

# Comparison of multi -tasking and single tasing computation of some cloud parameters

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**Abstract** Radiative transfer governs Earth's energy balance and climate by influencing the interaction of radiation with the atmosphere. Liquid Water Path (LWP) and Ice Water Path (IWP) are key cloud parameters that affect the Earth's radiation budget by regulating solar reflection and terrestrial radiation. Accurate prediction of LWP and IWP is crucial for improving climate models and understanding cloud feedback mechanisms. This study compares single-task and multi-task approaches for predicting LWP and IWP using Artificial Neural Networks (ANN) and Gated Recurrent Units (GRU). The multi-tasking approach, which predicts both variables simultaneously by leveraging their interdependence, outperformed single-tasking for both models. These findings highlight the effectiveness of multi-task learning in modelling cloud properties and enhancing climate predictions.

**Keywords:** Single variable prediction, multi variable prediction, Liquid water path, Ice water path , Machine Learning, CERES data, Artificial Neural Network, GRU

## 1 Introduction

Radiative transfer refers to the process by which electromagnetic radiation is emitted, absorbed, scattered, and reflected as it propagates through the Earth's atmosphere. This phenomenon plays a crucial role in governing the Earth's energy balance, climate system, and weather dynamics. Solar radiation, predominantly shortwave in nature comprising ultraviolet, visible light, and near-infrared radiation enters the atmosphere where it is absorbed, scattered, or reflected. A portion of this energy is reflected back into space, while the remainder is absorbed and subsequently re-emitted as terrestrial longwave radiation (infrared) into the atmosphere and beyond. The intricate interplay of these processes determines atmospheric heating, cooling, and the Earth's overall climate equilibrium.

At the core of this equilibrium lies the Earth's radiation budget, which represents the balance between incoming shortwave solar radiation and outgoing longwave terrestrial radiation. This balance is fundamental for maintaining a stable climate system. If the absorbed energy exceeds the energy radiated back into space, the Earth experiences warming, contributing to rising global temperatures and climate change. Conversely, if the energy radiated exceeds absorption, cooling occurs. Various components, such as clouds, greenhouse gases, aerosols, and surface albedo, influence the radiation budget, with clouds playing a particularly significant role due to their ability to regulate both incoming and outgoing radiation.

Clouds, composed of tiny water droplets or ice crystals, play a dual role in Earth's climate system. They act as both reflectors and absorbers of radiation. Thick, low-altitude clouds reflect substantial amounts of solar radiation back into space, increasing Earth's albedo and creating a cooling effect. In contrast, high-altitude clouds, predominantly composed of ice crystals, absorb and scatter terrestrial longwave radiation, trapping heat and contributing to atmospheric

warming. The radiative properties of clouds are influenced by factors such as optical depth, particle size, phase composition (liquid or ice), and altitude, all of which determine how clouds interact with solar and terrestrial radiation.

Two critical parameters that describe cloud radiative properties are the Liquid Water Path (LWP) and the Ice Water Path (IWP). LWP represents the total amount of liquid water contained in a vertical column of a cloud, while IWP measures the total ice water content. Low-level clouds with high LWP, primarily composed of liquid water droplets, are highly effective in reflecting solar radiation, thereby cooling the Earth's surface. In contrast, high-altitude clouds with significant IWP, composed predominantly of ice crystals, absorb and trap terrestrial radiation, contributing to a warming effect through their greenhouse-like properties.

Predicting Ice Water Path (IWP) and Liquid Water Path (LWP) is essential for understanding and modelling Earth's climate system. These parameters provide critical insights into the radiative properties of clouds, which significantly influence global temperature and weather patterns [1]. By analysing IWP and LWP, scientists can assess the impact of clouds on global warming, cloud feedback mechanisms, and extreme weather events. Since clouds can either cool or warm the planet depending on their type, altitude, and water content, accurately predicting IWP and LWP is key to evaluating the extent of cloud feedback mechanisms, which can amplify or mitigate global warming.

Furthermore, clouds play a significant role in the formation and intensity of extreme weather events such as storms, cyclones, and droughts. Predicting IWP and LWP helps scientists improve weather forecasting models and enhance early warning systems, ultimately enabling better preparation and mitigation strategies for such events.

