Retrieving 3D Humidity Profiles from FY-2F Geostationary Satellite Infrared Images Using a Deep Learning Fusion Model

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Abstract

Obtaining high-resolution three-dimensional atmospheric humidity profiles remains a major challenge for improving numerical weather prediction and global environmental monitoring. This study proposes a deep learning-based method to directly retrieve three-dimensional humidity profiles from infrared images of the Fengyun-2F (FY-2F) geostationary satellite. First, the reliability of the official FY-2F humidity product as a training target was validated using radiosonde data. Subsequently, we developed an end-to-end CNN-Transformer hybrid model that takes dual-channel IR2 and IR3 images as input and outputs three-dimensional relative humidity fields across six pressure levels (1000–400 hPa). The results indicate that the model performs excellently in the middle and upper atmosphere (700–400 hPa), with average correlation coefficients exceeding 0.93 and R^2 exceeding 0.84; however, in the lower atmosphere (e.g., R^2=0.35 at 925 hPa), performance is limited due to satellite sensitivity constraints and near-surface complexity. The model maintains low error (MAE of 0.01–0.05%) and high computational efficiency, demonstrating its potential for operational, near-real-time humidity monitoring within the Digital Earth framework.

Full Text

Preamble

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Abstract

Acquiring high-resolution 3D atmospheric humidity profiles remains a major challenge for improving numerical weather prediction and global environmental monitoring. This study proposes a deep learning-based method to retrieve 3D humidity profiles directly from FY-2F geostationary satellite infrared images. First, radiosonde data validated the reliability of the official FY-2F humidity product as training targets. We then developed an end-to-end CNN-Transformer hybrid model that takes dual-channel IR2 and IR3 images as input and outputs 3D relative humidity fields across six pressure levels (1000–400 hPa). Results show excellent performance in the mid-to-upper atmosphere (700–400 hPa), with an average correlation coefficient >0.93 and R^2 >0.84, while performance is limited in the lower atmosphere (e.g., $R^2 = 0.35$ at 925 hPa) due to satellite sensitivity constraints and near-surface complexity. The model maintains low error (MAE 0.01–0.05%) and high computational efficiency, demonstrating its potential for operational, near-real-time humidity monitoring within Digital Earth frameworks.

Keywords

FY-2F satellite; deep learning; humidity retrieval; infrared remote sensing; artificial intelligence; digital earth; geostationary satellite; operational monitoring; climate services

1.Introduction Accurate, high-resolution three-dimensional monitoring of atmospheric humidity is essential for advancing global Earth system science and operational environmental services[1]. As the primary carrier of latent heat and a key driver of phase changes in water vapor[2], the three-dimensional distribution of humidity fundamentally governs cloud microphysical processes[3], convective initiation, and precipitation formation[4].

Obtaining such profiles with high spatiotemporal resolution is therefore critical not only for improving numerical weather prediction[5], but also for enhancing large-scale

environmental monitoring, disaster early warning, and climate adaptation strategies[6].

However, persistent limitations in conventional observational systems hinder the achievement of continuous, high-fidelity 3D humidity monitoring, which in turn constrains the development of integrated, data-driven Earth observation platforms—a core pursuit within the Digital Earth paradigm[7].

Atmospheric humidity serves as the direct carrier of water vapor phase changes and latent heat release, and its three-dimensional distribution plays a decisive role in cloud microphysical processes, convective initiation, and precipitation formation.

Acquiring high spatiotemporal-resolution three-dimensional atmospheric humidity profiles is not only essential for improving the accuracy of numerical weather

prediction initial fields and optimizing water vapor parameterization, but also central to understanding the evolution mechanisms of mesoscale convective systems.

Especially in short-term nowcasting, real-time and accurate humidity data can significantly enhance convective predictability, and is crucial for predicting the location and intensity of precipitation. However, due to limitations in the spatiotemporal coverage and detection capabilities of existing observational methods, achieving high-resolution, continuous three-dimensional monitoring of atmospheric humidity fields remains a major technical challenge.

