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Risk-based Flood Evacuation Decision using a Distributed Rainfall-Runoff Model

Paul James SMITH*, Toshiharu KOJIRI and Katsuyoshi SEKII*

* Graduate School of Engineering, Kyoto University

Synopsis

A probabilistic approach to evacuation decision-making is preferred over the traditional approaches based on 'best guess' flood predictions as decision can be made based on an understanding of the risk involved and the potential outcomes of each decision. As an inundation risk level is assigned in real-time to each area within the target watershed, the optimal evacuation path can be rapidly identified from a number of alternatives by selecting that route which avoids at high risk. Application of the proposed framework with distributed runoff model is discussed considering the Nagara River watershed.

Keywords: probabilistic flood forecast, flood risk, evacuation decision-making, distributed runoff

1. Introduction

It has long been the goal of flood forecasting to provide timely and accurate estimates of future discharge conditions at specific watershed locations. In order to achieve a shift away from the traditional flood prediction framework which focuses primarily on using point rainfall observations and lumped parameter or statistical models to make deterministic best-guess predictions of runoff rates for only a handful of locations within a river basin, a distributed rainfall-runoff model is chosen to simulate rainfall-runoff dynamics. Distributed rainfall-runoff models have been used in recent years for a range of different water quantity and quality simulations, though little attention has been given to the task of short-term flood forecasting. The distributed nature of such models provides the potential for simulations of superior accuracy to purely data-driven or lumped parameter forecasts, and allows flood forecasts to be made at all locations within a watershed.

Information about the uncertainty in forecasts, otherwise referred to as predictive uncertainty, can be beneficial in a number of ways, especially when this uncertainty is described in the form of a probabilistic forecast, which gives the probability distribution of the variable being forecasted. Risk-based decision-making becomes possible when probabilistic forecasts rather than deterministic one are provided, with the potential for social and economic benefits resulting from the operation of floodgates and pumps, and other mitigation measures, with a view to risk minimization. Risk-based flood warning is also made possible through probabilistic flood stage forecasting, where the probability of exceedance of design flood levels can be provided. This has the benefit of reminding the user that a given forecast is not certain, and alerts the user to the range of flood stage heights that could potentially be experienced. This would help to remove the confusion during flood events that would otherwise likely occur if a flood stage prediction were exceeded in a major flood event, leading to damage or loss of life as a result of misguided faith in what was a 'best' but by no means perfect estimate of future conditions.

2. Modeling uncertainty in flood forecasts

Uncertainty in watershed runoff predictions results as a consequence of an inability to perfectly predict future rainfall conditions, and the inadequacy of the mathematical model used to approximate a highly complex physical system. The uncertainty related to estimates of future rainfall conditions are referred to here as precipitation uncertainty, and the uncertainty related to the model structure, estimated model parameters, and data observations, is referred to as hydrologic uncertainty.

Precipitation uncertainty is generally regarded as the most influential cause of uncertainty in a flood forecast (Moore, 2002). Ensemble or Monte Carlo simulation-based forecasts of future hydrological conditions may be used to estimate the uncertainty in a flood stage forecast due to uncertainty in the rainfall forecast input.

Ensemble forecasts, however, cannot alone produce a complete probabilistic forecast, as they are only capable of estimating an output distribution of model flood stage, incorporating uncertainty in the precipitation input, while ignoring the hydrologic uncertainty arising from all other sources of uncertainty (Krzysztofowicz, 2001). Additionally, an ensemble forecast often does not take into account the precipitation measurement error, assuming that the precipitation forecast is made based on perfectly observed climatic conditions.

One attempt at incorporating all known uncertainties in a short-term flood stage forecast involved a Bayesian forecasting system, which determines the probability distribution of a model flood stage, under the hypothesis that there is no hydrologic uncertainty, quantifies hydrologic uncertainty under the hypothesis that there is no uncertainty in the precipitation input (Krzysztofowicz and Herr, 2001), and integrates these uncertainties to produce a probabilistic flood stage forecast.

Attempts to date to produce probabilistic forecasts of flood stage have considered rainfall as an averaged or point process using a coarse temporal resolution of the order of one hour, and have used lumped physical models or black box models to model the rainfall-runoff process. Examples include the precipitation uncertainty processor developed by Kelly and Krzysztofowicz (2000) for the aforementioned Bayesian forecasting system, which used a time series of 6-hour watershed average precipitation amounts as input for a lumped hydrologic model, and the real-time flood forecasting system of Lardet and Obled (1994), which uses stochastically generated hourly time series of rainfall as a lumped input to a rainfall-runoff model. A framework for probabilistic forecasting of discharge conditions throughout a watershed, considering rainfall at a fine spatial and temporal resolution, and using a distributed physically-based rainfall-runoff model, is presented here.

The probabilistic short-term forecast of watershed flood stage conditions presented in this research is based on a rainfall translation model and a deterministic rainfall-runoff model. Consideration is given to the effects of uncertainty in the rainfall forecast, as well as observational and modeling uncertainties. These hydrologic and precipitation uncertainties are handled as follows:

- A Monte Carlo simulation of rainfall conditions is used to produce an ensemble forecast considering precipitation uncertainty.
- Two independent error correction approaches are proposed to reduce the influence of observation and model errors, and to provide an estimate of the uncertainty in the forecast due to hydrologic uncertainty.

A recursive adaptive updating technique which updates the state of the target watershed in real-time based on runoff observations. An AI technology-based error prediction strategy that works to reduce the rainfall-runoff model error at locations where runoff observations are available in real-time, and uses these corrected model rates to predict the runoff at surrounding locations in the watershed.

2.1 Probabilistic flood forecast formulation

An effective means by which to unambiguously convey the degree of certitude in a forecast is a predictive probability distribution function involving a numerical measure of the degree of certitude regarding the occurrence of an event. Charts of the probability density function (pdf), or the equivalent cumulative distribution function (cdf) describing the probability $P(Q \le q)$ of flood discharge Q being less than or equal to a designated discharge level q, are proposed as an appropriate means of describing a flood forecast for a given location within a watershed for each required forecast lead time. Additionally, a convenient method of displaying results of a distributed flood forecast, so as to provide information at a glance regarding future distributed watershed conditions, is to provide a color-coded plot of probability of exceedance in terms of percentage of design flood level for each location across a watershed.

If an appropriate distribution can be fitted to the ensemble forecast results, a single aggregated forecast in pdf or cdf form can be provided for each watershed point. This is achieved through combining the distributions resulting from consideration of precipitation uncertainty and hydrologic uncertainty

(1) Precipitation uncertainty

A translation vector model for analysis of rainfall pattern movement is extended to include a time series analysis of observed pattern translation to allow for stochastic generation of future rainfall patterns based on the statistical properties of rainfall pattern translation and growth-decay characteristics. These generated future rainfall patterns are subsequently input into a distributed rainfall-runoff model, resulting in a distributed ensemble forecast of watershed flood stage based on the range of possible precipitation conditions that could be experienced. The goal of the Monte Carlo simulation is to use a stochastic rainfall generator and hydrologic model to generate numerous realistic future rainfall-runoff events such that an ensemble forecast of flood stage carrying a probabilistic meaning can be given.

