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Probabilistic Short-term Distributed Flood Forecasting

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Synopsis

A framework is proposed for using distributed rainfall-runoff models for real-time probabilistic flood forecasting. A stochastic rainfall pattern simulation model capable of generating input for a distributed rainfall-runoff model is developed to facilitate a short-term probabilistic forecast of river discharge at multiple locations in a watershed. Generation of rainfall patterns over a 6-hour period is achieved using a translation vector rainfall forecasting process modified to account for uncertainties in rainfall pattern development. The stochastic rainfall generation model is coupled with a distributed rainfall-runoff model in a Monte-Carlo simulation to provide a short-term ensemble forecast of distributed flood discharge. An adaptive updating procedure for the real-time reduction of forecast error suitable for use with a distributed rainfall-runoff model is developed for the system. An example application of the proposed probabilistic flood stage forecasting system is provided for a typhoon event that occurred in the vicinity of the Nagara River watershed located in Gifu, Japan.

Keywords: distributed rainfall-runoff model, Monte Carlo simulation, flood prediction, probabilistic forecasting, rainfall generation

1. Introduction

It is the goal of flood forecasting to provide timely and accurate estimates of future discharge conditions at specific watershed locations. The wide variety of forecasting techniques available to the hydrologist today include physically-based rainfall-runoff modeling techniques, data-driven techniques, and varying degrees of mixtures of the two, with forecasts ranging in scale from short-term involving a number of hours, through to long-term involving a number of months or years.

The use of physically-based models allows an understanding of the hydrological process being modeled to be incorporated in the equations that describe it. Provided that the model can be suitably described and calibrated, a reasonably accurate model output can be produced. The forecasting ability of these models can be improved by coupling them with statistical models that use flood stage or discharge observations to account for inaccuracies in the model resulting from errors introduced by boundary conditions, model parameters, and input data. The time required for model development and calibration, however, is considered a drawback associated with the use of physically-based models. These models have also been criticized for often ignoring the spatially-distributed, time-varying, and stochastic properties of the rainfall-runoff process (Zealand et al., 1999), and for difficulties associated with the availability of data for real-time forecasting. An attempt is made here to further the understanding of how these issues can be tackled in modeling the rainfall-runoff process under typhoon conditions.

Distributed hydrological models have been used in recent years for a range of different water quantity and quality simulations, but have not yet found widespread use in the field of flood forecasting. The distributed nature of such models provides the potential for simulations of superior accuracy to purely data-driven models, and allows simulation results to be provided for multiple locations within a watershed. For this reason their use is investigated in this research.

While it is necessary to increase the accuracy of flood forecasts, there is also a largely unfilled need to provide a measure of the confidence that can be placed in a given forecast. No forecast of hydrological conditions can be perfect, and often is the case that too much faith is placed in a ëbestí prediction of future conditions, which can potentially lead to non-optimal decisions being made during the period leading up to a flood.

A Monte Carlo simulation approach that involves the generation of numerous future rainfall pattern series, and the input of these patterns into a deterministic rainfall-runoff model to generate simulated forecast hydrographs and allow the future discharge of a river to be described in a probabilistic sense, is proposed. The proposed framework calls for the following system components:

- A rainfall simulation model capable of analyzing weather radar-observed rainfall patterns and extrapolating these patterns to provide an estimate of future rainfall conditions.
- A distributed rainfall-runoff model capable of describing a watershed in terms of its distributed geographical properties, and capable of converting rainfall patterns into discharge at each location within the watershed.
- A Monte Carlo simulation strategy for combining the rainfall simulation model and the distributed rainfall-runoff model to provide a probabilistic forecast of future watershed discharge conditions.
- An add-on for the rainfall simulation model to allow stochastic generation of rainfall patterns considering past weather radar observations.
- An adaptive updating scheme for a distributed rainfall-runoff model capable of utilizing real-time river discharge observations to reduce forecast error.

A system comprising the above components is described and discussed. An example application for the Nagara River located in Gifu Prefecture, Japan, is provided for a typhoon event that occurred in September, 2000. A 6-hour-ahead forecast is desired so as to provide sufficient time for the issuing of flood warnings and appropriate operation of flood mitigation structures and machinery.

2. Probabilistic forecasting

Combined rainfall prediction and rainfall-runoff simulation procedures for estimation of future flood stage conditions generally attempt only to offer a ëbestí estimate of future river watershed discharge conditions without giving any information in regards to the confidence of the forecast being made. Information about the uncertainty in forecasts, however, can be beneficial in a number of ways, especially when this uncertainty is described in the form of a probabilistic forecast.

Risk-based decision-making becomes possible when probabilistic rather than deterministic forecasts are provided. 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 and after flood events that would otherwise likely occur if a flood stage prediction were exceeded, leading to damage or loss of life as a result of misguided faith in what was a ëbestí but by no means perfect estimate of future conditions.

