A Geographic Primitive-Based Bayesian Framework to Predict Cyclone-Induced Flooding*

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ABSTRACT

The effectiveness of managing cyclone-induced floods is highly dependent on how fast reasonably accurate predictions can be made, which is a particularly difficult task given the multitude of highly variable physical factors. Even with supercomputers, collecting and processing vast amounts of data from numerous asynchronous sources makes it challenging to achieve high prediction efficiency. This paper presents a model that combines prior knowledge, including rainfall data statistics and topographical features, with any new precipitation data to generate a probabilistic prediction using Bayesian learning, where the advantages of data-oriented and heuristic modeling are combined. The terrain is partitioned into geographic primitives (GPs) based on manual inspection of flood propagation vector fields in order to simplify the stochastic system identification. High calculation efficiency is achieved through statistically summarizing simultaneous events spread across geography into primitives, allowing a distributed updating algorithm leading to parallel computing. Markov chain processes identified for each of these GPs, based on both simulation and measured rainfall data, are then used in real-time predictions of water flow probabilities. The model takes a comprehensive approach, which enables flood prediction even before the landfall of a cyclone through modularizing the algorithm into three prediction steps: cyclone path, rainfall probability density distribution, and temporal dynamics of flood density distribution. Results of comparative studies based on real data of two cyclones (Yasi and Tasha) that made landfall in Queensland, Australia, in 2010/11 show that the model is capable of predicting up to 3 h ahead of the official forecast, with a 33% improvement of accuracy compared to the models presently being used.

1. Introduction

The vulnerability to natural disasters has increased all over the world during the past few years, leading to social, economic, and environmental tragedies. The

tragic flooding in 2010–2011 in the state of Queensland, Australia, alone has resulted in over 200 000 people affected, with 35 confirmed deaths, as stated by BBC News (2011) and ABC News (2011). The resulting damage was over AUD \$1 billion, with an estimated reduction of AUD \$30 billion in gross domestic product (GDP). According to the Intergovernmental Panel on Climate Change, economic losses from weather- and climate-related disasters have increased in the past few decades, and heavy rainfalls associated with tropical cyclones (TCs) are likely to increase with continued warming (Allen et al. 2012).

Apart from the increase in the importance of disaster monitoring, there has been some decline in monitoring

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infrastructure as a result of disasters themselves (Asante et al. 2008). Millions of dollars are being spent on disaster management sensor networks, signifying the importance of efficient sensor deployment and management. One method of extending the lifetime of a wireless sensor network is to optimize the onboard energy consumption of nodes. To conserve onboard energy, many design approaches have been researched, such as network architecture, efficient sensing circuitry, algorithms, and communication protocols (Nanayakkara et al. 2011; Albers 2010). Various dynamic power management techniques have also been proposed, which mainly address sleeping patterns and idle states dynamically (Passos et al. 2005). In addition to power management in sensor nodes, efficiency and the effectiveness of a network can be improved drastically using the just-in-time sensor deployment, as described in Yee et al. (2006).

A predicted time of flooding for a given area prone to cyclone-induced flooding will immensely improve the effectiveness of disaster management operations. This includes power management techniques and dynamic deployment of sensor networks, which would help obtain a perfect balance between reducing network cost and capturing the most important data. It has been shown in Ding et al. (2010) that the losses in a catastrophic event, such as a natural disaster, decrease with the increase of predictability of the event. There are several deterministic flood models in use today, predicting likely inundations resulting from TC activity. A digital elevation model (DEM) of increasing resolution is used to model water flow (Asante et al. 2008; Bates and De Roo 2000; Bates et al. 2003), taking into consideration that flood inundation extent is highly dependent on topography (Bates and De Roo 2000). It has been shown in Bates and De Roo (2000) that the predictive ability deteriorates with the decrease in resolution of DEM data used. This was especially true when levee structures were smoothed with lower-resolution landscapes. However, it has also been shown that the improvement of prediction accuracy with increased resolution is marginal for smoother landscapes. Therefore, one drawback of this approach is the fact that it uses high-resolution data throughout the landscape, which results in increased computational cost. This raises the importance of using different resolutions based on the geography of the area. To address this issue and to improve prediction efficiency through offline calculations, this paper introduces the concept of geographic primitives (GPs). A GP can be defined as a portion of landscape where the main driving force of a disaster shows statistically stereotypical behavior (e.g., distinguishable water flow patterns can define GPs in the

process of flood prediction, where a few identifiable GPs would be basins, mountain ranges, valleys, flat land, etc.). Identifying GPs is done through visual inspection of contour patterns that would give low modal vector fields with patterns typical to the GP type. A detailed discussion comparing the concept of GPs with other methods used for spatial discretization is included in section 1 of the supplemental information.

Models have also been developed to incorporate data assimilation (Bates et al. 2003; Zerger and Wealands 2004). In Bates et al. (2003), the authors have addressed the problem of obtaining a topographically optimum model to improve the representation of “raw” topographic data so that its integration with lower-resolution numerical inundation models is optimal. Zerger and Wealands (2004) integrate flood model outputs with a Geographical Information System (GIS). A model currently in use for streamflow monitoring is the Geospatial Stream Flow Model (GeoSFM), which is a semidistributed hydrological model developed as an extension of the ArcView GIS software (Asante et al. 2007). GeoSFM software uses a wide range of inputs, including satellite rainfall estimates, soil data, land cover, and elevation data, to predict streamflow. One shortcoming of this model is its inability to predict absolute flow magnitudes because of the absence of regional and seasonal bias correction (Asante et al. 2008), which is a difficult task with data limitations when trying to use a generic model for diverse regions. The GeoSFM model only finds abnormalities in water flow. One other limitation is that the output is numerical and the probability aspects are not present in the output.

