A Review of Super resolution Technology for Extended-Range Precipitation Forecasting

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***Abstract*—In the field of meteorology, precipitation holds significant importance for human activities and environment. Extended-range precipitation forecasting, covering a timeframe of weeks to months, is crucial across various sectors, including water resource management, agriculture, and disaster prevention. However, the conventional meteorological forecasting models often fail to satisfy the precise demand for accurate and detailed precipitation predictions due to the inherent limitations in resolution and data collection frequency associated with these methods.**

Recently, super resolution technology has emerged as a promising solution with the potential to transform the resolution of meteorological data. By leveraging advanced algorithms and computational prowess, this technology can generate high-resolution images from low-resolution inputs. In this comprehensive review, we meticulously dissect the state-of-the-art super resolution techniques utilized in extended-range precipitation forecasting tasks. By classifying and analyzing the literature based on various methodologies, including convolutional neural networks (CNNs), generative adversarial networks (GANs), and diffusion models, we uncover their performance characteristics, strengths, and limitations. Our in-depth exploration reveals that while these methods have shown promise, they also face significant challenges. For example, CNNs struggle with capturing ultrafine details, GANs exhibit training instability, and diffusion models require further optimizations in terms of their computational efficiency.

Future research efforts should focus on enhancing model architectures, seamlessly incorporating physical constraints to ensure the physical consistency of the generated data, and optimizing the current data utilization strategies. Furthermore, it is crucial to develop comprehensive evaluation metrics, conduct extensive long-term and regional validation studies, and establish effective uncertainty quantification methods. Additionally, the seamless integration of super resolution forecasts into practical applications such as decision support systems for flood prevention and water resource management, as well as their applications in climate change studies, will be pivotal for unlocking the full potential of this technology and addressing the longstanding challenges faces in precipitation forecasting scenarios.

Keywords—Super resolution technology; Extended-range precipitation forecasting; CNNs; GANs; Diffusion models

I. Introduction

Precipitation is an important meteorological variable with profound impacts on various facets of human life and the environment [1]. Extended-range precipitation forecasting, which entails predicting rainfall amounts over a timeframe of weeks to months, plays a crucial role in various domains including water resource management, agriculture, and disaster prevention [1-2]. Nevertheless, the traditional meteorological forecasting models frequently falter in meeting the need for precise and detailed precipitation forecasts due to the inherent limitations in resolution and data collection frequency associated with these methods.

In recent years, super resolution technology has emerged as a promising solution for increasing the resolution of meteorological data [3-6]. By leveraging advanced machine learning algorithms and robust computational power, these techniques can generate high-resolution images or datasets from low-resolution inputs. This methodology holds the potential to substantially improve the accuracy and reliability of precipitation forecasts, especially in extended-range cases.

The application of super resolution technology in meteorology has been driven by the need to better understand and predict complex weather patterns. With the increasing availability of high-resolution satellite and ground-based observational data, as well as the continuous development of computational capabilities, it has become possible to explore the utilization of super resolution techniques in precipitation forecasting scenarios [3, 6]. This review aims to provide a comprehensive overview of the current state-of-the-art super resolution technology for extended-range precipitation forecasting, highlighting the different algorithms and techniques that have been proposed and their effectiveness in enhancing forecast accuracy.

Furthermore, this review delves into the challenges and limitations associated with the application of super resolution technology in precipitation forecasting tasks, encompassing data quality concerns, computational complexity issues, and the necessity for precise physical models. By tackling these obstacles, future research can concentrate on creating more resilient and efficient super resolution models that can more accurately capture the intricate spatial and temporal patterns of precipitation.

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Overall, the application of super resolution technology in extended-range precipitation forecasting situations holds immense potential for enhancing our comprehension and prediction of precipitation patterns [7]. Consequently, this advancement can facilitate more informed decision-making across various domains, ultimately aiding in the mitigation of extreme weather impacts and the efficient management of water resources.

II. Literature Review

In this section, we conduct a comprehensive review of the literature pertaining to the application of super resolution technology in precipitation forecasting, categorizing the relevant studies based on the techniques they utilize.

A. *CNN-Based Superresolution Methods for Precipitation Forecasting*

Convolutional neural networks (CNNs) have been extensively employed in super resolution tasks due to their capacity to learn intricate spatial patterns. Within the realm of precipitation forecasting, CNNs can be trained to enhance low-resolution precipitation data, thereby improving the precision of forecasts.