Uncertainty in watershed runoff predictions results as a consequence of an inability to perfectly observe and predict rainfall conditions, and the inadequacy of the mathematical model used to approximate a highly complex physical system. The uncertainty related to the estimations of future rainfall conditions can be referred to as precipitation uncertainty, and the uncertainty related to the model structure, estimated model parameters, and observed hydrological data, can be collectively referred to as hydrologic uncertainty (Krzysztofowicz, 2001).

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.

An ensemble forecast produced in this manner, however, cannot alone provide a complete probabilistic forecast, as it is 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).

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), which uses a time series of 6-hours 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. 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 involving generation of future rainfall patterns is proposed for the production of an ensemble flood stage forecast considering precipitation uncertainty.
- A recursive adaptive updating technique is 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.

3. Monte Carlo simulation

A Monte Carlo simulation based probabilistic flood forecasting procedure is proposed here. 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.

The simulation proceeds as follows:

(a) Observation: Radar observation of rainfall patterns at regular intervals of Δt up to the present ($t = 0$).

(b) Identification and analysis: Identification of translation and growth-decay properties of observed rainfall patterns over each Δt interval. Time series analysis of observed patterns to determine suitable time series models to describe the fluctuations in translation vector parameters.

(c) Rainfall pattern generation: Generation of future rainfall patterns through extrapolation of observed rainfall patterns based on identified time series models of translation vector parameter fluctuation, together with inclusion of randomly generated white noise.

(d) Rainfall-runoff simulation: Running of the rainfall-runoff model using observed rainfall patterns to t = 0 and each generated rainfall pattern series to desired lead time t = $n\Delta t$ as input, where n refers to the number of desired future time steps.

(e) Probabilistic description of flood stage: Description of forecast up to t = $n\Delta t$ $n\Delta t$ using partial cumulative distribution functions (pcdfís) for each channel position of interest in the watershed.

4. Rainfall modeling and pattern generation

The translation vector model for analysis of rainfall pattern movement developed by Shiiba et al. (1984) is extended to include a time series analysis of observed pattern translation to allow for generation of future rainfall patterns based on the statistical properties of rainfall pattern translation and growth-decay characteristics.

4.1. Rainfall pattern translation model

Rainfall at time t at a point on a horizontal surface with the Cartesian coordinates of x, y, is given as $z(x,y,t)$. The translation model can be described as:

$$\frac{\partial z}{\partial t} + u\frac{\partial z}{\partial x} + v\frac{\partial z}{\partial y} = w \tag{1}$$

where u and v are the translation vectors and w is the growth-decay head. These terms are further described with the following one-dimensional functions:

$$\begin{aligned} u &= c_1 x + c_2 y + c_3 \\ v &= c_4 x + c_5 y + c_6 \\ w &= c_7 x + c_8 y + c_9 \end{aligned} \tag{2}$$

4.2. Identification of translation vector parameters

The parameters $c_1 \sim c_9$ are identified through analysis of past rainfall patterns using the method of linear least squares. A rectangular area within the observation range of the precipitation gauging radars is divided into rectangular mesh cells of dimension $\Delta x \cdot \Delta y$. The coordinates of this system are defined as follows:

$$\begin{aligned} x_i &= (i - 1/2)\Delta x, \quad i = 1,\ldots,M \\ y_j &= (j - 1/2)\Delta y, \quad j = 1,\ldots,N \\ t_k &= k\Delta t, \qquad\quad k = 0,\ldots,-K-1 \end{aligned} \tag{3}$$

Here, Δt is a time step, M and N are the number of mesh in the x and y directions, respectively, and $(K+1)\Delta t$ is the length of observed precipitation data required for determination of the movement of the precipitation patterns. In order to identify the parameters,

$$J_c = \sum_{k=-K}^{-1}\sum_{i=2}^{M-1}\sum_{j=2}^{N-1} v_{ijk}^2 \tag{4}$$

is minimized. v_{ijk} is defined as follows:

$$v_{ijk} = -\left[\frac{\partial z}{\partial t}\right]_{ijk} - \left\{\left(c_1 x_i + c_2 y_j + c_3\right)\left[\frac{\partial z}{\partial x}\right]_{ijk} + \left(c_4 x_i + c_5 y_j + c_6\right)\left[\frac{\partial z}{\partial y}\right]_{ijk} - \left(c_7 x_i + c_8 y_j + c_9\right)\right\} \tag{5}$$

4.3. Time series analysis of translation and growth-decay parameters

A time series analysis of observed rainfall patterns is conducted to identify the time series characteristics of rainfall pattern translation and growth-decay. Autoregressive moving average (ARMA) models, and the closely-related autoregressive integrated moving average (ARIMA) models (Box and Jenkins, 1976) are convenient as they are capable of taking into account the noise in the translation and growth-decay of rainfall patterns. Forecasting of short-term rainfall assuming that hourly rainfall follows an autoregressive moving average (ARMA) process was investigated by Burlando et al. (1993). The time series analysis was applied directly to a rainfall intensity data series at a point and the accuracy of the forecasts was limited, even at short lead times of 1 and 2 hours. The authors noted the intrinsic limitations of the at-site linear model used in their research, and cited the need for a forecast capable of taking into account the influence of storm movement and based on data monitored at a finer temporal and spatial scale.

