

This paper describes the use of a neural network for predicting convective wind gusts at lead times of 6-120 minutes. The neural network includes several architectural components that have recently been developed in the field of deep learning. These include pieces of the recurrent neural net (RNN) architecture, where the prediction at the  $k^{\text{th}}$  lead time becomes an input (predictor) to the neural network to predict at the  $(k + 1)^{\text{th}}$  lead time; the attention mechanism, where the neural network can automatically determine the most important steps in a time series of predictor values; and PhyCell, which incorporates partial differential equations (PDE). The neural network predicts convective wind gusts on a 1-km grid covering eastern China. The authors compare their results to a baseline model called INCA and demonstrate (albeit without significance-testing) that their neural network, which they call CGsNet, outperforms INCA. Overall, the quality of both the writing and science are very good. I have a handful of major comments, which are made as inline comments in the attached PDF but also summarized below. Minor comments are not summarized below and can be seen only in the attached PDF.

### Major comments

1. The abstract contains several unclear/unjustified statements. See inline comments.
2. Most hyperparameter choices are not justified at all. Whether hyperparameter choices were made via experimentation or *a priori* reasoning, the justification should be included in the paper. If hyperparameters were chosen by experimentation, the experiments should be documented (although I'm okay with putting most of the details in the Appendix or Supplemental Material); if chosen by *a priori* reasoning, the *a priori* reasoning should be explained. For examples of unjustified hyperparameter choices, see lines 84-85, lines 150-152, and Table 1 (and inline comments at these places).
3. It seems like the authors used some kind of subsetting to create their dataset, but the subsetting methodology is unclear. See inline comment on lines 86-88.
4. It is unclear how the authors handle radar data at different heights. See inline comment on lines 96-97.
5. The target variables (what the CGsNet is predicting) eventually become clear, but quite late in the paper. The target variables should be clear from the beginning. See inline comment on line 107.
6. Section 3.1 needs to be written more clearly. See inline comments for specific points that are unclear.
7. I don't understand how the authors split their data. Specifically, (a) I don't understand how the training and validation data are split; (b) I don't understand why they have such an incredibly small testing dataset for wind gusts. See inline comments on lines 146-149.
8. It seems like the authors inappropriately used their testing data for model selection; only the validation data should be used for model selection. See inline comment on line 153.
9. The comparison of a custom loss function to data augmentation is highly erroneous. See inline comment on line 164.

10. The results contain no confidence intervals or significance-testing -- in other words, no measure of uncertainty. I emphasize this comment the most, since results without uncertainty are nearly meaningless. All results in Figure 4 and Tables 2-4 should be accompanied by at least confidence intervals, if not also significance tests. See inline comments for details.
11. The model evaluation is lacking in detail. The authors present evaluation metrics based on the full testing dataset (least granularity) and some individual case studies (most granularity) -- but nothing in between (intermediate scales of granularity). The paper should include evaluation metrics as a function of time of day (e.g., by hour), time of year (e.g., by month), geographic location (e.g., maps with POD, CSI, FAR, etc. at each 1-by-1-km grid cell), and predicted wind speed (i.e., the reliability curve). At the very least, I want to see reliability curves and some division by time (either time of day or time of year). Ideally, I would like to see the evaluation metrics broken down in all 4 ways that I have listed. Presenting evaluation metrics at varying levels of granularity is crucial for understanding a model, especially for understanding its strengths and weaknesses.
12. The authors' interpretation of Figure 5 does not seem to be justified. See inline comments on Figure 5 itself and also lines 226-227.



# Convective Gusts Nowcasting Based on Radar Reflectivity and a Deep Learning Algorithm

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## Abstract.

Convective wind gusts (CGs) are usually related to thunderstorms, and they may cause great structural damage and serious hazards, such as train derailment, service interruption, and building collapse. Due to the small-scale and nonstationary nature of CGs, reliable CGs nowcasting with high spatial and temporal resolutions has remained unattainable. In this study, a novel nowcasting model based on deep learning - namely, CGsNet - is developed for 0-2 h of quantitative CGs nowcasting, first achieving minute-kilometer-level forecasts. CGsNet is a physics-constrained model established by training on large corpora of average surface wind speed (ASWS) and radar observations, it can produce realistic and spatiotemporally consistent ASWS predictions in CGs events. By combining the gust factor (1.77, the ratio of the observed peak wind gust speed (PWGS) to the ASWS) with the ASWS predictions, the PWGS forecasts are estimated with a spatial resolution of  $0.01^\circ \times 0.01^\circ$  and a 6-minute temporal resolution. CGsNet is shown to be effective, and it has an essential advantage in learning the spatiotemporal features of CGs. In addition, quantitative evaluation experiments indicate that CGsNet exhibits higher generalization performance for CGs than the traditional nowcasting method based on numerical weather prediction models. CGs nowcasting technology can be applied to provide real-time quantitative CGs forecasts and alerts the damaging wind events in meteorological services.

## 1 Introduction

Convective wind gusts (CGs) are nontronic, straight-line winds (Mohr et al., 2017; Yu and Zheng, 2020). They predominantly occur in Eastern China in the warm summer months (Yang et al., 2017), and they are usually associated with thunderstorm clouds, in particular squall lines and supercells, which generate conditions conducive to the appearance of whirlwinds and squalls (Kolendowicz et al., 2016). Severe convective gusts are caused either by mesoscale cold pools associated with horizontal pressure gradients large enough to produce high wind speeds in the absence of strong downdrafts or by local-scale downbursts that create strong divergent horizontal winds near the ground (Wakimoto, 2001). These severe convective gusts may cause

Anonymous: Do you mean "at 0–2-hour lead time"?

Anonymous: What do you mean by "first"? That your approach is the first ever to achieve minute-/km-level forecasts?

Anonymous: What do you mean by "spatiotemporally consistent"? This was never discussed in the paper.

Anonymous: This suggests that your model is used in operations already – based on the rest of the paper, it sounds like your model is not yet operational.

Anonymous: Typo. Replace with "nontornadic".



considerable damage to communication, transport, buildings and other structures, and even the health and life of humans in many parts of the world (Mohr et al., 2017; Wang et al., 2020).

CGs as defined by the China Meteorological Administration (CMA) are usually recognized as a PWGS  $\geq 17.2$  m/s caused by severe atmospheric convection (Yu and Zheng, 2020). Compared with large-scale wind storms, many observations show that convectively induced storm events can reach higher wind speeds (Mohr et al., 2017). For example, the CGs observed in 1983 during a microburst in the United States had a peak gust of 67 m/s (Fujita, 1990), for which wind speeds are comparable to those of an F3 tornado based on damage assessments. Thus, forecasting the occurrence of CGs in advance is valuable for reducing the risk and threat of damaging wind events.

Currently, accurate CGs nowcasting is still a challenging issue in operational meteorology despite its severe impact (Ray, 2015; Stensrud et al., 2009). This is primarily for several reasons. One is the small-scale and nonstationary nature of CGs. Due to the rapid evolution of fine-scale convective systems and their complicated interactions with environmental features, it is difficult for mesoscale numerical models or statistical models to capture and forecast CGs. In addition, the sparsity of wind observations is a factor that hinders the development and verification of gust nowcasting models. The most frequently cited record-breaking wind speeds are usually associated with wind gust values. This refers to a maximum momentary (2-3 sec.) wind speed that exceeds the 2-minute mean wind speed by at least 5 m/s (WMO, 2010). At present, wind gusts between full hours of observation have been recorded in Eastern China, which makes it possible to determine the actual maximum wind gusts/peak wind gusts (PWGS) for each hour. Obviously, these existing meteorological observation networks cannot record fine-scale CGs accurately (Kahl et al., 2021; Mohr et al., 2017), and a significant portion of the highest wind gusts may be missing.

Many previous studies have mainly focused on potential severe convective weather (SCW) forecasting (McNulty, 1995; Doswell et al., 1996) or the possibility of classified SCW forecasting (Zhou et al., 2019; Lagerquist et al., 2017), while quantitative CGs nowcasting has rarely been reported. Currently, some studies focus on wind gust forecasting by using physically based methods, empirical results and tuning, statistical analysis or machine learning methods (Kahl, 2020; Kahl et al., 2021; Lei et al., 2009; Sheridan, 2018; Nerini et al., 2014; Chaudhuri and Middey, 2011). Although some progress has been made in these studies, their performance on wind gust nowcasting (0-2 h) is poor (Wang et al., 2016), especially in terms of spatial and temporal resolution. For example, the wind forecasted by Integrated Nowcasting through Comprehensive Analysis (INCA) (Haiden et al., 2011) or the newly developed meteorologically stratified gust factor (MSGF) model (Kahl et al., 2021) has a 1-hour temporal resolution, which is not sufficient for describing the evolution of wind gusts. Most importantly, few gust forecasting models have been evaluated for effectiveness in CGs nowcasting.

Recent advances in deep learning (Yang et al., 2017), especially recurrent neural networks (RNNs) and convolutional neural networks (CNNs), have provided some useful insights into the meteorological field (Duan et al., 2021; Sadeghi et al., 2020). Many approaches based on RNNs and CNNs have been applied successfully to short-term weather forecasting due to their ability to capture temporal and spatial variations in image features, e.g., short-term drought (Danandeh Mehr et al., 2022) and quantitative precipitation forecasts (Shi et al., 2015). An evaluation of the applications indicates that the deep learning solutions can model complex nonlinear systems and better extract advanced features.