1) Weather4cast Challenge and the Related Studies

The Weather4cast 2022 NeurIPS competition was a pioneering machine learning challenge dedicated to advancing research on the application of machine learning techniques in high-resolution weather forecasting. During this competition, numerous studies delved into various precipitation forecasting methods. Notably, Li et al. [5] leveraged 3D U-Nets and EarthFormers to forecast rainfall using satellite data. They sought to tackle the challenges associated with precipitation prediction by effectively leveraging the synchronous-scale and mesoscale background information of variables in the visible, near-infrared, water vapour, and infrared bands. In the initial stage of the competition, which involved determining the presence of rain, they experimented with several neural network models, including U-Nets (U-Net, 3D U-Net, and U2Net), recurrent neural network (RNNs) (convolutional long short-term memory (ConvLSTM) and Trajectory GRU (trajGRU), and transformers (the Swin Transformer and EarthFormer). For the second stage, which involved predicting rainfall events with a rainfall rate threshold of 0.2 mm, they used 3D U-Nets and EarthFormers to conduct 8-hour probabilistic rainfall forecasts. Additionally, researchers employed multimodel integration with threshold optimization to generate the final probabilistic rainfall predictions. As shown in Fig 1, the 3D U-Net model consists of five encoder blocks, four decoder blocks and one output block. The encoder blocks perform 2-fold down sampling and include a 3D convolutional layer, a maximum pooling layer, a BatchNorm layer, a rectified linear unit (ReLU) activation function, and a Dropout3d layer. The decoder module consists of 3D convolutional layers, layers that are unsampled via transposed convolution, BatchNorm and a ReLU activation function. Convolutional layers of different depths enable the extraction of spatial features at different resolutions, which is crucial for precipitation prediction because of the multiscale nature of weather phenomena [8]. As shown in Fig 2a, EarthFormer is a hierarchical transformer codec based on cuboid attention. The cuboid attention layer consists of three steps: 'Decompose', 'Attend', and 'Merge', as shown in Fig 2b. The “Decompose” step decomposes the input spatiotemporal tensor into cuboid sequences; ‘Attend’ applies self-attention within each cuboid attention layer parallel to the overlapping cuboid sequences from the decomposition step; and “Merge” merges the cuboid sequences obtained after completing the attention step back into the original input shape to obtain the final cuboid attention output.

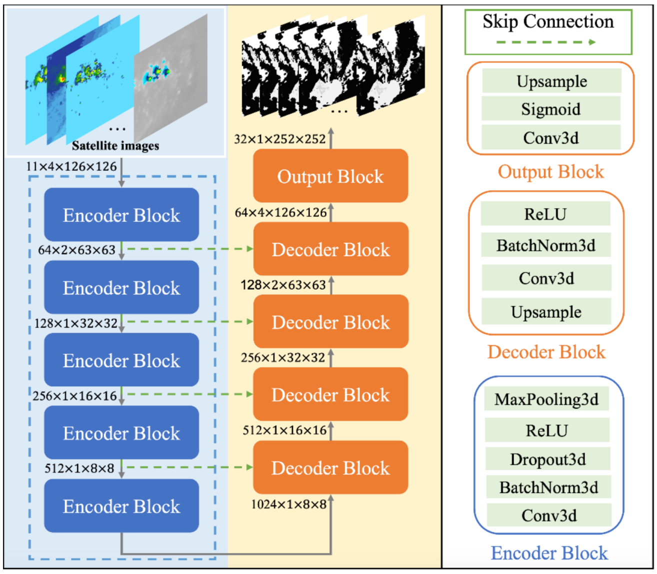

Fig 1. Illustration of the 3D U-Net model. The 3D U-Net model consists of five encoder blocks, four decoder blocks, one output block and skip connections [5].