An ARIMA model is applied here to the translation vector and growth-decay head of the rainfall pattern translation model, and through identification of appropriate model structure and parameters, the model is used to stochastically generate rainfall patterns based on past observed rainfall translation characteristics. This theory is applied to a series of rainfall patterns observed by radar at 5-minute intervals and defined on a 1-kilometer mesh grid.

A general ARIMA model of order (p,d,q) can be expressed as:

$$\phi(B)\nabla^d c^t = \theta(B)a^t \tag{6}$$

where c^t is the translation vector parameter at time t, and a^t is the random error term at time t having mean zero and variance σ_a^2. $\phi(B)$ is a stationary autoregressive operator, and $\theta(B)$ is a moving average operator. B is a backward shift operator defined by $Bc^t = c^{t-1}$ and related to the backward difference operator ∇ by $\nabla^d = (1-B)^d$, where d is the order of differencing. The Autoregressive (AR) operator of order p and the Moving Average (MA) operator of order q can be expanded as

$$\phi(B) = 1-\phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \tag{7}$$

and

$$\theta(B) = 1-\theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{8}$$

respectively, where $\phi_1, \phi_2, \ldots, \phi_p$ are AR parameters, and $\theta_1, \theta_2, \ldots, \theta_q$ are MA parameters.

In fitting an ARIMA model, p+q+2 unknown parameters $\mu; \phi_1, \ldots, \phi_p; \theta_1, \ldots, \theta_q; \sigma_a^2$ must be estimated. Here μ is the mean of the difference $\nabla^d c^t$ and is assumed to be zero unless a deterministic trend in the series is in evidence. For details regarding parameter estimation, the reader is referred to Box and Jenkins (1976), Walker (1931) and Yule (1927).

4.4. Rainfall pattern generation

Future rainfall patterns can be stochastically generated through extrapolation of parameters using a time series model estimated using the methodology proposed above. With each extrapolation step, the random variable a^t is sampled from a normal distribution based on the mean and variance of the error determined during model identification. Initial values c^{t-1} and c^{t-2} are also estimated during the identification process, and likewise an initial a^{t-1} can be estimated by fitting observed values of c^j into the estimated time series model, where $j = t$-1, t-2,Ö t-m, and m is the number of observed rainfall patterns for the storm event under analysis.

The simulation proceeds through solution of (6) for each future time step. In order to achieve this for each step, noise terms a^t must be generated for each translation parameter c_i.

Each future noise term a^t is sampled by first generating a random number ϕ between 0 and 1. Note that here ϕ is used in reference to the standard normal variable and has no connection to the AR parameters introduced above. The corresponding value of z is then extracted from a normal distribution with a probability density function described by:

$$\phi(x) = \frac{e^{-(x-\mu_i)^2 / 2\sigma_i^2}}{\sigma_i \sqrt{2\pi}}, \quad -\infty < x < \infty \tag{9}$$

and a corresponding distribution function

$$P(Z \le z) = \Phi(z) = \int_{-\infty}^{z} \phi(x)dx, \quad -\infty < z < \infty \tag{10}$$

where μ_a is the distribution mean and σ_a is the standard deviation of the error term. This is achieved by sampling

$$Z = \phi^{-1} \tag{11}$$

from a table describing the standard normal distribution ($\mu = 0$, $\sigma = 1$), and then converting this z value to a corresponding value taken from a normal distribution with mean μ and standard deviation σ such that

$$a_i = (\sigma_i z) + \mu_i \tag{12}$$

An ARIMA (1,0,1) model is considered here for parameters c_3 and c_6, and a white noise process is considered for parameters c_7, c_8, and c_9. A time series plot of the c_3 parameter calculated from observed rainfall patterns in the vicinity of Nagara River over the period 11/9/2000 17:05 ñ 20:00, is shown in Fig. 1 together with an example simulated time series for the following 6 hours. Note that it is not important that the simulated series matches the observed series, but rather that the nature of the fluctuation in the series is similar. It should be remembered that the simulated series contains a random input and will be different for each generated rainfall pattern set.

