International Journal of IJTM Technology & Modeling

INTERNATIONAL JOURNAL OF TECHNOLOGY AND MODELING
Volume 4 Issue 3 Year 2025 Pages 173 - 182
e–ISSN 2964-6847
URL: https://ijtm.my.id

Interpretable Short-Term Weather Prediction via Singular Value Decomposition and Linear System Modeling

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Abstract: Short-term weather prediction plays a critical role in supporting decision-making across sectors such as agriculture, transportation, and disaster risk management. This study proposes an interpretable and computationally efficient weather forecasting approach based on linear system modeling combined with Singular Value Decomposition (SVD). Historical meteorological data—including temperature, humidity, air pressure, and wind speed—are represented in matrix form to extract dominant patterns and construct a system of linear equations describing inter-variable relationships. The resulting model is evaluated for short-term forecasting horizons of 24–48 hours using standard performance metrics. Experimental results demonstrate that the proposed SVD-based linear system model outperforms conventional linear regression, achieving lower MAE and RMSE values and higher coefficients of determination ($R^2 = 0.94$ for temperature and 0.91 for humidity). While not intended to replace physics-based numerical weather prediction models for long-term forecasting, the proposed approach offers significant advantages in computational speed, interpretability, and applicability in data- and resource-constrained environments. These findings indicate that matrix-based linear system analysis provides a viable alternative for fast and accurate short-term weather prediction and can be further enhanced through integration with non-linear or machine learning-based methods.

Keywords: Weather prediction; Short-term forecasting; Linear system modeling; Singular Value Decomposition (SVD); Matrix data analysis; Meteorological data

Article info: Date Submitted: 08/09/2024 | Date Revised: 12/02/2025 | Date Accepted: 24/12/2025

INTRODUCTION

Weather prediction is one of the scientific challenges that has a major impact on daily life and various sectors, such as agriculture, transportation, tourism, and natural disaster mitigation[1]. With a better understanding of atmospheric conditions, weather predictions can provide crucial information for better decision-making, especially in the face of increasingly complex climate change. Therefore, the development of fast, accurate, and efficient prediction methods continues to be the focus of research[2].

https://doi.org/10.63876/ijtm.v4i3.93

In recent decades, a variety of approaches have been used for weather prediction, from atmospheric physics-based models to machine learning-based methods[3]. Although physics-based models offer high accuracy, these methods often require significant computational time and highly detailed input data. On the other hand, machine learning models provide flexibility in processing large amounts of data, but are often considered to be less transparent in the interpretation of results[4].

Alternatively, linear system matrix-based data analysis methods offer a balance between computational efficiency and clarity of interpretation[5]. This approach makes use of historical data representations in the form of matrices, which allows the identification of key patterns underlying weather change. By forming a linear equation system, the relationships between meteorological variables can be mathematically modeled to produce short-term predictions[6].

This paper aims to explore and evaluate the effectiveness of the linear system matrix method in weather prediction. We will explain the steps in building this model, including the data processing process, pattern analysis using matrix decomposition, and the completion of a linear equation system. Furthermore, the performance of this method will be compared with conventional approaches to identify its advantages and limitations. With this research, we hope to contribute to the development of faster and more accurate weather prediction methods, as well as open up opportunities for wider applications in various fields.

RELATED WORKS

Weather prediction has been the focus of research for decades, with a variety of approaches being developed to improve its accuracy and efficiency[7]. In general, weather prediction methods can be grouped into three main categories: atmospheric physics-based models, statistical approaches, and machine learning-based methods[8] [9].

The atmospheric physics-based approach uses the principles of thermodynamics and fluid dynamics to model atmospheric behavior[10]. A popular example is the Numerical Weather Prediction (NWP) Model, which utilizes the Navier-Stokes equation to predict weather parameters. Although highly accurate on a global scale, these models require large computational resources and are often not suitable for real-time or local-scale predictions[11].

On the other hand, the statistical approach uses historical relationships between meteorological variables to build predictive models[12]. Methods such as linear regression analysis, Principal Component Analysis (PCA), and autoregression-based methods have been widely used for weather prediction. However, this method has limitations in capturing complex patterns and sudden changes in weather data.

