Systematic investigation of skill opportunities in decadal predictions of air temperature over Europe

Giovanni Sgubin, Didier Swingedouw, Leonard F. Borchert, Matthew B. Menary, Thomas Noël, Harilaos Loukos, Juliette Mignot

01 Rationale

- Decadal Climate Prediction (DCP) systems may promote support to **Climate Services**: customized information for decision makers in clima

- Effective **applicability of DCP to targeted problems** is conditional on the evaluation of its **prediction skill**.
- Retrospective predictions (**hindcasts)** are usually evaluated *vs* **observations** :

1. over the whole period of data assimilation, i.e. 1960-present;
2. for fixed forecast times, i.e. 1-5 yr and 6-10 yr;
3. on annual bases, i.e. averages from January to December.

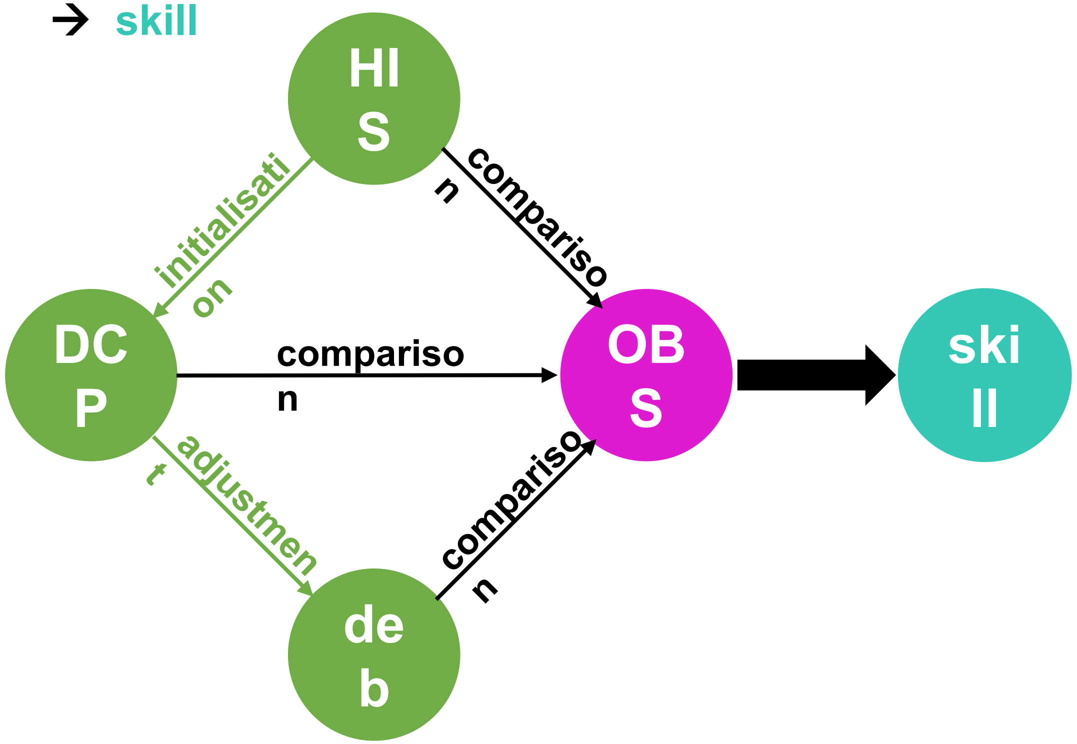
This is not necessarily what the different sectors might search for, and they might exist some sweet spots with strong predictability