Anonymous: I don't understand the difference between the two approaches you're highlighting: "potential SCW-forecasting or classified SCW-forecasting" versus "quantitative CG-nowcasting". Do you mean that the previous approaches were doing classification (probability of wind exceeding a threshold) while you're doing regression (predicting the exact wind speed in m/s)?



Complex physical processes and dynamic characteristics are often involved in convective systems at small spatial and temporal scales (Doswell, 2001). It is critical to fully extract convective characteristics automatically to improve the forecast accuracy, and deep learning provides a practical tool for this purpose. In particular, Zhou et al. (2019) developed a forecasting solution for SCW using a CNN, producing objective-possibility forecasting products. Their results showed that deep learning methods achieve better performance than traditional forecasting methods. Thus, as it is a similar problem, deep learning may have considerable application potential in CGs nowcasting, and it is promising to test CGs forecasting using deep learning methods, which has rarely been documented before.

Anonymous: ?

The objective of this study is to achieve quantitative nowcasting of CGs speed in eastern China using the deep learning method, in principle down to the minute-level timescale. Doppler weather radar is an important device for observing and forecasting CGs because of abundant weather information in radar reflectivity (e.g., bow echo and hook echo) (Holleman, 2001; Yuan et al., 2018; Yu and Zheng, 2020). Thus, in this study, we aim to forecast quantitative CGs based on observed wind and radar data, which has rarely been considered in previous studies. We also compare the nowcasting performance of the deep learning method with that of the INCA approach. Notably, we concentrate on the nowcasting and evaluation of the average surface wind speed (ASWS) and PWGS, which are both key factors that reflect the strength and influence of CGs. We believe this work will have significant application potential in small-scale hazard assessment and alerting of threats to the economy and human activities.

## 2 Data

The study area is in Eastern China (Figure 1), including Jiangsu Province and its adjacent area. The latitudinal and longitudinal ranges of the study area are 30.4°N–35.2°N and 116.33°E–121.93°E, respectively. Considering that CGs associated with thunderstorms occur predominantly in the warm season in eastern China (Yang et al., 2017), April to September of each year was selected as the period of the experiments in this study.

### 2.1 Wind data

For the ground-truth reference, the ASWS data comprise in situ observations with a 5-minute time interval, which is the 2-minute average of the 3-second wind measured using automatic weather stations (AWSs) (Figure 1b) at a height of 10 meters above the ground. Note that there are few wind observation data on the seacoast. To match the spatiotemporal resolution of the observed radar reflectivity mosaics (RMOSs), the ASWS data were first interpolated to 6 minutes using linear interpolation. Inverse distance-weighted (IDW) interpolation has the advantages of being fast to calculate and easy to understand, and it is suitable for eastern China, where the automatic stations are dense and evenly distributed. Then, the IDW interpolation method was employed to regrid the ASWS data to a spatial resolution of  $0.01^\circ \times 0.01^\circ$  by using the four nearest stations within 15 km with a power of 2. In this study, the interpolated wind data are assumed to be close to the true observed wind field.

Anonymous: Replace with "Thus"

Anonymous: Why did you choose these values (radius of influence = 15 km, 4 stations, and power of 2)? Did you try other combinations?

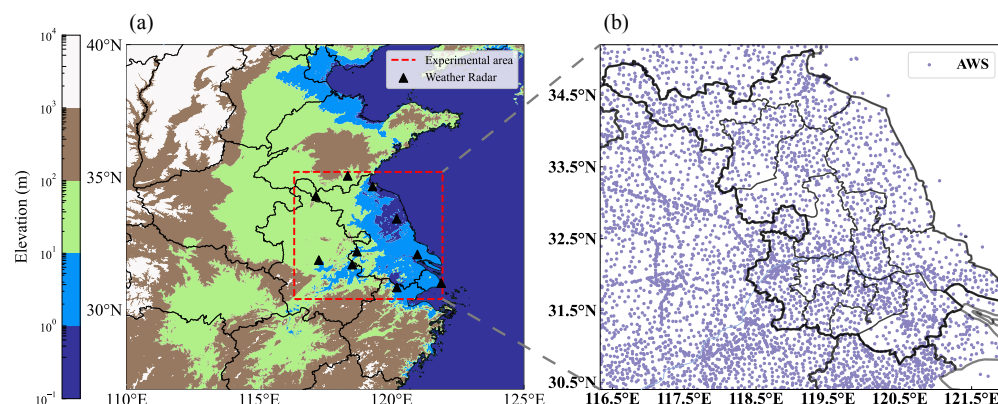


ASWS data from 2016 to 2022 were considered. To further select ASWS data associated with CGs, the samples were selected using two principles: 1) more than 2% of stations recorded ASWS > 10.8 m/s; and 2) the precipitation at more than 5% of the stations within an hour was greater than 0.1 mm.

In addition, observed peak wind gust speed (PWGS) from 2021 to 2022 was used in this study for subsequent gust factor calculation and model evaluation; it is the maximum 3-second average gust recorded over 1 hour by the AWS.

## 2.2 Radar reflectivity

Weather radar provides a highly detailed representation of the spatial structure and temporal evolution of thunderstorms over a large area (Knupp, 1987). Weather radar data may also indicate the time and location of the CGs that occurred (Holleman, 2001). Thus, the constant-altitude radar RMOSs at 3 km are used as auxiliary data along with observed wind data to forecast the speed of CGs. The RMOS data is from 10 weather radar stations in eastern China (Figure 1a). The type of radar sensor is the CINRAD/SA Doppler weather radar (Sheng et al., 2006). The RMOS is determined by projecting the base reflectivity factor onto equal longitude and latitude coordinates. The time interval of the RMOS data is 6 minutes, the spatial resolution is 0.01°, and the grid data are arranged from west to east and north to south.



**Figure 1.** The selected study area: the red dotted line in (a) represents Eastern China (30.4°N–35.2°N, 116.33°E–121.93°E); the black triangles in (a) represent the locations of the weather radar; and the purple dots in (b) are the locations of the AWSs that currently measure ASWS and PWGS.

## 2.3 Workflow

The workflow of this study is illustrated in Figure 2. First, the RMOS data were preprocessed, and the ASWS data were interpolated and regrided as mentioned above. Second, the spatial-temporal resolutions of the RMOS and ASWS samples were matched, and the time of the RMOS samples was determined by the selected ASWS samples. Third, the dataset was divided into three parts (training, validation and testing datasets) according to the observation time. Fourth, the ASWS data

Anonymous: ?? I don't understand this sentence. You list two properties of the ASWS data (how many stations recorded winds > 10.8 m/s and how many stations recorded 1-hour precipitation > 0.1 mm) – but you say "the samples were selected using two principles". So... are those two properties based on (a) the whole dataset, or (b) just a subset of the data that you sampled? If (b), \*how\* exactly did you subset the data to ensure that the two properties are satisfied?

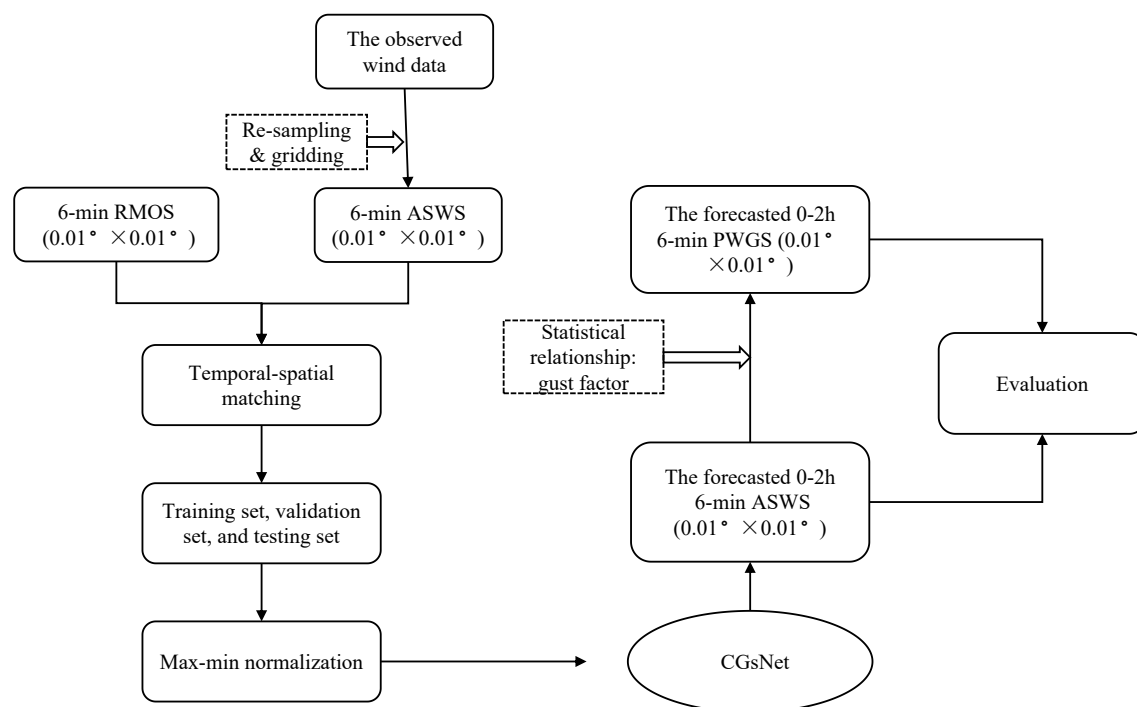
Anonymous: How do you deal with data at different heights? Do you interpolate to a constant-height grid? Or do you create a grid of composite (column-maximum) reflectivity? Or what?

