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Development of a Water Surface Level Prediction Method Affected by River Mouth Sandbar Collapse

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Abstract

The purpose of this study is to apply a non-linear filtering methods (Particle Filter) to a flood prediction system to improve the accuracy of flood water level. The uniqueness of the flood prediction system is to estimates the water level considering temporal change of the sandbar collapse at the backwater reach in the Kumano River. A one dimensional hydrodynamic model of unsteady flow was applied to predict the longitudinal profile of the water level at the reach affected by the sandbar collapse of the river mouth. It was shown that the bed deformation height as one of the state quantities could explain the timing of the sandbar collapse. Other state quantities are discharge at the upstream and the lateral discharge from the branches. These were given from the results of a distributed rainfall-runoff model. Error coefficients are included to update the state quantities by using filtering method with the observed water level. The water level at the objective river of the study was predicted by using the updated initial condition after the filtering, which showed a good agreement with observed water level. It is concluded that the precision of the flood prediction system combined the water surface level prediction model are improved more than before.

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Keywords: *flood prediction, sandbar collapse, non-linear filtering technique, unscented Kalman filter, particle filter, bed deformation*

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1. Introduction

During Japan's Typhoon No. 12 in September 2011, many people were killed in landslides in mountain areas, and in the heaviest flood recorded. In addition to major events like this, various small and large floods occur almost yearly in the Kumano River due to its geographical location.[1] The Kumano River is also famous for its large amounts of sediment discharge[1].

The flood prediction system described in this paper aims to predict the water surface levels of the area from the Kumano River mouth (managed by Japan's Ministry of Land, Infrastructure, Transport and Tourism) to Ouga Point (a flood control reference point), and to the tributary called Onodani River. Our flood prediction system was more complex due to a river mouth sandbar, as shown in Fig.1, which makes flood prediction more difficult. A river mouth sandbar fluctuates in shape and location every year. Since it is formed after flooding in the previous year, it is assumed that its form varies according to its collapse level. Observation records indicate that a flow rate greater than approximately 8,500 m^3/s triggers collapse of the river mouth sandbar. However, in cases where several floods occur in one year, no river mouth sandbar is formed, and there is no sandbar influence.

For a river with these features water surface level prediction generally involves sequential observation of the river mouth and sandbar formation, with estimates of flood volume and sandbar collapse. It is difficult, however, from the aspect of observation facilities and available systems, to collect the data required accurate for calculation for timely predictions.

Since the current observation system cannot determine the physical change of the river mouth sandbar during the collapse process, we use a non-linear filtering technique to estimate the condition of the Kumano River. This method uses a water surface level determined from a system-calculated flow rate and observed water surface levels, to determine behavior of a variable that explains occasional observation values with the filtering technique. In other words, to predict water surface levels, we try to predict a flood and simultaneously track sandbar behavior using a non-linear filtering technique as a correction method for the observed water surface level at the current time. As an example of this effort, Tachikawa et al. [2], [3] and Tanaka et al. [4] considered the applicability of the particle filter method to the water surface level prediction system. Tachikawa et al. estimated (using a height-quantity [HQ] equation estimation [2]) the zone of the Katsura River, a tributary of the Yodo River. They also estimated the flow rate of the Kumano River during Typhoon No. 12 in 2011. [3] Tanaka et al. improved the accuracy of predicted water surface levels of the backwater zone, for which a unique HQ relation was not guaranteed, using the particle filter method, for their flood prediction system for the Yodo River Water System.

Although research cases using this method are still being accumulated, there are practical issues that need to be addressed in calculation speed and system operation. We conducted our study as part of a system development effort for flood prediction in the Kumano River Water System.

For our water surface level prediction method for the sandbar zone, we integrated observations of current water surface levels with adaptable state quantities (e.g., remaining basin flow rate) to predict the most probable future water levels. We used the particle filter method for analysing sandbar flush in the river mouth, which is a nonlinear phenomenon. We examined if we can assess the state quantities that explain sandbar deformation and water level changes caused by river mouth sandbar flushing, aiming at construction of a feedback system to predict future water levels.