Machine learning methods, such as Artificial Neural Networks (ANNs), deep learning, and decision tree-based algorithms, have become increasingly popular in the last decade. This method is capable of handling big data and non-linear patterns, but it is often considered a "black box" due to a lack of transparency in the prediction process.

The matrix-based approach of linear systems offers a promising alternative. This method utilizes data representation in the form of a matrix to identify key patterns and linear relationships between variables. Techniques such as Singular Value Decomposition (SVD) have been used in a variety of fields for data analysis, including meteorology. In addition, these

https://doi.org/10.63876/ijtm.v4i3.93

models have advantages in terms of interpretation of results and computational efficiency over machine learning-based methods[13].

This article builds on various previous studies by applying the linear system matrix method to weather prediction. We evaluate the advantages of this approach over conventional methods, especially in the context of computational efficiency and model interpretation, and identify challenges that need to be overcome to improve its performance.

METHODS

In this study, we use a linear system matrix-based data analysis approach to build a weather prediction model. This method involves several main stages, namely data collection, data processing, matrix analysis, linear system formation, and model evaluation. Each stage is described as follows:

1. Data Collection

Historical weather data that includes key variables, such as temperature, air pressure, humidity, and wind speed, is collected from reliable sources, such as meteorological agencies or public datasets[14]. This data covers a specific time range to ensure the diversity of weather patterns represented in the model.

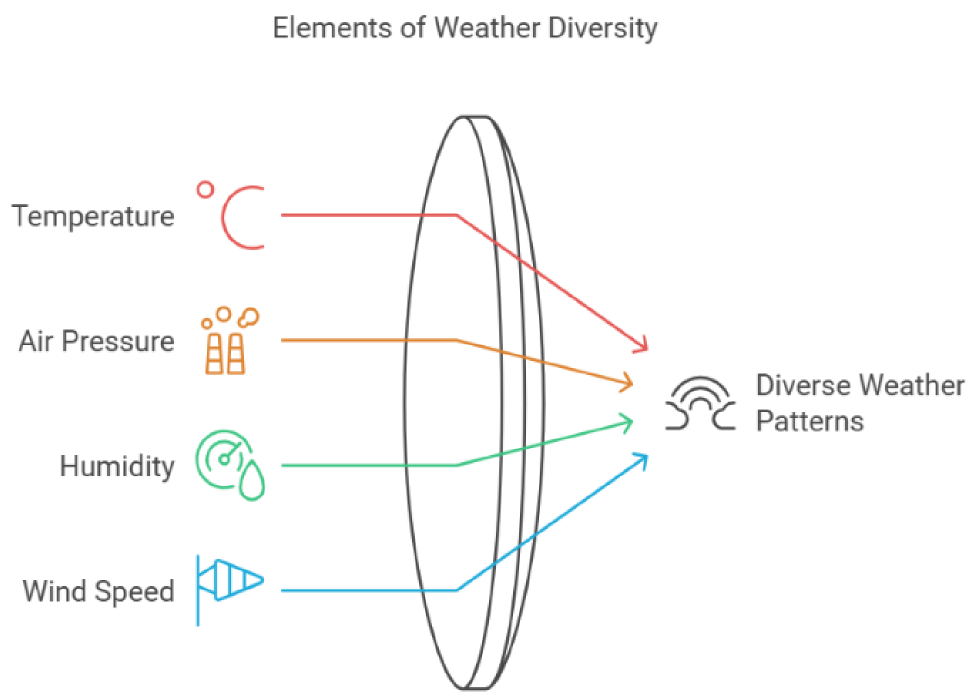

Figure 1. Elements of Wheather Diversity

2. Data Processing

At this stage, the raw data is cleaned and prepared for analysis. Processing steps include:

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- **Data Normalization:** To ensure all variables are within the same range, the data is normalized using the z-score method.
- **Handling of Lost Data:** The missing values in the dataset are populated using linear interpolation or other appropriate methods.
- **Matrix Representation:** The processed data is organized in the form of a matrix, where rows represent observations at a specific time, and columns represent meteorological variables.