The results of their study revealed that both 3D U-Net and EarthFormer exhibited commendable predictive prowess in scenarios featuring continuous and extensive precipitation. However, they encountered challenges in accurately forecasting localized, small-scale precipitation, particularly when dealing with longer lead times (e.g., 3 hours later). The study concluded that for shorter lead times (within 2 hours), an input spatial context that was equal to the target context (42×42) yielded better performance, whereas for longer lead times (3-8 hours), an input spatial context that was three times larger than the target context (126×126) was more favorable. This finding highlights the importance of considering different spatial and temporal scales in precipitation prediction tasks and the need for further explorations to determine the optimal input contexts for different lead times. Additionally, the authors put forth the notion that mesoscale and local-scale information are crucial for scenarios with brief lead times. In comparison, larger weather-scale and mesoscale information is necessary for situations with longer lead times [5]. Upon comparing rainfall forecasts generated across diverse durations, the authors noted that none of the models effectively anticipated localized, small-scale precipitation, especially over extended forecasting horizons. Upon comparing rainfall forecasts generated across diverse durations, the authors noted that none of the models effectively anticipated localized, small-scale precipitation, especially over extended forecasting horizons.

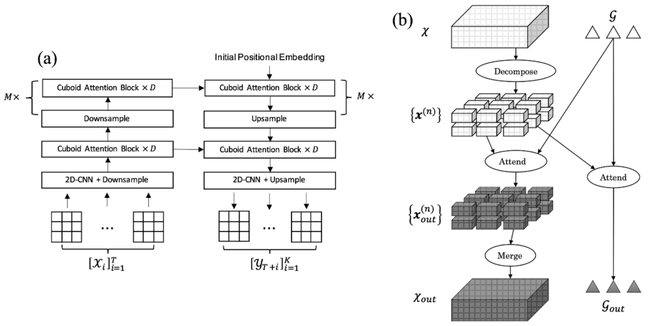

Fig 2. Illustration of (a) the EarthFormer architecture and (b) the cuboid attention layer with global vectors. The EarthFormer is a hierarchical transformer encoder-decoder that is based on cuboid attention. The input sequence has a length if T, and the target sequence has a length of K. "×D" denotes stacking D cuboid attention blocks with residual connections. "×M" represents the case with M layers of hierarchies [5].

Similarly, Moran et al. [6] also participated in this competition, introducing a physics-aware ConvLSTM network integrated with a U-Net architecture. They utilized coarser-resolution meteorological satellite images as inputs to predict high-resolution rainfall occurrences. As illustrated in Figure 3, the ConvLSTM network was designed to capture the temporal dynamics of those satellite images, while the U-Net architecture facilitated spatial upscaling. The results of their study demonstrated that SR-PhyDNet outperformed the baseline 3D U-Net model in rainfall event prediction tasks. It achieved better scores in terms of recall, precision, the F1 score, and the critical success index and the intersection over union. Furthermore, the predicted rainfall maps exhibited significantly reduced visual artefacts, underscoring the efficacy of the proposed method in generating more accurate and visually pleasing precipitation forecasts. While satellite data-driven deep learning models cannot replace weather radar-derived rainfall measurements, they are well-suited for precipitation prediction in areas lacking ground-based instruments [6]. This study emphasized the potential of CNNs in handling precipitation prediction tasks and showcased the advantage of incorporating physical constraints into the model to enhance its performance.

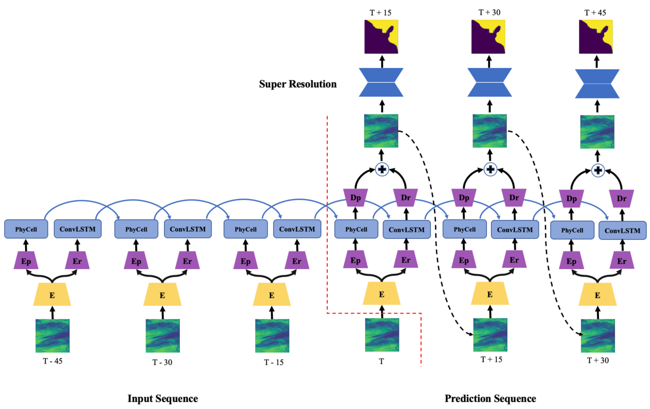

Fig 3. Overview of the SR-PhyDNet architecture proposed for satellite image sequence prediction, superresolution and segmentation tasks. The input consists of satellite images, and a binary mask (with rain in yellow and no rain in purple) is the output [6].

