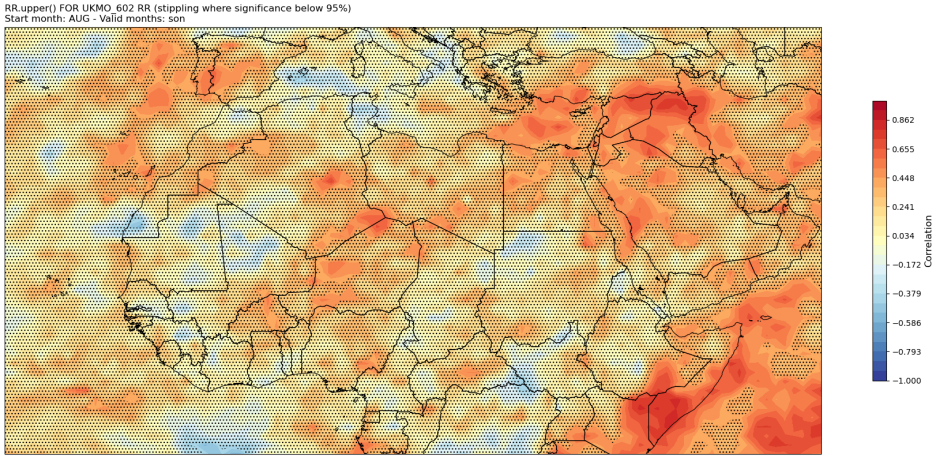
Probabilistic Evaluation of Climate Models For Seasonal Forecasting in the MENA Region

Identification of Windows of Opportunity



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Preface

The MENA seasonal forecasting models have undergone both probabilistic and deterministic evaluations. This research study is regarded as the pioneering work and the first of its kind in this area which helps in situational context improvement in seasonal forecasting models. Given the alarming rate of increase in the impacts caused by extreme climatic events including severe droughts, and extreme heat and other climate sensitive issues in the MENA region, this work is a key contribution towards alleviating these issues=

Due to climatic extremes in the MENA region, agriculture, human livelihood, and natural resources are heavily affected. Consequently, it has become almost necessary to have forecasts of seasons that are credible so as to characterize the impacts, or to enhance preparedness. Although seasonal forecasting models have been widely researched and practiced in many parts of the world, their use in MENA countries' local level remains scarce. This gap is resolved in this study, providing new knowledge and tools for climate scientists working in the region.

In this work, we intend to broaden the knowledge fabric of climate change science by focusing on the climate change and variability vulnerability of the MENA region. The results obtained not only improve the comprehension of the dynamics of the local climate, but also lays a framework for specific approach to be employed for adaptation strategies.

We are immensely grateful to every individual or organization who has helped support this project and guided us through uncharted territory in the spectrum of MENA climate predictions.

Overview and Rationale of the Study

The last couple of decades have witnessed a surge in demand for seasonal climate forecasting. Global advancements in space science and technology have lead to the better anticipation of climate seasons up to a thorugh range of 3-12 months. This is crucial for effective planning in major industries like agriculture or energy management, amongst others. These advancements breed an increased dependence on seasonal forecasting and in turn create a higher demand for accurate forecasting mechanisms. Therefore two central methodologies have witnessed prominence – deterministic and probabilistic methods. A hindsight understanding of these mechanisms is imperative, as they are useful for evaluating and understanding the shortcomings and effectiveness of different models employed in forecasting seasonal amps.

Probabilistic forecasts take one step forward, do not try to predict an ideal scenario and present different potential outcomes, each with a defined probability. Efforts, though different, instruct towards the same ends; meeting a specific operational/strategic need. Lorenz's butterfly effect presents the case for one such endeavor- it shows how a non-linear system's response can drastically alter depending on the initial conditions. Such chaos is especially present in weather and climate systems where even the slightest details can have large ramifications over longer periods.

The study on the other hand tries to develop such relationships that integrate conceptual developments in seasonal forecasting efforts with applicable methods.

1 Introduction

1.1 Context

1.1.1 Overview of Climate Modeling and Seasonal Forecasting

Climate modeling is the process of using mathematical representations of the Earth's atmosphere, oceans, land surface, and ice systems to simulate and predict climate dynamics. These models are based on fundamental physical principles, such as the conservation of mass, energy, and momentum, and are implemented through numerical methods that solve complex equations governing the interactions between these systems.[1] Climate models range from global circulation models (GCMs), which simulate large-scale atmospheric and oceanic processes, to regional climate models (RCMs), which provide localized projections by incorporating finer-scale topographic and land-use details.[2] Seasonal forecasting, a subset of climate modeling, refers to the prediction of climate conditions, such as temperature and precipitation, over a period of one to six months. These forecasts rely on initial conditions (e.g., sea surface temperatures, soil moisture) and slowly varying components of the climate system, such as oceanic or atmospheric anomalies like the El Niño-Southern Oscillation (ENSO).[3] The basic principle behind seasonal forecasting is to leverage these slowly varying components, which have a predictable influence on regional weather patterns, using ensemble simulations to quantify uncertainties and provide probabilistic predictions.[4]

Seasonal forecasts play a crucial role in decision-making and planning across various sectors, including agriculture, water management, and climate risk mitigation. These forecasts provide early warnings of high-impact climate scenarios, enabling proactive decisions that result in financial savings, risk reduction, and optimized resource use. For instance, in agriculture, they assist farmers in selecting appropriate crops and determining optimal planting times based on anticipated water availability, thereby mitigating risks associated with droughts or excessive rainfall.[5] Seasonal forecasts also support pre-harvest strategies, such as hedging decisions, which help shield farmers from price volatility, although their adoption is often hindered by perceptions of inaccuracy and complexity.[6] In water management, seasonal forecasts are vital for mitigating drought impacts, particularly in semi-arid regions, by enabling improved reservoir operations and efficient water allocation to reduce losses.[7] Additionally, these forecasts, when linked to hydrological models, improve predictions of water balance and inform critical decisions regarding water storage and distribution, despite occasional discrepancies between predicted and desired variables.[8] Seasonal forecasts are increasingly applied in climate risk management, where they help predict extreme weather events, providing decision-makers with tools to minimize societal and economic damages.[9]

[1] McGuffie, K. and Henderson-Sellers, A., 2014. A Climate Modelling Primer. https://doi.org/10.1002/9781118687853

[2] Flato et al., 2013. Evaluation of Climate Models. IPCC AR5 Chapter 9. https://www.ipcc.ch/report/ar5/wg1/chapter-9-evaluation-of-climate-models/

[3] Doblas-Reyes, F. J., García-Serrano, J., Lienert, F., Biescas, A. P., & Rodrigues, L. R., 2013. Seasonal climate predictability and forecasting: Status and prospects. https://doi.org/10.1038/ngeo1714

[4] Palmer, T. N., & Anderson, D. L., 1994. The prospects for seasonal forecasting—a review paper. https://doi.org/10.1256/smsqj.50402

[5] Werner, M. and Linés, C., 2024. Seasonal forecasts to support cropping decisions. https://doi.org/10.5194/egusphere-egu24-13436

[6] Hunt et al., 2020. Seasonal Forecast Based Preharvest Hedging. https://doi.org/10.22004/AG.ECON.309761

[7] Portele et al., 2021. Seasonal forecasts offer economic benefits for hydrological decision-making. https://doi.org/10.1038/s41598-021-89564-y

[8] MacLeod et al., 2023. Translating seasonal climate forecasts into water balance forecasts. https://doi.org/10.1371/journal.pclm.0000138

[9] Castino et al., 2023. Towards seasonal prediction of extreme temperature indices. https://doi.org/10.5194/

For example, accurate predictions of heatwaves or floods allow authorities to implement adaptive measures, reducing infrastructure damage and safeguarding public health. In economic sectors such as energy and water management, tailored seasonal forecasts enhance decision-making efficiency by aligning forecasts with user needs, thereby optimizing outcomes.[10] Despite their significant potential, the effectiveness of seasonal forecasts depends on their accuracy, relevance to user needs, and ease of use. Improved communication, stakeholder training, and efforts to bridge the gap between forecast complexity and user understanding are essential to maximize their utility.

1.1.2 Importance of Seasonal Climate Forecasts in MENA

Seasonal climate forecasts are critically important across the MENA region, where high temperatures, low water availability, and vulnerability to climate variability create substantial challenges for sustainable development. Forecasts provide early warnings of droughts, heatwaves, and other extreme weather events, enabling decision-makers to implement proactive measures to mitigate impacts on water resources, agriculture, and infrastructure.[11] In agriculture, these forecasts help farmers optimize crop selection and planting schedules, reducing the risks of crop failure in this water-scarce region.[12] In the water sector, seasonal forecasts guide reservoir management by predicting rainfall variability, improving water storage strategies, and ensuring more equitable water distribution.[13] With increasing climate risks, these forecasts also support disaster risk management by allowing governments to prepare for extreme events, such as heatwaves and floods, which are becoming more frequent in the region due to climate change.[14] Moreover, the economic benefits of using seasonal forecasts are significant. By enabling energy companies to anticipate peak demand periods driven by heatwaves, and by helping municipalities optimize water usage during droughts, these forecasts provide cost savings and efficiency gains.[15] However, challenges persist in ensuring the accuracy and usability of these forecasts. The arid and semi-arid nature of much of the MENA region, coupled with complex interactions between regional climate drivers, makes it difficult to provide highly localized forecasts.[16] Addressing these challenges through improved modeling techniques and stakeholder engagement will be critical to maximizing the value of seasonal forecasts in the MENA region, ensuring better preparedness and resilience against a changing climate.

1.2 Objectives of the Work

The primary objective of this work is to evaluate the effectiveness of climate models, focusing specifically on their performance in predicting key climate variables such as temperature, precipitation. This evaluation incorporates both deterministic and probabilistic approaches to identify the most skillful models and their suitability for practical applications.

ems2023-590

[10] Goodess et al., 2022. The Value-Add of Tailored Seasonal Forecast Information. https://doi.org/10.3390/cli10100152

[11] Dunn et al., 2020. The changing climate of MENA. https://pubs.giss.nasa.gov/abs/gu00200u.html

[12] Werner, M., and Linés, C., 2024. Seasonal forecasts to support cropping decisions. https://doi.org/10.5194/egusphere-egu24-13436

[13] Portele et al., 2021. Seasonal forecasts for hydrological decision-making. https://doi.org/10.1038/s41598-021-89564-y

[14] Castino et al., 2023. Towards seasonal prediction of extreme temperature indices. https://doi.org/10.5194/ems2023-590

[15] Goodess et al., 2022. Value-Add of tailored seasonal forecast information. https://doi.org/10.3390/cli10100152

[16] Latif et al., 2011. ENSO predictability and regional climate impacts. https://doi.org/10.1175/2010JCLI3405.1

1.2.1 Specific aims of evaluating deterministic and probabilistic models.

The evaluation of deterministic and probabilistic models is essential for understanding their unique strengths, limitations, and potential applications in diverse fields. Deterministic models, which generate a single, precise outcome based on initial conditions, are widely used when exactness and reproducibility are critical, such as in engineering and physical simulations.[17] Their evaluation focuses on assessing accuracy and reliability under specific conditions, providing clarity in cause-and-effect relationships. In contrast, probabilistic models incorporate uncertainty by assigning probabilities to various potential outcomes, enabling the representation of real-world complexities and variability.[18] These models are particularly beneficial for strategic planning and risk management, where understanding a range of possible scenarios is crucial. The evaluation of both types of models includes conducting sensitivity analyses to determine how changes in input variables affect outcomes, which helps in identifying key drivers of uncertainty and improving model performance.[19] Additionally, risk assessment is a vital component, with deterministic approaches offering straightforward estimations for defined scenarios, while probabilistic approaches address uncertainties by simulating a spectrum of possible outcomes.[20] These evaluations also aim to support decision-making processes by identifying which type of model is more appropriate for specific contexts—deterministic models for precise predictions and probabilistic models for flexible planning under uncertainty.[21] Finally, probabilistic models are often recognized for their adaptability in dynamic environments, as they can incorporate new data and adjust probability distributions to reflect evolving conditions, making them indispensable for complex systems where deterministic models may fall short.[22] Together, the evaluation of deterministic and probabilistic models provides invaluable insights into their suitability for addressing specific challenges, supporting informed decision-making, and advancing model development.

1.2.2 Description of Content

This report is designed to provide a comprehensive analysis of climate model evaluation, focusing on both deterministic and probabilistic approaches. The structure of the report follows a logical progression, starting with an introduction to the fundamental concepts behind climate models. The first section lays the groundwork for understanding the key differences between deterministic and probabilistic models, describing how each approach is used to simulate climate systems and predict future outcomes. The methodology chapter follows, detailing the specific techniques employed to assess the models. This includes the use of both deterministic and probabilistic metrics such as Root Mean Square Error (RMSE), Anomaly Correlation Coefficient (ACC), and Brier Score, which are critical for evaluating the models' accuracy and performance in predicting climate variables like temperature and precipitation.

Next, the report moves on to the results and analysis, where the performance of the selected

[17] McGuffie, K., and Henderson-Sellers, A., 2014. *A Climate Modelling Primer*. Wiley. https://doi.org/10.1002/9781118687870

[18] Palmer, T., and Hagedorn, R., 2006. *Predictability of Weather and Climate*. Cambridge University Press. https://doi.org/10.1017/CBO9780511617652

[19] Seneviratne, S.I., et al., 2021. *Metrics for climate model evaluation: A review*. Nature Communications. https://doi.org/10.1038/s43247-021-00094-x

[20] PreventionWeb, 2021. *Deterministic and Probabilistic Risk*. https://www.preventionweb.net/understanding-disaster-risk/key-concepts/deterministic-probabilistic-risk

[21] Goodess, C.M., et al., 2022. *The Value-Add of Tailored Seasonal Forecast Information for Industry Decision Making*. Climate. https://doi.org/10.3390/cli10100152

[22] Latif, M., and Keenlyside, N., 2011. *El Niño/Southern Oscillation Predictability*. Journal of Climate. https://doi.org/10.1175/2010JCLI3405.1

models is presented and compared. This section highlights the models' strengths and weaknesses, providing insight into how well they predict climate patterns across various geographical regions and time periods. Special attention is given to the models' skill in forecasting extreme weather events, which are particularly relevant to sectors like agriculture, water resource management, and disaster risk reduction.

The final section of the report provides conclusions and recommendations based on the analysis. This chapter synthesizes the findings, offering practical suggestions for improving the accuracy, usability, and application of climate forecasts. Recommendations also address how future developments in climate modeling can better meet the needs of decision-makers and stakeholders. The report as a whole seeks to contribute valuable insights into the ongoing development of climate prediction systems, aiming to enhance their effectiveness in real-world applications.

2 LITERATURE REVIEW

2.1 Overview of Climate Models

2.1.1 Deterministic Models

Deterministic models rely on mathematical equations that describe the physical processes of the atmosphere. These models use fixed initial conditions to provide precise predictions, making them suitable for short-term forecasting. However, due to the chaotic nature of atmospheric systems, as demonstrated by Lorenz's theorem, deterministic models are limited in their ability to predict long-term outcomes. Small errors in initial conditions can lead to significant differences in results, reducing their reliability for seasonal or long-term forecasting.[23]

Deterministic climate models operate based on fixed initial conditions and mathematical equations that simulate physical processes in the atmosphere. These models are particularly useful for short-term predictions as they provide precise and singular forecasts. However, deterministic models are significantly limited when forecasting over extended periods. This limitation arises due to the inherent sensitivity of atmospheric systems to initial conditions—a concept known as the *butterfly effect*, introduced by Edward Lorenz in 1963. His research demonstrated that even minute changes in the initial conditions of a system could lead to vastly different outcomes over time, emphasizing the chaotic nature of weather systems.

For seasonal forecasting, deterministic models often fail because minor errors in the initial conditions can amplify, resulting in inaccurate predictions for longer timescales. Despite these challenges, deterministic models are vital for understanding specific phenomena over shorter durations with high spatial and temporal resolution.

2.1.2 Probabilistic Models

Probabilistic models address the limitations of deterministic approaches by incorporating uncertainty into forecasts. Instead of producing a single outcome, these models generate a range of possible scenarios, each with an associated probability, using ensemble simulations or statistical techniques. This makes probabilistic models particularly useful for medium- to long-term forecasts and risk assessment in climate-sensitive sectors such as agriculture, water management, and disaster mitigation.[24]

The evaluation of probabilistic models relies on metrics that assess their ability to represent uncertainty and provide actionable insights:

[23] Lorenz, E. N. (1963). Deterministic Nonperiodic Flow. *Journal of the Atmospheric Sciences, 20*(2), 130–141.

[24] World Meteorological Organization (2024). *Guidance on Verification of Operational Seasonal Climate Forecasts.* https://library.wmo.int/records/item/56227-guidance-on-verification-of-operational-seasonal-climate-forecasts

- **Reliability:** Measures how well predicted probabilities align with observed frequencies.
- **Resolution:** Assesses the model's ability to distinguish between different outcomes.
- **Discrimination:** Evaluates the model's ability to separate events from non-events.[25]

Probabilistic models are especially valuable for decision-making under uncertainty, as they provide stakeholders with a clearer understanding of risks and potential scenarios, enabling proactive measures to mitigate impacts.

Comparison of Deterministic and Probabilistic Models
Deterministic and probabilistic models serve complementary roles in climate modeling and forecasting. Their distinct features and applications are summarized in Table 1.

Table 1: Comparison of Deterministic and Probabilistic Models

Feature	**Deterministic Models**	**Probabilistic Models**
Predictability	Produces a single fixed outcome based on initial conditions	Generates a range of outcomes with associated probabilities
Sensitivity to Initial Conditions	Highly sensitive, leading to reduced accuracy over long timeframes	Less sensitive due to ensemble techniques reducing error amplification
Application Domain	Suitable for short-term, high-resolution tasks, e.g., extreme event analysis	Ideal for medium- and long-term decision-making under uncertainty
Use of Historical Data	Limited emphasis on historical variability	Extensively relies on historical data for statistical projections
Examples	Global Circulation Models (GCMs), Regional Climate Models (RCMs)	Ensemble forecasting, statistical downscaling

While deterministic models are preferred for precise and short-term predictions, probabilistic models provide critical insights into the likelihood of various scenarios, making them indispensable for managing climate-related risks.

2.2 STUDIES IN "MENA" REGION

2.2.1 The current and changing climate in MENA

Much [26] of the MENA region is characterised by high temperature and low water availability, a combination of variables that have the potential to lead towards the environmental limits/threshold for safe human habitation. This makes the region particularly vulnerable to climate change and climate variability, as small variations in climate can easily produce high temperatures or extensive droughts that are harmful to human lives and livelihoods.