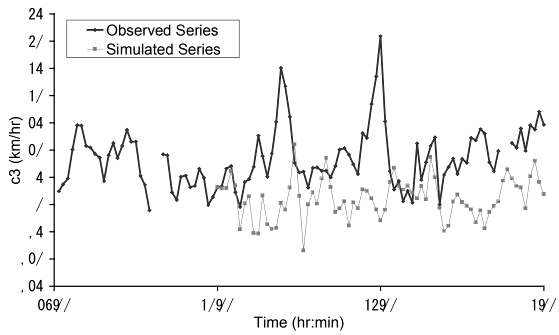

Fig. 1 Time series of c_3 and example randomly generated series

Generation of future rainfall patterns then proceeds through tracing the pattern movement backwards along a characteristic curve defined by a set of c_i generated using (6) at each time step, together with the following differential expressions:

$$\begin{aligned} \frac{dx(t)}{dt} &= c_1 x(t) + c_2 y(t) + c_3 \\ \frac{dy(t)}{dt} &= c_4 x(t) + c_5 y(t) + c_6 \\ \frac{dz(t)}{dt} &= c_7 x(t) + c_8 y(t) + c_9 \end{aligned} \tag{13}$$

The above expressions can be rearranged to generate a pattern for a time step of τ into the future:

$$z(x, y, t_0 + \tau) = z(x(t_0), y(t_0), t_0) - S(\tau; c_1, \cdots, c_9) \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}, \tag{14}$$

$$\begin{bmatrix} x(t_0) \\ y(t_0) \end{bmatrix} = R(-\tau; c_1, \cdots, c_6) \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

where S and R are 3×3 and 2×3 matrices, respectively.

5. Distributed rainfall-runoff model

The distributed rainfall-runoff model Hydro-BEAM (Kojiri et al., 1998) is a tool that was initially developed for simulating water quantity and quality in rivers, based on an understanding of the hydrological processes that occur within a watershed. It has since been used in a pioneering work on comparative hydrology, where a methodology for assessing the similarity between watersheds was proposed (Park et al., 2000), to investigate sediment transport processes in the large watershed of the Yellow River, China (Tamura and Kojiri, 2002), and to investigate pesticide levels in rivers and their effects on hormone levels in fish (Tokai et al., 2002).

Hydro-BEAM is used for the first time here for real-time flood stage forecasting. The use of a distributed rainfall-runoff model allows simulation of discharge levels at every point within a watershedís channel network, rather than just at a few specified locations as with lumped-parameter hydrological models.

Hydro-BEAM is configured for this research to accept radar-observed precipitation inputs at a 1-kilometer mesh scale at 5-minute intervals. The watershed is modeled as a uniform array of multi-layered mesh cells, each containing information regarding surface land use characteristics, ground surface slope and runoff direction, and the presence/absence of a channel. An approximation of the kinematic wave method is used to model watershed runoff on the surface and in the upper subsurface layer. The applied Hydro-BEAM model is calibrated to include only two subsurface layers, to allow for a fast real-time calculation. Evaporation losses during a flood event are ignored, as the impact of these losses is considered negligible.

6. Distributed adaptive updating

In order to facilitate the real-time updating of the calculated discharge given by the distributed rainfall-runoff model used for this research, such that an accurate real-time discharge prediction can be achieved, observed discharge data available in real-time from discharge observation stations within the watershed must be utilized. The rainfall-runoff model cannot merely rely on the correct prior identification of model parameters and the accuracy of observed and predicted rainfall patterns in attempting to produce an accurate model output. It is clear that no matter how accurately model parameters are calibrated, the uniqueness of each hydrological event, and the inherent weaknesses of the model as a simplified representation of a physical reality, ensures that an error between model output and actual discharge will always be present.

A large number of studies (Kitanidis and Bras, 1980; Puente and Bras, 1987) have successfully used discharge observations to improve flood forecast accuracy through application of the state-space Kalman filter (Kalman, 1960) to the problem of real-time adaptive estimation of lumped rainfall-runoff model parameters. A number of novel schemes have also been proposed in recent years for directly improving forecasts of future discharge based on discharge observations. One example is that of Khu et al. (2001) where a genetic programming technique was used to estimate a function relating the error between a time series of model outputs and observed discharges to improve forecasts of river discharge.

The problem of updating a distributed rainfall-runoff model in real-time to reflect actual river discharge conditions poses two main challenges. The first challenge is that of how to combine a filtering algorithm with a kinematic wave-based model. Secondly, how can an entire watershed model be suitably updated using discharge observations available at only a limited number of locations? The above two issues are discussed in detail in Smith (2003) where a scheme suitable for a distributed rainfall-runoff model such as the one being used in this research is proposed. In this scheme, the recursive updating of the watershedís discharge is achieved through individual recursive updating of gain parameters at each of the watershedís observation points.