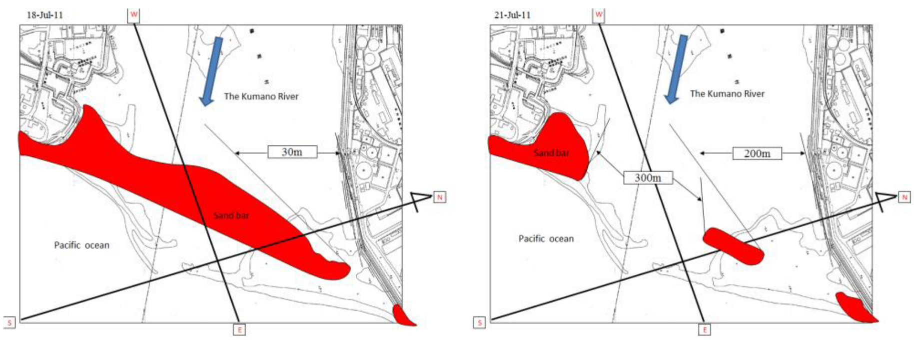

Fig.1 River mouth sandbar collapse (Typhoon No. 6 in 2011)

2. Sandbar deformation at the Kumano River mouth

A sandbar frequently develops near the Kumano River mouth, and the Narukawa water level gauging station upstream has been significantly affected by backwater. During flooding, there is often collapse of the river mouth sandbar (hereafter, "river mouth sandbar flush"). At the time of flooding during Typhoon No. 6 in 2011, as shown in Fig.1, collapse of the river mouth sandbar was visually observed to be approximately 500 m long.

Fig.2 shows the relationship of height and quantity, derived from the water level observations at the Akebono water level gauging station near the river mouth, and HQ estimated flow rates at Ouga Point. As shown in Fig.2, the height and quantity relation (hereafter, "HQ relation") during the flood was not unique, and the height decreased even as the quaintly increased. As a result, we found that the sandbar collapse significantly affected the water surface level.

From observations of the river mouth sandbar flush and the HQ relation during multiple floods, the river mouth sandbar flush occurred when the flow rate was approximately 8,500m3/s, as observed at Ouga Point. On the other hand, significance of the impact of the river mouth sandbar flush varied significantly according to the state of sandbar development before the flood. In the case of the flood caused by the Typhoon No. 6 in 2011, the river mouth sandbar flush occurred at a large scale, but after that, in the smaller floods of 2012 when sand deposition continued, the flush did not affect water surface levels significantly.

As discussed earlier, since we cannot express the HQ relation with the monodromy HQ relation, due to the influence of river mouth sandbar flush,

It is difficult to use a flood prediction method that converts estimated and predicted flow rates derived from the HQ relation. In other words, the impossibility of the current status estimation may cause prediction inaccuracy of the following calculation.

Additionally, for the unsteady flow model (or water surface level tracking model), we needed a method for incorporating variations in water surface levels caused by sandbar collapse and other factors. Assuming the water surface level prediction system operates every day, a model is required that can reproduce the current sandbar status. Since a riverbed-deformation model cannot monitor riverbed conditions in real time during flooding, we determined that such models were not suitable for practical use. Even if such models could monitor riverbed conditions in real time, they need considerable time to process system parameters, such as water flow and sediment accumulation with observation values, and are therefore not practical.

As discussed above, we considered that an effective water surface level prediction method for backwater reach of river mouth sandbars requires a filtering technique, which allows assimilation of current observed water surface levels with adaptable state quantities (such as sandbar deformation height) .

