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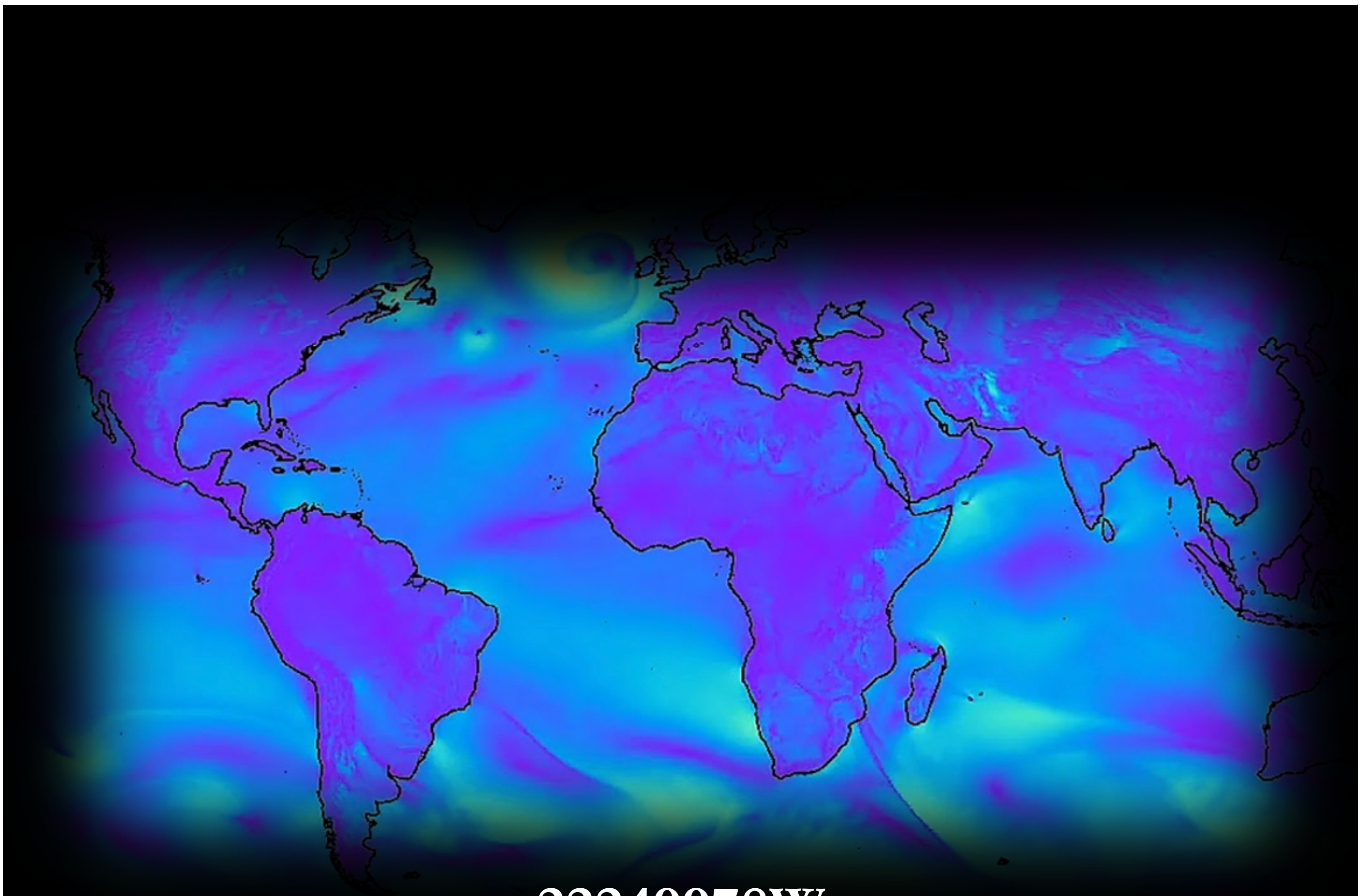
How does the effectiveness of Google Graphcast compare to traditional numerical weather prediction, and can it serve as a viable replacement?



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Abstract

The study investigated the viability of Google Graphcast, an AI-powered weather prediction model, as an alternative to Numerical Weather Prediction (NWP) models, which included comparisons with Open-Meteo and ERA5. The research was motivated by the need for more efficient and accurate weather predictions, particularly in light of global warming. Graphcast's benefits include its speed, accuracy, and open-source nature. The study focused on evaluating Graphcast's potential viability as a replacement to NWP models, emphasising its potential to revolutionise weather forecasting and improve responses to extreme weather events.

The investigation approach consisted of three primary stages: data collection, data modelling, and data analysis. During data collection, Google Graphcast was used to forecast weather predictions over a 10-day timeframe. This data was processed and displayed in graphs during modelling, before being subsequently analysed during analysis, with Graphcast's forecast being compared to Open-Meteo's NWP forecast against the ERA5 data (observed weather) for its accuracy. Melbourne, Australia was chosen as the location for comparison because of its complicated weather patterns and high-quality weather data. The accuracy and potential of Graphcast as a substitute for conventional NWP models were evaluated using statistical metrics and visualisations.

The findings indicated that although Graphcast showed high precision at first, its predictions became more inconsistent when the temperature varied quickly. Although Graphcast performed approximately 0.5°C worse than OM Forecast in terms of accuracy overall (though it varied across points), it was noted that it showed potential due to its minimal computational resource consumption. This demonstrates Graphcast's promise as well as its shortcomings in regard to its viability as a replacement. The study comes to the conclusion that while Graphcast is not yet able to regularly outperform NWP models in every aspect, its effectiveness and room for development could make it a viable tool for weather forecasting in the future, especially for consumer applications.

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Introduction

The fusion of artificial intelligence (AI) and numerical weather prediction (NWP) has initiated a revolutionary transformation in the field of weather forecasting. This study investigates how effective Google's Graphcast, an AI-based weather forecasting tool, is when compared to conventional NWP models, particularly examining its potential as a replacement.

Weather forecasting is used widely across various sectors, including agriculture, transportation, and emergency management for decision making, especially in the case of extreme weather events. NWP models have long been the centrepiece of prediction, relying on complex algorithms grounded in atmospheric physics, that take in various states as inputs, and using mathematical equations model how weather evolves over a time period. NWP models require enormous computational resources, utilizing supercomputers that can perform calculations in one second that would take a human 1.5 billion years. However, they are constrained by the resolution of input data and the inherent unpredictability of weather systems, which they cannot fully adapt to (Jian et al., 2021). As a result of this, it has been recognised that the current NWP models may no longer suffice to meet the evolving needs of weather prediction, and that a new solution must be innovated.

