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A tropical cyclone intensity model based on the conditional generative adversarial network

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SUMMARY: (10 pt)
A tropical cyclone (TC) intensity evolution model is proposed by utilizing the conditional Wasserstein generative adversarial network with gradient penalty (CWGAN-GP). In this model, the change of TC intensity over six hours is treated as a random variable conditional on the TC state at the previous step and environment (e.g., vertical wind shear and sea surface temperature). The CWGAN-GP is used to train a generator which represents the conditional probability distribution of TC intensity change. The model is trained with 1010 historical TCs from the western North Pacific basin. Numerical results indicate that the proposed model can replicate the probabilistic properties such as the strong non-Gaussian marginal distribution of the intensity change and the input-output joint distribution and moments between the TC intensity and predictors.

Keywords: Tropical cyclone intensity, conditional Wasserstein generative adversarial network

1. INTRODUCTION

A tropical cyclone (TC) is one of the most devastating natural disasters. The probability distribution of maximum TC-induced surface wind is fundamentally useful not only in assessing the reliability of the engineering systems but also in estimating the economic loss caused by TCs. Within the most modelling techniques, the TC intensity prediction model is an essential component. For engineering applications, statistical approaches aiming to relate the TC intensity change to the environmental variables (Jing and Lin, 2019; Vickery et al., 2000) are commonly adopted. Nevertheless, the statistical models would mandate assumptions on the relation between the TC intensity change and the input variables. Therefore, the traditional statistical models might be suboptimal to fully represent the complex nonlinear feature of TC. On the other hand, the deep learning method, that is well recognized as useful tool to represent the nonlinearity, has already been applied in the operational forecast of TC intensity (Kozar et al., 2016). The literature review indicates that the deep learning methods used in the real-time forecast are mainly focused on representing the deterministic relation between the input (environmental variables) and output (TC intensity). However, the probabilistic description of the TC intensity is imperative in the TC risk assessment, which suggests the need of incorporating uncertainty and its propagation with the deep learning approach. To address the preceding concern, this study proposes a TC intensity model using the CWGAN-GP (Gulrajani et al., 2017; Mirza and Osindero, 2014), which aims to train a multilayer perceptron generator that can represent the probability distribution of TC intensity change conditional on the environmental variables. Numerical results demonstrate the proposed CWGAN-GP model is advantageous because it can well represent probabilistic properties such as the strong non-Gaussian feature of the probability distribution of TC intensity change.

2. MODEL DEVELOPMENT

The GWGAN-GP model is comprised of a generator and a critic, both of which are multilayer perceptron. The function of the generator is to map a latent standard Gaussian random variable z to the TC intensity y conditional on the environmental variables $\boldsymbol{x}$, i.e.,

$$y = G(\boldsymbol{z}|\boldsymbol{x}) \tag{1}$$

Where $G(\cdot|\cdot)$ denotes the generator. The critic $D(\boldsymbol{y}|\boldsymbol{x})$ receives values of TC intensity change y and the environmental variables $\boldsymbol{x}$ in the input layer and outputs a score to indicate the possibility that the input $\boldsymbol{x}$ and y are coming from the real probability space. The generator and critic are trained simultaneously in an adversarial manner so that the conditional probability of y on $\boldsymbol{x}$ converges to the real one. Specifically, this forms a minimax optimization problem, i.e.,

$$\max_{G} \min_{D} V(D,G) = \mathop{\mathbb{E}}_{\boldsymbol{y}_g \sim p_g}\left[D(\boldsymbol{y}_g|\boldsymbol{x})\right] - \mathop{\mathbb{E}}_{\boldsymbol{y}_r \sim p_r}\left[D(\boldsymbol{y}|\boldsymbol{x})\right] + \lambda \mathop{\mathbb{E}}_{\boldsymbol{y}_c \sim p_c}\left[\left(\left\|\nabla_{\boldsymbol{y}_c} D(\boldsymbol{y}_c|\boldsymbol{x})\right\|_2 - 1\right)^2\right] \tag{2}$$

where $\mathbb{E}[\cdot]$ is the expectation operator, $\|\cdot\|_2$ is the Euclidean norm operator, $\boldsymbol{y}_c = \epsilon \boldsymbol{y}_g + (1-\epsilon)\boldsymbol{y}_r$, $\epsilon \sim U[0,1]$, $p_c(\boldsymbol{y}|\boldsymbol{x})$ is the conditional probability distribution of $\boldsymbol{y}$ given $\boldsymbol{x}$, and λ is the penalty coefficient.