Currently, operational meteorological observations primarily rely on three data sources: ground-based stations, weather radars, and satellite remote sensing. However, each exhibits significant limitations. Ground-based observations lack sufficient spatial representativeness; radars cannot directly provide vertical profiles of temperature, humidity, and pressure; and satellite radiance observations require complex physical inversion processes to convert into atmospheric parameters, introducing uncertainties and limiting their direct application in numerical weather prediction. Effectively integrating these multi-source heterogeneous observational datasets to construct a temporally continuous, spatially coherent, and physically consistent three-dimensional atmospheric initial field[8] remains a critical bottleneck to be overcome in the field of data assimilation[9].

In recent years, artificial intelligence technologies represented by deep neural networks have provided novel solutions to the aforementioned challenges[10]. Deep learning, capable of autonomously learning complex nonlinear mapping relationships from massive datasets, has demonstrated significant potential in the field of meteorology[11]. Studies have shown that satellite image recognition models based on convolutional neural networks can effectively extract features related to atmospheric states, such as cloud system structure and texture, and have achieved excellent

performance in applications like short-term precipitation nowcasting and convective initiation warning[12]. Unlike traditional retrieval methods that rely heavily on prior physical assumptions[13], deep learning can establish an end-to-end mapping from raw satellite radiance observations to atmospheric physical quantities[14], substantially simplifying data processing workflows and opening new pathways for the real-time operational application of satellite data[15].

The Fengyun-2F (FY-2F) satellite, as a geostationary meteorological platform[16], provides multi-channel observational data that serve as a rich information source for retrieving atmospheric parameters[17]. Among its channels, the IR2 band (11.5–12.5 μm) is sensitive to cloud-top height and temperature[18], while the IR3 band (6.3–7.6

μm) primarily responds to atmospheric water vapor radiation within the 600–300 hPa layer[19]. The secondary Humidity Profile (HPF) product[20] released by the China Meteorological Administration offers a reliable data foundation for training and validating deep learning models[21].

To this end, this study proposes a deep learning-based intelligent retrieval method for FY-2F infrared remote sensing imagery[22], aiming to achieve rapid and accurate acquisition of atmospheric humidity profiles[23]. A two-stage technical approach is adopted: First, high-precision radiosonde data are used as a benchmark to systematically evaluate the reliability of the HPF product[24], thereby confirming its suitability as a training target. Subsequently, a hybrid architecture integrating convolutional neural networks and Transformer modules is constructed to establish an end-to-end mapping from dual-channel infrared images to 3D relative humidity fields.

This approach circumvents the complex radiative transfer calculations and parameterization processes inherent in traditional physical retrievals, offering a novel technical pathway for the in-depth development and operational application of Fengyun satellite data.

2. Experimental Design and Model Description

2.1. Data Sources and Preprocessing

This study employs a systematic, scalable data pipeline designed to support future integration into multi-source Digital Earth monitoring platforms. Two types of observational data were utilized: (1) high-precision radiosonde data from the University of Wyoming, serving as an independent validation benchmark; and (2) FY-2F geostationary satellite infrared data, used as model inputs and training targets.

This dual-source approach ensures robustness and aligns with the multi-sensor integration paradigm commonly adopted in Digital Earth infrastructures.

Validation Data: Radiosonde Observations.The global radiosonde dataset released

University

Wyoming

(accessible

at: https://weather.uwyo.edu/upperair/sounding.shtml) was adopted. This dataset provides accurate vertical profiles of temperature, pressure, and humidity with a temporal resolution of 12 hours[25]. For this study, radiosonde station data from the period July 1 to September 30, 2021, spatiotemporally matched with FY-2F observations, were selected [2] to serve as the "ground truth" for evaluating the accuracy of the official FY-2F Humidity Profile Product (HPF)[26].

Satellite Remote Sensing Data: FY-2F Observations. Hourly observational data from the FY-2F geostationary satellite during the same period (July 1 to September 30, 2021) were used, including:

Raw infrared radiance images: IR2 channel (11.5–12.5 μm) and IR3 channel (6.3-7.6 μm), with a spatial resolution of approximately 5 km.

Secondary product: The officially released Humidity Profile Product (HPF)[27].

This product is generated based on a physical retrieval algorithm[28] and provides vertical distributions of relative humidity at six standard pressure levels (1000, 925, 850, 700, 500, and 400 hPa) from the surface up to approximately 400 hPa[29].