Large file size problems for high-resolution topography can be addressed by dividing the landscape into multiple primitives. This division could be a regular grid or an irregular division, as suggested in the deployment of disaster management wireless sensor networks in Da Silva et al. (2010). We propose the concept of GPs is a physically meaningful strategy to simplify calculations. Figure 1 shows some identified geographic primitives on the landscape of Queensland, leading to some stereotypical flood distributions including scattering, converging, and diverging. As topography will not always give clearly distinguishable primitives, catchments need not have strict boundaries, and using overlapping boundaries is more appropriate. It should also be noted that the runoff between certain GPs would show stereotypical behavior.

The lead time for TC-induced flood prediction can be further increased by predicting TC-induced rainfall, which results in floods. Although there have been great advancements in numerical prediction models in the past decade (Lonfat et al. 2004, 2007; Ebert et al. 2010),

(a) Some GP's on the landscape of Queensland

(b) A valley

(c) A flat land

(d) A mountain range

(e) An isolated crest

FIG. 1. Identifying geographic primitives that define the accuracy of prediction.

these models still have room for improvement, owing to the multitude of factors affecting TC-induced rainfall; getting data on all these factors in real time is not practical, but a probabilistic approach would be more viable.

The Bayesian probability approach has been increasingly used in natural disaster prediction (Ding et al. 2010; Li et al. 2010; Lu et al. 2010) because of the many advantages and flexibility associated with it. One main advantage in the approach is that it incorporates prior knowledge, pragmatically optimized by the user, which allows for probabilistic predictions as opposed to binary true–false outcomes, which have a risk of misleading forecasts. In addition, this approach accounts for parameter uncertainty, reducing the error from the overfitting of training data, and provides a natural interpretation of regularization (Bermak and Belhouari 2006). Therefore, given the large amount of factors affecting cyclone-induced rainfall characteristics (Liu et al. 2012), the possibility of errors in observed data, and the ability to use prior knowledge in prediction (Madsen and Jakobsen 2004), using a Bayesian framework can be suggested as a suitable candidate for TC-induced rainfall prediction.

Including the prediction of the path of a cyclone could further increase the lead time of flood prediction by the model. Cyclone track prediction models have come a long way since the use of purely statistical models such as the Climatology and Persistence (CLIPER) model, proposed by Bessafi et al. (2002), which is now used solely as a benchmark for assessing the skill of other models. Dynamic models, which use numerical weather prediction, are the most widely used at present. These models generally require supercomputers to solve the mathematical equations governing the physics of the atmosphere and use numerical methods to solve these equations in order to generate forward-in-time forecasts of the track of the cyclone (University of Rhode Island 2012). The Geophysical Fluid Dynamics Laboratory (GFDL) model (Bender et al. 2007) is one of the most widely used dynamic models. The dynamic models use a large range of data sources for assimilation, including satellite data, specialized aircraft data, and local area sensor networks. Gall et al. (2011) states that GFDL is a regional model as well a “late” model, where the first prediction is only available 4–6 h after the initial track advisory is released, though it is high in accuracy. Considering these limitations, the output of this model could be used for the flood prediction model.

The rest of this paper is organized as follows. In section 2, we describe the proposed model, expanding on all steps. Section 3 shows simulations of the model using

real data from Cyclone Yasi and Cyclone Tasha, which made landfall in early February 2011 and late December 2010, respectively, in Queensland, Australia. Simulation results of the above are discussed in section 4, and section 5 gives the concluding remarks of the paper.

2. Proposed model for flood prediction

The purpose of the model is to calculate the earliest possible prediction of the expected time of flooding resulting from cyclone-induced rain for a given geographical area. This knowledge is to be used in optimizing disaster management operations and disaster management sensor networks.

Consider a geographical area, prone to TCs, with a height profile $h(x_1, x_2)$, where x_1 and x_2 describe the location in terms of latitudinal and longitudinal coordinates, respectively. Prediction starts with available minimal data of the cyclone while it is refined with incoming data. Let $t = T, 2T, 3T, \dots, kT$ be prediction times for k number of periodic predictions at T time intervals. Let the geographical area consist of many GPs, where the propagation of floods show statistically stereotypical behavior (e.g., basins, mountain ranges, valleys, and flat land). Let Π be the set of node clusters with data currently available and Π' be those which are yet to sense any data. Prediction of failure time (i.e., time to flood) for node i with data $FT_{i \in \Pi}$, as well as for nodes in Π' , start as soon as cyclone data is sensed anywhere in the total network. This data is used initially for cyclone path prediction, where the output is used in the rainfall density distribution prediction phase, and finally into flood density distribution prediction, as explained in Fig. 2.

Any subsequent data (cyclone path and rainfall) is used in refining the prediction as data becomes available. The failure time for the nodes in clusters ($i \in \Pi'$) can be inferred from available data ($i \in \Pi$). This estimate can be recalculated as more data is obtained, and the FT_i estimate at a given time can be used to deploy and manage the i th node cluster. This is possible even when there is no current available data at any of the nodes (i.e., $\Pi \in \emptyset$), where the prior value is mainly decided by historical data and mathematical simulations of water flow. The summary of the symbols used in describing the model are listed in Table 1.

The basic sections under the development of the proposed model are given in Fig. 2. Prediction starts with incoming cyclone best-track data, which are used for cyclone path prediction to get a linear approximation of the path using a sliding window of samples where the window size and deviation depends on the speed of the eye of the cyclone. The output is used as an input to the rainfall

FIG. 2. Flowchart of the proposed model.

prediction phase. Probability distribution of rainfall is predicted using Bayesian learning, with the initial prior value taken from the rainfall (R)-CLIPER model and a likelihood function generated using the available rainfall data. The rainfall prediction is used for the next stage for flood prediction by considering the dynamics of water flow on a landscape approximated by a linear combination of Gaussian functions. The area is segmented into geographic primitives identified by water flow patterns during the learning phase, and the calculation of time to failure is made more efficient with the use of probability transition matrices for each segment. Figure 2 gives the flowchart of prediction steps, which are discussed in detail in the following subsections.