Anonymous: How exactly do you separate the three datasets? Do training, validation, and testing all contain different years (example: 2016-2019 for training, 2020-2021 for validation, 2022 for testing)? Or what?



were clipped to between 0 and 35 m/s and subsequently normalized to the range [0.0, 1.0] through min-max normalization.  
105 Similarly, the RMOS values were clipped to between 0 and 70 dBZ and subsequently normalized to between 0 and 1. Fifth,  
the ASWS and RMOS data in the past 60 minutes were used as input data to train and validate the deep learning nowcasting  
model, and the outputs were the forecasted **ASWS and RMOS** with lead times of 6-120 minutes ahead, with a spatial resolution  
of  $0.01^\circ \times 0.01^\circ$  and a 6-minute temporal resolution. Sixth, the performance of the deep learning model in forecasting ASWS  
was evaluated by different statistical variables. Seventh, the mean gust factor (GF) was determined by comparing the observed  
110 PWGS and ASWS. Subsequently, the PWGS forecasts were estimated by multiplying the GF by the forecasted ASWS. Finally,  
the PWGS forecasts were compared with INCA results, and two cases were also showed to demonstrate the accuracy of PWGS  
forecasts.

Anonymous: I thought your model predicted only ASWS – not ASWS and RMOS.



**Figure 2.** Workflow of deep learning model-based CGs nowcasting.



### 3 Model and settings

#### 3.1 Model architecture

115 We started by adapting the network structure proposed by Guen and Thome (2020b), namely, PhyDNet, which is a sequence-  
 to-sequence network. Unlike traditional networks, it has a two-branch deep architecture, i.e., the newly proposed recurrent  
 physical cell (PhyCell) and ConvLSTM. Specifically, PhyCell is inspired by data assimilation techniques for performing partial  
 differential equation (PDE)-constrained prediction in latent space. It explicitly disentangles PDE dynamics from unknown  
 complementary information and allows for a generic class of linear PDEs through varying differential orders, e.g., wave equa-  
 120 tions. In PhyDNet, the physical knowledge is represented by PDEs, which can enforce physical constraints for future image  
 prediction well. PhyDNet has been successfully employed in many fields, e.g., solar irradiance forecasting using fisheye images  
 (Guen and Thome, 2020a) and nitrogen prediction (Jahanbakht et al., 2022).

The attention mechanism can focus on the important information among a large amount of input information and ignore  
 most of the unimportant information (Niu et al., 2021). Thus, an attention mechanism is applied to improve the performance  
 125 of PhyDNet for nowcasting CGs in this study. Here, the PhyDNet with an attention mechanism for CGs nowcasting is called  
 CGsNet, and its architecture is illustrated in Figure 3. An input sequence  $\{x_{t-K}^{a,r}, \dots, x_t^{a,r}\} \in \mathbb{R}^{K \times n \times m \times c}$  including ASWS  
 ( $a$ ) and RMOS ( $r$ ) with spatial size  $n \times m$  and  $c$  channels is projected into  $\{h_{t-K}^E, \dots, h_t^E\}$  by the convolutional units and  
 processed by the recurrent block unfolded in time. This forms a sequence-to-sequence architecture suited for multistep predic-  
 tion, outputting  $T$  future CGs predictions  $\{\hat{x}_{t+1}^{a,r}, \dots, \hat{x}_{t+T}^{a,r}\}$ . For time  $t$ , we learn a weight vector  $\langle \alpha_{t1}, \dots, \alpha_{tK} \rangle$  for  $K$  hidden  
 130 states  $\{h_{t-K}^m, \dots, h_{t-1}^m\}$ , where the weight  $\alpha_{tk}$  can be interpreted as the relative importance of the  $k$ -th  $h^m$ . Each weight  $\alpha_{tk}$   
 is computed by taking  $h_t^E$  as input, followed by a softmax operation. Then, we perform summation over the weighted hidden  
 states to obtain an attention representation  $A_t$ , which will be incorporated into the decoder for prediction. The key equations  
 for generating the attention representation  $A_t$  for the  $t + 1$ -th output prediction are summarized as follows.

$$s_{tk} = W * h_t^E + b, \quad \forall k \in [1, K] \quad (1)$$

$$135 \quad \alpha_{tk} = \frac{\exp(s_{tk})}{\sum_{k=1}^K \exp(s_{tk})}, \quad \forall k \in [1, K] \quad (2)$$

$$A_t = \sum_{k=1}^K \alpha_{tk} h_k^m \quad (3)$$

$$h_{t+1}^D = \text{PhyCell}([h_t^E, A_t]) + \text{ConvLSTM}([h_t^E, A_t]) \quad (4)$$

where ‘\*’ denotes the convolution operator and the kernel matrices  $W$  and biases  $b$  are parameters to be learned. The high-  
 level representation  $h_{t+1}^D$  is then fed into the deconvolutional units, and  $\hat{x}_{t+1}^{a,r}$  is calculated. Similarly, by inputting  $\hat{x}_{t+1}^{a,r}$   
 140 into the decoder, combined with the attention mechanism, the forecasted  $\hat{x}_{t+2}^{a,r}$  can be calculated. In this cycle, we can obtain the  
 ASWS and RMOS forecasts in the future, i.e.,  $\{\hat{x}_{t+1}^{a,r}, \dots, \hat{x}_{t+n}^{a,r}\}$ . This attention mechanism operation can better model both  
 short-term and long-term dependencies.

Anonymous: What does K refer to here? The number of hidden states, or the number of time steps in the input sequence? Or does num\_hidden\_states = num\_time\_steps\_in\_sequence somehow?

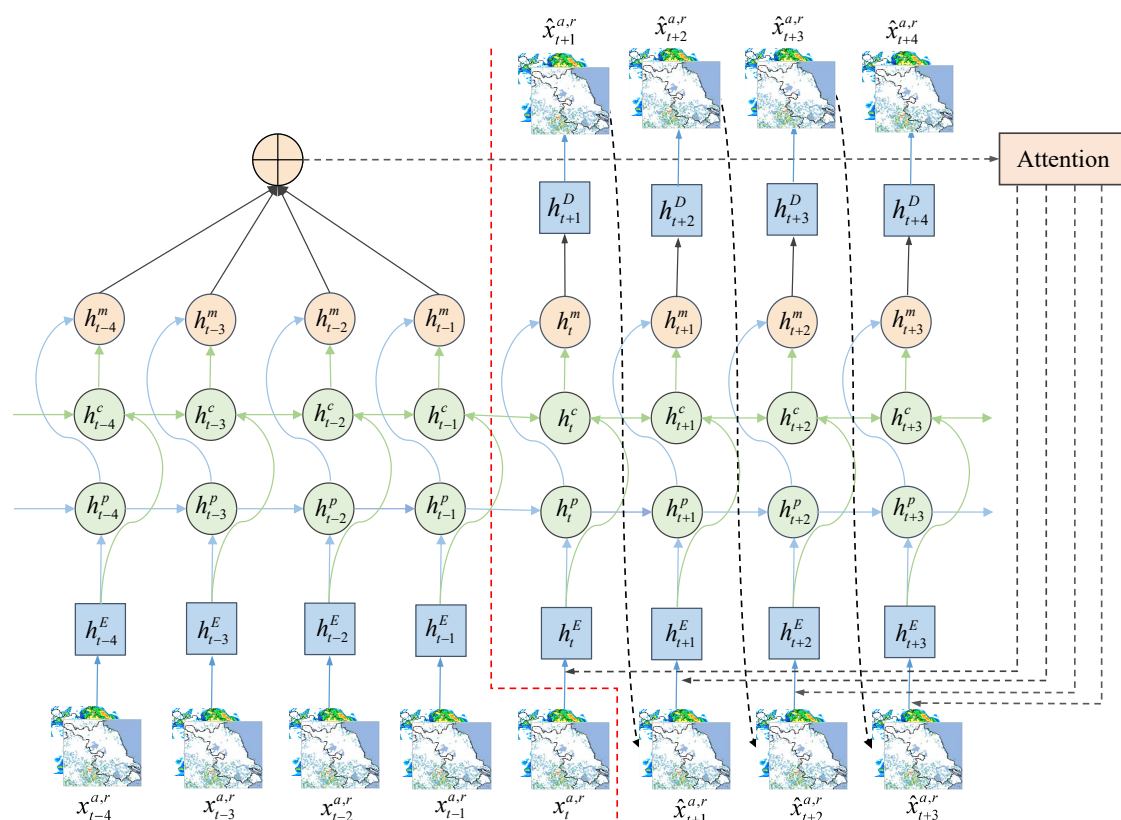
Anonymous: Why do the predictions have both the superscripts a (for ASWS) and r (for RMOS)? I'm confused about what you're predicting – is it just ASWS, or RMOS? This should be clear.

Anonymous: What is m? Why is this superscript needed?

Anonymous: Where do the weights come from??

Anonymous: Section 3.1 needs to be written more clearly, for readers who are not already familiar with the neural-net architecture being used.





**Figure 3.** Illustration of CGsNet. The encoder is to the left of the dotted red line, and the decoder is to the right.  $x_i^{a,r}$  and  $\hat{x}_i^{a,r}$  are the observed and forecasted ASWS/RMOS fields, respectively.  $h_i^E$  and  $h_i^D$  indicate the input and output tensors calculated by the convolution and deconvolution units, respectively.  $h_i^c$  and  $h_i^p$  indicate the hidden states of ConvLSTM and PhyCell, respectively.  $h_i^m$  represents the hidden state that combines the values from  $h_i^c$  and  $h_i^p$ .