Data Preprocessing Pipeline. To ensure spatiotemporal consistency, the following preprocessing steps were implemented: (1) Spatiotemporal Matching: Radiosonde data were strictly matched with satellite observations in time and space. Nearest-neighbor interpolation was applied to resample the point-based radiosonde data onto a unified grid. (2) Normalization: Infrared images were normalized to eliminate scale effects. (3) Quality Control: Observations with satellite zenith angles greater than 60° were excluded. (4) Dataset Splitting: The data were randomly divided into training and test sets in a 7:3 ratio, ensuring independence in both temporal and spatial distributions for each set.

2.2. Model Architecture

To meet the specific requirements of retrieving three-dimensional atmospheric humidity fields from two-dimensional infrared images, this study designed a hybrid deep learning architecture that integrates a Convolutional Neural Network (CNN) with a Transformer encoder. The architecture adopts an encoder-decoder paradigm,

aiming to simultaneously extract local texture features from satellite imagery and capture large-scale spatial dependencies.

The model takes the preprocessed dual-channel FY-2F IR2 and IR3 images (dimensions: H × W × 2) as input. Through three stages—feature extraction, spatial relationship modeling, and three-dimensional reconstruction—it directly outputs a three-dimensional relative humidity field across six standard pressure levels (6 × H × W). This end-to-end design achieves a direct mapping from raw satellite images to a three-dimensional physical quantity field, circumventing the complex intermediate

physical parameterization processes inherent in traditional methods.

hybrid architecture. Conv2d(C, L) denotes a two-dimensional convolutional layer, where C is the number of output channels and L is the number of vertical layers.

As illustrated in Figure 1 [Figure 1: see original paper], the proposed model follows an encoder–Transformer module–decoder architecture. The encoder begins with a 7$×$7 convolutional layer to extract fundamental spatial features. This is followed by four sequential blocks, each consisting of "Convolution (Conv2d) →

Activation Function (ReLU) → Pooling (MaxPool2d)" , which progressively expand the receptive field and compress the spatial dimensions, thereby capturing cloud system structural features from local to regional scales. To model large-scale spatial dependencies associated with moisture transport, a Transformer encoder module is incorporated. This module employs a feedforward neural network to apply nonlinear transformations to the attention outputs. Residual connections and layer normalization are utilized throughout to ensure training stability and facilitate gradient flow.

2.3. Model Training and Evaluation

The model was implemented based on the PyTorch framework. The training process was configured as follows:

Optimizer: The Adam optimizer was employed, with an initial learning rate set to 0.001.

Learning Rate Scheduling: A ReduceLROnPlateau strategy was adopted to adaptively adjust the learning rate: when the validation loss did not decrease for 30 consecutive epochs, the learning rate was multiplied by a factor of 0.5. This adaptive scheduling strategy enhances training efficiency by monitoring the validation loss and automatically reducing the learning rate if no improvement is observed over 30

training epochs, thereby facilitating finer convergence towards the optimal solution.

The model was trained for approximately 300 epochs, with each epoch covering the entire training dataset, and a batch size of 32.

Loss Function: The training objective is to minimize the difference between the predicted humidity field and the HPF product. The Mean Squared Error (MSE) was selected as the loss function. MSE is more sensitive to larger prediction errors, effectively driving the model to prioritize correcting significant deviations. Its computational efficiency and smooth gradient properties also contribute to stable training.

Evaluation Metrics: Model performance was evaluated using the Mean Absolute Error (MAE). This metric measures the average absolute difference between predicted and actual values, offering intuitive physical interpretability. MAE is less sensitive to outliers in the data and provides a more robust reflection of the model' s overall accuracy under complex atmospheric conditions. =

(− ,)2

Formulation 1 defines the error calculation used as the Mean Squared Error (MSE), where N represents the total number of samples, yi is the true humidity value of the i-th sample (from the HPF product), and ysimu,i is the corresponding simulated value from the model.