Several assumptions were made in developing this model, mainly for simplicity and to focus more on the new concepts introduced in the paper. The main assumptions are 1) that the terrain is frictionless, 2) that soil absorption is negligible, 3) that evapotranspiration during prediction time is negligible, and 4) that topography of the area remains unchanged during the time of prediction. Although the first three effects are out of the scope of this paper, they can be readily integrated into the model in the motion equations and probability transition matrices, which are described in detail later in the paper, and thereby improve the accuracy. Assumption 4 is the basis of the proposed offline calculations.

TABLE 1. Parameters used.

Symbol	Definition	Units
T	Prediction time interval	s
h	Height profile	m
v	Velocity	m s^{-1}
x_1	Distance in latitudinal direction	degrees
x_2	Distance in longitudinal direction	degrees
GP	Geographical primitive	—
Π	Node clusters with data	—
$\text{FT}_{i \in \Pi}$	Failure time for i th cluster in Π	s
$\text{FT}_{i \in \Pi'}$	Failure time for i th cluster in Π'	s

a. Predict cyclone path with available data

Prediction of the future track of the cyclone was done in this step using a curve-fitting technique. After comparative studies with many standard curves, including exponential, higher-order polynomials, and Gaussian, the best prediction was obtained with fitting a first-order polynomial with track data available at each step using a windowing technique. A description of the comparison is given under section 2 in the Supplement. This selection was chosen mainly for the nonexistence of any bias to the origin of the fit. The first-order polynomial used can be expressed as

$$x_{1,t} = a + bx_{2,t}, \quad (1)$$

where $x_{1,t}$ is the latitude and $x_{2,t}$ is the longitude at time t , b is the slope, and a is the intercept of the line. The unknown coefficients a and b are computed through linear regression using a least squares fitting technique on past track data. The sum of the squares of the deviations of the linear approximation (R^2) of a set of n data points can be expressed as

$$R^2(a, b) = \sum_{i=1}^n [x_{1,i} - (a + bx_{2,i})]^2,$$

and the regression coefficients can be found by solving

$$\frac{\partial R^2}{\partial a} = -2 \sum_{i=1}^n [x_{1,i} - (a + bx_{2,i})] = 0 \quad (2)$$

and

$$\frac{\partial R^2}{\partial b} = -2 \sum_{i=1}^n [x_{1,i} - (a + bx_{2,i})] \times x_{2,i} = 0. \quad (3)$$

The central track of the predicted motion of the cyclone (before adding the allowable deviation) is calculated using Eq. (1) and $x_{1,t} = [x_{1,p} - x_{1,(p-1)}]t/(\delta t)$, where p is the position of the cyclone according to latest data and δt

is the time interval between readings. The probability distribution of the cyclone path is iteratively predicted with incoming data using a sliding window technique with a window size n , which reduces as the speed of travel of the eye of the cyclone decreases. This is because a cyclone slows down when it turns. The calculation algorithm is as described in Algorithm 1 in the appendix. The predicted probability distribution of cyclone path, refined as data arrives, is used as an input to the calculation of rainfall probability distribution.

b. Predict rainfall density distribution with available data

The positions of the eye of the cyclone at future times are obtained using the predicted probability distribution of the cyclone path. As the cyclone path prediction is refined with incoming data, the rainfall prediction also changes accordingly. Probability density distributions of the locality of rainfall are calculated through the Bayes filtering technique, where the prediction (i.e., posterior) for one time step is used as an a priori estimate for the next prediction step. The distribution of rainfall prediction is calculated as

$$\text{prediction} = \text{likelihood} \times \text{priori}. \quad (4)$$

Division by the probability of data, as used in the conventional Bayes theorem, is not used here as it is just a scaling factor. The predicted distribution is normalized to get the probability density distribution of rainfall locality, where the integral of the distribution over the considered area equals one. In the initial prediction, where there is no available data of rainfall, the a priori estimate is taken as the output from the R-CLIPER model. As soon as data is received, a likelihood function is computed, which is used in the prediction of rainfall after a T time period. Many models were attempted to obtain a suitable likelihood function that would produce a more accurate prediction as the posterior using Eq. (4). A surface-fitting technique was used on available rainfall data with common 3D functions. The first attempt was to approximate the available rain data to a 3D Gaussian function without orientation. Then, a sum of two Gaussians was used to replicate an inverted Mexican hat surface, which captures the low rainfall usually occurring within the eye of the cyclone (i.e., within a 50-km radius from the center of the cyclone). These methods are described in detail in section 5 of the Supplement. Finally, comparative studies on resulting posterior distributions showed that using a bivariate Gaussian function with orientation used as the likelihood function produced the best predictions. This function can be expressed as

$$f_l = f(x_1, x_2, r, \theta, \sigma) = r \exp\{-[a(x_1 - x_{1,o})^2 + 2b(x_1 - x_{1,o})(x_2 - x_{2,o}) + c(x_2 - x_{2,o})^2]\}, \quad (5)$$

where f_l is the likelihood function, $a = \cos^2\theta/2\sigma_x^2 + \sin^2\theta/2\sigma_y^2$, $b = -\sin2\theta/4\sigma_x^2 + \sin2\theta/4\sigma_y^2$, $c = \sin^2\theta/2\sigma_x^2 + \cos^2\theta/2\sigma_y^2$, θ is the angle, σ is the width, and r is the maximum rainfall. The distributions on all cases were limited to 500 km (i.e., $\sigma = 500$ km) around the center of the cyclone $(x_{1,o}, x_{2,o})$. The final rainfall probability distribution obtained under this stage is used as an input to the flood prediction stage.

c. Predict water deposit density distribution with available data

The next step in the proposed model is to calculate flood distribution through water flow calculations using the predicted rainfall distribution as input.

