A statistical-dynamical approach to improve subseasonal precipitation forecasts: application to the southwest tropical Pacific

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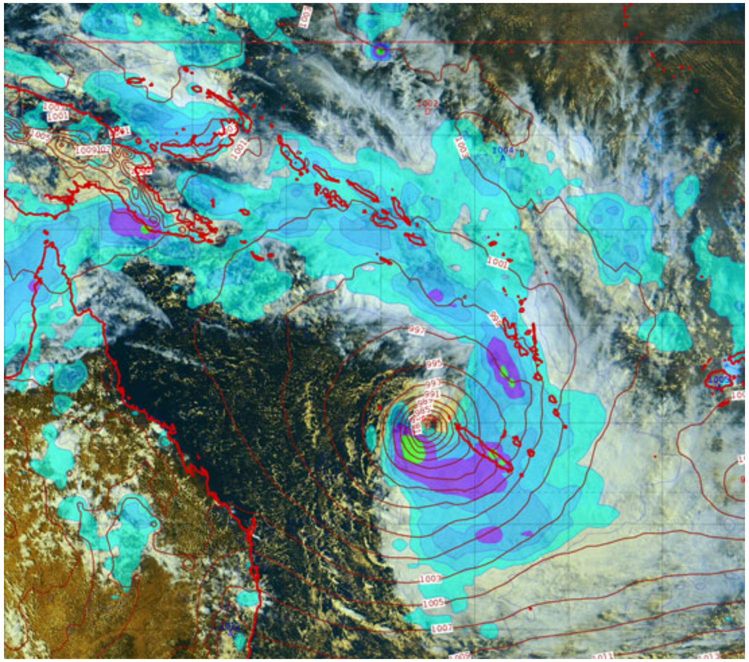
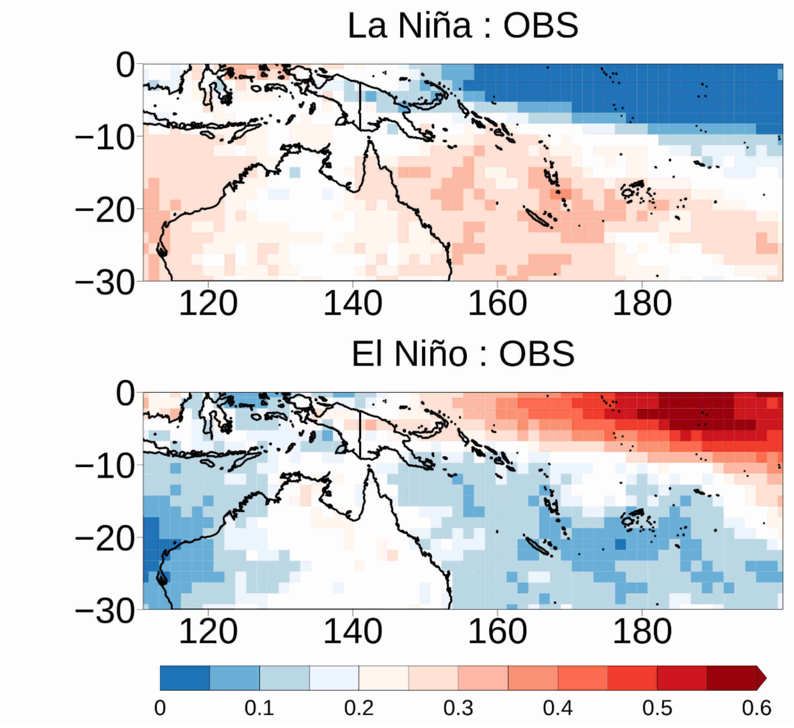


Predictability sources in the southwest tropical Pacific

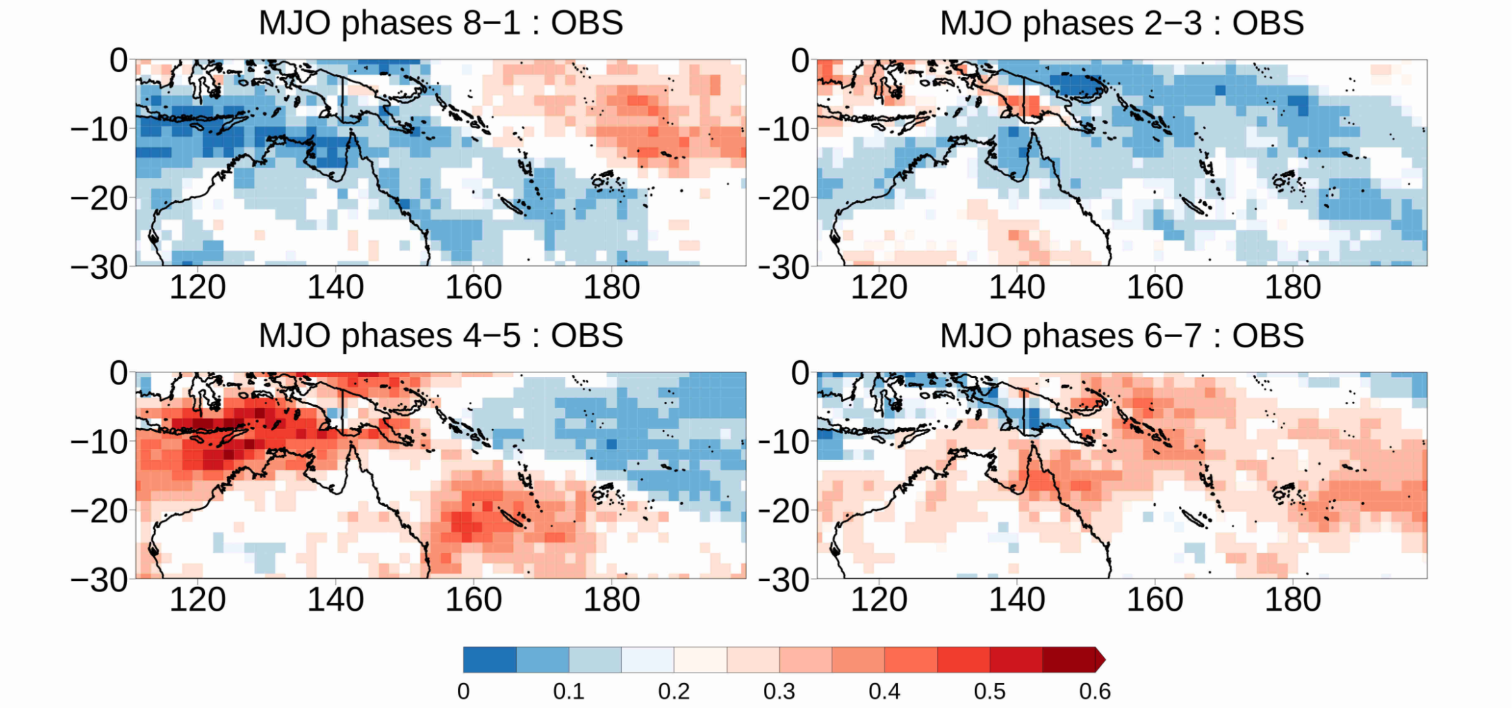
➢ ENSO : constrains the frequency of heavy rainfall at the seasonal timescale



▲ Frequency of the upper quintile of weekly precipitation depending on ENSO phase (MSWEP data, DJF 1996-2014).
In white : no significant difference with the 0.2 baseline frequency based on a 95% Student test.

Predictability sources in the southwest tropical Pacific

- MJO : constrains the frequency of heavy rainfall at a few weeks timescale



▲ Frequency of the upper quintile of weekly precipitation depending on MJO phase (MSWEP data, DJF 1996-2014).
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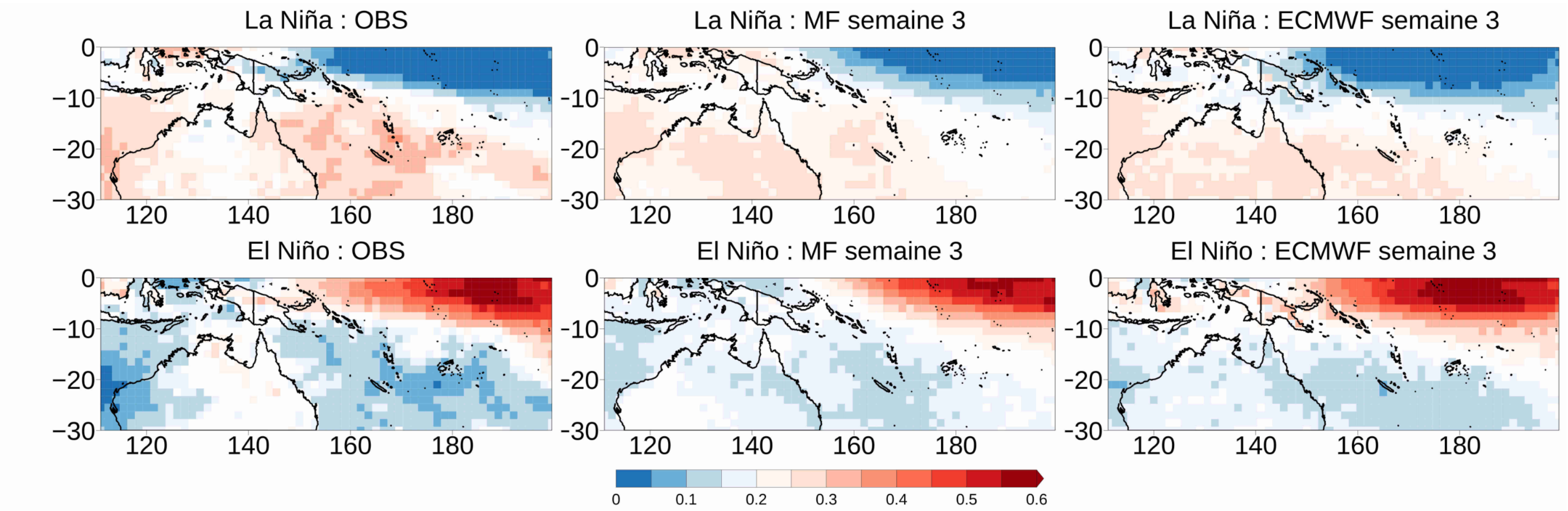
How are the impacts of ENSO represented in the models' world ?