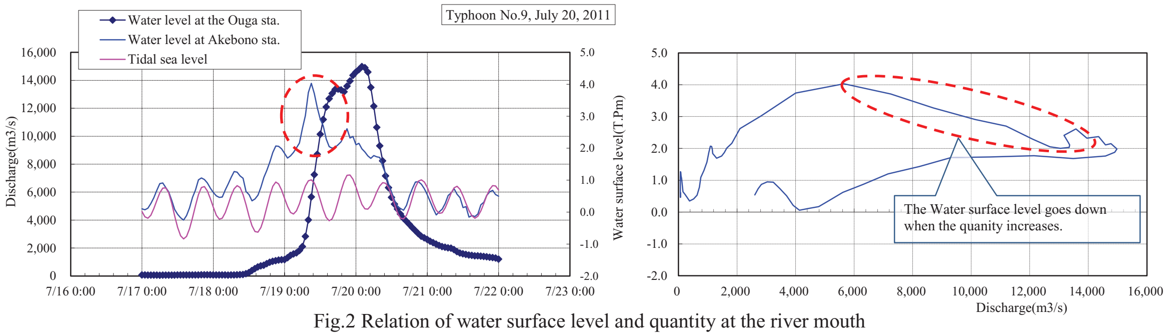

Fig.2 Relation of water surface level and quantity at the river mouth

3. Outline of the Kumano River water surface level prediction model

3.1. Application of the distributed rainfall-runoff model

The distributed rainfall-runoff model consists of a three-layer model vertically placed in all layers in the basin (surface layer, unsaturated layer, ground-water layer) and a river channel model. With this approach, runoff components from each layer are input into the river channel model along the water fall line, and a channel flow rate is calculated based on the Kinematic Wave method from point to point. Characteristically, this model allows parameters to be set for each layer including hydrological features such as land use, soil, and surface layer geology. In this study, we constructed the model by using the model that Inomata et al. [5] used as a reference.

3.2. Construction of the water surface level prediction model

To develop the water surface level prediction model for managed zones of the Kumano River (the main river) and the Onodani River (a tributary), we used the one dimensional unsteady flow model. The governing equations are the continuous and the momentum equations and are shown below the equation (1) and (2).

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = q \tag{1}$$

$$\frac{1}{g}\frac{\partial}{\partial t}\left(\frac{Q}{A}\right) + \frac{1}{g}\frac{Q}{A}\frac{\partial}{\partial x}\left(\frac{Q}{A}\right) + \frac{\partial H}{\partial x} = -\frac{n^2|Q|Q}{A^2 R^{4/3}} \tag{2}$$

Herein, Q is the discharge, A is the area of cross section, H is the water level, R is the hydraulic radius, g is the gravity acceleration, n is the Manning coefficient, q is the lateral discharge, x is the axis of the longitudinal length and t is temporal axes expressing the interval of the calculation step.

The upstream end condition is the calculated outflow based on the distributed rainfall-runoff model. The downstream end condition is the HQ-conversion water surface level or the observed water surface level (astronomical tide level in prediction calculation) at Akebono Point.

We verified the accuracy of the two methods, as described briefly in section 4, to confirm the applicability of the filtering technique used to determine water level changes caused by the river mouth sandbar flush. In this study, we set target points for feedback on water surface levels and state quantities as shown in Table.1 and Fig.3. As shown, we set the state quantity for the river mouth sandbar flush as a deformation height of dz and discuss its applicability. dz is included in the area of cross section at the downstream end in the equation (1) and (2). dz is expressed by the equation (3) and (4).

$$H = D + z \tag{3}$$

$$A = F(D + z) \tag{4}$$

Herein, D is the depth, z is the bed level at the downstream end and F is the function.

In this study, the state quantities which are shown in Table-1 were solved by the governing equations as the inverse problem.

Table-1: Point for feedback of water surface level, and filtering state quantity

Point	State quantity
・Narukawa Point (Kumano River) ・Takaoka Point (Onodani River)	・Coefficient applied to upstream end discharge Q of Kumano River and Onodani River ・Coefficient applied to remaining basin outflow ・River bed deformation height dz at the downstream end

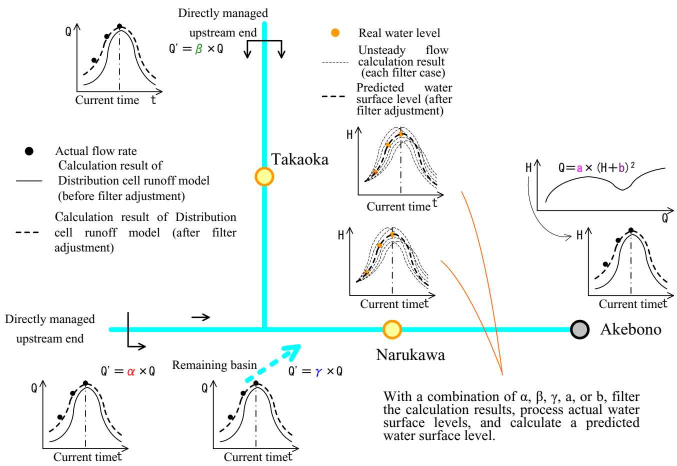

Fig.3 Outline of water surface level prediction model (Downstream end condition: HQ equation)

4. Brief explanation of the filtering technique

4.1. The fundamental filter equation

The fundamental filter equation is expressed with a prediction equation and an observation equation. The equation (5) is used to estimate the current state quantity based on the last state quantity. Because the value after time update at the last period has an error, compared with the current time, a prediction noise (system noise) w is added to the prediction equation.