Google Graphcast, developed by Google Deepmind and released in late 2023, addresses this need, an open-source AI-based Machine Learning model (MLM). It utilizes machine learning to predict weather predictions, and Google has claimed that it boasts unprecedented accuracy in global forecasting, as well as operating at a remarkable speed, outperforming NWP by 99.7% in some cases (optimize IAS et.al, 2023). In its essence, Graphcast represents a shift from NWP to a data-driven approach, analysing and processing historical weather patterns to make more accurate predictions (Lam et al., 2023).

The concept of a “viable replacement” refers to an alternative that not only fulfills the same role as its predecessor but also does so with equal or improved efficacy, efficiency, or convenience. In the context of weather forecasting, a viable replacement would need to deliver accurate predictions, operate within reasonable resource constraints, and potentially offer improvements over traditional methods (McGovern et al., 2017).

The timeliness of this research is emphasized by the escalating challenges posed by climate change, where accurate weather predictions are increasingly crucial for preparing for and mitigating the effects of extreme weather events (Boukabara et al., 2021), and NWP has trouble adapting to these varying temperatures. While there are other AI weather prediction models available, such as Huawei's 'Pangu-Weather' Model and Nvidia's 'CorrDiff' Model, neither of them are open-source or have the extensive documentation and support that comes with Graphcast. Furthermore, currently existing research on these models has not been tested to gather credible primary data, and as such cannot be used in this research.

The potential impact of Graphcast on climate change adaptation and tropical storm prediction could be revolutionary, offering a tool that not only forecasts weather more efficiently but also aids in understanding and responding to the broader implications of a changing climate (Jain et al., 2023), which is also concurred by (Slater et al., 2023). By assessing the effectiveness of Google Graphcast, the findings learned could have significant advances for the future of weather forecasting, potentially initiating in a new era of AI-based weather forecasting.

Since the method is Statistical Analysis, there will be negligible risk involved, as no human participants will be involved with the analysis. Ethical considerations in this research will be limited to obtaining permission to use historical weather data from CDS Copernicus, as well as adhering to data privacy regulations.

In conclusion, this introduction sets the stage for a comprehensive examination of Google Graphcast as a potential replacement to traditional NWP models. By evaluating its effectiveness and viability as a potential replacement, this research aims to contribute to the advancement of the understanding of weather forecasting technology and enhance our ability to predict and respond to the weather challenges of the future caused by climate change and global warming.

Method

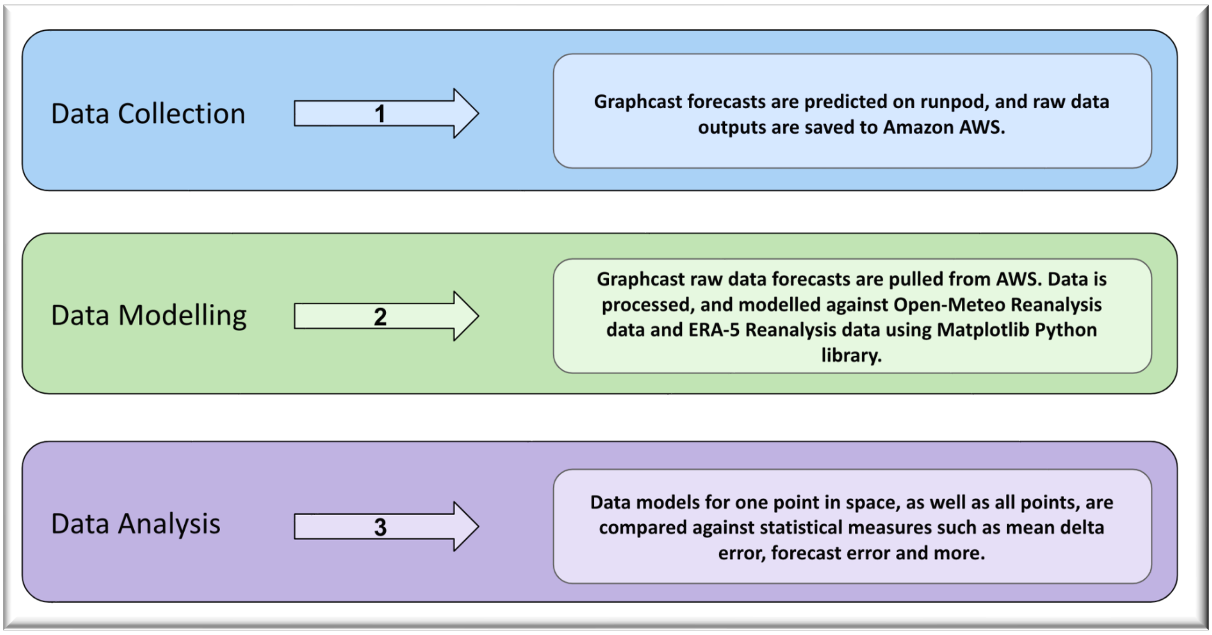

Figure 1 – Method Diagram

The research process used included a 3-step methodology, with Data Collection, Data Modelling, and Data Analysis.

During Data Collection (Figure 1), forecasts were generated using Graphcast on a remote server by utilizing the runpod package (an online service for running a remote server) and were saved to Amazon S3 AWS, a cloud storage service. This involved installing dependencies, setting credentials, creating forecasts, and saving outputs. The justification for running it remotely was due to the computing requirements of Graphcast, with the 10-day forecasts consuming at least 61GB of RAM, which was unfeasible to run on a laptop.

The evaluation of Graphcast's predictions on a singular location (Melbourne) was required for several reasons. By limiting the geographical area, variables could be more easily controlled that could affect the evaluation process. This helped in accurately attributing performance metrics to the AI model itself rather than external, location-based factors. Melbourne also already had high-quality, precise reanalysis data from ERA5 available due to its well-established meteorological infrastructure, ensuring that the baseline data used for comparison was accurate and reliable. Furthermore, evaluating Graphcast in one specific location provided a clear baseline for its performance, and if it performed well in these controlled settings, it could potentially be generalized for other similar locations. Lastly, Melbourne, being a major urban centre, provided a complex environment for weather forecasting, including urban heat islands, diverse microclimates, and varied weather patterns. Successfully predicting weather in such a setting would owe to its effectiveness as a model.

