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Abstract

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The strengths of this novel approach lie in the joint consideration of probabilistic and communicative risk aspects of a dynamic setting, in the simultaneous consideration of escalation and de-escalation phases and of two differently exposed risk groups, which requires differential risk communication. For each scenario, we derive the explicit and generic solution of the model, which makes it possible to identify the scope for warning compliance and its effects independent from the parameter constellation.

Applying empirical data from flood and risk studies yields plausible results for the escalation-scenario of the model and reveal the limits of compliance if people face a Black Swan flood event.

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1. Introduction

Natural disasters cause severe damage worldwide, with an upward trend (Alfieri et al. 2016; Bruine de Bruin et al.).Whenever natural catastrophes may endanger human life and sufficient warning time precedes the occurrence of the event, the immediate evacuation of the population is required. Evacuation can be defined as "the process of alerting, warning, deciding, preparing, departing and (temporarily) holding people, animals, personal belongings and corporate stock and supplies from an unsafe location at a relatively safer location given the actual circumstances" (Kolen & van Gelder, 2018). In the context of an evacuation, the questions of whether, and – if answered with yes – when and to what extent are among the most difficult decisions to be made by responsible actors such as (local) government and civil protection agencies. The decision problem can be divided into three different elements or tasks. First, the occurrence of the potentially dangerous event that could make an evacuation necessary must be predicted as accurately as possible by a *hazard forecast*. In practice, this task is performed by Early Warning Systems (EWS), which are usually developed and operated by research institutes and commercial (early warning) services specialized in this field. Whether timely evacuation is possible at all depends on the scientific and technical performance of these systems on the one hand and the specific characteristics of the concrete natural hazard on the other.

The second task comprises *evacuation planning* and the evacuation decision itself, which can be either a mandatory evacuation request ("order") or a voluntary evacuation request ("recommendation") but either way this decision is eventually based on a comprehensive *cost-benefit analysis* of public decision-makers, weighing up the advantages and disadvantages of an evacuation. While the potential lives to be saved play the primary role in this consideration, an evacuation can also involve securing critical assets and thus avoiding direct economic damage. However, the measures and operations, which have to be put in place within a short period, require a systematic preparation and planning in combination with pre-disaster risk communication with the potentially affected population living in the risk-prone area. For example, one of the most frequently reported bottlenecks for an effective evacuation is unnecessary traffic congestion, i.e. congestion which could have been overcome by timely planning of escape-routes as well as pre-disaster planning and training to overcome problems of coordination during the evacuation.

The third aspect, which constitutes a necessary precondition for a successful evacuation, concerns the acceptance and *evacuation compliance* of the population, which requires a good communication strategy but also a high credibility of the political decision makers. It should be understood that an evacuation, which usually involves leaving one's own home for up to several weeks, is a very consequential decision for those affected. There can be many reasons why potentially affected people do not comply with an evacuation order. The target group does not perceive the order or it does not take it seriously (enough) because it fails to understand the gravity of the situation and instead considers the measure to be exaggerated. On the other extreme, people may consider the order as too drastic an intervention in their private affairs and therefore give priority to their own crisis micro-management in the first instance (in particular to stay with vulnerable family members, pets or to protect their belongings), which can entail a dangerous loss of time. Further reasons are that people perceive their homes as a safe place, that they don't know where to go or that they have distrust into the public decision makers' "true objectives". The last aspect is relevant if people think that e.g. tourists are more relevant to the local government's decision or even in highly problematic contexts where the local government misuses an evacuation request in order to get rid of marginalized groups. Hence, evacuation compliance depends crucially on the population's trust and credibility in the official decision-makers.

"Approaching evacuation as a process and not as an outcome is key to understanding why some evacuate and some do not, and more important, to determining what can be done to motivate more compliance." (Dash & Gladwin, 2007). Following Dash & Gladwin, the objective of this contribution is a model-based analysis of an interaction of the three before mentioned tasks of evacuation: hazard forecast and early warning, strategic evacuation-decision making as well as evacuation compliance. At the center of the warning response model is the evacuation decision of a public decision maker (local government) and the evacuation compliance of the potentially affected population.

The decision problem is as follows: A public decision maker (PDM), e.g. the local government of a hypothetical seaside town, receives a forecast or warning from a stylized EWS and has to decide whether to issue an non-mandatory evacuation order. We choose an approach from information economics and model the EWS as an *information system* (Bikhchandani et al. 2013). The sequence of events and the occurrence of informative signals (emissions or "warnings" in our context) can be depicted as a Hidden Markov Model (HMM). Both, the hazard and the evacuation decision, are scalable over two levels. The hazard, e.g. a flood, can have an severe impact affecting the residential area near the coast (this corresponds to state S1 where a proportion of γ% of the population would be affected by flood) or an extreme impact affecting all residents of the whole town (this corresponds to state S2 affecting the entirety of the local population). *Figure 1* illustrates the two potential levels of impact taking the example of New Jersey (left picture), a state which was severely hit by hurricanes in the past (e.g. hurricane Sandy in 2012) and which led to the identification of flood-risk zones by FEMA. The picture to the right in *Figure 1* shows the zones of Southeast Louisiana as an example for three risk categories (indicated by the colors red, orange and yellow). Depending on the specificities of the locations and the local vulnerability profile of the population, there are very often up to five or more categories. Although we use the case of two zones for the sake of simplicity it is to note that a higher number of risk or evacuation zones increases operational complexity, in particular it becomes more difficult to communicate each citizen which risk zone it belongs to and what this means in terms of preparation and reaction.

Accordingly, conditional on the received signal the authority can either issue a partial evacuation focusing at the residential area in the coastal (risk) zone or it can issue a full evacuation for the whole region. For the evacuation decision, the authority takes three types of cost into account: The potential damage to the population in the case of flooding in an non-evacuated region (either just the coastal region or the entire town), the cost of an evacuation incurred by the government and the burden for the population in the case of a false alarm. Further details are given in section 4.

Although the model has a relatively simple structure, it makes it possible to depict two different levels of risk and to derive an optimal decision for every outcome based on the Markov chain structure.

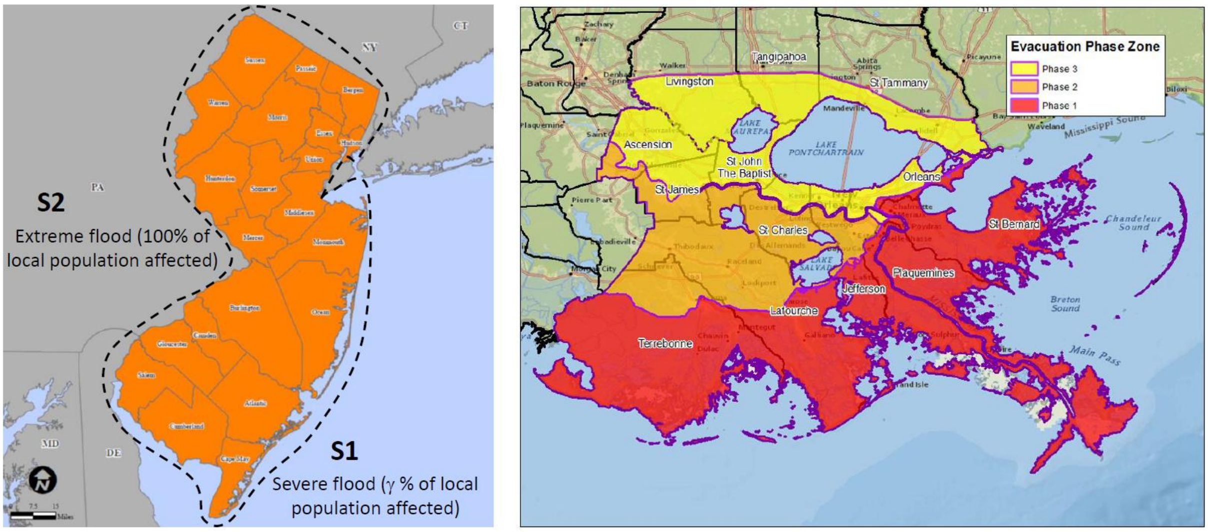


Figure 1. Examples of flood risk zones -left: New Jersey (FEMA 2012), right: Southeast Louisiana(State of Louisiana)

The scalability of the decision is an important feature of the model as this often constitutes a major problem in practice. Closely related is also the consideration of different population groups (heterogeneity). This aspect is considered very important in the literature, as different groups act from very different motives and under different circumstances. In the literature, a distinction is made above all between groups in risk areas and those outside risk areas, between vulnerable and (less) vulnerable groups, and groups that are differentiated according to socio-demographic criteria (age, gender, ethnicity). In our model, we limit ourselves to the first point and distinguish between people living inside and outside risk areas. This criterion is usually highly relevant for high tide and hurricanes, since coastal inhabitants are exposed to a higher risk and usually are well aware of this (official classification into risk zones). We would like to stress that we have not integrated the other criteria into the model primarily for reasons of complexity, and not because we consider these further group differentiations to be unimportant. On the contrary, our model approach can be extended to include these groups relatively easily, provided that data on hazard characteristics, local conditions and demographics are available.

In addition, the model also allows to analyze the de-escalation-decisions (return to "normal"), which are absent in most evacuation models. While a situation where no flood yet occurred corresponds to the escalation-phase (just evacuation-decisions have to be made), situation S2 represents the de-escalation-problem. Here, the whole town is already flooded and the people either evacuated the period before or they were "forced out of the region" by the flood itself which implied a high risk for life and health. Those who evacuated or were lucky to escape in time, now feel the urge to return as fast as possible. However, if the flood situation worsens again this can put these people at a new risk, which is a frequently overlooked issue in evacuation-modeling. As Sorensen & Sorensen state, „the time period for the span of withdrawal is elastic in that the evacuation may last for any amount of time, and may occur more than once or sequentially should there be secondary hazards or a reoccurrence or escalation of the original threat. For example, while the primary hazards form hurricanes are wind and storm surge flooding, secondary threats could include inland riverine flooding that might necessitate a second evacuation effort." (Sorensen & Sorensen, 2006). To protect the people from this kind of "second wave", the government can decide whether to issue an order to remain outside the region. Note that an "evacuation-order" and a "remain-order" just differ with respect to the status quo (i.e. whether people are already out of the region or not) because in both cases the government aims to incite the population to be absent from home. In situation S1, just the coastal area is flooded. This situation represents a combination of escalation (relevant for the rest of the town, which is not yet flooded) and de-escalation (relevant for the inhabitants of the coastal area, who had to leave the region and are about to return). It is one central feature of this dynamic model that it comprises both escalation and de-escalation as well as the more intricate constellation in between. The challenge for the authority is to find an optimal policy – conditional on the current state and future prediction – which fits to both groups at the same time.

One further important element of our model is *trust* of the potentially affected population in the government's communication. Although theoretically the government can enforce an evacuation order, police coercion is for sure the “means of last resort” for public officials. In principle, large-scale enforcement in a stressful situation will most probably fail due to lack of time, lack of staff, increased opposition by the public and personal discomfort of the executive personnel. Therefore, we assume in our model that the government cannot force people to evacuate but it can just influence them in a direct and indirect way while both channels depend on trust.

The first type of trust is the people’s trust in a competent impact assessment on the side of the government. While the (unconditional and conditional) event probabilities are common knowledge to all decision-makers of our setting, we assume an information asymmetry between the government and the public with respect to the *impact* of a potential flooding event. To put it plainly, people know how probable a flood event is but they do not know (as precisely as the regional government knows) how severely this flood could hit them. While probabilities and warnings are publicly issued by the weather forecasting service, the question how dangerous this event could be for a specific region is still a different aspect. By contrast, the local government has access to more and deeper expertise, which makes *competence-trust* valuable at this point. We see a concrete example and further justification for this assumption in the first wave of the current Corona-pandemics. Although data about the spread of the virus and the upsurge of infections was publicly available at any time, in many countries people were skeptical about the drastic restrictions and did not believe in potential damaging impacts for themselves. However, in a country like Germany, where trust in government is comparatively high, people showed a high degree of acceptance accordingly.

The second trust component is *reliability-trust*, which exerts an indirect effect on the public’s evacuation decision because it affects the chance for a smooth evacuation. Wilson (2018): “Issuing mandatory evacuation orders (…) prior to the landfall of hurricanes can be as or even more disruptive and dangerous than the storm itself. For example, 107 of the 120 deaths attributable to Hurricane Rita occurred because of extreme temperatures in jammed traffic during the Houston’s evacuation (…). More recently, Hurricane Irma in 2017 prompted the evacuation of up to 6.3 million Floridians, one of the largest such displacements in American history (…). The storm’s aftermath raised serious questions about overburdened infrastructure and the social vulnerability of communities that were unable to leave via their own means (…).” Before all events unfold (let’s say in an imaginary period zero) the government can invest in better evacuation conditions, such as improved evacuation planning and training, contracting for vehicle capacities (e.g. busses which can bring the people out of the affected region) or even the construction of additional roads. We assume that the government has a fixed budget for this investment but must decide about the allocation answering the question which region (coastal area versus rest of the city) should receive which share of it. As the public cannot directly observe all taken measures, it again has to trust that the government did the most to make a smooth evacuation possible. A low level of reliability trust leads to the conviction of the inhabitants of both regions that they have to cope with the congestion-problem on their own. This will eventually increase the expected degree of congestion and thus prevent a (possibly life-saving) evacuation. In the model we deal mainly with the first type of trust but treat congestion as an intensification of the evacuation problem.

The remainder of the article is organized as follows. After a brief outline of the related literature in section 2, we present the early warning or information system in section 3 and the decision-model and communication-game in section 4. In section 5, we derive the model's results, in particular the Nash-Equilibrium of the compliance-game. In section 6 we give a brief summary and discuss the implications and possible extensions of our approach.