1) WATER FLOW CALCULATIONS

In the proposed model, water flow calculations were carried out in latitudinal and longitudinal directions. In this model, it is assumed that the rainwater would go down a slope at a constant velocity between two sample times. The algorithm used for calculating water flow for one direction in one subportion of a time period is given in Algorithm 2 in the appendix, and the initial simulation steps used in developing the model are described in section 4 of the Supplement.

In calculating the two-dimensional displacement, partial derivatives of the landscape height profile h , on two perpendicular horizontal axes, $\partial h/\partial x_1$ and $\partial h/\partial x_2$, are used to get the slopes for calculating the water flow. The volume of water initially at $(x_{1,s}, x_{2,s})$ would end up at (x_1, x_2) after a time period of T . The displacement equations in these directions are given by

$$x_1 = x_{1,s} - vT \cos\left[\arctan\left(\frac{\partial h}{\partial x_1}\right)\right], \quad (6)$$

$$x_2 = x_{2,s} - vT \cos\left[\arctan\left(\frac{\partial h}{\partial x_2}\right)\right], \quad (7)$$

where v is the velocity of water flow. For the above calculations, the landscape needs to be approximated with some differentiable function. Alternatively, numerical gradients could have been used at the cost of requiring a large amount of memory to store the gradient matrix. This would also have the disadvantage of a roughness in landscape height profile resulting from the limitation of resolution of available topology data. Therefore, in the proposed model, the

landscape was approximated using a sum of bivariate Gaussian functions.

2) GAUSSIAN APPROXIMATION OF REAL LANDSCAPE

The landscape of Queensland, Australia, is used in the simulations of the proposed model. The area was simulated using 250-m data from the Shuttle Radar Topography Mission (SRTM) (CGIAR-CSI 2011), and resolution was coarsened to 25 km by taking the simple arithmetic mean. It should be noted that the model would give better results with the original higher-resolution data if computational resources were not a limitation. The landscape of Queensland was reconstructed using a bootstrapping technique to approximate it with a linear combination of bivariate Gaussian functions with orientation. The reasons for this step are that the landscape was required to be approximated by a differentiable function in order to be used in Eqs. (6) and (7), to generate unlimited offline data from limited available topography data, to remove errors in calculation resulting from the roughness of raw data, and to reduce computational costs associated with large datasets when dealing with numerical gradients. The approximation was done with an initial equally spaced matrix of Gaussian functions, the iterative minimization of a cost function dependent on error, and the adjustment height and angle variables as explained in the steps below.

A bivariate elliptical Gaussian function centered at location $(x_{1,o}, x_{2,o})$ can be given as

$$h = f(x_1, x_2, w, \theta, \sigma) = w \exp\{-[a(x_1 - x_{1,o})^2 + 2b(x_1 - x_{1,o})(x_2 - x_{2,o}) + c(x_2 - x_{2,o})^2]\}, \quad (8)$$

where $a = \cos^2\theta/2\sigma^2 + \sin^2\theta/2\sigma^2$, $b = -\sin2\theta/4\sigma^2 + \sin2\theta/4\sigma^2$, $c = \sin^2\theta/2\sigma^2 + \cos^2\theta/2\sigma^2$, θ is the angle, σ is the standard deviation, and w is the Gaussian weight.

Let h_c be the initial combination of Gaussians forming the height equation for the landscape. It can be expressed as a linear summation of elliptical Gaussian functions [using Eq. (8)]:

$$h_c = \sum_{i,j} f(x_{1,i}, x_{2,j}, w_{ij}, \theta_{ij}, \sigma_{ij}). \quad (9)$$

Errors at each coordinate point (i, j) could be obtained by subtracting the current height (h_c) obtained from Eq. (9) from the actual height for each coordinate point as $e_{ij} = h_{ij} - h_{ij}$. Since error is a scalar, the cost function is $J = (1/2)e^2$, and the new weights can be obtained minimizing the cost function

$$w_{ij_{\text{new}}} = w_{ij} - \eta \frac{\partial J}{\partial w_{ij}},$$

which can be calculated using the chain rule for $\partial J/\partial w$ as

$$\frac{\partial J}{\partial w_{ij}} = e_{ij} \exp\{-[a(x_1 - x_{1,o})^2 + 2b(x_1 - x_{1,o})(x_2 - x_{2,o}) + c(x_2 - x_{2,o})^2]\}. \quad (10)$$

These steps were iterated until the error was below tolerance and stable. The same procedure was followed with angle θ as the variable. The above steps are summarized in Algorithm 3 in the appendix. This method reduces the amount of raw data that is needed for the calculations, thereby reducing the computational cost. If the cost function does not go below the recommended value, the number of Gaussians used is increased, but the amount of data needed to reconstruct the landscape would always remain below the amount of raw data by a large margin. The method was validated with data for one subarea of landscape in simulations where the model accurately predicted the area of flooding with respect to the flood distribution map downloaded from the Australian Bureau of Meteorology website.

Although using a Gaussian-approximated function for landscape reduces the limitations of using numerical gradients in calculations, the water flow calculations for any given landscape take up a considerable amount of processing since the water displacements need to be calculated for each sampling period and for each coordinate point on the landscape. This is especially true when the area of the landscape considered is large and would not be efficient on a real-time system. Using the fact that dynamics of water would not change with time for the given landscape, the products of the calculations are stored in a matrix, which is used to get the probability distribution of water accumulation at any future referencing time, given the initial rainfall distribution probability.