The intricate relationship between cloud microphysics and climate dynamics underscores the importance of accurately understanding and modelling cloud properties. By studying and predicting LWP and IWP, scientists can enhance the accuracy of climate models, leading to more precise predictions of future climate change scenarios. This, in turn, provides policymakers with critical information to formulate effective climate mitigation and adaptation strategies. Ultimately, advancing our understanding of cloud microphysics and improving our ability to predict IWP and LWP contributes not only to better climate and weather predictions but also to a more sustainable and resilient future.[2]

Traditional methods for predicting IWP and LWP often rely on complex radiative transfer models and satellite observations. These models use physical principles to simulate the interaction of radiation with atmospheric constituents, including clouds. By analysing satellite measurements of reflected and emitted radiation, researchers can infer cloud properties like IWP and LWP. However, these methods can be computationally intensive and sensitive to uncertainties in atmospheric conditions, limiting their accuracy and applicability.

Machine learning, on the other hand, offers a powerful and data-driven approach to predicting IWP and LWP [3]. By training machine learning models on large datasets of satellite observations and meteorological reanalysis data, researchers can learn complex patterns and relationships between atmospheric variables and cloud properties. This enables more accurate and efficient estimation of IWP and LWP, surpassing the limitations of traditional methods. Machine learning models can analyse various factors like temperature, humidity, pressure, and wind patterns to predict cloud formation and water content with greater precision [4].

Furthermore, machine learning techniques can incorporate diverse data sources, including radar, lidar, and radiometer observations, to enhance the accuracy of predictions.

Recurrent Unit (GRU) and Artificial Neural Network (ANN) models. GRU is a type of Recurrent Neural Network (RNN) designed to effectively capture long-term dependencies in sequential data, making it particularly suitable for time series data like meteorological observations. ANN, on the other hand, is a computational model inspired by the human brain, consisting of interconnected nodes (neurons) that excel in pattern recognition and prediction tasks.

The study uses the CERES (Clouds and the Earth's Radiant Energy System) dataset, covering the period from 2018 to 2023. The CERES project, led by NASA, aims to measure the Earth's radiation budget, including incoming solar radiation, reflected shortwave radiation, and outgoing longwave radiation. By providing critical information on cloud properties, radiation fluxes, and atmospheric processes, the CERES dataset serves as a reliable foundation for studying Earth's climate system.[5]

Predictions are conducted using two approaches: single-variable prediction, where Liquid Water Path (LWP) and Ice Water Path (IWP) are predicted individually, and multi-variable prediction, where both parameters are predicted simultaneously. Multi-variable prediction has shown noticeable differences in previous studies because it also considers the correlation between these parameters [6]. Our dataset reveals a strong correlation of 0.84 between LWP and IWP, which we plan to leverage in the multi-variable prediction framework. The study further compares the results from these approaches to determine which method provides superior accuracy and reliability. By analyzing the performance of GRU and ANN models under both prediction frameworks, the research aims to enhance the understanding of cloud microphysics and improve the modeling of Earth's climate system.

## **2 Data and Methodology**

### **2.1 Dataset**

The Clouds and the Earth's Radiant Energy System (CERES) project plays a vital role in understanding Earth's energy budget by providing satellite-based observations of radiative energy fluxes. CERES instruments measure both shortwave radiation (incoming solar radiation reflected by the Earth's surface and atmosphere) and longwave radiation (outgoing thermal radiation emitted by the Earth). This data is fundamental for studying the delicate balance between incoming and outgoing radiation, which directly influences the Earth's climate system.

Deployed on multiple satellites, CERES instruments collect critical atmospheric parameters such as cloud cover, cloud height, and cloud optical thickness. These parameters, when integrated with other satellite observations, enable a comprehensive analysis of cloud properties and their role in Earth's energy budget. The CERES dataset serves as a benchmark for validating climate models, monitoring climate variability, and enhancing weather forecasting accuracy.[7]

In this study, CERES data from South India, spanning the months of June to September from 2018 to 2022, was utilized for model training, while data from 2023 was reserved for validation and testing. These months are typically dominated by Liquid Water Path (LWP) and Ice Water

Path (IWP) due to seasonal variations in atmospheric conditions and cloud formation. During this period, regions in South India experience heightened atmospheric moisture, increased temperatures, and enhanced convective activity, which foster the formation of deep convective clouds with substantial amounts of liquid water and ice.