▲ Frequency of the upper quintile of weekly precipitation in La Niña and El Niño phases in observations (MSWEP) and S2S week-3 forecasts.
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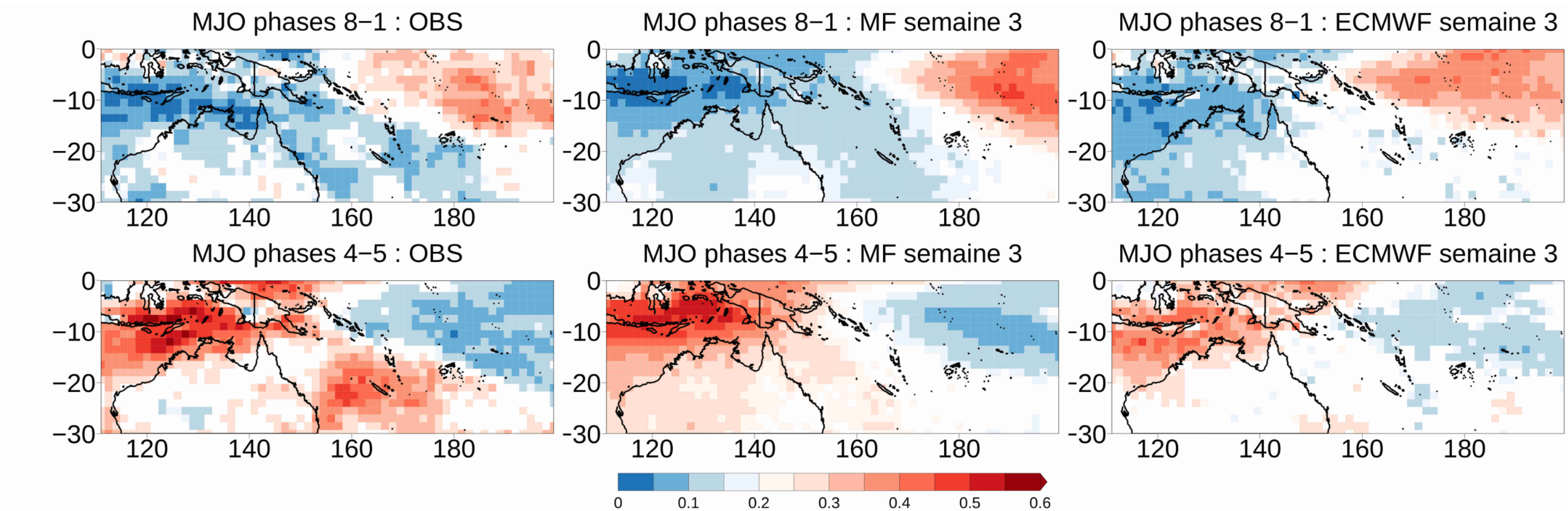
How are the impacts of the MJO represented in the models' world ?



▲ Frequency of the upper quintile of weekly precipitation in MJO phases 8-1 and 4-5 in observations (MSWEP) and S2S week-3 forecasts.
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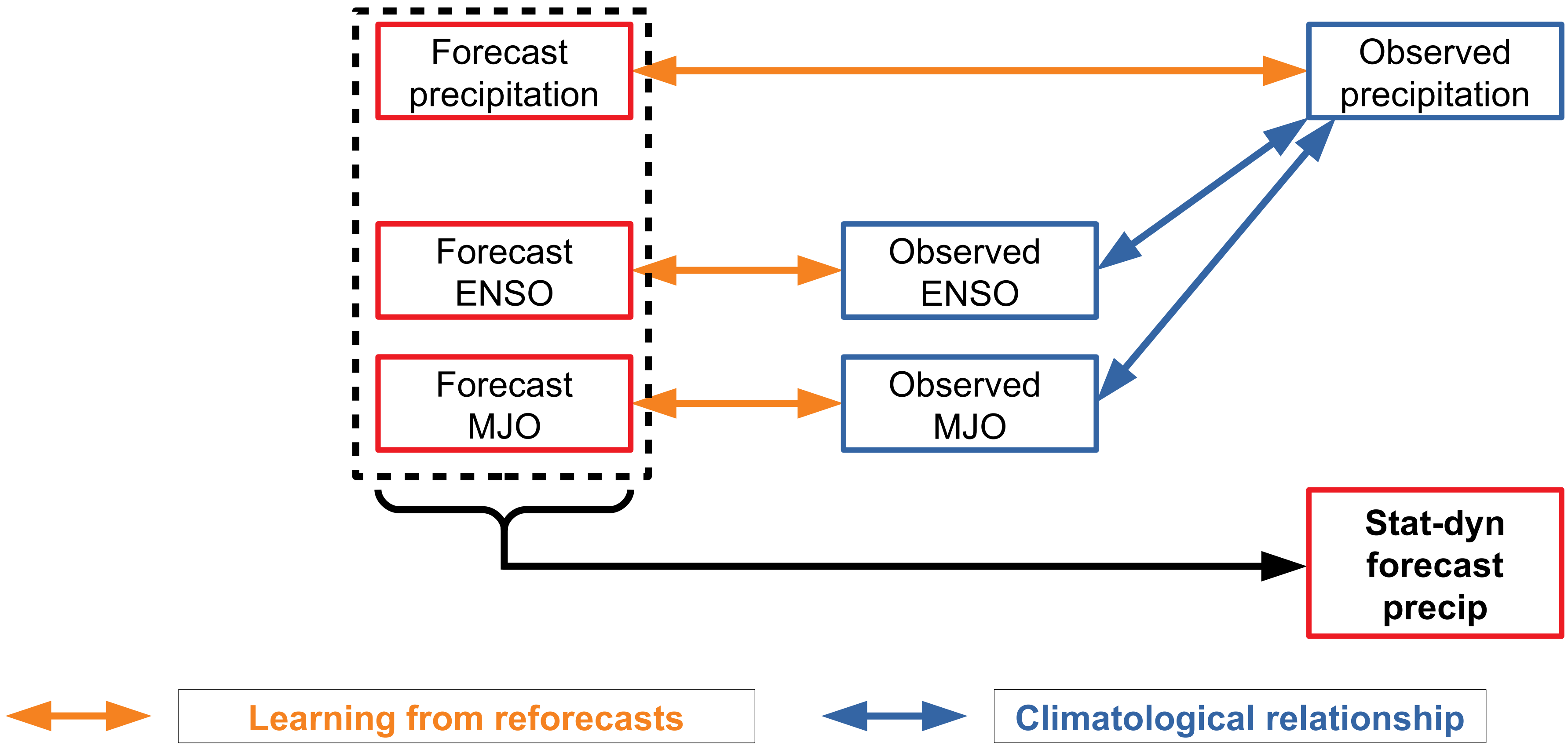
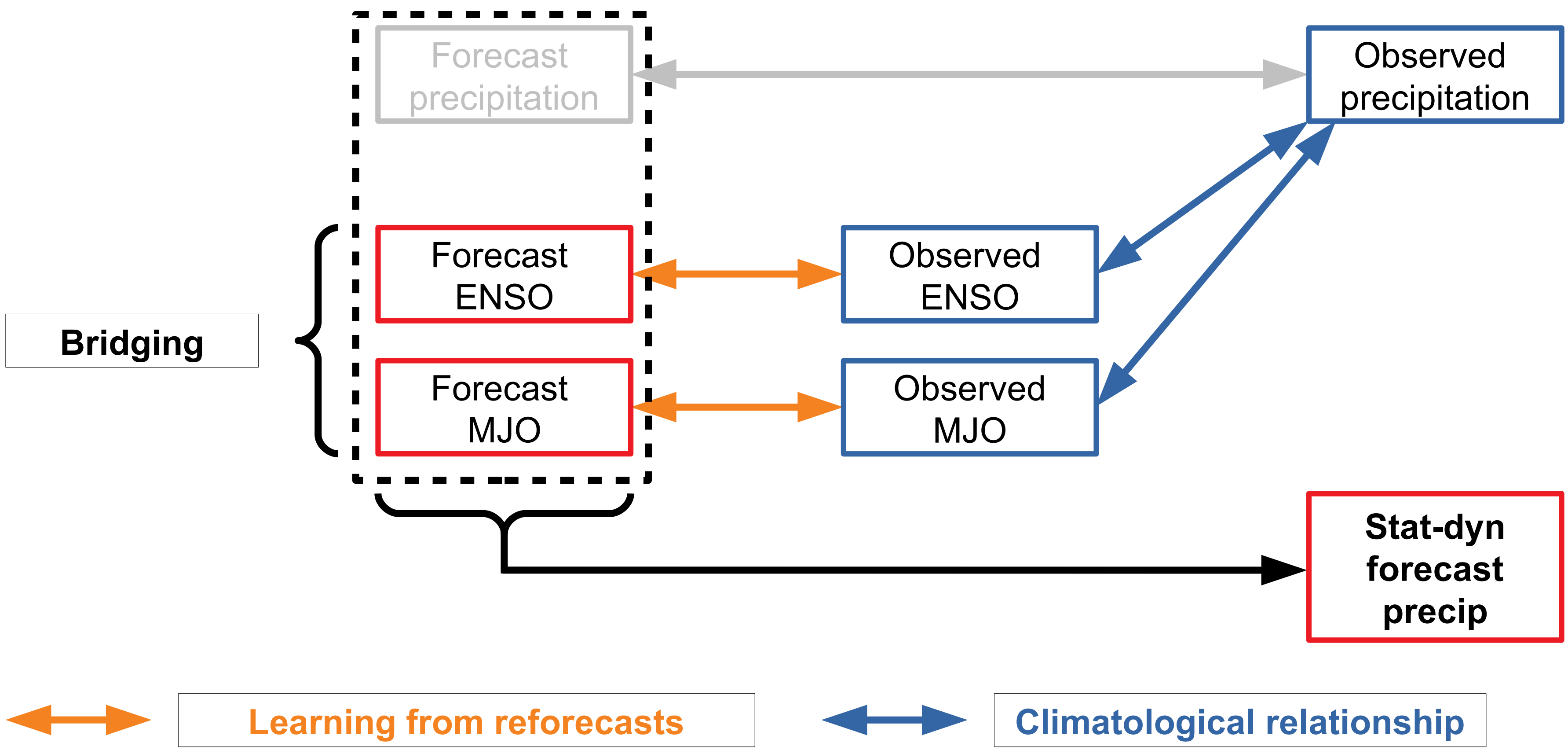
Statistical-dynamical prediction : framework



