WMO Northern Africa RCC Network

WMO RA VI RCC Network

AEMet Agencia Estatal de Meteorología

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Framework for Objective SF Roadmap

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Some history

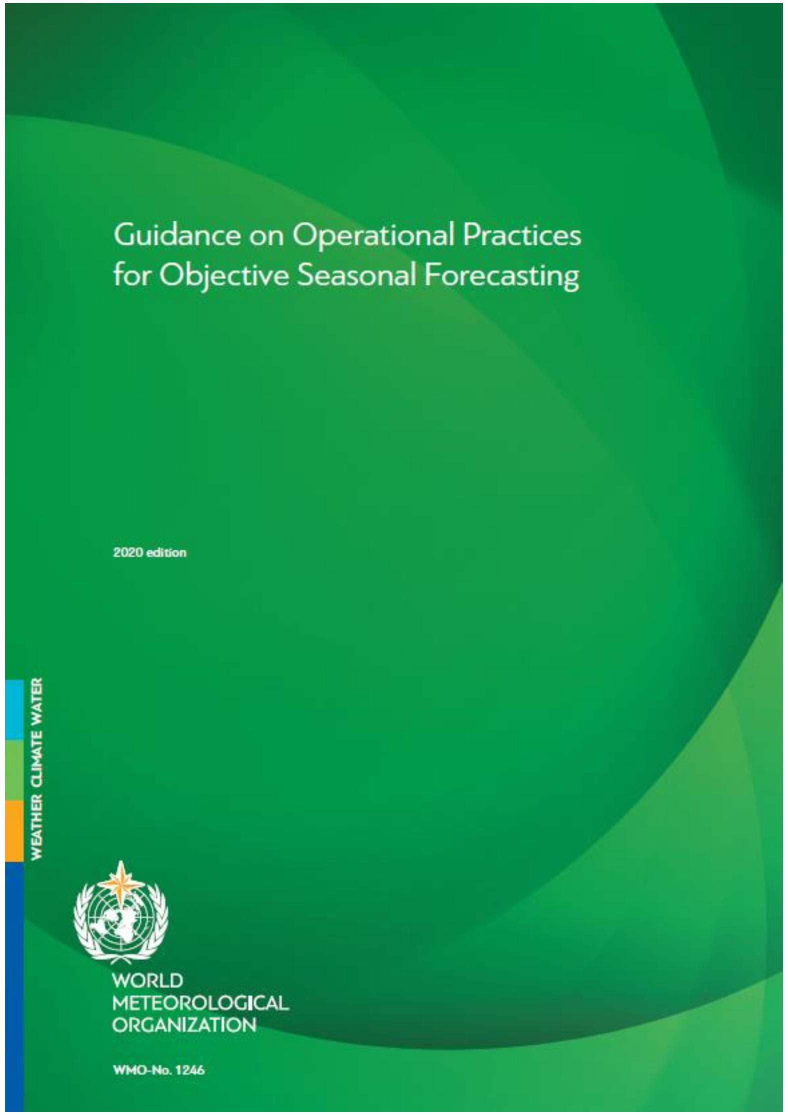
- WMO International Workshop on Global Review of RCOFs (CIIFEN, Guayaquil, Ecuador, Sep 2017) → way forward towards the new generation of RCOFs should include the mainstreaming of OSF RCOF products with an expanded product portfolio
- 72nd WMO Executive Council (2020) → endorse a proposal on operationalization of OSFs and tailored products on sub-regional scales with country-level service delivery
- WMO requests production of “Guidance for MedCOF sub-region to enable operational production of objective seasonal forecasts” (2021)

Outline

1. Introduction to seasonal predictions
2. Components of a seasonal forecast system
3. Seasonal forecast products
4. Guidance on good practices for developing objective seasonal forecasts
5. WMO infrastructure and resources for seasonal forecasts
6. Other sources of seasonal prediction products
7. Other aspects of seasonal predictions and variability
8. Examples of good practices currently followed at NMHSs, RCCs and RCOFs
9. Future prospects for seasonal and other long-range forecasts

Objective Seasonal Forecast (OSF):

set of steps in a forecast procedure that are **traceable, reproducible, and well documented** and which allow quantification of forecast quality



