

W-MAE: Pre-trained weather model with masked autoencoder for multi-variable weather forecasting

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Abstract

Weather forecasting is a long-standing computational challenge with direct societal and economic impacts. This task involves a large amount of continuous data collection and exhibits rich spatiotemporal dependencies over long periods, making it highly suitable for deep learning models. In this paper, we apply pre-training techniques to weather forecasting and propose W-MAE, a Weather model with Masked AutoEncoder pre-training for multi-variable weather forecasting. W-MAE is pre-trained in a self-supervised manner to reconstruct spatial correlations within meteorological variables. On the temporal scale, we fine-tune the pre-trained W-MAE to predict the future states of meteorological variables, thereby modeling the temporal dependencies present in weather data. We pre-train W-MAE using the fifth-generation ECMWF Reanalysis (ERA5) data, with samples selected every six hours and using only two years of data. Under the same training data conditions, we compare W-MAE with FourCastNet, and W-MAE outperforms FourCastNet in precipitation forecasting. In the setting where the training data is far less than that of FourCastNet, our model still performs much better in precipitation prediction (0.80 vs. 0.98). Additionally, experiments show that our model has a stable and significant advantage in short-to-medium-range forecasting (i.e., forecasting time ranges from 6 hours to one week), and the longer the prediction time, the more evident the performance advantage of W-MAE, further proving its robustness.

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Keywords: Weather forecasting, Self-supervised learning, Pre-trained model, Masked autoencoder, Spatiotemporal dependency

1 Introduction

Weather forecasting is crucial for assisting in emergency management, reducing the impact of severe weather events, avoiding economic losses, and even generating sustained fiscal revenue [1]. Numerical Weather Prediction (NWP) has emerged from applying physical laws to weather prediction [2, 3]. NWP models [4, 5] use observed meteorological data as initial conditions and perform numerical calculations with supercomputers, solving fluid dynamics and thermodynamics equations to predict future atmospheric movement states. Although modern meteorological forecasting systems have achieved satisfactory results using the NWP models, these models are subject to various random factors due to their reliance on human understanding of atmospheric physics, and may not meet the diverse forecasting needs of complex climatic regions [6]. Moreover, numerical weather forecasting is a computation-intensive task that requires the integration and analysis of large volumes of diverse meteorological data, necessitating powerful computational capabilities. Therefore, it is necessary to explore other possibilities that can perform weather forecasting more computational-efficiently and labor-savingly.

In recent years, Artificial Intelligence (AI)-based weather forecasting models using deep learning methods have attracted widespread attention. Integrating deep learning methods into weather forecasting requires a comprehensive consideration of the characteristics of meteorological data and the advantages of advanced deep learning technologies. Delving into the field of meteorology, meteorological data involved in weather forecasting exhibits characteristics such as vast data and lack of labels [7, 8], diverse types [9], and strong spatiotemporal dependencies [10, 11], which pose several challenges for the AI-based weather forecasting models:

- **Massive unlabeled data mining:** Meteorological data is commonly collected for monitoring and forecasting purposes, rather than for targeted research or analysis. As a result, large amounts of data accumulated over a long period of time may lack specific labels or annotations about events or phenomena, which presents challenges for effectively training and testing deep learning models.
- **Data assimilation [12]:** Meteorological data is not solely based on perceptual data but is numerical data that integrates various sources of physical information and exhibits diverse types. Therefore, weather forecasting requires the integration of various meteorological data sources, which can be noisy and heterogeneous. Many AI-based models [13, 14] struggle to effectively assimilate and learn from such diverse data.
- **Spatial and temporal dependencies:** Meteorological data is highly correlated and dependent in spatial and temporal distributions due to

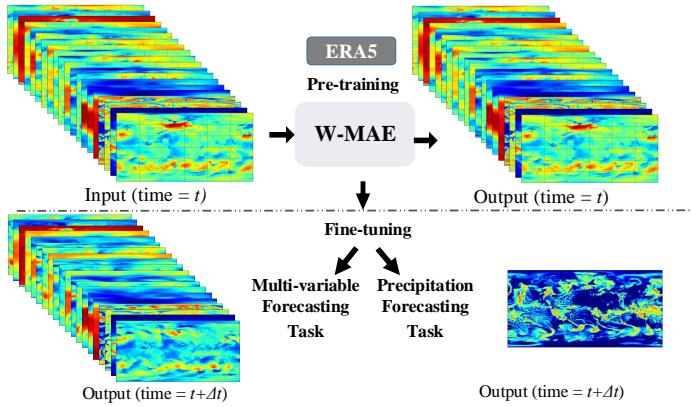


Fig. 1 A showcase of W-MAE pre-trained on the ERA5 dataset and then fine-tuned on two weather forecasting tasks, *i.e.*, multi-variable forecasting and precipitation forecasting. The word in the grey boxes indicates the dataset used for pre-training and fine-tuning our W-MAE.

the interplay and feedback mechanisms among meteorological variables. Therefore, weather forecasting needs to take these strong spatiotemporal dependencies into account. However, most AI-based models [15, 16] may not sufficiently capture these dependencies, limiting their forecasting accuracy.