[25] Rapport de projet 2024–2025, *3rd Year Meteorology Modeling Project*.
[26] Met Office WISER Report

Changes in temperature and rainfall patterns have already been observed in the region and are expected to change further in the near future, especially if global warming exceeds 1.5 to 2 °C above the pre-industrial level. Annual mean temperatures across the MENA region have increased between 0.3–0.5°C per decade1 over the period 1980–2015 [27]. Since the 1950s, hot and cold extremes have become warmer, the number of cold days has decreased, and the number of warm days has increased (Dunn et al., 2020). There has been an increase in heat waves intensity, frequency and duration [28]. Annual mean precipitation shows a high level of spatial variability over the MENA region. During the period 1980–2015 there have been downward trends in mean annual precipitation [29] . Dry conditions, drought intensity and frequency has increased in the past over the region [30]

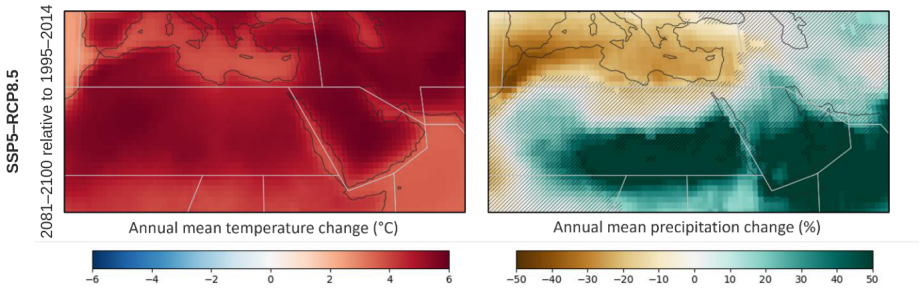

Figure 1: Projected change in annual mean temperature (left) and annual mean precipitation (right) between 1995–2014 and 2081–2100 under the SSP5–RCP8.5 scenario based on CMIP6 models (Gutiérrez et al., 2021). Note that precipitation change is given as a percentage: the large increases projected over Sahara and Arabian deserts equate to only a few millimetres of additional rainfall.

2.2.2 Impact-Based Evaluation

Impact-based forecasting refers to a type of weather or climate forecasting that goes beyond predicting the meteorological parameters (e.g., temperature, rainfall, wind speed) and instead focuses on predicting the potential impacts of those conditions on society, infrastructure, and ecosystems. The goal is to provide actionable insights that help communities and decision-makers prepare for and mitigate the effects of extreme weather and climate events.

Evaluation of Seasonal Forecast Models

An impact-based evaluation[31] [32] was conducted as global study on five seasonal forecast models to identify the most effective for extreme precipitation forecasting (focuses on regions which were vulnerable to wildfire and flooding). The models assessed included:

- Centro Euro-Mediterraneo sui Cambiamenti Climatici (CMCC: version 35),
- Deutscher Wetterdienst (DWD: version 21),
- Environment and Climate Change Canada (ECCC: version 3),
- Météo-France (version 8),

[27](Gutiérrez et al., 2021)
[28](Perkins-Kirkpatrick and Lewis, 2020)
[29](Gutiérrez et al., 2021)
[30](Seneviratne et al., 2021).
[31]https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2024EF004936
[32]Zahir Nikraftar, Rendani Mbuvha, Mojtaba Sadegh, Willem A. Landman

- UK Met Office (UK-Met: version 601).

The findings highlighted the ***UK-Met*** and ***Météo-France*** models as consistently superior across all four seasons. Meanwhile, the ECCC and CMCC models exhibited strong performance on specific indices and in particular regions, ranking just below the top two models.

ROC Scores and Regional Performance

The ROC scores indicate that forecast models perform exceptionally well in tropical and subtropical regions. This result is consistent with our study and can be attributed to the general predictability of oceanic conditions and the influence of climate drivers such as the El Niño-Southern Oscillation (ENSO). The Météo-France and UK-Met models exhibited superior performance during the SON and MAM seasons.

However, the prevalence of grids with no discrimination ROC categories is more common in extratropical regions. This can be attributed to:

- Lower predictability of extratropical variations,
- Model limitations in capturing interactions between tropical and extratropical regions,
- Challenges in representing land surface processes (De Andrade et al., 2019).

The CMCC, DWD, and ECCC models often fail to detect extreme events in many extratropical areas, underscoring the stronger performance of the UK-Met and Météo-France models in these scenarios.

Percent Bias Analysis

The analysis of Percent Bias across four seasons demonstrates a consistent underestimation by forecast models for most extreme wet precipitation indices. Key observations include:

- Forecast models underestimate extreme wet precipitation indices while overestimating light precipitation.
- Models perform better in capturing the intensity and magnitude of extreme events (e.g., highest daily and multi-day rainfall) compared to the frequency of wet or dry days.

In tropical and subtropical regions, models like ***UK-Met*** and ***Météo-France*** exhibit strong performance due to their ability to capture large-scale climate patterns. In contrast, extratropical regions show higher biases, reflecting challenges in modeling complex interactions and seasonal variations.

Global Model Comparison

The ***UK-Met*** model consistently demonstrates lower biases and stronger performance globally compared to the ***Météo-France*** model, highlighting its effectiveness in representing climate patterns. However, all models show limitations in accurately modeling persistent extreme wet and dry periods, particularly in extratropical areas.

2.2.3 SYSTEM 7 FRANCE

seasonal forecasting evaluation has been the subject of numerous studies, with a focus on improving the accuracy and reliability of predictions related to precipitation and other weather parameters. One such study[33] conducted a probabilistic evaluation of seasonal precipitation re-forecasting from May to November over a period of 23 years (1993–2015). The study utilized the Brier Score (BS)

[33]https://www.mdpi.com/2674-0494/1/3/16

and its decomposition to assess forecast performance, with the aim of providing more reliable and actionable predictions for extreme weather events.

The evaluation was conducted on the operational seasonal forecasting system of Meteo-France, which used 25 ensemble members, perturbed model dynamics, and initial conditions. The system aimed to provide a more detailed probabilistic forecast, in addition to existing deterministic metrics, for both seasonal and intra-seasonal forecasts. The BS was estimated using tercile probabilities and a non-parametric counting estimator, with the GPCP[34] observation data serving as the reference.

Multiple analyses were performed to evaluate the robustness of the BS score, revealing that spatial distributions of the BS can vary significantly based on the sampling methods, reference data, and ensemble types used. The analysis showed that large errors, especially in the tropical ocean, could be reduced by using hindcast ensemble climatological samples. In particular, errors over the Nino region in the Pacific Ocean could be mitigated using these methods. This highlights the importance of employing various ensemble data sources and reference climatology to enhance the reliability of seasonal forecasts.

A notable finding was the reduction in BS when using ensemble observations, especially in the tropical ocean, suggesting that increasing ensemble size can improve forecast accuracy up to a point. However, this was not the case in all regions, as some areas, such as the tropical Indian Ocean, exhibited high BS even with different analysis methods. The study also found that intra-seasonal analyses showed similar patterns to seasonal hindcasts, but with higher BS due to reduced sample sizes, highlighting the need for higher-resolution models and improved initial conditions.

The study concluded that, despite improvements, probabilistic forecasting still faces challenges, particularly in the tropical regions, where errors fluctuate with lead time. The study emphasized the need for continued development of forecasting methods, particularly in reducing uncertainties in evaluation scores. Future evaluations should expand beyond the BS to include other metrics, such as the forecast skill score and the relative operating characteristic (ROC), to better assess forecast performance and identify system deficiencies.

This study's findings underline the importance of ensemble forecasting and the use of diverse data sources to improve the accuracy of seasonal precipitation forecasts, particularly in tropical regions where predictability remains challenging.

2.3 Evaluation Approaches

In the WMO[35] . Guide, several criteria are provided for evaluating a good forecast. Each criterion offers insight into specific aspects of the model but cannot, on its own, fully determine the forecast's quality. By combining all the criteria, we can comprehensively assess the performance of the model.

2.3.1 Resolution

Resolution measures whether the outcome differs given different forecasts, while discrimination measures whether the forecasts differ given different outcomes.

Discrimination looks at how well your forecast separates cases when the event (outcome) happens (pass) from when it doesn't happen (fail). It's about telling apart the events. Resolution looks at how well your forecast adapts to different situations, giving distinct probabilities for different cases. It's about adjusting to the situation.

Resolution measures how well a forecast distinguishes between different outcomes. A forecast has high resolution if the predicted probabilities vary significantly depending on the actual outcome.

[34] Global Precipitation Climatology Project (GPCP)

[35] https://library.wmo.int/records/item/56227-guidance-on-verification-of-operational-seasonal-climate-forecasts

In other words, resolution tells us whether the forecast changes (e.g., gives different probabilities) when the actual outcome changes. High resolution: The forecast gives distinct and varying probabilities when different events (outcomes) occur. For example, if in one case the forecast predicts a high probability of rain and it rains, and in another case predicts a low probability and it doesn't rain, the forecast shows good resolution. Low resolution: If the forecast probabilities don't change much regardless of whether it rains or not (e.g., always predicting a 50% chance of rain), the forecast has poor resolution because it fails to capture the differences in actual outcomes. Resolution can be determined by measuring how strongly the outcome is conditioned upon the forecast. If the outcome is independent of the forecast, the forecast has no resolution and is useless Forecasts with no resolution are neither "good" nor "bad", but are useless. Metrics of resolution distinguish between potentially useful and useless forecasts, but not all these metrics distinguish between "good" and "bad" forecasts.

The following equation represents the "resolution" component of the Brier Score (BS) decomposition, which quantifies how well a set of probability forecasts differentiates between events and non-events:

$$\textbf{Resolution} = \frac{1}{n} \sum_{k=1}^{d} n_k \left(\bar{y}_k - \bar{y}\right)^2 \tag{1}$$

where:

$$\bar{y}_k = \frac{1}{n_k} \sum_{i=1}^{n_k} y_{k,i} \tag{2}$$

- n is the total number of forecasts,
- d is the number of discrete probability bins,
- n_k is the number of forecasts in the k-th bin,
- $\bar{y}_k$ is the observed relative frequency for the k-th probability bin,
- $\bar{y}$ is the overall observed relative frequency.

The term $\left(\bar{y}_k - \bar{y}\right)^2$ captures the variance between individual forecast categories and the overall event frequency. Higher resolution indicates that forecasts better differentiate between events and non-events.
so the resolution tells us how the model change with different situations.
the scores used to evaluate resolution are Brier Score and Reliability.

2.3.2 Discrimination

Discrimination measures how well the forecast separates cases where the event occurs from cases where it does not. In other words, it examines whether the forecast probabilities differ for events that happen versus those that don't. High discrimination: A forecast has high discrimination if, for example, when rain occurs, the forecast consistently predicts a high probability of rain, and when rain doesn't occur, it predicts a low probability. It means the forecast is good at distinguishing between rain and no-rain days. Low discrimination: If the forecast provides similar probabilities regardless of whether it rains or not (e.g., predicting a 60% chance of rain every day), it has poor discrimination because it doesn't effectively differentiate between days with and without rain. The score used to evaluate descrimination is ROC[36].

[36]Relative operating characteristics

2.3.3 Reliability

A forecast is reliable if the predicted probabilities match the actual frequencies. For instance: If you forecast a 40% probability for below-normal rainfall, below-normal rainfall should occur in 40% of the cases where you make that prediction. Similarly, if you forecast a 25% chance of above-normal rainfall, above-normal rainfall should happen 25% of the time when you give that probability. If this relationship holds consistently over many forecasts, the forecasts are well-calibrated (or reliable). A Reliable but Uninformative Forecast A forecast that always gives the climatological probability (e.g., always predicting a 33% chance for each category: below, normal, above normal) would be reliable because the climatological average matches the observed frequencies. However, this forecast wouldn't provide any information about changing conditions from case to case—it doesn't adapt to the current situation, making it uninformative.

$$\textbf{Reliability} = \frac{1}{n} \sum_{k=1}^{d} n_k \left(\bar{p}_k - \bar{y}_k\right)^2 \tag{3}$$

- n is the total number of forecasts,
- d is the number of discrete probability bins,
- n_k is the number of forecasts in the k-th bin,
- $\bar{y}_k$ is the observed relative frequency for the k-th probability bin,
- $\bar{p}_k$ is relative frequency for the k-th probability.

2.3.4 Sharpness

Sharp forecasts provide a strong signal about the expected outcome. For example, a sharp forecast might assign a 70% chance to a certain outcome, like above-normal rainfall. This high probability communicates more confidence in that specific outcome. On the other hand, when the forecast probabilities are close to the climatological values (like assigning a 40% chance to above-normal, 35% to normal, and 25% to below-normal), the forecast is not very sharp, meaning the forecaster isn't very confident in predicting any one outcome. The climatological probabilities are reliable, but aren't sharp.

3 Methodology

3.1 DATA

The hindcast data used in this study was obtained using the OSOP package[37], a tool developed by the UK Met Office to facilitate the retrieval of climate and meteorological data. The dataset comprises monthly mean seasonal forecasts for temperature over the MENA (Middle East and North Africa) region.

The hindcast data spans the common period 1993–2016 and was downloaded from the Copernicus Climate Change Service (C3S) platform.

The data was retrieved for the following configurations:

- Variable: 2-meter air temperature (t2m).

[37] https://github.com/OSFTools/osop/tree/main/scripts

- Forecast Range: Lead times of interest (1–3 months), it includes DJF[38], JJA[39], MAM[40], SON[41]
- Geographical Area: MENA region.
- Temporal Coverage: 1993–2016
- the used centers are $UKMO, ECMWF, ECCC_2, ECCC_3, CMCC, Meteo-France_8, DWD$

In addition to the hindcast data, this study utilized ERA5 reanalysis data, a state-of-the-art atmospheric reanalysis product produced by the European Centre for Medium-Range Weather Forecasts (ECMWF).

3.2 Deterministic Evaluation Metrics

3.2.1 Spearman rank correlation

Spearman's correlation is a non-parametric measure of rank correlation (statistical dependence between the rankings of two variables). It assesses how well the relationship between two variables can be described using a monotonic function (whether linear or not).

$$r_s = \frac{cov(R[H], R[O])}{\sigma_{R[H]} \cdot \sigma_{R[O]}}$$

where :

- r_s : spearman rand correlation
- H : the Hindcast.
- O : the Observation.
- R[x] : the rank of the variable x.
- σ_x : standard deviation of the variable x.

[38] December,January,February
[39] June,July,August
[40] March,April,May
[41] September,October,November

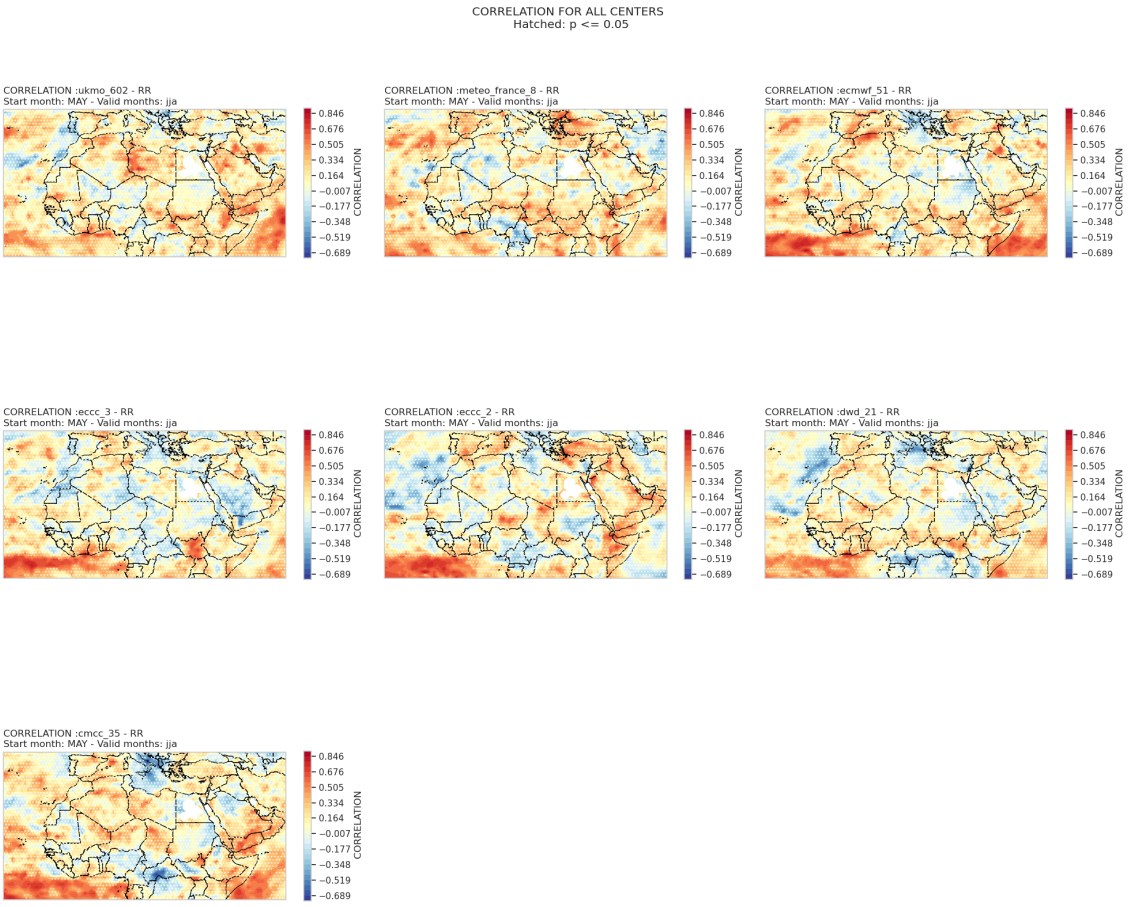

Figure 2: 3-months Rolling mean of Spearman Correlation in MENA Region for all centers JJA

we can show in the figure above that the best model in term of spearman correlation is the **ECMWF** center due to the great correlation in all the MENA region especially for SON[42],JJA[43] and MAM[44].