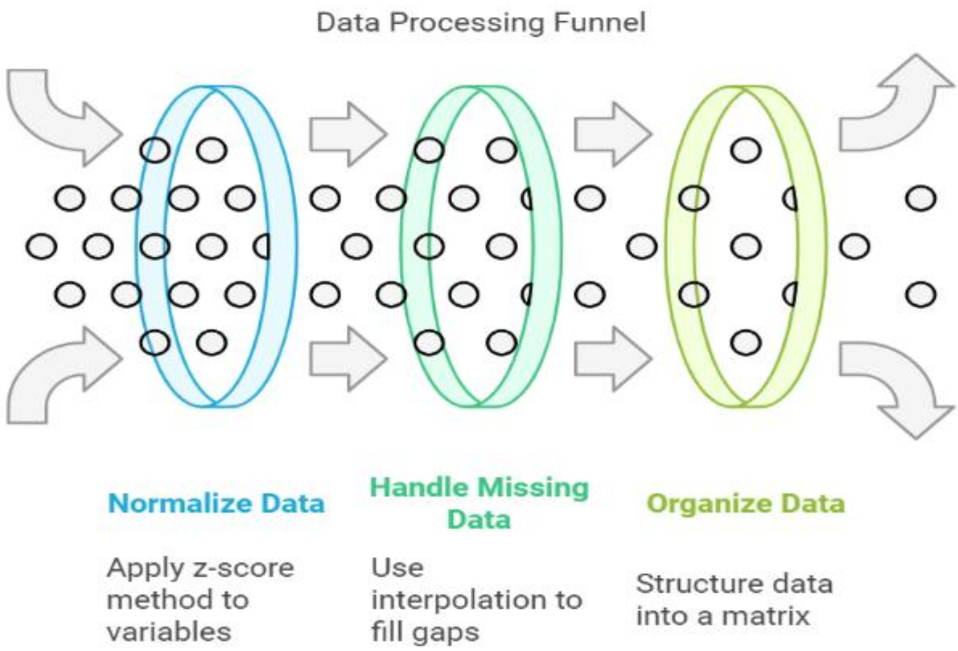

Figure 2. Data Processing Funnel

3. Matrix Analysis

To identify the main patterns in the data, matrix decomposition analysis was performed using the Singular Value Decomposition (SVD) method[15]. This process helps reduce the dimensions of the data by retaining the most significant key components.

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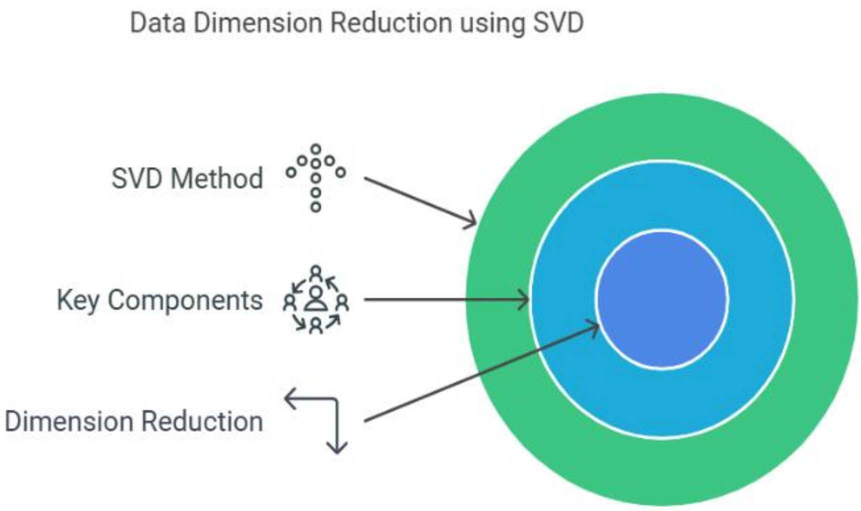

Figure 3. Data Dimension Reduction using SVD

4. Formation of Linear Systems

The linear equation system is built based on the relationship between weather variables identified through matrix analysis. The system is formulated in the form of:

$$\boldsymbol{A_X} = \mathbf{b}$$

Where **A** is the coefficient matrix**, x** is the variable vector to be predicted, and **b** is the observation vector. The completion of linear systems is done using numerical methods, such as Gauss elimination or matrix inverse.