Moreover, the monsoon season in South India brings abundant rainfall, further elevating atmospheric moisture levels. This moisture, combined with warm and humid conditions, promotes the development of deep convective clouds. These clouds are characterized by their high-water content, which results in elevated LWP and IWP values, playing a crucial role in modulating regional radiative transfer and energy dynamics [8].

Additionally, the seasonal cycle of solar radiation influences cloud formation and properties [9]. In the summer months, increased solar radiation leads to higher surface temperatures and increased evaporation, which can contribute to the formation of clouds with higher LWP and IWP.

## 2.2 Atmospheric Parameters used

*Wideband Longwave (WLW)*: Refers to broadband longwave radiation measurements, typically in the thermal infrared spectrum (wavelengths longer than 4  $\mu\text{m}$ ).

*Shortwave (SW)*: Represents shortwave radiation from the Sun, including ultraviolet (UV), visible, and near-infrared wavelengths (0.3–4  $\mu\text{m}$ ).

*Surface Temperature (ST)*: The temperature at the Earth's surface, which is influenced by solar heating, atmospheric conditions, and local environment.

*Land Surface Temperature (LST)*: Measure of the temperature of the Earth's land surface, derived from satellite data.

*Surface Pressure (SP)*: Atmospheric pressure at the surface level, unit hPa (hectopascals).

*Wind Speed (WS)*: The horizontal velocity of air near the Earth's surface, expressed in meters per second (m/s) or kilometres per hour (km/h).

*Cloud Top Pressure (CTP)*: The atmospheric pressure at the highest altitude of a cloud.

*Cloud Top Temperature (CTT)*: The temperature at the upper boundary of a cloud.

*Cloud Base Temperature (CBT)*: The temperature at the base of a cloud.

*Cloud Top Height (CTH)*: The vertical distance from the Earth's surface to the top of a cloud.

*Cloud Particle Radius (CPR)*: The average size of cloud particles, whether liquid droplets or ice crystals.

*Cloud Optical Depth (COD)*: A measure of a cloud's thickness or opacity.

*Liquid Water Path (LWP)*: The total mass of liquid water in a vertical column of the atmosphere, expressed in grams per square meter (g/m).

*Ice Water Path (IWP)*: The total mass of ice particles in a vertical column of the atmosphere, expressed in g/m.

### 2.3 Models used for prediction:

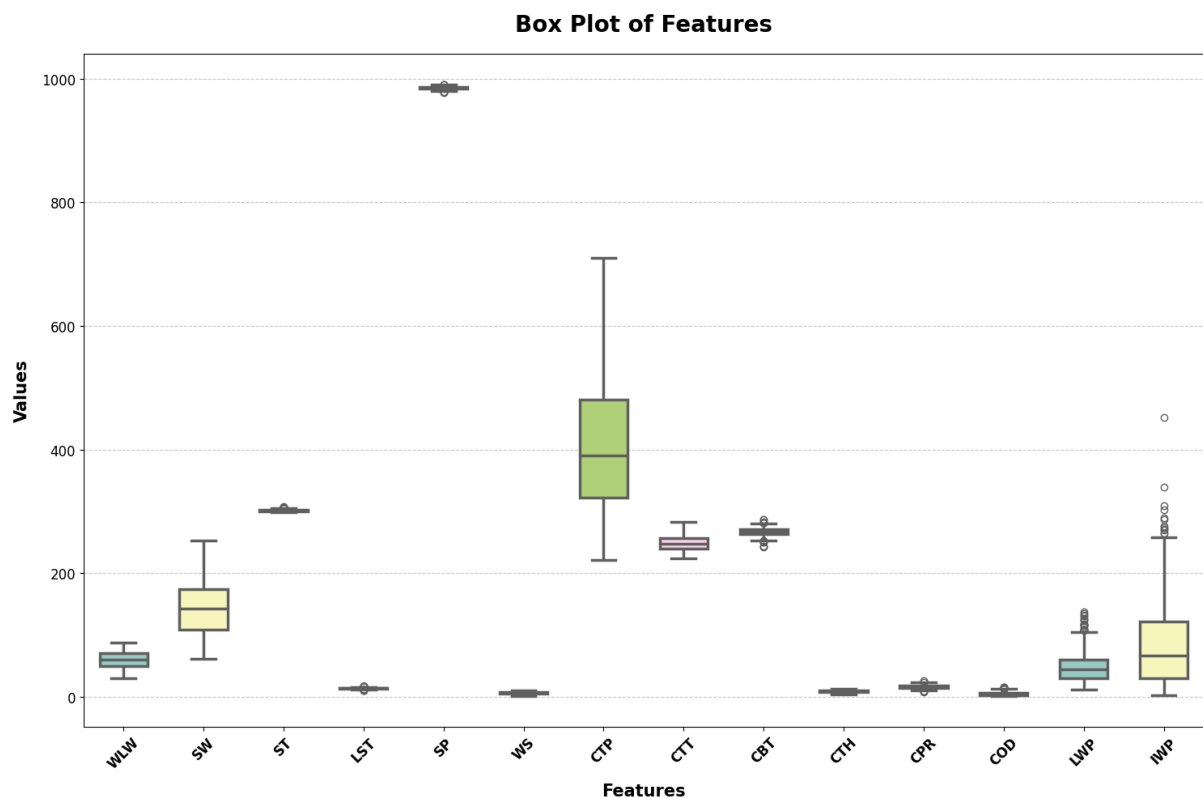
*Artificial Neural Networks (ANN):* They are biologically inspired models with interconnected layers of artificial neurons. They learn by adjusting connections between neurons to map inputs to outputs, making them suitable for complex pattern recognition tasks.