Aims of this work

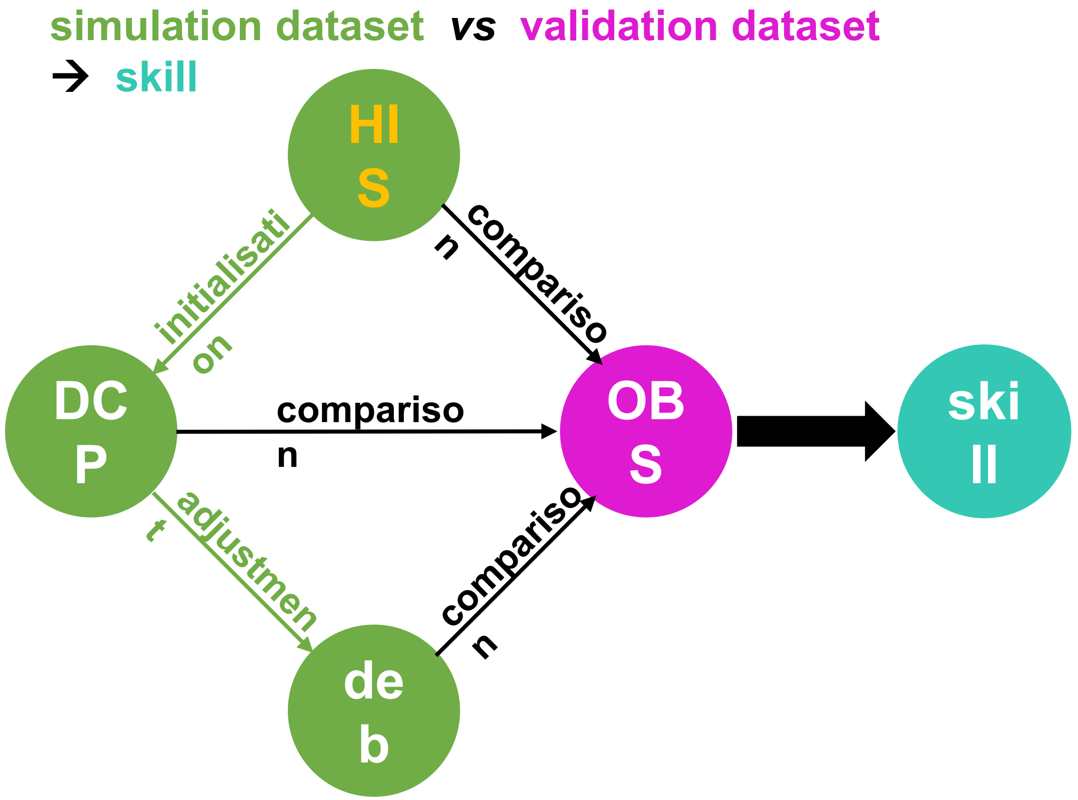
- **Systematic analysis** of the prediction skill in different "contexts", i.e. **different time windows** (periods on the calendar time, forecast times, and months/seasons).
- **Skill opportunities**, i.e. conditions for better DCP performance, and preliminary **interpretation** of their source.