2) ESM Data Downscaling Using CNNs

A notable study by Pawar et al. [9], published in the realm of Energy Exascale Earth Systems Model (E3SM) data downscaling]. They evaluated five different CNN-based super resolution models, namely, the super resolution CNN (SRCNN), the fast super resolution CNN earth system model (FSRCNN-ESM), the efficient subpixel CNN (ESPCNN), the enhanced deep residual network (EDRN), and the super resolution GAN (SRGAN). The SRCNN model uses double cubic interpolation on its inputs and adopts a shallow structure [10]. In contrast, both the FSRCNN and ESPCNN techniques use coarse-resolution images directly as their inputs [11]. The also employs coarse-resolution images, but it features a deep architecture with skip connections to retain important features from earlier layers [10]. Lastly, the SRGAN architecture consists of a generator and a discriminator, where the generator uses coarse-resolution inputs to generate fine-resolution outputs [10]. The E3SM dataset, utilizing paired monthly data of fine-resolution (0.25°) and coarse-resolution (1°), served as the foundation for training and validation. Evaluation was conducted using various metrics, encompassing Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), LPIPS, and Absolute Percentage Error (APE). The results showed that the EDRN exhibited excellent performance in terms of the PSNR, SSIM, and MSE, indicating its proficiency in generating high-quality super-resolved images with minimal errors. However, it struggled to capture intricate details present in the data. Conversely, SRGAN, a generative model incorporating a perceptual loss, demonstrated an exceptional ability to capture fine details of boundaries and internal structures, evident from its lower LPIPS value compared to other methods. This demonstrated SRGAN's capacity to generate images that are perceptually closer to the ground truth. This comprehensive comparison provided valuable insights into the strengths and weaknesses of different CNN-based models for ESM data downscaling and precipitation forecasting, guiding future research in selecting the most suitable models for specific applications.

B. GANs-Based Superresolution Methods for Precipitation Forecasting

Generative adversarial networks (GANs) have also shown great potential for use in super resolution applications, where GAN-based super-resolution models typically excel over CNN-based models in numerous super-segmentation tasks, both in terms of performance and downscale range. A GAN consists of a generator and a discriminator that are adversarial trained to generate high-quality, high-resolution images. Below are some precipitation forecasting methods that leverage GANs.

1) SRGAN for Precipitation Data Downscaling

Kumar et al. [12] conducted a comparison of the SRGAN with other deep learning approaches, including the stacked SRCNN, U-Net, ConvLSTM, and DeepSD, for the purpose of precipitation data downscaling. The results indicated that the SRGAN outperformed the other methods, achieving a correlation coefficient of 0.8806, which was higher than that of U-Net (0.8399), ConvLSTM (0.8311), and DeepSD (0.8037). The SRGAN was capable of generating more precise and intricate precipitation patterns, thereby enhancing the resolution of the data and potentially refining the output precipitation forecasts.

2) Physics-Informed SRGAN

Oyama et al. [13] introduced two variants of SRGAN: the physics-informed SRGAN (πSRGAN) and the ψSRGAN. The πSRGAN incorporates a low-resolution pressure field and topographic information as auxiliary inputs to achieve high-resolution temperature and precipitation downscaling with a factor of up to 50. As shown in Fig 4, the πSRGAN demonstrated comparable performance to the traditional CDFDM method in terms of basic statistical properties, such as precipitation probability density functions (PDFs). Furthermore, this method significantly enhanced the accuracy achieved when reproducing the natural spatial distribution of the precipitation correlation coefficient, which was a limitation of the conventional methods. However, the πSRGAN relies on topographic information that is specific to the training area, leading to a lack of generalizability, as evidenced by inferior performance in a generalization test where the downscaling computation area was shifted.

The ψSRGAN, which solely utilizes low-resolution temperature and pressure data to generate high-resolution temperature and precipitation fields, surprisingly exhibited excellent downscaling performance in the precipitation field, particularly in regions like Shizuoka where pressure plays a pivotal role in determining precipitation. This indicates the robust ability of SRGAN-based methods to express natural results, even in cases with limited input information.

Overall, the GAN-based methods examined in this study offer the advantage of generating more realistic and intricate precipitation patterns, as evidenced by their ability to capture fine structures such as localized heavy rain events. The integration of physical information into the πSRGAN enhances the physical consistency of its outputs. However, the generalization issue needs to be addressed before more broadly applying these models, and the computational cost and stability issues faced during training are also potential challenges that need to be considered in future research.