(2) Hydrologic uncertainty

In addition to improving the accuracy of the real-time flood stage forecast, the methods proposed for assimilation of observed runoff data can be used to provide an estimate of the variance of the prediction error due to errors in measurement of hydrologic inputs and shortcomings associated with the model and its parameterization.

An estimate of the hydrologic uncertainty can be made through using the adaptive updating algorithm to recursively estimate the forecast error variance. A drawback of this approach is that it is limited to locations where real-time discharge observation data is available. An estimate of the hydrologic uncertainty is also required for other non-observation point locations. As no observation data is available for these locations, the assumption is made that the predictive ability of Hydro-BEAM at these locations is at least as good as a naïve prediction whereby future discharge rates are estimated as being the same as the currently observed discharge rate. Error distributions can thus be determined based on Hydro-BEAM simulated hydrographs using observed rainfall, comparing n-hour ahead discharge rates with current rates for various locations to determine error distributions for the naïve prediction. Under the assumption that the error distributions are similar for runoff events of similar magnitude, these distributions can then be used in real time to estimate the degree of uncertainty of a runoff rate prediction for a given location and prediction lead-time. In this way a prediction of a runoff rate can be converted to a cumulative distribution function of the range of possible runoff rates that may eventuate under the given rainfall time series when considering hydrologic uncertainty.

Error distributions resulting from hydrologic uncertainty are assumed to be lognormally distributed. This assumption is necessary to allow the error to be combined with the distribution resulting from the Monte Carlo simulation for precipitation uncertainty. In order to satisfy this assumption, adaptive updating is performed on the logarithm of the discharge, rather than the discharge itself. This is achieved using a simple preprocessor for converting the discharge to the lognormal scale prior to updating together with a postprocessor for converting the discharge back to a real number scale once updating is completed:

$$Q' = \log Q \quad \varepsilon'_h = \log \varepsilon_h \tag{1}$$

Here ε_h is the forecast error due to hydrologic uncertainty.

In order to produce a complete probabilistic forecast of future runoff conditions it is necessary to combine the effects of both precipitation uncertainty and hydrologic uncertainty together in the one pdf or cdf distribution. The forecast of future discharge can be represented in the logarithmic scale as

$$Q' = Q'_p + \varepsilon'_h \tag{2}$$

where Q_p is a lognormally distributed variable with mean μ_p and variance σ_p^2 representing discharge modeled under precipitation uncertainty, and $Q'_p = \log Q_p$ is a normally distributed variable with mean m_p and variance s_p^2. The logarithm of the forecast error due to hydrologic uncertainty, ε'_h, is normally distributed with mean m_h (assumed equal to zero) and variance s_h^2.

Equation can be expressed as

$$Q' = m_p + s_p r_p + m_h (=0) + s_h r_h \tag{3}$$

where subscripts p and h relate to precipitation and hydrologic uncertainties respectively, and r_p and r_h are independent random normal variables defined by:

$$\begin{aligned} &E(r_p) = 0, \quad E(r_p^2) = 1, \quad E(r_h) = 0, \\ &E(r_h^2) = 1, \quad E(r_p r_h) 0 \end{aligned} \tag{4}$$

The mean m and variance s_p^2 of Q' can be described in terms of m_p, s_p^2 and s_h^2 as follows:

$$m = E(m_p + s_p r_p + s_h r_h) = m_p \tag{5}$$

$$s^2 = E(Q'^2) - E(Q')^2 = s_p^2 + s_h^2 \tag{6}$$

Defining Q in terms of a single lognormal distribution then becomes a simple matter of converting Q' from the logarithmic scale to the real scale. The mean, variance, skewness and kurtosis of Q are:

$$\begin{aligned} &\mu = e^{\left[\frac{2m_p + s_p^2 + s_h^2}{\;}\right]}, \\ &\sigma^2 = e^{\left(2m_p + 2s_p^2 + 2s_h^2\right)} - e^{\left(2m_p + s_p^2 + s_h^2\right)}, \\ &\eta_1 = \left[e^{\left(s_p^2 + s_h^2\right)} + 2\right]\sqrt{e^{\left(s_p^2 + s_h^2\right)} - 1}, \\ &\eta_2 = e^{4\left(s_p^2 + s_h^2\right)} + 2e^{3\left(s_p^2 + s_h^2\right)} + 3e^{2\left(s_p^2 + s_h^2\right)} - 3 \end{aligned} \tag{7}$$

3. Evacuation decision

One of the most important features of a short-term flood forecast is its utility in helping to make decisions during times of flood risk. Such decisions include those related to the operation of hydraulic structures and the inundation of flood plains to reduce flood risk, and the evacuation of citizens from locations threatened by flood inundation. As an example application for the probabilistic flood forecast developed in this research the development of a decision support system for evacuation decision is investigated.

The problem of evacuation decision is essentially that of choosing an action from a variety of alternatives each with different consequences which depend on the combination of the choice of action made and an uncertain future state of nature. Since by definition a probabilistic flood forecast can provide either an estimate of the probability with which a flood will occur or the probability at which different water levels may be experienced, and since the losses involved with each action-state combination can be estimated, the evacuation decision can be modeled as an engineering decision-making problem. In this way it is possible to use a distributed probabilistic flood forecast to provide an optimal decision regarding evacuation of residents that is based on the probability of flood occurrence at their location. This is considered superior to a decision based purely on a deterministic prediction of water level with no information as to the uncertainty involved in the prediction or the range of possible water levels that could be experienced.

A number of approaches for estimating damage due to inundation are discussed and recommendations are given for using the probabilistic flood forecast system in making evacuation decisions. The following discussion considers flooding which results from overtopping of embankments only, though flooding due to embankment failure may also be an issue requiring attention.

3.1 Decision model

The decision regarding whether or not to evacuate an area involves making a choice as to a course of action based on a limited available knowledge. The courses of action open to the decision maker in a time of flood risk are considered to be the action of issuing an evacuation order or not issuing an evacuation order for each location within a river basin. The knowledge available on which this decision can be made includes the probabilistic flood forecast issued for each location, the costs associated with flooding, evacuation costs, and relevant topographical and demographical information for the river basin.

Ultimately, a course of action is desirable for each location within an area at risk that leads to zero casualties. Although in the interest of saving lives it may be necessary to issue evacuation orders even at times of low inundation risk, it is important to minimize such disruption to communities when possible. The approach suggested for this decision model is one that aims to minimize loss of life and disruptions to communities through identification of the evacuation decision and strategy that has the maximum expected value under current conditions.