Statistical-dynamical prediction : framework



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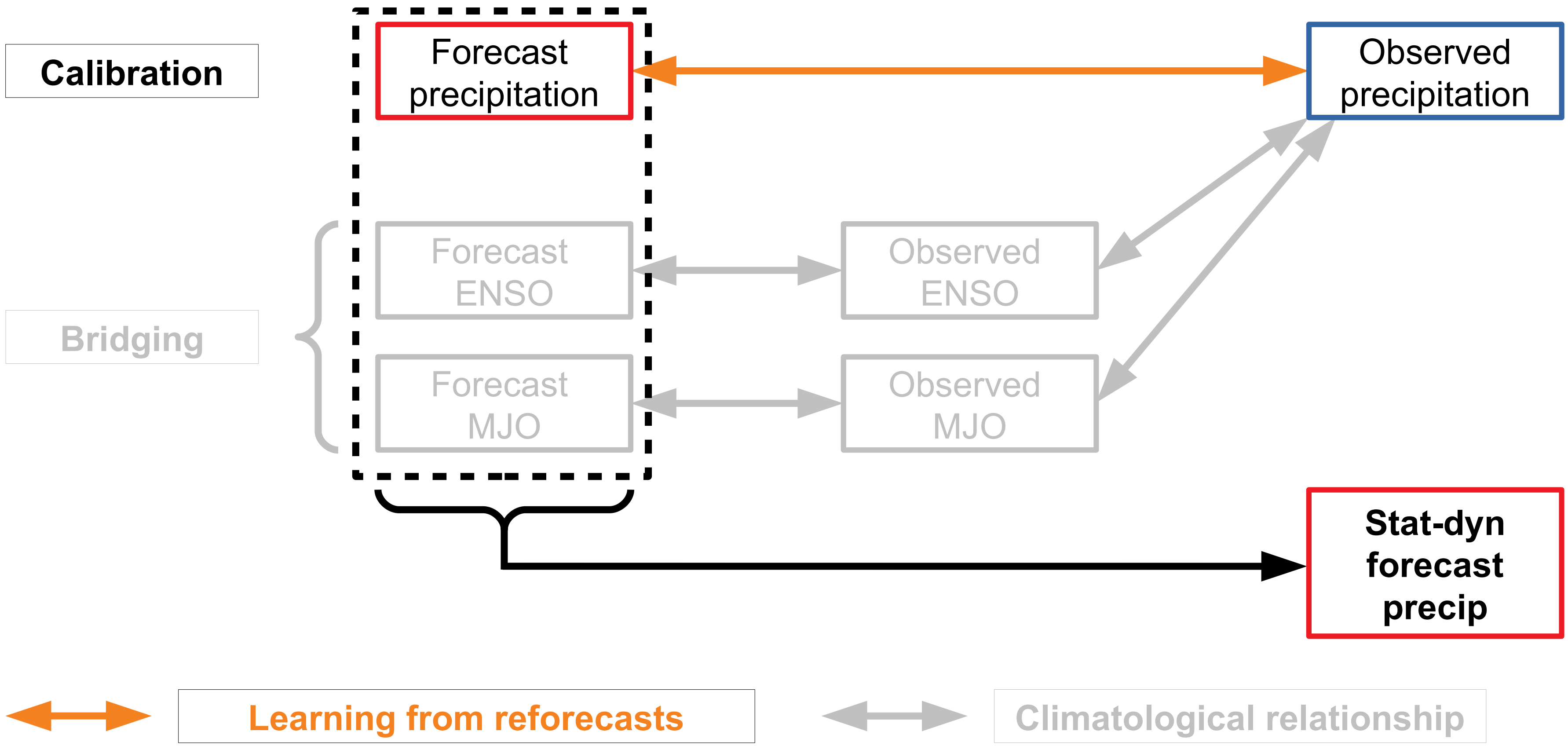
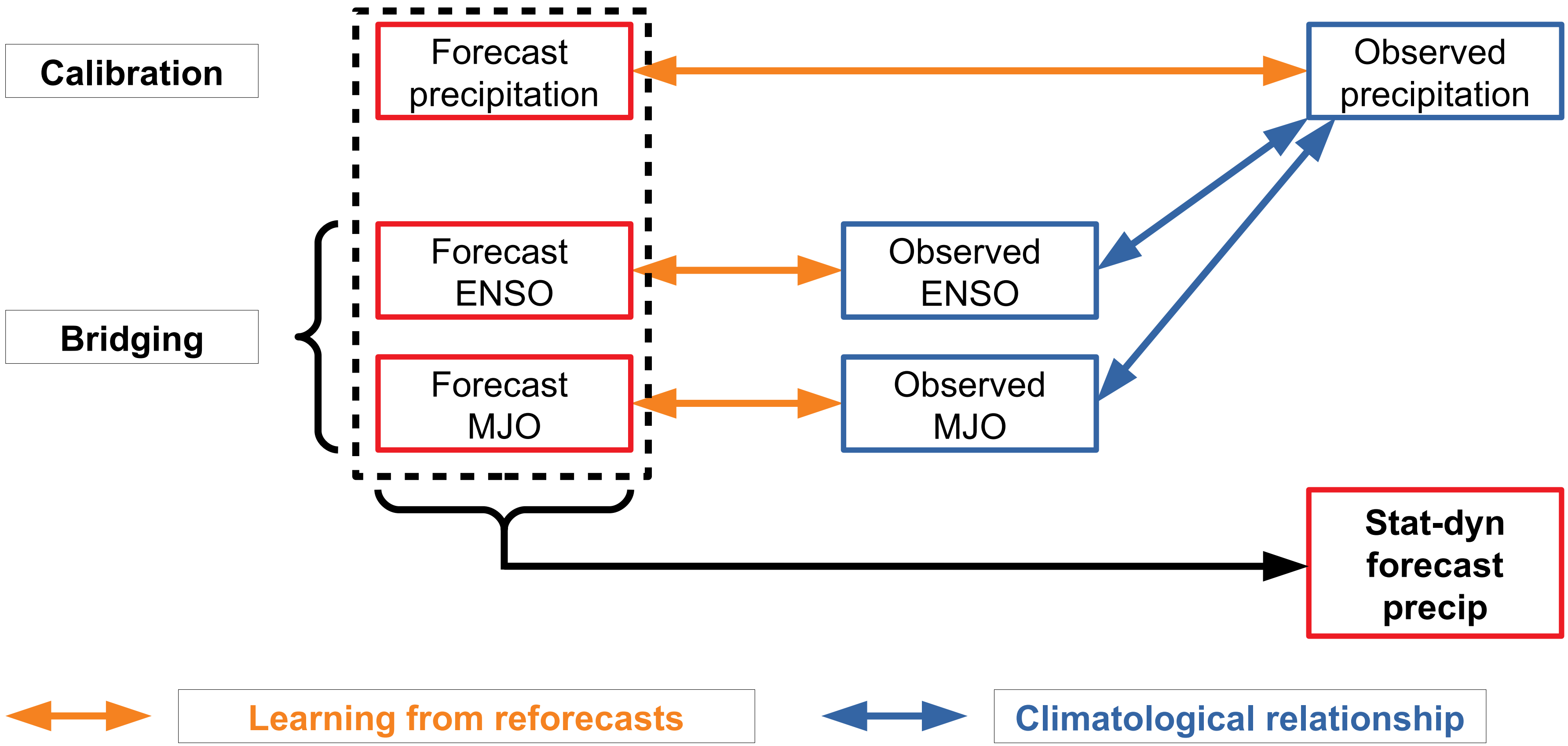


Statistical-dynamical prediction : framework

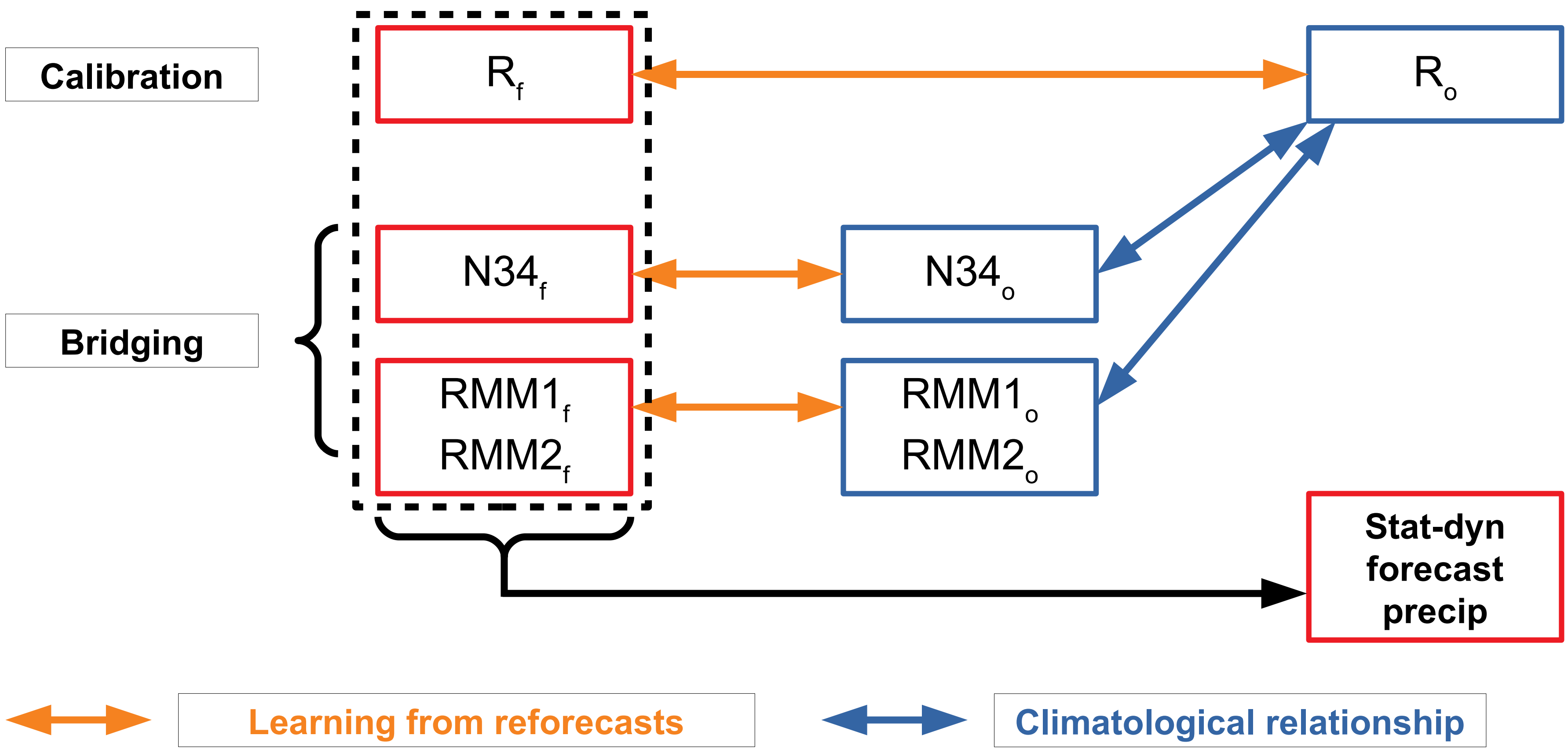
Objectives :