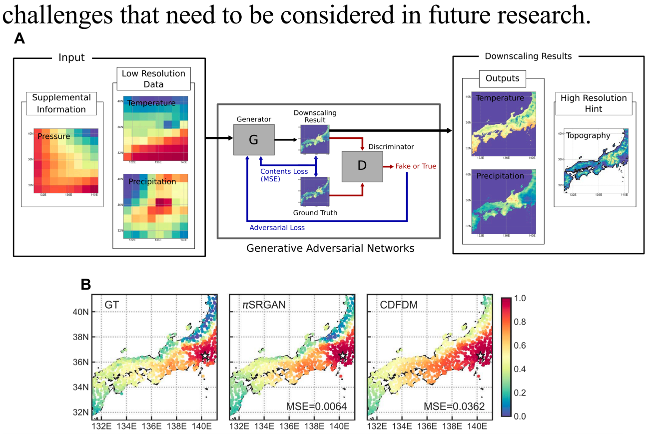

Fig 4. Schematic diagram of the πSRGAN and the spatial correlation coefficient distribution. (A) High-resolution topography and low-resolution sea-level pressure data, in addition to the low-resolution data corresponding to the output, are supplied to GANs. (B) The reconstructed distributions of the spatial correlation coefficients, indicating the correlation strength with the reference site in Tokyo [35.735°N, 139.6683°E], obtained via the πSRGAN and a conventional CDFDM are compared with the ground truth (GT) [13].

C. *Diffusion Models for Performing Superresolution in Precipitation Forecasting Tasks*

Diffusion models have recently emerged as powerful approaches in the field of super resolution, particularly in the context of weather data analysis. Their capacity to capture intricate patterns and detailed information has garnered significant attention.

1) *SR3 and ResDiff Models*

In a study conducted by Martin° et al. [4], the SR3 and ResDiff architectures were used for the super resolution of weather data, with a specific focus on the 2-m humidity variable. SR3 [14] , the pioneering diffusion model for super-resolution tasks, operates by iteratively refining image details to yield high-resolution outputs. This study provided a foundation for exploring the potential of diffusion models to enhance the resolution of meteorological data.

The ResDiff model [15], which is an enhanced version of SR3, combines a CNN with an improved diffusion model. Several innovative techniques have been introduced for this model. As shown in Fig. 5, for example, the high-frequency guided diffusion technique was designed to better capture and reconstruct fine details that are often crucial aspects of weather data, where small-scale variations can have significant implications. Additionally, the frequency-domain information splitting technique, which uses a two-dimensional fast Fourier transform (FFT) to process interpolated and noisy images, enables the model to directly analyses and handle the frequency components of the input image data. This approach provides a deeper understanding and manipulation of the spectral characteristics of the data, potentially leading to more accurate reconstruction results.

In the implemented experimental setup, the Weather Bench dataset was used, and the evaluation was carried out via metrics such as the MSE, SSIM, and PSNR. The study's results unequivocally demonstrated that SR3 was less effective than ResDiff. ResDiff was capable of generating more precise and detailed high-resolution images of the 2-meter humidity variable, providing a superior representation of atmospheric conditions. This demonstrated the importance of the enhancements made in ResDiff, causing it to be superior to the basic SR3 model.

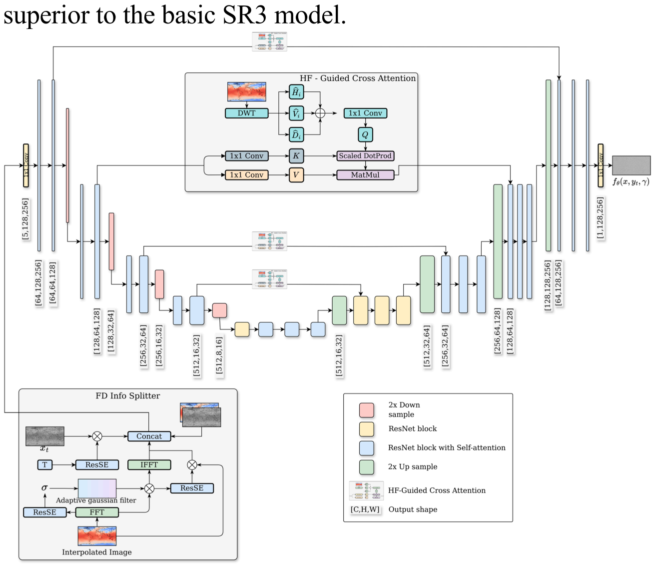

Fig 5. Architecture of the ResDiff model used for climate variable downscaling [4].