The equation (6) expresses the relation between the estimated observation value $h(x_t)$ and observation value y_t, and a similar observation noise v added to the observation equation.

(1) Time update step (prediction equation)

$$x_t = f(x_{t-1}) + w \tag{5}$$

(2) Observation value update step (observation equation)

$$y_t = h(x_t) + v \tag{6}$$

The state quantities of the unsteady flow model are coefficients applied to the upstream end flow rate, the remaining basin flow rate, and other factors. The prediction equation indicates change of these parameters.

Also $h(x_t)$ of the equation (6) calculates an estimated observation value based on the state quantity, and indicates that the steady flow model is used for analysis.

4.2. Characteristics of the filtering technique

For monitoring change in non-linear water surface levels, the methods based on the assumption of Gaussian error distribution, such as Kalman filters, were not considered highly applicable. However, recent research indicates progress in the development of non-linear state space models. In this study, we considered the applicability of two methods: unscented Kalman filter[6], which allows comparably high-speed calculation even though restriction of the

Gaussian distribution is strict; and particle filter[7], which has no restriction of the Gaussian distribution, but cannot perform fast calculations in some cases where particle numbers are high. The following section describes the characteristics of these methods:

a) Unscented Kalman Filter

With the ensemble Kalman filter method, we have to prepare many ensemble members to acquire stable solutions. In the case of the unsteady flow model, which needs considerable time for analysis, it is difficult to operate the filter in real time. The unscented Kalman filter uses the unscented transform method (also known as U transform) to reduce the number of members required, in order to reduce analysis time. For a detailed outline of the unscented transform and the unscented Kalman filter algorithms, refer to Tsujikura et al[8].

The procedure of the Kalman filter is provided below. This procedure combines an estimated state quantity value and an error covariance, and repeatedly updates the time and observation values. The procedure is as follows: The methods other than the Kalman filter also use this procedure.

(1) Update the time of the estimated state quantity value.

$$\hat{x}(t \mid t-1) = A\hat{x}(t-1 \mid t-1) \tag{7}$$

(2) Update the time of the error covariance of the state quantity.

$$P(t \mid t-1) = AP(t-1 \mid t-1)A^T + W_x \tag{8}$$

(3) Acquire an observation value and calculate Kalman gain.

$$K = P(t \mid t-1)B^T\left[BP(t \mid t-1)B^T + vv^T\right]^{-1} \tag{9}$$

(4) Update the observation value of the estimated state quantity value.

$$x(t \mid t) = x(t \mid t-1) + K\left[y(t) - B\hat{x}(t \mid t-1)\right] \tag{10}$$

(5) Update the observation value of the error covariance of the state quantity.

$$P(t \mid t) = (I - KB)P(t \mid t-1) \tag{11}$$

b) Particle Filter

We use the Monte Carlo approach method that gives state quantity to each particle and approaches probability distribution with particle density. Use of the Bayes' theorem for updating the time and the observation value eliminates the restrictions of the Gaussian distribution that is the assumption for the Kalman filter, and allows filtering of random distribution. Concerning the particle filter algorithm and others, please refer to Tanaka et al[4]. In this section, we clarify difference between weighed sampling, which is one of the particle filter characteristics, and the Kalman gain used for the Kalman filter.

In the space of the estimated observation values and the state quantities shown in Fig.4, tendency of variations in the values of particles or members shows a theoretical solution. When we approach the theoretical solution linearly, appearing inclination shows the Kalman gain, and when we acquire an observation value, an estimated state quantity value is counted backward from the straight line. On the other hand, with the weighed sampling, state quantities around the observation value are weighed and averaged, for calculation of an estimated value.