In the Data Modelling stage (Figure 1), Graphcast raw data was processed and compared against Open-Meteo and ERA5 using Matplotlib. An overview of each model that Graphcast was processed and compared to is as follows:

Definition and justification of each comparison dataset

*Open-Meteo Reanalysis (**OM Reanalysis**):*	*Open–Meteo Forecasts (**OM Forecast**):*	*ERA5 Reanalysis – ECMWF: (**ERA5**):*
OM Reanalysis provides an additional data set of observed weather that can be used for comparison. Comparing Graphcast with the OM Reanalysis dataset will help confirm the accuracy of ERA5 as a reanalysis dataset. By evaluating how well Graphcast predictions align with both OM Reanalysis and ERA5, we can identify any discrepancies or consistencies between the datasets. This serves as an	The OM forecast serves as an average case NWP model. The OM forecast simulates the atmosphere based on initial conditions and is often used for short-term weather planning. By comparing Open Meteo with Graphcast, we can evaluate how accurately Google Graphcast predicts weather compared to the average of established NWP models.	ERA5 serves as the 'true' state of the weather in the research comparison. It is widely considered the most authoritative source of reanalysis data globally (Yu et al., 2021 & Hersbach H et al., 2020) and provides initial weather conditions for Graphcast during autoregression. The data is generated using a combination of historical observations and advanced modelling techniques, which offer detailed insights

additional point of comparison, helping to validate ERA5's reliability and offering a more robust assessment of the AI model's performance.		into past weather and climatic conditions. Comparing Graphcast to ERA5 allows us to evaluate the AI's performance in predicting long-term trends and assess it’s effectiveness in prediction accuracy.

The forecasts and reanalysis data extracted were subsequently organized into a Data Frame (coordinate point for comparison), facilitating comparison across points of interest. Visualizations such as bar charts, line graphs, and scatter plots were employed to compare forecasted values from Graphcast, Open-Meteo, and ERA5 for both individual points and all points collectively. For a single point in space, visualizations depicted values over time, allowing for a detailed analysis of trends and patterns. Aggregate statistics were also graphed to visualize the overall accuracy and precision of the forecasts over all points.

The final stage - Data Analysis (Figure 1) involved comparing the predictions generated by Google Graphcast with Open-Meteo and ERA5 in processed graphs. Statistical measures like mean delta error, forecast error, and others were employed, providing objective insights into the accuracy, precision, and overall performance of Graphcast in weather forecasting. This was done for one coordinate point, as well as across all points, to ensure that a holistic view of its accuracy could be determined (see *Appendix 1*) This approach aligned with the statistical analysis methodology employed by the Google DeepMind Team (Lam et al., 2023), who found that Graphcast had greater weather forecasting skill than HRES (a reanalysis model from ECMWF) when evaluated on 10-day forecasts at a resolution of 0.25 degrees.

The research method used was multivariate graphical exploratory data analysis as a form of statistical analysis, as used by Lam et al. (2023), altering both the prediction model and the data point under measurement to assess the effectiveness of Google Graphcast in weather forecasting and compare it with Open-Meteo and ERA5. The reason for choosing this method was that exploratory data analysis offered a quantitative approach to evaluating the accuracy and reliability of forecasting models, making it more suitable for addressing the research question - regarding the potential of Graphcast as a viable replacement for NWP, rather than other research methods. It was also efficient, as it analysed data sets to summarize their main characteristics to discover patterns, identify errors, and find interesting relations among the data, which aided in answering the research question.

The limitations of the method were related to data availability and coverage, as the effectiveness of the method may have been limited by the availability and coverage of data from Open-Meteo and ERA-5 for analysis. Incomplete or sparse data could have impacted the accuracy of comparisons. Moreover, the method assumed that Graphcast, Open-Meteo, and ERA-5 models had equivalent or directly comparable metrics; however, differences in coordinate referencing, model parameters, or data assimilation techniques may have introduced biases into the analysis that could not be controlled for under the time restrictions.

Results

Primary data used for the following Graphcast predictions can be found in [Appendix 1](#).

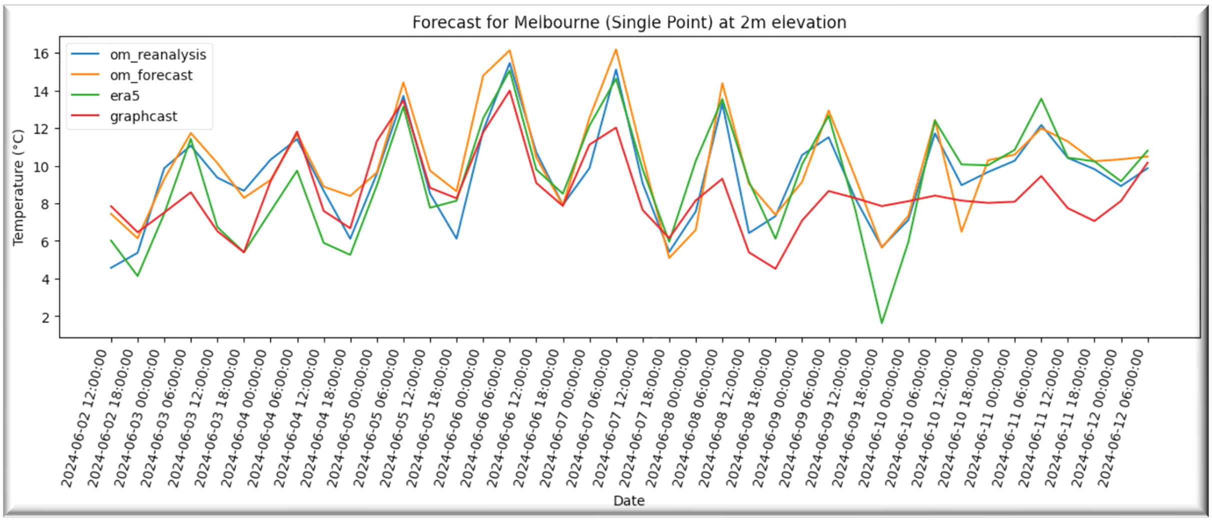

Figure 2 *(strong alignment to green line means higher accuracy)*

Figure 2 shows the temperature forecasts of the various models over a 10-day prediction timespan. The OM Forecast, OM Reanalysis, and Graphcast forecasts all showed a high alignment with the ERA5 Reanalysis data throughout approximately 70% of the prediction period. However, all models failed to predict the sharp drop in temperature on the 10th of June at 21:00, which highlights a common shortcoming in these models for capturing sudden temperature changes.