(1) Estimating potential costs

The costs considered in the decision model for evacuation can be categorized as losses resulting from preventable flood damage and losses resulting from evacuation. Preventable flood damage is considered to be losses which could have been avoided through appropriate evacuation of citizens from an affected area, such as death and injury. Potential damage to buildings and property should not be considered when making an evacuation decision as this damage is the same regardless of whether an evacuation is ordered or not. Losses resulting from evacuation include costs associated with coordinating an evacuation and providing emergency services, lost profits due to business interruption, and costs associated with the inconvenience and lost time associated with vacating a residential dwelling. A tradeoff, therefore, occurs between the number of hours or amount of money saved as a result of no evacuation against the potential for loss of life that could result from flooding.

Assigning equivalent cost values in terms of yen, dollars or other units to each of the above items is difficult and can be rather subjective. There are many arguments both for and against assigning a monetary value to human life, and in the case where a value is assigned the figure can vary greatly depending on the approach and background assumptions used.

(2) Estimating inundation probability and severity

The probabilistic flood forecast is capable of providing a forecast of when and where river banks are likely to be overtopped. In order to utilize this information for evacuation decision making, it is necessary to be able to determine the risk that overtopping presents to residents in regions adjacent to rivers. The ability to determine this depends on the detail to which urban flooding dynamics are understood and modeled in each region. In any given watershed, depending on the resources available and geographic and demographic characteristics, a combination of strategies may be employed throughout the watershed to estimate flood depths resulting from embankment overtopping, such as linking the river network model with a detailed urban flood model, making estimates based on pre-existing flood hazard maps, or using a simple tank model strategy. The use of the probabilistic flood forecasting strategy with each of these scenarios is discussed below.

The most detailed approach to modeling flood depths resulting from embankment overtopping is that of employing an urban flood model. Ideally, this would allow for dynamic real-time mapping of inundation risk across a watershed and give a visual guide as to safe locations to evacuate to and the lowest risk routes to take. The kinematic wave equation is acceptable for modeling one-dimensional flow in a relatively steep channel network, though a fully-distributed two-dimensional urban flood model is more suitable for accurately modeling flood dynamics once floodwaters overtop embankments and enter urban regions. There exist a wide range of urban flood models and strategies that could be suitably adapted for use together with Hydro-BEAM (Kojiri et al., 1998) for providing a probabilistic forecast of spatially-distributed inundation levels.

Once a forecast of inundation levels is made available, it then becomes necessary to estimate how the potential for loss of life should occur. The procedure proposed here assigns a severity index to each potential inundation level which varies from zero inundation through to a specified inundation level which would result in the death of the entire unevacuated population of the area being

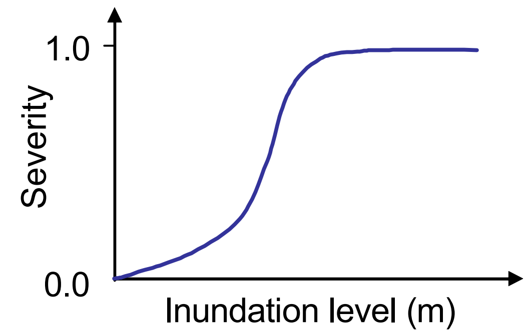


Fig. 1 Severity curve against inundation level

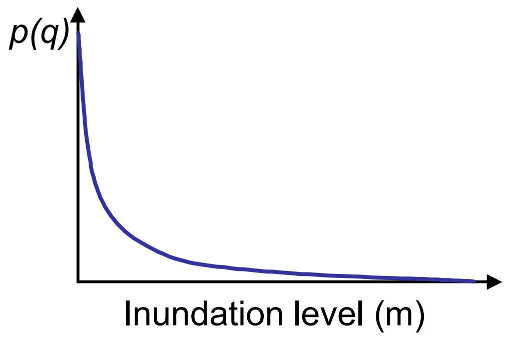


Fig. 2 Probability density function against inundation level

considered in Fig.1. The combined use of this severity curve with a probabilistic forecast of inundation levels in Fig.2 can be considered equivalent to a measure of the risk to life posed by future flood condition。

While the use of an urban flood model is attractive as it is capable of detailed flood modeling and consideration of facilities such as underground malls and subway stations which are at the highest risk during flood events, the large amount of time and considerable difficulty involved with the development and calibration of such models often makes their use prohibitive.

For many regions within a watershed, especially highly-populated areas close to major rivers, flood hazard maps may be available as a viable alternative to the development of a detailed urban model. Flood hazard maps depict the inundation depths that may result from embankment overflow or embankment failure during a severe flooding event, based on past flooding experience and regional topography. Such maps are quite subjective in which they rely heavily on the assumptions made regarding the flood event and overflow/failure scenario, though in the absence of an urban flood model they can be used as a rough reference from which to assess the potential risk to urban locations posed by flood levels in adjacent river channels.

When using flood hazard maps, the shape of the severity curve must be determined individually for each location within the target region based on the potential for inundation as suggested by the hazard map, and the distance of the location from the river being considered. In this case the curve is given in terms of the river flood rate in the adjacent river, and varies from zero for the maximum flood discharge rate in the adjacent river that would lead to no flood damage (assumed for demonstration purposes here to be approximately equal to 100% of the design discharge rate for locations adjacent to a river) through to a specified discharge rate which would result in the death of the entire unevacuated population (see Fig.3).

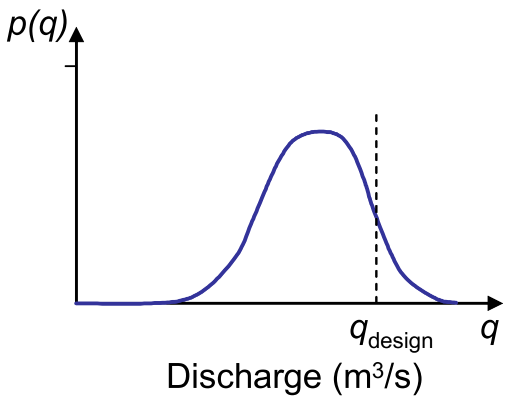


Fig. 3 Probability density function against discharge rate for a location under analysis for a given future

In many cases neither an online urban flood model nor a flood hazard map may be available for assessing the risk associated with potential flood conditions. A third and much less resource-intensive option that is available to the decision maker is to estimate urban flood levels that would result from predicted flood conditions through the use of a simple tank model representation of the regions adjacent to rivers. Elevation data is available at 50m intervals within Japan, and a tank model based on this data can be used to estimate which regions will experience urban flooding and to what degree, based on predicted flood levels within a river basin's channel network and the associated embankment overflow rate. In this case a curve such as depicted in Fig.4 would be used to describe the severity associated with each inundation level.