When the observation value is in scattering particles and also the theoretical solution shows high non-linearity, the weighed sampling gives a good result. If the observation value is outside scattering particles, the weighed sampling indicates a particle value that is closest to the observation value as an estimated value, and we find that extrapolation is not allowed. On the other hand, the method with the Kalman Gain finds an estimated value by extrapolation of a straight line, we can expect a certain level of accuracy. Therefore, to prevent extrapolation even in case of the particle filter, we have to collect the number of particles as much as possible.

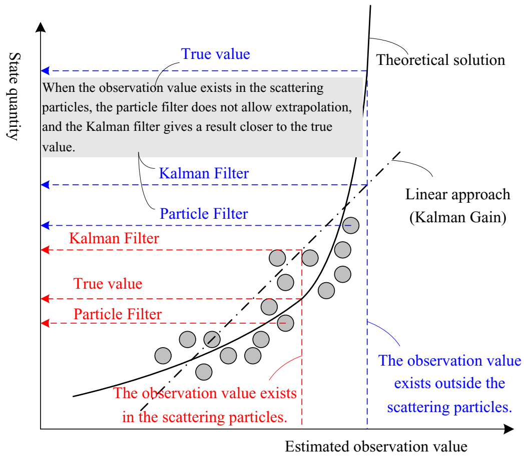

Fig.4 Difference between Kalman Gain and weight sampling

5. Prediction results of the non-linear filtering technique

We analyzed unsteady flow by determining flow rates upstream of the main river and upstream of the tributary upstream, calculated using the distributed rainfall-runoff model for upstream conditions. The remaining basin outflow was estimated separately, based on the distributed rainfall-runoff model, as lateral inflow.

We analyzed recent floods: Typhoon No. 6 in 2011, Typhoon No. 15 in 2011, Typhoon No. 4 in 2012, and Typhoon No. 17 in 2012.

5.1. Change of state quantities

Fig.5 shows the time series change of state quantities based on the applied filtering technique (particle filter). We show the time series change in riverbed deformation height, *dz* of the downstream end section (which is the state quantity) and the calculated flow rate before and after filtering at the Narukawa point.

At the initial stage and end stage of flooding, when flow rates are relatively low, the variation of *dz* tends to be large. We considered that *dz* indicates backwater influence, and shows characteristics of the relevant zone affected by the backwater of the river mouth sandbar. We also considered that the reasons for the variation of *dz* at initial flood stages was that the measurement result of the channel we use for calculation is the data of the year close to the flood occurrence time, and the river mouth sandbar status does not exactly match the status at the time of flood, and therefore, the status is adjusted by filtering at the initial stage of flood.

At the time of Typhoon No. 6 in 2001, when there was a significant river mouth sandbar flush, the *dz* value was approximately −3.0 m when the flush started. We find that assimilation with the real phenomenon called the degradation of the riverbed actually occurred. However, from the following time point after the first flush-start-time, the state quantity (*dz*) representing sandbar deformation did not change significantly, and the flow rate, which was the remaining state quantity, changed significantly instead. We determined that this is because the water surface level at the Narukawa point is not determined by the river mount sandbar flush, but by the flow rate under the condition where the flow rate is large, to provide explainable feedback concerning the water surface level of the Narukawa point at the current time.