Evaluation Metrics. To comprehensively assess model performance, the following metrics were applied for validation on an independent test set: (1) Mean Absolute Error (MAE)

=

− , =1

(2) Root Mean Squared Error (RMSE) =

(3) Correlation Coefficient (CC)

(− ,)2

=1 (−)(, −)

=1 (−)

(4) Coefficient of Determination (R2)

2 = 1 −

=1 (, −)

=1 (− ,) =1 (−)

where y denotes the sample mean of the true humidity values, and y simu,i is the sample mean of the simulated values.

These metrics collectively evaluate the model' s performance from four dimensions: error magnitude, error distribution, linear correlation, and model explanatory power.

3.1. Validation with Radiosonde Data

To verify the accuracy of the FY-2F humidity profile product, radiosonde data were used to extract relative humidity (RH) values at corresponding pressure levels, and the distributions of RH from both sources were compared.

As shown in Figure 2a [Figure 2: see original paper], the warm-colored portion represents the RH distribution from FY-2F at 500 hPa, while the cool-colored portion represents the RH distribution from radiosonde observations. The red smooth curve denotes the smoothed FY-2F RH results, and the gray smooth curve denotes the smoothed radiosonde RH results. It can be observed from the figure that the radiosonde RH exhibits stronger fluctuations.

Assuming the smooth curves represent the mean states, the radiosonde curve shows considerable deviation from its mean. In contrast, the FY-2F RH distribution converges more closely around the mean, which is likely attributable to the mean regression processing inherent in the generation of this secondary product.

In the figure, red bars indicate errors within 2%, green bars represent errors between 2% and 4%, and gray bars correspond to errors between 4% and 6%.

The results indicate that the RH differences between the radiosonde data and FY-2F are confined

within $±$8%, suggesting that the errors between the two datasets are within an acceptable range.

FY-2F-based distribution, while cool colors represent the radiosonde-based distribution. (b) Distribution of RH errors, calculated as radiosonde RH minus FY-2F RH.

These results demonstrate that the FY-2F RH product can effectively capture the overall RH characteristics at the 500 hPa level, confirming the feasibility of using the FY-2F humidity profile product as target training data.

3.2. Validation of Model Retrieval Results

In operational meteorological practice, while the FY-2F satellite can acquire infrared remote sensing images in real time, its humidity profile product (HPF) typically undergoes multi-stage verification before release, resulting in a certain time lag that may cause it to miss the forecast validity window. To enhance short- to medium-term weather forecasting capabilities, this study adopts the HPF product as the target and employs a deep learning model trained on infrared imagery to achieve rapid retrieval of atmospheric humidity fields, thereby providing robust support for real-time weather prediction.

Prior to training, the target data were divided into training and test sets, with the training subset used for model development. In this section, samples from the test set are selected to validate the model' s performance.

the test case. (b) FY-2F humidity profile product (HPF) result at 700 hPa. (c) Humidity distribution at 700 hPa simulated by the neural network model. (d) Difference between (b) and (c).

700 hPa level. Panel (a) shows the FY-2F satellite IR2 channel infrared image, which reflects the distribution characteristics of cloud systems. Panel (b) displays the relative humidity distribution from the HPF product at 700 hPa. Panel (c) illustrates the 700 hPa relative humidity field retrieved by the model. Panel (d) shows the difference distribution between the retrieval results and the HPF product. It can be observed that the model effectively captures the humidity distribution characteristics at the 700 hPa level, with differences predominantly confined within $±$8%, indicating that the model exhibits good retrieval consistency at this altitude.

humidity profile product. (b) RH distribution simulated by the neural network model. (c) Difference between (a) and (b).

distribution of humidity retrieved by the model (Fig. 4b [Figure 4: see original paper]) shows high consistency with the HPF product (Fig. 4a) in terms of overall trend, with differences in the vast majority of regions controlled within

$\pm$8%. This further validates the feasibility of the model for humidity retrieval in the mid-to-upper atmosphere.