Recursive filtering of a time-variable gain parameter ϕ_t^* is performed for each model mesh cell containing a river discharge observation station. A predictor-corrector algorithm based on that of Young (1984) is employed for the recursive estimation of the gain parameter, and is outlined in Fig. 2. Q_t and $\hat{Q}_t$ are the observed discharge and the predicted discharge, respectively, for time *t*. Here C_{NVR} is a noise variance ratio (NVR), and is used together with *P* to control the degree to which the time-variable gain is allowed to change between steps, with filter memory decreasing for increasing values of C_{NVR}.

In order to apply filter results from a limited number of locations to every mesh cell in the model, an interpolation scheme is developed for a watershed based on the characteristics of the watershedís flow routing map. In this scheme a weight vector $\alpha = (\alpha_1, \alpha_2, \cdots, \alpha_m)$ is determined for each observation point, denoting the influence from 0 to 1 of the gain estimated for each of the *m* observation points, such that $\sum_{i=1}^{m} \alpha_i = 1$. An example array of weight vectors calculated based on four observation stations located in Nagara River watershed, Gifu, Japan (seeFig. 4), is shown in Fig. 3. A complete description of the algorithm for the determination of the distributed weight vectors can be found in Smith (2003).

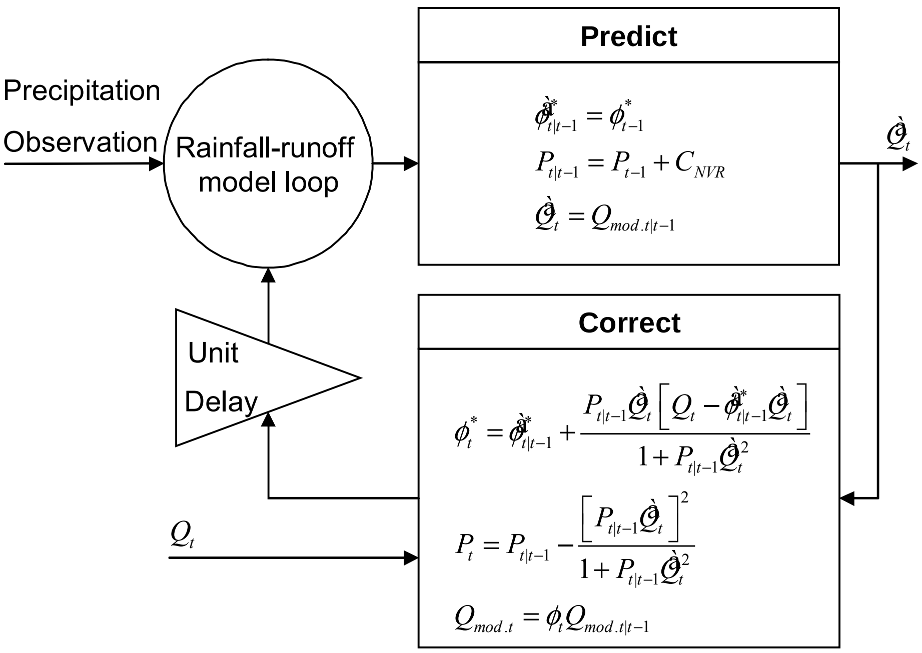

Fig. 2 Recursive filtering algorithm for estimation of adaptive gain parameter and updating of a distributed rainfall-runoff modelís discharge