*Gated Recurrent Units (GRU):* They are type of Recurrent Neural Network (RNN) designed to handle sequential data. They incorporate "gates" that control the flow of information, enabling them to learn long-term dependencies more effectively than traditional RNNs. This makes them well-suited for time-series data where past information is crucial.

### 2.4 Data pre-processing:

*Feature selection:* The covariance matrix of dataset pointed out the high covariance between target variables (IWP and LWP) which can negatively impact machine learning models by introducing redundancy, increasing complexity, and reducing interpretability. This redundancy can lead to overfitting, hindering generalization to unseen data. To address this, highly covariant features of target variables were removed.

*Detection of outliers:* Box plots, a valuable tool for quickly visualizing the spread and distribution of data, identifying potential outliers, and comparing the distributions of data were used to detect and analyse outliers with any data points beyond a certain threshold (typically 1.5 times the IQR) considered as one.



*Scaling:* To address the high number of outliers, present in the dataset, robust scaling was applied. This method scales the data based on the interquartile range (IQR), effectively minimizing the influence of extreme values.

*Handling Of missing values:* To address missing values in the dataset, three distinct imputation techniques were employed: Mean Imputation, Linear Regression, and K-nearest Neighbours (KNN). Among these, KNN emerged as the optimal method due to its efficiency and ability to preserve data patterns.

## 2.4 Processing

This study utilized the imputed CERES dataset, spanning from 2018 to 2023. The data was divided into a training set (2018-2022) and a testing set (2022-2023).

Initially, an Artificial Neural Network (ANN) model was employed to predict Liquid Water Path (LWP) and Ice Water Path (IWP) as separate target variables in two independent models. Subsequently, the ANN model was extended to a multi-target prediction task, simultaneously predicting both LWP and IWP using a single model.

Following this, a Gated Recurrent Unit (GRU) model was implemented, replicating both the single-target (predicting LWP and IWP individually) and multi-target (predicting LWP and IWP simultaneously) prediction scenarios.

This approach allowed for a comparative analysis of the performance of ANN and GRU models in both single-target and multi-target prediction settings for LWP and IWP.

To optimize the performance of both ANN and GRU models, the study employed Optuna, a powerful hyperparameter optimization framework. Optuna leverages techniques like Bayesian optimization and grid search to efficiently explore the hyperparameter space, identifying the optimal model configurations for each scenario. This rigorous hyperparameter tuning ensures that both ANN and GRU models achieve their best possible predictive accuracy on the given dataset.