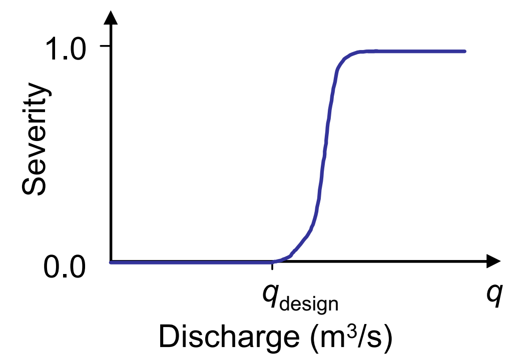


Fig. 4 Severity curve against discharge

3.2 Evacuation decision formulation and timing of the evacuation

The evacuation decision problem can be formulated as a multi-stage model. At regular time steps throughout the duration of a rainfall event a distributed probabilistic forecast of discharge is generated for each location of interest within the watershed for several time steps into the future. For a given location, a decision based on the forecasted flood conditions at each future time step is required. A choice is offered between two actions, A_E: order evacuation, or $A_{\bar{E}}$: do not order evacuation and delay decision one time step. In making a decision when faced with a potential flood risk there is a trade-off between ordering an evacuation too early based on a highly-uncertain forecast which risks unnecessarily disturbing the public, and leaving the evacuation order until a point in time when it is too late to evacuate the majority of the public.

In choosing between actions A_E and $A_{\bar{E}}$ the decision method must be able to determine the optimal timing of the evacuation based on the amount of time it takes to evacuate a population. An evacuation progress index *R(τ)* is proposed to indicate the fraction of a population that would remain unevacuated for evacuation orders given at various warning lead times. This index can be plotted against lead time for each target location as

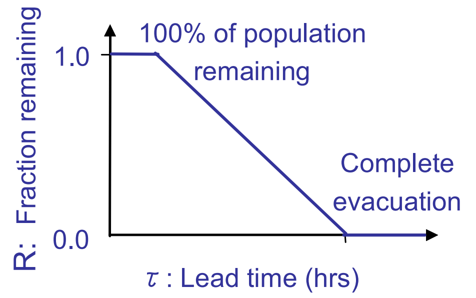


Fig. 5 Evacuation progress index

a function decreasing from one to zero as given in Fig.5. The shape of the function will depend on the characteristics and demographics of the location being modeled.

As both evacuation success and evacuation costs are modeled as being dependent on the period of time allocated for the evacuation (lead time), the decision model is able to optimize the timing of an evacuation should one be necessary.

This can be achieved through considering the decision in terms of a multi-stage decision model in Fig.6. Although flood-related costs are modeled as a continuous function in this research, for the sake of this explanation a decision tree for the multi-stage model for the discrete (no flood / flood) evacuation problem is assumed. In this example the probability of flooding at the given lead time being considered is denoted Pf and evacuation cost and flood damage are labeled C and D respectively. In using this multi-stage model, the expected value of action $A_{\bar{E},\tau}$ is calculated as being the expected value of the optimal choice at the next time step. Once this is calculated it can be compared with the expected value of $A_{E,\tau}$ and a decision can be made. In order to calculate the expected values of the actions $A_{E,\tau-1}$ and $A_{\bar{E},\tau-1}$, the probability of flooding from the point of view of the next step P_F* is required. Although this probability can not be known at the present time step, the optimal estimate for this value can be considered equal to the value of Pf from the point of view of the current time step. In the case where action $A_{\bar{E}}$ is chosen, this probability will be updated based on the newly-available probabilistic flood forecast made at the next time step, which is likely to include less uncertainty.

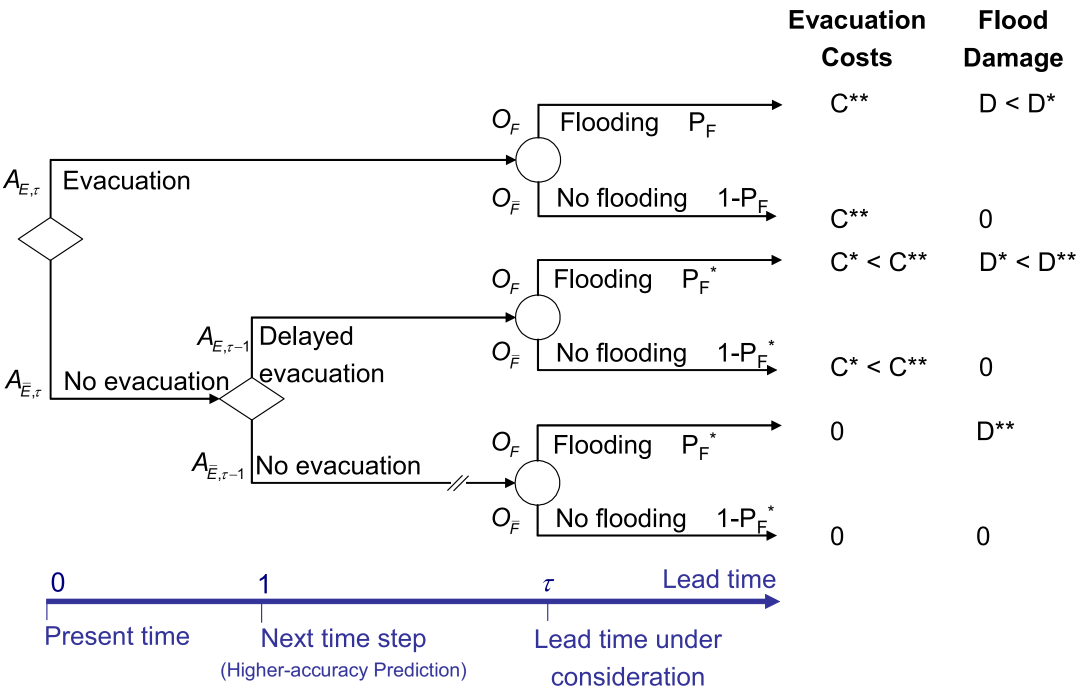


Fig. 6 Multi-stage decision model

(2) Objective function formulation

A function is developed here to calculate the expected value of a given action at a given lead time. The function estimates the combined flood damage (D) and evacuation costs (C) for the location and lead time being considered. Flood damage is defined for a location as the product of the number of people killed by the flood and the value attributed to an average human life, λ:

$$D = S(q)R(A,\tau)n_{pop}\lambda \tag{8}$$

where S is the severity index representing the fatality rate associated with a flood of magnitude q, n_{pop} is the number of people in the target location prior to the evacuation and $R(A, \tau)$ is the fraction of a population expected to remain unevacuated in the target location at a time τ after action A is taken, such that:

$$R(A_E,\tau) = R(\tau), \quad R(A_{\bar{E}},\tau) = 1.0 \tag{9}$$

Evacuation cost is defined as:

$$C = (1 - R(A,\tau))(\alpha + \beta\tau)n_{pop} \tag{10}$$

where A is action (A_E: evacuate; $A_{\bar{E}}$: don't evacuate), α is the average estimated cost of evacuating an individual and β is the average value associated with one human hour that would be lost due to the disruption caused by an evacuation (assumed to end after τ time steps).

The expected value (EV) of a given action per unit of population can therefore be calculated by integrating over the range of forecasted discharge rates as

$$EV(A,\tau) = -\int p(q,\tau)S(q)R(A,\tau)\lambda dq - (1 - R(A,\tau))(\alpha + \beta\tau) \tag{11}$$

where p is the probability distribution function for discharge q at lead-time τ.