2. Related literature and state of the art

This section gives a brief overview on the relevant literature in this field. We start with some stylized facts about EWS and refer to selected case studies, which looked at specific challenges such as information processing, information aggregation, information communication as well as coordination between experts, such as services for flood control, who bear a large part of the responsibility for the public when making proficient use out of this information. The second part refers to literature on evacuation decision making and evacuation compliance. Although slightly dominated by social scientists this is a very interdisciplinary area of research, which comprise empirical studies, simulation models and guidelines.

Literature on EWS and in particular models, which aim at improved forecasts, abound. An EWS belongs to the so-called non-structural measures of hazard protection (as compared to structural measures, such as dams or levees in the case of flood, which constitute a physical barrier). According to Salit et al. (2013) and Mileti & Sorensen (1990), an EWS for flood risk comprises three basic components: “the detection system (collection and analysis of information, flood forecasting), the management system (composed of national and local emergency management officials) and the response system (transmission and reception of warnings to the population concerned)" (Salit et al. 2013). With respect to the last there is again a long list of requirements concerning the interface between sender and receiver of the message. These requirements refer to issuance and dissemination (outreach), perception, comprehension and interpretation, personalization (anticipating the receiver's interpretation as people contextualize the information for themselves and ask questions such as: What does this message mean to me? Do I need further information?) and sender credibility. Warnings must be perceivable and clear (Sorensen 2000) and an EWS has to be adopted to the local conditions (Salit et al. (2013).

Although floods and hurricanes are easier to predict than e.g. earthquakes, there are numerous examples of wrong forecasts also for these two types of events. The difficulty with hurricanes is that they can change their direction shortly before landfall. A well-known example is hurricane Rita in the Gulf of Mexico in the year 2005: "Although originally projected to hit the Houston/Galveston area, Rita took an easterly turn while still in the Gulf, a shift in direction that spared these metropolitan areas a direct hit" (Carpender et al. 2006, p. 777). There is a comparable level of uncertainty for floods as the movement of water masses, which break their path through inhabited districts, can be highly dynamic and therefore difficult to predict (Salit et al. 2013).

With respect to the subtopic *evacuation* and *evacuation decisions*, research over the last two decades has constantly shifted towards a stronger focus on risk communication and people's reactions to the combined events of an upcoming hazard and an evacuation order. From a practical perspective, there are guidelines such as the MEND-guide for humanitarian interventions who provide useful orientation for decision makers (Goldschmidt et al. 2014). In natural disasters all around the world the number of fatalities among those who did not evacuate in time is still remarkable. Therefore, research focused on the guiding question which group of people typically don't evacuate in time, which are their characteristics and what can be done to influence their decision in an effective way. Basically, there are two main strands of literature: empirical case studies and evacuation simulation models. The former looks at specific events in a specific country and runs post-event surveys to understand people's perceptions and motivations. Among the key insights is that personal risk perception plays an influential role in the evacuation decision (Dash & Gladwin 2007), that people tend to "hedge" their risk in the sense that they collect information from different sources, cross-check information and tend to wait for a clearer picture unless they are fully convinced. A special focus lies on vulnerable groups with restricted mobility but also those who are socially vulnerable, such as marginalized groups.

With respect to government communication in general and evacuation orders in particular, the impact of the official nature of an evacuation order on people's decisions seems to be quite differentiated. Basically, people trust public authorities, they trust local authorities more than central government, they show a higher willingness to follow government orders even if this is in conflict with family's/peers recommendation and they closely screen the authority's credibility.

For the context of evacuation decisions, *evacuation compliance*, *acceptance* and *trust* in public authorities and government agencies was subject to quite a number of contributions. The two main strands of literature focus on intention-based and credibility-based trust. People can doubt the intention of public officials if they feel that the government abuses the event as a pretext for the pursuit of other goals or that different groups of stakeholders (other than the directly affected population, such as tourists, investors, voters etc.) are the true addressees of a consequential measure. Although we do not focus on intention-based trust, we nevertheless take explicitly potential conflicts of interests into account. In our model, the government can pursue different objectives. While saving lives and protecting the population from injuries is the government's primary objective, there are also secondary objectives, which can be "added to" the primary one by assigning weights and thus influencing the final decision. Secondary goals can also focus on the population to prevent nuisance or even deprivation caused by an evacuation. Alternatively, secondary goals can focus on the prevention of economic losses in the affected region. The Corona-crisis 2020 illustrates in a very evident way that the trade-off between impairments of the population and economic losses must not be ignored.

With respect to credibility-based trust, the impact of false alarms is a frequently studied topic. The problem that people cease to take a warning seriously, if they experienced a false alarm is known as the *Crying Wolf*-phenomenon (Roulston & Smith 2004). Although it is difficult to empirically analyze the effects of sequential observations if the events at question are very rare, there were some occasions, which can shed some light into this issue. Studies find a rather modest effect of the Crying Wolf-phenomenon indicating that false alarms don't exert a crushing effect on the sender's credibility but rather shift some weight moderately into the direction of other information sources. Hence, people learn that they should not trust entirely the public announcements although they are still willing to trust to a sufficient degree.

To the best of our knowledge, competence trust and compliance as conceptualized in this paper have not yet been under study in the context of evacuation modelling. Regarding competence trust, the idea that people hold their own belief about the severity of a risk is close to approaches dealing with subjective risk perception (SRP). In SRP, the salience of communicated risk depends, among other factors, on the credibility of the source (e.g. media, government), which in turn leads to changes of subjective probabilities (Lindell & Prater 2002). However, our approach assumes objective risk perception, i.e. there are neither information asymmetries nor (preference-based) distortions of the event probabilities. In our model, we assume an information asymmetry between government and public regarding the impact of a potential flood. If people trust the government's competence regarding the impact assessment, they interpret an evacuation-order (and equally a remain-order) as an indicator of the (partially) unknown future impact.

The account of *simulation models* takes a formal approach and models evacuation decisions with a strong focus on congestion (Santos & Aguirre 2004). For example, Teo et al. (2015) present an agent-based evacuation model; their model also incorporates government advice. However, the task of the government is to find the optimal assignment of people to avoid congestion.

In our model, we deal with the problem of congestion in a rather different way. We neither focus on a routing model, nor do we solve a problem of pure coordination. Instead, congestion represents a further bottleneck, which can be effectively influenced by the government as a third party and which can influence the public's incentives for evacuation via the trust channel. With respect to cost-benefit-analyses in the context of forecasting models, our approach is akin to the classic Quickest Change Detection (QCD) problem (Li 2012). A QCD-problem distinguishes between two states ("regimes") of a system. These are two conditions of which one is harmless but the other is problematic and should therefore be avoided. For example, an economy can be on its way into a recession or just experience a random and transient decline in output. Or a patient can show symptoms which indicate an infection but which can also just be due to other factors. The first, problematic, reason requires a more comprehensive and also more painful therapy than the second. The decision maker's task is then to detect the switch to the problematic regime as fast as possible. A QCD-problem is a dynamic setting where time approaches a fixed terminal date. In our approach, timing is not relevant for the decision but time rather structures the sequence of the events. In addition, our approach has the Markov chain-properties.

3. Problem structure and information system

This section describes the statistical part of the model, the Information System (IS).

3.1 The information ("warning") system

The basic structure of the problem, in particular the randomness and sequence of events, follows the properties of a Hidden-Markov-Model (HMM). Markov-models are stochastic automata, which share the property that future developments just depend on the current state and not from preceding states. A Markov-model is characterized by stochastic transitions between states, which are characterized by transition probabilities. In a HMM, the decision maker cannot directly observe the states but receives a signal ("omission") which makes inferences about the true state possible (Zucchini & MacDonald 2009). *Figure 2* represents the three-state, first-order HHM for the decision problem described in the introduction.

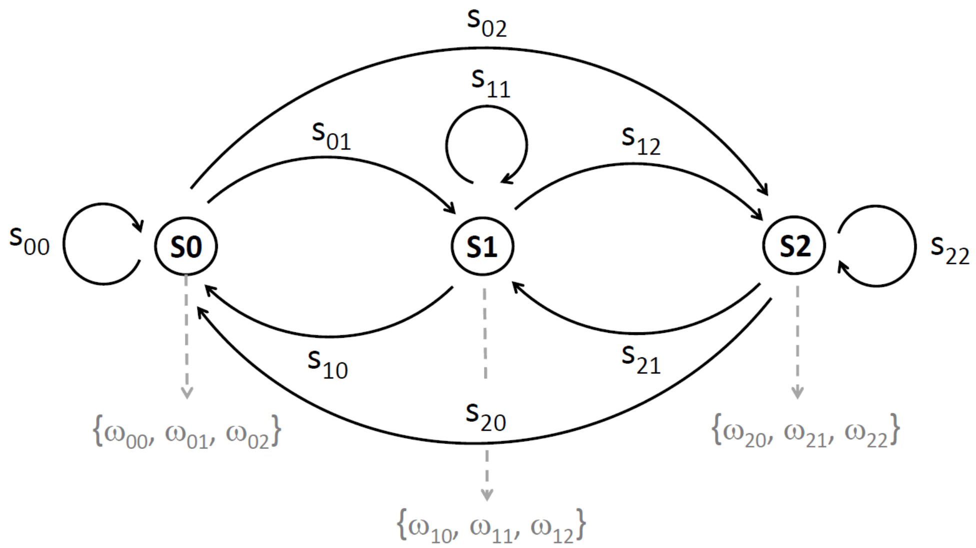


Figure 2. Hidden-Markov-Chain

There are nine possible transitions between the three states. The initial state is S0, which corresponds to the situation where either no or just a harmless flood occurs. The state S1 represents a severe flood, which affects just the coastal region (the "risk zone" A) and the state S2 stands for an extreme flood with extraordinary water-levels affecting the whole town (regions A and B). The transition from state *i* to state *j* is depicted by the variable s_{ij}. Starting from S0, three transitions to the state in the next period are possible: Either we remain in S0 (this corresponds to transition s_{00}), which is the most probable transition, or we are hit by a flood event and end up in state S1 (s_{01}) or even in state S2 (s_{02}).

According to *Figure 2*, every state is reachable from any other state, which is a realistic model of natural disaster events. For example in the case of a tsunami or a hurricane, which can rapidly change its direction, the direct transition s_{02} would be highly relevant whereas for floods, which develop over time (depending on precipitation, the confluence of rivers etc.), also the other two sequences {s_{01} , s_{12}} are plausible. In general, a probability of occurrence refers to 1 year and to a pre-defined area. It is usual that intensity and frequency are mapped on the same scale so that events of extraordinary intensity are also extraordinarily rare. This is why the frequency of a flood (e.g. a 100-year flood) is used as a proxy for severeness. Most risk-metrics for natural disasters are just restricted to the meteorological or geophysical factors and thus provide information about the occurrence of an extreme weather event or specific constellations thereof. However, in general these metrics do not include information about the vulnerability of the specific location. Recently so-called impact forecasts are increasingly coming into focus, which do not only answer the question "What is the weather?" but also "What is the weather doing?" (Merz et al. 2020). Our probabilities are best understood as joint event and impact forecasts.

We term state S0 the *escalation-state* because the two transitions leaving S0 move towards the dangerous states S1 and S2. In the escalation-state S0, the decision-maker has to decide whether to order evacuation for (at least one of) the groups or not. State S2 represents the opposite case, the *de-escalation-state*. As described above, in S2 just return-decisions have to be made. In the diagram, the arrows in the opposite direction, indicating the "way back to normal", consider the de-escalation phases. Finally, we call state S1 the *mixed state*, because it comprises both escalation and de-escalation. All available transitions can alternatively depicted in a more efficient way as a *Transition-Matrix* $\boldsymbol{S}$ (*Table 1*). If a Markov chain is *ergodic*, a property which will be fulfilled for the numerical applications of our model, it has a unique stationary distribution, which can be determined by solving the equation $\boldsymbol{S}^T\pi = \pi$, where $\pi = (\pi_0, \pi_1, \pi_2)^T$. The resulting distribution $\pi*$ tells us the "average" probability for each state (S0, S1 or S2), which remains unchanged when time progresses (Zucchini & MacDonald 2009).

We now turn to the main part of the information system as illustrated in *Table 1*. The grey variables in brackets indicate the warnings, which are available one period before the forecasted event occurs. The variable ω_{ik} reads as "the (warning) signal received in state i predicts state k as the state of the next period". For flood, the time between two events could be between 12 and 24 hours; in the last case the warning represents a classic day-ahead forecast.

The warning signal ω_{ik} is a discrete, trinary random variable $\omega_{ik} \in \{0,1,2\}$, which is sufficiently informative in a sense described below. The quality or precision of the information system is described by the conditional probability $q(\omega_{ik} \mid s_{ij})$, which is the probability that a warning signal predicts the transition from the current state i to the future state k given that the true future state is j. The so-called *Likelihood-Matrix* $\mathbf{L}$ (*Table 1*) summarizes all constellations for this conditional probability. It is straightforward that the rows of this matrix add up to 1.