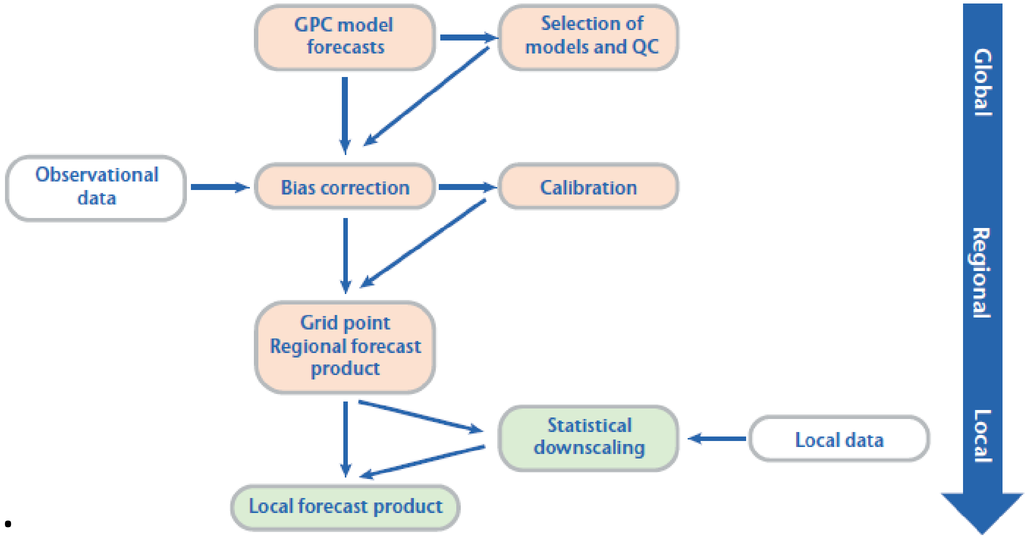
Guidance on Operational Practices for Objective Seasonal Forecasting, WMO-No. 1246.
https://library.wmo.int/doc_num.php?explnum_id=10314

Principles for OSF

- Follow a **traceable, reproducible, and well-documented** procedure (including model selection, bias correction, calibration and statistical downscaling) that is amenable to assessments of forecast quality (verification);
- Use dynamical climate models, including **multi-model ensembles**, as the primary basis for seasonal forecasts;
- Establish and maintain **observational databases** (including databases associated with reanalysis and other blended analysis products) of adequate quality, length of record and spatial resolution for verification, bias correction and calibration and to monitor drivers of seasonal predictability;
- Identify and monitor **drivers** of predictable climate variability and assess their representation and prediction skill in models;
- Ensure that forecasts are **verified** according to established standards, keep archives of past forecasts, and conduct post-season assessments;
- Provide forecast information together with **historical performance** (for example, skill and reliability);
- Use clear and non-technical language to **communicate** seasonal forecasts, including emphasizing the probabilistic nature and inherent uncertainty of seasonal forecasts;
- Collaborate across regions influenced by the same climate drivers in forecast production though mechanisms such as **RCOFs**;
- Provide seasonal forecasts as well as regular updates on a fixed **operational schedule** tailored to the applicable decision-making context;
- Establish **user feedback** and product upgrade mechanisms and support co-production of tailored products.

Recommended approach for producing operational objective SFs (WMO 2020) consist of:

- **Select** the appropriate models to be used.
- Bias **correction and calibration** at the grid point level.
- Method for **combination**
- **Discuss** the first estimate (or guess), and if necessary and justified, alter the forecast if there are strong reasons for doing so.
- Keep a record of all the discussions conducted concerning altering the MME based forecast in order to build a **traceable/documented** forecasting process.
- Use **local data**, either station or gridded, to better understand the local climate and the statistical **downscaling** process