- Taking advantage of the models' information about large-scale predictors
- Producing better calibrated probabilistic precipitation forecasts



Statistical-dynamical prediction : methodology

- Notations



Statistical-dynamical prediction : methodology

Bayesian method adapted from Coelho et al. (2004) and Luo et al. (2007)

- What we are looking for : *a posteriori* observed precipitation distribution (R_o) knowing the forecast predictors $\mathbf{x_f} = (R_f, N34_f, RMM1_f, RMM2_f)$
- Use of Bayes' formula

$$p(R_o \mid \mathbf{x_f}) \sim p(\mathbf{x_f} \mid R_o) \,.\, p(R_o)$$

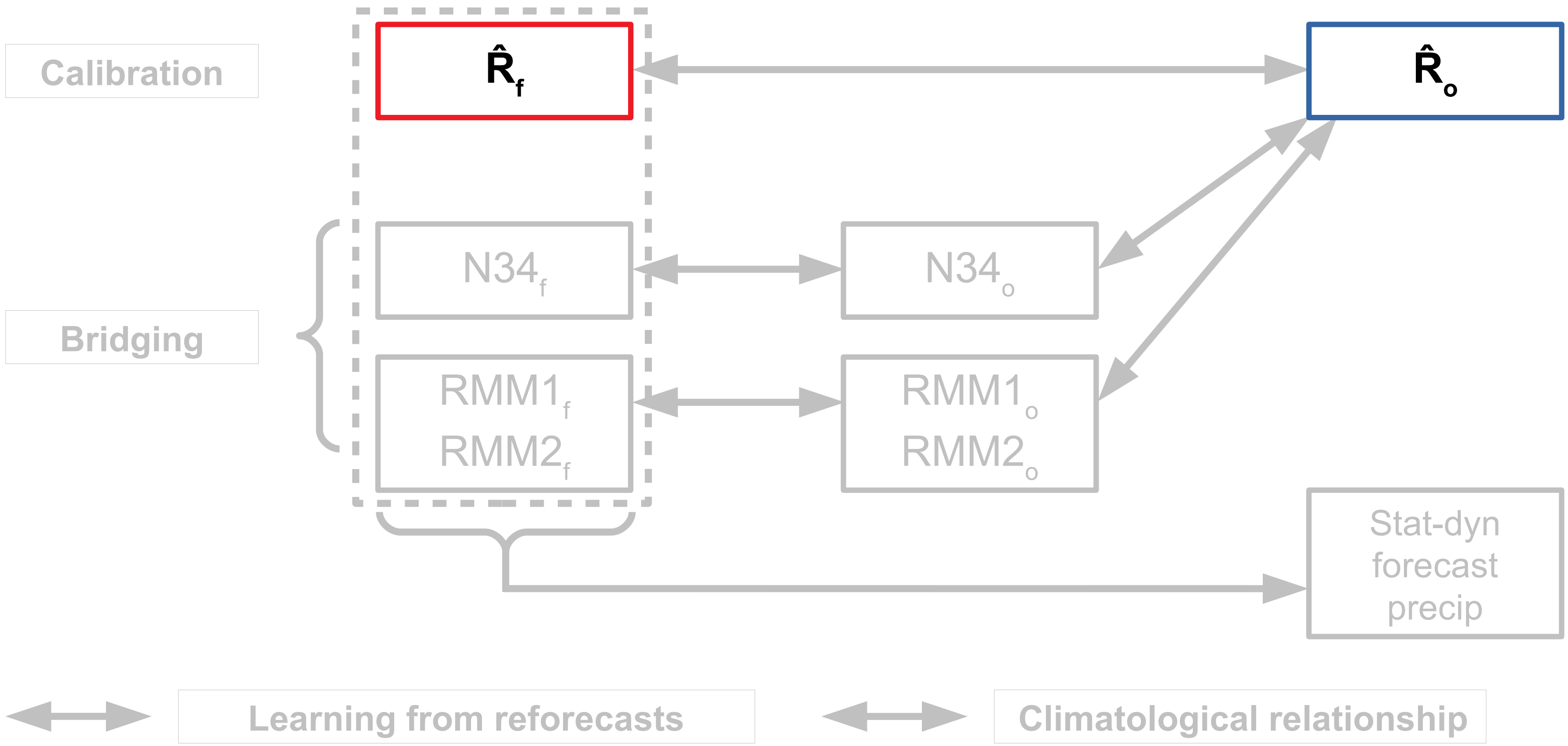
A posteriori distribution

Likelihood = distribution of $\mathbf{x_f}$ predictor knowing R_o predictand

A priori distribution of predictand R_o

Statistical-dynamical prediction : methodology

Bayesian method adapted from Coelho et al. (2004) and Luo et al. (2007)
(1) *A priori* distribution : observed and forecast **weekly precipitations are normalized** with a quantile-quantile method (mean $\mu = 0$; standard deviation $\sigma = 1$)



Statistical-dynamical prediction : methodology

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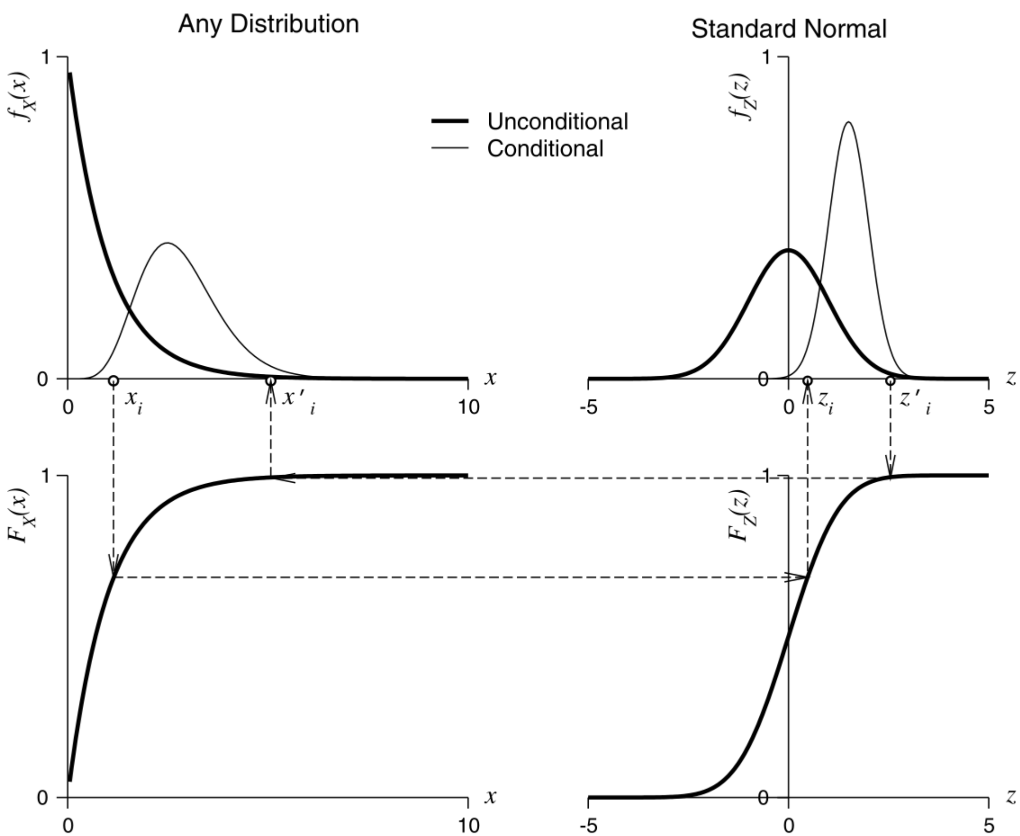
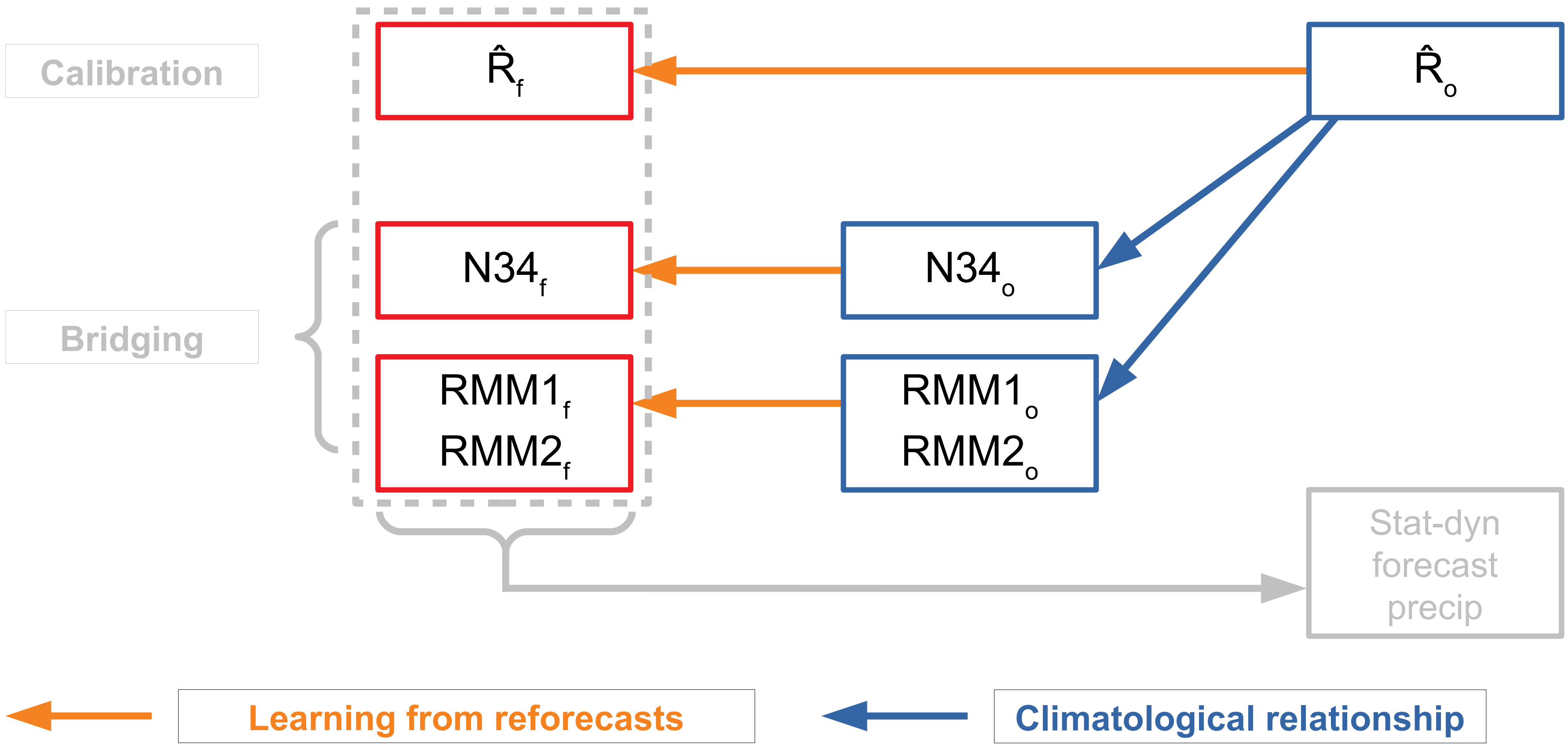