3) USING A PROBABILITY TRANSITION MATRIX TO IMPROVE CALCULATION EFFICIENCY

The fact that the geography remains almost unchanged with time is used to increase the efficiency of water flow calculations using a probability transition matrix (PTM). This removes the need to recalculate the water flow using the gradient method for every different rainfall distribution and prediction time. When there is no further precipitation on the land, the water deposit distribution at some future time would only depend on that at the earlier time step. In this calculation, we only consider surface runoff and do not take into account soil

moisture or evapotranspiration for reasons stated earlier. The probability transition matrix for a landscape with n states (i.e., grid locations) can be expressed in a matrix $\mathbf{A} = (p_{ij})_{n \times n}$ and is given by

$$\mathbf{A} = \begin{matrix} & \text{Next States} \\ \begin{matrix} \text{Current} \\ \text{States} \end{matrix} & \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix} \end{matrix},$$

where p_{ij} denotes the probability of the water deposit at location i to be moved to location j after a time interval of T . The matrix is obtained by considering the dynamics of a unit rainfall distribution at each grid location of the considered landscape and calculating water flow resulting from it. The columns in the matrix are normalized.

The PTM possessed the following properties:

$$\sum_{i=1}^n p_{ij} = 1, \quad \forall j \in \{1, 2, \dots, n\},$$

$$0 \leq p_{ij} \leq 1, \quad \forall i, j \in \{1, 2, \dots, n\}.$$

Therefore, it is a Markov matrix, and the water deposit distribution for any future time can be obtained by multiplying the water deposit distribution at the earlier time step by the PTM when there is no further precipitation and no inflow from outside the GP. If the time step is defined as T and the current state is k , the probability distribution at time $(k + 1)$ can be obtained by

$$P(k + 1) = \mathbf{A}P(k), \quad (11)$$

where $P(k)$ is the probability distribution at time k . The states at future times (for intervals of T) can be obtained as a Markov chain. Therefore, the probability distribution after m time steps is

$$P(k + m) = \mathbf{A}P(k + m - 1). \quad (12)$$

From Eqs. (11) and (12), water deposit distribution at any future time m is given as

$$P(k + m) = \mathbf{A}^m P(k). \quad (13)$$

As time to failure is calculated for each GP, PTMs are calculated for each of them. In addition, dividing the landscape into GPs reduces the sizes of PTMs, thus increasing efficiency in calculations. The characteristics of the GP are encapsulated in the properties of its PTM. For example, if the GP is a valley, there would be an absorbing state, and the PTM would be an absorbing matrix where water deposit at any initial location would

FIG. 3. (a) Landscape of Queensland generated using SRTM topology data, compared to (b) that approximated through bootstrapping technique using a linear combination of Gaussian functions with orientation.

eventually end up at one of the absorbing states. But if the GP is a flat land, although there would be absorbing states, the PTM would not be an absorbing matrix. In this case, although some water deposit will be stagnated at those points, another portion would flow away. The importance is that the properties of the topography in a given area can be identified mathematically through the properties of its PTM. The absorbing rate of the Markov matrix is defined by its second-largest eigenvalue (SLEV), which bounds the time needed to reach the steady state. Therefore, for the PTM of each geographic primitive, the time to failure can be defined through $1/(1 - \text{SLEV})$.

In a situation where water is being added to the current distribution through precipitation or through boundaries of a GP, Eq. (13) cannot directly be applied. For this scenario, the water distribution calculations are done for each time step using a slightly different form of Eq. (11) as

$$P(k+1) = \mathbf{A}[P(k) + D(k)], \quad (14)$$

where $D(k)$ is the water deposit distribution introduced at time k through runoff and inflow. The water deposit distribution prediction after m time periods [at time $(k+m)$] can be generalized as

$$P(k+m) = \mathbf{A}^m P(k) + \sum_{i=0}^{m-1} \mathbf{A}^{m-i} D(k+i). \quad (15)$$

Equation (15) reduces to Eq. (13) when there is no water introduced during m time periods, and the second portion of Eq. (15) reduces to a geometric series when the only amount of water introduced into the GP is from inflow. In all three scenarios, maximum complexity

is $O(n^m)$. In all calculations, conversion of distance between positions to metric lengths and vice versa is done as described in the supplemental information (section 6).

3. Simulation results

Here we compare the proposed model with two datasets from Cyclone Yasi and Cyclone Tasha, which made landfall in Queensland, Australia, in January–February 2011 and December 2010, respectively. We discuss the simulations of Cyclone Yasi in detail, while we only include a few simulation steps with data from Cyclone Tasha. The landscape of Queensland was taken as the considered land with x_1 (latitude) ranging from 30°S to 10°S and the x_2 (longitude) between 135°E and 155°E . The velocity of water flow was taken to be $v = 0.25 \text{ m s}^{-1}$ and computing time interval as $T = 15 \text{ min} = 900 \text{ s}$. The radius of the earth was taken as $6\,378\,100 \text{ m}$. The topography of Queensland was modeled using the coarsened SRTM terrain data, as previously described. The 48×48 Gaussian functions were linearly combined to approximate the landscape of Queensland as described in section 2, setting $i = 1, 2, \dots, 48$ and $j = 1, 2, \dots, 48$ in Eq. (9). The landscape plotted from the SRTM data is compared to the landscape simulated using the above method in Fig. 3.

The rainfall data for the time period under Yasi's effect was obtained from NASA's Goddard Earth Sciences (GES) Data and Information Services Center (DISC) Interactive Online Visualization and Analysis Infrastructure (GES DISC 2011). The best-track data of Cyclone Yasi, which entered Queensland, Australia, in January–February 2011, was obtained from the Regional and Mesoscale Meteorology Branch (RAMMB 2011) and is plotted in Fig. 4. The same data was

FIG. 4. Path followed by Cyclone Yasi in January–February 2011. The cyclone track is shown plotted over the landscape of Queensland (the surrounding white space denotes sea and land that is not a part of Queensland).

obtained for Cyclone Tasha, which entered Queensland on 24 December 2010.