[42]September,October,November
[43]June,July,August
[44]Mars,April,May

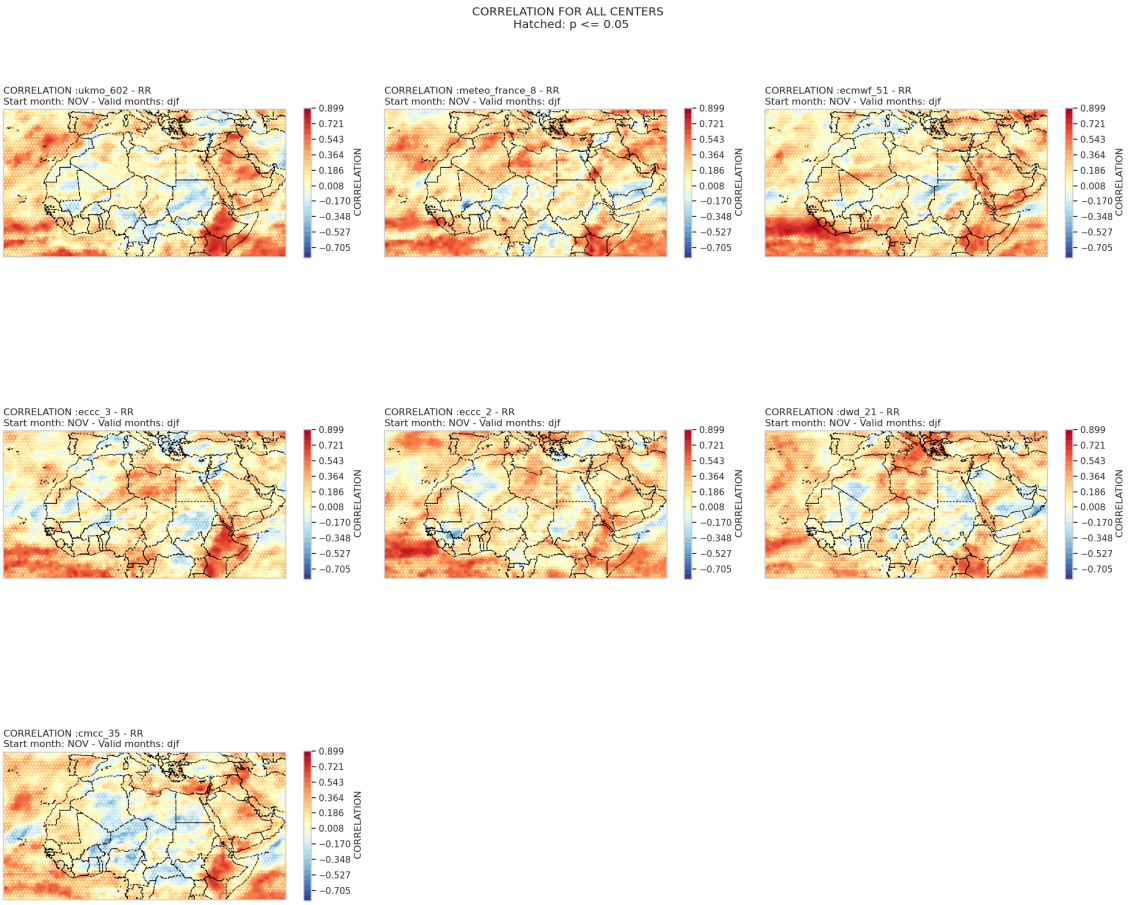

Figure 3: 3-months Rolling mean of Spearman Correlation in MENA Region for all centers DJF

althought, for DJF[45] the ECMWF[46] , ECCC3[47], UKMO[48] and CMCC 35 [49] have the same performance.

[45]December,January,February
[46]European Centre for Medium-Range Weather Forecasts
[47]Environment and Climate Change Canada (ECCC) generation 3
[48]UK Met Office
[49]Centro Euro-Mediterraneo sui Cambiamenti Climatici version 3.5

Figure 4: The Heatmap of correlation for the mena region for every period ***(1 for perfect Correlation)***

3.2.2 RMSE

$RMSE$ measures the average difference between a the hindcast and the observation.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_i - O_i)^2}$$

where :

- H : the Hindcast.
- O : the observation.
- i : the valid time.

for the RMSE[50], the Meteo-France and ECMWF have the best scores for MAM ans SON. Althought, for DJF Météo-France is better, and for JJA ECMWF is the best.

[50]Root Mean Square Error

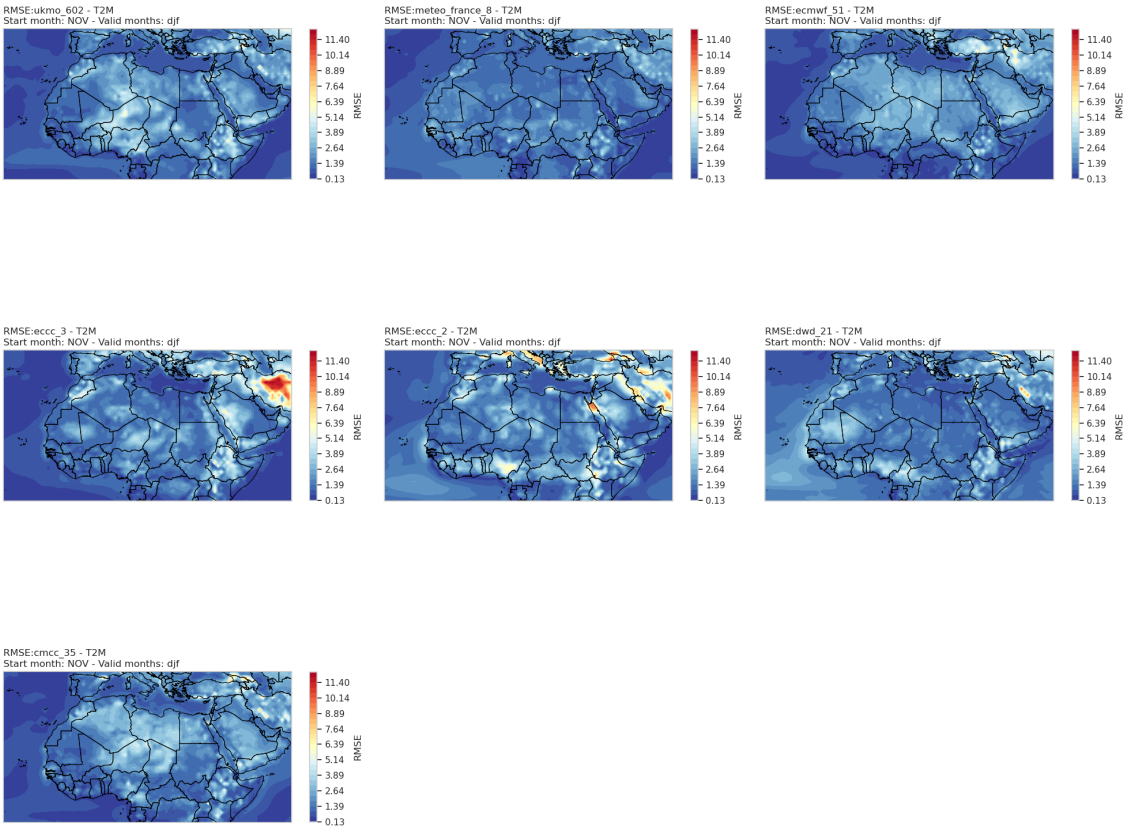

Figure 5: 3-months Rolling mean of RMSE in MENA Region for all centers DJF

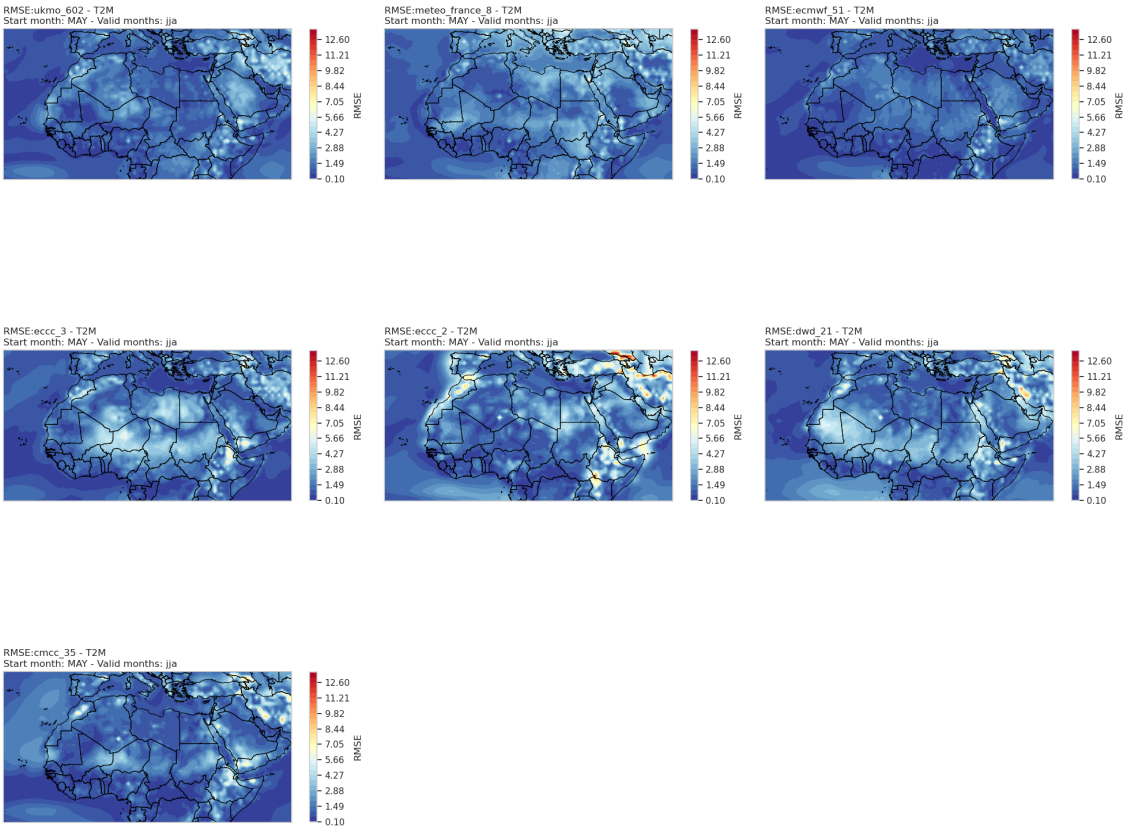

Figure 6: 3-months Rolling mean of RMSE in MENA Region for all centers JJA

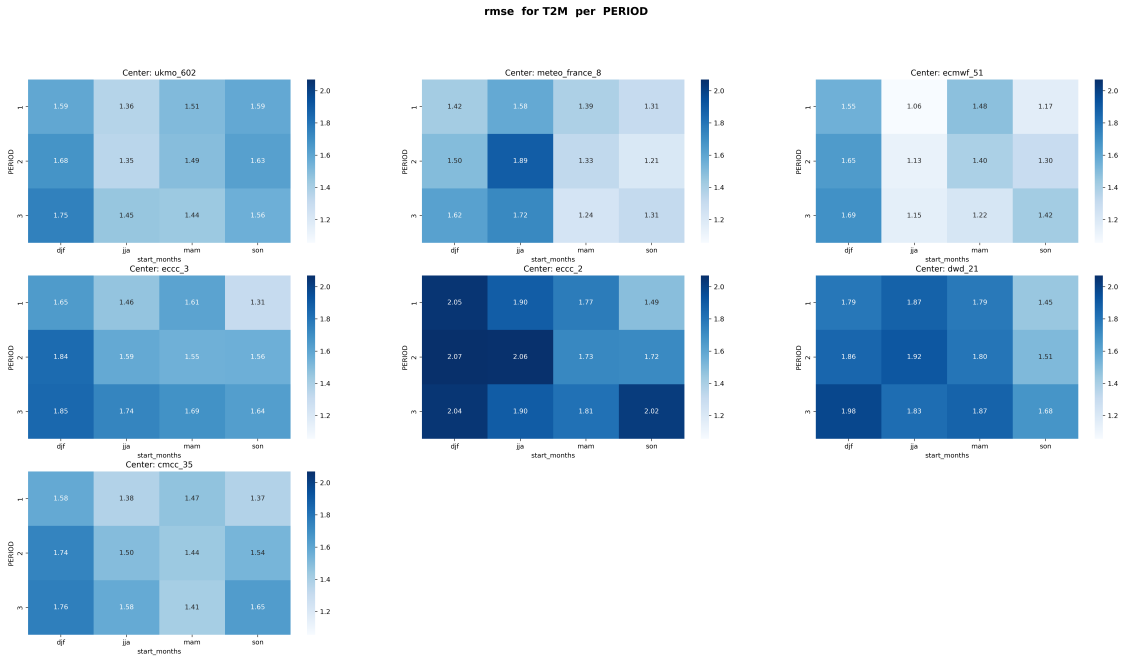

Figure 7: The Heatmap of RMSE for T2M in the MENA region ***(0 for perfect RMSE)***

3.2.3 Coefficient of Determination (R^2)

The coefficient of determination, R^2, is a statistical measure used to evaluate the goodness of fit of a model. It indicates the proportion of the variance in the dependent variable that is predictable from the independent variable(s). A value of R^2 close to 1 suggests that the model explains a large portion of the variance, while a value close to 0 indicates a weak relationship.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - H_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2}$$

where:

- R^2: Coefficient of determination.
- H_i: Predicted value (Hindcast).
- O_i: Observed value (Observation).
- $\bar{O}$: Mean of the observed values.
- $\sum_{i=1}^{n}(O_i - H_i)^2$: Residual sum of squares (unexplained variance).
- $\sum_{i=1}^{n}(O_i - \bar{O})^2$: Total sum of squares (total variance).

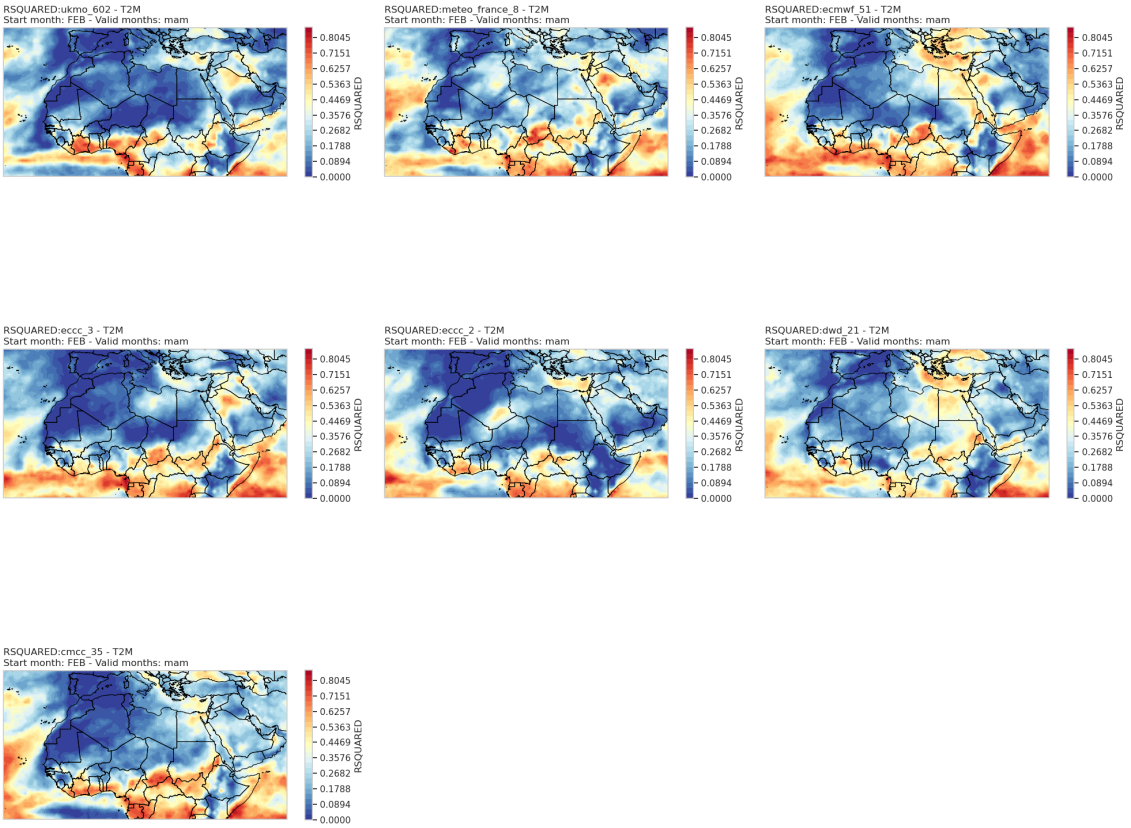

Figure 8: 3-months Rolling mean of RSQUARED in MENA Region for all centers MAM

we can show in the figure above that the best model in term of R-SQUARED is the **ECMWF** center for all periods.