◄ Normalization of precipitation data, taken from Luo et al. (2007).

Statistical-dynamical prediction : methodology

Bayesian method adapted from Coelho et al. (2004) and Luo et al. (2007)
(2) Likelihood : the relationships expressing the **prédictors as a function of the predictand** are learnt by linear regressions
→ The predictors follow normal distributions depending on the predictand



Statistical-dynamical prediction : methodology

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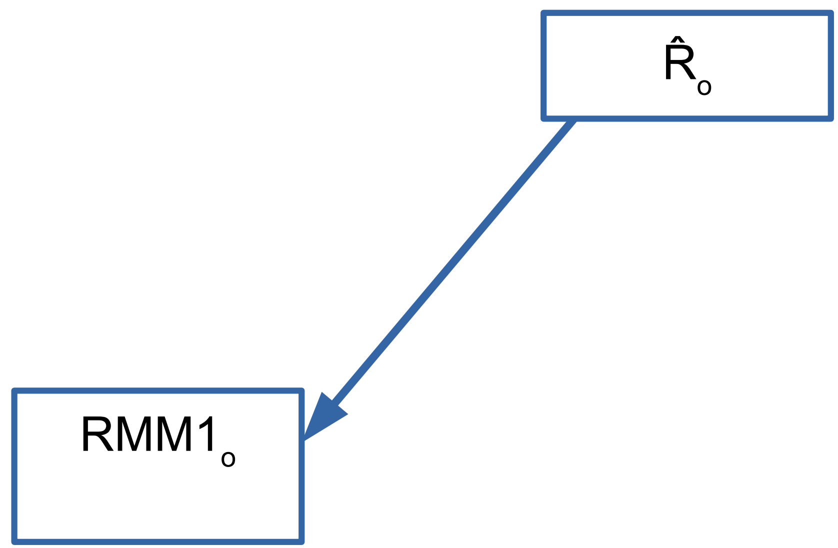
→ The predictors follow normal distributions depending on the predictand

Example : $RMM1_o$ follows a normal distribution
- mean $\mu = a_{o,RMM1} + b_{o,RMM1}\hat{R}_o$
- variance $\sigma^2_{o,RMM1}$



← **Climatological relationship**

Statistical-dynamical prediction : methodology

Bayesian method adapted from Coelho et al. (2004) and Luo et al. (2007)
(2) Likelihood : the relationships expressing the **prédictors as a function of the predictand** are learnt by linear regressions
→ The predictors follow normal distributions depending on the predictand

Example : $RMM1_f$ follows a normal distribution
- mean $\mu = a_{f,RMM1} + b_{f,RMM1} RMM1_o$
- variance $\sigma^2_{f,RMM1}$

$$RMM1_f \leftarrow RMM1_o$$

← **Learning from reforecasts**

Statistical-dynamical prediction : methodology

Bayesian method adapted from Coelho et al. (2004) and Luo et al. (2007)
(2) Likelihood : the relationships expressing the **prédictors as a function of the predictand** are learnt by linear regressions
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Example : $RMM1_f$ follows a normal distribution
- mean $\mu = (a_{f,RMM1} + b_{f,RMM1}\, a_{o,RMM1}) + b_{f,RMM1}\, b_{o,RMM1} \hat{R}_o$
- variance $\sigma^2_{f,RMM1} + b^2_{f,RMM1}\, \sigma^2_{o,RMM1}$