## 2.5 Evaluation matrixes used

The model performance was assessed based on the values of three statistical evaluation metrics, such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Coefficient of determination ( $R^2$ )

Evaluation Matrix Used	Formula
Mean Absolute Error	$MAE = \frac{\sum_{i=1}^n  y_i - x_i }{n} = \frac{\sum_{i=1}^n  e_i }{n}.$
Root Mean Square Error	$RSME = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{N - P}}$
Coefficient of determination	$R^2 = 1 - \frac{SS_{res}}{SS_{tot}}$

**Table 1 :** Evaluation Matrixes

### 3 Results and Discussion

The prediction of Liquid Water Path (LWP) and Ice Water Path (IWP) was conducted using both single-task and multi-task approaches, leveraging Artificial Neural Networks (ANN) and Gated Recurrent Units (GRU).

*Model Performance Comparison:* GRU demonstrated a superior ability to capture the intrinsic relationships in the dataset, resulting in more accurate predictions compared to ANN. The sequential nature of GRU allowed it to better understand the temporal dependencies and non-linear dynamics present in the data.

*Single-Task vs. Multi-Task Learning:* For both models, the multi-task approach, where LWP and IWP were predicted simultaneously, outperformed the single-task approach of predicting them individually. The multi-task approach effectively leveraged the correlation between LWP and IWP, leading to improved accuracy and better generalization.