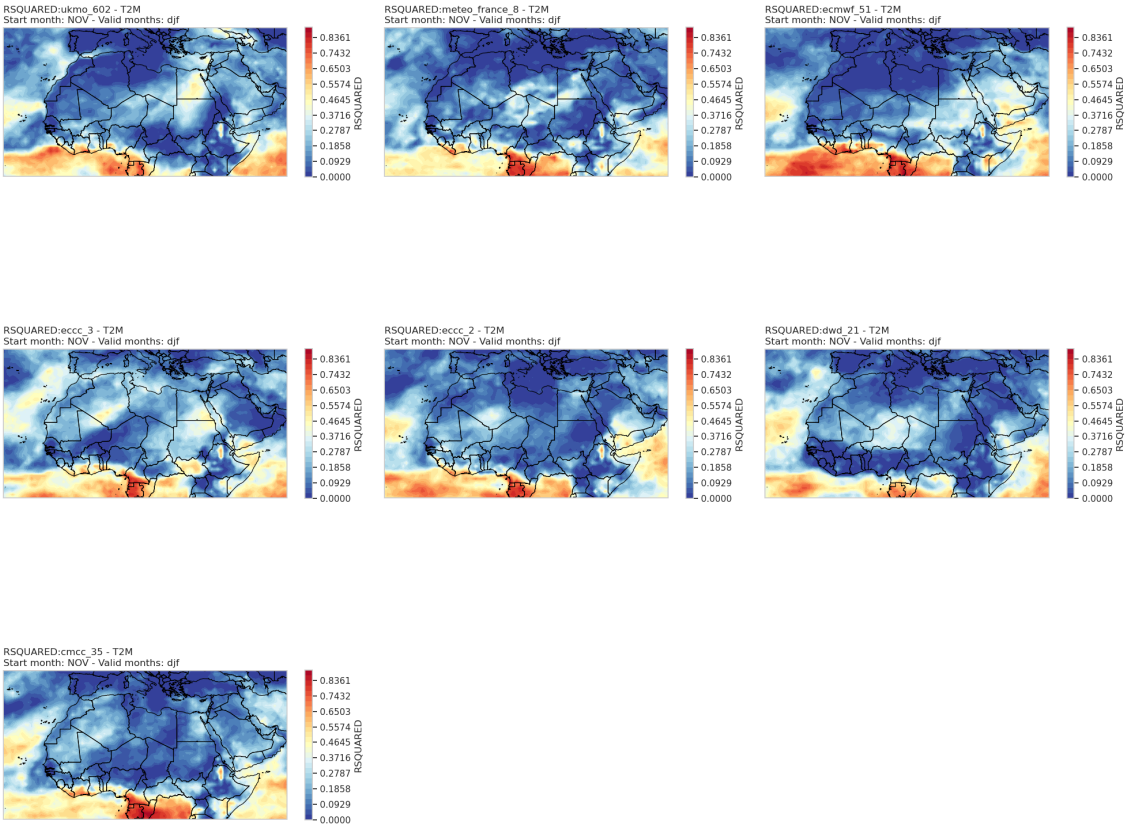

Figure 9: 3-months Rolling mean of RSQUARED in MENA Region for all centers DJF

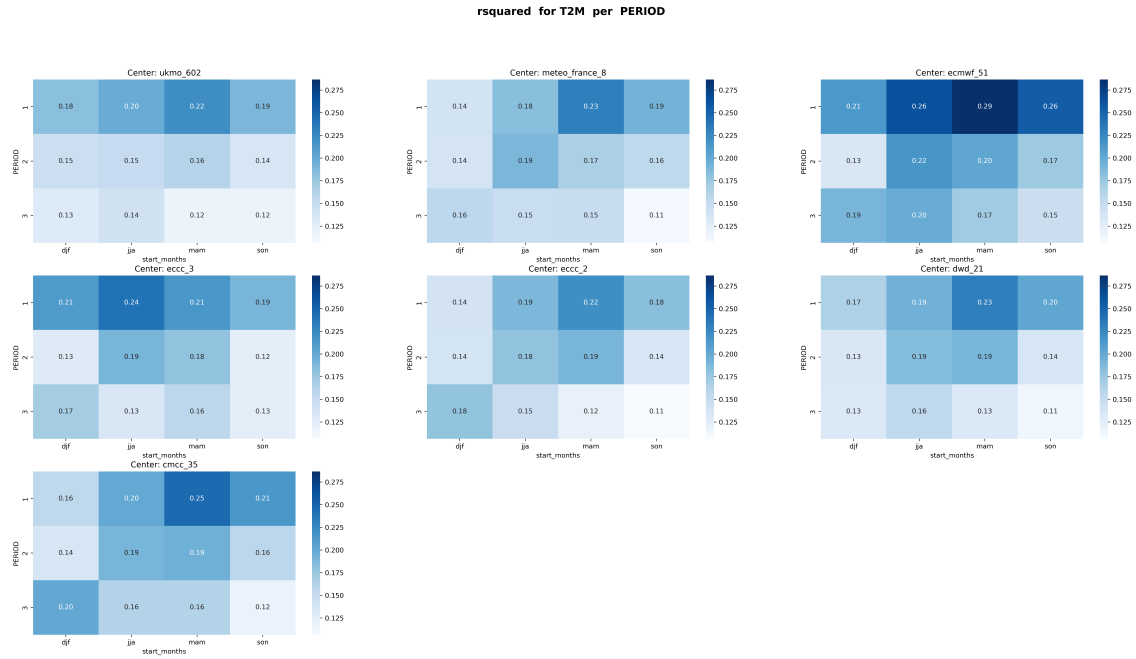

Figure 10: The Heatmap of rsquared for T2M in the mena region for every period ***(1 for perfect RSQUARED)***

3.3 Probabilistic Evaluation Metrics

3.3.1 The Brier Score (BS)

The Brier Score (BS)[51] is the mean squared differences between pairs of forecast probabilities p and the binary observations y. N is the total forecast number. It measures the total probability error, considering that the observation is 1 if the event occurs, and 0 if the event does not occur (dichotomous events).

$$BS_j = \frac{1}{N}\sum_{i}^{N}(y_{j,i} - p_{j,i})^2$$

where:

- n is the number of forecasts
- $y_{j,i}$ is 1 if the i^th observation was in category j, and is 0 otherwise.
- $p_{j,i}$ is the i^th forecast probability for category j.

The BS takes values in the range of 0 to 1. ***Perfect forecasts receive 0*** and less accurate forecasts receive higher scores. Under the condition that x is 0.5 when the observation data is uncertain, the mean squared differences between the forecast probabilities and observation at 0.5 is calculated.

[51] wmo guidance verification

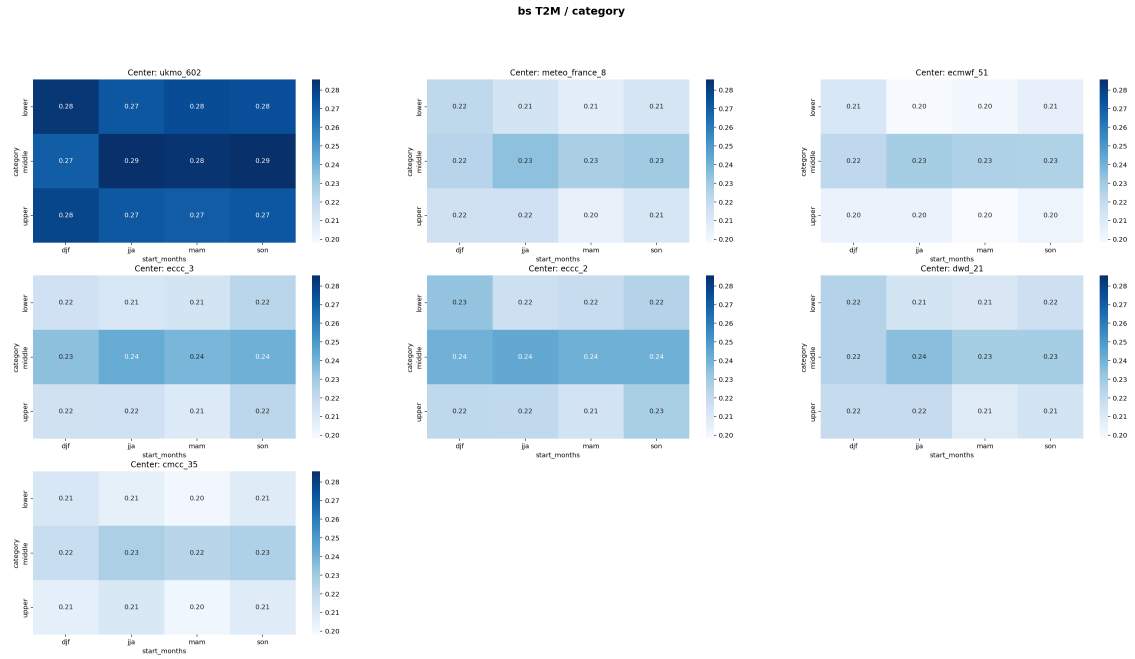

Figure 11: The Heatmap of Brier Score for each category . ***(0 represents perfect BS)***

we see in the figure above that Météo-France, ECMWF,DWD and CMCC35 are the best in Brier Score in the MENA region.

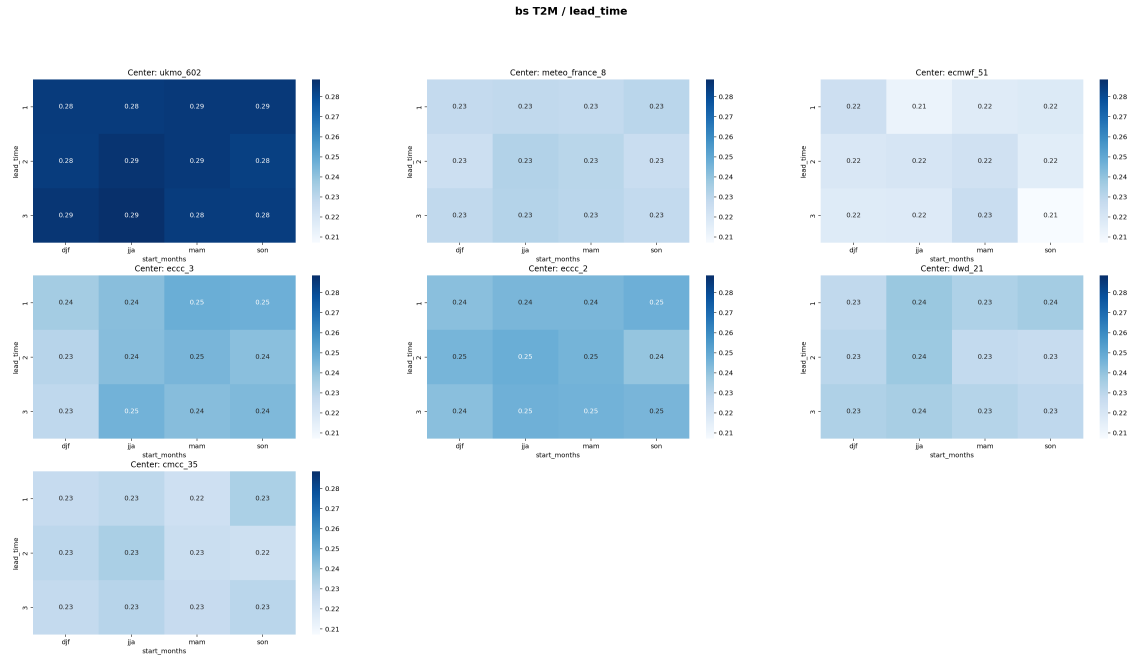

Figure 12: The Heatmap of Brier Score for lead-time. ***(0 represents perfect BS)***

A deep analyze on each tercile category confirms the previous performance.

3.3.2 Reliability

the reliability[52] measures the degree of correspondence between the forecast probability and the observed frequency for an event or outcome that is being predicted. It summarizes the conditional bias of the forecasts for a given event and is equal to the weighted average of squared differences between the forecast and conditional observed probabilities. If the reliability is 0, the forecast is perfectly reliable. To observe the frequency distribution, the forecast probability, from 0 to 1, is divided into 5 bins (0.1,0.3,0.5,0.7,0.9) to compare to the observed frequency in each of the same bin in this study.

$$Reliability = \frac{1}{n}\sum_{k=1}^{d} n_k(\bar{p_k} - \bar{y_k})^2$$

where:

- n_k is the number of forecasts for the k_th probability value ($\bar{p_k}$)
- ($\bar{y_k}$) is the observed relative frequency for that value.

[52] wmo guidance verification

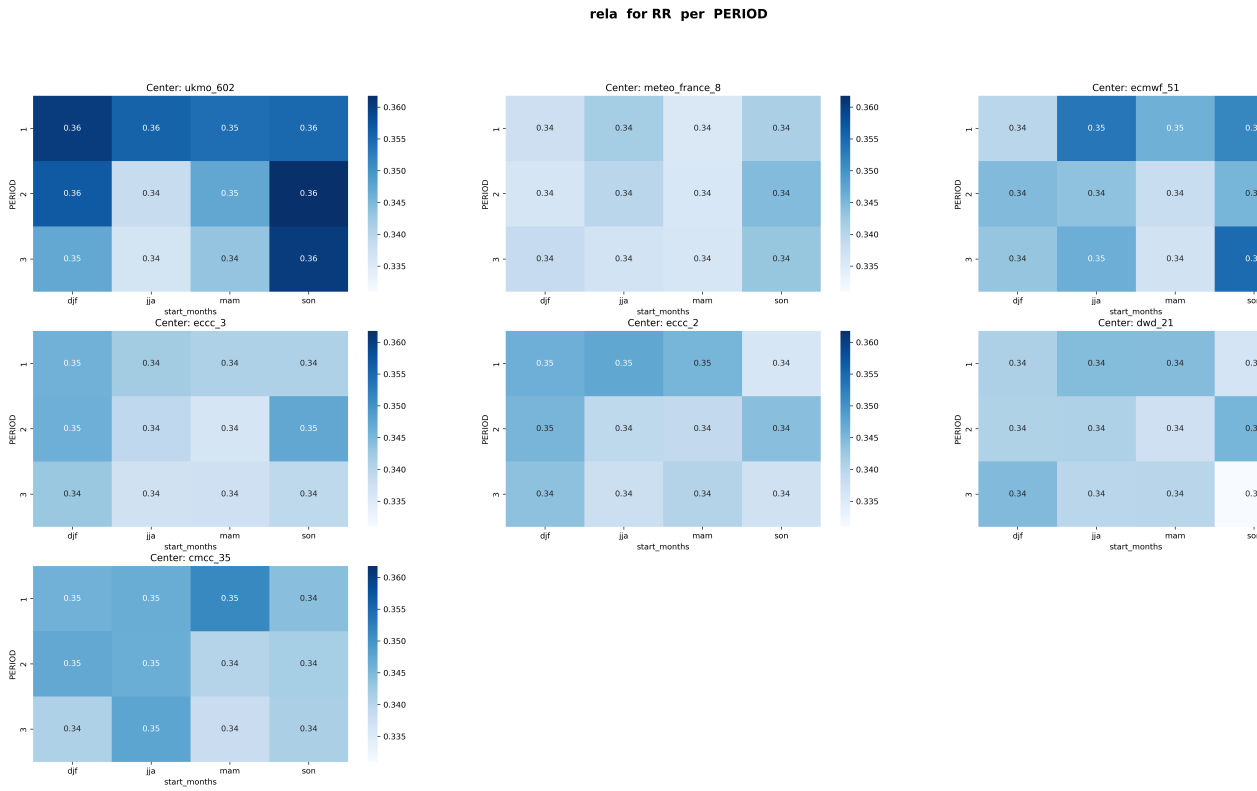

Figure 13: The Reliability Score . ***(0 means perfect Reliability)***

In the figure above, all centers demonstrate similar performance.

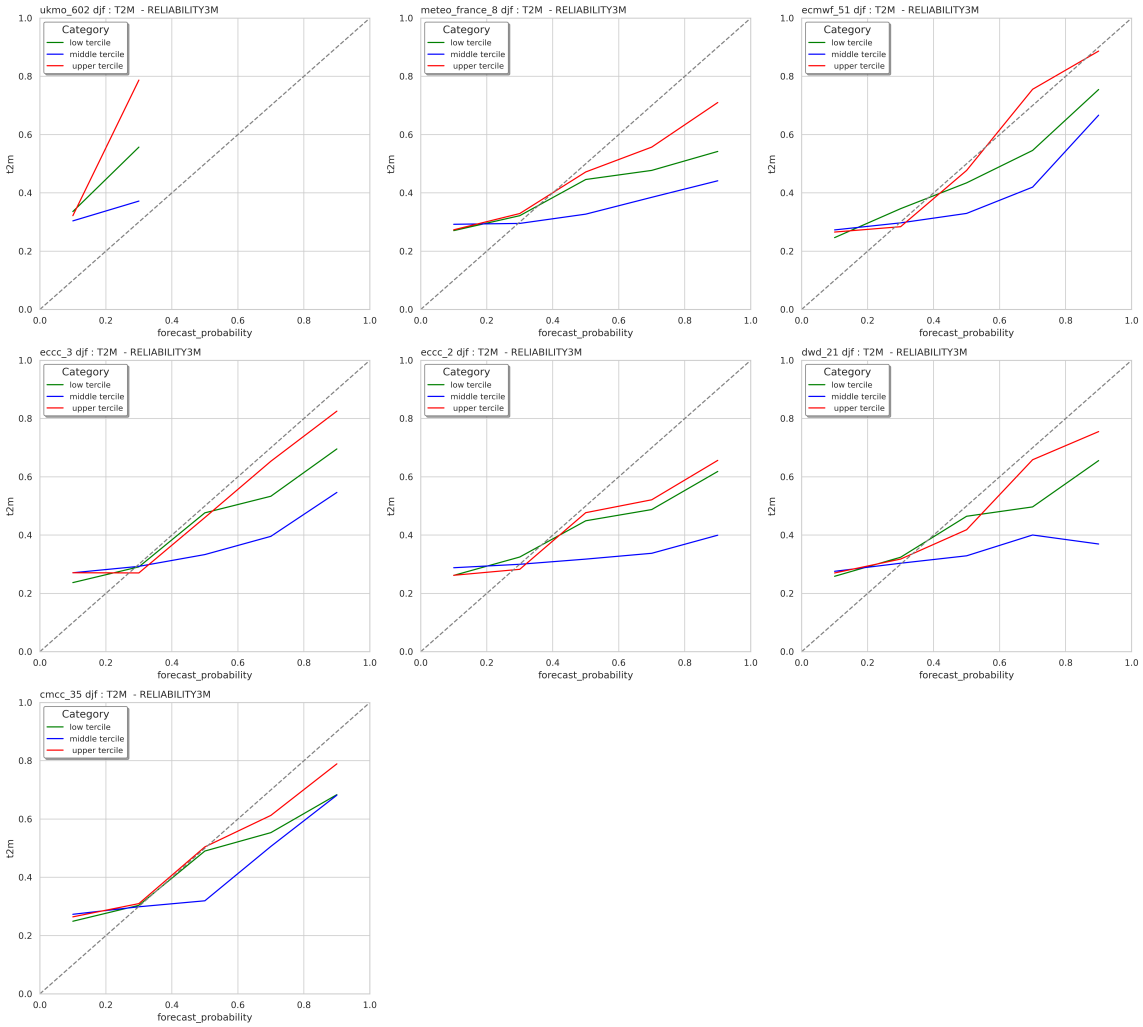

Figure 14: The 3-month rolling mean for Reliability DJF . ***Reliability is better in cases where the graphs are closer to the 45-degree line***

for the 3-months rolling mean, the ECMWF has the best performance in reliability. The other centers have similar moderate performance, but the ukmo has poor reliability.

3.3.3 The ranked probability score (RPS)

The Ranked Probability Score (RPS) is a performance metric used in probabilistic forecasting to assess how well the predicted probability distribution matches the observed outcome distribution. It is particularly useful when there are multiple categories (e.g., terciles such as lower, middle, and upper) and is commonly applied in fields such as meteorology, climatology, and economics.

$$RPS = \frac{1}{n(m-1)} \sum_{i=1}^{n} \sum_{k=1}^{m-1} \left(\sum_{j=1}^{k} (y_{j,i} - p_{j,i}) \right)^2$$

where :

- n is the number of forecasts.