The optimal decision at any given point in time during a rainfall event can thus be made by choosing the action that maximizes the expected value of the outcome with respect to A and τ. The expected value for both evacuate and don't evacuate options is calculated and compared for every lead time up to a limit set by the flood forecast horizon. If the expected value is optimal for the evacuate option for any of these future time steps, an evacuation is ordered.

$$\begin{aligned} &\text{IF } EV(A_{E,\tau}) \geq EV(A_{\bar{E},\tau}) \text{ for any } \tau = 1,2,\cdots,\tau_{horizon} \\ &\quad \text{THEN choose } A_E, \\ &\text{where } EV(A_{\bar{E},\tau}) = \max\{EV(A_{E,\tau-1}),\ EV(A_{\bar{E},\tau-1})\} \end{aligned} \tag{12}$$

(3) Risk aversion

The decision model is developed above under the assumption that monetary costs are a suitable measure of value. Furthermore it should be noted that outcomes associated with death due to inundation, while likely to occur far less often than outcomes associated with evacuation false alarms, are extremely costly in comparison, especially considering that the costs while measured in monetary terms are in reality associated with loss of lives. The public are far more likely to forgive a series of evacuation false alarms than they are to forgive a one-off failure to issue an alarm which results in death. For these reasons a risk aversion strategy may be preferred by the authority responsible for issuing floods. In such cases the authority may lean towards making decisions to order evacuations even when they are the less-than-optimal choice in terms of the expected value criterion.

For the case where the risk aversion can be assumed to arise from undesirable consequences associated with suffering a large one-off cost, a utility function (see Fig.7) can be utilized to convert the cost of all possible outcomes ranging from the worst O_* through to the most desirable O^* into their equivalent utility values as judged by the subjective views of the decision maker. The decision making process can then be carried out such that the action with the maximum expected value of utility is chosen as being the optimal solution from the viewpoint of the decision maker. The shape of the utility function (von Neumann and Morgenstern (1947)) is subjective and will vary between decision makers depending on their individual requirements.

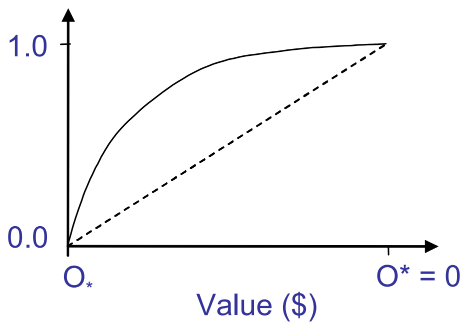


Fig. 7 Utility function

4. Application in the real catchment

4.1 Flood risk

An application of the probabilistic flood forecasting system is presented here. The probabilistic rainfall forecast results for 11 September 2000, comprising results from 100 Monte Carlo simulations of rainfall dynamics between 11 September 21:00 and 12 September 3:00 are used for the precipitation input, and the distributed adaptive updating algorithm is used for assimilating real-time discharge observations and updating the middle reach of the Nagara River and surrounding areas. The result of the ensemble forecast considering precipitation uncertainty based on 100 6-hour simulations is given for the location of Chusetsu in Fig.8. It can be seen from the ensemble that the generated rainfall input does not have a major influence on the hydrograph at downstream locations within the Nagara River watershed for the first 2 hours of the rainfall-runoff simulation. The influence on the hydrographs of midstream locations such as Mino and Akutami appears approximately an hour earlier. Generated hydrographs can be converted into cumulative distribution functions at each time step, thus describing the forecast of future discharge conditions at each point within a watershed in probabilistic terms. The ensemble data is found to fit a lognormal distribution function, and example cdfs are given for Chusetsu for 1 through 6-hour ahead forecasts (see Fig.9). As is expected, these figures suggest increasing uncertainty in the forecasts with time, with very little uncertainty due to the precipitation forecast present for 1 and 2-hour-ahead forecasts. Hydrologic uncertainty, considering observation errors and modeling errors, is not considered in these figures. A framework has been proposed for the production of a probabilistic forecast of future distributed discharge conditions in a watershed. Methods for quantifying the two sources of forecast uncertainty that affect a flood forecast, being precipitation uncertainty and hydrologic uncertainty, have been proposed so as to provide a complete probabilistic forecast. The system provides a forecast for a lead-time of up to 6 hour of discharge conditions at 1km intervals along each major tributary within the midstream region of