### 3.2 Experimental settings

Here, we aim to forecast 0-2 hour CGs; thus, 10 historical ASWS and RMOS grid fields  $\{x_1^{a,r}, \dots, x_{10}^{a,r}\} \in \mathbb{R}^{10 \times 480 \times 560 \times 2}$  were taken as the inputs, and the subsequent 20 ASWS and RMOS grid fields  $\{x_{11}^{a,r}, \dots, x_{30}^{a,r}\} \in \mathbb{R}^{20 \times 480 \times 560 \times 2}$  were the ground-truth outputs. The ASWS and RMOS grid fields from 2016 to 2020 were used for model's training and validation, and the fields in 2021 and 2022 were employed for ASWS testing and PWGS testing, respectively. Correspondingly, we obtained 15,629 CGs samples, including a training set of 13,155 samples, a validation set of 1,236 samples, and the testing sets of 1,184 and 54 samples for ASWS and PWGS.

Regarding the training settings, Adam (Kingma and Ba, 2014) was used as the optimizer, and the batch size was set as 2. The learning rate was initially set to 0.001 and then multiplied by 0.3 if the loss did not decrease when the model was trained for 2 epochs. The model was trained for a total of 50 epochs, and the model weight with the minimum loss on the validation

Anonymous: Besides the one unclear point in the caption, I \*really\* like this figure. It is very well done and informative. Kudos!

Anonymous: This part does not make sense. "The input and output tensors calculated by the conv and deconv units" = 4 things: input tensor for conv unit, output for conv unit, input for deconv unit, output for deconv. But you match this description with 2 variables ( $h_i^E$  and  $h_i^D$ ), not 4 variables.

Anonymous: Which years are for training, and which are for validation?

Anonymous: Why \*so\* few samples for PWGS? This is an extremely small dataset compared to the others. The confidence intervals for your PWGS-based evaluation scores must be huge...

Anonymous: Why such a small batch size? Did you experiment with other batch sizes?

Anonymous: How did you choose these



set was saved. The comparison and evaluation experiments were implemented on the testing set. All experiments in this study were conducted using Python and PyTorch and executed on 4 NVIDIA GeForce RTX 3090 GPUs with the CUDA-11.1 library.

### 155 3.3 Loss function

The loss function is used to adjust the weights of the deep learning model, and it is an instructive function that guides how to improve the weight coefficients. Most previous studies used the mean absolute error (MAE) loss or mean squared error (MSE) loss as the default to train their models (Tran and Song, 2019; Veillette et al., 2020; Franch et al., 2020). However, these losses will result in smoothing effects in the predicted fields, since they may make a good assumption about the global similarity of the two fields, meaning that the field's details may be lost (Tran and Song, 2019; Franch et al., 2020). Notably, with increasing forecast time, the problem of underestimating high values becomes more obvious, such as underestimating heavy rain or radar reflectivity. To address these problems and make the predictions sharper and more realistic, the weighted MAE loss (Shi et al., 2017) was adopted in this study. The weight for the MAE loss function is shown in Table 1, and it is set according to the six ASWS and RMOS value ranges. The weighted MAE loss is equivalent to data augmentation, as it gives a large weight to strong gusts and a small weight to weak gusts. Thus, this setting has a better effect on forecasting CGs than loss without weights. The weighted loss function can be calculated as follows.

$$loss = \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^{480} \sum_{j=1}^{560} w_{n,i,j} |y_{n,i,j}^a - \hat{y}_{n,i,j}^a| + \frac{1}{N} \sum_{n=1}^N \sum_{i=1}^{480} \sum_{j=1}^{560} w_{n,i,j} |y_{n,i,j}^r - \hat{y}_{n,i,j}^r| \quad (5)$$

where  $N$  is the number of samples, and  $i$  and  $j$  are the width and length of the ASWS/RMOS, respectively. Moreover,  $y_{n,i,j}^a$ ,  $y_{n,i,j}^r$ ,  $\hat{y}_{n,i,j}^a$ , and  $\hat{y}_{n,i,j}^r$  are the observed ASWS, observed RMOS, forecasted ASWS and forecasted RMOS values, respectively.

170  $w_{n,i,j}^a$  and  $w_{n,i,j}^r$  denote the weights of the ASWS and RMOS values, respectively.

**Table 1.** The weights of the ASWS and RMOS in the MAE loss.

Wind (m/s)	Weights	RMOS (dBZ)	Weights
$y \leq 5.5$	0.5	$y \leq 15$	0.5
$5.5 \leq y \leq 8.0$	1	$15 \leq y \leq 25$	1
$8.0 \leq y \leq 13.9$	2	$25 \leq y \leq 35$	2.5
$13.9 \leq y \leq 17.2$	10	$35 \leq y \leq 45$	5
$17.2 \leq y \leq 20.8$	20	$45 \leq y \leq 50$	10
$y \geq 20.8$	30	$y \geq 50$	15

### 3.4 Model evaluation

To quantify the capabilities of CGsNet, the critical success index (CSI), probability of detection (POD), false alarm rate (FAR), bias score, and Heidke skill score (HSS) were implemented for evaluating the CGsNet forecasts. The following equations

hyperparameters? By experimentation, or based on a priori reasoning? Please specify.

Anonymous: How did you choose this hyperparameter? Please specify.

Anonymous: Do you mean that model selection was based on testing results? Model selection should be based on validation results. The testing set should be left untouched until the final models have been selected; the testing set should then be used as one final, independent assessment of the models' performance. If model selection is based on the testing data, then you \*cannot\* use the testing data for one final, independent assessment of performance -- which is a problem. See here for more: [https://en.wikipedia.org/wiki/Training,\\_validation,\\_and\\_test\\_data\\_sets](https://en.wikipedia.org/wiki/Training,_validation,_and_test_data_sets)

Anonymous: How do you figure that using a custom loss function is equivalent to data augmentation? Data augmentation is the practice of perturbing the inputs (predictors) -- e.g., by rotating, translating, flipping, or noising images -- while assuming that the outputs (targets) remain the same. In other words, data augmentation is the practice of creating fictitious data to increase the size of the dataset. Using a custom loss function, to my mind, is not at all equivalent to data augmentation.

Anonymous: How did you choose this weight structure? Please justify.



describe these indices.

$$175 \quad CSI = \frac{TP}{TP + FP + FN} \quad (6)$$

$$POD = \frac{TP}{TP + FN} \quad (7)$$

$$FAR = \frac{FP}{TP + FP} \quad (8)$$

$$BIAS = \frac{TP + FP}{TP + FN} \quad (9)$$

$$HSS = \frac{(TP \times TN - FN \times FP)}{(TP + FN) \times (FN + TN) + (TP + FP) \times (FP + TN)} \quad (10)$$

180 where TP, TN, FN, and FP are the numbers of true positives, true negatives, false negatives, and false positives, respectively. Moreover, the MAE and RMSE are also used for model evaluation, and are calculated as follows.

$$MAE = \frac{1}{Q} \sum_{i=1}^Q |y_i - \hat{y}_i| \quad (11)$$

$$RMSE = \sqrt{\frac{1}{Q} \sum_{i=1}^Q (y_i - \hat{y}_i)^2} \quad (12)$$

185 where Q is the number of predicted ASWS pixel values.  $y_i$  and  $\hat{y}_i$  represent the observations and forecasts, respectively. Note that the value of BIAS is greater than 0, and the closer to 1 the value is, the better. The remaining indices range between 0 and 1. An excellent model should present high CSI, POD, and HSS values but low FAR, MAE, and RMSE values.

In addition, the baseline method, INCA (Haiden et al., 2011), is compared with CGsNet in forecasting PWGS in CGs. INCA is a nowcasting system developed with complex terrain adaptability at the Austria National Weather Service. In this study, the nowcasts start with a three-dimensional analysis based on a first guess obtained from the output of the numerical weather prediction model (here, the PWAFS model (Li et al., 2016) is used), with observation corrections superimposed. It can provide 190 wind forecasts, for which the update frequency (temporal resolution) is 1 h.

In particular, we concentrate on evaluating ASWS in the range of 8.0-13.9 m/s and PWGS in the range of 10.8-20.8 m/s in CGs events, which has broad value for disaster warning in meteorological operations and aviation applications.

Anonymous: Why these specific ranges? Also, why is there an upper bound on these ranges? Why not just evaluate ASWS in the range > 8.0 m/s and PWGS in the range > 10.8 m/s?