02 Methods

simulation dataset *vs* validation dataset
→ skill



02 Methods



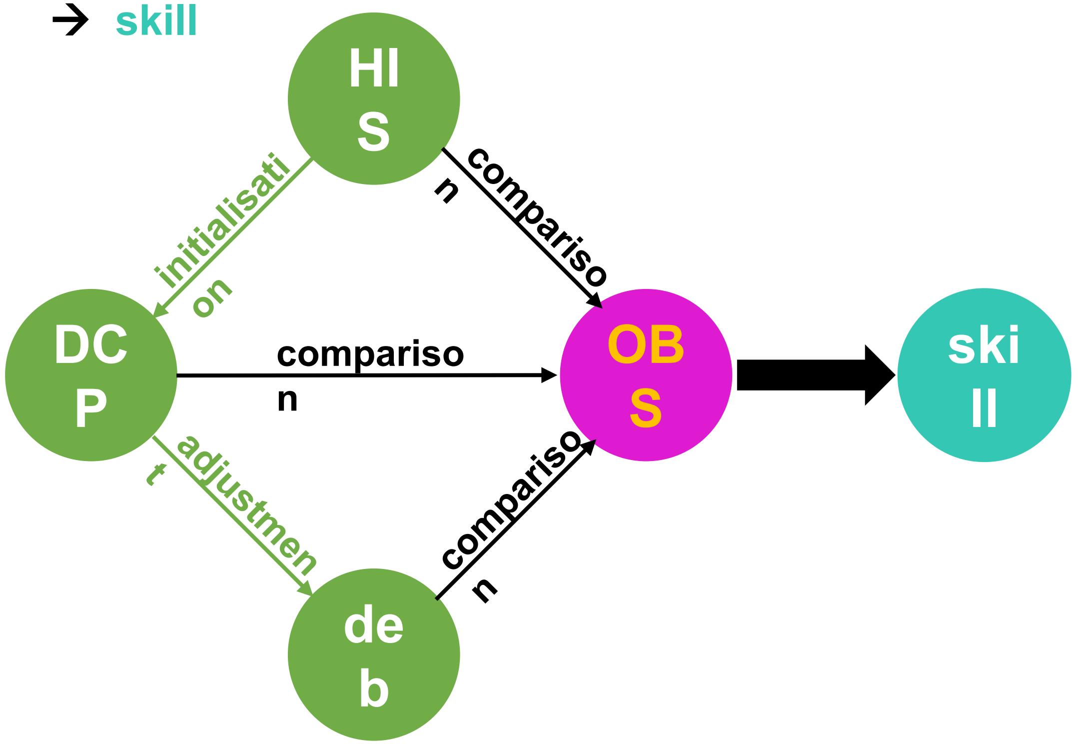
OBS=NOAA-20CR reanalysis data
HIS=IPSL-CM5A-LR historical simulations

IPSL-CM5A-LR historical

- **Non-initialised** simulations.
- 3 members running until 2005.
- **Boundary conditions**: prescribed radiative forcing estimations from observed aerosol and greenhouse gases concentrations in the atmosphere.