Table 1: Transition matrix and Likelihood-Matrix

$$\boldsymbol{S} = \begin{array}{c|c} & \begin{matrix} S0 & S1 & S2 \end{matrix} \\ \hline \begin{matrix} S0 \\ S1 \\ S2 \end{matrix} & \begin{pmatrix} s_{00} & s_{01} & s_{02} \\ s_{10} & s_{11} & s_{12} \\ s_{20} & s_{21} & s_{22} \end{pmatrix} \end{array} \qquad \boldsymbol{L}_i = \begin{array}{c|c} & \begin{matrix} \omega_{i0} & \omega_{i1} & \omega_{i2} \end{matrix} \\ \hline \begin{matrix} s_{i0} \\ s_{i1} \\ s_{i2} \end{matrix} & \begin{pmatrix} q(\omega_{i0} \mid s_{i0}) & q(\omega_{i1} \mid s_{i0}) & q(\omega_{i2} \mid s_{i0}) \\ q(\omega_{i0} \mid s_{i1}) & q(\omega_{i1} \mid s_{i1}) & q(\omega_{i2} \mid s_{i1}) \\ q(\omega_{i0} \mid s_{i2}) & q(\omega_{i1} \mid s_{i2}) & q(\omega_{i2} \mid s_{i2}) \end{pmatrix} \end{array} \qquad (1)$$

For the information system to be sufficiently informative, it is required that the warning signals display a minimal degree of precision with respect to the state of nature they predict. In concrete terms, we impose the following *Informativeness-Condition* (IC) on the information system (expression (2)).

Informativeness-Condition (IC): $$q(\omega_{ij} \mid s_{ij}) > q(\omega_{i-j} \mid s_{ij}) \qquad (2)$$

Assume the transition s_{ij}, i.e. the true future state is state j. Then the warning should have higher probability to signal state j than to signal any other state $-j$. If IC is fulfilled, the information-system is valuable or useful for the decision maker in the sense that it generates "better than random" results, which is an empirically correct assumption regarding the forecasting precision of EWS in practice.

Both, the prior transition probabilities and the Likelihood-Matrix are common knowledge of all decision makers of our setting: the (local) government G and the populations of the two regions, which we term group A and group B. In each period, all actors know the current state, the issued warning signal with respect to the next state (both pieces of information are summarized in the variable ω_{ik}) and the Likelihood-Matrix. The warning signal is issued e.g. by a weather forecasting service and is therefore publicly observable. With this information, the DMs can calculate the up-dated posteriori-probability according to *Bayes' Theorem* $p(s_{ij} \mid \omega_{ik}) = \dfrac{s_{ij}\, q(\omega_{ik} \mid s_{ij})}{s_{ij}\, q(\omega_{ik} \mid s_{ij}) + \sum\limits_{-j \neq j} s_{i-j}\, q(\omega_{ik} \mid s_{i-j})}$. Formally, for a given state i, we combine $\boldsymbol{S}$ and $\boldsymbol{L}$ and thus derive the conditional Posterior-Matrix $\boldsymbol{P}$ according to expression (3).

$$\boldsymbol{S} \bullet \boldsymbol{L}_i \rightarrow \ \boldsymbol{P}_i = \begin{pmatrix} p(s_{i0} \mid \omega_{i0}) & p(s_{i0} \mid \omega_{i1}) & p(s_{i0} \mid \omega_{i2}) \\ p(s_{i1} \mid \omega_{i0}) & p(s_{i1} \mid \omega_{i1}) & p(s_{i1} \mid \omega_{i2}) \\ p(s_{i2} \mid \omega_{i0}) & p(s_{i2} \mid \omega_{i1}) & p(s_{i2} \mid \omega_{i2}) \end{pmatrix} \tag{3}$$

3.2 Rough calibration based on minimal assumptions

Although this model serves mainly analytical purposes to understand the basic factors of interactive decision making on theoretical grounds, we nevertheless strive to achieve a rough calibration and put the model into an empirically plausible “frame”. Throughout this paper we use two types of calibration. We use a set of simple and arbitrary numbers as parameter values if our main purpose is to show the main mechanism of the model, how it works and to illustrate a comprehensive range of potential solutions. We call these parameter values “arbitrary numbers”. With respect to model validation, we apply (and partly adjust) parameter values where we could find some reference or benchmark data. We call this set of numbers “hypothetical data” and apply it where we want to illustrate, for example, which of the derived solutions comes closest to a real world-setting.

Now, what is the data availability with respect to the parameters of an information system as described in Section 3.1? First, it is needless to say that EWS are complex and specific tools with still a very low level of standardization for data generation and data sharing. Although many EWS use probabilistic forecasting and apply Bayesian tools, which makes them to a minimum degree compatible to our approach, unfortunately there are no databases existing which could be used for parametrization. However, at least for an escalation to scenario S1 of an extreme flood, i.e. for the transition s_{01}, there are some insights from the *European Flood Awareness System* about the expected frequency of severe coastal inundation (Merz et al. 2020, p. 16). A flood, which heavily affects the coastal residents roughly corresponds to a frequency of 20 to 80 years, depending on geological and geographical factors of the built environment, the technical resilience of the region and the flood protection measures. As our model takes vulnerability as given, we take a 50-year-flood as a plausible case, which corresponds to an expected rate of occurrence of 2% per year and 0.0055% per day respectively. For the case of an extreme flood it is even more difficult to identify a good proxy for at least two reasons. First, there is less experience and data with extreme events and second, very extreme floods result from more complex hazard scenarios. Most frequently, they can be caused by meteorological compound events of severe convective storms, marine gusts and long periods of heavy precipitation. In addition, hurricanes can cause extreme floods and one of the most deterrent candidates are Tsunamis. EWS for Tsunamis determine the earliest arrivals, the time of arrival, the wave amplitude and the propagation of a tsunami (Chaturvedi et al. 2017, p. 84). For such very extreme events, the range lies between 200 and 1.000 years but even reaches up to 10.000 years. The latter number refers to a flood protection exercise in the Netherlands, executed by the Task Force for Flood Event Management (FLOODsite, p. 115). We again take a medium value as an average guess and take a 500-year flood (daily event probability of 0.00055%) as an appropriate proxy. Hence, the first row of the transition-matrix gets the entries 0.99993950, 0.0000550 and 0.0000055 (see *Figure 4*). For transitions starting in state S1 and S2, it is not possible to extract benchmark numbers from literature or flood reports because the further worsening of an already bad situation (transition s_{12}) is usually not registered as a separate event. In addition, the warning process during a de-escalation is partly different from an escalation because a warning system has to fall below a certain threshold before the alarm is deactivated and the region is declared safe again. Hence, although it is important to understand the interactions and dynamics of the de-escalation events, too, evidence is scarce. For this reason we filled the rest of the Transition-Matrix together with two flood experts, taking the warning bias (threshold-deactivation of the EWS) into consideration. The left matrix in expression (4) shows the calibrated *Transition-Matrix* $\boldsymbol{S}$**.** For these values, we get $\pi^* = \left(\pi_0 = 99.9797\%,\ \pi_1 = 0.0167861\%,\ \pi_2 = 0.00347298\%\right)$ as the stationary distribution of the Markov Model.

$$\boldsymbol{S} = \begin{pmatrix} 0.99994 & 5.5\times10^{-5} & 5.5\times10^{-6} \\ 0.3500 & 0.6000 & 0.0500 \\ 0.0500 & 0.3500 & 0.6000 \end{pmatrix} \quad \boldsymbol{L} = \begin{pmatrix} a & b & c \\ d & e & f \\ g & h & m \end{pmatrix} \quad \boldsymbol{L}_0 = \begin{pmatrix} 0.9800 & 0.0155 & 0.0045 \\ 0.3334 & 0.5511 & 0.1155 \\ 0.1056 & 0.2444 & 0.6500 \end{pmatrix} \qquad (4)$$

In the next step we look for empirical values of the Likelihood-Matrix, i.e. data which tells us something about the precision and effectiveness of flood-EWS, also called *EWS-verification*. In verification of weather warning, most approaches apply contingency tables and corresponding scores, as e.g. the equitable threat score (ETS) in UK and a combination of ETS, the probability of detection (POD), the false alarm ratio (FAR) together with the frequency bias is used in Austria (Wilson 2018, Wilson & Giles 2013). The most advantageous account was provided by Wilson & Giles (2013). The authors evaluated contingency-table data between 2009 and 2011 of a Canadian flood-EWS in order to arrive at an improved warning index. For a severe flood-event they derive a HIT-rate of 75% and a False-Alarm (FA)-rate of 2%. For an extreme flood the EWS-precision is lower according to the literature. Although, for example, nearly all tsunamis can be detected by modern EWS, there is uncertainty about under- and overestimating the wave height and the exact localization. Here the uncertainty can be considerable with fluctuations between 30-50% (Lauterjung & Letz, 2017, p. 41). Therefore we consider this uncertainty and adjust for noise. We assume a HIT-rate of 60% and a FA-rate of 6% for S2. We use these values for our study but have to adjust the calculation because our setting considers three states (including warning states). Matrix $\boldsymbol{L}$ (matrix with letter-entries in the middle of expression (4)) represents a general Likelihood-Matrix which helps to understand the calculations. The HIT-rate for state S1 is calculated by taking the HITS (cells e + f + h + m) and divide them by HITS and misses (cells d + g). For state S2 we have the same procedure but different cells are relevant, here we have m divided by (m + g + h). The FA-rates are the ratio of the false alarms in the numerator and the false alarms together with the "correct negatives" in the denominator. This corresponds to the ratios (b + c)/(a + b + c) for S1 and (c + f)/(a + b + c + d + e + f) for S2. We further have to consider the *Informativeness-Condition* (IC), which requires a > b > c, m > h > g, e > d and e > f. The right part of expression (4) shows all entries of the matrix $\boldsymbol{L_0}$, which fulfill the ensemble of the before mentioned conditions. The likelihood-matrices for the mixed-scenario (S1) and the de-escalation-scenario (S2) could not be derived in a similarly precise way. Here again we took $\boldsymbol{L_0}$ as anchor and consulted the two flood experts. The resulting matrices are shown in expression (5).

$$\boldsymbol{L}_1 = \begin{pmatrix} 0.75 & 0.24 & 0.01 \\ 0.35 & 0.60 & 0.05 \\ 0.05 & 0.30 & 0.65 \end{pmatrix}; \quad \boldsymbol{L}_2 = \begin{pmatrix} 0.55 & 0.35 & 0.10 \\ 0.20 & 0.60 & 0.20 \\ 0.01 & 0.19 & 0.80 \end{pmatrix} \tag{5}$$

Expressions (4) and (5) comprise the "hypothetical dataset" for the IS-validation. By applying Bayes' rule we get the corresponding conditional Posterior-Matrices $\boldsymbol{P_0}$, $\boldsymbol{P_1}$ and $\boldsymbol{P_2}$ as given by expression (6).

$$\boldsymbol{P}_0 = \begin{pmatrix} 0.99997 & 0.99824 & 0.99815 \\ 2.4\times10^{-5} & 1.7\times10^{-3} & 1.1\times10^{-3} \\ 1.4\times10^{-6} & 8.6\times10^{-5} & 7.1\times10^{-4} \end{pmatrix}; \quad \boldsymbol{P}_1 = \begin{pmatrix} 0.625 & 0.225 & 0.043 \\ 0.365 & 0.704 & 0.266 \\ 0.010 & 0.070 & 0.691 \end{pmatrix}; \quad \boldsymbol{P}_2 = \begin{pmatrix} 0.266 & 0.051 & 0.009 \\ 0.676 & 0.615 & 0.126 \\ 0.058 & 0.334 & 0.865 \end{pmatrix} \tag{6}$$

Altogether, these numbers are oriented at real EWS-data reflecting current performance of an EWS for (coastal) flood risk without imposing too many restrictions, which otherwise bear the risk to be unjustified on empirical grounds. In the first place, this model provides the formal "infrastructure" for an analysis and if transferred to a concrete context, assumptions can be fine-tuned towards the specific forecasting technology and data basis as illustrated by the reference above.

4. Decision Model

In this section, we briefly describe the objective functions and strategies of the local government G and the citizens of the two regions A and B. For the ease of exposition, we talk about "group A" and "group B" and an objective function reflects the (dis)utility of one representative member of each group. As all objective functions are scenario-dependent, for each type of decision maker we have an objective function for the escalation-state (S0), the mixed-state (S1) and the de-escalation state (S2). In the model, we express all types of payoffs in disutility-units, such as damage, deprivation and economic loss. Therefore, the resulting objective functions are *cost functions*, where the term "cost" is just shorthand for disutility reflecting different forms of negative consequences for the individuals. In each state, the groups and the local government G observe the warning signal ω_{ik}, update the priors accordingly and make their respective decision. For the description of the model structure but even for the derivation of the equilibrium conditions it is not necessary to take the warning-levels explicitly into consideration. Therefore, for the most part of this section, we suppress the warning-level k in the notation and just use the short form p_{ij} to describe the conditional probabilities $p_{ij} \equiv p(s_{ij} \mid \omega_{ik})$ of a transition to state j given the current state i and "any" warning-level k. This way, the analysis is more general but also more comprehensible. Later, we evaluate the p_{ij}-values for different warning-levels.

4.1 Decision variables, payoff parameters and trust variables

Decision variables

The discrete, binary decision variable $v_A \in \{0,1\}$ for group A (and v_B for group B respectively) describes the decision of a representative member of group A. The choice $v_{A,B} = 1$ always represents the cautious option of the decision, which is "evacuation" in the escalation-state and "stay evacuated" in the de-escalation-state. Accordingly, $v_{A,B} = 0$ represents the risky option of a decision corresponding to "no evacuation" in the escalation-state and "return home" in the de-escalation-state. While both groups choose an *action strategy*, the government G chooses a *communication strategy*. In particular, G picks one out of three types of requests $E \in \{\text{E0,E1,E2}\}$. The request E0 is equivalent to the message "no evacuation necessary in both regions" in the escalation-state and "return to both regions is possible" in the de-escalation-state. Although G has a trinary strategy set, each group receives a binary signal $E_{A,B} \in \{0,1\}$. For request E0, the received signals are identical $(E_A = 0, E_B = 0)$ because the order is the same for both groups. Request E1 is equivalent to the message "evacuation in region A but no evacuation necessary in region B" in the escalation-state and to "stay evacuated in region A but return to region B is possible" in the de-escalation-state. Hence, request E1 generates the signals $(E_A = 1, E_B = 0)$. Finally, request E2 corresponds to the message "evacuation in both regions" in the escalation-state and "stay evacuated in both regions" in the de-escalation-state. By observing the request E2, each group receives the same signal $(E_A = 1, E_B = 1)$. Note that there is no possibility for the signal-combination $(E_A = 0, E_B = 1)$ because this would imply a contradiction (if evacuation is ordered to the whole town, this automatically includes group A, too).