## 4 Results

### 195 4.1 Model performance on ASWS nowcasting

To validate the effectiveness of CGsNet on forecasting ASWS in CGs, the CSI, HSS, POD, FAR, MAE, and RMSE are calculated in Table 2 for the investigated nowcasting lead time. The thresholds at 8.0 m/s, 10.8 m/s and 13.9 m/s of ASWS are evaluated, and the results reveal that CGsNet achieved outstanding performance on these criteria. In detail, for an ASWS threshold of 8.0 m/s, CGsNet has excellent performance with HSS = 0.54, POD = 0.59, MAE = 1.6 m/s, and RMSE = 2.26 200 m/s. When the threshold is raised to 10.8 m/s, the forecast ability degrades slightly. For strong wind (the threshold is at 13.9



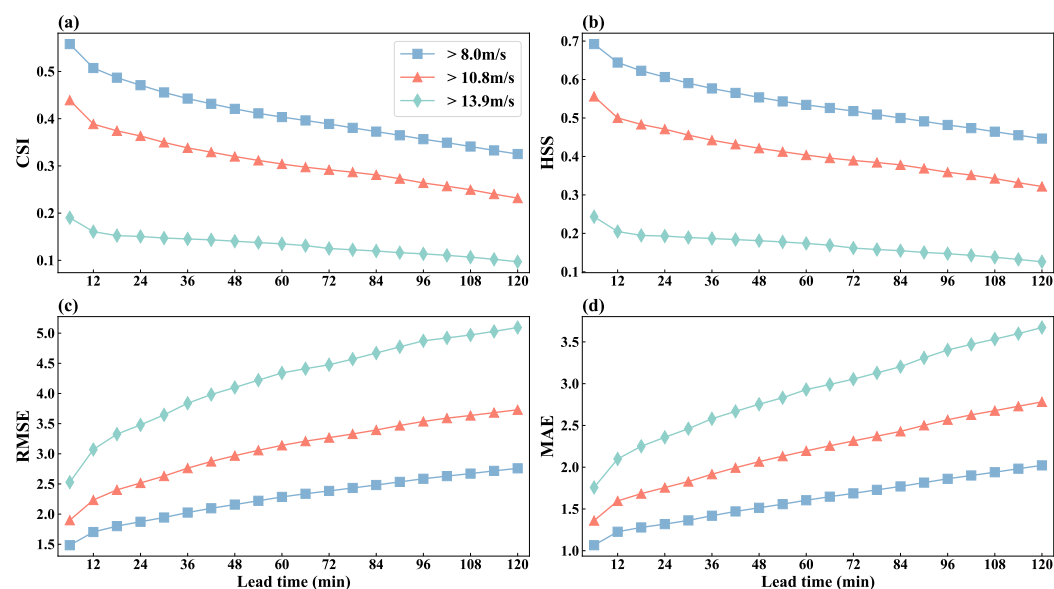
m/s), CGsNet still has a certain forecasting ability, with an HSS of 0.20 and a POD of 0.22. This means that the developed CGsNet can retain a decent modeling capability and is useful for ASWS nowcasting in CGs events, especially for strong gusts that are difficult to forecast by traditional methods.

**Table 2.** Quantitative results of CGsNet on ASWS nowcasting.

ASWS threshold (m/s)	CSI	HSS	POD	FAR	MAE	RMSE
<b>8.0</b>	0.41	0.54	0.59	0.45	1.60	2.26
<b>10.8</b>	0.31	0.42	0.47	0.54	2.19	3.07
<b>13.9</b>	0.15	0.20	0.22	0.61	2.90	4.22

Anonymous: This table should contain confidence intervals (created, e.g., by bootstrapping the testing samples). Without a measure of uncertainty, it is hard to understand these results.

We further investigated the performance of CGsNet by drawing the CSI, HSS, MAE and RMSE curves at all nowcasting lead time stamps. As shown in Figure 4, in the cases with ASWS > 8.0 m/s, the prediction quality gradually decreased as the forecasting time increased. Specifically, the value of CSI/HSS dropped from approximately 0.56/0.70 (lead time at 6 min) to 0.40/0.45 (lead time at 120 min) in the nowcasting results, and the RMSE (MAE) increased from approximately 2.5 (1.7) m/s for the first lead time to 5.1 (3.7) m/s for the last lead time. The case of ASWS > 10.8 m/s (Figure 4b and 4e) is similar to that of ASWS > 8.0 m/s; its prediction quality gradually decreases as the lead time increases, but the performance is degraded compared to that with a threshold of 8.0 m/s.



Anonymous: This figure should also contain confidence intervals – displayed, e.g., as error bars.

**Figure 4.** The CGsNet results for different nowcasting lead times of ASWS at thresholds of 8.0 m/s, 10.8 m/s, and 13.9 m/s.



In addition, the evaluation curves are depicted with respect to different nowcasting lead times at the 13.9 m/s threshold. The results are similar to the ASWS at the other two thresholds. In the first 12 minutes, the performance of CGsNet decreased rapidly and then gradually decreased slowly. Although the performance is worse than that with the other two thresholds, CGsNet still exhibits forecasting skill within 2 h. Overall, the above results confirm the effectiveness of the developed CGsNet model, which is skillful for nowcasting ASWS in CGs events.

#### 4.2 Case study of ASWS nowcasting

To further prove the usefulness of CGsNet in detail, we show examples in two meteorologically important weather cases produced by CGsNet. The first case occurred on April 30, 2021, when eastern China was affected by cold air due to the influence of the Northeast Cold Vortex in China. This cold air accompanied by the cold vortex moved eastward and southward, intersecting with some warm and humid air currents in eastern China. Then, the areas along the Yangtze River and north of Jiangsu suffered from SCW, including sudden CGs and hail. Because of the small scale and rapid development of these CGs, numerical models usually cannot forecast this process accurately.

Specifically, hail and large-scale thunderstorms occurred from 18:00 to 22:00 (BJT) in parts of Nantong, Jiangsu, with a maximum wind speed of up to 47.9 m/s in some areas. Figure 5 shows the in situ observations and forecasted ASWS during this period. The CGs developed strongly at 20:12, and the ASWS exceeded 17.2 m/s in some areas. Then, the ASWS gradually decreased after 20:12 for 120 minutes. It is clear that the CGsNet model has good forecasting skill. CGsNet accurately forecasts the position of the CGs and their weakening trend. In particular, the CGsNet model can preserve the strong gust regions (ASWS>10.8 m/s) (Figure 5). The reason for this is that CGsNet employs attention schemes, which better model the short-term and long-term dependency of wind gusts. Additionally, the observed strong gusts continuously moved to the southeast as the lead time continued. CGsNet forecasted this phenomenon precisely, although in the later stage, the locations of the forecasted strong gusts were not exactly the same as in the observations.

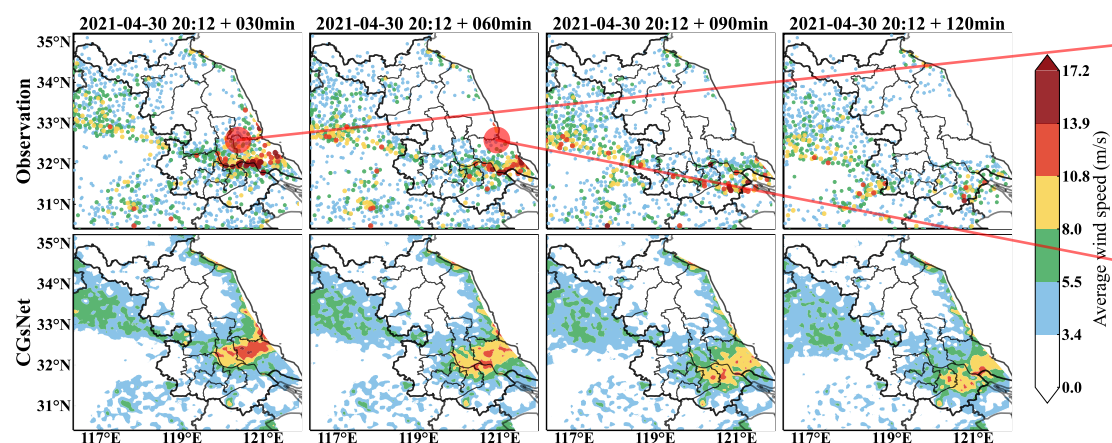
The second case is also typical convection weather. It was influenced by the low-level shear lines and strengthened by southwest warm and humid airflow on 15 May 2021. This process occurred in central and eastern Jiangsu, accompanied by heavy precipitation and strong gusts, causing serious economic losses. The observations and forecasts of ASWS for this case are presented in Figure 6.

In the second case, CGs are produced with the development of the squall line in the Jiangsu area. The strong gust position is linearly distributed, moving eastward from western Jiangsu to central Jiangsu between 13:00 and 15:00 (BJT). Figure 6 clearly shows that CGsNet has good forecasting skill for the moving trend due to the improved modeling capability. Additionally, the results demonstrate that CGsNet can accurately forecast the ASWS values in most areas, although the strong gust values are slightly smaller than the observations in some areas. Similar results can also be found in the RMOS forecasts (Figure A1 and A2), which are the other output variables of CGsNet. This further confirms that CGsNet is effective and accurate for ASWS nowcasting. Based on the reliable ASWS forecasts, nowcasting on the PWGS of CGs may be conducted.

Anonymous: I'm unsure what to think about all your subjective assessments of skill (the adjectives "outstanding," "decent," "skillful," etc.). Is there a baseline, i.e., another method you can compare against? Because a lot of these results – especially for the thresholds of 10.8 and 13.9 m/s, but also for the longer lead times at all thresholds – seem quite poor.

Anonymous: This is not a proper name, so it should not be capitalized.

Anonymous: I disagree. See my comments on Figure 5.

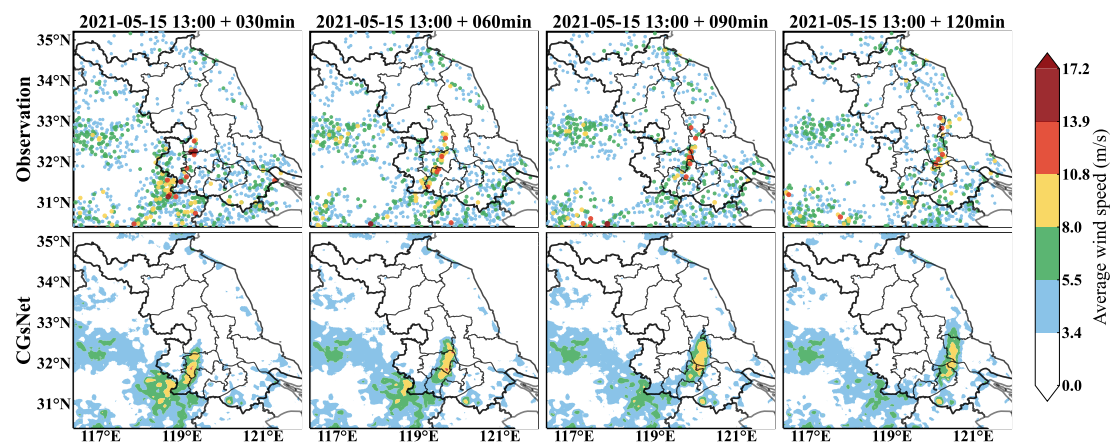


Anonymous: The neural network does not capture small areas of CG at all (anywhere outside of the big blob south of where I have placed this dot). There are a lot of small areas with observed wind speed in the red (> 10.8 m/s) but forecast wind speed much, much lower.