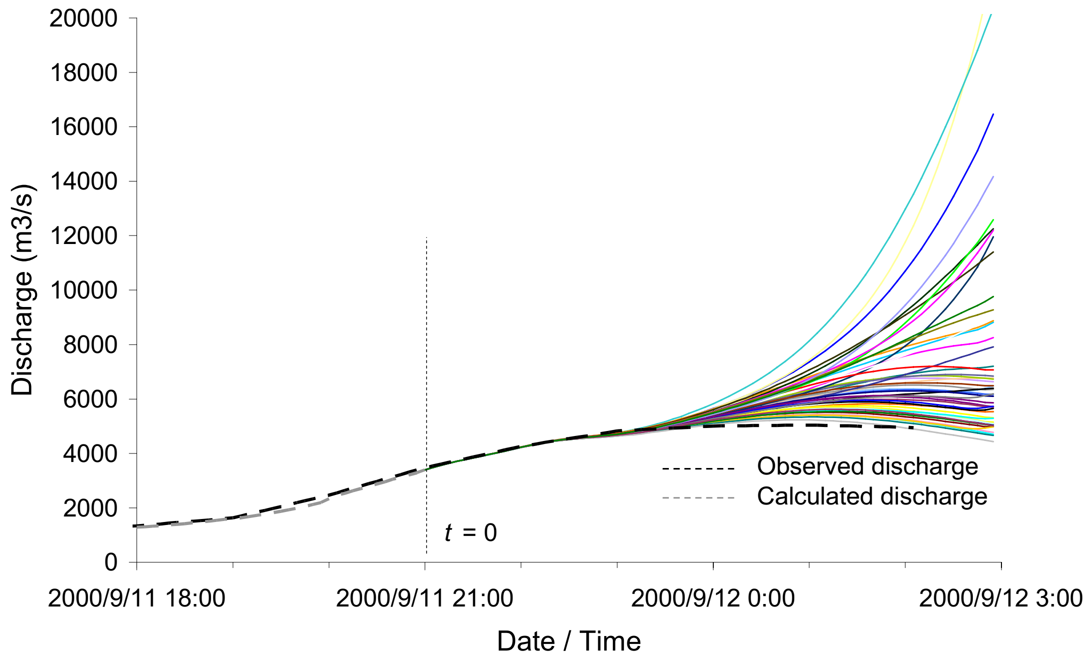


Fig.8 Ensemble forecast for Chusetsu made at 21:00 11 September 2000

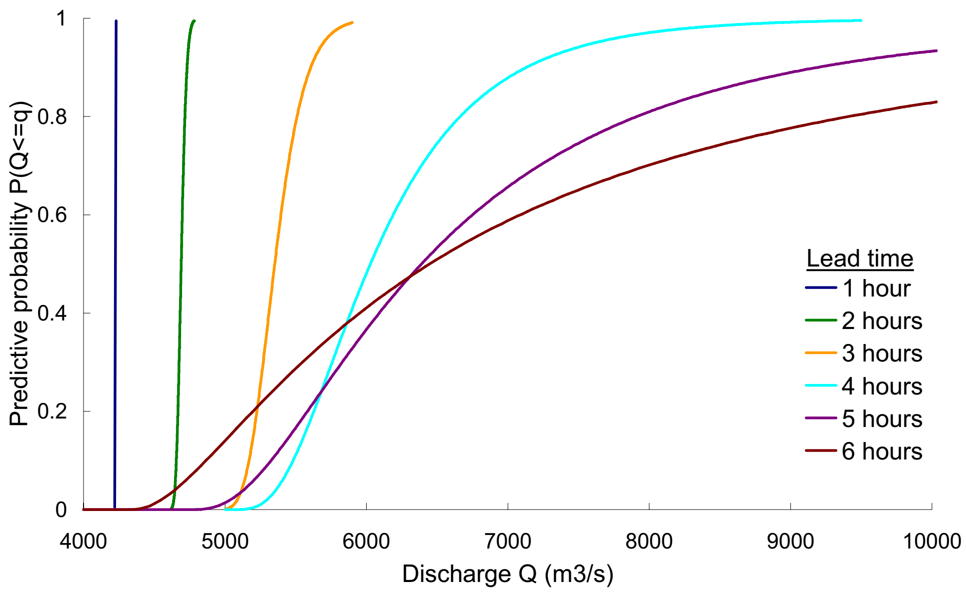
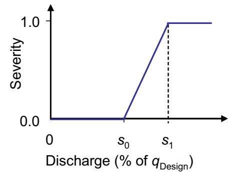


Fig. 9 Probabilistic forecast of discharge considering precipitation uncertainty, at 21:00 11 September 2000, Chusetsu

the Nagara River watershed. A forecast of discharge presented in both a distributed and probabilistic manner has a considerable benefit over the traditional approach of providing best-guess predictions for a small number of locations, as it allows the range of potential flood conditions to be identified for all populated areas in a watershed, which is necessary for effective planning of flood prevention and evacuation strategies. An approach for using such a forecast for providing optimal evacuation decisions is explored. Reduction of modeling error associated with hydrologic

Table 1 Severity curve parameters

Rating	Water depth	s_0	s_1
Extreme	2.0 – 5.0m	100%	100%
Very high	1.0 – 2.0m	100%	110%
High	0.5 – 1.0m	100%	120%
Moderate	0.0 - 0.5m	100%	200%



uncertainty was made possible during the ensemble forecast using the adaptive updating algorithm. An advantage of using the adaptive updating algorithm is that it can also be used to provide an estimate of hydrologic uncertainty, however this ability is limited to locations where real-time discharge observations are available.

4.2 Demonstration of the evacuation decision framework

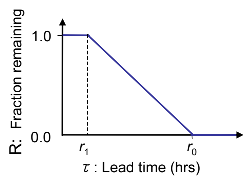
In order to demonstrate the value of the evacuation decision framework, it is used here for a hypothetical flood event occurring in the vicinity of the city of Mino. Mino is home to 24,100 residents in 7533 households (as at 2005). The valley region located in the vicinity of the Mino discharge observation station at 35°32’58’’ N and 136°54’32’’ E is considered. The Nagara River traverses this valley region flowing north to south, with residences located along each bank.

The areas within the region that are in risk of flood are identified on a flood hazard map provided by Mino City Council. Potential flood levels that could be experienced due to bank failure or overtopping are given, and these are used as the basis for determining a set of severity curves for the region as described in Table 1, where the values of s_0 and s_1 are used to denote the points between which the curves vary from a severity rating of zero through one. A severity level of zero indicates that conditions produced by the corresponding discharge at the adjacent river location carry no risk of taking life, and a severity level of one indicates conditions with the potential of taking the lives of all unevacuated residents remaining in the region. For example, areas given the extreme rating are judged to be at maximum risk for any discharge level exceeding 100% of the design discharge, and for this reason s_0 = s_1 = 100%. Conversely, it is recognized that in areas given the moderate ranking, that overtopping of river banks, although promoting dangerous conditions, will not cause conditions as severe as for locations with the extreme rating, where flood levels have the potential of exceeding a depth of 2.0m. For this reason s_1 is set at 200% for moderate areas which has the effect of creating a mild sloping severity curve.

Each area is also rated in terms of estimates of the time required to evacuate residents from the area at risk of flooding as given in Table 2. The curve described by r_0 and r_1 recognizes that evacuation time will vary between residents depending on factors such as physical ability, access to transportation and preparedness. Furthermore, it is recognized that there is likely to be a significant time lag between when the evacuation decision is made and when the warning reaches each resident in the area.

Table 2 Evacuation curve parameters

Rating	Distance to shelter	r_1	r_0
A	0.0 – 1.0km	1 hr	2 hr
B	1.0 km –	1 hr	2.5 hr



For the example given here the initial cost associated with disrupting and evacuating an individual is assumed to be 10,000 yen, the average value associated with each human hour lost due to the evacuation is assumed to be 1000 yen, and the value associated with a human life is set at 50,000,000 yen. Probabilistic flood forecast data for 1, 2 and 3-hour ahead forecasts made for Mino at hourly steps between midday and 15:00 are given in Table 3 for a hypothetical event. Although the example given considers only three forecast periods, the use of a 6-hour ahead forecast would be used in the same manner. Probabilistic flood forecast data are provided in pdf and cdf formats as demonstrated, and for the purpose of this example the forecasted cumulative probabilities of discharge not exceeding 100%, 105% and 110% of the design discharge at Mino are tabulated. The design water level at Mino is given at 6.60m, corresponding to a discharge of approximately 6750 m3/s. This event demonstrates a scenario where forecasts made at 12:00, 13:00 and 14:00 indicate a low yet significant probability that river banks will be overtopped.

Using the severity curves and evacuation curves and equations, an evacuation decision can be made for each area within the proximity of the river cross-section adjacent to the Mino discharge observation station. Based on this information, the optimal decisions made for each location in the region are as follows;

12:00: Evacuation ordered for locations with severity ratings of high or greater located at a distance greater than 1km from a shelter.

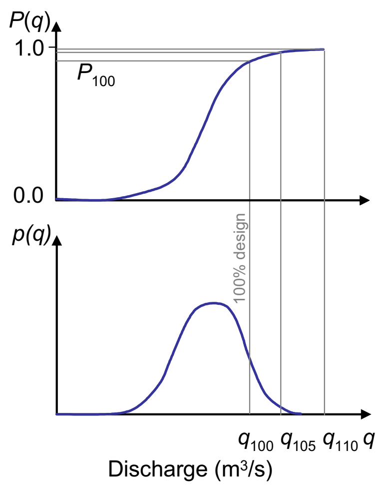
13:00: Evacuation ordered for locations with a severity rating of moderate at a distance greater than 1km from a shelter, and for all remaining locations with severity ratings of very high or greater.