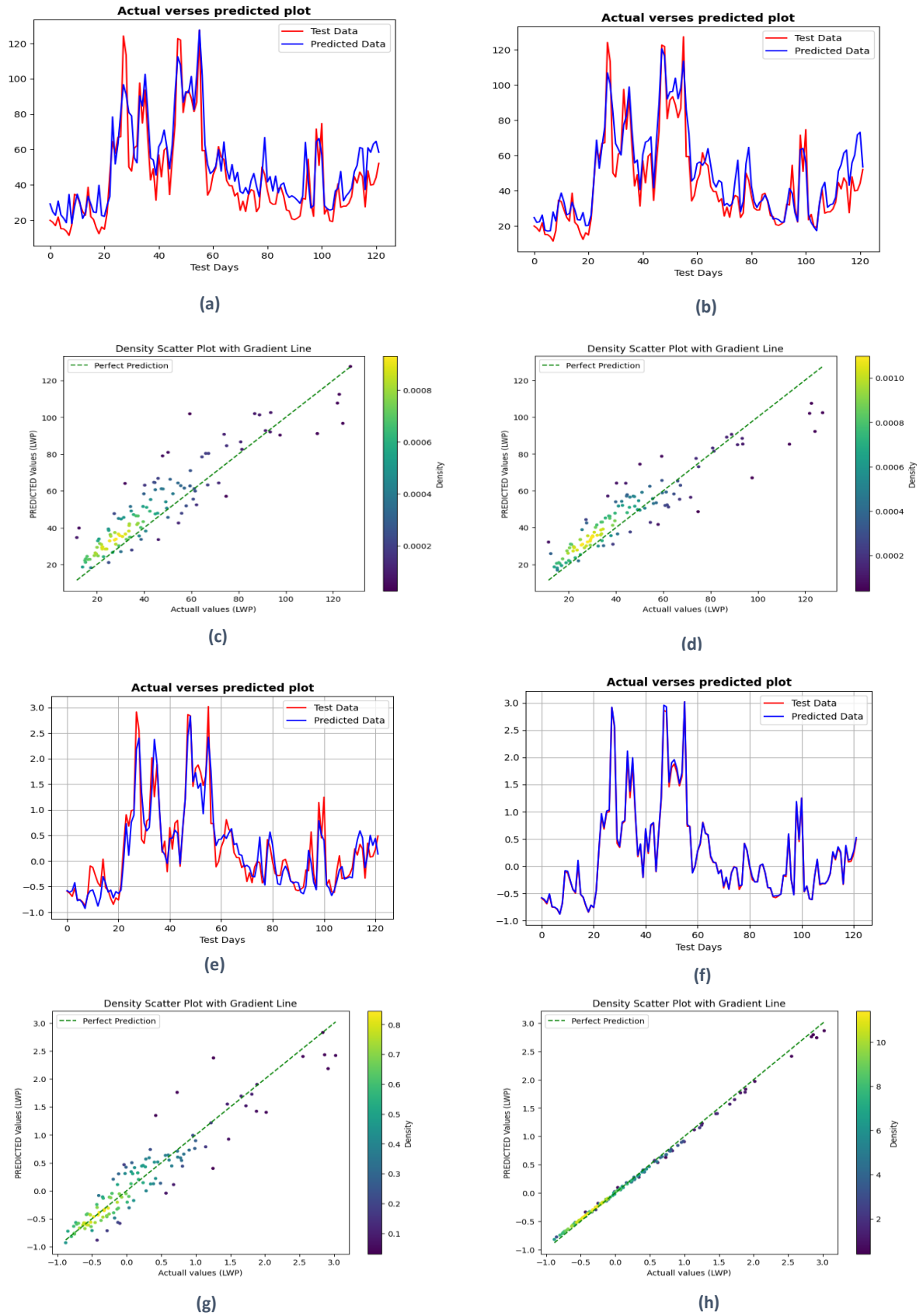
#### 3.1 LWP Prediction

**Table 2 :** Evaluation Matrixes of LWP

	SINGLE TASKING			MULTI TASKING		
	MAE	RMSE	R <sup>2</sup>	MAE	RMSE	R <sup>2</sup>
<b>ANN</b>	9.63097	12.2344	0.7685	7.96147	10.41351	0.8323
<b>GRU</b>	0.039699	0.3059	0.87213	0.02723	0.02693	0.999

Table 2 showcases the evaluation metrics (MAE, RMSE, and  $R^2$ ) for Liquid Water Path (LWP) predictions using ANN and GRU models under single-tasking and multi-tasking approaches. It highlights the superior performance of multi-tasking compared to single-tasking. For both models, multi-tasking resulted in lower MAE and RMSE values and higher  $R^2$ , indicating more accurate predictions. Notably, GRU in multi-tasking achieved exceptional accuracy ( $R^2=0.999$ ), outperforming ANN significantly in both approaches.

Figure 2 highlights the performance of ANN and GRU models for LWP predictions. For both models, multi-variable predictions align more closely with actual values in the actual vs. predicted plots and show tighter clustering along the perfect prediction line in gradient density scatter plots. GRU outperformed ANN, showcasing its ability to better capture temporal dependencies and variable interdependencies for improved predictions.



**Figure 2 :** (a) Actual versus predicted plot of LWP with ANN using single variable prediction. (b) Actual versus predicted plot of LWP with ANN using multi variable prediction. (c) Gradient density scatter plot of LWP with ANN using single variable prediction. (d) Gradient density scatter plot of LWP with ANN using multi variable prediction. (e) Actual versus predicted plot of LWP with GRU using single variable prediction. (f) Actual versus predicted plot of LWP with GRU using multi variable prediction. (g) Gradient density scatter plot of LWP with GRU using single variable prediction. (h) Gradient density scatter plot of LWP with GRU using multi variable prediction.

### 3.2 IWP Prediction

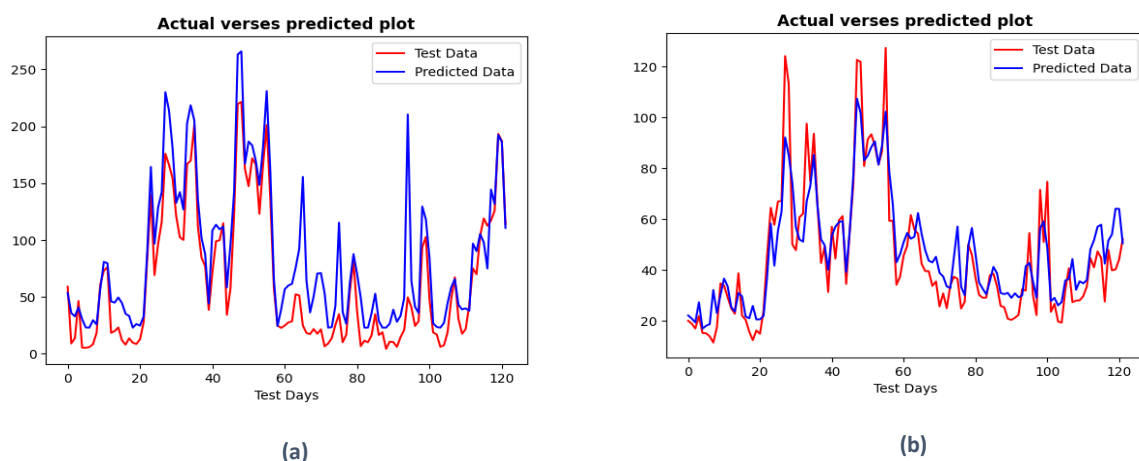
**Table 3** : Evaluation Matrixes of IWP