Pre-training techniques [17–19] are data-hungry, which is in line with the characteristic of large amounts of weather data. Naturally, we introduce a self-supervised pre-training technique into weather forecasting tasks. The self-supervised pre-training technique [20, 21] aims to learn transferable representations from unlabeled data by utilizing their intrinsic features as supervisory sources. The learning paradigm involves pre-training models on large-scale unlabeled data, followed by fine-tuning for specific downstream tasks. Through task-agnostic self-supervised pre-training, on the one hand, models can fully mine massive unlabeled meteorological data and learn rich meteorological-related basic features and general knowledge, facilitating specific downstream task fine-tuning; on the other hand, pre-trained models can better handle heterogeneous data integration by learning transferable representations.

To model the spatial relationships in weather data, we employ the Vision Transformer (ViT) architecture [22] as the backbone network and apply the widely-used pre-training scheme, Masked AutoEncoder (MAE) [23], to propose a pre-trained weather model named W-MAE for multi-variable weather forecasting. We choose the fifth-generation ECMWF Re-Analysis (ERA5) data [24] to establish our meteorological data environment. Specifically, we select data samples at six-hour intervals, where each sample comprises a collection of twenty atmospheric variables across five vertical levels, and use only two years of data for training. This necessitates two considerations during the model-building process:

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- **Spatial dependency:** Unlike traditional computer vision data, meteorological data is highly complex, and its interrelationships are not straightforward. To address this challenge, we use MAE to model twenty meteorological variables, each represented as a two-dimensional pixel field of shape 721×1440 , which contains global latitude and longitude information [25]. Notably, the size of the two-dimensional pixel image of meteorological data is nearly three times larger than the images (224×224) processed in traditional computer vision, which raises computational overheads. To optimize the modeling ability of MAE while controlling computational overheads, we modify the decoder structure by only applying self-attention [26] to the second dimension of the two-dimensional meteorological variables image.
- **Temporal dependency:** Considering the temporal dependencies in meteorological data [27], models should learn from historical data and forecast future atmospheric conditions. In this work, we fine-tune our pre-trained W-MAE to predict future states of meteorological variables.

Figure 1 shows an example of our W-MAE pre-trained on the ERA5 dataset and then fine-tuned on multiple downstream tasks. Compared with FourCastNet [28], a recent AI-based weather forecasting model, our W-MAE model exhibits significant performance advantages in predicting multiple meteorological variables. FourCastNet also employs VIT as its backbone network but replaces the attention block (included in VIT) with a Fourier transform-based token-mixing scheme [29]. Experiments are performed on the ERA5 dataset with two years of data for training, and our model outperforms FourCastNet in several meteorological variables (e.g., low-level winds and geopotential height at 500 hPa). For the more challenging precipitation forecasting task [30], our W-MAE achieves up to 10% performance improvement over FourCastNet.

To further investigate the effectiveness of pre-training, we apply our proposed method to FourCastNet still using two years of training data. Compared with FourCastNet without pre-training, pre-trained FourCastNet exhibits nearly 30% performance improvement in the task of precipitation forecasting. More significantly, pre-trained FourCastNet (two years of training data) outperforms FourCastNet without pre-training (trained on thirty-seven years of data) by almost 20% in precipitation forecasting. This suggests that applying pre-training to weather forecasting is promising.

In a nutshell, our W-MAE shows stable prediction results, and the longer the prediction time, the more evident the performance advantage of our pre-trained W-MAE. This further demonstrates the robustness of our model and the benefits of pre-training techniques. The main contributions of this work are four-fold:

- We introduce self-supervised pre-training techniques into weather forecasting tasks, enabling weather forecasting models fully mine rich meteorological-related basic features and general knowledge from large-scale, unlabeled meteorological data, and better handle heterogeneous data integration.

- We employ the ViT architecture as the backbone network and apply the widely-used pre-training scheme MAE, to propose W-MAE, a pre-trained weather model for multi-variable weather forecasting.
- By using a self-supervised pretraining and then fine-tuning process, our W-MAE can learn rich spatiotemporal dependencies inherent in meteorological data, ultimately achieving more efficient, time-saving, and labor-saving weather forecasting.
- Extensive experiments show that our model has a stable and significant advantage in short-to-medium-range forecasting.

2 Related work

In this section, we briefly review the development of weather forecasting, as well as some technologies related to our work, mainly involving numerical weather prediction, AI-based weather forecasting and pre-training techniques.

