandbags that need to be distributed (Fig. 7). We saw that coping time increased both with increasing total demand, N_{Sandbags}, as well as with a higher number of disaster sites, $N_{\mathrm{Disasters}}$. At first, we saw that a doubling of the total demand (Fig. 7a, b) does not lead to the same doubling of the coping time t_{cope}. Rather, coping time increase was between 79 and 98 %, depending on the number of disaster sites, as well as the information access of DMOs. Here, we saw a clear difference in how strongly coping time increased between simulations where DMOs had partial knowledge, compared to full knowledge. Whereas for partial knowledge and a total demand $N_{\mathrm{Sandbags}} = 50\,000$ (Fig. 7a) an increase from 5 to 80 disaster sites leads to a prolongation of the coping time t_{cope} of nearly 11 h (from 19 to 29 h 45 min), it resulted only in a 3 h 30 min longer coping time when DMOs had full knowledge (from 19 h 30 min to 23 h). For a total demand of 100 000 sandbags (Fig. 7b), the increase of coping time and also the difference depending on the information access was comparable. Thus, better information access of DMOs can mitigate, to some degree, the additional demand posed by the increased number of disaster sites.

Variations in flood lead times have been considered in terms of the minimum number of DMOs $N_{\mathrm{DMO}}^{\mathrm{min}}$ needed to achieve a certain lead time t_{lead}. We determined this number from fitting Eq. (3) to the coping times obtained from the simulation. Results for this analysis are displayed in Fig. 8. Here, we first analyze panels a–c, whereas the comparison of panels a–c and d–f will be presented in the following section.

We saw that, in general, the minimum number of DMOs $N_{\mathrm{DMO}}^{\mathrm{min}}$ increased when the lead time threshold t_{lead} increased as well (Fig. 8b, c). This is not surprising, as with lower lead times, the same number of tasks need to be solved in shorter time. However, this increase was nonlinear: for high to

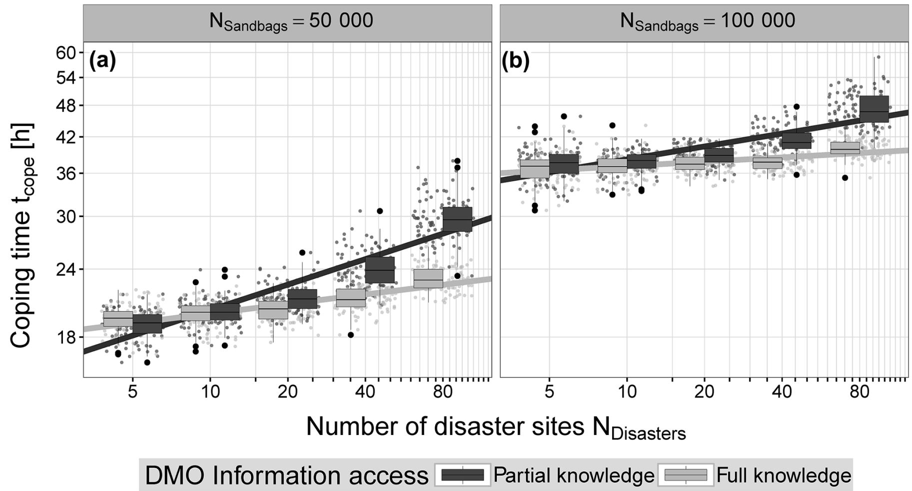

Figure 7. The distribution of coping time depending on flood characteristics: (i) the total demand of sandbags N_{Sandbags} that need to be distributed (**a** and **b**), and (ii) the number of disaster sites $N_{\mathrm{Disasters}}$ (x axis). Results are additionally split by the information access of DMOs (dark grey/light grey). Dots represent results of single simulations, where overlapping dots result in darker colors, and superimposed box plots show the distribution of the results. Thick line shows the fitted power law. Results are presented on a double logarithmic scale. Results correspond to a setting with $N_{\mathrm{DMO}} = 40$ and a DMO capacity of 500 sandbags.

medium lead times (48–24 h), the increase in DMOs needed was only subtle. However, once we crossed the threshold to very short lead times below 24 h, the numbers increased sharply. In such areas, e.g., cities in the upper reaches of rivers, the number of disaster management organizations is the crucial factor that determines the performance of disaster management.