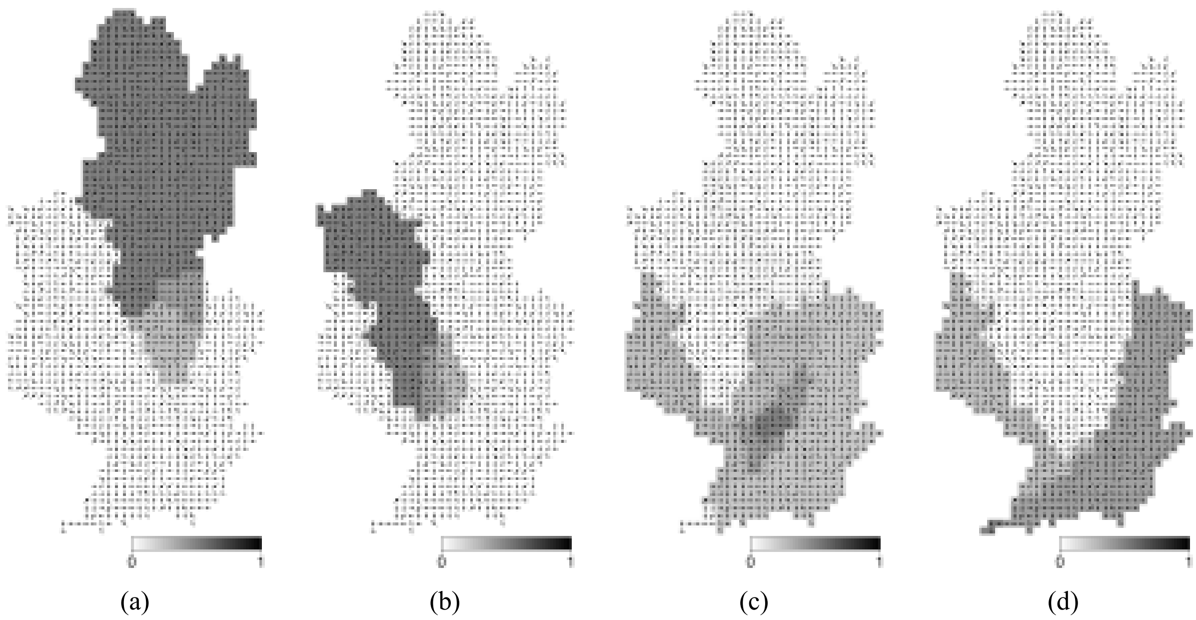

Fig. 3 Influence of four water stage observation points on each mesh cell of the Nagara River watershed: (a) Inari, α_1, (b) Shimohorado, α_2, (c) Mino, α_3, and (d) Chusetsu, α_4

7. Application

An application is conducted for a typhoon event that occurred in the vicinity of the Nagara River watershed in Japanís Chubu region over the period of the 10th to 13th of September, 2000.

The Nagara River is a southward flowing river located in the Gifu and Mie prefectures of Japan. It has a total catchment area of 1985 km^2 (Ministry of Construction, 2000) and a long history of flooding. Radar observations of precipitation conditions over the entire landmass of Japan are made available in real-time by the Japanese Ministry of Land, Infrastructure and Transport. Radar data is currently provided at five-minute intervals at a spatial resolution of 1km by weather radars located at Gozaisho and Jyatoge, which cover the Nagara River watershed and surrounding areas.

The Hydro-BEAM distributed rainfall-runoff model is fitted to the Nagara River watershed using a combination of digital survey data and printed materials to generate a flow routing map (Fig. 4) and a land use map, and using rainfall and discharge observations for calibration of runoff and infiltration parameters. 1556 mesh cells of approximately 1km^2 in area are used to describe the upper and middle catchment areas existing upstream of Chusetsu. The land use of this area is divided into 5 categories, and the percentage cover of each land use for each mesh cell is extracted from data sets obtained from satellite images. The model parameters are calibrated through trial and error using observations from typhoon events that occurred between 1992 and 1999.

A data set of the most recently observed 36 sequential 160×160 km rainfall patterns measured on a l km scale at 5-minute intervals is used for the rainfall model identification, which is repeated for each 5-minute time step during the simulation. The patterns are converted to translation vectors through the use of the rainfall pattern translation model. The simplified case of parallel translation is considered here, whereby only the translation vector parameters

c_3, c_6, and the growth-decay parameters c_7, c_8, and c_9 are used. The time series characteristics are determined for each parameter, and based on the resulting time series equations, time series of each parameter are stochastically generated and converted into 25 sets of 6-hour rainfall events.