02 Methods

simulation dataset *vs* validation dataset
→ skill



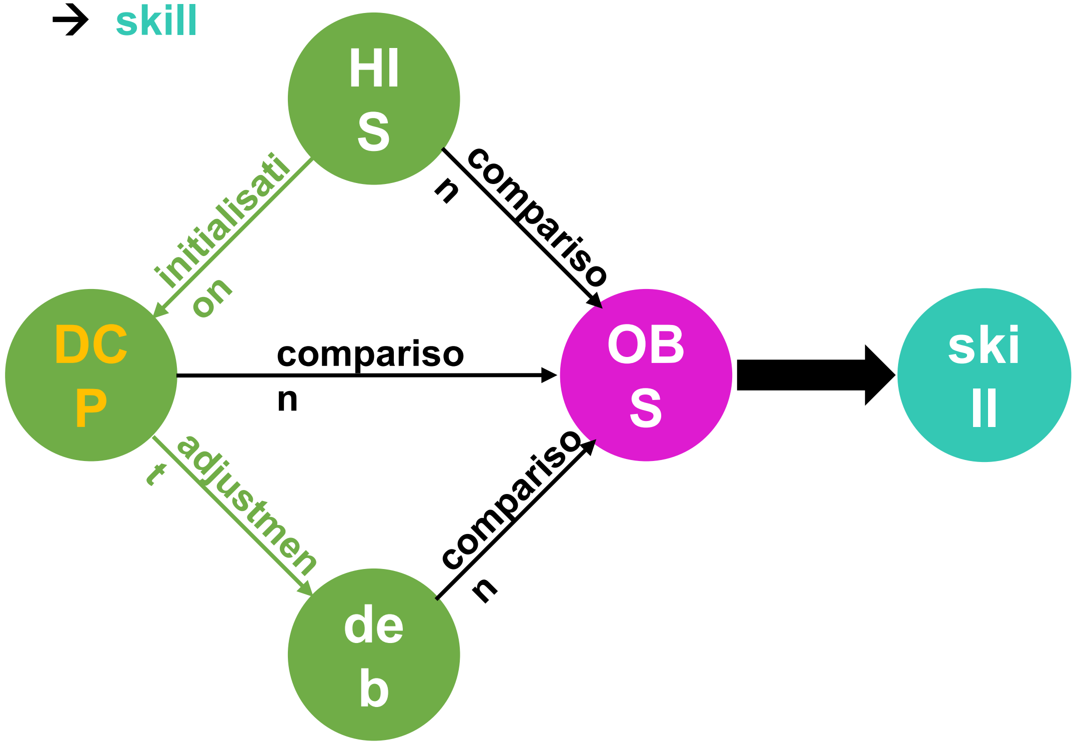
OBS=NOAA-20CR reanalysis data

Observation-based data

- **NOAA-20CR reanalyses data** interpolated on the IPSL model grid (ensemble mean of all the 56 different realisations).
- Used both for the **skill measures** and for the **de-biasing procedure**.

02 Methods

simulation dataset *vs* validation dataset
→ skill



OBS=NOAA-20CR reanalysis data
HIS=IPSL-CM5A-LR historical simulations
DCP=raw hindcasts with IPSL-CM5A-LR

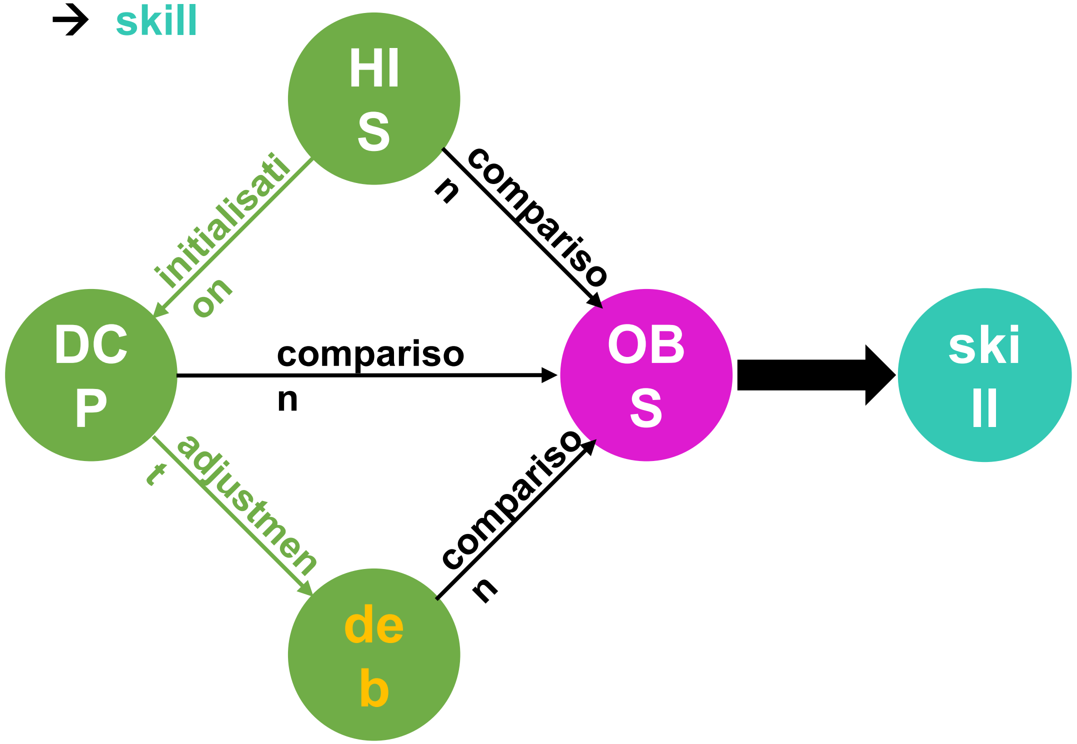
The IPSL-CM5-LR DCP system (raw hindcasts)

- **3 members** initialised **every year** from 1960 to 2013.
- **Initialisation** through **SST anomalies** assimilation, i.e. nudging HIS experiment to observed surface SST anomalies (ERSST).
- **Boundary conditions**: same as for HIS experiment.