In line with the previous analyses, the increase did also depend on (a) the demand posed onto the DMOs, here in terms of the number of disaster sites, as well as (b) the capabilities of the DMOs, in terms of their transportation capacity and information access. When we compare Fig. 8a and b, we see that the curves show a much steeper increase when DMOs only had partial knowledge (Fig. 8a). Also, lower capacity (thin lines) and a higher number of disaster sites (orange and red lines) lead to an increase in the minimum number of DMOs needed. However, when we look at Fig. 8b where DMOs had full knowledge (i.e., they know the status of all disaster sites at all times) this increase was much more subtle. The role of information access is also reflected in the average distances moved by DMO agents (not displayed here): while for full knowledge, higher numbers of disaster sites lead to no noticeable rise of the distance moved, partial knowledge showed a strong increase here. A reason for this rise lies in the unnecessary extra trips that DMO agents carry out when their information about disaster sites is not up to date. Of course, the number of such trips increases with a higher number of disaster sites. This shows again that information access can play a large role to overcome either increased demands (higher number of disaster sites, shorter lead times) or shortcomings in resource supply (the number of DMOs = manpower). Especially the combination of full knowledge and high transportation capacity effectively eliminated the need for more DMO agents when the number of disaster sites increased, which becomes apparent from the overlapping bold lines in Fig. 8b. Full knowledge (Fig. 8b, thin lines) or high transportation capacity (Fig. 8a, bold lines) alone did not achieve this effect.

3.4 Scenario 3: regional comparison

The two case study sites that we compared for this scenario, (a) an urban area and (b) a rural region, roughly have the same spatial extent, (a) 35 km × 31 km and (b) 35 km × 23 km, but are very different in their geographic location, their demographic situation and their infrastructure; e.g., the transportation network is much more dense in the urban area than in the rural region (see the maps in Fig. 8a and d). When we compare the performance of DMOs across both regions it should be noted that the general qualitative behavior of the model did not change, similarly as shown before, which confirmed that the model performance is robust also under different spatial settings. Comparing both regions quantitatively revealed some interesting results. At first, because of the differences in the transportation network, we would have expected larger differences in the average distance moved of the DMO agents. However, there was no noticeable difference in the full knowledge scenario, and we observed a difference for large numbers of disaster sites only for partial knowledge; e.g., for $N_{\mathrm{Disasters}} = 80$ one DMO agent moved on average 250 km in the urban case and 300 km in the rural region (in one simulation run). We compared the increase of minimum DMO numbers, $N_{\mathrm{DMO}}^{\mathrm{min}}$, depending on