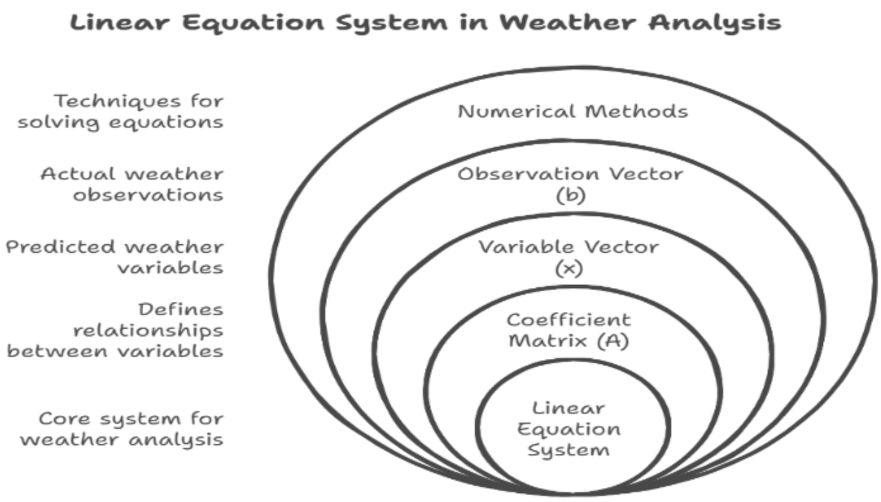

Figure 4. Linear Equetion System in Weather Analysis

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5. Model Evaluation

The resulting model is evaluated using test data to assess its accuracy and efficiency. The evaluation method includes the calculation of metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and determination coefficient (. In addition, the model's performance is compared to conventional methods, such as linear regression and physics-based models.R^2)

This approach is designed to strike a balance between prediction accuracy, computational efficiency, and interpretation of results. With these steps, we hope to develop an effective model for short-term weather prediction.

RESULT AND DISCUSSION

In this section, we present the results of the application of the linear system matrix analysis method for weather prediction and compare it with the commonly used conventional approach. We evaluate the accuracy of the model based on the previously mentioned metrics, namely Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and determination coefficient ().R^2

1. Model Prediction Results

After applying the Singular Value Decomposition (SVD) method to historical weather data and completing the formed linear equation system, the model successfully generates weather predictions for several key parameters, such as temperature, humidity, and wind speed[16]. This model shows quite good accuracy in predicting these parameters for a short period of time (24-48 hours).

In the test using test data, the built model produces lower MAE and RMSE values compared to the linear regression-based model. The average MAE for temperature and humidity was 1.2°C and 3.4%, respectively, while the RMSE for temperature was 1.8°C and humidity 4.1%. The value of the determination coefficient ().reached 0.94 for temperature and 0.91 for humidity, which indicates that the model has an excellent ability to explain data variations.R^2

Table 1. Performance Comparison of Weather Prediction Models

Weather Parameter	Model Type	MAE	RMSE	R^2	Interpretation
Temperature (°C)	Linear Regression	1.9 °C	2.6 °C	0.86	Moderate explanatory power, higher prediction error
Temperature (°C)	SVD-Based Linear System	1.2 °C	1.8 °C	0.94	High accuracy and excellent variance explanation
Humidity (%)	Linear Regression	5.1 %	6.2 %	0.83	Less stable short-term prediction
Humidity (%)	SVD-Based Linear System	3.4 %	4.1 %	0.91	Strong predictive performance and robustness
Wind Speed (m/s)	SVD-Based Linear System	—	—	—	Accurate short-term trend capture (qualitative validation)

https://doi.org/10.63876/ijtm.v4i3.93

2. Comparison with Other Methods

To compare the effectiveness of these models, we also evaluated them with conventional approaches, such as linear regression models and atmospheric physics-based models (NWPs). The linear regression-based model results in lower () values, which are about 0.80 for temperature and 0.75 for humidity, as well as higher MAE and RMSE compared to the linear system matrix model.R^2