Does initialisation imply a skill improvement?

02 Methods

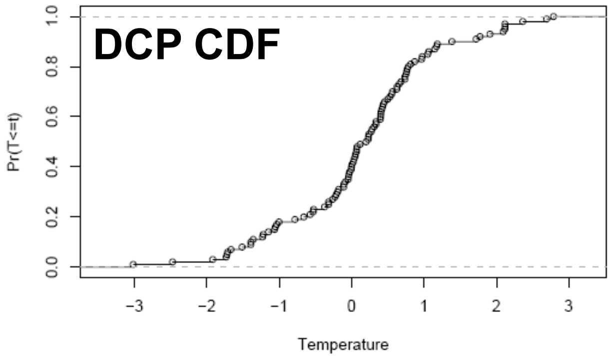
simulation dataset *vs* validation dataset
→ skill

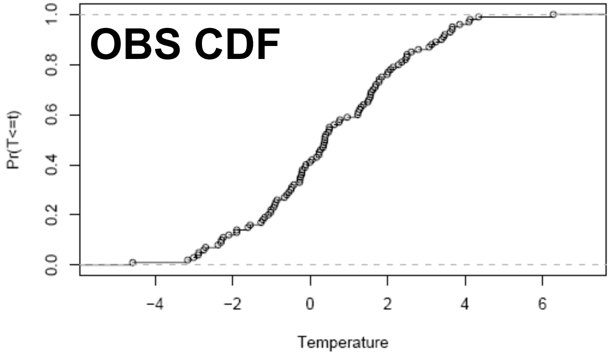


OBS=NOAA-20CR reanalysis data
HIS=IPSL-CM5A-LR historical simulations
DCP=raw hindcasts with IPSL-CM5A-LR
deb=adjusted hindcasts

De-biased hindcasts

- Intrinsic model biased are a limit for impact analyses.
- **De-biasing=data adjustment** based on **quantile mapping**.
- Cumulative Distribution Function transform (**CDF-t**)