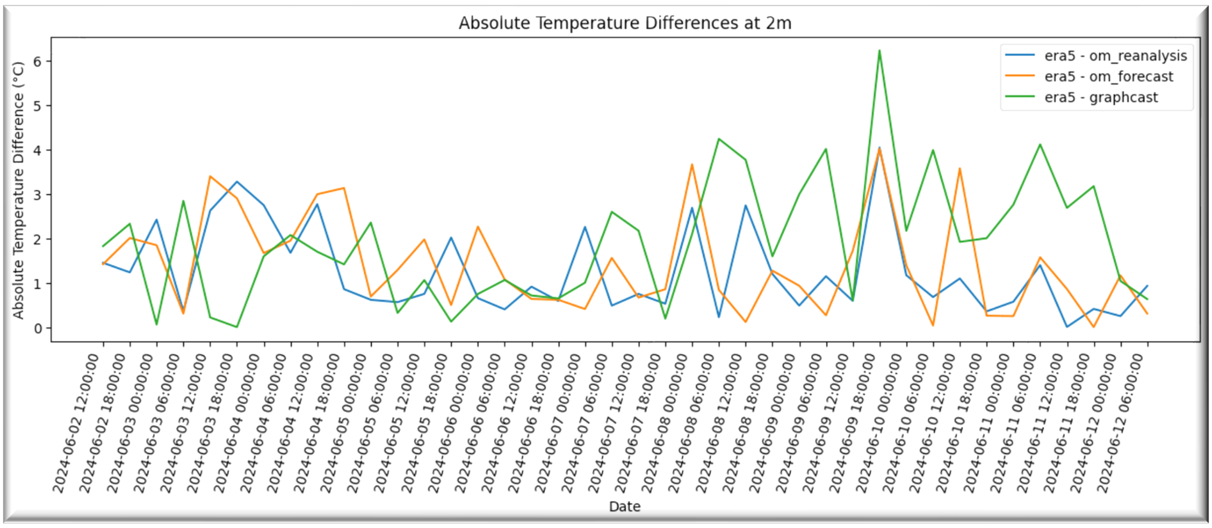

Figure 3 *(the lower the line is to the x axis, the more accurate it is)*

Figure 3 shows the temperature differences between the OM Forecast, OM Reanalysis, and Graphcast forecast when compared to the ERA5 Reanalysis data. The Y-axis represents the temperature deviation from the ERA5 data. Throughout the timespan, Graphcast has more variability in temperature differences compared to the OM Forecast and OM Reanalysis. This variability is particularly noticeable in the latter half of the period (during the last 5 days), indicating that while Graphcast can achieve high accuracy, its consistency in maintaining temperature predictions is less stable than that of traditional NWP models and reanalysis data.

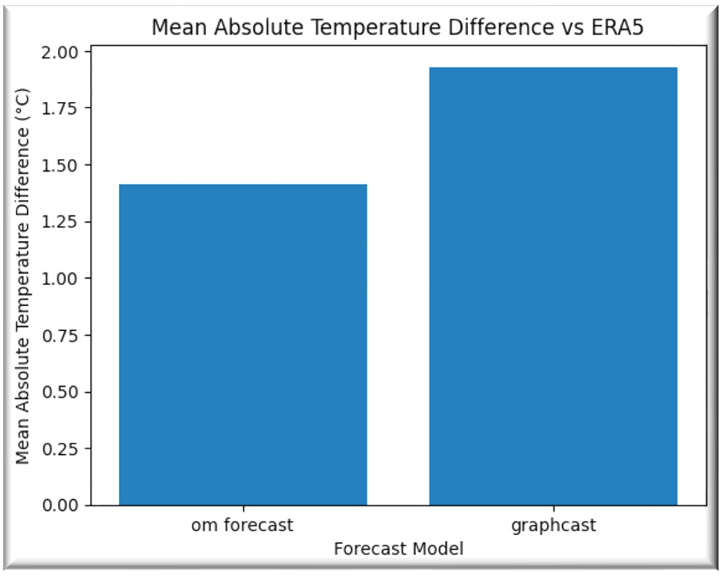

Figure 4 *(the lower the bar, the more accurate)*

Figure 4 maps the absolute temperature difference between the OM Forecast and Graphcast, in comparison to ERA5 data. The OM Forecast is approximately 1.50°C less accurate than the ERA5 Reanalysis data, whilst Graphcast is approximately 1.90°C less accurate than the ERA5 Reanalysis data. This indicates that Graphcast prediction for one point is approximately 0.4°C less accurate than OM Forecast (NWP) for a single point.

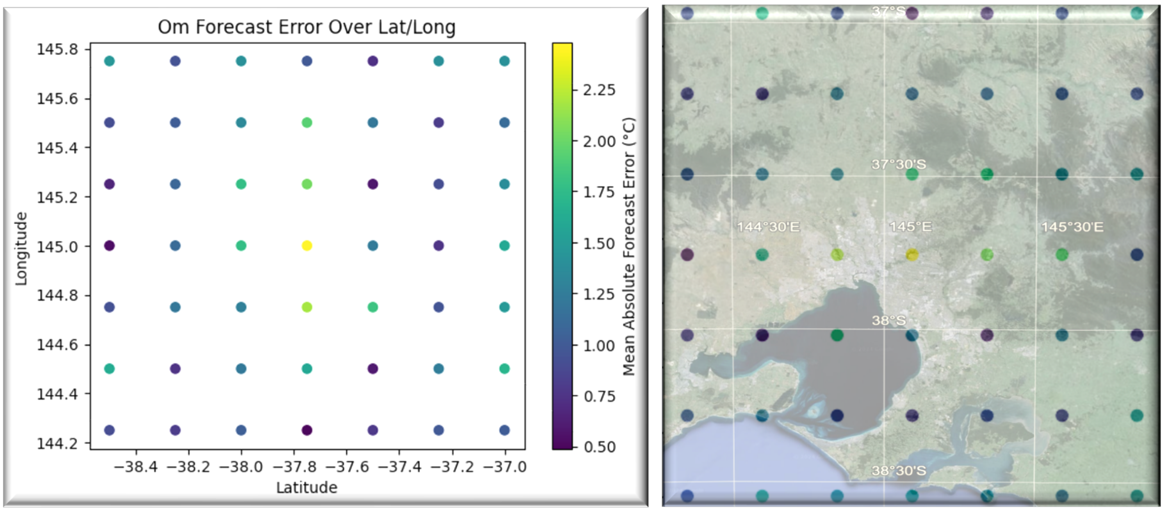

Figure 5 *(darker dots mean greater accuracy); source: google.com/maps (right)* ***<u>to scale</u>***

Figure 5 maps the OM Forecast error in a visually interpretative manner. This figure highlights the limitations of traditional NWP models, with significant error observed at [-37.8, 145.0], approximately the Melbourne CBD of approximately 2.25°C. This is likely attributable to the Urban Heat Island (UHI) effect, where artificial surfaces trap heat and increase temperatures. The graph shows that the closer the model predicts to the centre of Melbourne, the more error is present.