Meanwhile, the NWP model, although it has a higher accuracy on long-term predictions, requires much larger computational resources and is not as fast as the matrix model in providing prediction results for a short time span[17]. The NWP model also requires more detailed input data and more parameters, which are not always available for all regions or weather conditions.

Table 2. Comparison of Weather Prediction Methods for Short-Term Forecasting

Aspect	Linear Regression Model	SVD-Based Linear System Model	Numerical Weather Prediction (NWP)
Temperature R^2	~0.80	0.94	>0.95 (long-term)
Humidity R^2	~0.75	0.91	>0.90 (long-term)
Temperature MAE	High (≈1.8–2.0 °C)	Low (≈1.2 °C)	Low–Moderate
Humidity MAE	High (≈5–6 %)	Low (≈3.4 %)	Low–Moderate
Temperature RMSE	High (≈2.5–2.8 °C)	Low (≈1.8 °C)	Low
Prediction Speed (24–48 h)	Fast	Very fast	Slow
Computational Cost	Low	Very low	Very high
Input Data Requirements	Limited	Moderate	Extensive (multi-parameter)
Applicability to Data-Sparse Regions	High	High	Low
Strength	Simple implementation	High short-term accuracy & efficiency	High physical realism (long-term)
Limitation	Lower accuracy	Limited physical interpretability	High cost, complex setup

3. Advantages and Limitations of the Linear System Matrix Model

The main advantage of linear system matrix models lies in their ability to make predictions quickly and efficiently, with fairly accurate results even though they use simpler input data compared to physics-based or machine learning-based models[18]. The lighter computational process makes these models easier to implement for real-time weather prediction applications, especially in regions with limited computing resources[19].

However, this model also has some limitations. First, while it is able to capture key patterns in the data, it is less effective at dealing with extreme weather phenomena, such as hurricanes or sudden changes in weather. Second, the model only captures linear relationships between variables, so it is not able to capture the more complex non-linear interactions that often occur in atmospheric systems. To overcome these limitations, integration with other methods, such as machine learning or physics-based models, can improve model performance, especially in handling unexpected weather events[20].

https://doi.org/10.63876/ijtm.v4i3.93

4. Discussion

Although this linear system matrix model shows promising results, more research is needed to improve its ability to predict long-term weather and extreme weather phenomena. One step that can be taken is to introduce regularization techniques or combine matrix analysis with machine learning algorithms to capture non-linear relationships in the data. Additionally, the collection of more diverse data and covering more weather factors can improve the accuracy of the model and provide a more comprehensive understanding of the atmospheric system.

This approach provides an efficient and effective alternative to short-term weather prediction, which can be useful in real-time applications such as weather early warning and extreme weather risk management.

CONCLUSION

This research has successfully developed a weather prediction model using linear system matrix-based data analysis, which offers an efficient and accurate solution for short-term weather prediction. The results of the evaluation show that this model is able to produce good predictions with a high degree of accuracy, measured by the metrics of MAE, RMSE, and determination coefficient (). Compared to conventional approaches such as linear regression, the matrix model of a linear system shows better performance, especially in terms of computing speed and efficiency.R^2. The main advantages of this model are its ability to make predictions with lower computing resources, as well as ease in interpreting results. However, the model also has limitations in dealing with extreme weather phenomena and complex non-linear relationships between weather variables. Therefore, to improve the accuracy of the model in more complex weather scenarios, it is recommended to integrate this method with other approaches, such as machine learning or physics-based models. A linear system matrix-based approach can be a useful alternative in short-term weather prediction, especially in applications that require fast and accurate predictions, such as weather early warning and extreme weather risk management. Further research is needed to address existing limitations and expand the application of this model in a broader weather context.

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