Anonymous: Also, in the large area of CG (south of where I have placed this dot), although the neural network accurately predicts strong wind (> 10.8 m/s) \*kind of\* in the same neighbourhood, there is still a large spatial offset between the forecast and observed strong winds. The forecast strong winds (red) are about 50 km north of the observed strong winds (red).

Anonymous: Neither of the shortcomings I pointed out in this figure are addressed in your discussion of the figure.

**Figure 5.** Observations (first row) and forecasts (second row) of ASWS in eastern China, 30 April 2021, 20:12-22:12 BJT. Note that forecasting started at 20:12, and the observations and forecasts are shown at intervals of 30 min.



**Figure 6.** Same as Figure 5, but for 15 May 2021, 13:00-15:00 BJT.



### 4.3 Peak wind gusts speed nowcasting

ASWS reflects the average speed of CGs, which is not sufficient to determine the actual impact of CGs. The maximum  
245 momentary wind speed (e.g., PWGS) can reflect the actual peaks of CGs and is the key factor for the assessment and analysis  
of weather hazards. Thus, this section focuses on evaluating the reliability and accuracy of CGsNet on nowcasting PWGS.

#### 4.3.1 Gust factor

The gust factor (GF) is the ratio of the wind gust to the wind speed (Harris and Kahl, 2017), and it plays an important role  
in wind conversion, the practice of converting between average wind speeds over different time periods (Harper et al., 2010).  
250 Kahl et al. (2021) showed that gust factors associated with strong winds (>7.65 m/s) were approximately 1.5 in the NW  
and NNW sectors of Rapid City, South Dakota, and ranged from 1.61 to 2.31 on different directionals at Waukegan. This  
directional variation in the GF was largely due to the site-specific heterogeneity in surface roughness (Suomi et al., 2013).  
Harris and Kahl (2017) investigated the GF in Milwaukee, Wisconsin, using Automated Surface Observation System (ASOS)  
wind measurements from 2007 to 2014 and calculated a mean GF of 1.74. Similarly, we determined the GF using the measured  
255 wind data, i.e., ASWS and PWGS observations. Here, we do not consider the direction due to the relatively flat terrain in  
eastern China; instead, the average GF is explored.

We take the observed maximum ASWS within an hour as the hourly maximum ASWS to match the temporal resolution of  
the PWGS because the observed PWGS was reported for each hour at all sites in eastern China. Then, the GF is calculated as:

$$GF = \frac{PWGS}{\text{hourly maximum ASWS}} \quad (13)$$

260 According to the above formula, the observed wind data from April to September 2021, including 32015 stations data, were  
used to calculate the GF. The corresponding scatter plots of the hourly maximum ASWS and PWGS can be found in Figure  
A3. As a result, we found a GF of 1.77.

#### 4.3.2 Model performance on PWGS nowcasting

Utilizing the calculated GF, we first estimated the 0-2 h PWGS nowcasts by multiplying the GF by the ASWS nowcasts from  
265 CGsNet. Then, the PWGS nowcasts were compared with INCA results to demonstrate the accuracy of CGsNet model and  
confirm the justifiability of the GF. Note that the results are in one-hour forecasts because the in situ PWGS observations and  
INCA results are reported for each hour.

The overall evaluation results of CGsNet and INCA on PWGS nowcasting are given in Table 3. The results reveal that  
CGsNet significantly outperforms INCA on our testing dataset, and it achieved outstanding performance of all criteria. More-  
270 over, as the threshold increases, the superiority of CGsNet becomes more and more obviously, e.g, for the PWGS thresholds  
is 17.2 m/s, CGsNet still keep a decent modeling capability(CSI =0.15, POD=0.25), which is much higher than INCA (CSI  
=0.03, POD=0.07).

Anonymous: compared

Anonymous: obvious

Anonymous: Replace with "threshold of"



**Table 3.** Quantitative results of CGsNet and INCA on PWGS nowcasting.

Evaluation indices	CSI				POD				BIAS				FAR			
	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8
PWGS threshold (m/s)	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8
CGsNet	0.27	0.22	0.15	0.06	0.35	0.31	0.25	0.12	0.63	0.73	0.94	1.21	0.45	0.57	0.73	0.90
INCA	0.11	0.06	0.03	0.02	0.30	0.13	0.07	0.04	2.07	1.51	1.27	1.14	0.85	0.91	0.94	0.96

Anonymous: This table should contain confidence intervals (created, e.g., by bootstrapping the testing samples). Without a measure of uncertainty, it is hard to understand these results.

Anonymous: Also, for each pair of numbers in this table (16 pairs – CSI for 10.8 m/s, CSI for 13.9 m/s, POD for 10.8 m/s, POD for 13.9 m/s, etc.), please conduct a formal significance test to show whether the difference between the CGsNet value and INCA value is \*significantly\* different – as opposed to noise.

Anonymous: Delete.

Anonymous: shown

Anonymous: I have two problems with the statement about bias:

(1) This is not true. For the threshold of 20.8 m/s, CGsNet has a greater bias than INCA.

(2) Lower bias is not always better. For example, suppose that the two bias values are 0.50 and 1.00.

Anonymous: ?

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Anonymous: Please apply both comments on Table 3 to this table also.

Anonymous: Should not be capitalized.

For a more detailed comparison, the the PWGS results from CGsNet and INCA for 0-2 h nowcasting lead times at different thresholds are showed in Table 4. At the lead time of 0-1 h, the CSI and POD of CGsNet always keep top positions at different thresholds. Meanwhile, the BIAS and FAR of CGsNet are also lower than those of INCA. Besides, the quality of CGsNet and INCA both degraded with the forecasting time increasing. Specifically, the performance of CGsNet still keep a forecasting skill at the lead time of 1-2 h, while INCA is similar to the first hour, it is lack of skill, the CSI at all thresholds are lower than 0.1. It's worth noting that the POD of INCA at the threshold of 10.8 m/s is a little larger than the CGsNet (0.29 vs. 0.28) at the lead time of 1-2 h. This is due to the high false alarm ratio of INCA, thus, it has the high FAR and BIAS. Overall, the results indicate that the developed CGsNet is helpful to improve the accuracy of CGs nowcasting and more skillful than INCA.

**Table 4.** The PWGS evaluation results from CGsNet and INCA for different nowcasting lead times at thresholds of 10.8 m/s, 13.9 m/s, 17.2 m/s and 20.8 m/s.

Lead time of 0-1 h																
Evaluation indices	CSI				POD				BIAS				FAR			
	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8
PWGS threshold (m/s)	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8
CGsNet	0.31	0.26	0.17	0.06	0.40	0.37	0.28	0.14	0.69	0.79	0.99	1.43	0.42	0.53	0.71	0.90
INCA	0.13	0.06	0.04	0.02	0.31	0.13	0.07	0.03	1.74	1.30	1.10	1.00	0.82	0.90	0.93	0.97
Lead time of 1-2 h																
Evaluation indices	CSI				POD				BIAS				FAR			
	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8
PWGS threshold (m/s)	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8	10.8	13.9	17.2	20.8
CGsNet	0.22	0.18	0.13	0.05	0.28	0.26	0.21	0.09	0.56	0.66	0.88	0.98	0.49	0.61	0.76	0.91
INCA	0.09	0.05	0.03	0.02	0.29	0.14	0.07	0.05	2.43	1.73	1.45	1.29	0.88	0.92	0.95	0.96

280

### 4.3.3 Case study of PWGS nowcasting

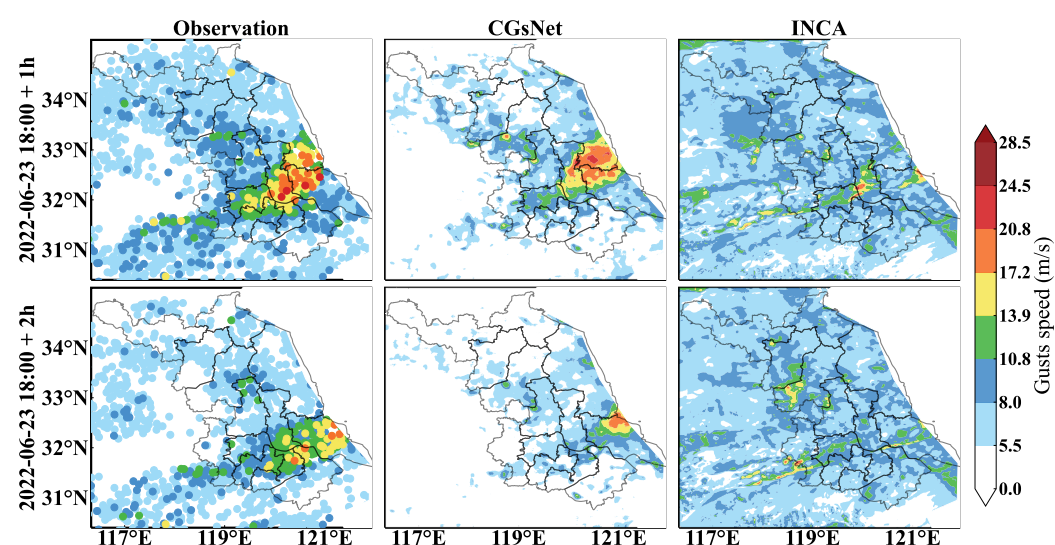
To illustrate the performance of CGsNet more intuitively, the INCA forecasts in two instances are presented for comparison. The first case is on June 23, 2022, short-term heavy precipitation and CGs occurred over a large area in Jiangsu Province because of the influence of the Northeast Cold Vortex in China. As shown in Figure 7, for the first nowcasting hour (19:00 BJT), the CGs were mainly located in central Jiangsu, and the PWGS at some sites exceeded 20.8 m/s. Then, the CGs moved