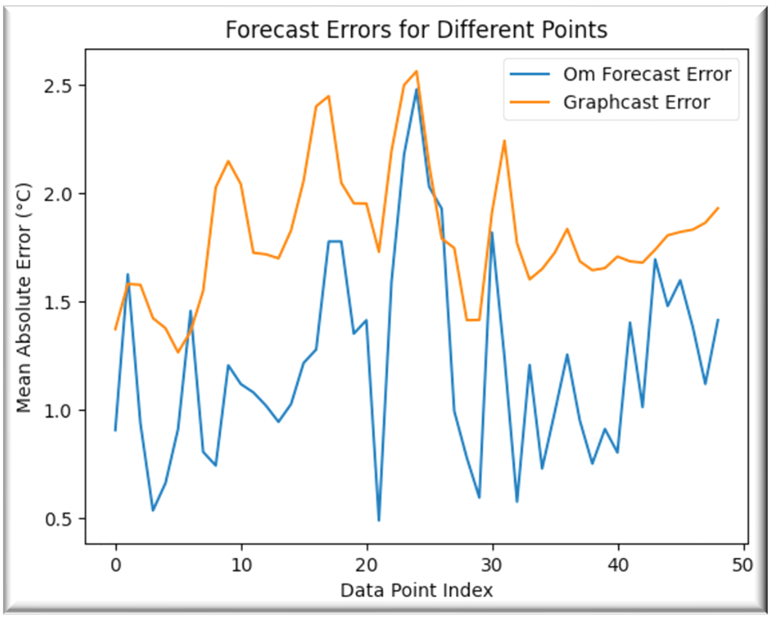

Figure 6 *(the closer to x axis, the lower the error)*

Figure 6 shows the difference between the Graphcast error and the OM Forecast error in comparison to the ERA5 dataset, plotted against various randomly selected points with no spatial relationship to one another. The graph indicates that the OM Forecast has greater variance in terms of mean absolute error (°C) but an overall lower mean error, whereas Graphcast is more consistently inaccurate with less variance in terms of mean absolute error (°C) but an overall higher degree of mean error.

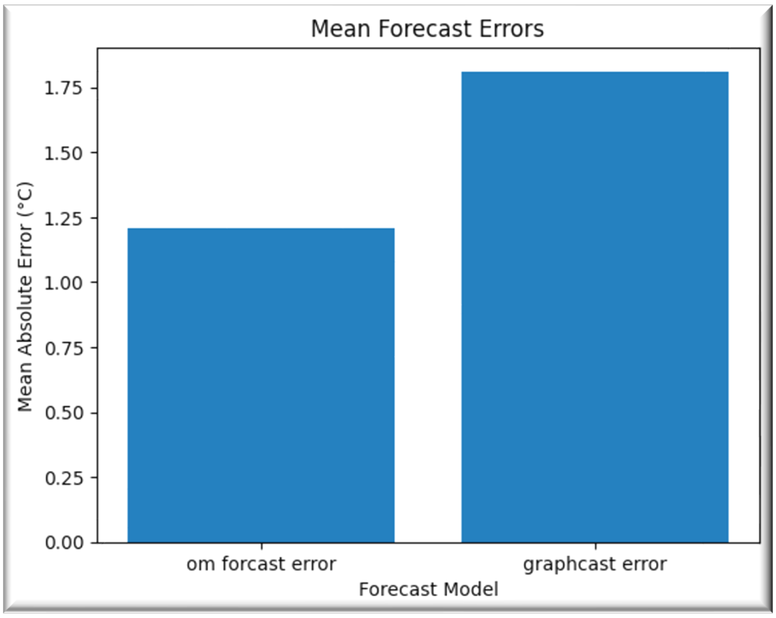

Figure 7 *(the lower the bar, the more accurate)*

Figure 7 shows the difference between Graphcast error and the OM Forecast error against the ERA5, averaged out as a mean across all points in Melbourne, indicative of typical performance. The OM Forecast was approximately 1.25°C less accurate than ERA5 for all points, whereas Graphcast was approximately 1.75°C less accurate. The overall mean error of Graphcast is approximately less accurate 0.5°C than the OM Forecast error.

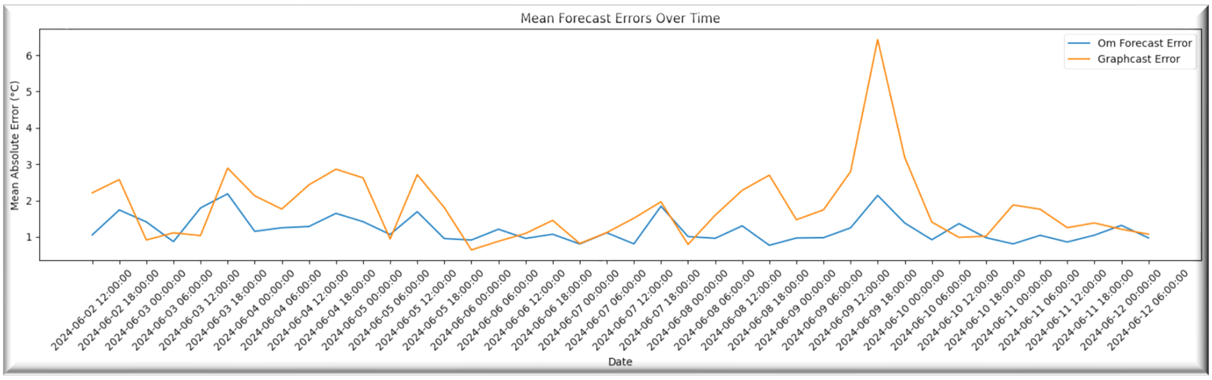

Figure 8 *(the closer the line to the x axis, the more accurate)*

Figure 8 shows the difference between Graphcast error and OM Forecast error against the ERA5, averaged out as a mean over time. The graph indicates that the OM Forecast maintains a consistent level of error, while Graphcast experiences a significant spike in error on the 9th of June. Generally, Graphcast forecasts are very accurate, to within 3°C of the ERA5 Reanalysis data.