Figure 5 shows the predicted path, with 95% confidence bounds, of Cyclone Yasi with incoming data,

using the prediction steps, with a moving window, described earlier. The four graphs show how the prediction changes with incoming data and the use of the moving window and compares it with the actual track of the cyclone. The allowable deviation is calculated taking the speed of the cyclone into consideration, and the window size for prediction is dependent on the R^2 value of linear fit and the speed, as discussed under the proposed model. An animation of path predictions is included in the Supplement (file E1.mpg), and Table 2 compares the official 12-h track forecast from the Joint Typhoon Warning Center (JTWC) advisories to the proposed model's track forecast. A similar simulation for Cyclone Tasha is shown in Fig. 6.

The next step of the process was predicting rainfall distribution resulting from the cyclone. In Fig. 7, the output of the proposed model is compared with actual rain gauge data for Queensland in January–February 2011. We compare this with the predictions using the R-CLIPER model and using the same Bayesian inference model proposed, with a bivariate Gaussian likelihood function without orientation. The equations for the R-CLIPER model from Marks et al. (2002) are given in

FIG. 5. Prediction of the path of the cyclone using a moving window (size dependent on speed of cyclone) of past data of Cyclone Yasi at (a) 6, (b) 11, (c) 14, and (d) 17 available data points of the past cyclone track. Dots show the past track, bold line shows the center of predicted path up to 30 h ahead, the shaded area is the allowed deviation (changing depending on R^2 value of linear fit), and the asterisks (*) show the actual path taken by the cyclone after prediction time.

TABLE 2. Comparison of errors (to the nearest kilometer) of official 12-h cyclone track forecasts with the proposed model's forecasts.

Prediction time	Official forecast error (km)	Model forecast error (km)
1200 UTC 31 Jan 2011	78	44
0000 UTC 1 Feb 2011	31	53
1200 UTC 1 Feb 2011	24	76
0000 UTC 2 Feb 2011	60	54
1200 UTC 2 Feb 2011	31	9
0000 UTC 3 Feb 2011	81	49

section 3 of the Supplement. The error for each step of the rainfall prediction stage, as shown in Fig. 7, is calculated as the distance of the prediction mean's contour centroid from that of the mean rainfall. The same comparison for Cyclone Tasha is shown in Fig. 8, which made landfall in Queensland, Australia, in late December 2010.

Initially, the landscape was divided into overlapping subareas of dimensions 3° latitude by 3° longitude, with overlapping of 0.833° in each direction. This was done for simplicity in simulations. Flood distribution with time was simulated using a PTM for each of these subareas. File E2.mpg, included in the Supplement, is an animation showing how the water deposit distribution changes with time for particular subareas (in all figures, the water deposit distributions are scaled up to be visually comparable with height). More details of the simulation steps followed are described in the Supplement. The fact that accuracy of prediction depends on the GP type is elaborated in Fig. 9. The GP is a valley in the top two figures, where the flood prediction is less affected by a small error in the rainfall distribution approximation. In contrast, the error in flood prediction stage is magnified for the terrain in the bottom two

figures where the GP is composed of a mountain range dividing the area into two portions. Therefore, in the output prediction, the variance of the output is highly dependent on the GP type. The topographic contour plots of three subareas with the contour plots of their PTMs are given in Fig. 10, illustrating the PTM's dependency on landscape. The absorbing states of the PTM of the landscape in Fig. 10c show that the valley is an absorbing state for water deposit distributions. Therefore, it is evident that the properties of the topography in a given area can be identified mathematically through its probability transition matrix and its properties. This is especially important when the landscape is complex and the PTM can be used to identify GPs.

The same simulations were run on identified GPs of irregular shapes. Two such GPs are plotted in Fig. 11. First, GP is a valley that can be treated as an independent portion of calculations where water would neither enter nor leave the GP. The absorbing states plotted as dots show that the bottom of the valley is an absorbing state, and there are two such minimum points in this subarea. Figures 11c,d show another GP of one side of a mountain range. There are no absorbing states in this PTM, and water will only flow out of it and never into it. Therefore, in both these GPs, we could run water flow calculations, ignoring the inflow term in Eq. (15). An animation of the water deposit distribution with time for the former GP is included in the Supplement (file E3.mp4).

4. Discussion

Numerous uncertain environmental factors shaping the formation, development, and propagation of a cyclone pose complex computational challenges to predict

FIG. 6. As in Fig. 5, but for Cyclone Tasha at (left) 4 and (right) 9 available data points of the past cyclone track.

FIG. 7. Comparison of real rainfall gauge data with predicted rainfall over Queensland, Australia, as a result of the activity of Cyclone Yasi. (top to bottom) Three prediction steps are compared with: (a) 50.9, (d) 202.2, and (g) 163.5 km error; (b),(c) 43.0, (e),(f) 100.9, (h) 70.0, and (i) 70.2 km error. (left to right) Prediction using the R-CLIPER model, using a bivariate Gaussian likelihood function with Bayesian inference, and using a bivariate Gaussian likelihood function with orientation with Bayesian inference. In all three cases, the predictions (sets of contours that are unique for each figure) are plotted on top of actual rain data (the irregularly shaped contour sets that repeat in all three figures in a row). Prediction error is taken as the distance of the centroid of contour of the prediction's mean from contour centroid of actual rain mean.

the damage caused after its landfall. We have presented a distributed Bayesian framework defined across a given set of geographical primitives to integrate prior knowledge with real-time measurements to make accurate and timely predictions. Moreover, it allows starting flood prediction as soon as sufficient data points of the cyclone path are received. This would be before the cyclone makes landfall, allowing preparation well in advance. The prediction gets more and more refined with any

incoming data. Furthermore, the partitioned approach allows asynchronous data to be input at any stage of the computation.