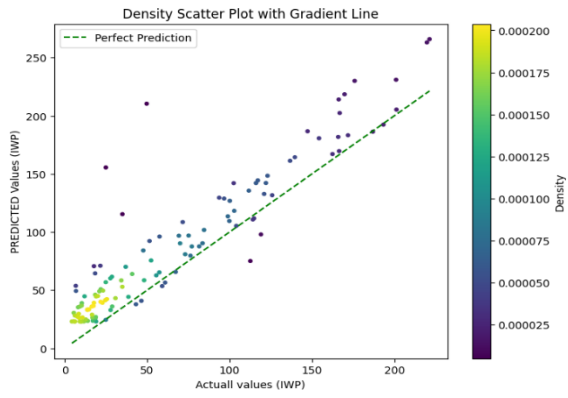
	SINGLE TASKING			MULTI TASKING		
	MAE	RMSE	$R^2$	MAE	RMSE	$R^2$
<b>ANN</b>	23.1449	31.40485	0.70973	18.538	22.72102	0.8480
<b>GRU</b>	0.18314	0.2557	0.85991	0.16899	0.0269	0.999

Table 3 extends the comparison to Ice Water Path (IWP) predictions, showcasing a consistent trend. Multi-tasking outperformed single-tasking with significantly lower MAE and RMSE values and higher  $R^2$ . Notably, the GRU model in multi-tasking achieved near-perfect accuracy ( $R^2=0.999$ ), further emphasizing its superior predictive capabilities over ANN in both tasks.

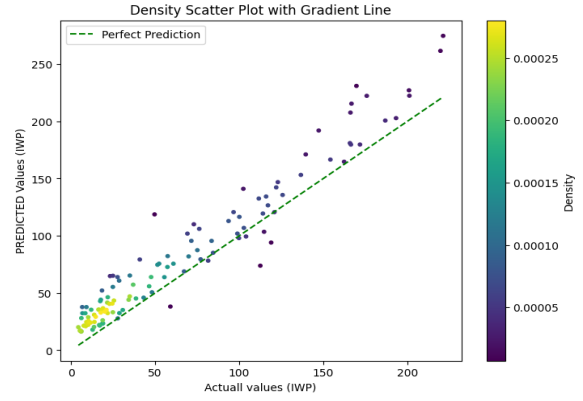
Figure 3 illustrates the superior performance of the multi-tasking approach compared to single-tasking for Ice Water Path (IWP) predictions across both ANN and GRU models. The actual vs. predicted plots (a, b, e, f) demonstrate that multi-tasking results in predictions that more closely follow the observed values, reflecting improved accuracy. The gradient density scatter plots (c, d, g, h) further highlight this advantage, with multi-tasking exhibiting tighter clustering along the perfect prediction line also among the models, GRU consistently outperformed ANN in both single- and multi-tasking scenarios, showcasing its ability to capture temporal dependencies and complex intervariable dynamics, particularly under the multi-tasking approach. This reinforces the effectiveness of multi-tasking in enhancing prediction accuracy for IWP.

Additionally, it is evident from **Figure 1** that the target variables, Liquid Water Path (LWP) and IWP, contain a substantial number of outliers, which could have potentially affected the prediction performance. Despite this challenge[11], the models, particularly GRU, performed exceptionally well. GRU's ability to capture temporal patterns and manage variable interdependencies proved crucial, delivering robust predictions even under the influence of data outliers. This highlights not only the strength of multi-tasking but also the resilience and efficiency of the GRU model in handling complex datasets.