$\hat{R}_o$

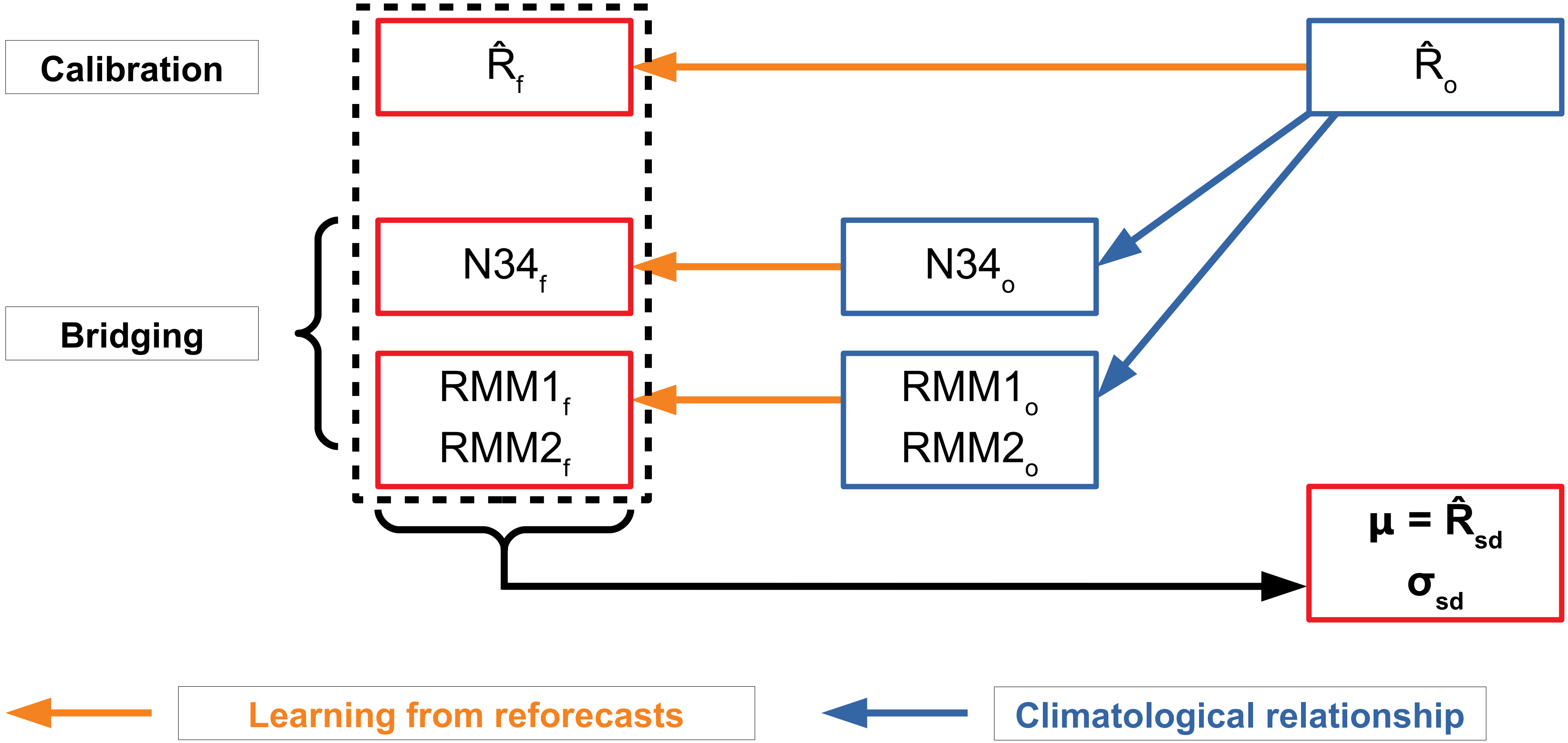
$RMM1_f$ $\leftarrow$ $RMM1_o$

Learning from reforecasts

Climatological relationship

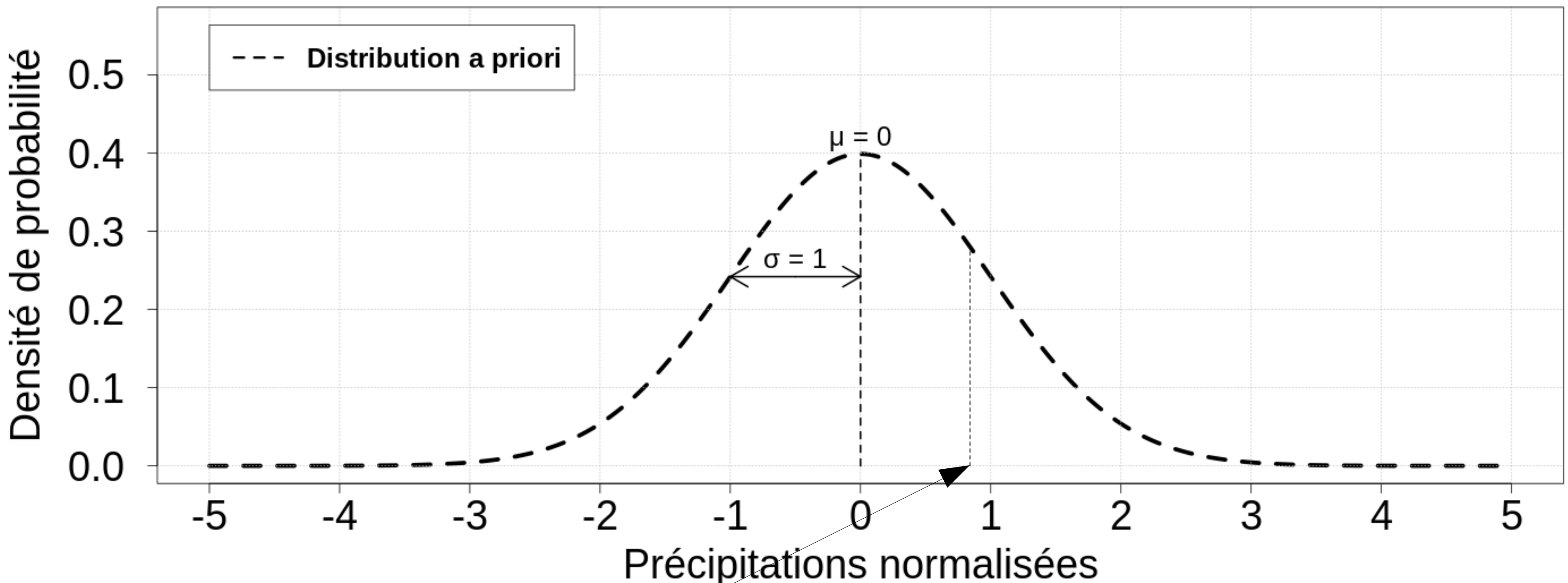
Statistical-dynamical prediction : methodology

Bayesian method adapted from Coelho et al. (2004) and Luo et al. (2007)
(3) The statistical-dynamical prediction (i.e *a posteriori* distribution) is also a **normal distribution**



How to use the statistical-dynamical prediction ?

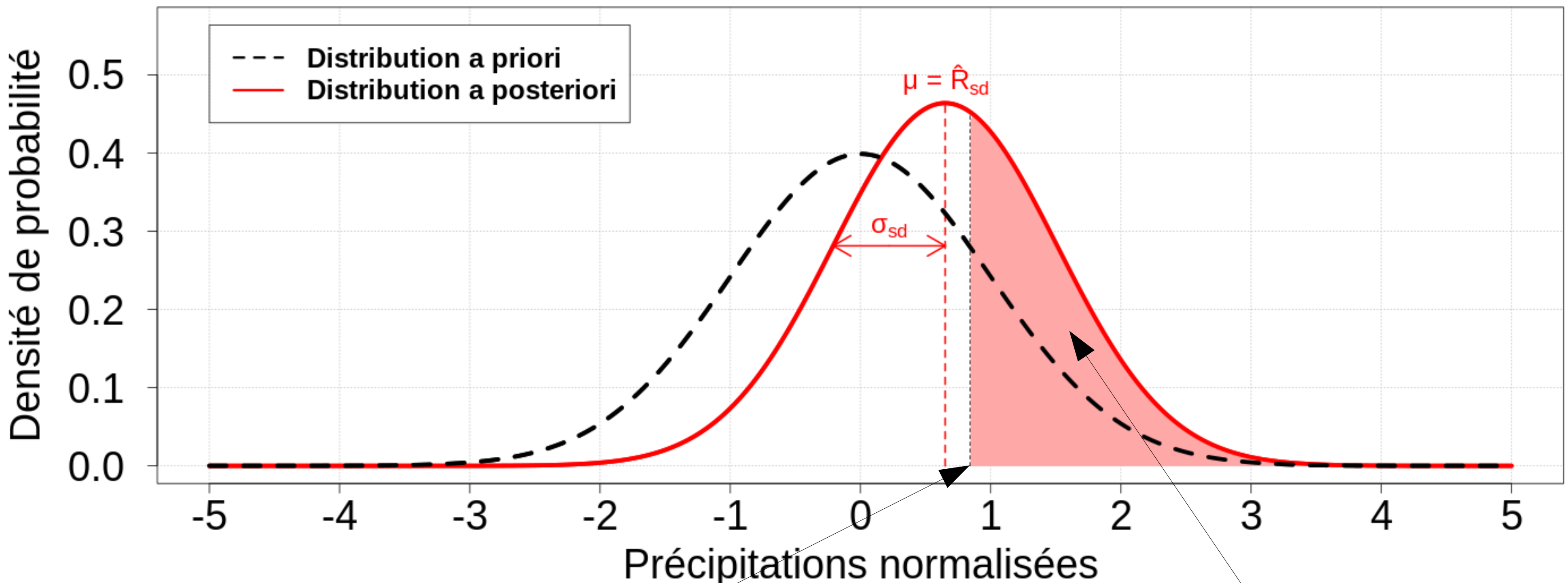
➢ Probabilistic forecasting of the upper quintile of weekly precipitation



Upper quintile of the *a priori* climatological distribution : ~ 0.84

How to use the statistical-dynamical prediction ?