In the rainfall prediction stage of the model, we have used all available rainfall data and not used any other features such as wind shear or topology. The results summarized in Table 3 show a 33% increase of accuracy for rainfall density distribution prediction, suggesting that, by using Bayesian inference technique with recurrent

FIG. 8. Rainfall prediction vs actual rainfall for Cyclone Tasha for (left) the proposed model and (right) the R-CLIPER model, each using two prediction steps (i.e., positions of cyclone eye). In both cases, the predictions (sets of contours that are unique for each figure) are plotted on top of actual rain data (the irregularly shaped contour sets that repeat in both figures in a row). Prediction errors (a) 139.5, (b) 142.6, (c) 54.5, and (d) 55.9 km with the error taken as the distance between the centroid of contour of the prediction mean from contour centroid of actual rain mean.

learning, the prediction could be better than with methods using more sophisticated data assimilation. The main reason for the increase in accuracy is the ability of the proposed Bayesian learning-based method to combine the advantages of data-driven and heuristic modeling by amalgamating past knowledge through the prior distribution and new data through the likelihood function.

The effectiveness of using a simple approach with minimal features is also apparent in the short-term cyclone path prediction approach included in the proposed

model, where the comparison results in Table 2 show that the model forecasts are better for most cases, while noting that official forecasts are released 3 h later than forecasts of models because of the need to collect a large amount of data from many sources.

A main feature of the model is the use of GPs, which encapsulate the dynamics of water flow on static landscape primitives. Through statistically summarizing simultaneous events that are spread across geography, it allows us to have a distributed updated algorithm that

FIG. 9. Flood prediction (a) for a valley using real rainfall gauge data; (b) for the same valley using rainfall prediction with added error; (c) for an area containing a mountain range using rainfall gauge data; and (d) for the same area containing a mountain range using rainfall prediction with added error. Flood distributions for all cases are predictions after three time steps.

leads to parallel computation. Clustering of these primitives permits better understanding of the distributed nature of flood propagation and its relation to any geographical feature. The speed of calculations increases by almost 20 times with the use of PTM on GPs, as opposed to using gradient-based calculations for each prediction time step. At this point, we use manual demarcation of GPs in order to simplify the computational process. However, this could be extended to mathematically identify GPs, for example, by using numerical methods such as the Delaunay triangulation (Lee and Schachter 1980). This is outside the scope of this paper but is included in our future work. The efficiency increases further when predicting for multiple time steps using Markov chains. All comparisons were done using an Intel® Core™ i7 CPU Q 740 @ 1.73 GHz processor with 16 GB available memory. The accuracy was reduced by the resolution of the states of the PTM, which resulted in a maximum possible error of 6 km (at

transition states of the PTM) with the resolution used in simulations. This reduces further with time as the PTM approaches absorbing states, where water would be stagnated, resulting in floods. The significance of this error is further reduced with the use of variable resolutions considering the type of GP (e.g., using higher resolution in valleys and lower resolution on flat land).

In addition to effective and accurate prediction, the proposed stochastic process for identifying GPs with overlapping boundaries, using complex intrinsic statistics of flood propagation, allows mathematical identification of areas with flood risk even before using any rain data. This knowledge can be used in optimizing disaster management strategies, including land use. The terrain approximation provides a differentiable function, permitting the development of a Markov chain process based on simulation data that bootstraps the real-time computation based on measured rainfall data.

FIG. 10. (a)–(c) Dependence of the PTM on landscape for three subareas of Queensland. The brown contours are of the landscape (shade gets lighter with increasing height), and the PTM contours are according to the color bar. In (c) the absorbing states of the PTM are shown as green dots that can be observed at the bottom of the valley.

Despite the mentioned advantages, there are a few limitations of the model which could be addressed in future work. One considerable limitation is that, in the rainfall prediction step, projection is limited to an area of 500 km around the eye of the cyclone. This neglects the resulting rainfall due to convergence along the coasts during extratropical transition (ET) and accumulation of rainfall in rainband echoes over specific regions farther away from the eye of the cyclone, as pointed by Lonfat et al. (2007). Additionally, although simplicity has its advantages, the model could be further improved by including some of the most significant features affecting cyclone activity, which will have less effect on efficiency. A more complete treatment of hydrologic aspects can make the predictions more generic by relaxing some of the assumptions such as frictionless and impermeable surfaces. If there are already existing relevant datasets for the area, they can be readily used to get a better flood vector field for the use in demarcation of GPs. It is still worth noting that, although such comprehensive approaches make the prediction more realistic, great care has to be taken to get high-quality data since the accuracy of prediction is highly sensitive to the used data. However, one important feature in using Bayesian updating is that it is purely data-driven, and therefore, for the rainfall prediction step, any error arising from the initial assumptions is suppressed after a few calculating time steps.

It was also noticed that, for the cyclone path prediction step, while the model's 12-h prediction was indicated to be better, the 72-h prediction of the JTWC advisory was generally better than the 72-h prediction of the proposed model. Therefore, the model's prediction could be further improved using these outputs as input to the model using its modularized structure. Meanwhile, it should be noted that the model produces the predictions 3 h before the official forecasts are available, which would be much helpful for just-in-time sensor deployment and management, and the JTWC advisories would serve only to improve on that prediction. The model's flood prediction does not consider existing water storage in the calculations. This could be included simply by considering the water levels of existing storage as a part of the landscape and building the Gaussian approximation of land from it. The flood levels can be defined by reducing the maximum capacities of water storage.

The proposed model has only been validated with datasets of two cyclones, both of which made landfall in the same state of Australia. But it is also worth noting that the mathematical framework presented in this paper does not use any assumptions specific to Queensland. Our proposal is a probabilistic model of which the

FIG. 11. (a) A valley identified as a GP and (c) a slope on one side of a mountain range identified as a GP over Queensland and (b),(d) their PTMs (according to the shading bar) and absorbing states (dots) plotted on top of landscape.

output is dependent solely on data. Therefore, datasets of any cyclone in any region could be used with the proposed model without further modification.