- m is the number of categories.
- $y_{j,i}$ is 1 if the i^th observation was in category j, and is 0 otherwise.
- $p_{j,i}$ is the i^th forecast probability for category j

The score is the average squared "error" in the cumulative probabilistic forecasts, and it ranges between 0% for perfect forecasts (a probability of 100% was assigned to the observed category on each forecast) to a maximum of 100% that can only be achieved if all the observations are in the outermost categories, and if the forecasts are perfectly bad (a probability of 100% was assigned to the opposite outermost category to that observed).

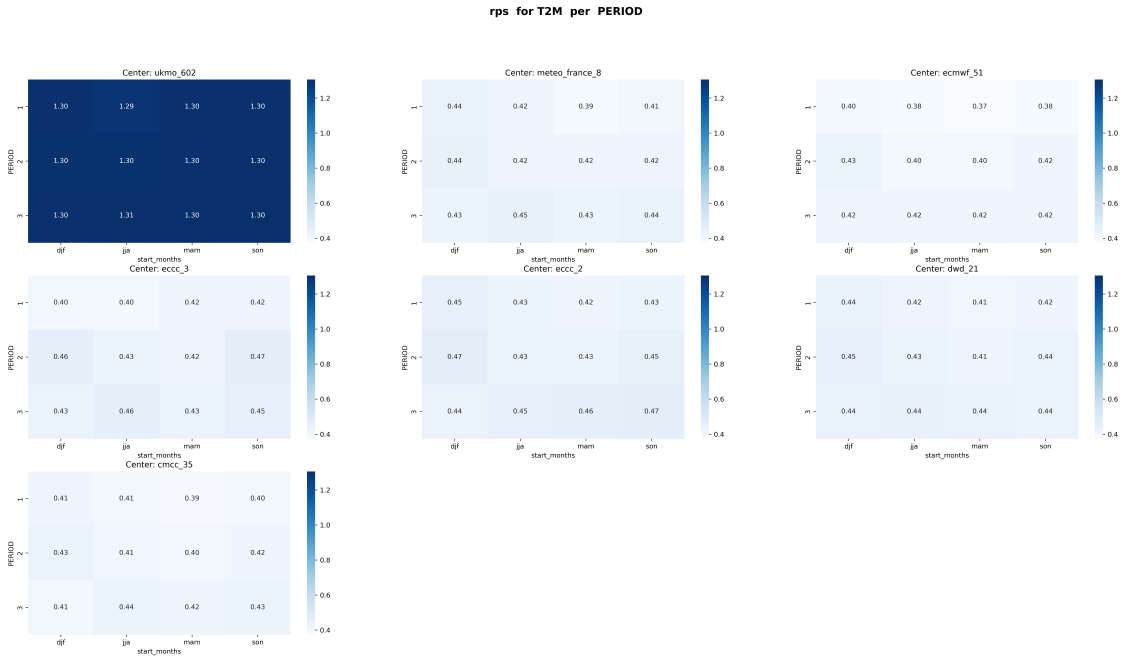

Figure 15: The Heatmap of RPS Score on MENA region for T2M . ***(0 means perfect RPS)***

In the figure above, all centers demonstrate similar performance, except for UKMO, which shows noticeably lower performance.

3.3.4 Relative operating characteristics

The ROC[53] can be used in forecast verification to measure ***the ability of the forecasts to distinguish an event from a non-event***. For seasonal forecasts with three or more categories, the first problem is to define the "event". One of the categories must be selected as the current category of interest, and an occurrence of this category is known as an event. An observation in any of the other categories is defined as a non-event and no distinction is made as to which of these two categories does occur. So, for example, if below normal is selected as the event, normal and above normal are treated equally as non-events.

[53]wmo guidance verification

the score indicates the probability of successfully discriminating below-normal observations from normal and above-normal observations. It indicates how often the forecast probability for below normal is higher when below normal actually does occur compared to when either normal or above normal occurs.

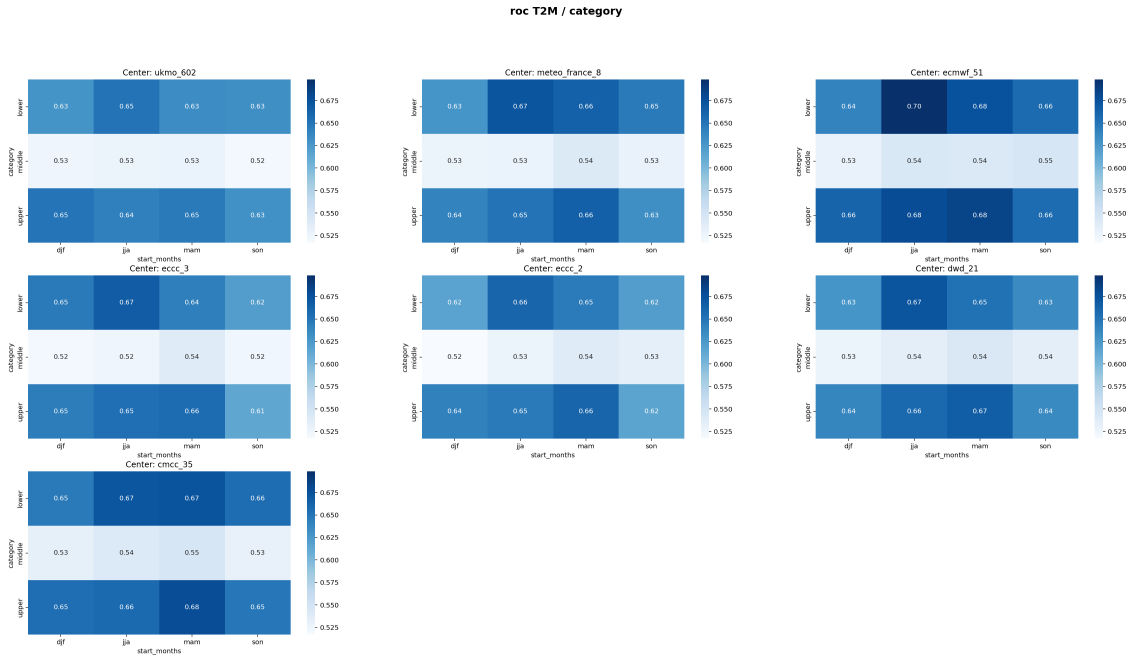

Figure 16: The Heatmap of ROC Score for each category . ***(1 means perfect ROC)***

In the figure above, it is evident that all centers exhibit similar performance levels. However, the middle tercile consistently achieves the lowest score.

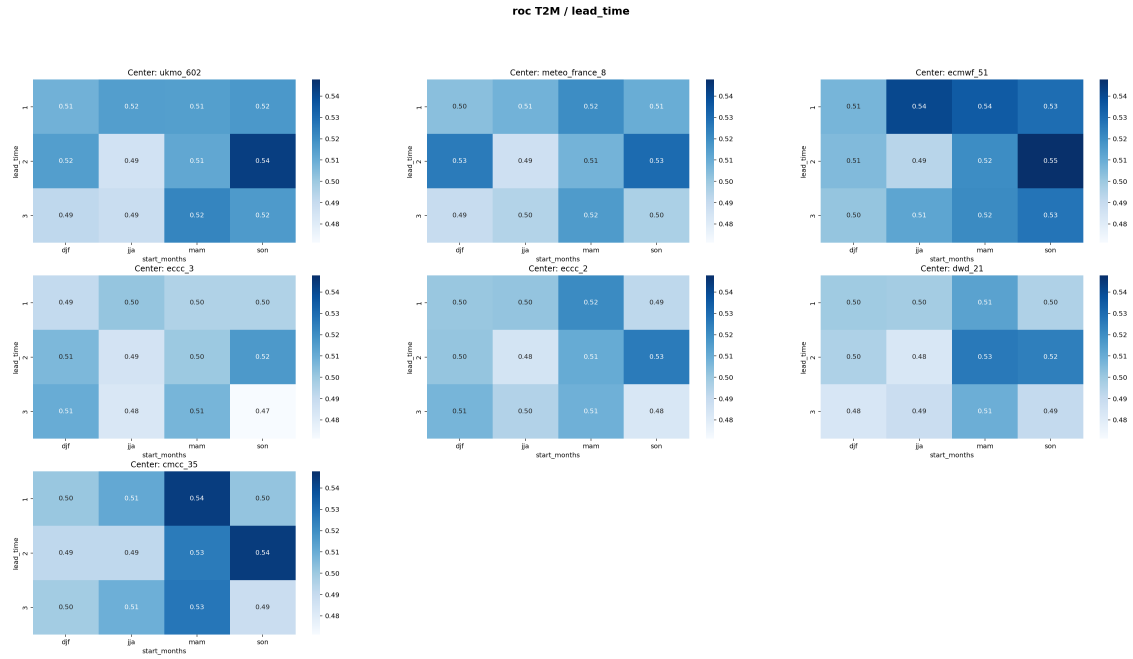

Figure 17: The Heatmap of ROC Score for lead-times. ***(1 means perfect ROC)***

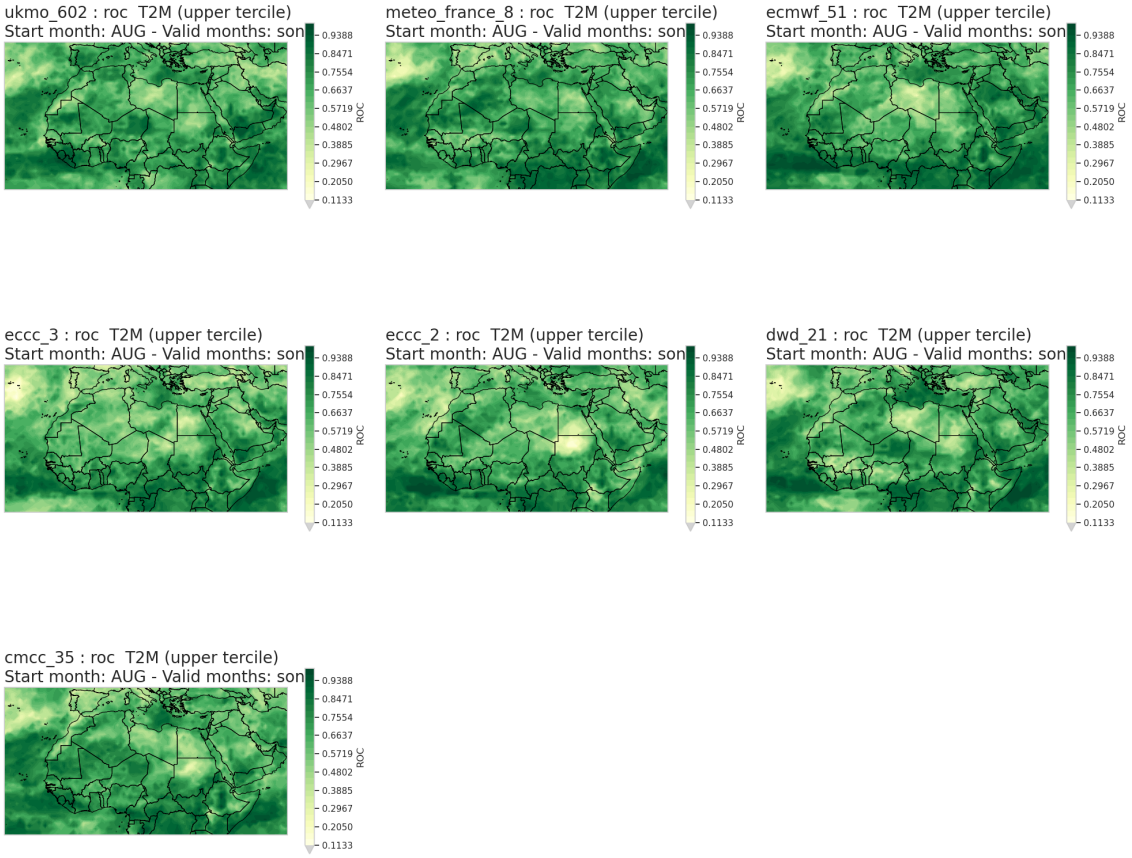

Figure 18: The ROC Score Upper tercile SON . ***(1 means perfect ROC)***

3.3.5 Relative operating characteristics Skill Score

The Relative Operating Characteristic Skill Score (ROCSS) is a measure used in forecast verification to assess the ability of probabilistic forecasts to discriminate between events and non-events. It builds on the Relative Operating Characteristic (ROC) curve, which plots the hit rate (true positive rate) against the false alarm rate (false positive rate) at various forecast probability thresholds.

- The ROC curve evaluates the discrimination capability of a forecast, i.e., how well the forecast can separate occurrences of an event (e.g., below-normal temperature) from non-events (e.g., normal or above-normal temperature).
- The ROC Skill Score quantifies the area under the ROC curve (AUC) and compares it to a no-skill forecast.

$$ROCSS = \frac{AUC - AUC_{no-skill}}{1 - AUC_{no-skill}}$$

where:

- AUC : Area Under the ROC Curve for the forecast being evaluated.
- $AUC_{no-skill}$: Area Under the Curve for a no-skill forecast 0.5 for our case.

Interpretation of ROCSS:

- 1: Perfect discrimination ability.
- 0: No skill (forecast performs no better than random guessing).
- Negative values: Forecast performs worse than random guessing.

In the figure above, it is evident that the ECMWF exhibit the best performance for all terciles and periods. HOwever, we should notice that the performance is very bad for the middle tercile in all centers.

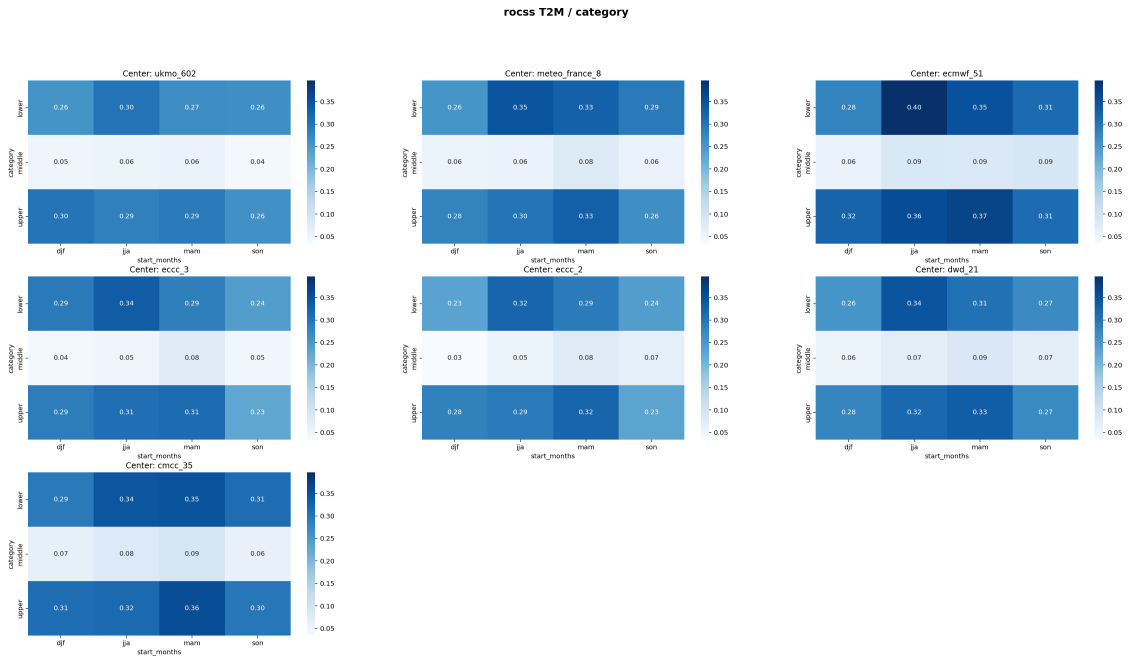

Figure 19: The ROCSS Score for each category . ***(1 means perfect ROCSS)***

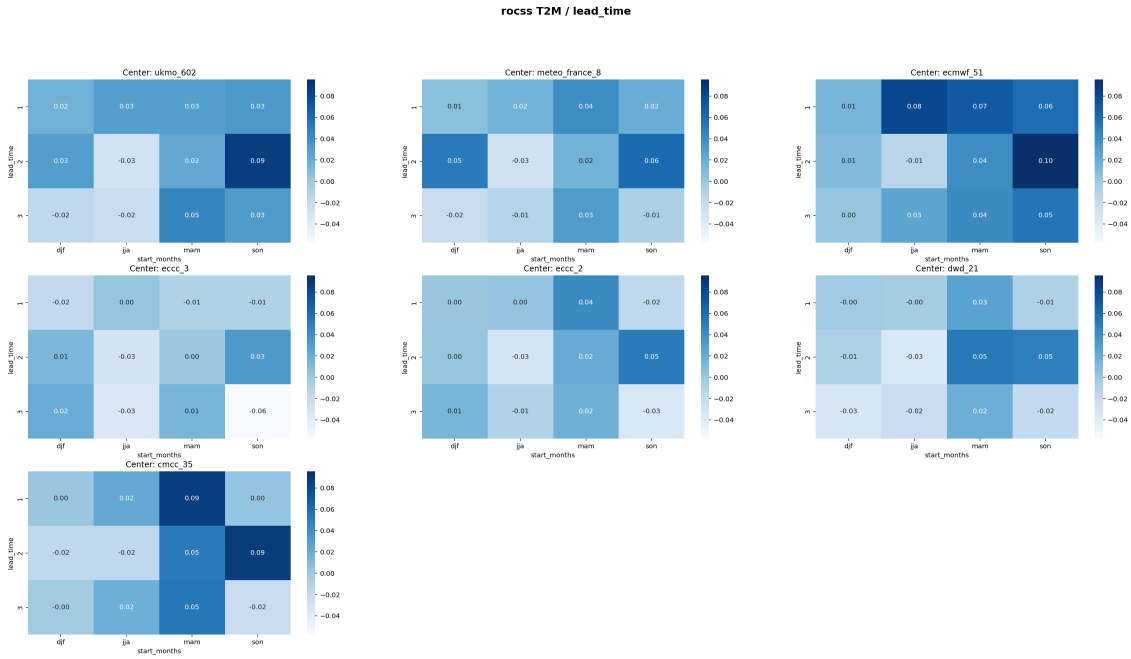

Figure 20: The average of ROCSS Score on all categories . ***(1 means perfect ROCSS)***