➤ Probabilistic forecasting of the upper quintile of weekly precipitation

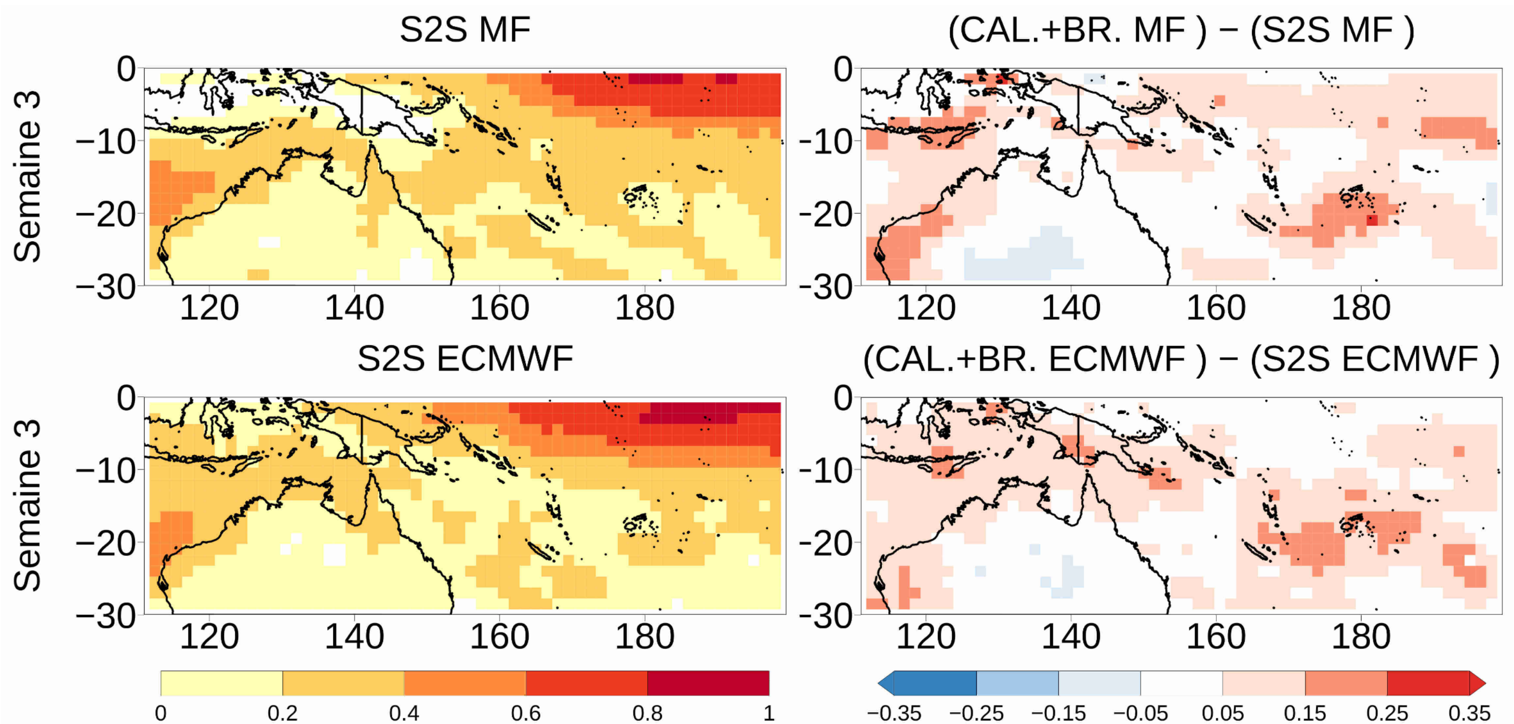


Upper quintile of the *a priori* climatological distribution : ~ 0.84

A posteriori probability of exceedance of the upper quintile threshold

Benefits of the statistical-dynamical prediction

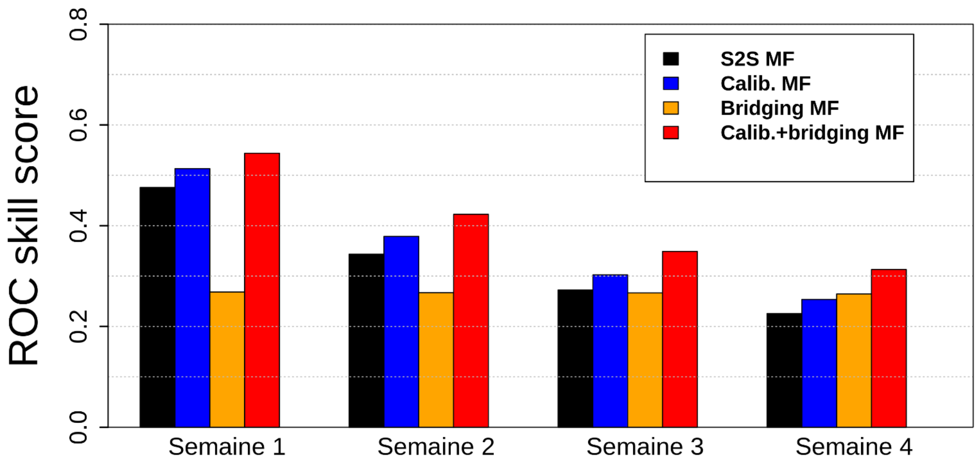
➢ Improvement of discrimination depending on the location (ROC skill score at grid point level)

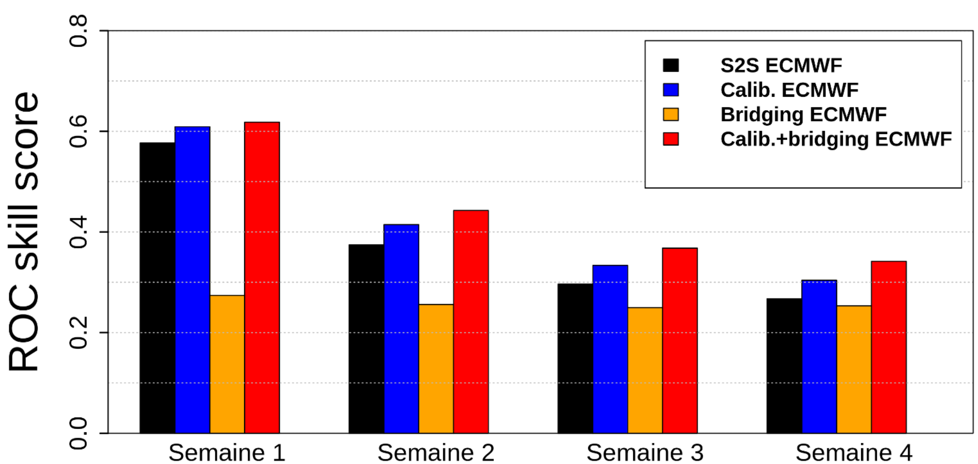


▲ Left: ROC skill score of week-3 S2S prediction of the upper quintile of weekly precipitation (3 x 3 grid points pooling).
Right: Différence between ROC skill score before and after implementation of the statistical-dynamical approach (calibration + bridging).
Reférence : MSWEP, DJF 1996-2014 period.

Benefits of the statistical-dynamical prediction

➢ Improvement of discrimination (ROC skill score over the whole domain)



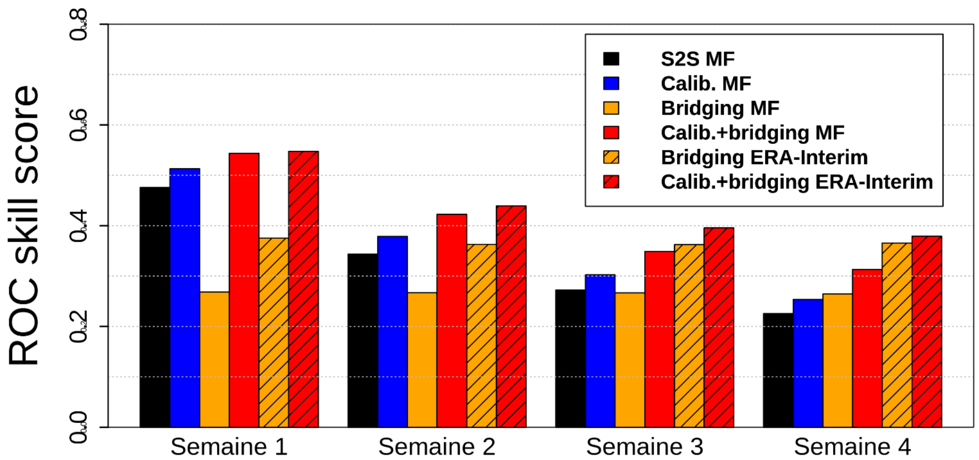


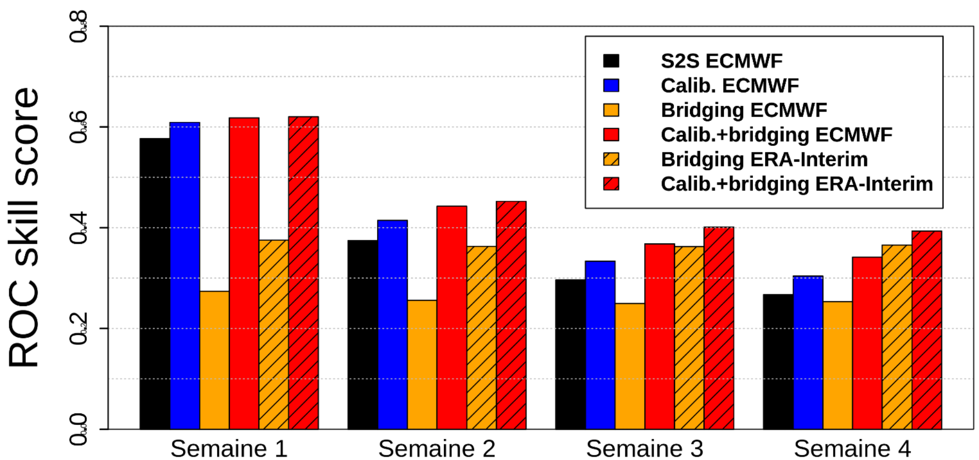
◀ Evolution of the ROC skill score of Météo-France and ECMWF S2S forecasts before the stat-dyn approach (black), after calibration (blue), after bridging (orange), after calibration + bridging (red).

Reference : MSWEP, DJF 1996-2013 period

Benefits of the statistical-dynamical prediction

➢ What if we were able to forecast ENSO and MJO perfectly ? Calibration + *bridging* from ERA-Interim

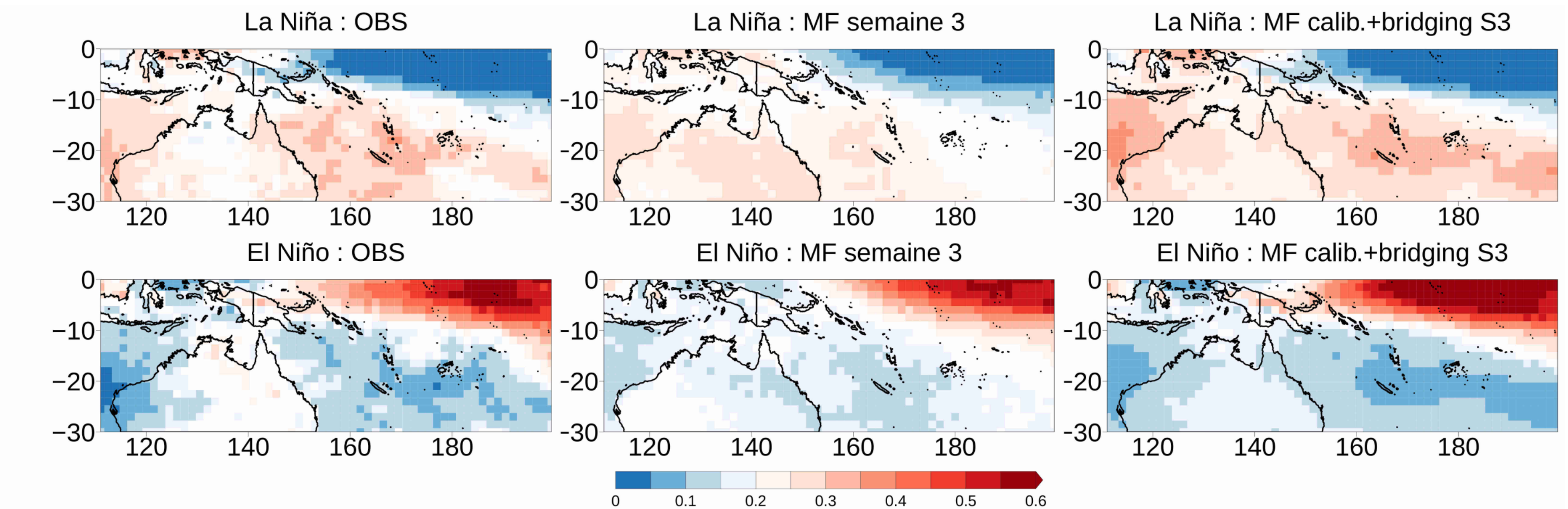




◄ Evolution of the ROC skill score of Météo-France and ECMWF S2S forecasts before the stat-dyn approach (black), after calibration (blue), after bridging (orange), after calibration + bridging (red), after bridging from ERA-Interim (dashed orange), after calibration + bridging from ERA-Interim (dashed red).
Reference : MSWEP, DJF 1996-2013 period