The described communication strategies of the government include both active and passive communication. With respect to the request E1, the government has to take into consideration that the very same message has different content for each group, i.e. the signals vary. However, as the analysis in section 5 shows, even an identical signal (as in the case of the requests E0 and E2) can cause different reactions by the two groups because their risk situation is different.

Payoffs

With respect to the disutility of the citizens, we distinguish three types of cost. The most important cost component is D, which is relevant if a person is hit by a flood. It represents potential death and injury or strong deprivation (in the case of lack of food, water, medicine). The other two cost components refer to the cost of evacuation and capture the inconvenience, nuisance or deprivation with less relevance for health. The parameter c^m reflects the direct cost of the evacuation itself ("cost for moving", therefore the index m) and c^d reflects the deprivation of one evacuated period. This cost term takes into account the fact that those affected by an evacuation are exposed to a particularly difficult and stressful situation together with the nuisance that the normal course of everyday life is disrupted. The superscript d therefore stands for either deprivation or disruption. We assume a clear-cut order of the cost-components $0 < c^m < c^d < D$.

The government takes the before mentioned disutility-components into account, too. In addition, G cares for two types of economic losses. The loss-parameter ℓ^L reflects the economic opportunity cost of an unjustified evacuation due to foregone business revenues in the region. The loss parameter ℓ^H captures the loss of human capital if people are hit by a flood. In addition to the direct physical damage D, affected people are either not available or not productive for a time span after the flood because they are in hospitals, suffer at home from injuries or psychical stress or they have to care for their peers. Note that all cost components refer to one period (the focal period of planning) except the human-capital-loss, which reflects a medium-term future loss. To consider this difference, we add a discount factor $0<\delta<1$ to the human capital-loss component. The superscripts L and H stand for "low" and "high", which should help to order the cost components visually. We assume $0<\ell^L<\delta\ell^H<D$.

Direct evacuation cost are not included in the government's decision because civil protection is the primary task of the local government. In addition, there are often soft budget constraints for disaster situations. Extra funds are made available by the central government because policy makers, and in particular their voters, will not tolerate a high death toll. However, budget issues always play a role and in the context of disasters, they most probably affect future decisions. As done in section 3, we also want to roughly calibrate these five cost components to get an approximate order of magnitude. The values used as a basis are provided by *Table 2*.

Table 2. Calibration of cost parameters

Variable	Value [€]	Description
D	$\approx 5\times 10^6$	Value of Statistical Life (VSL); Viscusi & Aldy (2003)
c^m	$\approx 1.6\times 10^2$	Lost net value of production (day); Schröter et al. (2008)
c^d	$\approx 2.5\times 10^3$	Lost net value of production x deprivation factor
ℓ^L	$\approx 1.25\times 10^3$	Lost net value of production (week); Schröter et al. (2008)
ℓ^H	$\approx 5\times 10^4$	Disability Adjusted Life Years (DALY); Cropper & Sahin (2009)

Expected flood impact μ and competence trust in the government

As already mentioned above, there is an information asymmetry between the government and the two groups with respect to the expected impact $\mu\in[0,1]$ of a potential flood. Although there are event probabilities available, there can remain doubts whether and how severely even an extreme flood could harm and affect individuals (Dow & Cutter 2000). In the context of flood risk, people often wrongly estimate the speed and power of water flows, the effects of an impairment of critical infrastructure and the destabilizing impact of high water levels on buildings (which is why people often prefer sheltering in high buildings to evacuation). The expected impact of a flood as perceived by group A is given by $\mu_A=\tau_A^c E_A+(1-\tau_A^c)\hat{\mu}_A$, $\mu_A\in[0,1]$. The variable $\tau_A^c\in[0,1]$ reflects the *competence* *trust* in the government's impact assessment and the variable $E_A \in \{0,1\}$ is the received binary signal, which directly results from G's request as described above. The variable $\hat{\mu}_A(\omega)$ is the independent belief of group A about the potential impact of a flood, which the individuals infer from the warning-level ω. The higher τ_A^c, the higher the willingness of group A to take the government's request into account, i.e. to interpret the government's request as credible information about flood risk (Basolo et al. 2009). The lower the trust parameter, the more weight is placed on the independent guess $\hat{\mu}_A(\omega)$. In the special case of full trust ($\tau_A^c = 1$), the expected impact equals the binary signal E_A, i.e. $\mu_A = E_A$ and $\mu_A \in \{0,1\}$. Note that a sufficiently high trust-level can either increase or reduce the motivation to evacuate (or to stay in the region if already evacuated), dependent on the type of request. In the opposite case of full distrust ($\tau_A^c = 0$), the expected impact equals the independent belief $(\mu_A = \hat{\mu}_A(\omega))$. As the independent belief $\hat{\mu}_A(\omega)$ depends on the warning-level, we need further assumptions about this parameter. In the case of "no warning" ($\omega = 0$), the independent belief of both groups is zero ($\hat{\mu}_A(\omega = 0) = \hat{\mu}_A(\omega = 0) = 0$). In the case of a flood-warning for region A ($\omega = 1$) we assume an arbitrary value $0 < \hat{\mu}_A(\omega = 1) < 1$ for group A, which depends on prior flood experience and the risk expertise of the population. As we neither look at path dependent outcomes nor incorporate issues of risk experience and risk communication, we treat this variable as exogenous. From the perspective of group B, the impact is expected to be very low, indicated by the variable $0 < \varepsilon << 1$, which stands for a very low probability. Hence, $0 < \hat{\mu}_B(\omega = 1) = \varepsilon << 1$. In the case of a level-2-warning ($\omega = 2$), group B expects an impact similar to the belief of group A for a level-1-warning, $0 < \hat{\mu}_B(\omega = 2) < 1$, and group A expects a "near to certain" strike based on the belief $0 << \hat{\mu}_A(\omega = 2) = 1 - \varepsilon$. If not otherwise stated, we make the assumption $\tau_A^c \geq \tau_B^c$, which implies that the parameters for competence-trust of both groups are either identical or the trust-level of group A is higher because the people in the risk-zone expect that the government has a special focus on this region.

Expected congestion (1 − φ) *and reliability trust in the government*

The second type of trust considered in ECM is the government's reliability with respect to evacuation preparation and congestion management. Let $\varphi \in [0,1]$ be a measure of *evacuation effectivity*, which is equal to zero if the roads are fully congested (in this case evacuation is impossible) and equal to one if there is no congestion at all. The complement (1 − φ) is then a measure of congestion. Depending on whether one group or both groups leave the region at the same time, there is congestion to the extent of $1-\varphi=\gamma\, v_A+(1-\gamma)\, v_B$. The government has the possibility to mitigate the congestion problem by an investment $I\in[0,1]$ into improved evacuation planning and emergency logistics, $1-\varphi=[\gamma\, v_A+(1-\gamma)\, v_B]\ (1-I)$. These measures comprise e.g. very detailed scenario planning, evacuation training with employees, special contracts with bus companies or even rent contracts to have helicopters available. We assume that this investment, i.e. the complete package of measures, is not observable to the public. A full investment, $I=1$, stands for a perfect preparation-level, which can reduce the congestion-problem completely. No investment, $I=0$, as the other extreme, implies that G has done absolutely nothing to improve the situation. In this case, the groups turn in on themselves. The required budget for an investment-level I is given by $B(I)=-Log[1-I]$. This function implies $B(I=0)=0$ and $B(I=1)=\infty$, i.e. the perfect preparation-level comes at an infinitively high cost. As the public cannot observe the investment-level, both groups need to trust the government to have taken the necessary precautions (Hamm et al. 2019). The trust-parameter for *reliability trust* $\tau^r\in[0,1]$ is assumed identical for both groups. Hence, from the perspective of both groups, the *expected evacuation effectivity* is given by $\varphi=1-[\gamma\, v_A+(1-\gamma)\, v_B]\ (1-\tau^r)$.

4.2 Cost functions of group A and B

Escalation-scenario S0

The cost-functions for both strategies of group A and S0 are given by the expressions (7) and (8).

$$C_A^{S0}(v_A=1)=p_{00}\left(2c^m+c^d\right)+\left(p_{01}+p_{02}\right)\left(c^m+(1-\varphi_A)\mu_A D+\left(1-(1-\varphi_A)\mu_A\right)c^d\right) \qquad (7)$$

$$C_A^{S0}(v_A=0)=\left(p_{01}+p_{02}\right)\mu_A D \qquad (8)$$

If group A evacuates ($v_A=1$) although the evacuation is unnecessary (to be expected with probability p_{00}), the group incurs twice the moving-cost c^m (the group moves out of the region but returns when the false alarm is realized) and once the cost for evacuation-deprivation c^d. These two cost-elements are not involved in the case of no evacuation ($v_A=0$). When the group evacuates and the region is hit by a flood (to be expected with probability $p_{01}+p_{02}$), it incurs the moving-cost and either physical damage $\mu_A D$, if evacuation fails due to congestion (determined by $1-\varphi_A$), or the evacuation-cost c^d, if the evacuation can be executed without congestion (to be expected with probability φ_A). If the group does not evacuate but a flood occurs, the group suffers from the high damage cost. Note that the value of the damage cost depends on the expected impact because we look at the problem from the group's perspective. The cost functions for group B in scenario S0 look nearly identical (9), the only difference is that group B is not affected by a flood in region A (expected with probability p_{01}), which implies a lower risk of damage but a higher risk of unnecessary evacuation.

$$C_B^{S0}(v_B = 1) = \left(p_{00} + p_{01}\right)\left(2c^m + c^d\right) + p_{02}\left(c^m + (1-\varphi_B)\mu_B D + \left(1-(1-\varphi_B)\mu_B\right)c^d\right) \tag{9}$$

$$C_B^{S0}(v_B = 0) = p_{02}\,\mu_A D \tag{10}$$

Mixed-scenario S1

In the de-escalation-state S1, region A is already flooded and the citizens are no longer there: Either they evacuated in a controlled manner (depending on their evacuation-strategy in S0) or the flood "forced" them out of the region. In this case, they had to hastily abandon their homes, had to be saved by rescue services or did not survive. The following cost functions, as depicted by (11) and (12), are therefore only relevant for those in group A who were able to leave the region unharmed and are now waiting to return. Remember that in a de-escalation-state the strategy $v = 1$ corresponds to "stay evacuated" and $v = 0$ means "return home".

$$C_A^{S1}(v_A = 1) = c^d \tag{11}$$

$$C_A^{S1}(v_A = 0) = c^m + \left(p_{01} + p_{02}\right)\mu_A D \tag{12}$$

If group A stays evacuated it suffers from evacuation-deprivation c^d. If A returns, it incurs the cost for moving back, c^m, and risks to be hit a second time by a returning flood ("second wave"). We don't consider congestion for the way back because there is less rush and – what is more important – if people get stuck on their way back they are still in a safe area. The cost functions of group B are the same as in scenario S0 because also in S1 region B is not flooded.

De-escalation-scenario S2

In S2, both groups face a de-escalation scenario. The cost-functions for A are the same as in S1 and those for group B, expressions (13) and (14), are equivalent.

$$C_B^{S2}(v_B = 1) = c^d \tag{13}$$

$$C_B^{S2}(v_B = 0) = c^m + p_{02}\,\mu_A D \tag{14}$$

4.3 Social cost function of the government G

In the ECM, the government has the role of a policy-maker who seeks to minimize the social cost. Basically, the "ingredients" to the social cost function are similar to the cost functions of both groups with mainly three differences. First, the government cannot decide about evacuation due to the strict no-enforcement-assumption. However, G seeks to optimally influence the groups' decisions by its communication-strategy E and this requires that G needs to know the parameter constellations for which no, partial or full evacuation is socially optimal. Second, the government communicates E to both groups at the same time; therefore the social cost function is an average of the outcomes in both regions, weighted by the population share γ. Third, G puts weight $\alpha \in [0,1]$ on the population's deprivation (caused by an evacuation) but also weight $\beta \in [0,1]$ on the economic losses. Hence, for $\alpha = 1$ and $\beta = 0$, the groups objectives and the government's objectives come closest (although they are still not identical due to the information asymmetries). The physical damage parameter D has an explicit weight of 1, however the implicit weight of D of course depends on α and β. Fourth, the government has full information on the trust-sensitive parameters μ and φ as G knows the expected impact ($\mu = 1$) and its own investment I into congestion reduction. The last parameter, which is specific to G's decision, refers to the de-escalation-scenario.

Escalation-scenario S0

$$\begin{aligned} C_G^{S0} = p_{00}&\left[\left(\gamma v_A + (1-\gamma) v_B\right)\left(\alpha(2c^m + c^d) + \beta \ell^L\right)\right] + \ldots \\ &+ (p_{01} + p_{02})\gamma\left[v_A\left((1-\varphi)(D + \beta\delta\ell^H + \alpha c^m) + \varphi\alpha(c^m + c^d)\right) + (1-v_A)(D + \beta\delta\ell^H)\right] + \ldots \\ &+ p_{01}(1-\gamma)\left[v_B\left(\alpha(2c^m + c^d) + \beta\ell^L\right)\right] + \ldots \\ &+ p_{02}(1-\gamma)\left[v_B\left((1-\varphi)(D + \beta\delta\ell^H + \alpha c^m) + \varphi\alpha(c^m + c^d)\right) + (1-v_B)(D + \beta\delta\ell^H)\right] \end{aligned} \quad (15)$$

The first two summands refer to group A (weighted by γ), the last two summands refer to group B (weighted by $1-\gamma$). In the case that an evacuation is unnecessary, the economic opportunity cost $\beta\ell^L$ occurs as an additional factor and if a necessary evacuation has not taken place – either due to congestion or due to a wrong decision) the medium-term cost $\beta\delta\ell^H$ come on top of D (both loss parameters are weighted by β as explained above).