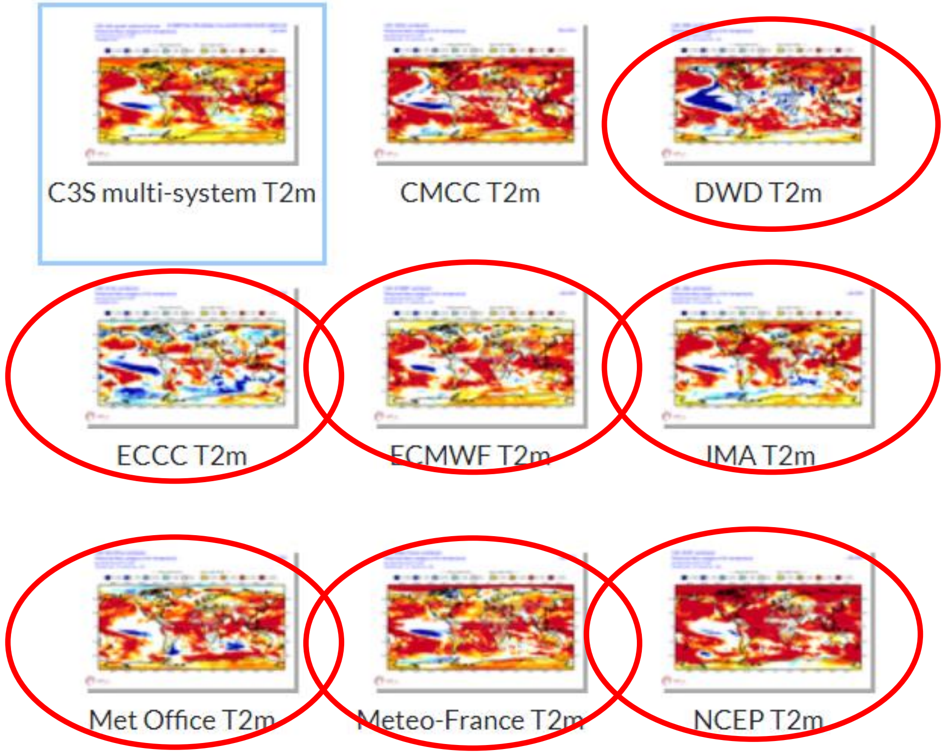


Select the appropriate models to be used

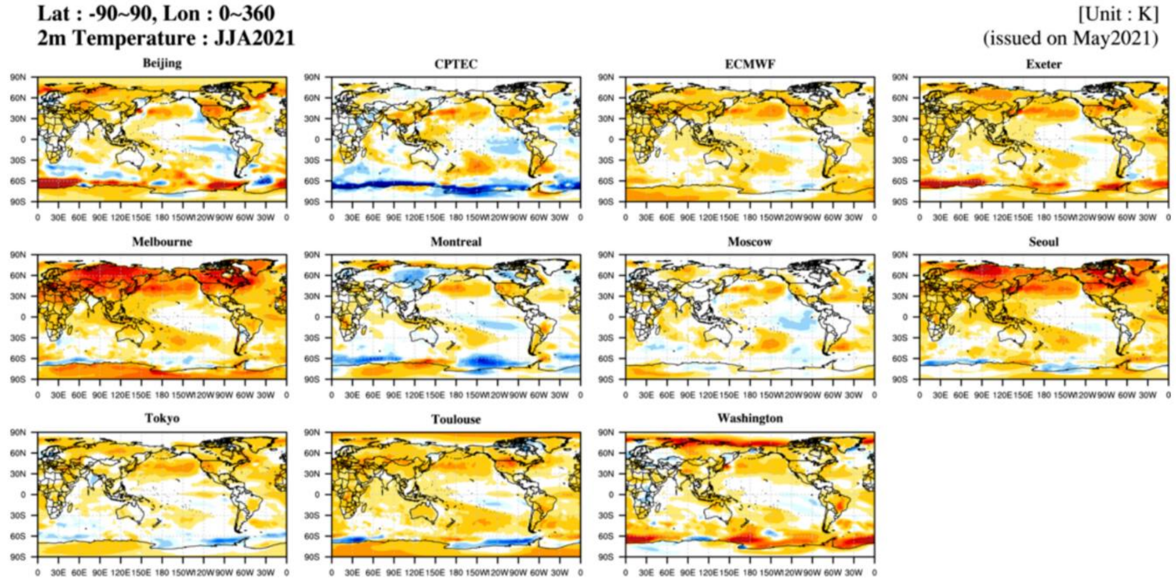
- **Initial pool:** WMO LRF MME (13 models), C3S MME (8 models)
- Different models have different biases that influence their ability to predict the observed climate in light of varying climate situations and for various regions. For one climate situation and region, one model may be preferable; however, this same model may not be appropriate for use in other regions and seasons. **Different hindcast periods may also influence the selection of the appropriate models**. In this respect. Whereas the C3S MME has a relatively long common hindcast period (1993-2016), the WMO LRFMME has a wider range of hindcast periods which in principle may pose some problems to the selection of models.
- The selected models should **share a minimum list of characteristics** related to spatial/temporal resolution, minimum hindcast period, minimum ensemble size for hindcast and forecast, coupled atmosphere–ocean systems versus two-tier systems, issuance time, etc.
- The next set of criteria for selecting models is related to the **regional performance of seasonal forecasting systems**. A comparison of **objective verification scores** computed over a common hindcast period provides insight on the quality of different systems. Also the ability of models **to simulate climate drivers, climate variability patterns and teleconnections** that are relevant at a seasonal scale over the region of interest. This analysis should be conducted month by month as the relevant large-scale features and processes depend largely on seasons. Initially this analysis could be carried out for the **4 main seasons**.