Benefits of the statistical-dynamical prediction

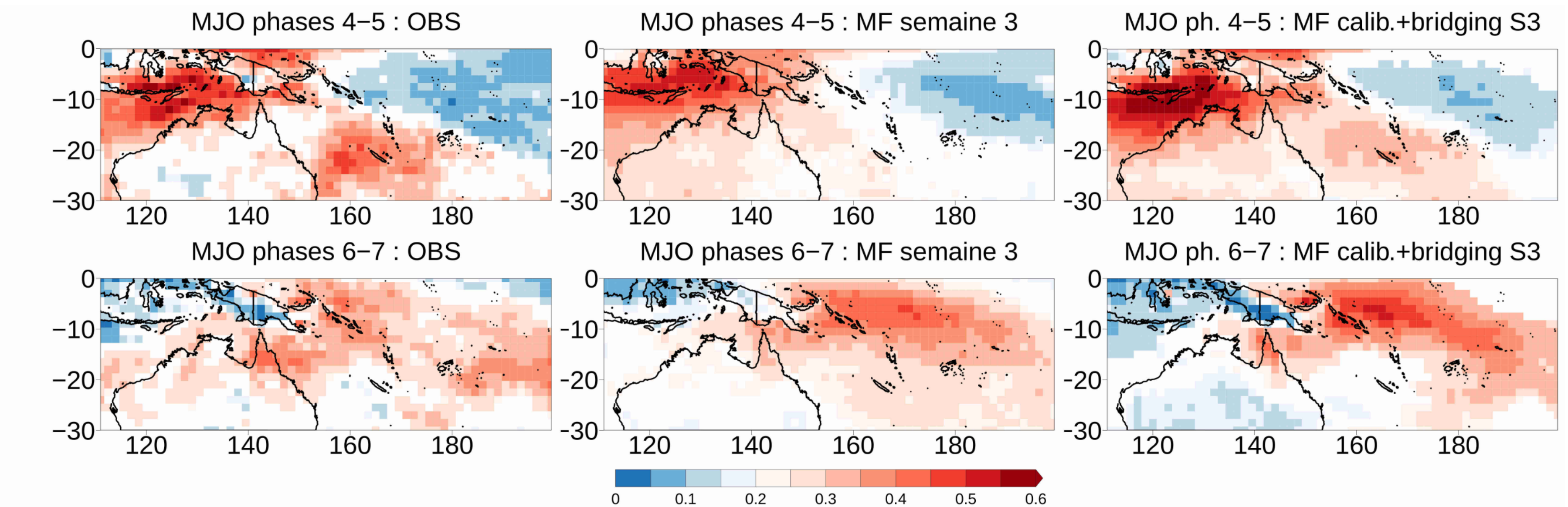
➢ Improvement of the representation of ENSO impacts



▲ Frequency of the upper quintile of weekly precipitation in La Niña and El Niño phases in observations (MSWEP) and Météo-France S2S week-3 forecasts before (middle) and after (right) implementation of the statistical-dynamical approach.
DJF 1996-2013 period.
In white : no significant difference with the 0.2 baseline frequency based on a 95% Student test.

Benefits of the statistical-dynamical prediction

➢ Improvement of the representation of MJO impacts



▲ Frequency of the upper quintile of weekly precipitation in MJO phases 4-5 and 6-7 in observations (MSWEP) and Météo-France S2S week-3 forecasts before (middle) and after (right) implementation of the statistical-dynamical approach.
DJF 1996-2013 period.
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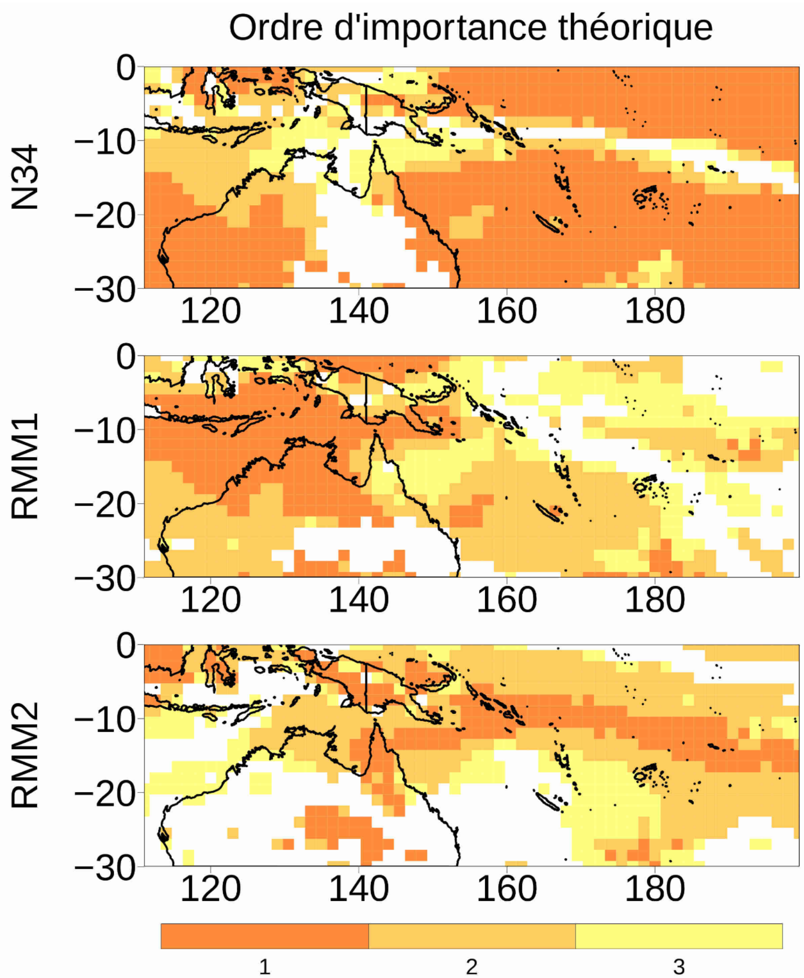
What is the importance of each predictor ?

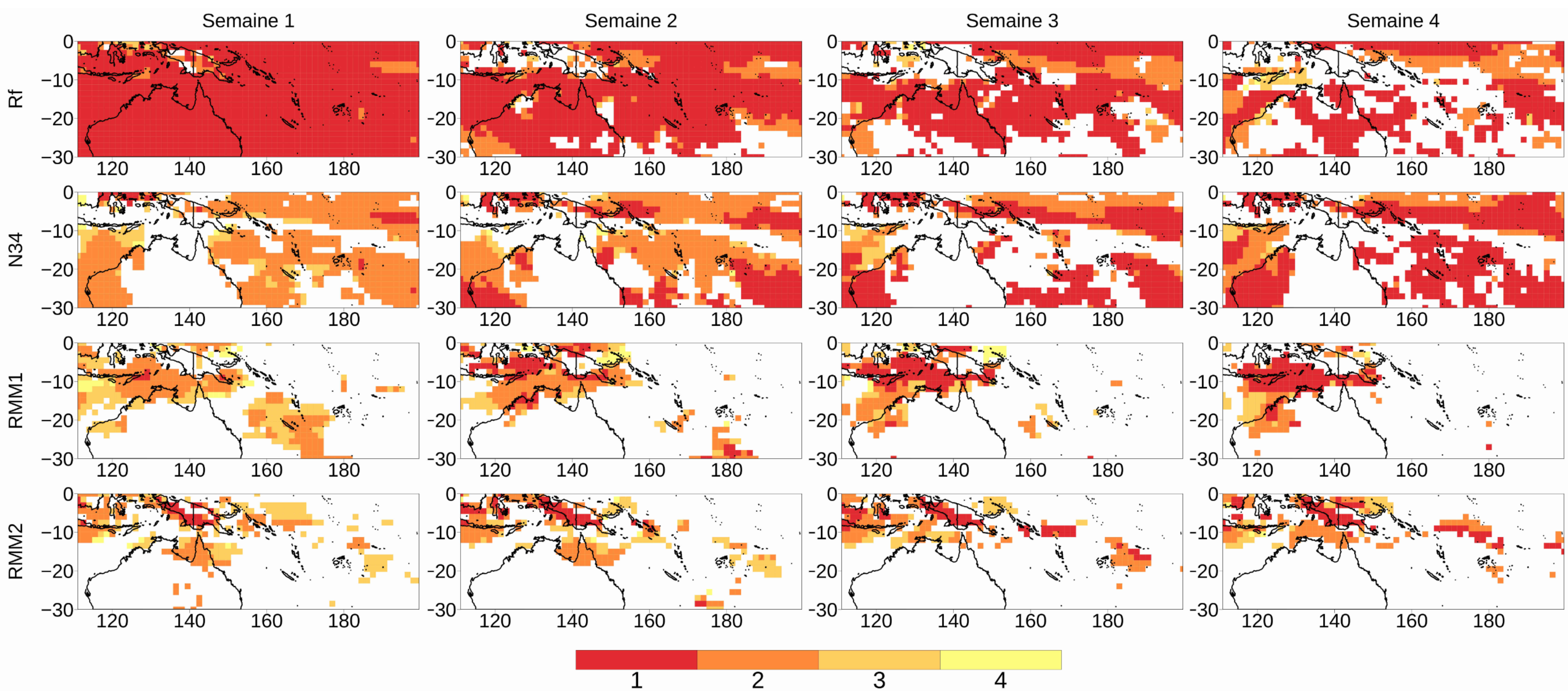
➢ Relative contribution of each large-scale predictor if forecast perfectly (i.e from ERA-Interim)



◄ Order of selection for each predictor in a stepwise forward selection scheme when considering only large-scale predictors from reference data (ERA-Interim).
In white : the predictor does not bring any additional information.

What is the importance of each predictor ?

➢ Relative contribution of each predictor in the calibration + bridging statistical-dynamical approach



▲ Order of selection for each predictor in a stepwise forward selection scheme, applied at each lead time for the calibration + bridging scheme applied to the Météo-France system. Forecast rainfall is also included in the selection.
In white : the predictor does not bring any additional information.

SUMMARY

- Separate fits on each predictor enable to custom the predictor set without a whole re-fitting
- Improved probabilistic forecasts (discrimination, reliability), with crucial role of calibration and additional rôle of briding
- Better representation of the impacts of ENSO and the MJO
- Bridging predictors become increasingly important with lead time at locations where provide information

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