285





to the southeast of Jiangsu from 19:00 to 20:00 (BJT), occurring in Nantong and surrounding areas, and the PWGS gradually decreased. During this process, it is clear that CGsNet can effectively forecast the location of the CGs, especially for the first hour of nowcasting (19:00 BJT). However, CGsNet underestimates the PWGS at some sites. INCA does not accurately forecast the occurrence of CGs at 19:00 (BJT); the area in which PWGS > 17.2 m/s is too small, and the PWGS is also significantly under-estimated. Besides, INCA failed to forecast the occurrence of CGs at 20:00 (BJT), and the forecasted PWGS values were all below 17.2 m/s.



**Figure 7.** Observations and forecasts of PWGS in eastern China on June 23, 2022, 18:00-20:00 BJT. Note that the forecasting started at 18:00. The first column shows the observations at 19:00 BJT and 20:00 BJT. The last two columns show the PWGS forecasts obtained by CGsNet and INCA.

The performance of CGsNet and INCA at different PWGS thresholds for the case on on June 23, 2022 are shown in Figure 8. In particular, the PWGS at thresholds of 10.8 m/s, 13.9 m/s and 17.2 m/s is compared because the PWGS is below 20.8 m/s over most of the study area at 20:00 (BJT). The performance of CGsNet and INCA both decrease as the threshold of PWGS increases, but CGsNet significantly outperforms INCA. For example, in the cases of PWGS > 10.8 m/s, CGsNet achieved outstanding performance on the criteria, with a CSI of 0.34, a POD of 0.43, and a FAR of 0.38, which are higher than the corresponding INCA values (CSI=0.15, POD=0.26, and FAR=0.73). It is worth noting that the BIAS of CGsNet (0.70) is worse than that of INCA (0.97) at a threshold of 10.8 m/s, which may be because some areas with PWGS < 10.8 m/s are mispredicted by INCA as PWGS > 10.8 m/s. In this condition, the BIAS of INCA is small, but the performance on FAR and POD is poor. Again, the advantages of CGsNet become increasingly obvious with increasing PWGS threshold (13.9 m/s and

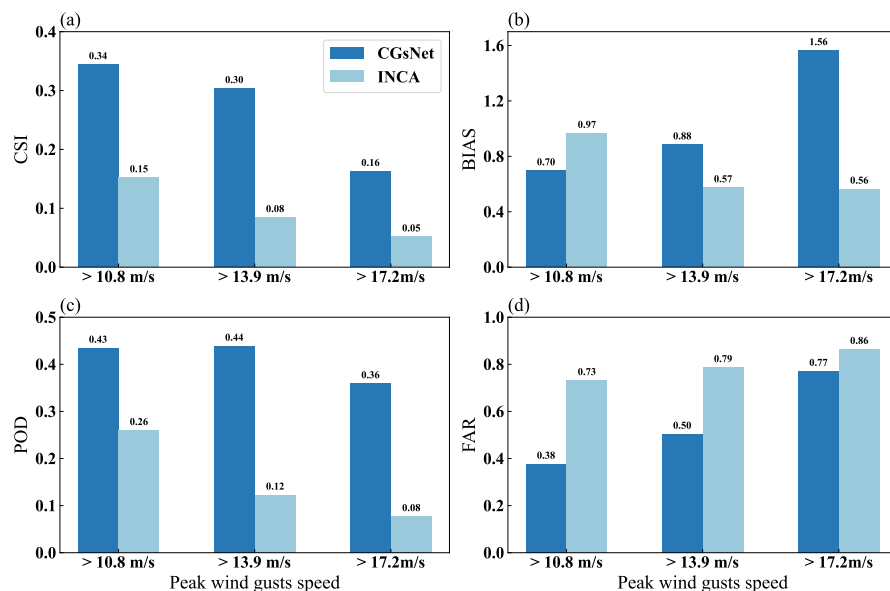
Anonymous: You cannot say "significantly" if you haven't conducted a statistical-significance test.

Anonymous: Replace with "better," since lower FAR is better.

Anonymous: Replace with "nearly optimal".



17.2 m/s); in particular, for PWGS > 17.2 m/s, INCA is nearly unable to perform CGs nowcasting, while CGsNet still shows nowcasting skill.



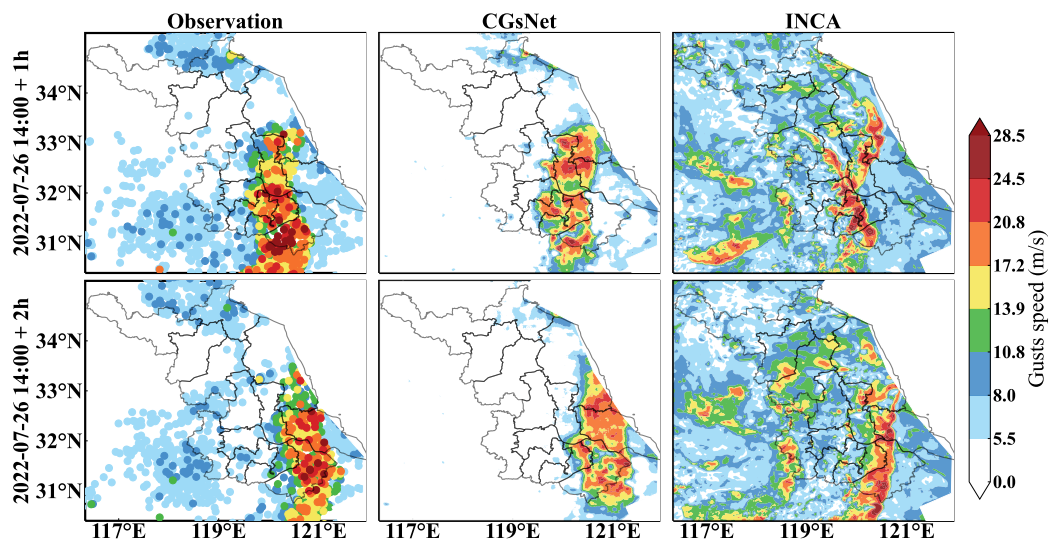
**Figure 8.** Comparison results of CGsNet and INCA on PWGS at thresholds of 10.8 m/s, 13.9 m/s, and 17.2 m/s on June 23, 2022, 18:00-20:00 BJT.

The other CGs case on 26 July 2022 was also selected to further verify the nowcasting ability of the CGsNet model. For this case, with the **movement and development derecho** in eastern China, Jiangsu and northern Zhejiang were hit by SCW (i.e., CGs, short-term heavy precipitation and tornadoes). Figure 9 shows the observed and forecasted PWGS. Specifically, central and southern Jiangsu suffered from CGs during 14:00-16:00 (BJT), and there was PWGS > 28.5 m/s in some areas. From 15:00 to 16:00 (BJT), the CGs gradually moved eastward with slight weakening. Compared with the observations, CGsNet was shown to be accurate in capturing the location of the CGs, despite underestimating the PWGS, which was greater than 20.8 m/s. INCA did not accurately forecast the area where the CGs would occur and underestimated the PWGS. In addition, neither CGsNet nor INCA accurately forecasted the CGs that occurred in northern Zhejiang at 15:00 and 16:00 (BJT); the CGsNet forecasts were weaker than the observations, while the INCA forecasts were in the wrong area. Overall, the results demonstrate that CGsNet is better than INCA and shows excellent performance in CGs nowcasting.