Discussion

One of the most significant findings from the results is the impact of the Urban Heat Island (UHI) effect on NWP models weather predictions accuracy. Figure 5 shows this by highlighting the limitations of these models in urban areas, particularly around the central business district (CBD) in Melbourne with 2.25°C of error from the OM Forecast compared to ERA5. This is caused by the UHI effect, where artificial surfaces trap heat and increase temperatures, thereby 'throwing off' these NWP models which don't account for this phenomenon. This localized phenomenon poses a challenge for traditional NWP models, leading to higher prediction errors, which is an expected result as evident from a study published in April 2024 highlighting the shortcomings of NWP prediction (Zhu et al., 2024). Conversely, Graphcast, which is trained on diverse data sets that include such anomalies, is less affected by the UHI effect, showcasing a potential advantage of its predictions in urban forecasting.

However, the variability of Graphcast's performance in accuracy is another critical observation. Figure 3 illustrates the temperature differences between the OM Forecast, OM Reanalysis, and Graphcast when compared to the ERA5 data. While all models demonstrated a high degree of alignment with ERA5 data (Figure 2) within the first 7 days, Graphcast exhibited more variability in temperature differences, particularly in the latter half of the period. This suggests that while Graphcast can achieve high accuracy, its consistency in maintaining temperature predictions is less stable than that of traditional NWP models and reanalysis data. The higher variability could be due to the model's sensitivity to rapid changes in weather patterns, which traditional models might handle more predictably. The OM-Reanalysis data, exhibits the least error from all comparison models, which is to be expected from a primarily reanalysis data set. This result also cannot be generalized for a larger set of data, as the error for one point could be different than the error for another point, which will be explained in the following results.

The accuracy of temperature predictions is crucial for evaluating model performance. Figure 4 shows the absolute temperature differences between the OM Forecast and Graphcast compared to ERA5 data. The OM Forecast is approximately 1.50°C off the ERA5 reanalysis data, whereas Graphcast is approximately 1.90°C off. This indicates that Graphcast predictions are close to 0.4°C less accurate than OM Forecast for a single point. Despite this, Graphcast's computational efficiency is a significant advantage. Graphcast requires substantially less computational power and time compared to traditional NWP models (supercomputer used by the ECMWF consumes as much power as a small city), making it a more accessible and resource-efficient option for weather forecasting.

Examining the error variance, Figure 6 compares the Graphcast error and OM Forecast error across 50 various randomly selected points. The OM Forecast exhibits greater variance but an overall lower error, while Graphcast is more consistently inaccurate with less variance. This indicates that Graphcast's performance is more stable across different locations, though not necessarily more accurate. The consistent error may potentially stem from inherent biases in the training data used by Graphcast, but this is unlikely due to the vast amount of data it has from the last 100+ years. Furthermore, the OM Forecast's greater variance suggests that while it can achieve lower errors in some instances, it is also prone to larger errors in others. This is an expected result, as evident through Figure 4, we know that NWP models struggle in predicting certain points, such as point 25 and 30 in this graph, whereas Graphcast is not affected to the same level of magnitude from the baseline error. This shows that Graphcast is potentially more reliable and less susceptible to extraneous factors affecting its weather prediction performance (such as the UHI effect).

Figure 8 provides insight into the temporal stability (meaning over a time frame) of the forecasts. While the OM Forecast maintains a consistent error level, Graphcast experiences a notable spike in error on the 9th of June. Despite this, the Graphcast forecast is generally very accurate to within 3°C of ERA5 Reanalysis data. If the level of error increased over time, then we could come to a conclusion about the accuracy of Graphcast's predictions over time, however, there are no large variations barring an anomaly on the 9th of June, which other models failed to pick up on as well (Figure 2 and Figure 8), albeit not to the same degree. This result can be generalised, as we can see that Graphcast does not become more inaccurate over time, as well as the OM Forecast not becoming more inaccurate over time.

Thus, this suggests that while Graphcast may not consistently outperform NWP models in every instance, it remains a viable and efficient alternative for many applications.

Figure 7 shows the mean forecast error from OM Forecast and Graphcast against ERA5, averaged across all points. The overall mean error of Graphcast is approximately 0.5°C off the OM Forecast error, which does not align with results gathered from (Lam et al., 2023). This could be due to a variety of reasons, from the specific 10 days in which this weather was forecasted for, as well as the location it was forecasted for etc. There are too many extraneous variables to account for in an investigation such as this. In order to gain a more holistic and accurate view of the accuracy, several periods of 10-day predictions would need to be gathered for various locations around the globe, and their error compared, however, it would be far too time consuming and resource intensive for an investigation of this scale and time limitations.

In order to assess Graphcast's viability as a replacement, we must look at how accurate its predictions are through the results, whether it operates within reasonable resource constraints, and whether there are any improvements over traditional methods. If we analyse the results, we can see that Graphcast predicts forecasts with a high accuracy of within 0.5°C mean error, for all points (Figure 7). The error of Graphcast also does not increase significantly over time, meaning that these results can be generalized for a longer time scale. From these results, it is evident that Graphcast performs accurately, but not to the same level of accuracy achieved by traditional NWP models. Graphcast's advantage over NWP models is highlighted by its predictions consuming significantly less computational power, only requiring around 61GB of RAM, and 15 minutes on a moderately powerful GPU, compared to 200 – 500 TB of RAM required by most NWP models, and 3 – 6 hours of prediction time.

This energy requirement for NWP models prediction is massive and wasteful, and results with a high degree of accuracy (less than 0.5°C off) can be achieved with a minute level of energy through new technologies such as Graphcast, one of the main advantages AI-based weather prediction poses over NWP models. As for whether Google Graphcast offers any improvements over these models, it can more accurately predict certain points where NWP struggles (such as specific locations affected by UHI effect), as well as the aforementioned lack of resources that Graphcast consumes in comparison to NWP. Graphcast also offers inherent improvements in the fact that it is democratizing in the field of weather prediction, as anyone with a laptop or any company can have access to on demand free weather predictions, whereas prior to its release it would be controlled by large agencies such as the ECMWF.