2.1 Numerical weather prediction

Numerical Weather Prediction (NWP) involves using mathematical models, equations, and algorithms to simulate and forecast atmospheric conditions and weather patterns [1]. NWP models generally use physical laws and empirical relationships such as convection, advection, and radiation to predict future weather states [31]. The accuracy of NWP models depends on many factors, such as the quality of the initial conditions, the accuracy of the physical parameterizations [32], the resolution of the grid, and the computational resources available. In recent years, many efforts have been made to improve the accuracy and efficiency of NWP models [4, 5]. For example, some researchers [33, 34] have proposed using adaptive grids to better capture the features of the atmosphere, such as the boundary layer and the convective clouds. Others have proposed using hybrid models [35] that combine the strengths of different models, such as the global and regional models [36].

2.2 AI-based weather forecasting

In recent years, there has been an increasing interest in the development of AI-based weather forecasting models. These models use deep learning algorithms to analyze vast amounts of meteorological data and learn patterns that can be used to make accurate weather forecasting. Compared with the traditional NWP models [4, 5], AI-based models [37, 38] have the potential to produce more accurate and timely weather forecasts, especially for extreme weather events such as hurricanes and heat waves. Albu *et al.* [14] combine Convolutional Neural Network (CNN) with meteorological data and propose NeXtNow, a model with encoder-decoder convolutional architecture. NeXtNow is designed to analyze spatiotemporal features in meteorological data and learn patterns that can be used for accurate weather forecasting. Karevan and Suykens [39] explore the use of Long Short-Term Memory (LSTM) network

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for weather forecasting, which can capture temporal dependencies of meteorological variables and are suitable for time series forecasting, but may struggle to capture spatial features. However, both LSTM-based and CNN-based models suffer from high computational costs, limiting their ability to handle large amounts of meteorological data in real-time applications.

Taking into account the computational costs and the need for timely forecasting, Pathak *et al.* [28] propose FourCastNet, an AI-based weather forecasting model that employs adaptive Fourier neural operators to achieve high-resolution forecasting and fast computation speeds. FourCastNet represents a promising solution for real-time weather forecasting, but it requires significant amounts of training data to achieve optimal performance and may have limited accuracy in certain extreme weather events. In this work, we apply our pre-training method to FourCastNet to explore its impact on model performance. The results show that pre-trained FourCastNet achieves nearly 20% performance improvement in precipitation forecasting, despite being trained on much less data (two years vs. thirty-seven years). This suggests that pre-training can be a feasible strategy to enhance the performance of FourCastNet and other weather forecasting models.

2.3 Self-supervised pre-training techniques

Self-supervised learning enables pre-training rich features without human annotations, which has made significant strides in recent years. In particular, Masked AutoEncoder (MAE) [23], a recent state-of-the-art self-supervised pre-training scheme, pre-trains a ViT encoder [22] by masking an image, feeding the unmasked portion into a Transformer-based encoder, and then tasking the decoder with reconstructing the masked pixels. MAE adopts an asymmetric design that allows the encoder to operate only on the partial, observed signal (i.e., without mask tokens) and a lightweight decoder that reconstructs the full signal from the latent representation and mask tokens. This design achieves a significant reduction in computation by shifting the mask tokens to the small decoder. Our W-MAE model is built upon the MAE architecture and also utilizes the ViT encoder to process unmasked image patches. However, we employ a modified decoder specifically designed to reconstruct pixels for meteorological data to reduce computational overhead.

3 Preliminaries

In this section, we provide a brief introduction to the ERA5 dataset and downstream weather forecasting tasks, as foundations for our subsequent presentation of the W-MAE model and training details.

3.1 Dataset

ERA5 [24] is a publicly available atmospheric reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The

Table 1 The abbreviations are as follows: U_{10} and V_{10} represent the zonal and meridional wind velocity, respectively, at a height of 10m from the surface; T_{2m} represents the temperature at a height of 2m from the surface; T , V , Z , and RH represent the temperature, zonal velocity, meridional velocity, geopotential, and relative humidity, respectively, at specified vertical levels; and $TCWV$ represents the total column water vapor.

Vertical level	Variables
Surface	$U_{10}, V_{10}, T_{2m}, sp, mslp$
10000 hPa	U, V, Z
850 hPa	T, U, V, Z, RH
500 hPa	T, U, V, Z, RH
50 hPa	Z
Integrated	$TCWV$

ERA5 reanalysis data combines the latest forecasting models from the Integrated Forecasting System (IFS) [40] with available observational data (e.g., pressure, temperature, humidity) to provide the best estimates of the state of the atmosphere, ocean-wave, and land-surface quantities at any point in time. The current ERA5 dataset comprises data from 1979 to the present, covering a global latitude-longitude grid of the Earth’s surface at a resolution of $0.25^\circ \times 0.25^\circ$ and hourly intervals, with various climate variables available at 37 different altitude levels, as well as at the Earth’s surface. Our experiments are conducted on the ERA5 dataset, and we use two years of data for training (2015 and 2016), one year of data for validation (2017), and one year of data for testing (2018). We select data samples at six-hour intervals, where each sample comprises a collection of twenty atmospheric variables across five vertical levels (see Table 1 for details).