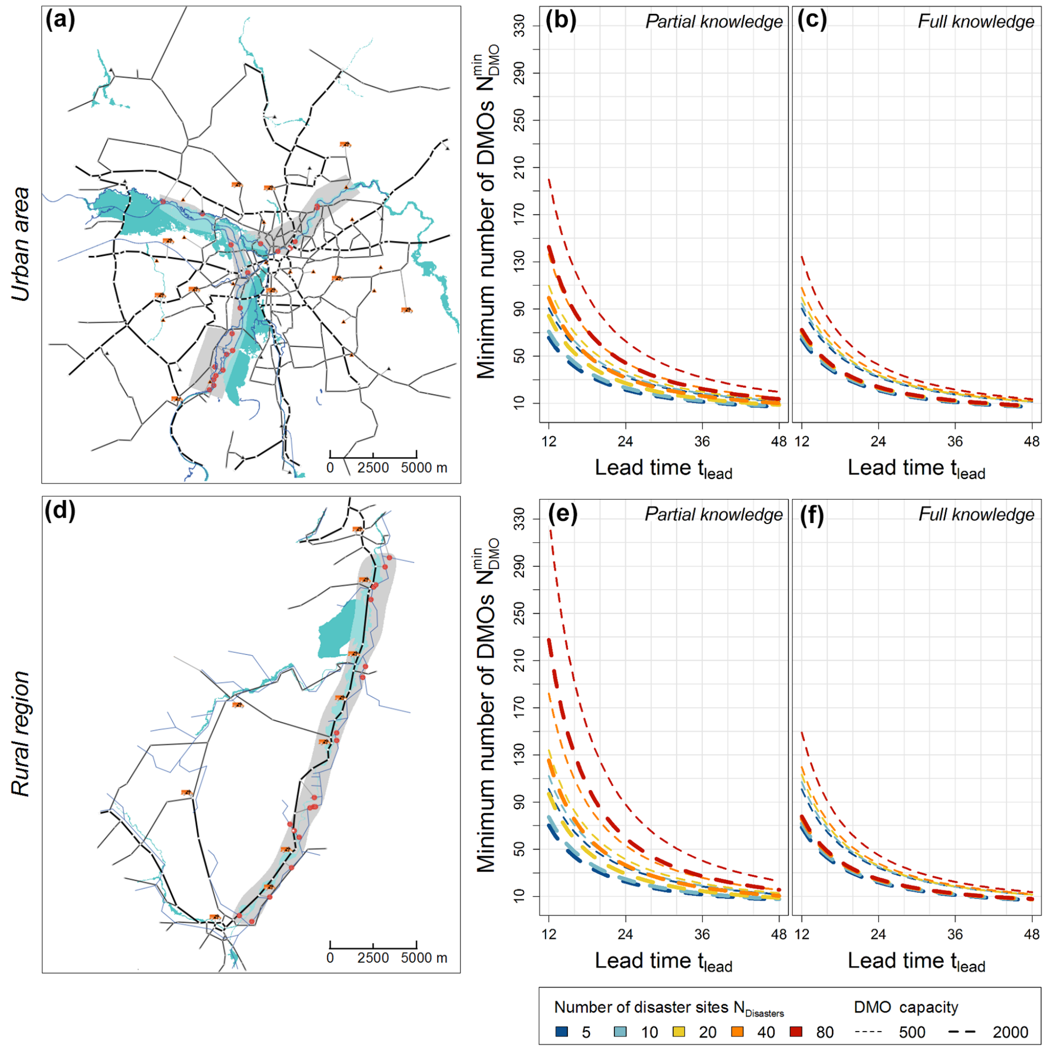

Figure 8. Minimum number of DMOs $N_{\mathrm{DMO}}^{\mathrm{min}}$ in depending on the flood lead time t_{lead}. The results are depicted for two spatial settings, an urban area **(a–c)** and a rural region **(d–f)**. The maps for each region **(a, d)** show rivers (blue lines), flood-prone areas (blue shaded area) and the transportation network (black and grey lines). The lines in the main graphs (**b**, **c** and **e**, **f**) are color-coded according to the number of disaster sites and their thickness shows the transportation capacity of the DMO agents.

the lead time between both spatial settings and saw that the general pattern is very similar in both regions, with only subtle increases $N_{\mathrm{DMO}}^{\mathrm{min}}$ for the full knowledge scenario (compare Fig. 8c and f). However, a more substantial increase could be seen in the rural region for the partial knowledge scenario and at very short lead times (Fig. 8e). Here, the limits in infrastructure seemed to amplify the bottleneck of the number of DMOs needed. Particularly low transportation capacity of the DMO agents and a high number of disaster sites showed a significantly larger number of DMO agents needed when compared with the urban area: whereas approximately 200 DMO agents were needed to ensure protection at 80 disaster sites and stay below a lead time of 12 h in the urban area, the same task required more than 330 DMO agents in the case of the rural region, an increase of 65 %.

4 Discussion

In this work, we present a "virtual lab" approach in the form of an agent-based simulation model in combination with a geographical information system to assess performance of disaster management under change in a spatially explicit way. As a main result we show that future performance of disaster management depends to a large degree on the demographic development, as manpower remains the most important resource, especially if flood lead times are very short (< 24 h). Technological advances such as better information access or improved transportation capacities of DMOs can help to overcome performance deficiencies, but only up to a certain degree.