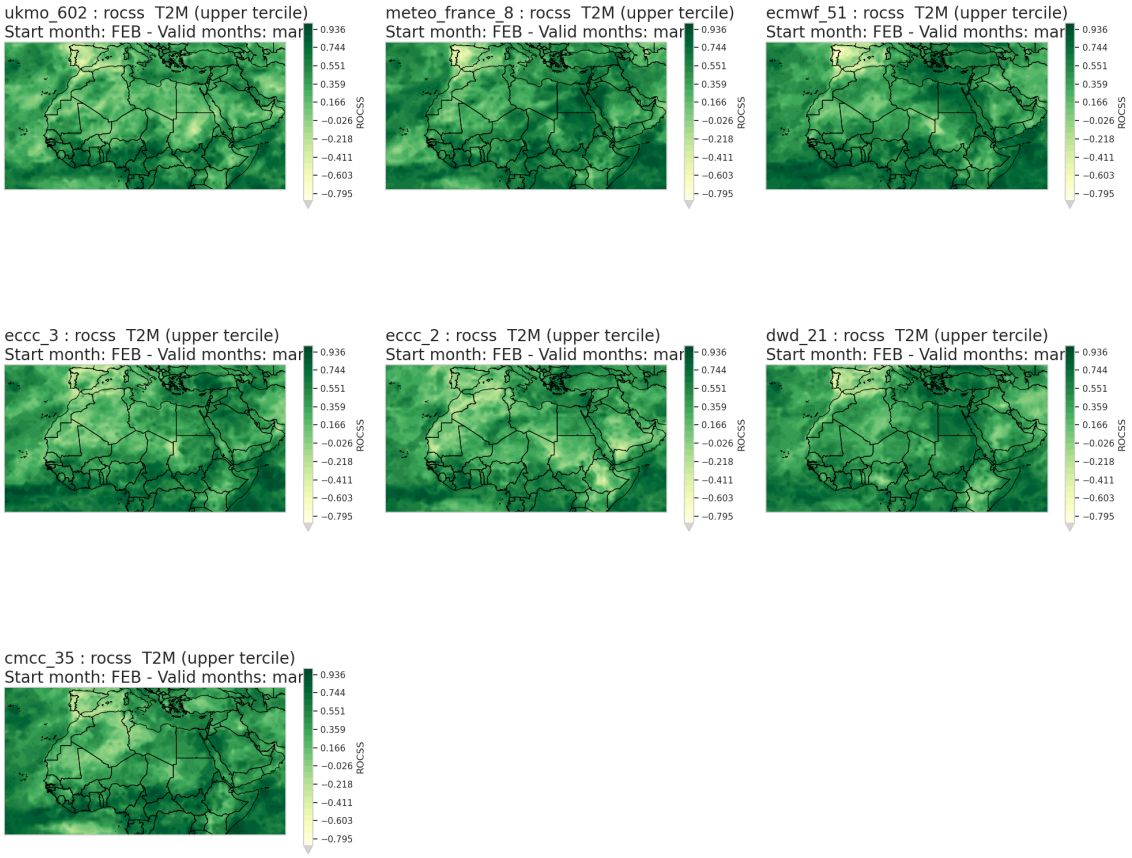

Figure 21: The ROC Skill Score Upper tercile MAM . ***(1 means perfect ROC)***

3.3.6 summary

Metric	Focus	What it Measures	Dependent on Observed Outcomes?	Visualization/Tools
Reliability	Probabilities match observed frequencies	Calibration of probabilities	Yes	Reliability diagram
Discrimination	Differentiating between outcomes	Ability to distinguish events from non-events	Yes	ROC curve, AUC
Sharpness	Boldness of probabilities (away from average)	Confidence of the forecast	No	Histogram of forecast probabilities
Resolution	Informativeness and variability of forecast	Ability to provide specific, useful info	Yes	Brier Score decomposition

Table 2: Key differences between reliability, discrimination, sharpness, and resolution in seasonal forecasting.

4 PRECIPITATIONS

IN general, the forecast of precipitations is more complicated than temperature, thus the scores are a little less good for this part especially the deterministic ones.

4.1 Deterministic Evaluation Metrics

4.1.1 Spearman rank correlation

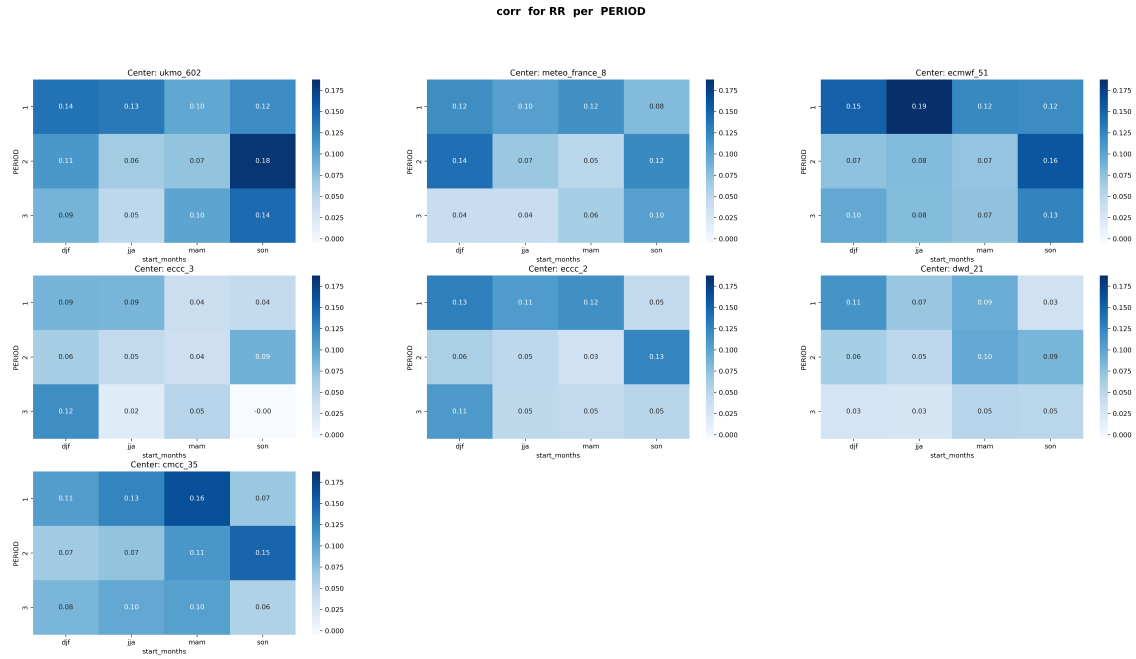

Figure 22: The Heatmap of correlation for the mena region for every period ***(1 for perfect Correlation)***

In general, correlation is very week for all centers, the maximum correlation is 0.175 for ecmwf. There is also some differences between centers. We can sea that in general the performance decrease with lead-time. the best models in term of Correlation are ***ecmwf , ukmo and meteo-france*** .In general the performance decreases with time for all periods except for the SON period where the performance may increase with lead-time.

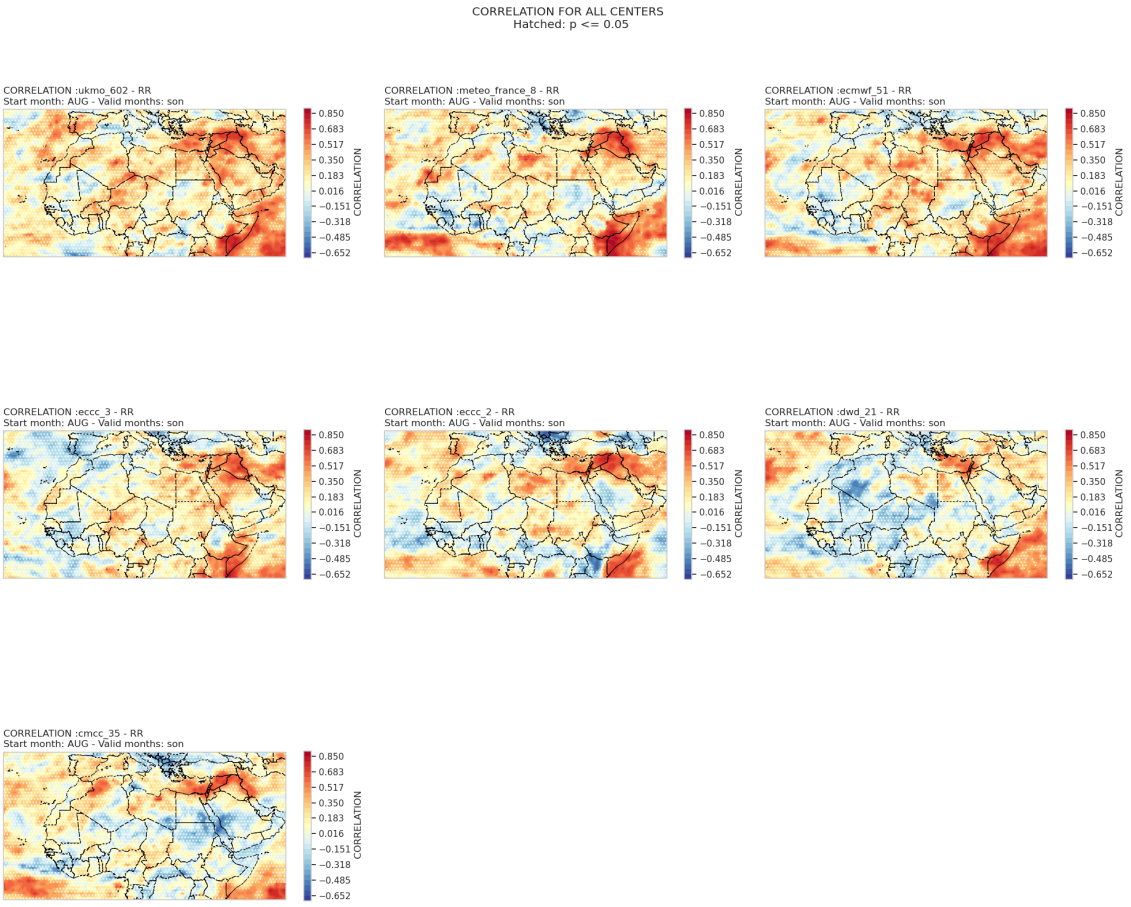

Figure 23: 3-months Rolling mean of Spearman Correlation in MENA Region for all centers DJF

For temperature, the models demonstrate the best performance in the tropical regions. However, for precipitation, the situation is different. In the figure above, we observe an unusual performance during SON, where the Middle East, East Africa, and North Africa exhibit the highest correlation performance.

4.1.2 RMSE

for the Root Mean Squared Error, the best models shown in the heatmap below are ***DWD, ECMWF and UKMO***. The RMSE score demonstrate an excellent performance for all models especially ***DWD, ECMWF and UKMO***. The performance is stable over lead-times and it is much better for djf in all centers.

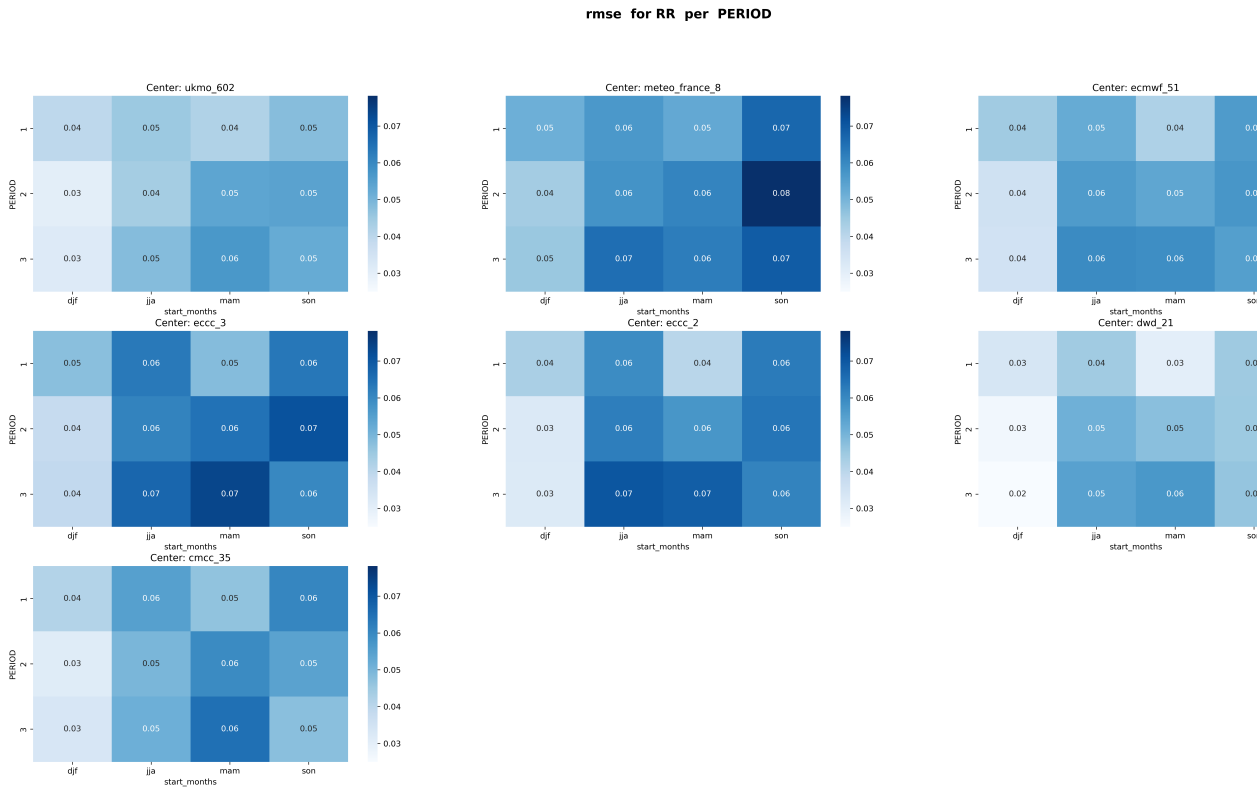

Figure 24: 3-months Rolling mean of RMSE in MENA Region for all centers DJF

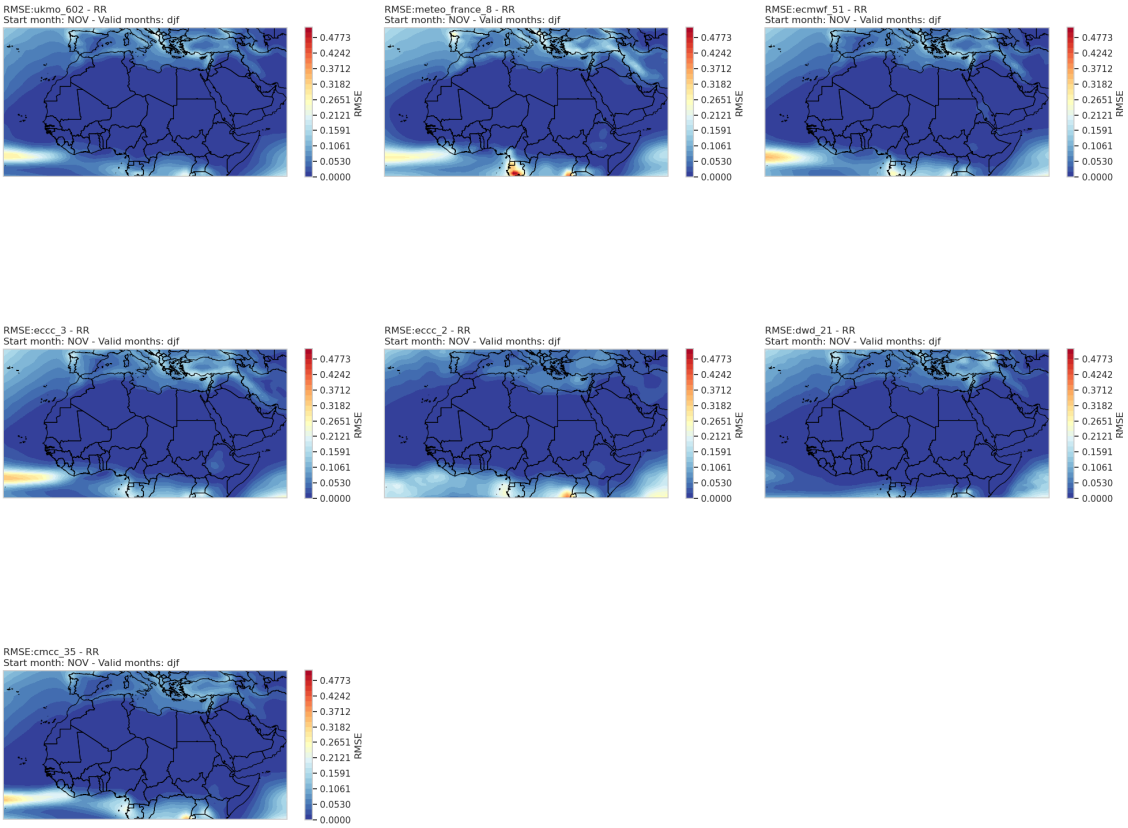

Figure 25: 3-months Rolling mean of RMSE in MENA Region for all centers JJA

also for the spacial dimension, the RMSE stay stable and exhibit very good performance for all centers.

4.1.3 Coefficient of Determination (R^2)

for precipitation, the R-SQUARED is very low, the maximum value is less than 0.1. However, the ecmwf is the best in term of R-SQUARED.