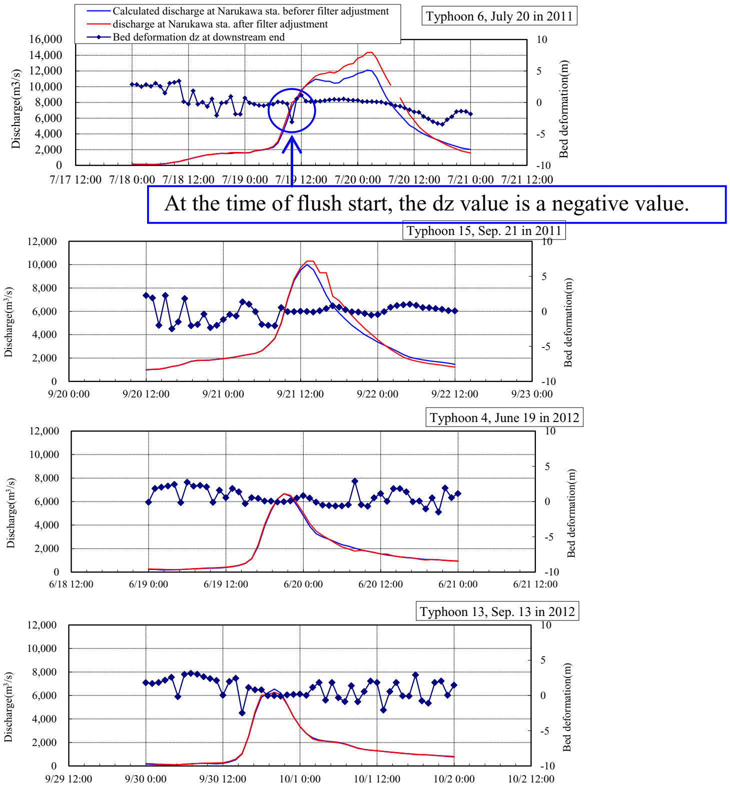

Fig.5 Time series change of state quantity

5.2. *Consideration of the applicability of the filtering technique*

As discussed above, we learned that we can consider river month sandbar deformation by filtering of state quantities (dz) that express the river mouth sandbar deformation. In this section, we consider the applicability of the unscented Kalman filter and the particle filter for filtering.

In our evaluation, we compared the water surface level of the actual flood with the predicted water surface level after 1 hour, 3 hours, and 6 hours, using the Nash value as an index (an index for evaluating waveform applicability). After 1 hour and after 3 hours, both methods show high applicability (80% or higher in most of the points) as shown in Table.2. After 6 hours, applicability of the unscented Kalman filter (UKF) is lower than the particle filter (PF). We concluded that both methods provide adequate accuracy for applicability to the model.

Fig.6 shows the prediction result after 12 hours against the actual water surface level of the Narukawa point, indicated with a solid line.

In all flood cases, initial flooding is predicted without delay. In the cases of floods caused by Typhoon No. 15 in 2011 and Typhoon No. 17 in 2012, the predicted water surface levels after 3 hours (and others around the peak point) are lower than the actual records. Compared to these two flood cases, the prediction accuracy of the flood caused by Typhoon No. 4 in 2012 is high even though its scale is similar. There may therefore be issues with filtering stability. We ultimately concluded that there was no significant difference between the prediction hydrographs of UKF and those of PF, which appear to have equal accuracy.

The results indicate that our water surface level prediction method is appropriate for the Kumano River zone affected by the river mouth sandbar collapse. We found that the filtering we applied is effective for assimilating data in real time, based on the unsteady flow model. We also adopted the flow rate and correction coefficients for riverbed deformation height of the downstream end section as state quantities. We successfully explained the validity of these state quantities by comparing prediction results with real time data.