Initial pool of SFSs

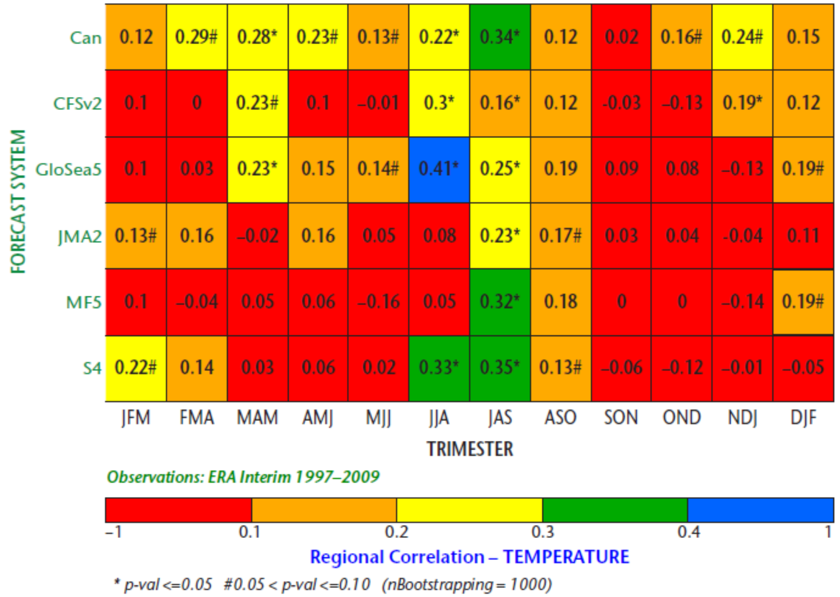
C3S

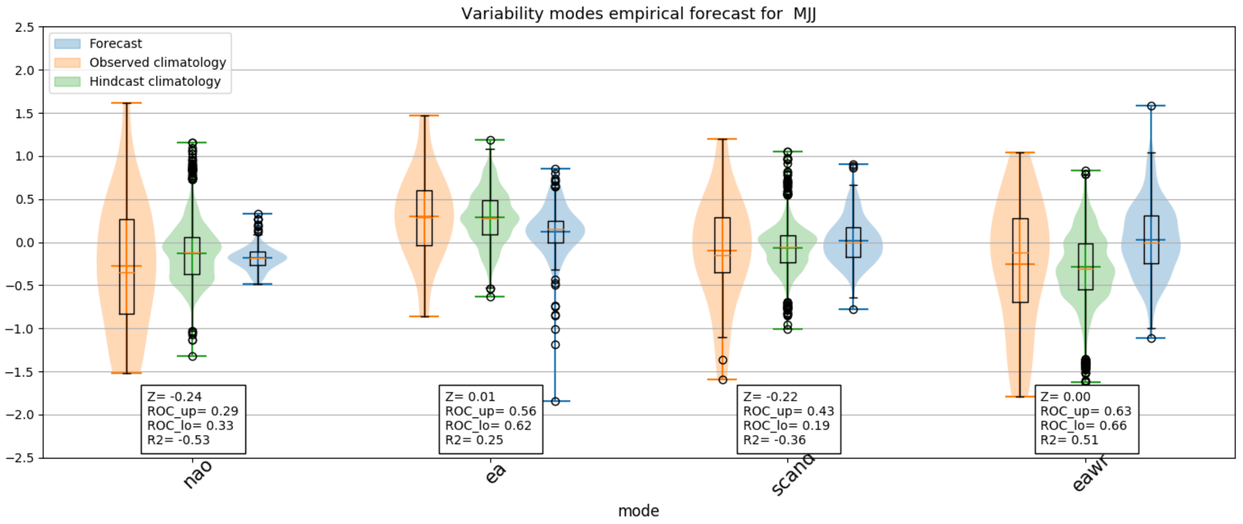


WMO LRF MME



Metrics for models selection





Selection based on:
- hindcast
- current forecast

If based on hindcast, selection should be carried out month by month as the relevant large-scale features and processes depend largely on seasons

Bias correction and calibration at the grid point level

- **Bias correction →** adjusts **modelled climate to observed climate** without reference to prediction quality or skill, in other words, without pairing hindcasts and observations
- **Calibration →** modify forecast values to **optimize skill**. It requires consideration of **paired hindcast and observed** values.

  A primary purpose of calibration is to improve the properties of probabilistic forecasts, especially their reliability. A typical approach to calibration is first to fit hindcast ensemble values to a parametric probability distribution, such as the normal distribution, which by itself provides an improved estimate of the forecast PDF, and then to adjust the parameters of that distribution to optimize a probabilistic forecast quality measure.
- Combining uncalibrated forecasts from multiple models also tends to improve reliability and may make probabilistic calibration less crucial than for individual models. Such an approach is applied in WMO LC-LRFMME.
- As the multi-model probabilistic forecasts based on uncalibrated individual models improve the reliability of individual models, **this step could be skipped in an initial implementation** aiming at speeding up the operations.

Combining seasonal forecasts from multiple inputs

- Combining predictions from different and complementary models helps improve our predictive ability.
- Over a single region, different models have different skills. Differences in the levels of model skills may suggest that different models should be weighted differently when combined into a single prediction. However, because of short hindcast periods, different authors have reported that **equal weighting generally performs better** than the use of unequal weights.