Mixed-scenario S1 and D*e-escalation-scenario* S2

For the social cost-functions in S1 (but also for S2 below), there appears one further parameter in the de-escalation-scenario. Suppose that group A was already affected by a flood and now has to decide whether to return. The return-decision can just be made by those who successfully evacuated, hence by a share of φ_A^{t-1} percent of the population of group A. The time-index $t-1$ indicates that the share of people who make the return-decision depends on both, the evacuation strategy and the evacuation-success of the period before. Therefore, the values $\varphi_{A,B}^{t-1}$ result endogenously from the equilibrium evacuation-strategies as well as from the equilibrium congestion-rate (see section 5). Apart from this detail, the social cost functions for scenario S1 and S2 are straightforward.

$$\begin{aligned} C_G^{S1} = {} & p_{10}\,\gamma\,\varphi_A^{t-1}\left(v_A(\alpha c^d+\beta\ell^L)+(1-v_A)\alpha c^m\right)+\dots \\ & +(p_{11}+p_{12})\gamma\varphi_A^{t-1}\left(v_A\alpha c^d+(1-v_A)(D+\beta\delta\ell^H+\alpha c^m)\right)+\dots \\ & +(p_{10}+p_{11})(1-\gamma)\left[v_B\left(\alpha(2c^m+c^d)+\beta\ell^L\right)\right]+\dots \\ & +p_{12}(1-\gamma)\left[v_B\left((1-\varphi)(D+\beta\delta\ell^H+\alpha c^m)+\varphi\alpha(c^m+c^d)\right)+(1-v_B)(D+\beta\delta\ell^H)\right] \end{aligned} \tag{16}$$

$$\begin{aligned} C_G^{S2} = {} & p_{20}\,\gamma\,\varphi_A^{t-1}\left(v_A(\alpha c^d+\beta\ell^L)+(1-v_A)\alpha c^m\right)+\dots \\ & +(p_{21}+p_{22})\gamma\varphi_A^{t-1}\left(v_A\alpha c^d+(1-v_A)(D+\beta\delta\ell^H+\alpha c^m)\right)+\dots \\ & +(p_{20}+p_{21})(1-\gamma)\,\varphi_B^{t-1}\left(v_B(\alpha c^d+\beta\ell^L)+(1-v_B)\alpha c^m\right)+\dots \\ & +p_{22}(1-\gamma)\,\varphi_B^{t-1}\left(v_B\alpha c^d+(1-v_B)(D+\beta\delta\ell^H+\alpha c^m)\right) \end{aligned} \tag{17}$$

5. Equilibrium analysis and game results

In this section, we derive the Nash-Equilibria (NE) of the Stackelberg-game for the scenarios S0, S1 and S2. We restrict the analysis on pure equilibria and solve the game by backward-induction, starting with the sub-equilibrium on stage 2 (group-interactions) and moving forward to stage 1 to identify the optimal evacuation-order of the government. The optimal government's investment decision (stage 0) will be derived in section 6.

In the escalation-scenario S0, both groups play a subgame on stage 2 because the groups influence each other via the evacuation-effectiveness parameter $\varphi \in [0,1]$, which is defined by expression (18). Note that although each group forms an ex ante belief about this parameter (φ_A and φ_B respectively), in equilibrium there results just one level of evacuation-effectiveness for the whole city.

$$\varphi_{v_A,v_B} = 1-\left(\gamma v_A + (1-\gamma) v_B\right)(1-y) \tag{18}$$

According to expression (18), for $y=0$ evacuation-effectiveness is partially reduced to $\varphi_{1,0}$ if just group A decides to evacuate ($v_A = 1$ and $v_B = 0$) and it is fully reduced to $\varphi_{1,1}$ if both groups evacuate ($v_A = 1$ and $v_B = 0$). As we assume $0 < \gamma < 0.5$, there will be less people in the street if group A evacuates compared to group B. Hence, $0 < \varphi_{1,1} < \varphi_{0,1} < \varphi_{1,0} < 1$. As already described above, by investing a share $y \in [0,1]$ of a given budget in improving the traffic conditions, the government can reduce congestion. As the citizens cannot observe the investment they form a belief $\tau^r_{A,B}$ about it, which reflects the public's trust in G's reliability.

In a first step we ignore the concrete warning-level and derive a general solution for each of the three situations S0, S1 and S2. The last requirements, $0 < p_{i0}, p_{i1}, p_{i2} < 1$ and $p_{i0} + p_{i1} + p_{i2} = 1$, are both straightforward and were already prescribed by section 3. Without loss of generality, we henceforth substitute p_{i0} according to $p_{i0} = 1 - p_{i1} - p_{i2}$.

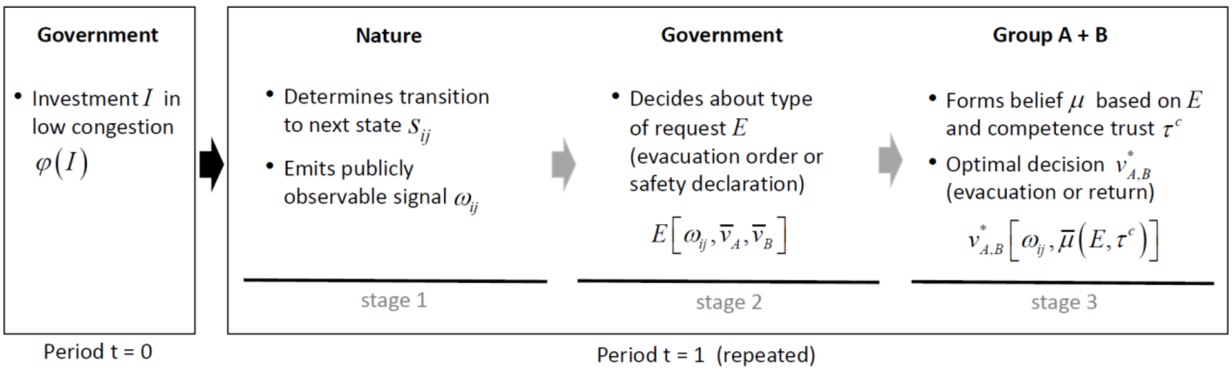


Figure 3. Game structure and sequence of events

5.1 Optimal strategies in the Escalation-Scenario S0

Optimal group strategies

We first define three terms $0 \le T^{S0}_{A,B} \le 1$, which constitute critical thresholds for the conditional probability p_{02} as given by

$$T_{A1}^{S0} \equiv \frac{2c^m + c^d}{c^m + \mu_A[\varphi_{10} D + (1-\varphi_{10})c^d]} - p_{01} \tag{19}$$

$$T_{B1}^{S0} \equiv \frac{2c^m + c^d}{c^m + \mu_B[\varphi_{01} D + (1-\varphi_{01})c^d]}, \tag{20}$$

$$T_{B2}^{S0} \equiv \frac{2c^m + c^d}{c^m + \mu_B[\varphi_{11} D + (1-\varphi_{11})c^d]} \tag{21}$$

Lemma 1a: For the threshold-terms (19) – (21) the following order applies: $T_{A1}^{S0} < T_{B1}^{S0} < T_{B2}^{S0}$.

Proof: The order can be easily verified by taking into consideration the parameter assumptions made above: $0 < \varphi_{1,1} < \varphi_{0,1} < \varphi_{1,0} < 1$, $0 < p_{01} < 1$, $\hat{\mu}_B \leq \hat{\mu}_A$ and $\tau_A^c \geq \tau_B^c$. ■

We can then state the following *Proposition 1a*.

Proposition 1a (Group-Equilibrium in S0)

The group-equilibrium of the sub-game on stage 2 for scenario S0 is given by

$$\left(v_A^* = 0, v_B^* = 0\right) \text{ if } p_{02} < T_{A1}^{S0}; \tag{22}$$

$$\left(v_A^* = 1, v_B^* = 0\right) \text{ if } T_{A1}^{S0} < p_{02} < T_{B2}^{S0}; \tag{23}$$

$$\left(v_A^* = 0, v_B^* = 0\right) \text{ if } T_{B2}^{S0} < p_{02} \tag{24}$$

Proof: For $(v_A = 0, v_B = 0)$ to be a NE, two conditions (I) $C_A^{S0}(v_A = 0, v_B = 0) < C_A^{S0}(v_A = 1, v_B = 0)$ and (II) $C_B^{S0}(v_A = 0, v_B = 0) < C_B^{S0}(v_A = 0, v_B = 1)$ must be fulfilled. In words, both groups must strictly prefer not to evacuate provided that the other group sticks to the no-evacuation-strategy, too. For each condition, there is a critical threshold for p_{02}: (I) $p_{02} < T_{A1}^{S0}$ and (II) $p_{02} < T_{B1}^{S0}$. Hence, a NE where no group evacuates requires $p_{02} < Min[T_{A1}^{S0} - p_{01}, T_{B1}^{S0}]$. According to *Lemma 1a,* it follows that $T_{A1}^{S0} < T_{B1}^{S0}$ and thus T_{A1}^{S0} is the required upper bound (if p_{02} is lower than T_{A1}^{S0}, it is also lower than T_{B1}^{S0} but not vice versa). Hence, if group A does not evacuate, then group B certainly does not either.

For $(v_A = 1, v_B = 0)$ to be a NE, two conditions (III) $C_A^{S0}(v_A = 1, v_B = 0) < C_A^{S0}(v_A = 0, v_B = 0)$ and (IV) $C_B^{S0}(v_A = 1, v_B = 0) < C_B^{S0}(v_A = 1, v_B = 1)$ must be fulfilled. Under this condition, group A must strictly prefer to evacuate given that group B does not and group B should not prefer to evacuate given that group A does. Again there result two conditions, constituting a critical threshold for p_{02}. The first is identical to (I) above with a reversed sign, and the second leads to (IV) $p_{02} < T_{B2}^{S0}$. Hence, $T_{A1}^{S0} < T_{B2}^{S0}$ is a necessary condition for the existence of a NE and according to *Lemma 1a*, this condition holds true.

The strategy-combination $(v_A = 1, v_B = 1)$ is a NE if the conditions (V) $C_A^{S0}(v_A = 1, v_B = 1) < C_A^{S0}(v_A = 0, v_B = 1)$ and (VI) $C_B^{S0}(v_A = 1, v_B = 1) < C_B^{S0}(v_A = 1, v_B = 0)$ are fulfilled. Both groups prefer to evacuate, given that the other group does so, too. The second condition is the same as condition (IV) above, just with the reversed sign. The first condition requires $p_{02} > T_{A1}^{S0}$ Hence, a NE for both groups evacuating requires $Max[T_{A1}^{S0}, T_{B2}^{S0}] < p_{02}$. According to *Lemma 1a,* we know that $T_{A1}^{S0} < T_{B2}^{S0}$ and thus T_{B2}^{S0} is the lower bound (if p_{02} exceeds T_{B2}^{S0}, it exceeds T_{A1}^{S0} anyway). Hence, if group B evacuates, then group A will certainly evacuate, too. This completes the proof of *Proposition 1a*. ■

Optimal government strategies

The optimal decisions of both groups on stage 2 are anticipated by G (the government), which tries to minimize the social cost by deciding about its communication-strategy E. The procedure comprises two steps: First, we derive the critical thresholds for which G prefers the outcomes “no evacuation”, “partial evacuation” and “full evacuation”. Second, once we know the government’s objectives, we derive the optimal communication-strategy of stage 1 of the Stackelberg-game. We first define two terms $0 \le T_G^{S0} \le 1$, which constitute critical thresholds for the conditional probability p_{02} as given by

$$T_{G1}^{S0} \equiv \frac{\alpha(2c^m + c^d) + \beta\ell^L}{\alpha(c^m + c^d) + \beta\ell^L + \varphi_{10}(D + \beta\delta\ell^H - \alpha c^d)} - p_{01} \tag{25}$$

$$T_{G2}^{S0} \equiv \frac{\gamma p_{01}(\varphi_{10} - \varphi_{11})\left[D + \beta\delta\ell^H - \alpha c^d\right] + (1-\gamma)\left[\alpha(2c^m + c^d) + \beta\ell^L\right]}{(\varphi_{11} - \gamma\varphi_{10})\left[D + \beta\delta\ell^H - \alpha c^d\right] + (1-\gamma)\left[\alpha(2c^m + c^d) + \beta\ell^L\right]} \tag{26}$$

Lemma 1b: Let $\gamma < \tilde{\gamma}_G^{S0} \equiv \frac{\varphi_{11}(D+\beta\delta\ell^H - \alpha c^d) - \alpha c^m}{\varphi_{10}(D+\beta\delta\ell^H - \alpha c^d) - \alpha c^m}$. Then for the threshold-terms (25) and (26) the order $T_{G1}^{S0} < T_{G2}^{S0}$ applies.

Proof: See Appendix 1.

Proposition 1b defines the socially optimal strategy-combinations as envisaged by the government. To distinguish socially optimal strategies from individually optimal (Nash-equilibrium) strategies, we use a small circle ($\circ$) as superscript.