3.2 Multi-variable and precipitation tasks

We focus on forecasting two important and challenging atmospheric variables (consistent with the work done on FourCastNet [28]): 1) the wind velocities at a distance of 10m from the surface of the earth and 2) the 6-hourly total precipitation. The variables are selected for the following reasons: 1) predicting near-surface wind speeds is of tremendous practical value as they play a critical role in planning energy storage and grid transmission for onshore and offshore wind farms, among other operational considerations; 2) neural networks are particularly well-suited to precipitation prediction tasks due to their impressive ability to infer parameterizations from high-resolution observational data. Additionally, our model reports forecasting results for several other variables, including geopotential height, temperature, and wind speed.

4 Pre-training method

The pre-training task is to generate representative features by randomly masking patches of the input meteorological image and then reconstructing the missing pixels. In this section, we provide a detailed description of our W-MAE

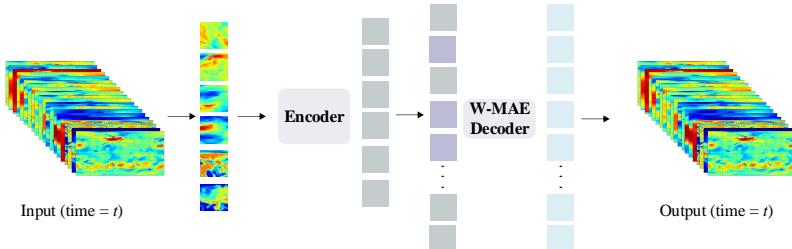


Fig. 2 Our proposed W-MAE architecture. Following the MAE framework, an input image is first divided into patches and masked before being passed into the encoder. The encoder only processes the unmasked patches. After the encoder, the removed patches are then placed back into their original locations in the sequence of patches and fed into our W-MAE decoder to reconstruct the missing pixels.

architecture, as illustrated in Figure 2. Our W-MAE employs the ViT architecture as the backbone network and applies the MAE pre-training scheme. Compared with the vanilla MAE, the proposed W-MAE uses a modified decoder structure to save computation. We formalize W-MAE in the following, by first specifying the necessary ViT and MAE background and then explaining our W-MAE decoder.

4.1 ViT and MAE

Vision Transformer (ViT) [22], with its remarkable spatial modeling capabilities, scalability, and computational efficiency, has emerged as one of the most popular neural architectures. Let $I \in \mathbb{R}^{H \times W \times C}$ denote an input image with height H , width W , and C channels. ViT differs from the standard Transformer in that it divides an image into a sequence of two-dimensional patches $\mathbf{x}_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$, where each patch has a resolution of (P, P) , resulting in $N = HW/P^2$ patches. The patches are flattened and mapped to a D -dimensional feature space using a trainable linear projection (Eq. 1). The output of this projection, referred to as patch embeddings, is then concatenated with a learnable embedding, which serves as the input sequence to the Transformer encoder. The encoder consists of alternating layers of Multi-headed Self-Attention (MSA) and Multi-Layer Perceptron (MLP) blocks (Eq. 2 and Eq. 3). The MLP block contains two fully connected layers with a GELU activation function. Layer Normalization (LN) is applied before each block, and residual connections are added. The overall procedure can be formalized as follows:

$$\mathbf{z}_0 = [\mathbf{x}_p^1 \mathbf{E}; \mathbf{x}_p^2 \mathbf{E}; \dots; \mathbf{x}_p^N \mathbf{E}] + \mathbf{E}_{pos}, \quad (1)$$

$$\mathbf{z}'_\ell = \text{MSA}(\text{LN}(\mathbf{z}_\ell - 1)) + \mathbf{z}_{\ell-1}, \quad \ell = 1 \dots L, \quad (2)$$

$$\mathbf{z}_\ell = \text{MLP}(\text{LN}(\mathbf{z}'_\ell)) + \mathbf{z}'_\ell, \quad \ell = 1 \dots L, \quad (3)$$

where $\mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}$, $\mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D}$ and L is the number of layers.