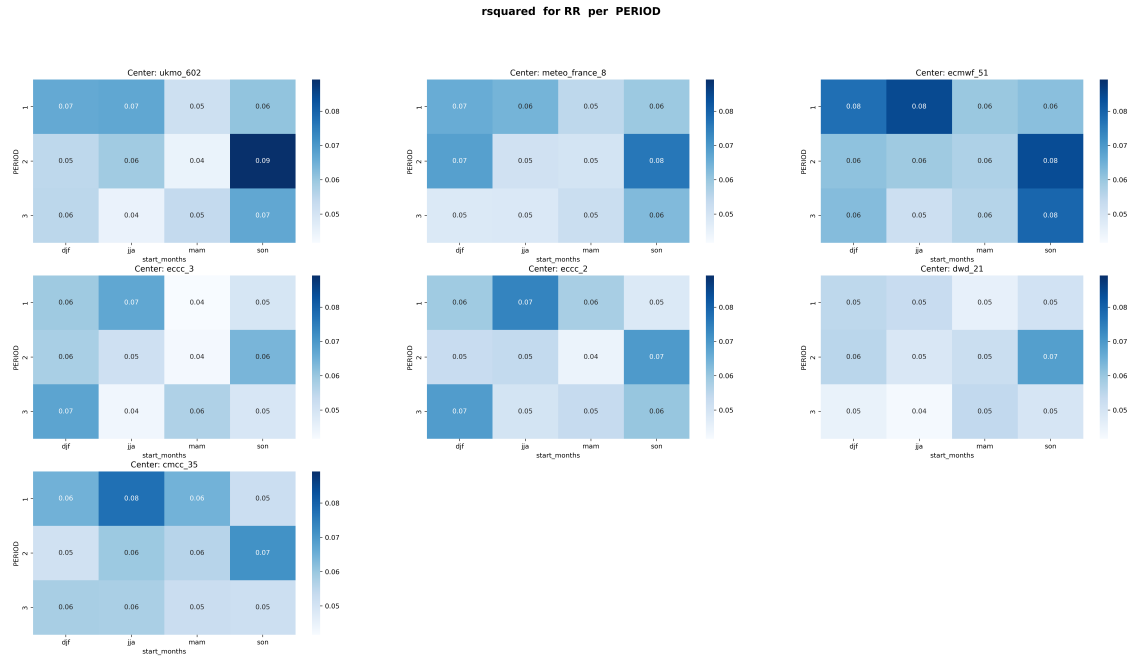

Figure 26: The Heatmap of rsquared for Precipitations in the mena region for every period ***(1 for perfect RSQUARED)***

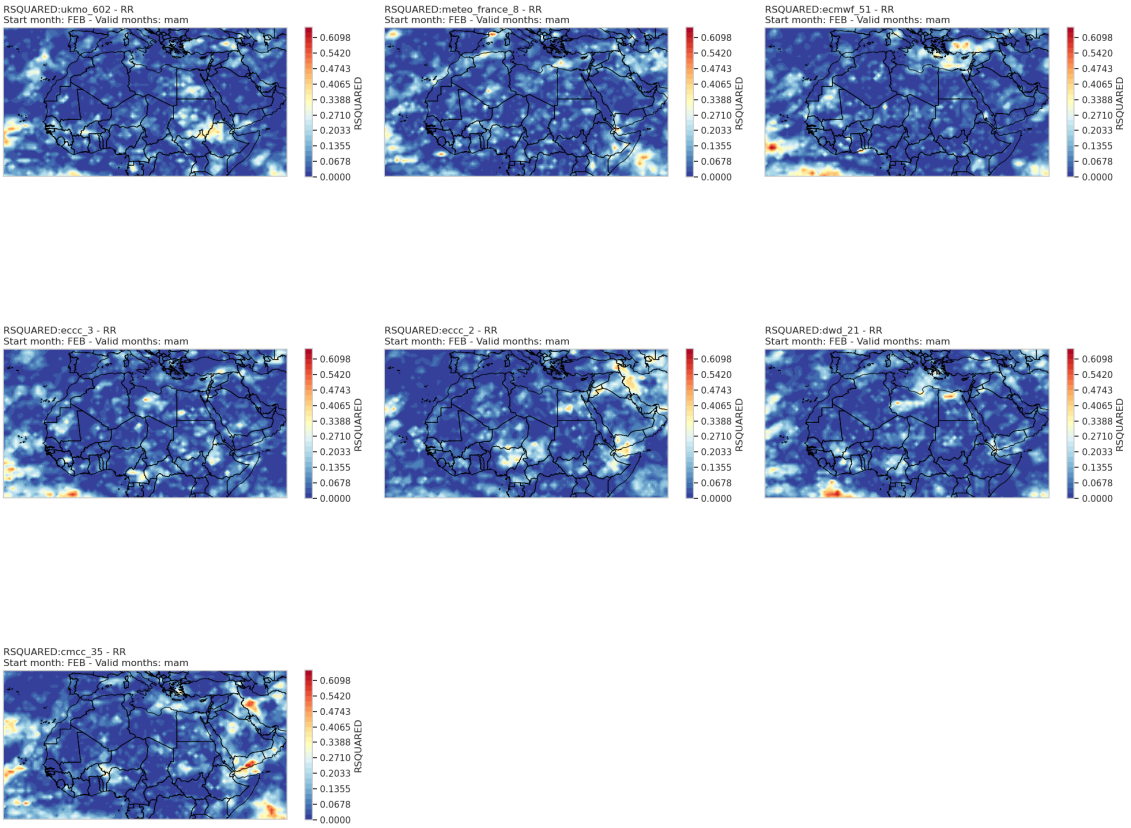

Figure 27: 3-months Rolling mean of RSQUARED in MENA Region for all centers MAM

there is some isolated zones where the rsquared is good especially in the Middle East for CMCC-35 Center or the equator for DWD, but in general the score is very low.

4.2 Probabilistic Evaluation Metrics

4.2.1 The Brier Score (BS)

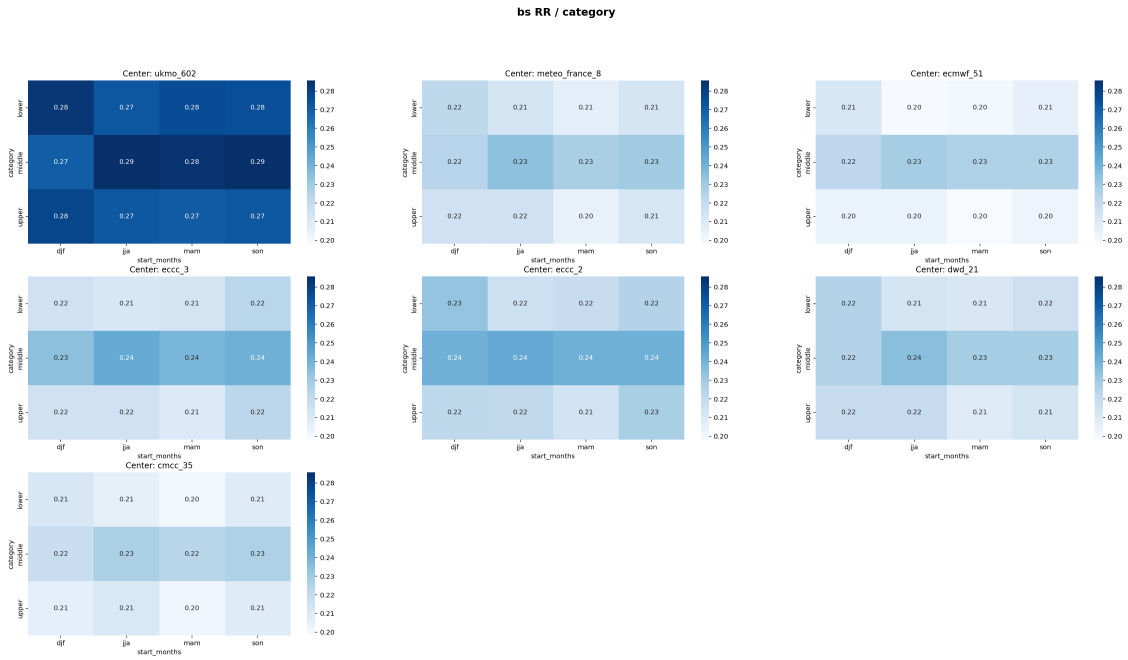

Figure 28: The Heatmap of Brier Score for each category . ***(0 represents perfect BS)***

for the analysis per category, we can see in the figure above that all centers exhibit good performance in term of Brier Score except the UMKO that shows moderate BS. the figure below shows the analysis per lead-time. the same result is found, but the ***ECMWF,METEO-FRANCE and CMCC-35*** are the best models in Brier Score for lead-time analysis.
In general, the performance stays stable over category, lead-time and space.

Figure 29: The Heatmap of Brier Score for lead-time. ***(0 represents perfect BS)***

4.2.2 Reliability

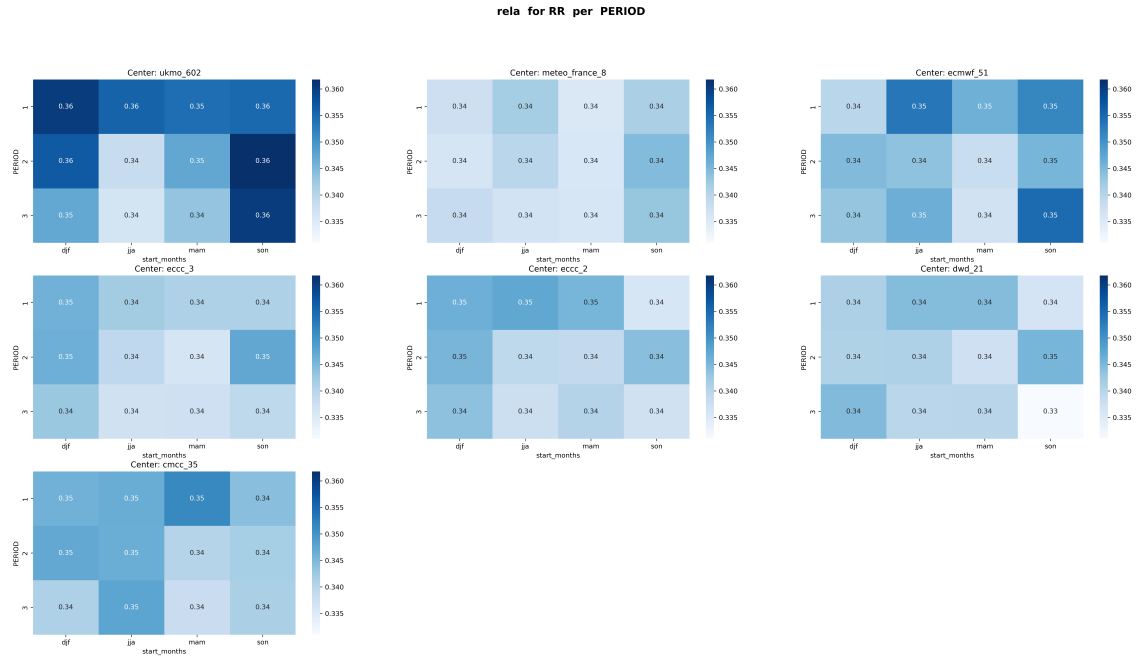

Figure 30: The Reliability Score . ***(0 means perfect Reliability)***

In the figure above, all centers demonstrate similar moderate performance in term of reliability. But deep analysis within the figure below, shows that UKMO has very bad performance, also we can distinguish three models that have the best reliability according to the reliability diagram, the centers are ***ECMWF,CMCC and METEO-FRANCE***.

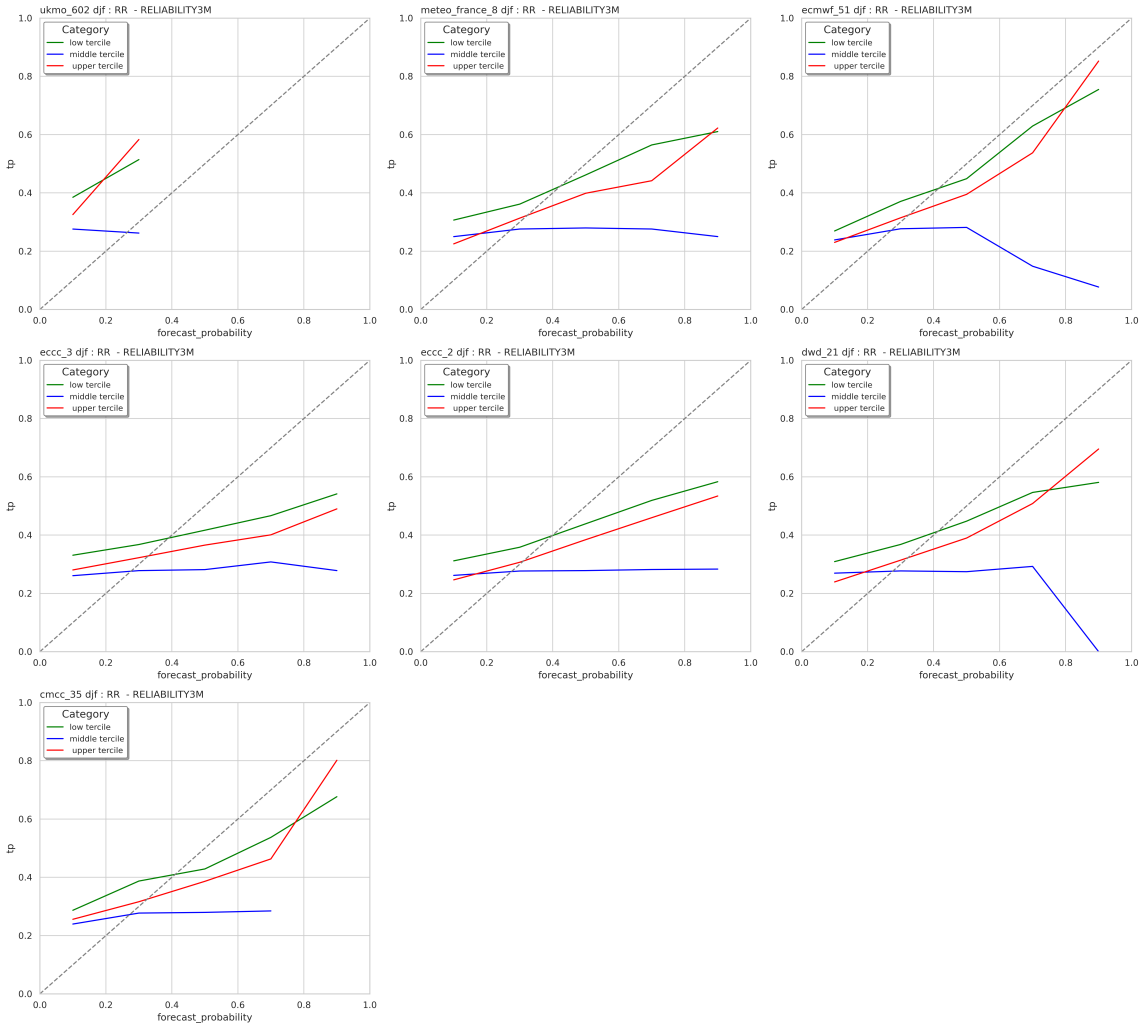

Figure 31: The 3-month rolling mean for Reliability DJF . ***Reliability is better in cases where the graphs are closer to the 45-degree line***

4.2.3 The ranked probability score (RPS)

The Ranked Probability Score (RPS) is a performance metric used in probabilistic forecasting to assess how well the predicted probability distribution matches the observed outcome distribution. It is particularly useful when there are multiple categories (e.g., terciles such as lower, middle, and upper) and is commonly applied in fields such as meteorology, climatology, and economics.

$$RPS = \frac{1}{n(m-1)} \sum_{i=1}^{n} \sum_{k=1}^{m-1} \left(\sum_{j=1}^{k} (y_{j,i} - p_{j,i}) \right)^2$$

where :

- n is the number of forecasts.
- m is the number of categories.

- $y_{j,i}$ is 1 if the i^th observation was in category j, and is 0 otherwise.
- $p_{j,i}$ is the i^th forecast probability for category j

The score is the average squared "error" in the cumulative probabilistic forecasts, and it ranges between 0% for perfect forecasts (a probability of 100% was assigned to the observed category on each forecast) to a maximum of 100% that can only be achieved if all the observations are in the outermost categories, and if the forecasts are perfectly bad (a probability of 100% was assigned to the opposite outermost category to that observed).

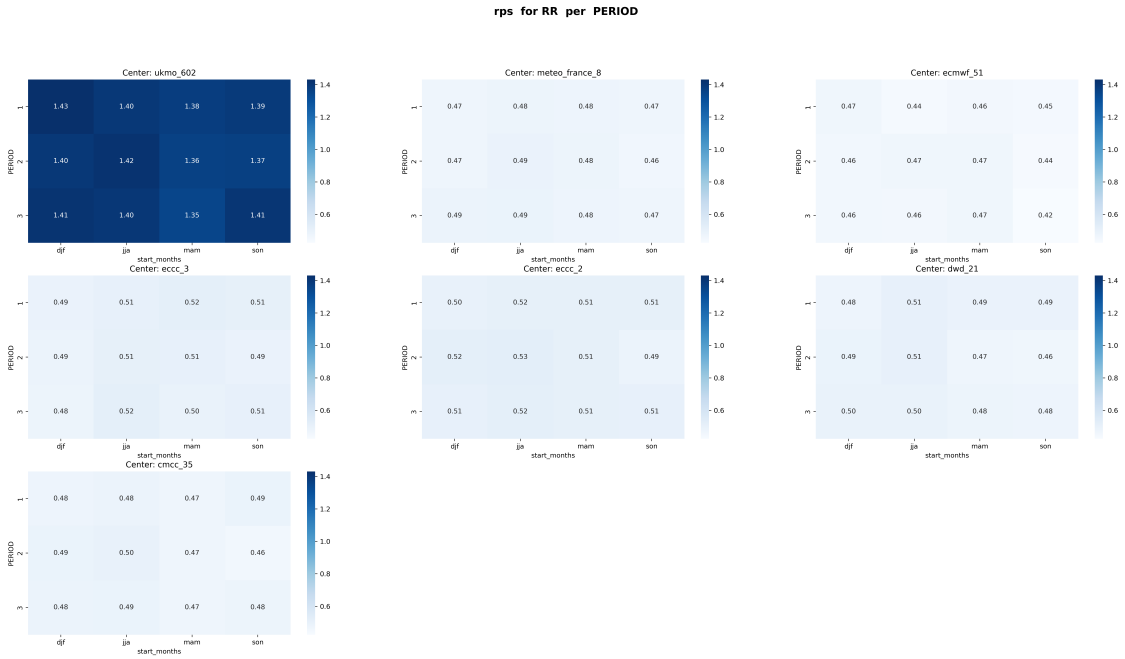

Figure 32: The Heatmap of RPS Score on MENA region for Precipitations . ***(0 means perfect RPS)***

In the figure above, all centers demonstrate similar performance, except for UKMO, which shows noticeably lower performance.

4.2.4 Relative operating characteristics

The ROC[54] can be used in forecast verification to measure ***the ability of the forecasts to distinguish an event from a non-event***. For seasonal forecasts with three or more categories, the first problem is to define the "event". One of the categories must be selected as the current category of interest, and an occurrence of this category is known as an event. An observation in any of the other categories is defined as a non-event and no distinction is made as to which of these two categories does occur. So, for example, if below normal is selected as the event, normal and above normal are treated equally as non-events.

[54]wmo guidance verification

the score indicates the probability of successfully discriminating below-normal observations from normal and above-normal observations. It indicates how often the forecast probability for below normal is higher when below normal actually does occur compared to when either normal or above normal occurs.