The model consists of two distinct branches to consider the difference between the over-ocean and over-land stages of a TC. The input environmental variables (predictors) include: latitude of TC center at the previous and current step (ϕ_1, ϕ_2), longitude of TC center at the previous and current step (λ_1, λ_2), potential intensity at the previous and current step ($\Delta p_{\max,1}$, $\Delta p_{\max,2}$), ocean mixed layer depth at the previous and current step ($h_{\mathrm{m},1}$, $h_{\mathrm{m},2}$), ocean sub-mixed layer thermal stratification at the previous and current step (Γ_1, Γ_2), translation speed of TC at the previous and current step ($V_{\mathrm{t}1}$, $V_{\mathrm{t}2}$), 850-250 hPa vertical shear at the previous and current step (S_1, S_2), natural logarithm of the relative intensity ($\ln I_1$), central pressure deficit at the previous step (Δp_1), time since the TC's landfall (T_1). Δp_1 and T_1 are not considered in the over-ocean branch; the over-land branch considers ϕ_1, ϕ_2, λ_1, λ_2, $V_{\mathrm{t}1}$, $V_{\mathrm{t}2}$, S_1, S_2, Δp_1 and T_1. The data sources of the environmental variables are presented in Table 1.

Table 1. Data sources for the environmental variables.

Data source	Variable	Data source	Variable
Best track dataset from CMA	ϕ, λ, V_{t} and Δp	Twentieth Century Reanalysis	S
COBE-SST dataset	T_{s}	NODC World Ocean Atlas	h_{m} and Γ
NCEP/NCAR Reanalysis 1	T_0		

The historical TCs of western North Pacific basin from 1980 to 2013 is used. The dataset is split into the training and validation sets with the ratio of 70% : 30%. The architectures of the generator and critic are 16×64×32×16×16×8×1 and 16×64×32×16×16×16×16×16×1, and 11×32×16×16×8×1 and 11×32×16×16×16×16×8×1 for the over ocean and overland branches. This minimax problem can be solved by a mini-batch algorithm (Mirza and Osindero, 2014).

3. RESULS

A linear regression model is also developed to relate the TC intensity change and the environmental variables. Figure 1 shows the PDFs of the simulated and observed intensity change for over-ocean and over-land TCs. The close match between the observation and CWGAN-GP demonstrates the advantage of the proposed model in reproducing the strong non-Gaussian probability distribution that could not be well parameterized. The linear regression model, however, fails to reproduce the multimodal probabilistic feature. Figure 2 shows the two-dimensional joint probability distributions between the TC intensity change and environmental variables in the over-ocean case, estimated by the observations, CWGAN-GP and linear regression model. The visual inspection suggests the CWGAN-GP-based model produces patterns in the joint distributions similar to the observations. On the contrary, the pattern in the results of the linear regression model is not that close to the observations. Figure 3 compares the simulated and observed TC intensity evolution of TYHOON Owen in 1998. It is shown that the median curves by the proposed model are in good agreement with the TC observations.