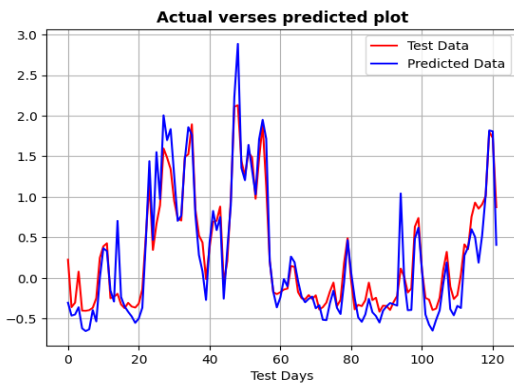




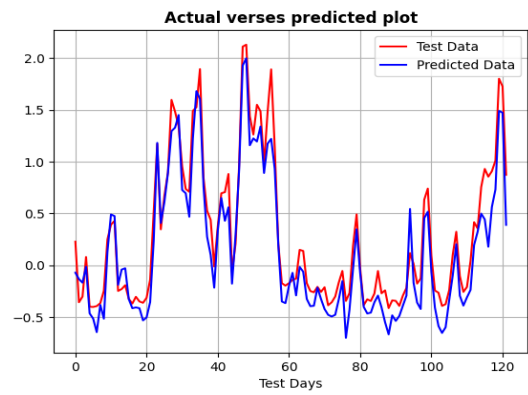
(c)



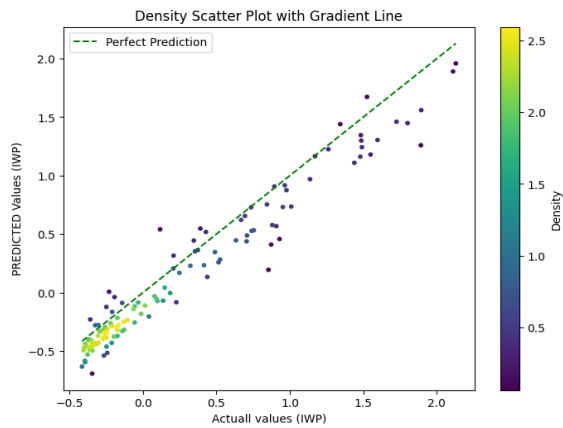
(d)



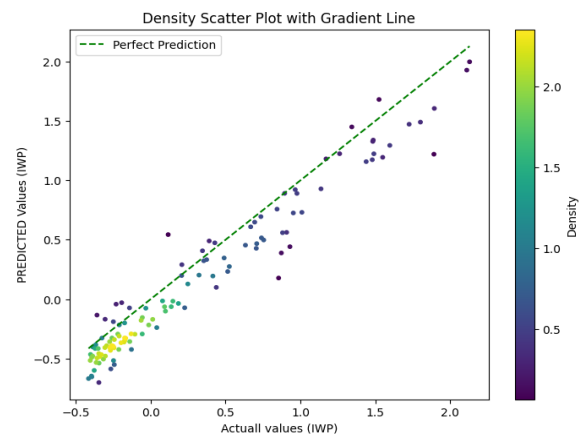
(e)



(f)



(g)



(h)

**Figure 3 :** (a) Actual verses predicted plot of IWP with ANN using single variable prediction. (b) Actual verses predicted plot of IWP with ANN using multi variable prediction. (c) Gradient density scatter plot of IWP with ANN using single variable prediction. (d) Gradient density scatter plot of IWP with ANN using multi variable prediction. (e) Actual verses predicted plot of IWP with GRU using single variable prediction. (f) Actual verses predicted plot of IWP with GRU using multi variable prediction. (g) Gradient density scatter plot of IWP with GRU using single variable prediction. (h) Gradient density scatter plot of IWP with GRU using multi variable prediction.

## 4 Conclusion

This study highlights the significance of predicting cloud microphysical properties, specifically Liquid Water Path (LWP) and Ice Water Path (IWP), for advancing our understanding of Earth's climate system. By employing Artificial Neural Networks (ANN) and Gated Recurrent Units (GRU), both single-task and multi-task learning approaches were explored to model and predict these critical parameters.

The results demonstrate that the multi-task learning approach, which leverages the correlation between LWP and IWP, yielded more accurate and robust predictions compared to the single-task approach. These findings underscore the potential of leveraging advanced machine learning architectures and task frameworks for improving predictions of cloud properties.

By integrating multi-task frameworks and effective hyperparameter tuning using tools like Optuna, this study provides a foundation for more precise modelling of cloud-radiative interactions. Accurate prediction of LWP and IWP can significantly enhance climate modelling, improve weather forecasting, and contribute to a deeper understanding of cloud feedback mechanisms in the context of global warming.

Future work could involve incorporating additional features, exploring ensemble learning techniques, and extending the analysis to other atmospheric parameters to further refine the predictive models and their applications in climate science.

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