MAE is a self-supervised pre-training scheme that masks random patches of the input image and reconstructs the missing pixels. Specifically, a masking

ratio of m is selected, and m percentage of the patches is randomly removed from the input image. The remaining patches are then passed through a projection function (e.g., a linear layer) to project each patch (contained in the remaining patch sequence S) into a D -dimensional embedding. A positional encoding vector is then added to the embedded patches to preserve their spatial information, and the function is defined as:

$$v_x(pos, 2i) = \sin \frac{pos}{10000^{\frac{2i}{D}}}, \quad (4)$$

$$v_y(pos, 2i + 1) = \cos \frac{pos}{10000^{\frac{2i}{D}}}, \quad (5)$$

where pos is the position of the patch along the given axis and i is the feature index. Subsequently, the resulting sequence is fed into a Transformer-based encoder. The encoder processes the sequence of patches and produces a set of latent representations. The removed patches are then placed back into their original locations in the sequence of patches, and another positional encoding vector is added to each patch to preserve the spatial information. After that, all patch embeddings are passed to the decoder to reconstruct the original input image. The objective function is to minimize the difference between the input image and the reconstructed image. Our proposed W-MAE architecture utilizes MAE to reconstruct the spatial correlations within meteorological variables.

4.2 W-MAE decoder

Our W-MAE uses the standard VIT encoder to process the unmasked patches, as shown in Figure 2. Subsequently, all patches are fed into the W-MAE decoder in their original order. The standard MAE learns representations by reconstructing an image after masking out most of its pixels, and its decoder uses self-attention for weight matrix computation over all input patches. However, since meteorological images are approximately three times larger than typical computer vision images, using the original MAE decoder would result in a significant increase in computational resources. Therefore, our W-MAE decoder splits the input one-dimensional patch sequence into a two-dimensional patch matrix, following the shape of the two-dimensional meteorological image. As a result, our decoder only considers the relationships between patch blocks along the second dimension when performing weight computation via self-attention, greatly reducing the computational resources required while still ensuring high-quality pixel reconstruction.

Our pre-trained W-MAE enables quick convergence for task-specific fine-tuning, saving time and resources required for training models from scratch (i.e., with randomly initialized network weights).

Table 2 Number of initial conditions used for computing ACC and RMSE plots with the assumed temporal decorrelation time for the variables $Z_{500}, T_{850}, T_{2m}, U_{10}, V_{10}, TP$.

Variables	N_f	d (days)
Z_{500}	36	9
T_{850}	36	9
T_{2m}	40	9
U_{10}	178	2
V_{10}	178	2
TP	180	2

5 Experiments

In this section, we present pre-training and fine-tuning details for W-MAE. As illustrated in Figure 1, our training framework includes three stages, i.e., task-agnostic pre-training, multi-variable forecast fine-tuning, and precipitation forecast fine-tuning. We also provide visualization examples to demonstrate the performance of W-MAE on the weather forecasting tasks. Additionally, we conduct ablation studies to analyze the effect of different pre-training settings. Our MindSpore implementation code is available at <https://github.com/Gufrannn/W-MAE>.

5.1 Implementation details of task-agnostic pre-training

Given data samples from the ERA5 dataset, each sample contains twenty atmospheric variables and is represented as a 20-channel meteorological image. Our W-MAE first partitions meteorological images into regular non-overlapping patches with a patch size of 16×16 . Next, we randomly sample patches to be masked, with a mask ratio of 0.75. The visible patches are then fed into the W-MAE encoder (depth=16, dim=768), while the W-MAE decoder (depth=12, dim=512) reconstructs the missing pixels based on the visible ones. The mean squared error between the reconstructed and original images is computed in the pixel space and averaged over the masked patches. We employ the AdamW optimizer [41] with $\beta_1=0.9$ and $\beta_2=0.95$, and set the weight decay to 0.05. The pre-training process takes 600 epochs in total.

5.2 Fine-tuning for multi-variable forecasting

We perform multi-variable forecast fine-tuning on the ERA5 dataset, with the task of predicting future states of meteorological variables based on the meteorological data from the previous time-step. We denote the modeled variables as a tensor $X(k\Delta t)$, where k represents the time index and Δt is the temporal spacing between consecutive time-steps in the dataset. Throughout this work, we consider the ERA5 dataset as the ground-truth and denote the true variables as $X_{true}(k\Delta t)$. For simplicity, we omit Δt in our notation, and Δt is fixed at 6 hours. After pre-training, we fine-tune our pre-trained W-MAE still

using the ERA5 dataset to learn the mapping from $X(k)$ to $X(k + 1)$. The fine-tuning process for multi-variable forecasting takes a further 120 epochs.

To evaluate the performance of our W-MAE model on multi-variable forecasting, we perform autoregressive inference to predict the future states of multiple meteorological variables. Specifically, the fine-tuned W-MAE is initialized with N_f different initial conditions, taken from the testing split (i.e., data samples from the year 2018). N_f varies depending on the forecasting days d , which differs for each forecast variable, as shown in Table 2. Subsequently, the fine-tuned W-MAE is allowed to run iteratively for t time-steps to generate future states at time-step $i + j\Delta t$. For each forecast step, we evaluate the latitude-weighted Anomaly Correlation Coefficient (ACC) and Root Mean Squared Error (RMSE) [37] for all forecast variables. The latitude-weighted ACC for a forecast variable v at forecast time-step l is defined as follows:

$$\tilde{\mathbf{X}}_{P/T} = \tilde{\mathbf{X}}_{\text{pred/true}}(l) [v, m, n], \quad (6)$$

$$L(i) = \frac{\cos(\text{lat}(m))}{\frac{1}{N_{\text{lat}}} \sum_j^{N_{\text{lat}}} \cos(\text{lat}(m))}, \quad (7)$$

$$\text{ACC}(v, l) = \frac{\sum_{m,n} L(m) \tilde{\mathbf{X}}_P \tilde{\mathbf{X}}_T}{\sqrt{\sum_{m,n} L(m) (\tilde{\mathbf{X}}_P)^2 \sum_{m,n} L(m) (\tilde{\mathbf{X}}_T)^2}}, \quad (8)$$

where $\tilde{\mathbf{X}}_{\text{pred/true}}(l) [v, m, n]$ represents the long-term-mean-subtracted value of predicted or true variable v at the location denoted by the grid co-ordinates (m, n) at the forecast time-step l . The long-term mean of a variable refers to the average value of that variable over a large number of historical samples. The long-term mean-subtracted variables $\tilde{\mathbf{X}}_{\text{pred/true}}$ represent the anomalies of those variables that are not captured by the long-term mean values. $L(m)$ is the latitude weighting factor at the coordinate m .

The latitude-weighted RMSE for a forecast variable v at forecast time-step l is defined as follows:

$$\mathbf{X}_{P/T} = \mathbf{X}_{\text{pred/true}}(l) [i, j, k], \quad (9)$$

$$\text{RMSE}(v, l) = \sqrt{\frac{1}{NM} \sum_{m=1}^M \sum_{n=1}^N L(m) (\mathbf{X}_P - \mathbf{X}_T)^2}, \quad (10)$$

where $\mathbf{X}_{\text{pred/true}}$ represents the value of predicted or true variable v at the location denoted by the grid co-ordinates (m, n) at the forecast time-step l .

We report the mean ACC and RMSE for each of the variables at each forecast time-step and compare them with the corresponding FourCastNet forecasts that use time-matched initial conditions. Figure 3 displays the latitude-weighted ACC and RMSE values for our W-MAE model forecasts (indicated by the red line with markers) and the corresponding FourCastNet forecasts (indicated by the blue line with markers). It can be seen that

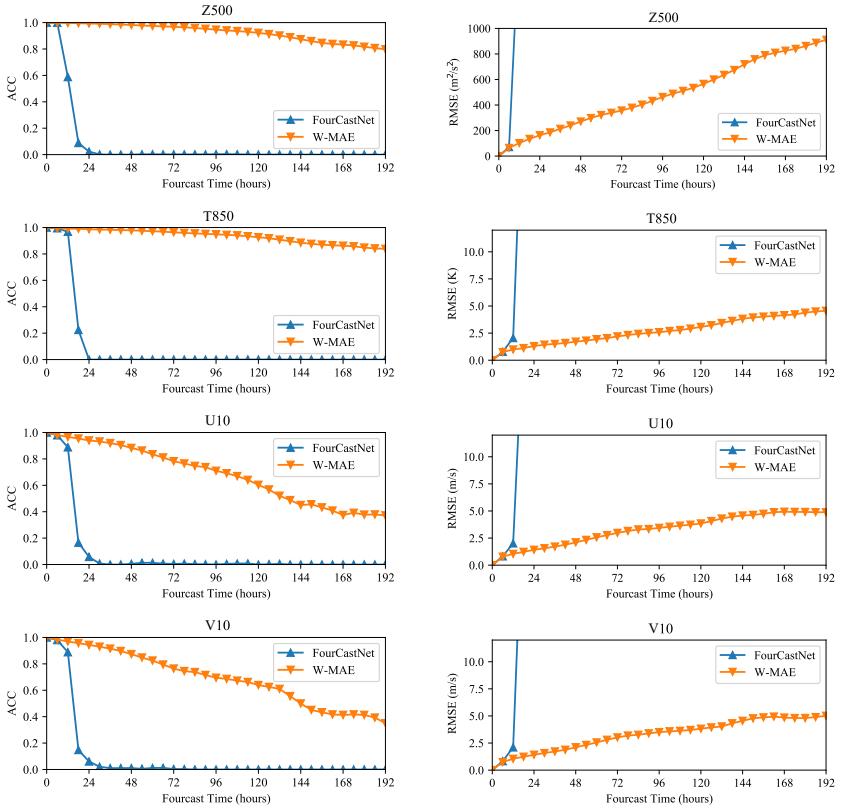


Fig. 3 Latitude weighted ACC and RMSE curves for our W-MAE forecasts and the corresponding matched FourCastNet forecasts at a fixed initial condition in the testing dataset corresponding to the calendar year 2018 for the variables, including Z_{500} , T_{850} , V_{10} , and U_{10} .

the W-MAE pre-trained on two years of data, delivers stable and satisfactory performance in forecasting the future states of multiple meteorological variables. In contrast, the performance of FourCastNet declines sharply as the forecast time-step increases (trained on two years of data). We provide some visualization examples of multi-variable forecast results in Figure 4.