In this study, both the training dataset and the test set were constructed from randomly sampled sequences during the training phase. To facilitate statistical analysis, 21 data groups were sequentially selected from the test set, corresponding to the following timestamps: 00:00 UTC on July 1, 2021; 02:00 on July 2; 06:00 on July 4; 14:00 on July 5; 11:00 on July 6; 04:00 on July 7; 21:00 on July 8; 03:00 on July 10;

07:00 on July 11; 11:00 on July 12; 05:00 on July 14; 02:00 on July 15; 22:00 on July 16; 05:00 on July 18; 05:00 on July 19; 13:00 on July 20; 20:00 on July 21; 20:00 on July 22; 23:00 on July 23; 04:00 on July 26; and 04:00 on July 27, 2021.These data will be used for further analysis to evaluate the overall performance of the model.

coefficient between the neural network model simulation and the FY-2F humidity profile product. (b) Mean Absolute Error (MAE) between the neural network model simulation and the FY-2F humidity profile product.

To further quantify model performance, Figure 5 [Figure 5: see original paper] presents the spatial correlation coefficient (Fig. 5a) and the mean absolute error (Fig. 5b) for the test set at the 500 hPa level. The spatial correlation coefficient exceeds 0.8 in most regions, with some areas surpassing 0.9. The mean absolute error is predominantly below 0.06, reaching 0.06–0.12 only in localized areas. These results indicate that the model achieves high retrieval accuracy and stability at this level.

Pressure Level (hPa)

Sample Size

MAE (%)

RMSE (%)

R2 Score

400hPa 500hPa

700hPa 850hPa 925hPa 1000hPa

different pressure levels. In the mid-to-upper atmosphere (400–700 hPa), the mean correlation coefficient exceeds 0.93, and the R^2 score is above 0.84, indicating that the model possesses excellent explanatory power and retrieval accuracy for humidity fields in these layers. In contrast, in the near-surface layers (850–1000 hPa), particularly at the 925 hPa level, the R^2 score drops significantly (only 0.35), reflecting the limited capability of satellite remote sensing to detect low-level water

vapor and the complexity of near-surface processes, which constrain the model' s ability to capture humidity variations in these layers. Nonetheless, the mean absolute error (MAE) across all layers is controlled within 0.01–0.05%, demonstrating that the model maintains a good overall error control capability.

4.1. Vertical Variation in Retrieval Performance

The results of this study demonstrate that the deep learning model based on FY-2F dual-channel infrared images exhibits significant height dependency in atmospheric humidity retrieval. In the mid-to-upper atmosphere (400–700 hPa), the model achieves excellent retrieval performance ($R^2 > 0.84$), whereas in the near-surface layer (850–1000 hPa), its explanatory capability markedly declines ($R^2 = 0.35$–0.57). This discrepancy may stem from the following reasons. First, the IR3 channel (6.3-7.6 μm) of the FY-2F satellite primarily responds to water vapor radiation within the 600–300 hPa layer, exhibiting higher spectral sensitivity to moisture distribution in the mid-to-upper atmosphere but limited direct detection capability for near-surface water vapor. Second, the near-surface atmosphere is influenced

multiple

complex

processes,

including

surface

radiation,

boundary-layer turbulence, and local circulation. The strong nonlinearity and spatiotemporal heterogeneity of these processes increase the difficulty of modeling the mapping relationship from satellite radiances to humidity fields.

4.2. Comparison with Traditional Retrieval Methods

Compared to traditional physical retrieval methods based on radiative transfer equations, the deep learning model proposed in this study offers the following advantages. First, it establishes an end-to-end mapping from raw satellite images to

three-dimensional humidity fields, bypassing complex intermediate physical parameterization processes. Second, this end-to-end training approach significantly reduces the modeling difficulty for real-time retrieval of remote sensing data, facilitating operational applications. Third, the model can autonomously extract deep semantic features from infrared images—such as cloud type and texture—which are often challenging to leverage effectively in conventional methods. However, the deep learning model also exhibits clear limitations: its performance is highly dependent on the quality and representativeness of the training data, and performance degradation may occur under weather conditions outside the coverage of the training dataset.