Proposition 1b (Optimal Government-Strategies in S0)

$$\left(v_A^\circ = 0, v_B^\circ = 0\right) \text{ if } 0 < p_{02} < T_{G1}^{S0}; \tag{27}$$

$$\left(v_A^\circ = 1, v_B^\circ = 0\right) \text{ if } T_{G1}^{S0} < p_{02} < T_{G2}^{S0}; \tag{28}$$

$\left(v_A^{\circ}=0, v_B^{\circ}=0\right)$ if $T_{G2}^{S0} < p_{02}$ (29)

Proof: If "no evacuation" of both groups $(v_A = 0, v_B = 0)$ minimizes the social cost-function, the social cost must be lower than in the two alternatives, (I) $C_G^{S0}(v_A = 0, v_B = 0) < C_G^{S0}(v_A = 1, v_B = 0)$ and (II) $C_G^{S0}(v_A = 0, v_B = 0) < C_G^{S0}(v_A = 1, v_B = 1)$. Condition (I) requires $p_{02} < T_{G1}^{S0}$ and condition (II) requires $p_{02} < T_{G2}^{S0}$. According to *Lemma 1b* $T_{G1}^{S0} < T_{G2}^{S0}$ holds and therefore $T_{G1}^{S0} - p_{01}$ is the upper bound for p_{02} in (21). The government prefers that just group A evacuates $(v_A = 1, v_B = 0)$ if the following two inequalities hold: (III) $C_G^{S0}(v_A = 1, v_B = 0) < C_G^{S0}(v_A = 0, v_B = 0)$ and (IV) $C_G^{S0}(v_A = 1, v_B = 0) < C_G^{S0}(v_A = 1, v_B = 1)$. Inequality (III) is the inverse constellation to (I) and condition (IV) requires $p_{02} < T_{G2}^{S0}$. According to Lemma 1b, we know that $T_{G1}^{S0} < T_{G3}^{S0}$, therefore p_{02} lies in between in constellation (22). If the inverse constellation of (IV) holds true, (v) $p_{02} > T_{G2}^{S0}$, joint evacuation $(v_A = 1, v_B = 1)$ minimizes the social cost. With $T_{G1}^{S0} < T_{G2}^{S0}$ from *Lemma 1b*, we identify T_{G2}^{S0} as the lower bound for p_{02}. This completes the proof. ■

5.2 Optimal strategies in the Mixed-Scenario S1

Optimal group strategies

We first define two terms $0 \le T_{A,B}^{S1} \le 1$, which constitute critical thresholds for the conditional probability p_{12} as given by

$$T_A^{S1} \equiv \frac{c^d - c^m}{\mu_A D} - p_{11} \tag{30}$$

$$T_B^{S1} \equiv \frac{2c^m + c^d}{c^m + \mu_B[\varphi_{01}D + (1-\varphi_{01})c^d]} \tag{31}$$

In situation S1, congestion is no longer a strategic issue between the two groups and therefore their objective functions are not interdependent. Thus, we are left with just one critical threshold for each group. Note that the optimal group strategies in S1 and S2 do not constitute a Nash-equilibrium because these are independent optimal strategies.

Lemma 2a: $0 < T_A^{S1} < T_B^{S1} < 1 \quad \forall\, p_{11} \in [0,1]$.

Proof: We just sketch the proof by contradiction. As T_B^{S1} does not depend on p_{11}, it is sufficient to show that $T_A^{S1}(p_{11} = 0) < T_B^{S1}$. In order to get the opposite result $T_A^{S1}(p_{11} = 0) < T_B^{S1}$, μ_B must exceed a lower bound $\tilde{\mu}_B^{S1}$. However, it is straightforward to show $\nexists \mu_B \in [0, \mu_A] : \mu_B > \tilde{\mu}_B^{S1} \wedge 0 < T_B^{S1} < 1$. ■

We then can state the following *Proposition 2a*. We skip the proof because it follows the same structure as for *Proposition 1a*.

Proposition 2a (Group-strategies in S1)

The optimal group-strategies for scenario S1 are given by

$$\left(v_A^* = 0, v_B^* = 0\right) \text{ if } p_{12} < T_A^{S1} \tag{32}$$

$$\left(v_A^* = 1, v_B^* = 0\right) \text{ if } T_A^{S1} < p_{12} < T_B^{S1} \tag{33}$$

$$\left(v_A^* = 0, v_B^* = 0\right) \text{ if } T_B^{S1} < p_{12} \tag{34}$$

Optimal government strategies

For the government we get the following two critical thresholds $0 \le T_G^{S1} \le 1$ for situation S1, as given by (35) and (36).

$$T_{G1}^{S1} \equiv \frac{\alpha(c^d - c^m) + \beta\ell^L}{D + \beta\delta\ell^H + \beta\ell^L} - p_{11} \tag{35}$$

$$T_{G2}^{S1} \equiv \frac{\alpha(2c^m + c^d) + \beta\ell^L}{\alpha(c^m + c^d) + \beta\ell^L + \left(D + \beta\delta\ell^H - \alpha c^d\right)\varphi_{11}} \tag{36}$$

Lemma 2b: For the critical thresholds (35) and (36), it holds $T_{G1}^{S1} < T_{G2}^{S1}$.

Proof: We again provide the proof by contradiction. As T_{G2}^{S1} does not depend on p_{11}, it is sufficient to show that $T_{G1}^{S1}(p_{11} = 0) < T_{G2}^{S1}$. In order to get the opposite result $T_{G1}^{S1}(p_{11} = 0) > T_{G2}^{S1}$, φ_{11} must exceed a lower bound $\tilde{\varphi}_{11}^{S1}$. However, for our assumptions any, value $\varphi_{11} > \tilde{\varphi}_{11}^{S1}$ will strictly exceed 1. We conclude $\nexists \varphi_{11} \in [0,1] : \tilde{\varphi}_{11}^{S1} < \varphi_{11} < 1$, which completes the proof. ■

Proposition 2b defines the socially optimal strategy-combinations from the government's perspective for situation S1. We skip the proof because it follows the same structure as for *Proposition 1b*.

Proposition 2b (Optimal Government-Strategies in S1)

$$\left(v_A^\circ = 0, v_B^\circ = 0\right) \text{ if } 0 < p_{12} < T_{G1}^{S1}; \tag{38}$$

$$\left(v_A^\circ = 1, v_B^\circ = 0\right) \text{ if } T_{G1}^{S1} < p_{12} < T_{G2}^{S1}; \tag{39}$$

$$\left(v_A^\circ = 0, v_B^\circ = 0\right) \text{ if } T_{G2}^{S1} < p_{12} \tag{40}$$

5.3 Optimal strategies in the De-Escalation-Scenario S2

Following our standard procedure, the two terms $0 \le T_{A,B}^{S2} \le 1$ constitute the critical thresholds for the conditional probability p_{22} in the de-escalation-state. In S2, both groups already evacuated. For group A the expression is identical to situation S1 and group B also makes the decision whether to stay evacuated or return into region B.

$$T_A^{S2} \equiv \frac{c^d - c^m}{\mu_A D} - p_{11} \tag{41}$$

$$T_B^{S2} \equiv \frac{c^d - c^m}{\mu_B D} \tag{42}$$

Due to $\mu_B \le \mu_A$ it is straightforward that $T_A^{S2} \le T_B^{S2}$. This brings us directly to *Proposition 3a*.

Proposition 3a (Group-strategies in S2)

The optimal group-strategies for scenario S2 are given by

$$\left(v_A^* = 0, v_B^* = 0\right) \text{ if } p_{22} < T_A^{S2} \tag{43}$$

$$\left(v_A^* = 1, v_B^* = 0\right) \text{ if } T_A^{S2} < p_{22} < T_B^{S2} \tag{44}$$

$$\left(v_A^* = 0, v_B^* = 0\right) \text{ if } T_B^{S2} < p_{22} \tag{45}$$

Optimal government strategies

For the government we get the following two critical thresholds $0 \le T_G^{S2} \le 1$ for situation S2, as given by (46) and (47).

$$T_{G1}^{S2} \equiv T_{G1}^{S1} \equiv \frac{\alpha(c^d - c^m) + \beta\ell^L}{D + \beta\delta\ell^H + \beta\ell^L} - p_{11} \tag{46}$$

$$T_{G2}^{S2} \equiv \frac{\alpha(c^d - c^m) + \beta\ell^L}{D + \beta\delta\ell^H + \beta\ell^L} \tag{47}$$

Proposition 3b defines the socially optimal strategy-combinations from the government's perspective for situation S2.

Proposition 3b (Optimal Government-Strategies in S2)

$$\left(v_A^\circ = 0, v_B^\circ = 0\right) \text{ if } 0 < p_{22} < T_{G1}^{S2}; \tag{48}$$

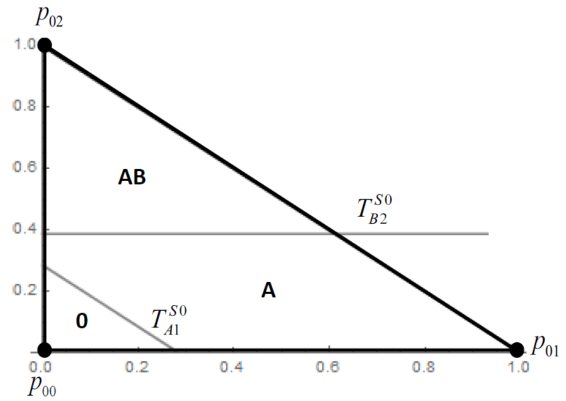
$\left(v_A^{\circ}=1, v_B^{\circ}=0\right)$ if $T_{G1}^{S2} < p_{22} < T_{G2}^{S2}$; (49)

$\left(v_A^{\circ}=0, v_B^{\circ}=0\right)$ if $T_{G2}^{S2} < p_{22}$ (50)

5.4 Zones of Compliance (ZoC)

Illustration in a probability triangle

In this section we analyze the scope for compliance in the government's interaction with both groups. For the main part of this subsection, we refer to the escalation-scenario S0. The left diagram of *Figure 4* shows the critical thresholds of both groups in S0 graphically in a probability triangle. The edges and the corner points of the triangle are highlighted in black. Any constellation of the conditional posterior probabilities, i.e. the discrete, conditional probability distribution $\left\{\wp_{s|\omega} : p_{i0}, p_{i1}, p_{i2}\right\}$, can be marked in this triangle as a probability-point P with coordinates (p_{i1}, p_{i2}). The higher one of these probabilities, the closer it is to "its corner". Assume for example that we are in state S0 and we receive "no warning" (ω_{00}). In this case, the first column of the conditional posterior matrix $\boldsymbol{P_0}$ (6) applies and gives back the probability-point $\mathrm{P}=(p_{00}, p_{01}, p_{02})=(0.999975, 0.000024, 0.000001)$. As the probability $p_{00} \equiv 1-p_{01}-p_{02}$ comes close to 1, this point would we drawn in the origin of ordinates.



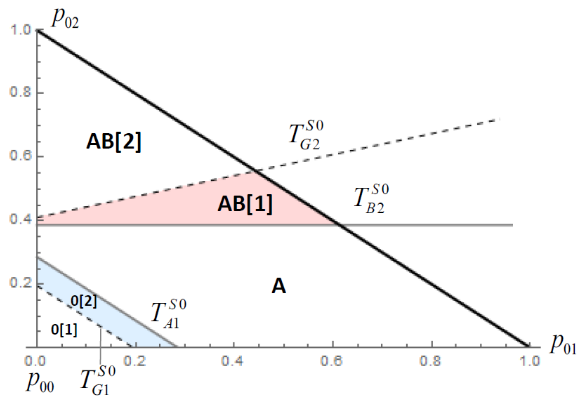


Figure 4. Probability triangle for optimal decisions, just groups (left) and with authority (right)

We now just need to spot the conditional probability in the plane and can directly infer the decisions of both groups. If P lies below T_{A1}^{S0} in the area labeled "0", then no group evacuates. If P is located between T_{A1}^{S0} and T_{B2}^{S0}, which corresponds to the area "A", just group A evacuates but group B does not. The last possibility is that the point lies above T_{B2}^{S0} in the upper corner "AB". In this case, both groups prefer to evacuate.

In the right diagram of *Figure 4* we added the critical thresholds of G as dotted lines. As both lines do not coincide with the groups' thresholds, there are constellations in which the groups and the government's preferences deviate from each other. These *zones of conflicting interest* are highlighted in the diagram. In zone 0[2] G prefers that group A evacuates, which is not the preferred strategy of group A. There is the exact opposite constellation in zone AB[1]: Here, G does not want group B to evacuate, however group B prefers evacuation. The conflicting interest between authority and groups results from three causes: the two information asymmetries (related to flood impact and anti-congestion investment) and the weighting factors α and β. With respect to the information asymmetries, people should be always better off to follow the government (whether they actually do depends on trust) but with respect to the preference parameters this is not necessarily the case. For example, it is possible that G puts highest weight on economic loss ($\beta = 1$) and lowest weight on citizens' deprivation ($\alpha = 0$). In such a case, G could act too cautiously not to endanger business activities too much and show less consideration for the affected population. However, in our model also economic losses have a short and long-term component and we assume that the long-term losses due to flood injuries exceed the short-run losses. Therefore, the outcomes of the compliance-game show a very low sensitivity with respect to changes in α and β.