5.3 Fine-tuning for precipitation forecasting

Total Precipitation (TP) in the ERA5 dataset is a variable that represents the cumulative liquid and frozen water that falls to the Earth's surface through rainfall and snowfall. Compared with other meteorological variables, TP presents sparser spatial characteristics. For the precipitation forecasting task, we aim to predict the cumulative total precipitation in the next 6 hours using multiple meteorological variables from the previous time-step. We compare the performance of our W-MAE model and FourCastNet using both ACC and RMSE as the evaluation metrics, as shown in Figure 5. Our W-MAE

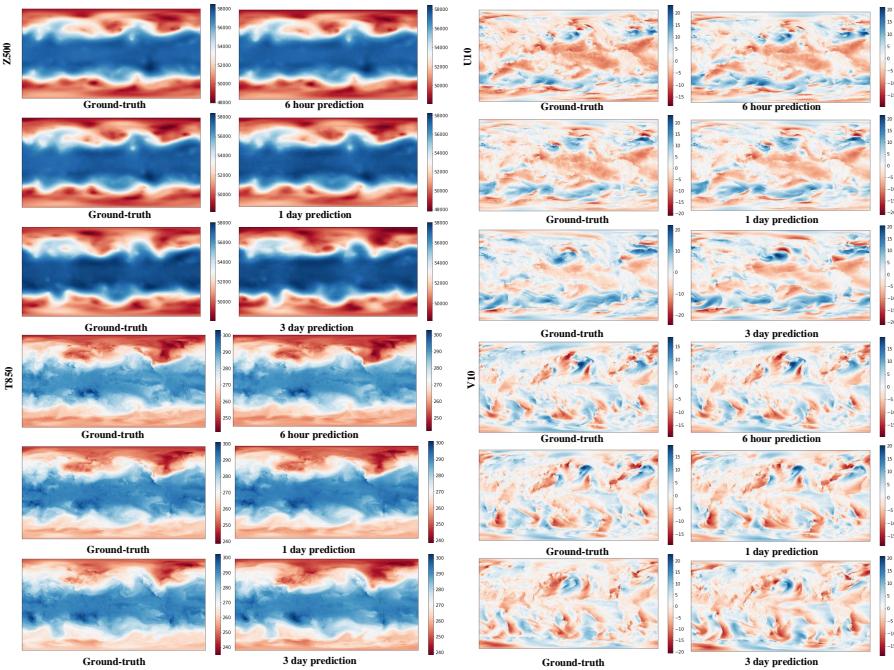


Fig. 4 Visualization examples of future state prediction for meteorological variables, including Z_{500} , T_{850} , V_{10} , and U_{10} .

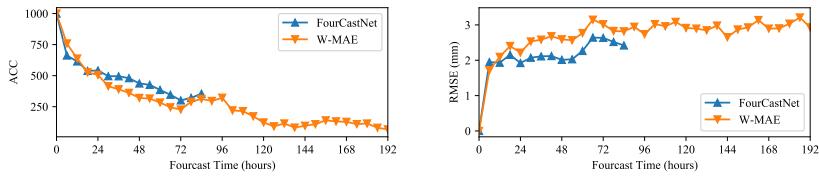


Fig. 5 Latitude weighted ACC and RMSE curves for our W-MAE forecasts and the corresponding matched FourCastNet forecasts at a fixed initial condition in the testing dataset corresponding to the calendar year 2018 for TP.

model outperforms FourCastNet in predicting the total precipitation at the 6-hour result.

5.4 Ablation study

Effect of pre-training. To fully validate the effectiveness of our method, we apply our pre-training technique to FourCastNet. During the pre-training stage, we set the patch size to 8×8 (same as that used in FourCastNet), the mask ratio to 0.75, and trained the model for 250 epochs. Then, we fine-tune the pre-trained FourCastNet for the precipitation forecasting task. We compared the performance of the pre-trained FourCastNet with that of the vanilla FourCastNet without pre-training. Our ablation results, as shown in Figure 6,

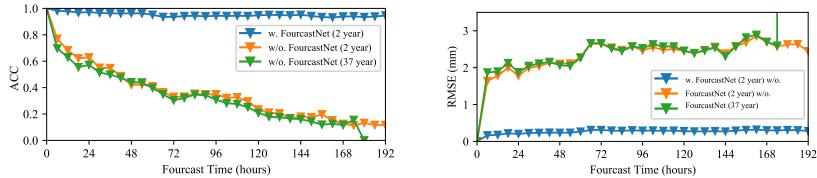


Fig. 6 Latitude weighted ACC and RMSE curves for our W-MAE forecasts and the corresponding matched FourCastNet forecasts at a fixed initial condition in the testing dataset corresponding to the calendar year 2018 for TP.