Therefore, whether Graphcast can serve as a viable replacement will be dependent on the needs of the companies and organisations who would use it. Everyday consumers of a weather application (Weatherzone/BOM Weather) are unlikely to be concerned with a < 0.5°C difference between actual and predicted temperatures. As a result, Graphcast could have potential applications in these consumer-facing services, potentially saving companies millions of dollars. However, corporations who rely on accurate weather predictions for business-making decisions such as financial investments and social security could be affected by this level of difference and as such it is not feasible to generalise a statement on its viability for an entire population when organisations and companies have different needs.

Ultimately, Graphcast demonstrates high accuracy and significantly lower computational resource requirements compared to the NWP models, making it a viable replacement in specific use cases, particularly for consumer-facing applications. However, due to its slight accuracy limitations, it might not be suitable for critical applications requiring precise predictions (such as those used by corporations for business-making decisions or extreme weather event decision making). Overall, Graphcast is promising but cannot universally replace all NWP models across all scenarios.

AI and ML powered weather prediction is evolving as we speak, and new innovations are always being developed to address the complexities of changing weather. In the future, these models will likely become more accurate and overtake NWP prediction in all metrics, so it is imperative that these models be developed with democratic principles, as well as with a focus on equity and justice, to ensure that certain demographics with less data available for prediction are not locked out of accessing this technology. Future research should aim to bridge the gap between businesses, governments, and organizations into accessing this revolutionary technology, such that those less fortunate in developing nations with little access to resources and technology can reap its benefits. Additionally, further research into its applications such as extreme weather event preparation alike to (McGovern et al., 2017), with an emphasis on Google Graphcast will likely have a lasting impact on millions of people's lives, and the protection of their livelihoods is crucial for sustainable development.

Despite its potential, Graphcast confronts issues that are prevalent across AI weather prediction models and must be solved in the future to assure success. AI systems rely on enormous volumes of data for training, and if that data is biased or only available in particular locations, it may result in erroneous predictions elsewhere. Furthermore, the complexity of AI systems can make them difficult to comprehend for non-technical staff in major businesses, hindering the detection of potential biases or errors (Jain et al., 2023). Ensuring the ethical use of large amounts of data is also critical for protecting the privacy of citizens and preventing misuse. By solving these problems, future research can help realise the full potential of AI in weather prediction while maintaining ethical norms.

Conclusion

This study assessed Google Graphcast's potential as a replacement for NWP models, demonstrating its high accuracy and capacity to operate with substantially less computational resources, democratising access to accurate weather predictions worldwide. Google Graphcast has showed promise as a potential viable replacement for consumer-facing weather applications, but further development may be necessary to ensure it can be applied to other fields such as business-facing applications and extreme weather prediction. Despite its inability to consistently outperform NWP models in all metrics, as well as the challenges it will face in terms of data bias, complexity, and ethical use, continued innovation in this field will pave the way for more accurate and sustainable predictions, better preparing us for the effects of a changing climate and world in the twenty-first century and beyond.

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Appendices

Appendix 1: Primary Data used for Prediction.

Prediction Dates: 2nd June 2024 -> 12th June 2024

Single Point Location used for comparison: [37°45'00.0"S 145°00'00.0"E]

Melbourne map of co-ordinates (all points):