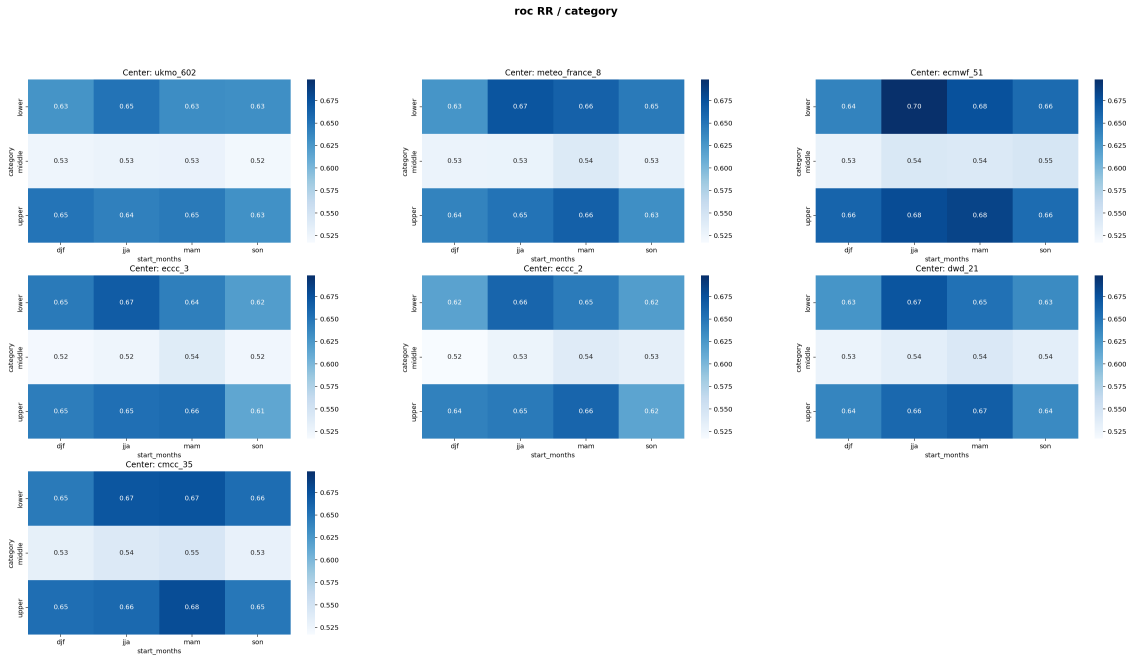

Figure 33: The Heatmap of ROC Score for each category . ***(1 means perfect ROC)***

In the figure above, it is evident that all centers exhibit similar performance levels. However, the middle tercile consistently achieves the lowest score.

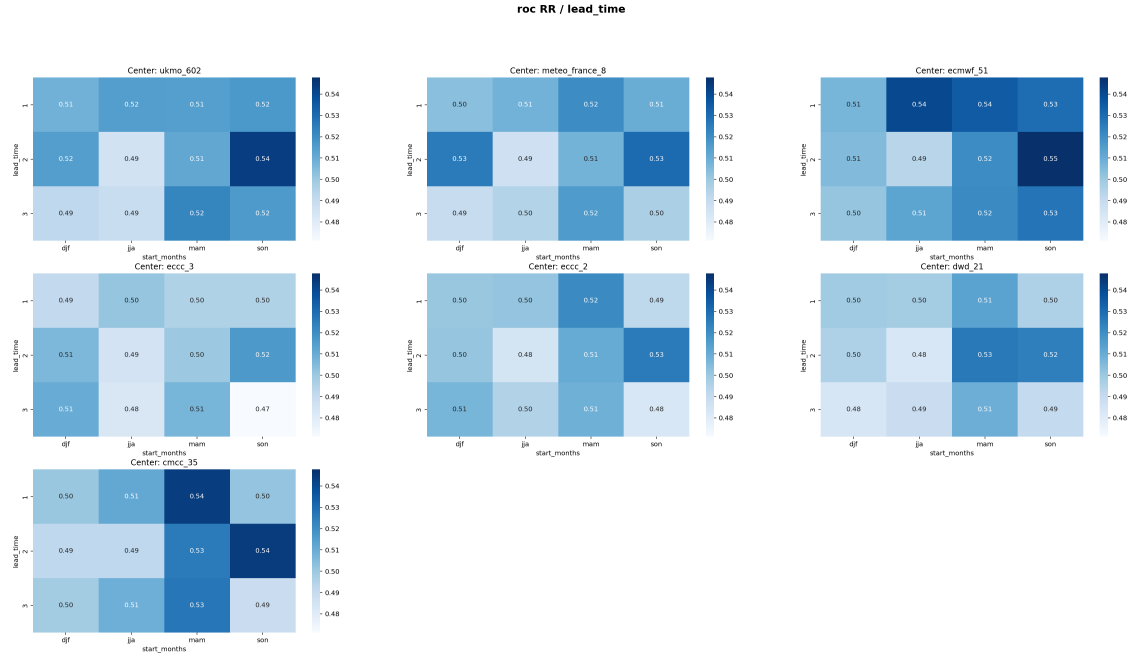

Figure 34: The Heatmap of ROC Score for lead-times. ***(1 means perfect ROC)***

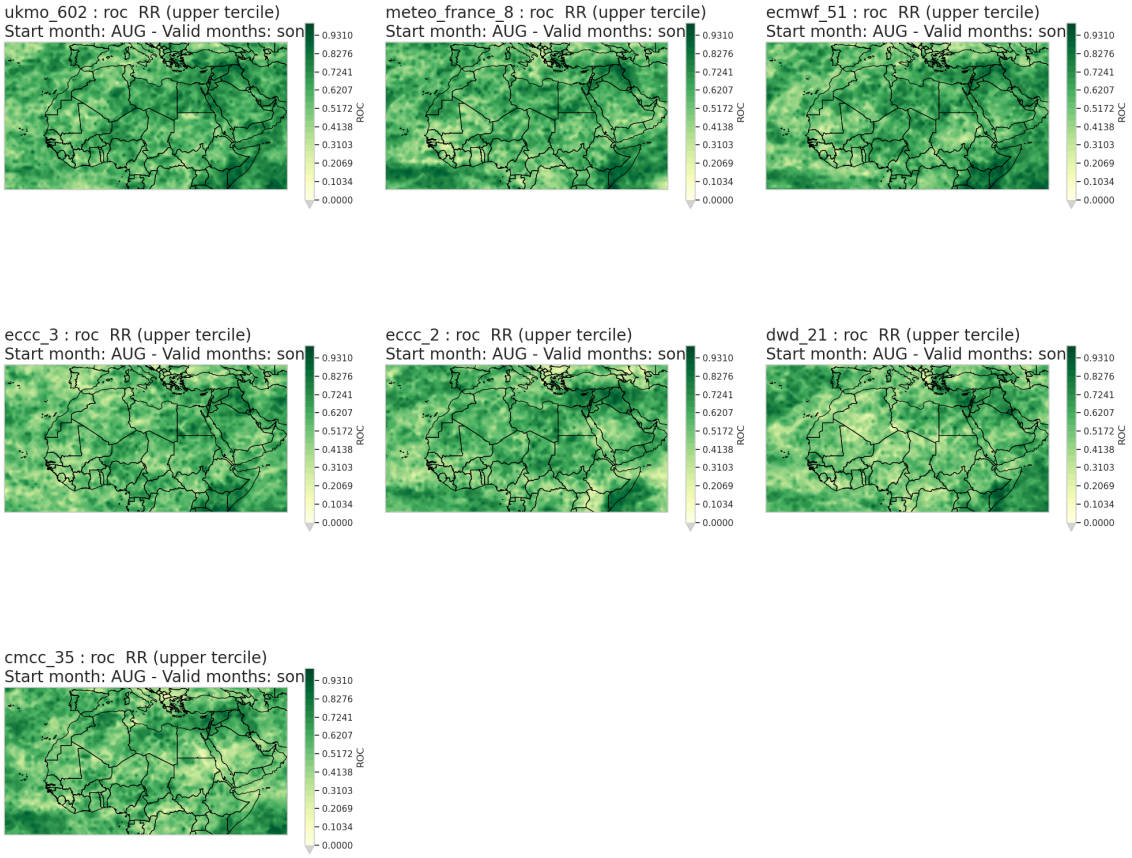

Figure 35: The ROC Score Upper tercile SON . ***(1 means perfect ROC)***

4.2.5 Relative operating characteristics Skill Score

The Relative Operating Characteristic Skill Score (ROCSS) is a measure used in forecast verification to assess the ability of probabilistic forecasts to discriminate between events and non-events. It builds on the Relative Operating Characteristic (ROC) curve, which plots the hit rate (true positive rate) against the false alarm rate (false positive rate) at various forecast probability thresholds.

- The ROC curve evaluates the discrimination capability of a forecast, i.e., how well the forecast can separate occurrences of an event (e.g., below-normal temperature) from non-events (e.g., normal or above-normal temperature).
- The ROC Skill Score quantifies the area under the ROC curve (AUC) and compares it to a no-skill forecast.

$$ROCSS = \frac{AUC - AUC_{no-skill}}{1 - AUC_{no-skill}}$$

where:

- AUC : Area Under the ROC Curve for the forecast being evaluated.
- $AUC_{no-skill}$: Area Under the Curve for a no-skill forecast 0.5 for our case.

Interpretation of ROCSS:

- 1: Perfect discrimination ability.
- 0: No skill (forecast performs no better than random guessing).
- Negative values: Forecast performs worse than random guessing.

In the figure above, it is evident that the ECMWF exhibit the best performance for all terciles and periods. HOwever, we should notice that the performance is very bad for the middle tercile in all centers.

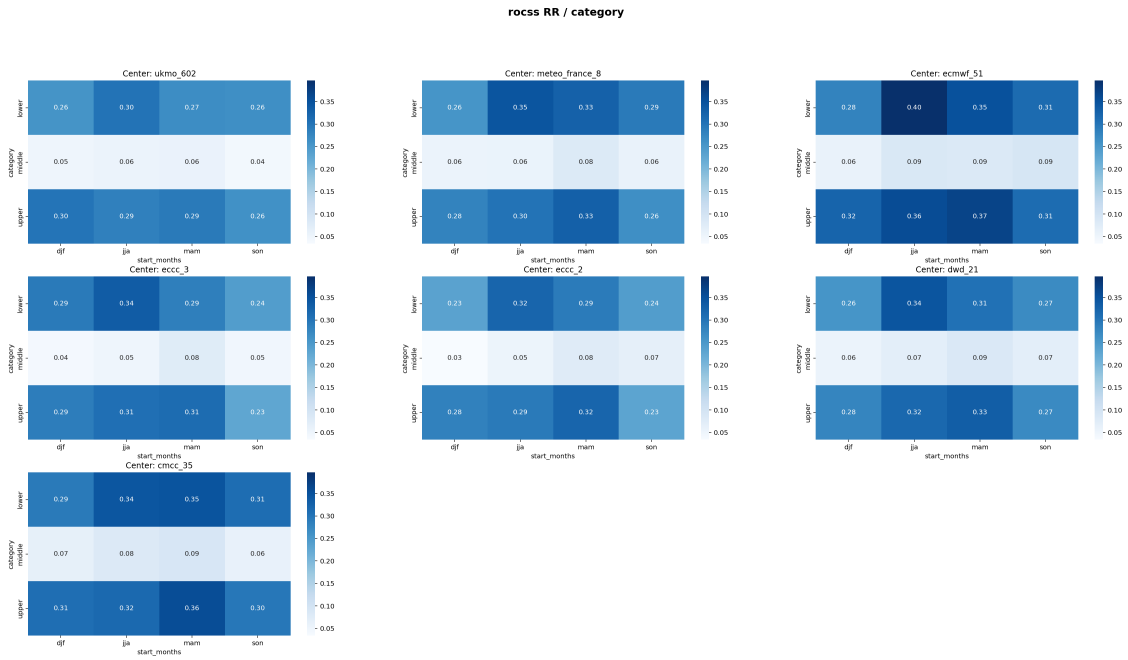

Figure 36: The ROCSS Score for each category . ***(1 means perfect ROCSS)***

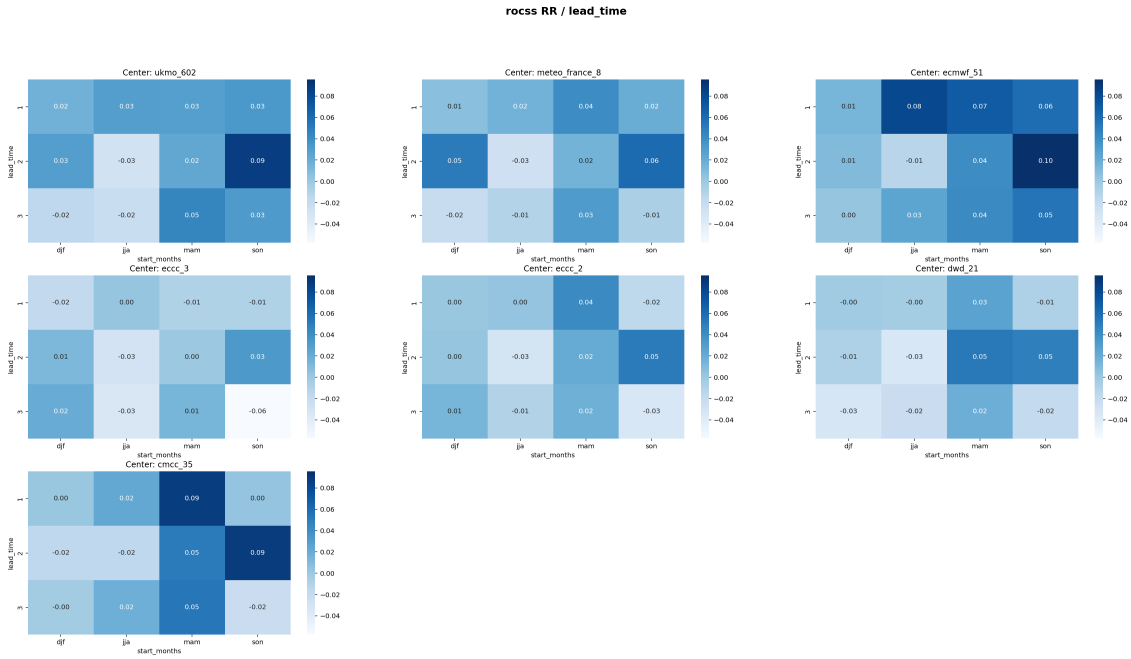

Figure 37: The average of ROCSS Score on all categories . ***(1 means perfect ROCSS)***

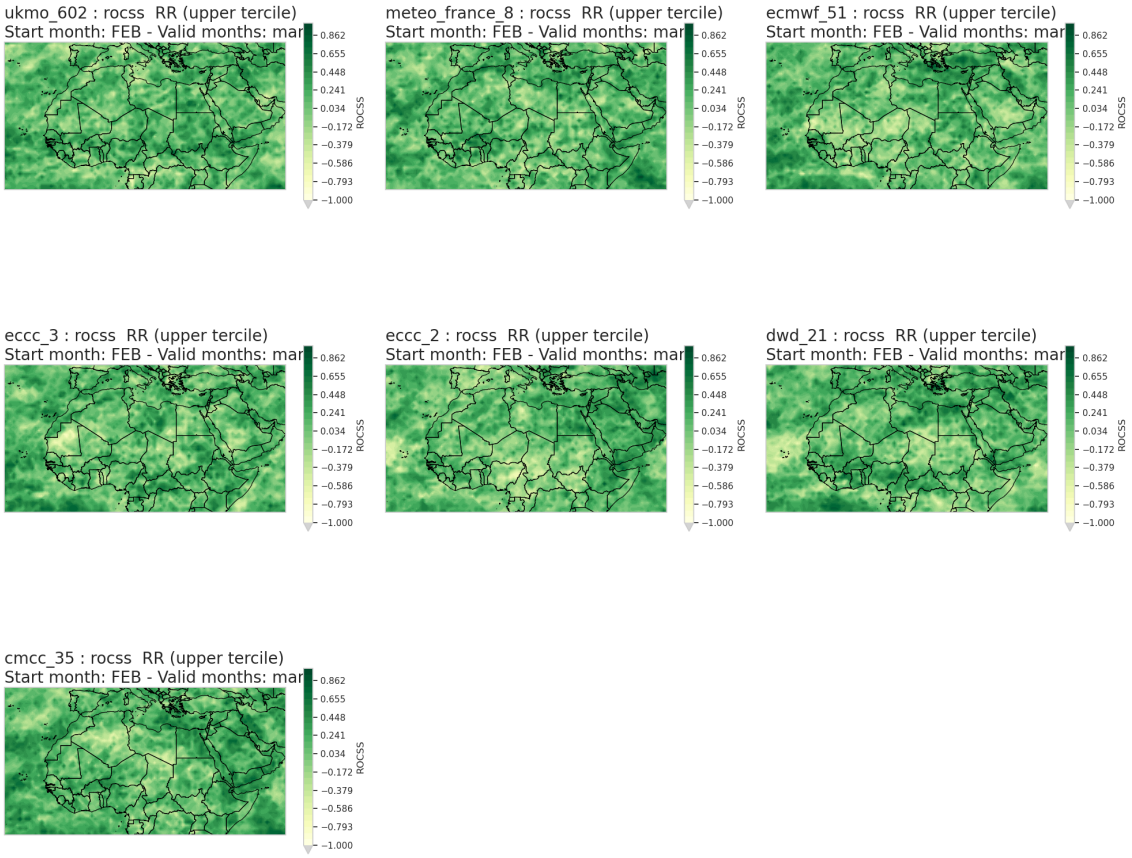

Figure 38: The ROC Skill Score Upper tercile MAM . ***(1 means perfect ROC)***

4.2.6 summary

Metric	Focus	What it Measures	Dependent on Observed Outcomes?	Visualization/Tools
Reliability	Probabilities match observed frequencies	Calibration of probabilities	Yes	Reliability diagram
Discrimination	Differentiating between outcomes	Ability to distinguish events from non-events	Yes	ROC curve, AUC
Sharpness	Boldness of probabilities (away from average)	Confidence of the forecast	No	Histogram of forecast probabilities
Resolution	Informativeness and variability of forecast	Ability to provide specific, useful info	Yes	Brier Score decomposition

Table 3: Key differences between reliability, discrimination, sharpness, and resolution in seasonal forecasting.

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