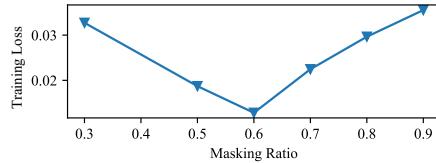


Fig. 7 Effect of masking ratio. The optimal masking ratio was found to be approximately 60%.

indicate that the pre-trained FourCastNet outperformed FourCastNet without pre-training by nearly 30% in precipitation forecasting when both were trained on two years of data. Moreover, the pre-trained FourCastNet outperformed FourCastNet without pre-training, which was trained on thirty-seven years of data, by nearly 20%. This suggests that applying pre-training to weather forecasting is promising.

Effect of masking ratio. Given the disparity in information density between meteorological images and images in computer vision, we conducted an investigation on the effect of mask ratios on meteorological image reconstruction. Specifically, the training loss under different mask ratios are compared and we set the maximum pre-training epoch to 1000. Figure 7 displays the effect of masking ratios on pixel reconstruction, with the optimal ratio found at approximately 0.6. To balance the computational efficiency and model performance, we set the mask ratio to 0.75, which is consistent with the value reported in MAE [23]. Furthermore, Figure 8 visualizes the pixel reconstruction results under varying mask ratio condition.

6 Conclusion

In this paper, we introduce self-supervised pre-training techniques to the weather forecasting domain, and propose a pre-trained Weather model with Masked AutoEncoder named W-MAE. Our pre-trained W-MAE exhibits stable forecasting results and outperforms the baseline model in longer forecast time-steps. This demonstrates the robustness of the proposed W-MAE and the benefits of the pre-training techniques. Our study also provides insights for modeling longer-term dependencies (ranging from a month to a year) in the tasks of climate forecasting [42, 43]. We hope that our work will inspire

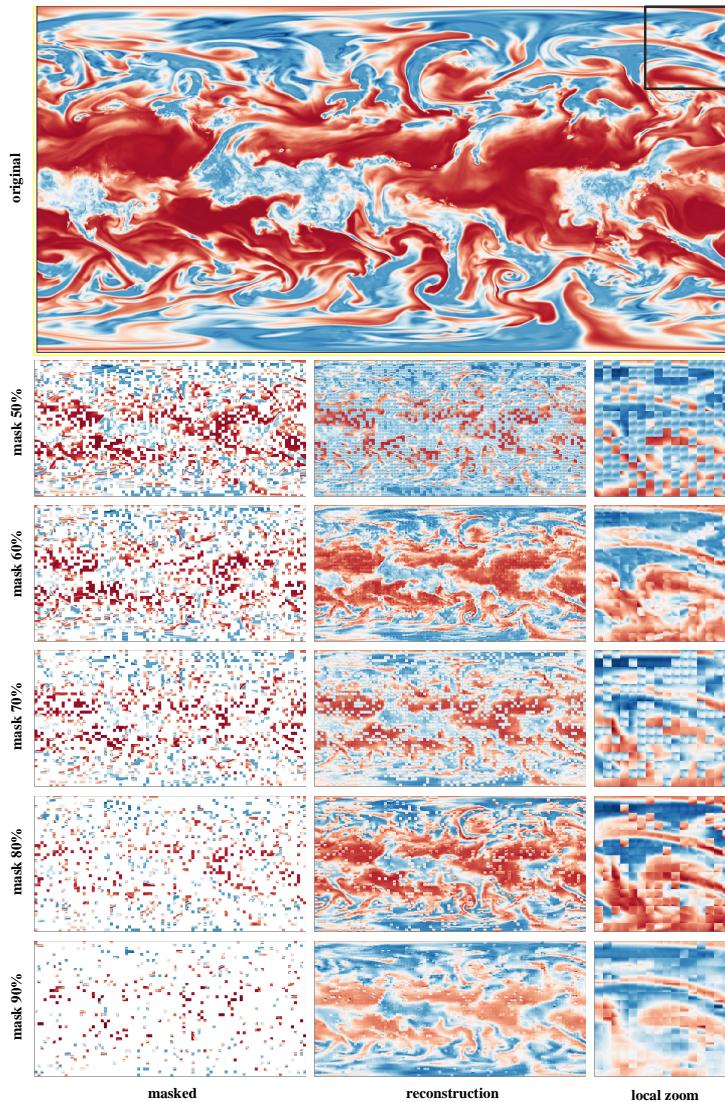


Fig. 8 Visualization of the pixel reconstruction results under varying mask ratio condition. The ‘local zoom’ column displays the magnified results of the local area wrapped by the black box in the original images.

future research on the application of pre-training techniques to a wider range of weather and climate forecasting tasks.

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