2) *ResDiff+Physics Model*

Another variant of SD3 is ResDiff+Physics [4], which integrates physically inspired convolutional filters. By doing so, it is able to focus on features that are related to fluid motion and atmospheric dynamics, which are essential components of weather systems. The integration of physical knowledge into the model marked a significant advancement, as it improved its capacity to produce results that are more consonant with the underlying physical processes governing the atmosphere.

When comparing ResDiff and ResDiff+Physics, ResDiff+Physics exhibited better performance in terms of most evaluation metrics, except for the PSNR. The incorporation of physical constraints into ResDiff+Physics enabled it to better capture the intricate relationships and dynamics within weather data, resulting in more reliable and physically coherent results.

The primary strength of these diffusion models lies in their capacity to capture intricate details and complex patterns in weather data, which is crucial for precise precipitation forecasting. By leveraging the power of diffusion processes, they can generate high-resolution outputs that potentially provide more accurate representations of the atmosphere. However, a potential drawback is the relatively high computational cost associated with training and implementing these models. The iterative nature of diffusion models, combined with the complexity of techniques such as the frequency-domain processing scheme in ResDiff, can necessitate substantial computational resources. This may limit their practical application in scenarios where computational power is limited or real-time processing is required.

In conclusion, diffusion models, especially when enhanced with physical knowledge such as in ResDiff + Physics, offer great potential for enhancing the resolution and quality of meteorological data. Future research could focus on further optimizing these models to reduce their computational costs and improve their performance under different weather conditions and in different regions.

D. Other Related Studies

Apart from the aforementioned mainstream super-resolution techniques rooted in CNNs, GANs, and diffusion models, several studies have delved into alternative or complementary methodologies for extended-range precipitation forecasting, each presenting its own distinct advantages and constraints.

1) Pattern-Based Forecasting Methods

Mastrantonas et al. [1] adopted a pattern-based approach, focusing on the Mediterranean region. They conducted an in-depth analysis of the relationship between large-scale atmospheric flow patterns and extreme precipitation events (EPEs). ERA5 [16], the latest ECMWF reanalysis dataset for 1979-2020, was used here as a reference dataset. ERA5 provides approximately 137 30 km × 30 km vertical horizontals in a horizontal grid at an hourly resolution from the surface up to an altitude of 80 km. In addition, the rainfall resolution of this dataset is 0.25° × 0.25°, and the rainfall data were generated from the ECMWF extension period model. The authors identified nine distinct atmospheric flow patterns by performing an empirical orthogonal function (EOF) analysis and K-means clustering on historical meteorological data. By leveraging the ECMWF model to predict these patterns and meticulously analyzing their associations with historical EPEs, they indirectly predicted the likelihood of future EPEs. The results showed that the ECMWF model effectively represented the Mediterranean region, with no significant deviation exhibited by its climatic frequency, even when advancing it by 44 days. In addition, a comparison with the available accuracy data showed that indirectly forecasting EPEs via predictive models can provide skillful forecasts up to 10 days in advance for many areas of the Mediterranean Sea [1]. This approach offers a novel perspective by emphasizing the significance of large-scale patterns in medium- and extended-range precipitation forecasting scenarios. The study provided profound insights into the potential precursors of extreme precipitation, which could be invaluable for early warning systems. However, it did not directly predict precipitation amounts, and the accuracy of the forecasts may have been contingent upon the reliability and temporal stability of the identified patterns.

2) Data-Driven Models

Araújo et al. [3] proposed a data-driven model (DDM) [17] leveraging long-term memory networks (LSTMs) for extreme precipitation prediction in southeastern Brazil, along with a method based on data mining (DM) techniques to forecast extreme rainfall events. They integrated a comprehensive set of reanalysis data, including isobaric-level, ground, and meteorological station data. The model aimed to identify and capture the atmospheric patterns associated with extreme rainfall events and subsequently predict future rainfall events on the basis of the historical patterns. The developed methodology demonstrated the possibility of using reanalysis data derived from global mathematical models to obtain regional models with lower computational costs [2]. One of the notable advantages of this DDM is its ability to handle entire time series without the need for elaborate preprocessing steps, thereby streamlining the prediction process. Additionally, it holds the potential to serve as a valuable decision support tool. Nevertheless, the model is not without its limitations. It lacks spatial abstraction capabilities, which means that it may not be directly applicable to different regions without significant modifications. Moreover, its performance is highly dependent on the historical data used for training, and the lack of a large amount of diverse data may limit its generalizability.