4.3. Potential for Operational Meteorological Applications

The model' s strong performance in the mid-to-upper atmosphere not only supports numerical weather prediction but also holds significant potential for global atmospheric monitoring within Digital Earth applications. For instance, the near-real-time humidity fields generated by our model could be integrated into global disaster risk reduction platforms (e.g., flood and drought early warning systems) and contribute to Sustainable Development Goal (SDG) 13 (Climate Action) by improving climate monitoring capabilities. Furthermore, the efficient inference design enables deployment on cloud-based geospatial platforms, facilitating scalable environmental surveillance. (1) For short-term nowcasting, the model can rapidly generate mid-to-upper atmospheric humidity fields, offering valuable references for monitoring convective initiation and development. Notably, humidity distribution at the 700 hPa level holds significant indicative value for precipitation forecasting, and the model achieves an excellent R^2 score of 0.84 at this level. (2) In data assimilation systems, the deep learning model can serve as an effective complement to traditional physical retrieval methods. In cloud-covered regions where conventional approaches often fail, the deep learning model can leverage structural information from cloud imagery to provide reasonable estimates of moisture distribution. (3) For operational implementation, the model' s efficient inference capability enables it to meet real-time operational demands. Combined with the high-frequency observations from the FY-2F satellite (hourly), the model can deliver near-real-time atmospheric humidity monitoring products.

4.4. Limitations and Future Prospects

This study has several limitations. First, the training data cover only the period

from July to September 2021, which may limit the model' s seasonal generalizability due to insufficient seasonal representation. Second, the model inputs are confined to the dual-channel IR2 and IR3 data, leaving other spectral information underutilized.

Additionally, the physical interpretability of the model remains to be improved.

Future research could focus on the following directions: collecting multi-seasonal data to enhance model robustness; integrating multi-channel and multi-satellite observations to improve information utilization; incorporating physical constraints into the model to enhance its physical consistency and interpretability; and exploring technical pathways for integrating deep learning retrieval results into numerical weather prediction assimilation systems.

5.1. Summary

This study systematically developed a novel deep learning-based method for retrieving three-dimensional atmospheric humidity profiles from FY-2F infrared remote sensing images. To address the complexity and low computational efficiency of traditional physical retrieval algorithms, an end-to-end deep learning model integrating convolutional neural networks and Transformer modules was constructed.

The model achieves direct intelligent mapping from dual-channel infrared satellite images to relative humidity fields across six standard pressure levels from 1000 to 400 hPa.

5.2. Key Findings

Through systematic validation and analysis, this study draws the following conclusions: (1) The model demonstrates excellent retrieval performance in the mid-to-upper atmosphere (400–700 hPa), with mean correlation coefficients of 0.93–0.94 and R^2 scores exceeding 0.84, indicating its ability to accurately capture moisture distribution characteristics at these heights. (2) Performance is relatively limited in the near-surface layer (850–1000 hPa), particularly at the 925 hPa level where R^2 is only 0.35. This is primarily due to the satellite' s limited sensitivity to low-level moisture and the complexity of near-surface atmospheric processes. (3) Compared to traditional physical retrieval methods, the proposed model maintains low error levels (MAE 0.01–0.05%) while offering significant

computational efficiency advantages, making it suitable for real-time operational applications.

5.3. Research Significance

The contributions of this study are threefold: Theoretically, it validates the effectiveness and applicability of deep learning in meteorological remote sensing retrieval. Methodologically, it proposes a CNN-Transformer hybrid architecture, offering a new approach for retrieving spatially correlated atmospheric parameters.

Practically, it provides a feasible technical solution for the operational development of FY-2F satellite data and real-time humidity monitoring, with positive implications for improving short-term nowcasting and numerical weather prediction capabilities.

In summary, this study advances the integration of artificial intelligence with geostationary

satellite

remote

sensing,

providing

scalable

solution

three-dimensional atmospheric humidity retrieval within the Digital Earth paradigm. The proposed CNN-Transformer hybrid model not only demonstrates technical feasibility but also offers a practical pathway toward operational, global-scale humidity monitoring. By enhancing the usability of Fengyun satellite data, this work contributes to smart Earth observation systems, supports climate-related

decision-making,

aligns

international

efforts

toward sustainable environmental governance. Future work will focus on extending this framework to multi-satellite, multi-seasonal scenarios to further strengthen its role in Digital Earth infrastructure.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author. The data are not publicly available due to data copyright issues.

Conflicts of Interest: The authors declare no conflicts of interest.

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Note: Figure translations are in progress. See original paper for figures.