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       144.5 , 144.75, 145.  , 145.25, 145.5 , 145.75, 144.25, 144.5 ,
       144.75, 145.  , 145.25, 145.5 , 145.75, 144.25, 144.5 , 144.75,
       145.  , 145.25, 145.5 , 145.75, 144.25, 144.5 , 144.75, 145.  ,
       145.25, 145.5 , 145.75, 144.25, 144.5 , 144.75, 145.  , 145.25,
       145.5 , 145.75, 144.25, 144.5 , 144.75, 145.  , 145.25, 145.5 ,
       145.75]
```

Extracted Prediction Metric: *Temperature at 2m above ground.*

Raw Data (one data frame): (-38.25, 144.25):

	Unnamed: 0	date	temperature_2m_reanalysis	latitude_reanalysis	longitude_reanalysis	requested_lat	requested_lon	temperature_2m_forcast	latitude_forcast	longitude_forcast	lat-lon	era5_2m	gc_2m
date													
2024-06-02 12:00:00	1860	2024-06-02 12:00:00	10.943000	-38.277679	144.24324	-38.25	144.25	8.848	-38.25	144.25	-38.25-144.25	9.208649	10.317169
2024-06-02 18:00:00	1866	2024-06-02 18:00:00	10.993000	-38.277679	144.24324	-38.25	144.25	6.648	-38.25	144.25	-38.25-144.25	7.762848	8.930939
2024-06-03 00:00:00	1872	2024-06-03 00:00:00	11.893000	-38.277679	144.24324	-38.25	144.25	9.598	-38.25	144.25	-38.25-144.25	10.290192	10.184296
2024-06-03 06:00:00	1878	2024-06-03 06:00:00	13.092999	-38.277679	144.24324	-38.25	144.25	12.048	-38.25	144.25	-38.25-144.25	12.726105	11.370911
2024-06-03 12:00:00	1884	2024-06-03 12:00:00	10.542999	-38.277679	144.24324	-38.25	144.25	7.348	-38.25	144.25	-38.25-144.25	9.538727	9.660370
2024-06-03 18:00:00	1890	2024-06-03 18:00:00	6.593000	-38.277679	144.24324	-38.25	144.25	5.798	-38.25	144.25	-38.25-144.25	6.560455	8.951874
2024-06-04 00:00:00	1896	2024-06-04 00:00:00	9.143000	-38.277679	144.24324	-38.25	144.25	8.998	-38.25	144.25	-38.25-144.25	9.756012	11.029999
2024-06-04 06:00:00	1902	2024-06-04 06:00:00	11.842999	-38.277679	144.24324	-38.25	144.25	11.198	-38.25	144.25	-38.25-144.25	11.314117	12.385040
2024-06-04 12:00:00	1908	2024-06-04 12:00:00	10.292999	-38.277679	144.24324	-38.25	144.25	7.798	-38.25	144.25	-38.25-144.25	9.329742	10.653961
2024-06-04 18:00:00	1914	2024-06-04 18:00:00	8.143000	-38.277679	144.24324	-38.25	144.25	6.948	-38.25	144.25	-38.25-144.25	8.167145	10.627594
2024-06-05 00:00:00	1920	2024-06-05 00:00:00	12.143000	-38.277679	144.24324	-38.25	144.25	9.148	-38.25	144.25	-38.25-144.25	10.649567	12.736603
2024-06-05 06:00:00	1926	2024-06-05 06:00:00	13.292999	-38.277679	144.24324	-38.25	144.25	13.898	-38.25	144.25	-38.25-144.25	13.474640	13.322266
2024-06-05 12:00:00	1932	2024-06-05 12:00:00	12.592999	-38.277679	144.24324	-38.25	144.25	10.848	-38.25	144.25	-38.25-144.25	9.305817	11.609711
2024-06-05 18:00:00	1938	2024-06-05 18:00:00	11.393000	-38.277679	144.24324	-38.25	144.25	10.848	-38.25	144.25	-38.25-144.25	9.722809	11.095184
2024-06-06 00:00:00	1944	2024-06-06 00:00:00	13.693000	-38.277679	144.24324	-38.25	144.25	13.898	-38.25	144.25	-38.25-144.25	12.774567	12.726257
2024-06-06 06:00:00	1950	2024-06-06 06:00:00	13.993000	-38.277679	144.24324	-38.25	144.25	14.448	-38.25	144.25	-38.25-144.25	14.353058	13.060028
2024-06-06 12:00:00	1956	2024-06-06 12:00:00	12.243000	-38.277679	144.24324	-38.25	144.25	11.798	-38.25	144.25	-38.25-144.25	10.691681	11.337646
2024-06-06 18:00:00	1962	2024-06-06 18:00:00	12.943000	-38.277679	144.24324	-38.25	144.25	11.698	-38.25	144.25	-38.25-144.25	9.693268	10.755219
2024-06-07 00:00:00	1968	2024-06-07 00:00:00	14.443000	-38.277679	144.24324	-38.25	144.25	13.648	-38.25	144.25	-38.25-144.25	13.252472	11.504517
2024-06-07 06:00:00	1974	2024-06-07 06:00:00	13.693000	-38.277679	144.24324	-38.25	144.25	13.398	-38.25	144.25	-38.25-144.25	13.443268	12.961823
2024-06-07 12:00:00	1980	2024-06-07 12:00:00	11.292999	-38.277679	144.24324	-38.25	144.25	10.798	-38.25	144.25	-38.25-144.25	11.092926	10.575714
2024-06-07 18:00:00	1986	2024-06-07 18:00:00	10.643000	-38.277679	144.24324	-38.25	144.25	9.498	-38.25	144.25	-38.25-144.25	8.821930	10.733032
2024-06-08 00:00:00	1992	2024-06-08 00:00:00	12.592999	-38.277679	144.24324	-38.25	144.25	10.948	-38.25	144.25	-38.25-144.25	11.643341	11.292480
2024-06-08 06:00:00	1998	2024-06-08 06:00:00	12.592999	-38.277679	144.24324	-38.25	144.25	13.298	-38.25	144.25	-38.25-144.25	12.800323	11.777496
2024-06-08 12:00:00	2004	2024-06-08 12:00:00	9.443000	-38.277679	144.24324	-38.25	144.25	9.198	-38.25	144.25	-38.25-144.25	9.952545	7.659821
2024-06-08 18:00:00	2010	2024-06-08 18:00:00	9.943000	-38.277679	144.24324	-38.25	144.25	10.048	-38.25	144.25	-38.25-144.25	10.960846	6.203491
2024-06-09 00:00:00	2016	2024-06-09 00:00:00	11.592999	-38.277679	144.24324	-38.25	144.25	11.998	-38.25	144.25	-38.25-144.25	11.754547	10.993195
2024-06-09 06:00:00	2022	2024-06-09 06:00:00	11.842999	-38.277679	144.24324	-38.25	144.25	11.248	-38.25	144.25	-38.25-144.25	11.989899	13.642670
2024-06-09 12:00:00	2028	2024-06-09 12:00:00	7.843000	-38.277679	144.24324	-38.25	144.25	6.598	-38.25	144.25	-38.25-144.25	8.706207	11.777496
2024-06-09 18:00:00	2034	2024-06-09 18:00:00	5.693000	-38.277679	144.24324	-38.25	144.25	3.648	-38.25	144.25	-38.25-144.25	5.101471	12.080658
2024-06-10 00:00:00	2040	2024-06-10 00:00:00	7.043000	-38.277679	144.24324	-38.25	144.25	7.448	-38.25	144.25	-38.25-144.25	8.183258	12.758698
2024-06-10 06:00:00	2046	2024-06-10 06:00:00	13.693000	-38.277679	144.24324	-38.25	144.25	13.348	-38.25	144.25	-38.25-144.25	13.041046	13.121124
2024-06-10 12:00:00	2052	2024-06-10 12:00:00	12.092999	-38.277679	144.24324	-38.25	144.25	11.398	-38.25	144.25	-38.25-144.25	12.825348	11.744659
2024-06-10 18:00:00	2058	2024-06-10 18:00:00	12.243000	-38.277679	144.24324	-38.25	144.25	13.548	-38.25	144.25	-38.25-144.25	12.416168	11.165924
2024-06-11 00:00:00	2064	2024-06-11 00:00:00	12.143000	-38.277679	144.24324	-38.25	144.25	13.598	-38.25	144.25	-38.25-144.25	13.698151	10.948608
2024-06-11 06:00:00	2070	2024-06-11 06:00:00	13.693000	-38.277679	144.24324	-38.25	144.25	13.748	-38.25	144.25	-38.25-144.25	13.471344	12.228516
2024-06-11 12:00:00	2076	2024-06-11 12:00:00	11.493000	-38.277679	144.24324	-38.25	144.25	11.698	-38.25	144.25	-38.25-144.25	12.237823	10.537231
2024-06-11 18:00:00	2082	2024-06-11 18:00:00	9.893000	-38.277679	144.24324	-38.25	144.25	10.248	-38.25	144.25	-38.25-144.25	10.144928	9.272614
2024-06-12 00:00:00	2088	2024-06-12 00:00:00	11.393000	-38.277679	144.24324	-38.25	144.25	10.448	-38.25	144.25	-38.25-144.25	10.219635	10.964935
2024-06-12 06:00:00	2094	2024-06-12 06:00:00	11.393000	-38.277679	144.24324	-38.25	144.25	10.798	-38.25	144.25	-38.25-144.25	11.007843	11.770660

Remote Graphcast python package: https://pypi.org/project/remote-graphcast/

Remote server used for prediction: https://www.runpod.io/