Table 3. Possible implications for disaster management performance in dependence of demographic and geographic settings. Implications are based both on model analysis as well as interpretation of results.

Disaster management performance	Demographic and geographic setting
Performance ensured	Urban areas: high population density, population largely growing, dense infrastructure → high number of DMOs with availability of helpers ensured. Downstream, lowland: plain floods, long flood lead times → sufficient preparation time to carry out protection measures. Performance of DMOs is likely to be ensured.
Performance uncertain	Small to medium sized towns: no clear population growth/shrinking trend → DMO number depends on the specific town. Downstream/middle reaches: mostly plain floods, medium flood lead times. Performance of disaster management depends on the specific local settings. Possible bottlenecks could be overcome by, for example, better information access or higher transportation capacity of DMOs.
Performance at risk	Rural regions/small towns: low population density, population shrinking, sparse infrastructure → low number of DMOs, availability of helpers likely to decrease. Upstream, mountainous: flash floods, short flood lead times → limited timespan to install protection measures. Performance of DMOs is likely to be at risk as resources (e.g., DMO numbers) are decreasing and demand (e.g., flood frequency) is likely to increase.

4.1 Implications for disaster management

The performance of disaster management is at stake when demand for protection and resources to cope and attain this protection are at a mismatch. Our model has shown that change can lead to such a mismatch on different levels. This becomes evident in our study region where we can observe a coincidence of change particularly in two dimensions: demographic change, leading to a decline in the number of disaster management organizations at hand, and climatic change, leading to an increase in flood frequency. Throughout all analyses demographic change has emerged as the factor with the strongest influence on the performance. In other words, under a “loss in DMOs scenario”, the performance that is expected from disaster management may no longer be guaranteed and even well-established and tested routines might then fall short. Therefore, disaster management performance depends strongly on the differences in the demographic development, as well as in the flood characteristics due to geographical conditions. Though we only compared two geographic settings that are examples for lowland and downstream regions, our parameter variation (e.g., the variation of the lead time threshold) allows us to draw implications beyond the two case sites (see Table 3). While performance is likely to be ensured in urban and downstream regions (with lead times of often more than 24 h), performance could be at risk in rural, upstream regions where lead times are short (12–24 h, or even shorter) and population shrinkage leads to a decline in DMO numbers. However, shrinkage does not necessarily lead to a reduction of exposure to flood risk, as areas of demolition rarely overlap with flood-prone areas. Also, the capacity to cope with and adapt to flood risk is very much restricted for communities in rural areas, due to both limited financial means and a loss of public services, which renders them highly vulnerable with respect to flood risk. Deficiencies in manpower can partly be substituted with technological advances such as better information availability or increased transportation capacity. Therefore, especially in regions where disaster management performance is at risk, a focus should be put, for example, on efficient communication and coordination strategies as a possibility for a transformation that could enhance the resilience of disaster management on the long term. If we link these results back to our case study area of Saxony, a combination of short lead times and more rural areas can be found, for example, in the upstream area of the Mulde river. A more in-depth analysis of disaster management performance, its drivers and possible improvement options should therefore focus on this region.

Despite the individuality of the spatial structure of the different study regions, the model results indicate strong robustness and therefore a certain transferability of the qualitative findings to other regions of the same type. The reason is that the spatial processes (here: transport) are averaging out the effects of small-scale spatial heterogeneities, which is a well-known effect from spatial systems dynamics (Fahse et al., 1998; Frank and Wissel, 2002; Banitz et al., 2016). In consequence, rules of thumb for management can be derived (Frank, 2004). Even though further analysis would be needed to provide reliable heuristics, one such rule could be that securing the availability of members should be a top priority to ensure operational readiness of disaster management.

A second rule could stem from the interchangeability of information access and transportation capacity, i.e., that better information access can compensate for lower transportation capacity.