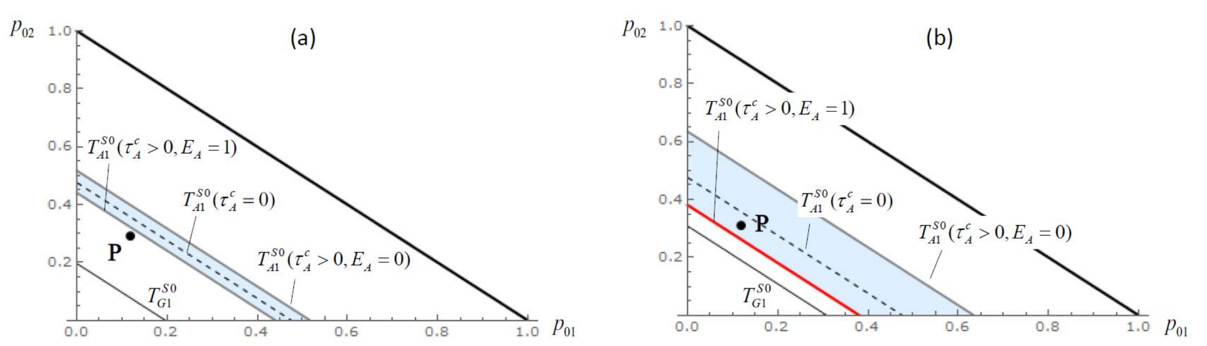
Government communication and compliance

For its communication-decision in scenario S0, the government is guided by *Proposition 1b*. However, G's communication must also be effective. The request of G is *effective* under two conditions. First, the respective addressee (group A, group B or both groups) of the request is *impact-sensitive* ($p_{i2} >$ ($T_{A,B}^{Si}(\mu_{A,B} = 1)$) and the level of *competence-trust* is *high enough* ($\tau_{A,B}^{c} > \tilde{\tau}_{A,B}$). The first condition refers to a situation where a group expects maximal impact (remember, impact is the subjective probability that "an event really hits me") but does not evaluate the consequences high enough compared to the less precautious alternative. In such a situation, impact-communication is effectless, even with the highest level of trust. The second requirement, a sufficiently high trust-level, is straightforward. If a group is impact-sensitive, their decision can theoretically be influenced but whether this influence is successful depends on the group's perception of the credibility and trustfulness of the sender. The lower the trust-level $\tau_{A,B}^{c}$, the more weight is put on the "autonomous" impact parameter $0 < \hat{\mu}_{A,B} < 1$ (the groups judge the impact on their own). We define $E^* | \oplus$ as the optimal strategy of G if the communication is *effective* and $E^*|\odot$ if communication is ineffective. Expression (51) summarizes the optimal strategies of the government.

$$E^*|\oplus = \begin{cases} E0 \vee (v_A^\circ = 0, v_B^\circ = 0) \\ E1 \vee (v_A^\circ = 1, v_B^\circ = 0) \\ E2 \vee (v_A^\circ = 1, v_B^\circ = 1) \end{cases} \qquad E^*|\odot = E^\Omega \equiv \{E0, E1, E2\} \tag{51}$$

If communication is effective, the government chooses the optimal strategy according to its objective. This strategy minimizes the social cost-function according to *Proposition 1b*. If, however, communication is ineffective, the chosen strategy is irrelevant and therefore the whole strategy-set applies. We use the symbol $E^*|\odot$ to indicate ineffective communication and E^Ω as a symbol for the universal set, which comprises the entire set of signals.

Before we present the equilibrium, we first illustrate graphically how to determine the government's optimal decision. For this example illustration we just focus on T_{A1}^{S0} as the decision-threshold, which determines whether just group A decides about evacuation. As known from expression (25), this threshold corresponds to a line with negative slope 1. To make the scope for communication visible, we express μ_A by its explicit term $\mu_A = \tau_A^c\, E_A + (1-\tau_A^c)\, \hat{\mu}_A$, which contains the binary signal $E_A \in \{0,1\}$ (as presented in section 4.1). As long as there is a minimum-level of trust ($\tau_A^c > 0$), the threshold-line T_{A1}^{S0} extends to a range or spectrum of threshold-lines with the lower and upper bound defined by $E_A = 1$ and $E_A = 0$ respectively. Diagram (a) of *figure 5* gives an example of such a threshold-spectrum. With respect to the threshold-line of group A (T_{A1}^{S0}), the spectrum is highlighted by blue color together with its lower bound $T_{A1}^{S0}(E_A = 1)$ and upper bound, $T_{A1}^{S0}(E_A = 0)$. The dotted line in the middle of the spectrum indicates the autonomous impact-level $\hat{\mu}_A$, which determines the decision if trust is absent. In the diagram, we also depict the threshold-lines of the government T_{G1}^{S0} (low black solid line) and an arbitrary probability-point P.



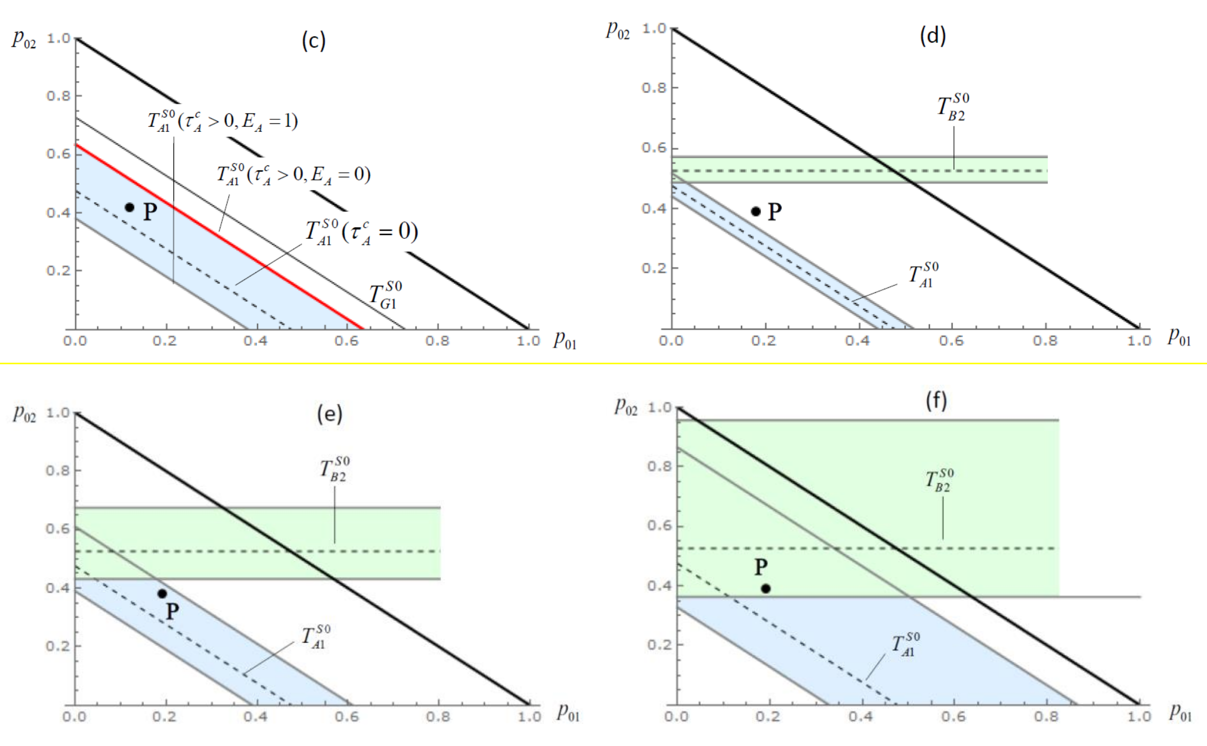


Figure 5. Zones of Compliance (ZoC) for different constellations

If the probability-point P lies within this range, the government can directly influence the group's decision with its request. Therefore, we call the threshold-spectrum "*zone of compliance*" (ZoC). Diagram (a) represents the case of a too narrow range (small ZoC) where the probability-point P lies outside ZoC ($\mathrm{P} \notin ZoC_{A1}^{S0}$). P is located below ZoC_{A1}^{S0} but above T_{G1}^{S0}, i.e. in this situation group A does not evacuate (regardless of any request) although G wants it to do so. Hence, in this case the trust-level is not high enough and the authority cannot convince the group. Diagram (b) shows the same situation with the only difference that the trust-level is higher. The higher trust-level widens ZoC so that P is now located inside of this range ($\mathrm{P} \in ZoC_{A1}^{S0}$). Although group A would be reluctant to evacuate in the case of an autonomous decision without trust (P lies below the dotted line), by sending the signal $E_A = 1$ (more precisely, G sends signal $E1$, which is received as $E_A = 1$ by group A), the government can realize the lower bound of ZoC (straight red line at the bottom of ZoC).

In diagram (c) we just switched the order of T_{A1}^{S0} and T_{G1}^{S0} with the consequence that now G prefers no evacuation of group A. By sending the signal $E_A = 0$ (signal $E_A = 0$ from group A's perspective), the government can realize the upper bound of ZoC (red black line at the top of ZoC). To summarize, given group A's equilibrium strategy T_{A1}^{S0}, its trust-level τ_A^c, the government's objective T_{G1}^{S0} and a current projection defined by P: As long as $\mathrm{P} \in ZoC_{A1}^{S0}$, the authority has influence on the decision of group A. Note that there is just a need to intervene by communication if P lies *between* the critical thresholds T_{A1}^{S0} and T_{G1}^{S0} (otherwise there is no conflict of interest, regardless of the scope for compliance).

The diagrams (d) – (f) show the critical thresholds and ZoCs for both groups; the ZoC of group A is colored blue and ZoC of group B is colored green. The only difference between these three pictures is again the trust-level while the position of P remains unchanged. In diagram (d) the trust-level is too low and the probability point lies outside both ZoCs. The optimal group strategies are evacuation for group A ($v_A^* = 1$) and no evacuation for group B ($v_B^* = 0$). These decisions are not influenced by G, which means that G's optimal strategy is $E^* \mid \odot = E^{\Omega} \equiv \{E0, E1, E2\}$. In words: As G's communication is ineffective, G can communicate anything; the signals do not matter. In diagram (e), the trust-levels of both groups are higher and now P lies inside ZoC_{A1}^{S0} but still outside of ZoC_{B2}^{S0}. Here G has influence on the decision of group A but not on the decision of B. In diagram (f), both ZoCs overlap. In this constellation, G has influence on the decisions of both groups. This overlapping constellation can easily occur for high levels of trust because in this case the groups are willing to adapt their impact-expectations mainly to the government's judgement. Therefore, this represents the best possible constellation for G because it can directly influence both groups by one signal.

5.5 Nash-Equilibrium (NE) of the Evacuation-Compliance-Game

We can now combine the interim results as stated by *Proposition 1a* and *Proposition 1b* to derive the main result of the *Evacuation-Compliance-Game*. As the general structure of the solution is not altered by the scenarios, we state the result for all three scenarios (S0, S1 and S2) together. Assume that the current situation is state Si and the decision makers receive the warning ω_{ij}. The Transition-Matrix $\boldsymbol{S}$, the Likelihood-Matrix $\boldsymbol{L}_i$ and the conditional Posterior-Matrix $\boldsymbol{P}_i$ are defined as described above. The probability-point $\mathrm{P}_{s_i|\omega_{ij}} = (\overline{p}_{i1}, \overline{p}_{i2})$ respresents the ω_{ij}-column of $\boldsymbol{P}_i$. Furthermore, the actors' payoffs are given as described in sections 4.1 – 4.3 and for both groups and the government there are critical thresholds T_A^{Si}, T_B^{Si}, T_{G1}^{Si} and T_{G2}^{Si}. Let $\hat{v}_A^*$ and $\hat{v}_B^*$ be the optimal group strategies under autonomous conditions (according to Propositions 1a, 2a and 3a), i.e. without government or with zero trust in the government ($\tau_A^c = \tau_B^c = 0$). ZoC_A^{Si} and ZoC_B^{Si} represent the *Zones of Compliance* of both groups. The time-structure of the Compliance-Game is given by *Figure 3*.

Result (NE of ECG)

The following strategies represent a *Nash-Equilibrium* of the underlying subgame on stage 1 and stage 2 of *Figure 3*.

$$
\mathrm{P}_{s_i|\omega_{ij}} \in \left\{ ZoC_A^{Si} \cap ZoC_B^{Si} \right\} \ \wedge \ \begin{array}{ll} T_{G2}^{Si}(\bar{p}_{i1}) \leq \bar{p}_{i2} \quad \Rightarrow & \left\{ E^* = E2, v_A^* = 1, v_B^* = 1 \right\} \\ T_{G1}^{Si}(\bar{p}_{i1}) \leq \bar{p}_{i2} < T_{G2}^{Si}(\bar{p}_{i1}) \Rightarrow & \left\{ E^* = E1, v_A^* = 1, v_B^* = 0 \right\} \\ \bar{p}_{i2} < T_{G1}^{Si}(\bar{p}_{i1}) \quad \Rightarrow & \left\{ E^* = E0, v_A^* = 0, v_B^* = 0 \right\} \end{array} \tag{52}
$$

$$
\mathrm{P}_{s_i|\omega_{ij}} \in ZoC_A^{Si} \ \wedge \ \mathrm{P}_{s_i|\omega_{ij}} \notin ZoC_B^{Si} \ \wedge \ \begin{array}{ll} T_{G1}^{Si}(\bar{p}_{i1}) \leq \bar{p}_{i2} \Rightarrow & \left(E^* = \{E1, E2\}, v_A^* = 1, v_B^* = \hat{v}_B^* \right) \\ \bar{p}_{i2} < T_{G1}^{Si}(\bar{p}_{i1}) \Rightarrow & \left(E^* = E0, v_A^* = 0, v_B^* = \hat{v}_B^* \right) \end{array} \tag{53}
$$

$$
\mathrm{P}_{s_i|\omega_{ij}} \notin ZoC_A^{Si} \ \wedge \ \mathrm{P}_{s_i|\omega_{ij}} \in ZoC_B^{Si} \ \wedge \ \begin{array}{ll} T_{G2}^{Si}(\bar{p}_{i1}) \leq \bar{p}_{i2} \Rightarrow & \left(E^* = E2, v_A^* = \hat{v}_A^*, v_B^* = 1 \right) \\ \bar{p}_{i2} < T_{G2}^{Si}(\bar{p}_{i1}) \Rightarrow & \left(E^* = \{E0, E1\}, v_A^* = \hat{v}_A^*, v_B^* = 0 \right) \end{array} \tag{54}
$$

$$
\mathrm{P}_{s_i|\omega_{ij}} \notin \left\{ ZoC_A^{Si} \cup ZoC_B^{Si} \right\} \Rightarrow \left(E^* = E^{\Omega} = \{E0, E1, E2\}, v_A^* = \hat{v}_A^*, v_B^* = \hat{v}_B^* \right) \tag{55}
$$

The equilibrium-conditions read as follows: Expression (52) considers the case where the probability-points lies in an area where the two *ZoC*s overlap. In this case, the government can advise both groups according to its own preferences, which can be summarized by the relative position of P and the critical thresholds of G. Note that the groups' preferences do not matter for this constellation: Even if there is no conflict of interest (i.e. the groups pursue the same goal as G) the government still needs to care about its communication because the groups follow the government with any order. In constellation (53), P lies in the *ZoC* of group A but not in the zone of B. In this case the government just communicates to group A. Expression (54) represents the analogue constellation for group B; G's communication just focusses on group B but group A cannot be reached. The final constellation, (55), represents the case where P lies outside both *ZoC*s. In this case, G has no communicative influence. Hence, in equilibrium the government communicates the universal set (signals are ignored by both groups) and the groups play their autonomous equilibrium strategies $\hat{v}_A^*$ and $\hat{v}_B^*$.