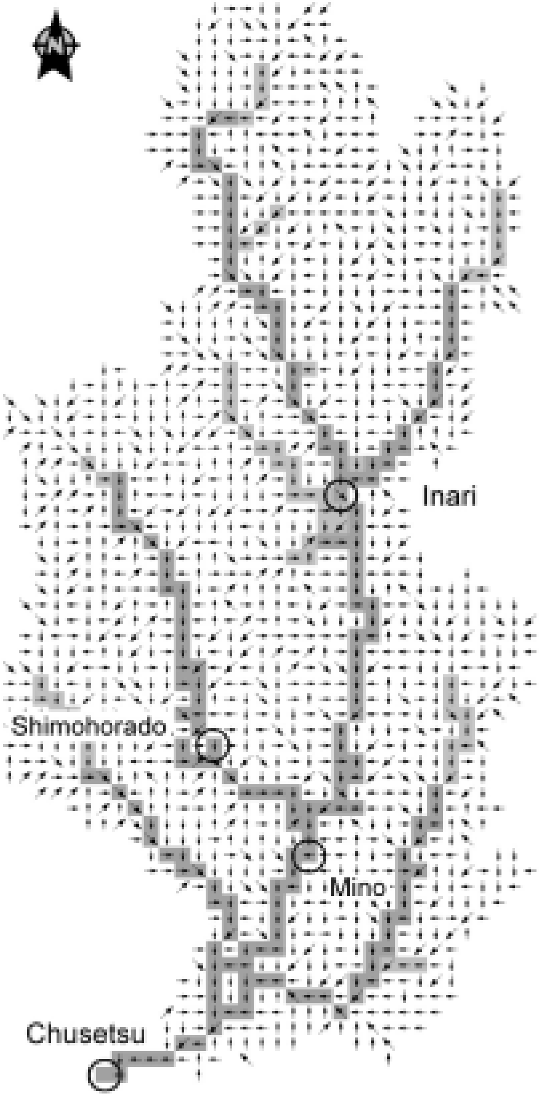

Fig. 4 Nagara River watershed flow routing map

The discharge results of 25 sets of 6-hour generated rainfall patterns at the midstream location of Inari and the downstream location of Chusetsu are given in Fig. 5 and Fig. 6, respectively. The simulated rainfall input does not have a major influence on the hydrographs of the downstream location for the first 3 hours of the rainfall-runoff simulation. The influence on the hydrographs of the midstream location appears an hour earlier. A probabilistic forecast of flood discharge considering only precipitation uncertainty is given for Inari and Chusetsu in Fig. 7 and Fig. 8, respectively. Plots of the 6-hours ahead 50% and 95% non-exceedance probability limits of discharge for all channel locations within the Nagara River watershed are shown in Fig. 9(a) and Fig. 9(b), respectively.

These results, when coupled with an estimate of hydrologic uncertainty, provided by the adaptive updating scheme outlined above, can provide a complete probabilistic forecast of flood stage conditions for an entire watershed.

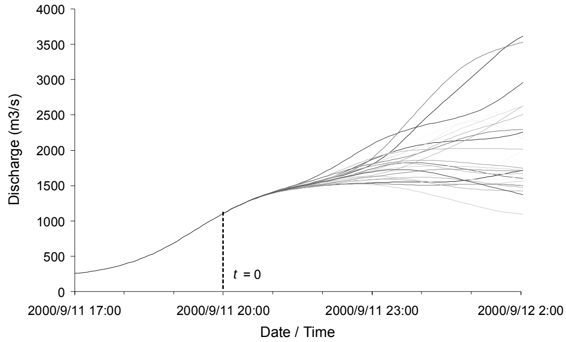

Fig. 5 Simulated future discharges for Inari, 20:00 11 September 2000

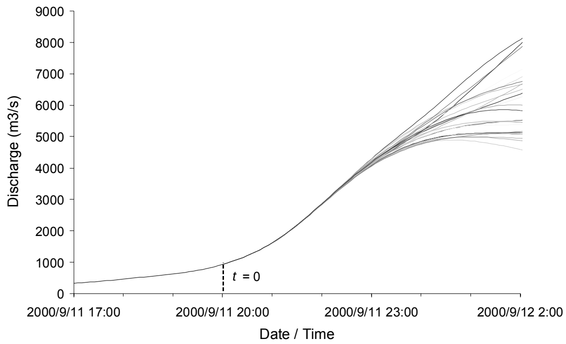

Fig. 6 Simulated future discharges for Chusetsu, 20:00 11 September 2000

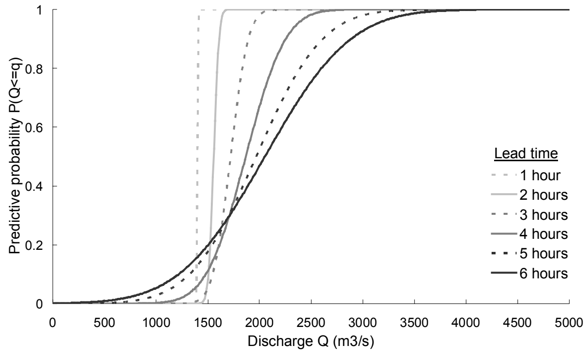

Fig. 7 Probabilistic forecast considering precipitation uncertainty for Inari, 20:00 11 September 2000

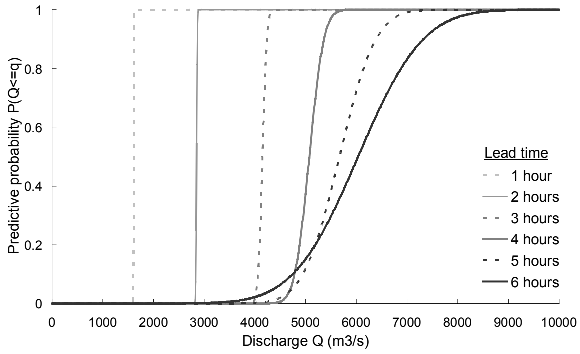

Fig. 8 Probabilistic forecast considering precipitation uncertainty for Chusetsu, 20:00 11 September 2000