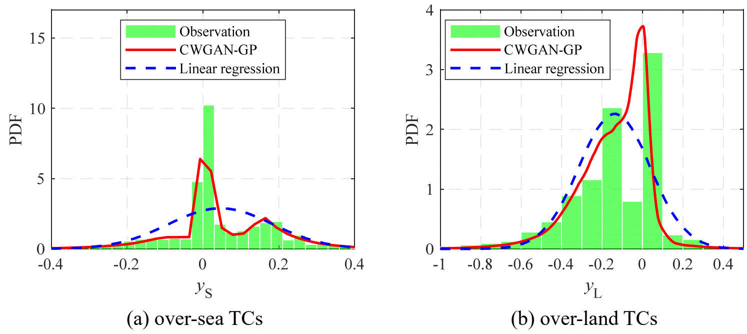

Figure 1. PDFs of the simulated and observed intensity change

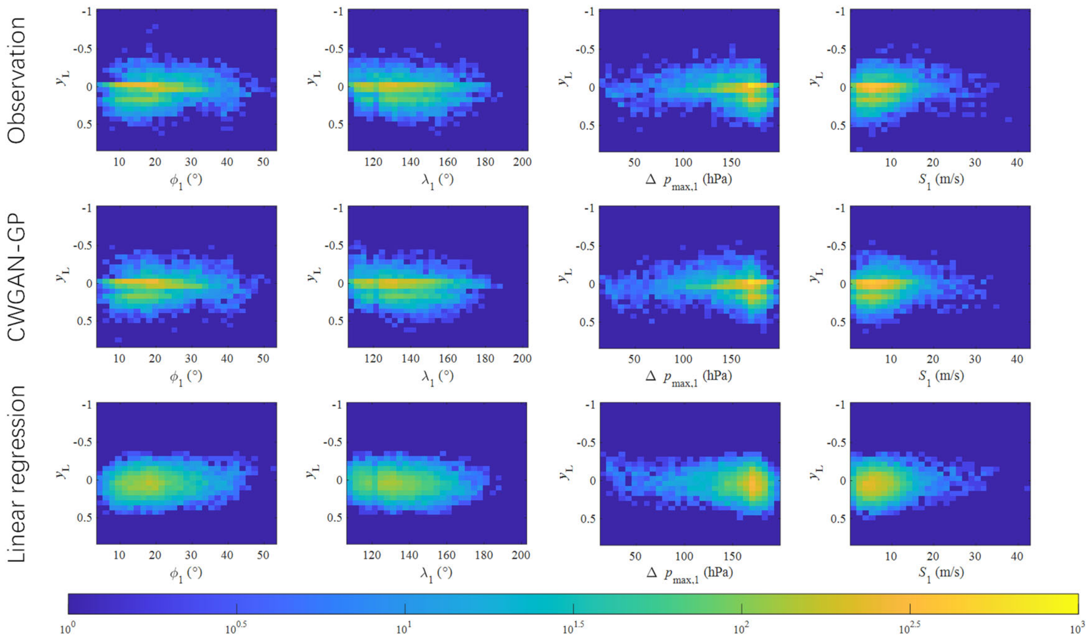

Figure 2. The two-dimensional joint probability distributions between the TC intensity change and 4 environmental variables

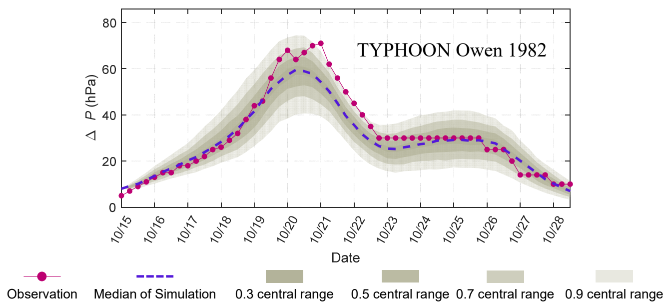

Figure 3. Simulated and observed TC intensity of TYPHOON Owen (1982).

4. CONCLUSIONS

This study proposes a CWGAN-GP-based model for predicting the TC intensity evolution. The TC intensity is regarded as a random variable conditioned on the predictors (TC state and environmental variables). The above investigation results indicate that the proposed model has successfully replicated the strong non-Gaussian multi-dimensional probabilistic characteristics between the TC intensity evolution and the predictors. The proposed CWGAN-GP model presents a useful application to the TC hazard assessment in TC prone areas.

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