14:00: No further evacuation required, residents in locations with a severity rating of high and lower at a distance less than 1km from a shelter remain unevacuated.

In the decision made at 12:00 for locations at a distance less than 1km from a shelter the action of

Table 3 Probabilistic flood forecast data

		t = 1	t = 2	t = 3
t = 0	$P_q=P(Q \le q)$	13:00	14:00	15:00
12:00	P_{100}	1.000	1.000	0.995
	P_{105}	1.000	1.000	1.000
	P_{110}	1.000	1.000	1.000
	$P_q=P(Q \le q)$	14:00	15:00	16:00
13:00	P_{100}	1.000	0.999	0.95
	P_{105}	1.000	1.000	0.98
	P_{110}	1.000	1.000	0.999
	$P_q=P(Q \le q)$	15:00	16:00	17:00
14:00	P_{100}	1.000	0.999	0.995
	P_{105}	1.000	1.000	1.000
	P_{110}	1.000	1.000	1.000
	$P_q=P(Q \le q)$	16:00	17:00	18:00
15:00	P_{100}	0.999	0.999	1.000
	P_{105}	1.000	1.000	1.000
	P_{110}	1.000	1.000	1.000



Design discharge at Mino:
q_{100} = 6750 m^3/s

delaying evacuation one hour is taken. As the decision model assumes a cost for each hour of disturbance due to evacuation, this option to delay the evacuation decision one hour is optimal based on the multi-stage decision model given in Fig.10 where the estimated value of flood damage D for evacuation is unchanged if the evacuation is delayed until 13:00 as complete evacuation can be achieved in under 2 hours, but evacuation costs C = ($\alpha + \beta\tau$) are reduced slightly for the one hour delay as the time period is reduced from τ = 3 hours to τ = 2 hours. This is the correct decision considering that all residents from this area can still be evacuated in time based on an evacuation order given at 14:00 if the new forecast available at that time deems it necessary, and delaying the evacuation decision has the added advantage that the decision can be made based on new information, which may allow a false-alarm to be avoided all together. In the example given here the 3-hour ahead forecast made at 13:00 indicated a 5% probability that overtopping of river banks would occur at 16:00, thus in this

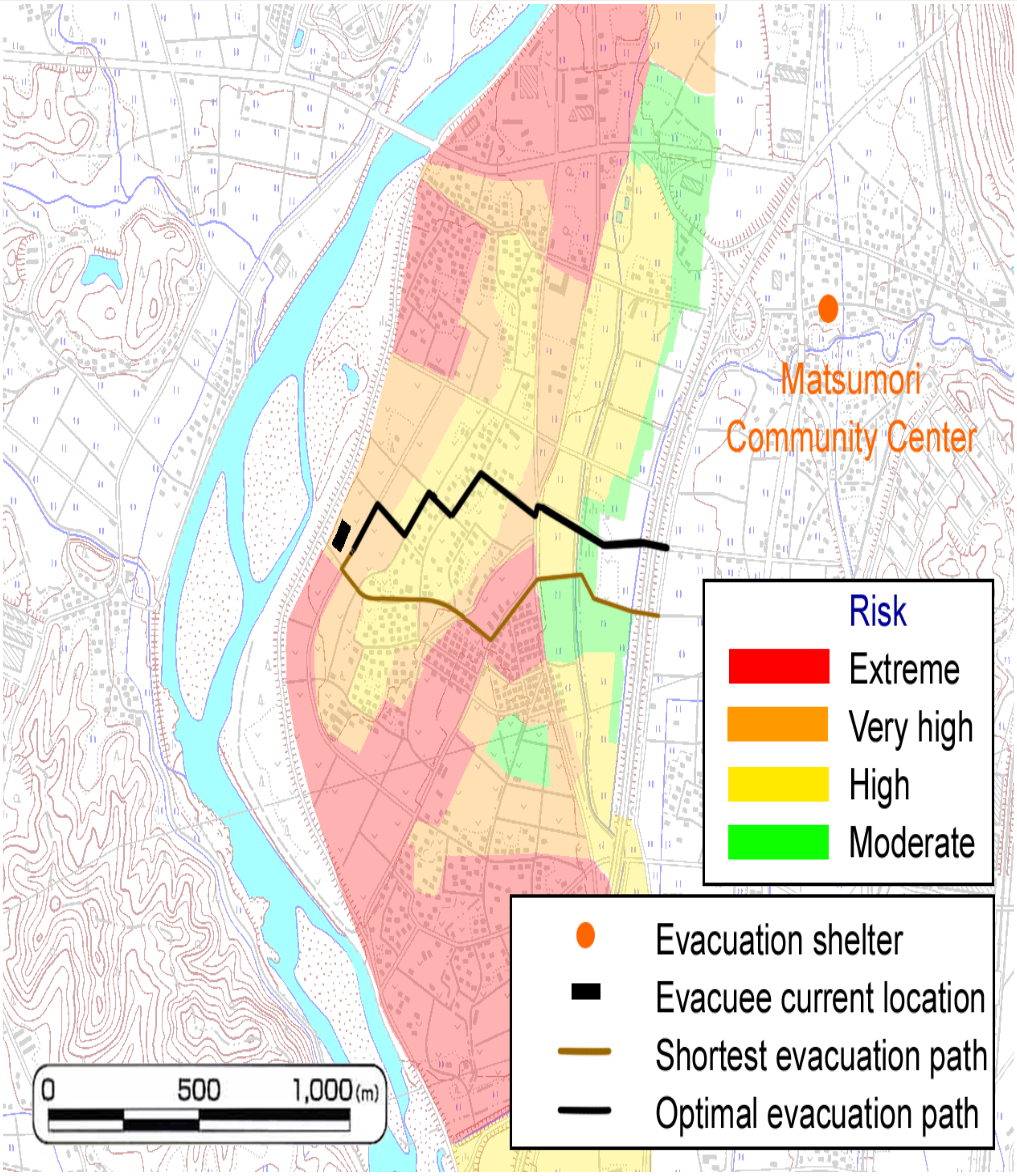


Fig. 10 Conceptual flood risk maps for real-time evacuation path planning

case it does eventually become optimal to evacuate all locations at distances of greater than 1km from a shelter. The decision for areas with severity rating high at a distance of greater than 1km from a shelter is demonstrated below:

$$EV(A_{E,3}) = -\int \big(p(q,3)S(q)\big)dq \cdot R(A_{E,3})\lambda - \big(1 - R(A,3)\big)\big(\alpha + \beta \times 3\big) = -\big(\alpha + \beta \times 3\big) = -13{,}000\,yen \quad (12)$$

$$EV(A_{E,3}) = \max\left\{EV(A_{E,2}), EV(A_{\overline{E},2})\right\} \quad (13)$$