5. Conclusions

A distributed Bayesian framework, defined across a set of predefined geographical primitives, is developed to predict the time to flood resulting from TC-induced rainfall. The purpose of our new model is to integrate prior knowledge with real-time measurements in order to produce accurate and timely flood predictions to be used in planning disaster response operations, including the deployment and management of wireless sensor networks. The flexibility in data assimilation resulting from the model's modularized structure is an important attribute of the proposed model. Another advantage of the model is that prediction starts well ahead of time, with minimal available data, and this prediction is refined with any subsequently available data. The numerical simulation results suggest that the proposed model outperforms alternative probabilistic and

numerical models that use multiple sources of data in terms of efficiency and accuracy for short-term forecasts. Further, the modularized and data-driven approach of the proposed model allows integrating prediction outputs available from any other models in subsequent predictions, which could increase the accuracy of long-term predictions of the model.

We have presented the model's performance on the data from Cyclone Yasi, which made landfall in Queensland in early 2011. The model proves to be relatively high in efficiency, resulting from the fact that there are numerous factors that affect the formation, development, and propagation of cyclones, and the more complicated models that use more features need time to collect the data, which in turn results in delays in prediction. However, these complex models do not show significant improvements in accuracy, as the used features are still limited. The results summarized in Table 3 show that the proposed model produced cyclone path predictions up to 3 h ahead of official cyclone path forecasts in the 12-h horizon with a 6.5% improvement of accuracy. The accuracy of rainfall prediction improved by

TABLE 3. Performance summary of major steps of the proposed model.

Prediction step	Efficiency comparison	Accuracy comparison	References
Cyclone path prediction (12-h horizon)	3 h before official forecast ^a	6.5% increase ^b	Table 2
Rainfall prediction	10% Reduction in processing speed ^c	33.7% increase ^d	Figs. 7, 8
Flood prediction	18.9 times faster ^e ; 3% faster with use of irregular GP	Max error = 6 km ^f	

^a Compared with official JTWC advisories.

^b Overall improvement over 12-h horizon compared to official JTWC advisories; distance error compared.

^c Compared to R-CLIPER prediction.

^d Distance error between centroids of mean rainfall contours taken for comparison; averaged from five prediction points and compared to the R-CLIPER prediction.

^e Compared to gradient-based method.

^f Depends on the resolution of PTM used in calculations. Error can be reduced with increase in resolution. Significance of error further reduces with the use of variable resolution in GPs.

33.7% compared to the R-CLIPER model with a mere 10% (in the order of a few seconds) increase of computing time. Finally, the flood prediction stage gave a considerable 18.9 times higher processing speed compared to using a gradient-based method for any given resolution.

In conclusion, we propose that the concept of using nonuniform geographical primitives with known statistical features for propagating a given disaster could be more generally used to improve the accuracy of estimating the time to pass a critical stage at a given place for other types of disasters, such as bush fires. For instance, in a bush fire scenario, the selection of GPs would be dependent on statistical features of wind direction in a given time frame.

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APPENDIX

Algorithms Used in Proposed Model

a. Algorithm used for cyclone path prediction

Algorithm 1: Simulate cyclone path

Step 1: Set $i = 0$;

Step 2: Collect i th location data input until $i = n$, where n is the default size of the moving window used for calculations;

Step 3: Calculate the current speed of the cyclone and adjust window size for Step 4 accordingly (a default step size of 5 is used in the calculation, which reduces to 3 when two consecutive readings show 30% below average speed and further reduces to 2 when three or more closest readings show 30% below average speed;

Step 4: Use linear regression from Eqs. (2) and (3) to get a and b ;

Step 5: Calculate upper and lower margins of the distribution using the standard deviation weighted by the speed of travel of the eye of the cyclone and the R^2 value of fit;

Step 6: Continue at Step 3 for each received location data point.

b. Algorithm used in calculating water flow

Algorithm 2: Simulate water flow

for time $\in \{t_1, \dots, t_m\}$ **do**

if |Current Slope – Last Slope| > |Current Slope| **and**

|Current Slope – Last Slope| > |Last Slope| **then**

Accumulate

end if

if Slope at $x < 0$ **then**

$$x = x + \text{velocity} \times \frac{T}{m} \times \cos[\arctan(\text{slope})]$$

end if

if Slope at $x > 0$ **then**

$$x = x - \text{velocity} \times \frac{T}{m} \times \cos[\arctan(\text{slope})]$$

end if

end for

Here, the T time period is broken down to m number of iterations for increased accuracy.

c. Algorithm used in approximating the landscape with a summation of bivariate Gaussian functions with orientations

Algorithm 3: Approximate Landscape

$i_t = 0$

$$h_c = \sum_{i,j} f(x_{1i}, x_{2j}, w_{ij_o}, \theta_{ij_o}, \sigma_{ij})$$

while $i_t \leq i_{t_{\max}}$ **do** {max no. of iterations = $i_{t_{\max}}$ }

$$i_t = i_t + 1$$

for each coordinate point i, j **do**

$$\text{error} = h_{\text{actual}} - h_c$$

if error $\leq \epsilon$ **then** {check stopping criterion}

break;

end if

$$J = (1/2)e^2$$

$$w_{ij_{\text{new}}} = w_{ij} - \eta \frac{\partial J}{\partial w_{ij}}$$

$$\theta_{ij_{\text{new}}} = \theta_{ij} - \eta \frac{\partial J}{\partial \theta_{ij}}$$

end for

$$h_c = \sum_{i,j} f(x_{1i}, x_{2j}, w_{ij_{\text{new}}}, \theta_{ij_{\text{new}}}, \sigma_{ij})$$

end while

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