4.2 Model limitations and future extensions

Of course, the developed model is a simplification of the reality and is based on a number of strong assumptions. We only focus on one task in the current model – the filling, transportation and distribution of sandbags – and omit a range of other tasks such as the evacuation of people or the protection and maintenance of critical infrastructure. This task of filling and distributing sandbags was chosen as it (a) is relatively simple to represent in the model and (b) demands a large number of resources (both technical as well as manpower) during a flood event. The model also omits more complex control structures such as management authorities or operation control that are responsible for the coordination of all DMOs and their tasks in a real disaster event. Including all these elements and processes would lead to a highly complex model that might more accurately represent reality but makes understanding key elements that drive the system performance nearly impossible (Sorenson, 2002). However, understanding these key elements and processes is the main goal of our model in the sense of a "virtual lab" approach. Highly complex models are also difficult to communicate, both to other researchers as well as to stakeholders and experts in disaster management. The virtual lab approach enables "computational experimentation" known as promising way of enhancing social learning, exploring chances and risks of upcoming developments and assessing the effectiveness of potential counteractivities (Chapin et al., 2010; Folke et al., 2010).

In the context of disaster management, agent-based modeling is still relatively new, but a couple of innovative models have emerged in recent years. The ABM developed by Zagorecki et al. (2008) puts an explicit focus on information exchange and cooperation between organizations and conclude that more flexible communication and information sharing between agents leads to a more efficient response. It is especially notable that information sharing between lowest level agents is more efficient than only between high level agents (e.g., managers). This relates well to our assumption of "full information" where DMO agents have instant knowledge about the state of all disaster sites, which could be compared to a very flexible and efficient information sharing between agents. While Zagorecki et al. (2008) focus on one very specific aspect of disaster management, the model of Dawson et al. (2011) addresses flood incident management of an entire coastal town. Their model is very detailed and allows a variation of hazard and defense characteristics as well as evacuation strategies. However, the model does only include citizens as agents and simulates their movement in response to flood warnings, not disaster management organizations. One strength of their model lies in the usage of only publicly available datasets so that the model is easily adaptable to other case sites. Even though less dependent on data, our model also only uses data from publicly accessible sources, facilitating an adaptation to a different regional setting. Including another case site that resembles a rural, upstream region would be a sensible next step.

Besides a spatial adaptation, the modular setup of the ABM allows for an easy extension of regarding additional entities (e.g., management structures) or processes (e.g., evacuation). One planned extension of the model (with an existing prototype version) addresses a fairly recent process of change: the fast development of the internet and mobile communication technologies has made information exchange very easy and fast. Moreover, the rise of social networks such as Facebook or Twitter has enabled civilians to exchange knowledge and organize relief efforts besides or in addition to official practices carried out by DMOs. This has been especially visible during the 2013 flood where a surge of so-called "free helpers" (*ungebundene Helfer*) that do not belong to any formal organization either followed the call for help or even organized themselves to help mitigating the consequence of the flood (DKKV, 2015, p. 166 ff). However, this self-coordination can also have unanticipated effects when helpers betake themselves to wrong sites or carry out tasks single-handedly that might be unnecessary or impede other tasks. Furthermore, the response of unbound helpers did not have the same intensity in every region: bigger cities benefitted much more from the willingness to help, whereas small towns or rural regions depended much more on DMOs alone. Therefore, the next planned extension focuses on the effective coordination of unbound helpers to determine when such helpers are useful to enhance the performance of disaster management and when not. Furthermore, we would like to include the possibility of infrastructure breakdown (e.g., road closures, bridge collapse) that can have significant impact on the performance as well as on the attainability of certain protection goals. These extensions can contribute to making the model more realistic; still, the current model has already proven to be both a robust as well as illustrative tool to investigate the impact of change on disaster management and highlight which future conditions might put its performance at risk.

5 Data availability

All data used in this publication was obtained from publicly accessible sources. River and street network data are pulled from OpenStreetMap (Geofabrik, 2014). Flood-prone areas are extracted from data of the Saxony State Office for Environment, Agriculture and Geology (Landesamt für Umwelt, Landwirtschaft und Geologie, LfULG, 2012). Raw data and preprocessed model input data is available at dx.doi.org/10.6084/m9.figshare.4056663.v1.

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