Here, p(q,3) is the best estimate for p(q,2), such that

$$EV(A_{E,2}) = -\int \big(p(q,3)S(q)\big)dq \cdot R(A_{E,2})\lambda - \big(1 - R(A,2)\big)\big(\alpha + \beta \times 2\big) = -19{,}000\,yen \quad (14)$$

$$EV(A_{\overline{E},2}) = \max\left\{EV(A_{E,1}), EV(A_{\overline{E},1})\right\} \quad (15)$$

$$EV(A_{E,3}) = EV\big(A_{\overline{E},1}\big) - \int \big(p(q,3)S(q)\big)dq\lambda = -31{,}000\,yen \quad (16)$$

Therefore,

$$EV(A_{\overline{E},3}) = -19{,}000\,yen \quad (17)$$

$$EV(A_{E,3}) > EV(A_{\overline{E},3}) \text{ and evacuation at } 12:00 \text{ is optimal} \quad (18)$$

At 13:00 the decision model suggests evacuation of residents from all remaining locations with severity ratings of very high or greater based on a 1 in 1000 chance of experiencing flooding at 15:00. This represents a very high probability that the evacuation will be a false alarm, but considering that flooding carries very high risk of death for these locations, this is not an unreasonable choice of action. In this way, the decision model demonstrates the ability to be more conservative in its approach toward areas that would suffer greatly due to flooding, and less conservative in dealing with areas were flooding would not be catastrophic.

4.3 Evacuation path planning using probabilistic information

Once a decision is made to evacuate a given location, it is necessary to give clear instructions as to where to evacuate to, and how to safely reach the evacuation shelter. Traditionally, residents living in areas at high risk of flooding have been educated as to the dangers of flooding and have been given advice as to where the nearest evacuation shelters are located should evacuation become necessary. While preparedness of this sort is invaluable for reducing confusion during flood evacuations, probabilistic modeling of urban flooding as discussed in the previous section can further improve the effectiveness of the evacuation effort through real-time flood hazard mapping and preparation of optimal evacuation routes based on flood risk.

Once an evacuation order is issued, safe and rapid evacuation becomes the focus of the decision making. As discussed in the previous section, depending on the urban flood modeling strategy used for the given region at risk, probabilistic forecasts of flood inundation levels across the region can be provided together with an estimate of the severity that the range of possible inundation levels would have for unevacuated residents. The risk to a resident remaining in or moving through a given location at a given lead-time is defined here as the integral of the product of the PDF of inundation and the severity curve:

$$risk(\tau) = \int p(q,\tau)S(q)dq \quad (19)$$

In this way, the risk at lead time τ for a given location can be described as ranging between zero for a location that will be completely safe at this lead time through to a value of one for a region that will experience extreme inundation. A plot of the risk across the region being considered can be made and an optimal evacuation path can be chosen such that evacuees travel between their current locations and a designated evacuation shelter by traversing locations with the lowest risk rating. When choosing between multiple paths, the location at highest risk along each path is identified and the path for which this value is lowest is chosen. This is demonstrated in the conceptual flood risk map given in where the optimal route in terms of lowest risk to the evacuee is calculated in real time and may not necessarily be the shortest route to the evacuation shelter. Depending on the time required for evacuation, it may be necessary to consult flood risk maps generated for multiple lead times when choosing an evacuation path. It is currently technologically feasible in Japan and many other countries to have mobile phone handsets pinpoint an individual's location using GPS satellites and communicate this location to a central emergency service. Ideally the probabilistic flood forecasting system developed in this research could be used as discussed in this chapter as the backbone of a flood warning and evacuation support service capable of supplying mobile phone handsets with a map of current and forecasted inundation levels and evacuation directions automatically generated and updated in real-time based on an individual's location and specific requirements.

5. Conclusions

A decision support system for making evacuation decisions using probabilistic distributed flood forecasts is proposed and demonstrated. The system provides timely evacuation orders tailor-made to each area within the watershed based on potential inundation levels for the area and the distance and corresponding evacuation time to the nearest available shelter. The risk to each area is considered through estimating the probability with which inundation levels will occur for each forecast lead time, and the severity associated with each of these inundation levels. Three strategies are discussed for estimating inundation levels in urban areas using probabilistic forecasts of discharge within adjacent rivers.

A benefit of the approach presented here is that it provides a framework for choosing an acceptable level of risk for each area that may be tolerated prior to issuing an evacuation order. Informed decisions based on the additional information offered by probabilistic forecasts become possible by considering not only the probability of flooding, but also the potential for loss of life based on the geography of the region concerned.

A framework for probabilistic forecasting of short-term distributed runoff conditions within a watershed has been proposed. The probabilistic forecast has been developed by dividing the various uncertainties inherent in a flood forecast into precipitation uncertainty for modeling of errors associated with distributed rainfall forecasts, and hydrologic uncertainty for modeling model structure, model parameterization and model input errors. These uncertainties have been modeled through the use of a distributed rainfall-runoff model and a Monte Carlo simulation, with the resulting forecast presented in the form of a cumulative distribution function for each required forecast lead-time and location.

A Monte Carlo simulation is developed based on these models which simulates the range of possible future rainfall patterns that may develop based on recently observed rainfall field dynamics. These rainfall pattern time series are input into Hydro-BEAM to allow an ensemble of future runoff conditions to be simulated considering the effects of precipitation uncertainty.

Although uncertainty in the rainfall forecast is largely responsible for error in forecasting runoff, especially at long lead-times, other factors such as limitations associated with the rainfall-runoff model, calibration errors, and errors in radar rainfall observation are also responsible for considerable errors in runoff modeling. Two methods for using real-time discharge observations to reduce this type of error resulting from hydrologic uncertainty are developed to be compatible with a distributed rainfall-runoff model. An example application is carried out of the Monte Carlo simulation of rainfall-runoff considering precipitation uncertainty coupled with the adaptive updating technique for reducing modeling error considering hydrologic uncertainty.

An engineering decision making approach is discussed which aims to minimize losses due to false evacuation alarms and deaths due to floods through making evacuation decisions and proposing evacuation routes that maximizes the expected value of the outcome.

There is a great need for a flood forecasting system such as the one presented here that can provide a clear picture of potential future flood risks at all locations within a watershed. Such information is valuable not only in planning evacuations, but also in operating hydraulic equipment for flood mitigation during times of emergency with the goal of minimizing losses across an entire watershed.

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分布型流出モデルを用いた確率論的洪水非難意思決定

Paul James SMITH*・小尻利治・関井勝善*

*京都大学大学院工学研究科

要旨

本論分は，分布型流出モデルとモンテカルロシミュレーションを用いた確率論的降雨パターン発生手法，および，実時間での洪水予測手法を結合させ，流域内の確率論的洪水予測を実施し，避難の意思決定支援システムを提案するものである。シミュレートされた洪水予測分布を集約し，洪水の確率分布とすると同時に，河川に設定された計画高水に対する氾濫の時間的確率予測として危険度を表現する。また，流域内での土地利用・標高情報を用いた水位予測モデルを結合させ，氾濫確率の危険度への変換を基に氾濫の危険性表示と必要な避難手順の提示可能性を示唆している。

キーワード：確率論的洪水予測，洪水リスク，避難意思決定，分布型流出