- The **simplest method of blending** is to take a simple average of the values predicted by each system (for deterministic forecasts) and an average of predicted probabilities (if forecasts are probabilistic).
    - In WMO LC-LRFMME weighting in proportion to the square root of the ensemble size.
    - In NMME weighting individual model probabilities proportionally to the ensemble size.
- Together with dynamical seasonal prediction systems, empirical prediction systems can also be used to improve model combinations
- Given the simplicity of **blending by averaging among the selected models**, it seems recommendable to start the operations using this approach and at the same time progress with the development of a more advanced weighting method.

Statistical and dynamical downscaling of real-time forecasts

- Dynamical downscaling is unable to enhance forecast skill over regions for which the global dynamical model used to force the regional model demonstrates poor skill. In contrast, **statistical methods involving spatial pattern correction can potentially improve regional skill** in cases where skill in representing climate variability patterns is degraded by model errors.
- Given the fact that high resolution and quality observational data are available over MedCOF domain -at over some part of the domain-, statistical downscaling can be performed to provide seasonal forecasts for those locations not resolved by the coarse resolution model. In general, downscaling may be **worthwhile in instances where the forecast being downscaled has skill and there is some reason to expect that downscaling will further add to skill** (and will provide further details).
- A general property of dynamical downscaling is that while the downscaled forecast fields show increased detail, particularly in topographically complex regions, dynamical downscaling does not correct large-scale errors in global model forecasts. Therefore, also due to the very demanding computing resources for its application, dynamical downscaling can in a first instance be disregarded as an alternative downscaling technique.
- Many statistical downscaling techniques have been developed to derive local information from large-scale GCMs outputs → **Select simple SDS (from MEDSCOPE CSTools)**

Current versus new approaches to SF