5.6 Equilibrium-analysis based on the empirical reference-data

In this section we take a closer look at the derived equilibrium-conditions by applying the reference-data introduced in sections 3.2 and 4.1. For the most part we focus on the escalation-scenario S0 with a warning-level 1 and 2 because we consider these two situations to be the most frequent and relevant ones. For the standard parameters we chose the values $\alpha = .5, \beta = .5, \gamma = .3, \hat{\mu}_{A,B} = .5, I = .5$ and rather low trust-levels between $\tau^c_{A,B} \approx [0.2, 0.4]$. The situation ω_{01} is depicted in *Figure 6(a)*. It can be seen that G would strongly advise evacuation but group A would also evacuate anyway. At a minimum trust-level of $\tau^c_A \approx .3$, which is illustrated in the graph, the ZoC is wide enough to embrace the probability-point. This means that – although group A would evacuate from alone – the government should advise evacuation to avoid misunderstandings: Compliant citizens could wrongly interpret a missing evacuation order as an all-clear signal. To summarize, for a warning-level 1 the risk-decision of group A and G are in line, but this needs an affirmation from the government if trust and compliance are sufficiently high. The critical threshold of group B is not shown in the graph because the (horizontal) ZoC of group B starts at a probability-value $p_{02} = 0.01$ and is thus far above the probability-point. In other words, in the case of a level-1-warning in S0, group B is very far from evacuating.

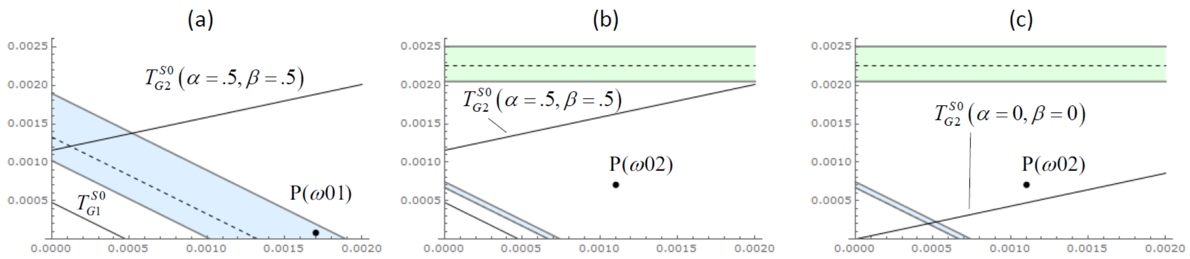


Figure 6: Variation of warning-level and preference-parameters for S0

But how does this change if the coastal city receives a level-2-warning? This situation is illustrated in diagram (b). The probability-point slightly moves to the upper-left and the critical threshold of group A shrinks downwards because the autonomous impact-expectation is close to 1 ($\mu^W_A = 1 - \varepsilon$). This means that group A would try whatever possible to get out of the region. However, for the chosen parameters, group B would not evacuate and the probability-point still remains below the critical threshold of the government. Hence, in spite of a level-2-warning, region B would not evacuate. Is this decision too risky? Above all, this decision takes into account the trade-off between physical damage and potential death on the one hand but also the cost of evacuation, which comprise deprivation and economic losses, on the other hand. If we ignore this trade-off and just take injuries and fatalities into consideration, the decision would be different as shown by *Figure 6*(c). Here we changed the government's preference parameters and eliminated any other factor ($\alpha = 0, \beta = 0$) so that physical damage alone determines the decision. We see that a government, which exclusively cares for lives, would order evacuation of region B. This, however, is without success because the probability-point is not covered by the ZoC of group B. Even maximal trust would not be sufficient to change this situation: Full trust ($\tau_B^c = 1$) would expand the ZoC and thus move the lower bound downwards, but only up to the value $p_{02} = 0.0011$, which is still above the probability-point. For the case of a level-2-warning we conclude that for the empirical reference data, which we took as a basis for our study, we find ourselves in the conflicting trade-off between "protection from damage" and "damage through protection" and the bad news is that this conflict cannot be overcome by trust and compliance. For the other two situations S1 and S2, we get quite clear results, which is mainly due to the high probability values of the (conditional) posterior probabilities. Once region A or region B is affected by a flood, the government and the groups decide to stay evacuated and not to return. These situations are so clear – in the sense that the probability-point is largely out of sight – that there is no issue for compliance. However, there is one constellation where compliance matters and this is exactly due to the high exposure: For our parameter constellation in S1, group B is close to evacuate when a warning-1-level is received. However, even for low values of trust the zone of compliance covers the probability-point so that unnecessary evacuation should not occur.

6. Summary and Discussion

In this contribution we presented the Warning-Compliance-Model (WCM) as a novel and comprehensive approach to study probabilistic and communicative aspects of public risk management and compliance within one coherent framework. The random events were modeled using a Hidden Markov chain and depicted both the escalation and de-escalation phases of hypothetical severe flood events. At the same time, the performance of the EWS can be taken into account by determining the Likelihood-Matrix accordingly. Since approaches of the literature on EWS-verification usually work with contingency tables, the information system of the WCM can also be linked empirically.

The second part of the model included the communication game between the government and the two population groups under consideration. First, the optimal strategies of the groups were determined for all states of the Hidden Markov chain, representing either the evacuation decision or the decision to return to the region. On the part of the government, the socially desired solutions were determined from the perspective of the policy maker. The model is kept as simple as possible from a technical point of view and allows the explicit derivation of the stationary solutions of the model in a generic form. The methodological core of the communication game is the compliance of the population with the (non-enforceable) orders of the government. Compliance helps the two groups (A and B) to overcome their information asymmetry vis-à-vis the state, provided their trust in the authority is sufficiently high. The higher the trust in the state, the more willing the two groups are to follow the instructions for a given probability distribution (as depicted in a compact form by the probability point).

First, it is clear that compliance is only necessary when the interests of the population and the state diverge. Nevertheless, it should be noted that even if interests are aligned and trust is sufficiently high (compliance without conflict of interest), the state must communicate affirmatively to avoid misunderstandings. Since in this model - but ultimately also in all real world communication - silence also represents a signal, it would be dangerous if the state did nothing, in the deceptive certainty that the population itself already knew best what to do. In this respect it is clear that not only compliance is needed for an effective communication strategy, but also an effective communication strategy is needed to give a compliant group orientation during a crisis. Second, if there is a conflict of interest, it is no longer the distance between the critical thresholds that determines the outcome of the communication game, but whether the probability-point lies in the Zone of Compliance. In other words: Not the interests or preferences of the state per se, but the credibility of its message together with the objective probability of the risk ultimately determine whether compliance can arise.

The application of empirical data from flood and risk studies to the model provides plausible results for the escalation scenario. For the de-escalation phase, the assumptions made and the probabilities suggested by the experts led to the clear result that the population in region A would already evacuate on its own initiative, but that the state would also order this evacuation. Since the probability point in this constellation lies with the Zone of Compliance for already rather low trust values, this is a quite clear case for the necessity of affirmative communication as described above.

The results for an announced Black Swan flood show that the inhabitants of region B would not react to an S2 warning. Remarkably, however, the government would not issue an evacuation order either, taking into account economic follow-up costs and the particular burden on the people that an evacuation would entail. Only when the government considers the costs of an evacuation to be very low compared to the expected consequences for life and limb caused by an extreme flood the authority would order an evacuation. In this case, however, the critical threshold lines of state and population group B, which in the model indicate readiness to evacuate, fall far apart. In order for Group B to be persuaded to evacuate via compliance, it must have a very high level of trust, since otherwise the probability-point of a black swan event would no longer lie in the (from the citizens' point of view) impact-relevant area.

What does all this imply for improved disaster management? The Warning-Compliance-Model illustrates the intricate interaction between objective event probabilities, the precision of forecasting technology, the authority's and public's preferences as well as the role of trust in a communication game. The model can be very helpful to determine the effects of e.g. a higher EWS-precision or a higher trust-level on the scope for compliance and hence on the outcome in the case of a severe or disastrous flood event. Furthermore, the model shows that many different and important problems in the context of flood evacuation, which are predominantly looked separately and from a purely empirical perspective, such as risk communication, the crying-wolf-phenomenon or conflicts of interest, can be better seen as elements of one comprehensive picture. The WCM is best understood as a first step to identify the interlinkages between these different areas. More concrete, policy makers could consider some implications of this study for the development or training application of Evacuation Maps (Wilson 2018). As different geographic areas correspond to different risk profiles and this in turn will influence people's expectations, it is possible to derive a rough and preliminary guess of people's probable decisions and the corresponding level of (expected) compliance. One further implication of the results of this study relates to risk communication. Risk communication in advance increases the impact expectation, which in turn requires less compliance. However, since both, compliance and risk communication, will depend on the same type of trust (competence trust in the authorities), this will enable the government to better empower people to make independent decisions before a crisis. This strategy, however, is particularly dependent on public trust, because it also means that too little trust in competence destroys both options: The population will not be convinced, either in advance or in the event of an approaching crisis, that the flood could affect them.

Finally, we also want to briefly discuss potentially problematic assumptions of the model as well as promising model extensions. As already mentioned we admit that the assumption of a representative decision maker for each group simplifies away some interesting and important aspects. It is promising to take the heterogeneity of people into account because differences in preferences of stakeholders will have an impact on their willingness to evacuate (e.g. vulnerable people, such as assisted care individuals, or gender differences (Bateman & Edwards 2002). We also assume that the assignments of buildings and individuals to zones is clear-cut. However, this is far from straightforward: "A study before Hurricane Irene found that 83% of adults without a high-school education (e.g. 46% of East Harlem's population in 2006) could not identify their evacuation zone." (Wilson 2018, p.9). Similarly, special forms of evacuation such as long term resettlements and relocations (Sorensen & Sorensen, 2006) are less well representable in the model, either. With respect to the preferences, we assume in our model that just the government takes economic losses into account. However, this will also be an important motive for small businesses. Finally, it could be very promising to apply more psychological approaches like risk perception theory, prospect theory or protection motivation theory to this framework. One complicating challenge of such an extension is that this introduces path-dependence into the model so that the derived closed-form solutions are just relevant for the described stationary solutions. Nevertheless, risk perception is ultimately a history-dependent phenomenon and it should be feasible to add this component to the Warning Compliance Model.

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Appendix 1

Proof of Lemma 1b: To proof $T_{G1}^{S0} < T_{G2}^{S0}$ we first show that $T_{G1}^{S0} < T_{G2}^{S0}(\gamma = 0)$, which is true for $\varphi_{11} < \varphi_{10}$. Increasing γ shifts T_{G2}^{S0} upwards. The highest admissible value for T_{G2}^{S0} is 1, because otherwise it would be an irrelevant threshold for p_{02}. Setting $T_{G2}^{S0} = 1$ and solving for γ provides us with the upper limit $\gamma < \tilde{\gamma}_G^{S0} \equiv \frac{\varphi_{11}(D+\beta\delta\ell^H - \alpha c^d) - \alpha c^m}{\varphi_{10}(D+\beta\delta\ell^H - \alpha c^d) - \alpha c^m}$. As both, T_{G1}^{S0} and T_{G2}^{S0} vary linearly in p_{01}, it remains to show that $dT_{G2}^{S0}(\gamma = \tilde{\gamma}_G^{S0}) / dp_{01} > dT_{G1}^{S0} / dp_{01} = -1$, which completes the proof. ■

Appendix 2

Proof of Proposition 2a: For $(v_A = 0, v_B = 0)$ to be a NE, two conditions (I) $C_A^{S1}(v_A = 0, v_B = 0) < C_A^{S1}(v_A = 1, v_B = 0)$ and (II) $C_B^{S1}(v_A = 0, v_B = 0) < C_B^{S1}(v_A = 0, v_B = 1)$ must be fulfilled. In words, both groups must strictly prefer not to evacuate provided that the other group sticks to the no-evacuation-strategy, too. For each condition, there is a critical threshold for p_{12}: (I) $p_{12} < T_{A1}^{S1}$ and (II) $p_{12} < T_{B1}^{S1}$. Hence, a NE where no group evacuates requires $p_{12} < Min[T_{A1}^{S1}, T_{B1}^{S1}]$. According to *Lemma 2a,* it follows that $T_{A1}^{S1} < T_{B1}^{S1}$ and thus T_{A1}^{S1} is the required upper bound (if p_{02} is lower than T_{A1}^{S1}, it is also lower than T_{B1}^{S1} but not vice versa). Hence, if group A does not evacuate, then group B certainly does not either. ■

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