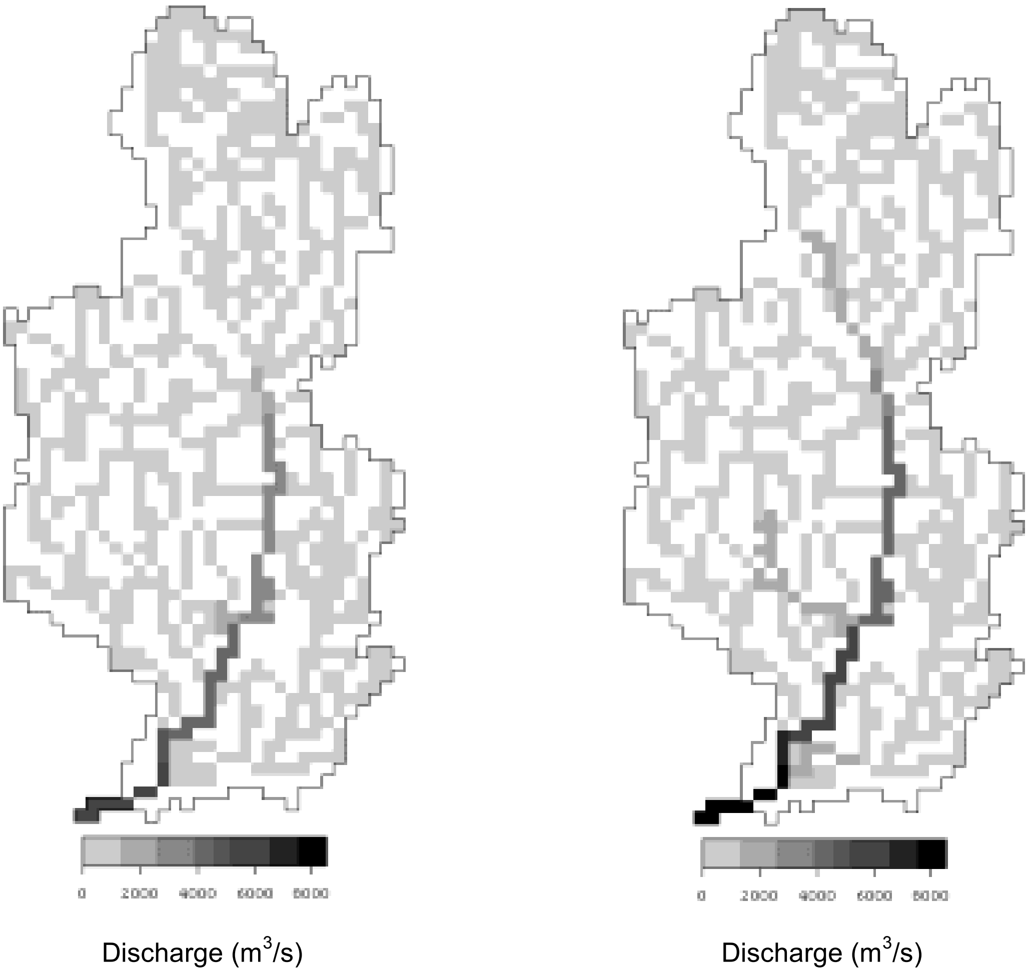

Fig. 9 Distributed discharge forecast for the Nagara River watershed, 6-hours ahead, (a) 50% non-exceedance probability limit (left), (b) 95% non-exceedance probability limit (right), 20:00 11 September 2000

8. Conclusions

A comprehensive strategy for providing a probabilistic forecast of flood stage at each point within a watershed has been proposed. A translation vector model for stochastic rainfall generation has been successfully developed and combined with a distributed rainfall-runoff model to account for the uncertainty that exists in a flood stage forecast due to an inability to perfectly forecast rainfall conditions. An application demonstrating the ability of the Monte Carlo Simulation-based system to provide an ensemble forecast of future flood stage conditions for a six-hour lead time has been demonstrated.

Distributed rainfall-runoff models hold great potential for application in the field of flood forecasting, and the strategies proposed and employed in this research serve as a basis for their future use.

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確率論的短期間分布型洪水予測

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要旨

本研究では、流域における洪水流出量の確率的短期間予測を提供するため、分布型流出モデルに適合する降雨入力データを発生させる確率論的降雨パターンシミュレーション過程を開発する。移流ベクトルによる降雨シミュレーションモデルを降雨パターンの発達による不確実性を考慮し修正することで、６時間にわたる予測降雨パターンの発生を可能にする。分布型でのアンサンブル短期間洪水流出予測を提供するために、モンテカルロシミュレーションを用いる。

キーワード：分布型流出モデル，モンテカルロ法，洪水予測，確率論的予測，降雨パターン発達