In addition, Figure 10 shows the performance of CGsNet and INCA at different PWGS thresholds. Unlike the first case, we evaluate the PWGS at a threshold of 20.8 m/s, since many sites have PWGS > 20.8 m/s in this case. The results indicate that the CSI and POD of both methods show a general decrease with increasing thresholds, and the BIAS and FAR increase. The CGsNet forecasts achieve better performance than those of INCA at all thresholds; e.g., the evaluated POD reaches 0.51 when the threshold is 17.2 m/s, which is 147.62% higher than that of INCA. Additionally, INCA has a poor performance on CSI and FAR at each PWGS threshold, which is due to the large location deviation of the INCA forecasts with respect to where

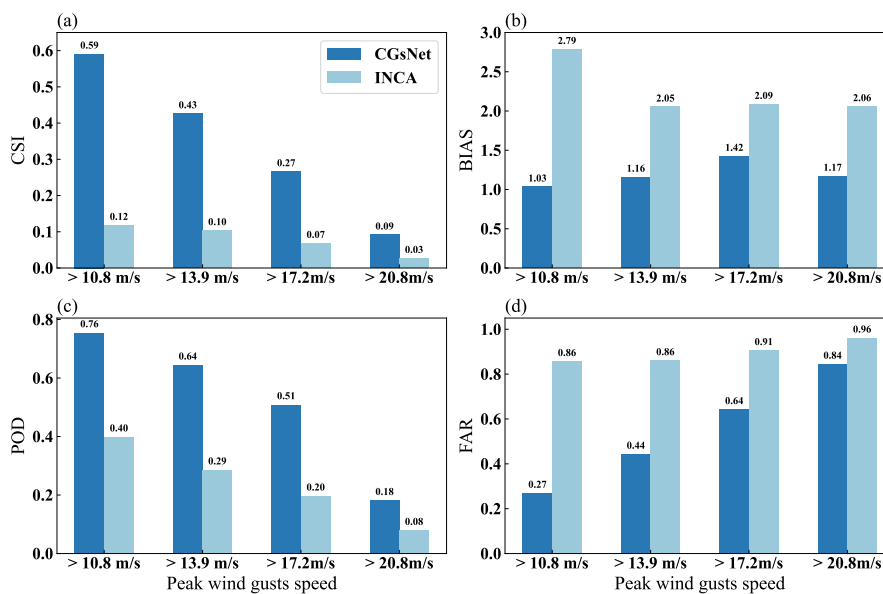
Anonymous: ?

Anonymous: Insert comma before "and"



**Figure 9.** Same as Fig. 7, but for July 26, 2022, 14:00-16:00 BJT.

CGs occurred. Again, the result illustrates the usefulness of the proposed CGsNet in CGs nowcasting. It also demonstrates the effectiveness of the GF.



**Figure 10.** Same as Fig. 8, but for July 26, 2022, 14:00-16:00 BJT.



## 5 Discussion and conclusions

In this study, a physics-constrained deep learning model was proposed for CGs nowcasting. This model was established based on the extended PhyDNet and is called CGsNet. Then, by using observed ASWS and RMOS datasets, CGsNet was trained for CGs nowcasting in eastern China. CGsNet can produce ASWS nowcasts of 6-120 min with a temporal resolution of 6 min and a spatial resolution of 1 km. To estimate the PWGS forecasts, we multiplied the forecasted ASWS by the GF, which was determined from the ratio of the historical observed ASWS to the PWGS. The PWGS forecasts had the same spatiotemporal resolution as the ASWS forecasts. This is the first time that minute-level CGs nowcasting has been achieved for eastern China.

Several metrics for evaluating the performance of CGsNet were analyzed, confirming the effectiveness of the CGsNet model for ASWS and PWGS nowcasting. The PWGS forecasts were also compared with the INCA results, and the results demonstrated that the performance of CGsNet is better than that of INCA. CGsNet can effectively forecast the location and evolution of CGs, and the PWGS forecasts are a good match with the observations. In contrast, INCA does not accurately determine the locations and strengths of CGs, with low POD and CSI and high BIAS and FAR. The superiority of the PWGS results also proves that the calculated GF is reliable.

In addition to these achievements, there are some points requiring further discussion and investigation. For example, CGsNet sometimes underestimates the intensity of ASWS and PWGS, which may be caused by several different factors. For ASWS forecasts, this may be due to the limited modeling ability of CGsNet; that is, the model has not fully learned the nonlinear variation characteristics of CGs. In addition, the input variables may be insufficient, and it is difficult to accurately forecast small-scale and nonstationary CGs with only radar data and observed wind data. For PWGS forecasts, the error from ASWS and GF, and thus their combination, leads to the deviation of the predicted PWGS.

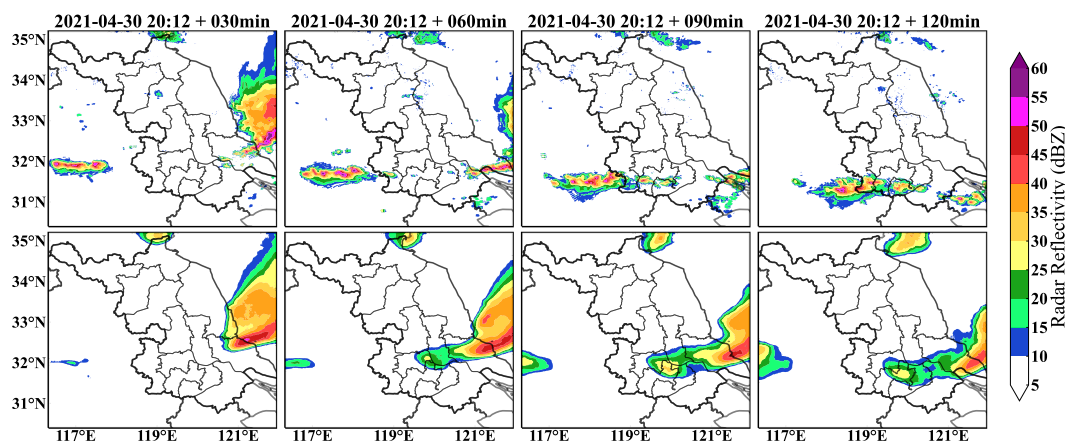
Therefore, in future work, more meteorological factors related to CGs, such as the three-hour pressure change and relative humidity, should be considered in CGs nowcasting. The predictive ability of the model can then be improved to some extent by reforming the training dataset. In addition, a more accurate GF should be calculated by using years of wind observations. Although our experiments were performed in eastern China, the proposed CGs nowcasting technology can be generalized to a wide range of areas. Besides, CGs nowcasting technology could also be applied to forecast other phenomena, such as convection or hail, for which real-time-response models are crucially needed.

Anonymous: Or you could compute site-specific GFs, direction-specific GFs, etc.

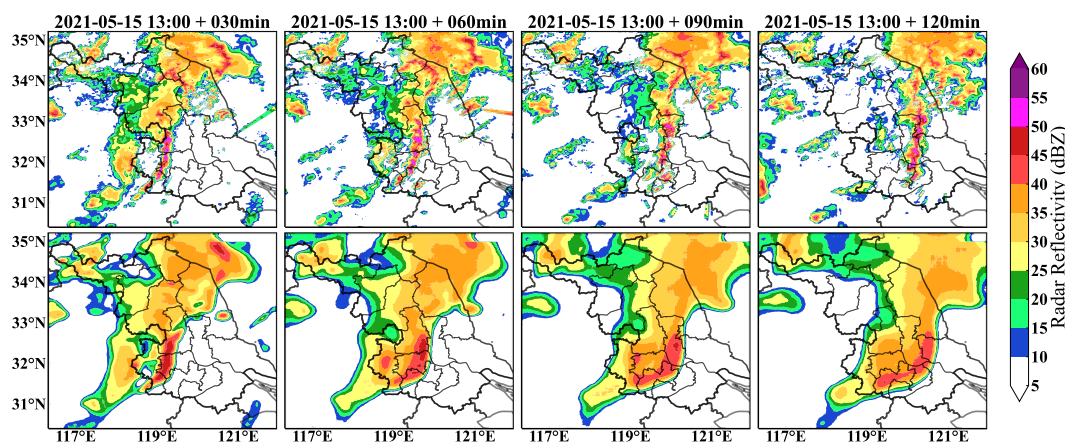
*Code availability.* The source code and the used data are available at this repository <https://doi.org/10.7910/DVN/PIZU7V>.



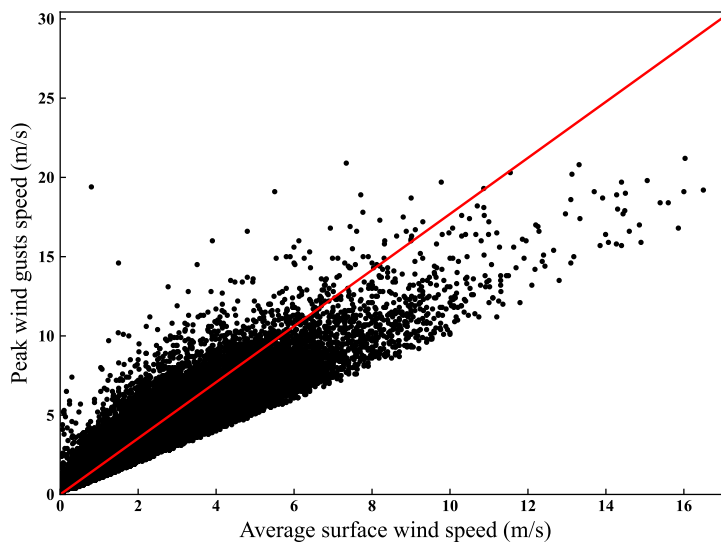
## Appendix A: appendix figures



**Figure A1.** Observations (first row) and forecasts (second row) of ROMS in eastern China, 30 April 2021, 20:12-22:12 BJT. Note that forecasting started at 20:12, and the observations and forecasts are shown for every 30 min.



**Figure A2.** Same as Figure A1, but for 15 May 2021, 13:00-15:00 BJT.



**Figure A3.** Scatter plot of the hourly maximum ASWS and PWGS. The red line represents the linear regression line for the GF.

*Author contributions.* Haixia Xiao was responsible for writing the original draft and completing the result analysis. Yaqiang Wang directed the study and wrote and reviewed the paper. Yu Zheng was responsible for developing the CGsNet model and visualizing the results.  
350 Yuanyuan Zheng provided useful comments on this study. The INCA and AWS datasets were processed by Xiaoran Zhuang. The RMOS data were acquired and processed by Hongyan Wang and Mei Gao.

*Competing interests.* The authors declare that they have no conflicts of interest.

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355 of China Meteorological Administration (CMA2022ZD07).



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