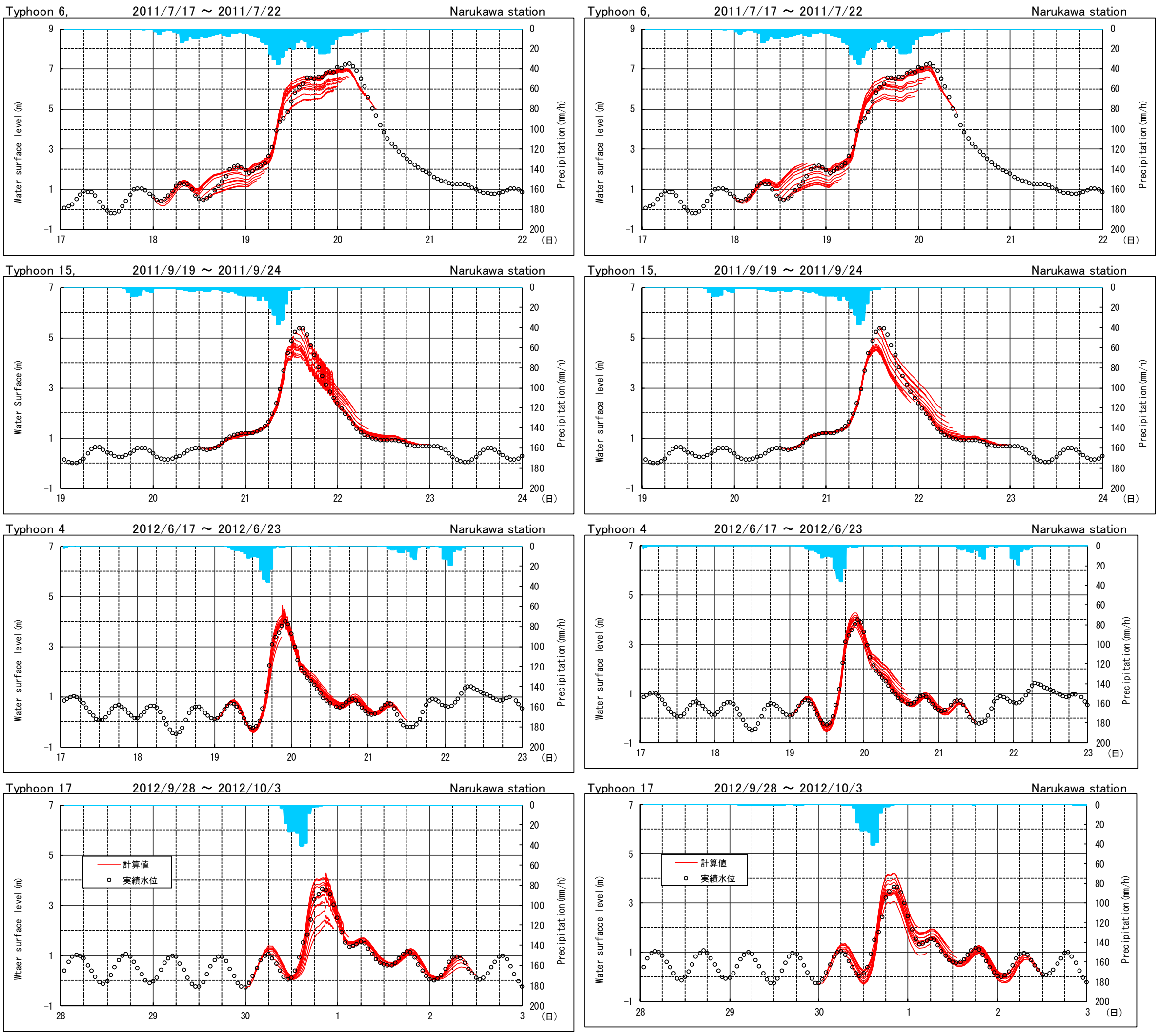

Fig.6 Change of predicted water surface level from current time (Left: UKF/ Right: PF)

Table-2: Evaluation of applicability of water surface level prediction base on Nash value

Typhoo No.		Station	Unscented Kalman Filter			Particle Filter		
			1hr after	3hr after	6hr after	1hr after	3hr after	6hr after
Typhoon 9	July,2011	Narukawa	0.99	0.96	0.93	0.99	0.97	0.94
		Takaoka	0.99	0.96	0.93	0.99	0.97	0.94
Typhoon 15	Sep., 2011	Narukawa	0.99	0.97	0.94	0.98	0.95	0.89
		Takaoka	0.99	0.97	0.93	0.99	0.96	0.91
Typhoon 4	June, 2012	Narukawa	0.99	0.97	0.97	0.99	0.96	0.95
		Takaoka	0.99	0.98	0.97	0.99	0.96	0.93
Typhoon 17	Sep., 2012	Narukawa	0.97	0.91	0.87	0.97	0.88	0.85
		Takaoka	0.97	0.91	0.91	0.97	0.89	0.85

6. Conclusion

In this study on the Kumano River, we showed successful results applying a non-linear filtering method for water surface level prediction. Our prediction model worked with level variations caused by river mouth sandbar collapse and other considerations. The specific achievements in this study are as follows:

- We applied the unsteady flow model to analyze water surface levels in zones affected by river mouth sandbar backwater and collapse. Our system analysis was based on the outflow in upstream areas derived from the distributed rainfall-runoff model. We considered the impact of sandbar collapse and other factors using a riverbed deformation height, dz, as a state quantity, which represents the sandbar deformation at the river mouth. We also used a correction coefficient for flow rate as another state quantity, and found that data assimilation was possible.
- We found high applicability of our model to water surface level prediction during real time. This was because the state quantities changed according to water surface levels. To demonstrate this validity, we calculated prediction by using the state quantities at the current time as the initial condition, and accordingly, found that it had very high applicability.

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