III. Future Works

The applications of super resolution technology in extended-range precipitation forecasting scenarios have shown great promise, but several areas still require further exploration and enhancement.

A. Model Improvements

Enhanced Network Architectures: More advanced CNNs, GANs, and diffusion models should be developed to more accurately capture the intricate spatial and temporal patterns of precipitation. This could involve deeper networks, novel layer designs, or improved connections between different components.

Incorporation of Physical Constraints: Physical knowledge should be more comprehensively integrated into super-resolution models to guarantee the physical consistency of the generated high-resolution precipitation data. This could involve the use of better representations of atmospheric processes, such as convection, advection, and evaporation in the developed models.

Multimodal and Multiscale Fusion: Different data sources and models should be combined to leverage the strengths of component. For example, satellite data can be fused with ground-based observations, or multiple super resolution models with different resolutions and characteristics can be integrated to improve the accuracy and reliability of precipitation forecasts.

B. Data Utilization

Big Data and High-Resolution Data: As high-resolution satellite and ground-based observational data become increasingly available, methods should be developed to effectively handle and use these extensive datasets. This may necessitate the development of advanced data preprocessing techniques, effective data compression methods, and distributed computing strategies to manage the associated computational demands.

Data Augmentation: More advanced data augmentation techniques should be explored to increase the diversity and quantity of training data. This could improve the generalizability of models and reduce overfitting, especially in regions with limited data availability.

Real-Time Data Integration: Systems that can integrate real-time observational data into super resolution models should be developed to enable more timely and accurate precipitation forecasts. This requires efficient data transmission, processing, and assimilation techniques.

C. Evaluation and Validation

Comprehensive Evaluation Metrics: A more extensive suite of evaluation metrics should be developed that encompasses not only traditional measures like accuracy and correlation but also the physical characteristics and practical applications of precipitation forecasts. For example, the ability of models to predict extreme precipitation events, spatial patterns, and temporal variability can be evaluated.

Long-Term and Regional Validations: More extensive long-term and regional validation studies should be conducted to assess the performance and stability of super resolution models across various climate regions and seasons. This will aid in identifying the limitations and applicability of different models and improving their robustness.

Uncertainty Quantification: Methods should be developed to quantify the uncertainty associated with super resolution precipitation forecasts. This will provide users with more information about the reliability of forecasts and help decision-makers make more informed decisions.

D. Applications and Impacts

Decision Support Systems: Super resolution precipitation forecasts should be integrated into decision support systems for various applications, such as flood prevention, water resource management, and agriculture. User-friendly interfaces and tools that can help stakeholders easily access and utilize forecast information should be developed.

Climate Change Studies: Super resolution technology should be applied to study the impact of climate change on precipitation patterns at finer spatial and temporal scales. This could improve our understanding of climate change mechanisms and lead to the development of more effective adaptation and mitigation strategies.

Cross-Disciplinary Research: Encouraging cross-disciplinary research among meteorology, computer science, mathematics, and other relevant fields can foster the advancement and implementation of super resolution technology in precipitation forecasting scenarios, potentially yielding novel insights and solutions to address the challenges in this domain.

IV. Conclustion

This review comprehensively analyzed the applications of super resolution technology in extended-range precipitation forecasting scenarios. We categorized the existing research based on various techniques, including CNNs, GANs, and diffusion models, and discussed their performance, strengths, and limitations. CNN-based methods, exemplified by SR-PhyDNet and the EDRN, have exhibited impressive capabilities in processing precipitation data, achieving promising outcomes across diverse applications. GANs, particularly the SRGAN and its variants, have demonstrated the ability to generate high-quality, detailed precipitation patterns. Diffusion models, such as SR3 and ResDiff, have the potential to capture complex atmospheric details. However, each method also encounters challenges. CNNs may struggle to capture extremely fine features, GANs may exhibit instability during training, and diffusion models require additional optimization to improve their computational efficiency and reduce time costs. Future work should prioritize enhancing model architectures, integrating more physical constraints, and making more effective use of data. Moreover, comprehensive evaluations and validations, as well as the integration of super resolution forecasts into practical applications, are crucial for the development and application of this technology. In summary, super resolution technology holds great promise for improving the accuracy and resolution of extended-range precipitation forecasts, which has significant implications for various fields related to weather and climate.

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