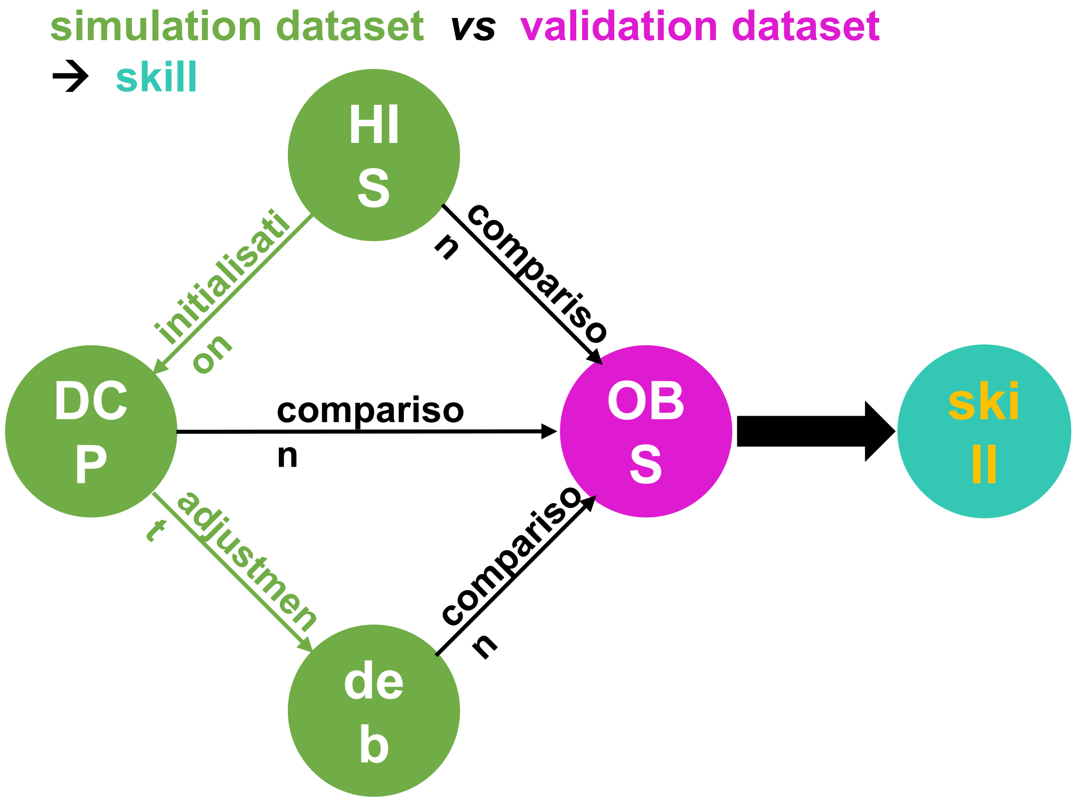




→ **Transfer function** such that: DCP CDF matches OBS CDF.

Does de-biasing imply a skill improvement?

02 Methods



OBS=NOAA-20CR reanalysis data
HIS=IPSL-CM5A-LR historical simulations
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deb=adjusted hindcasts
Skill metrics=ACC and RMSE

Skill metrics

- We consider **de-trended monthly temperature anomalies**.
- 2 skill metrics: **ACC** and **RMSE**.

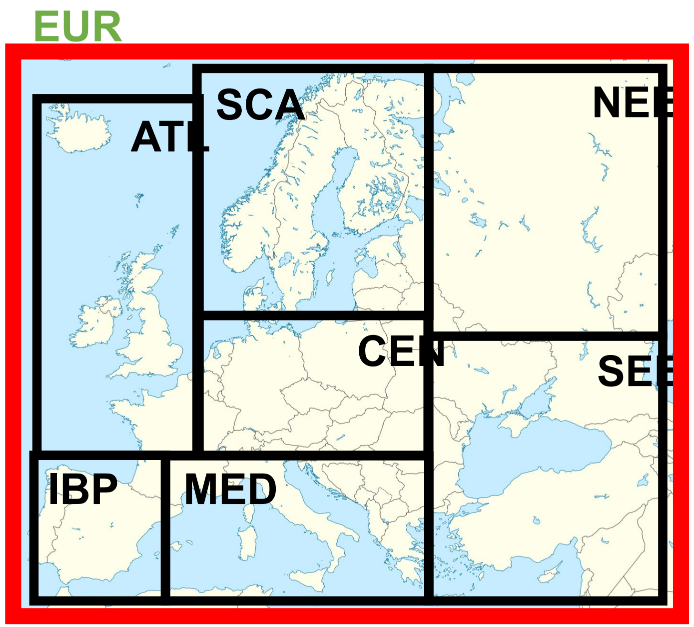
Statistical Significance

- (1) **Student's t-test** for ACC; (2) **Fisher z-transformation** for ACC differences; (3) **Welch's t-test** for RMSE differences.

02 Methods

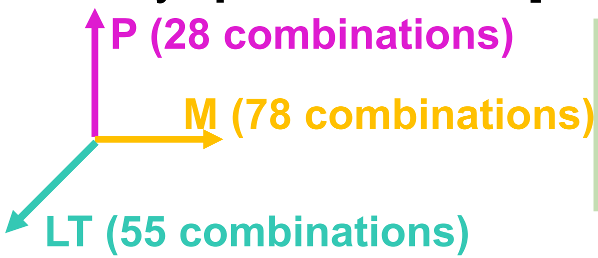
Systematic approach

1. Calculation of averaged air temperature over Europe and its 7 sub-regions.

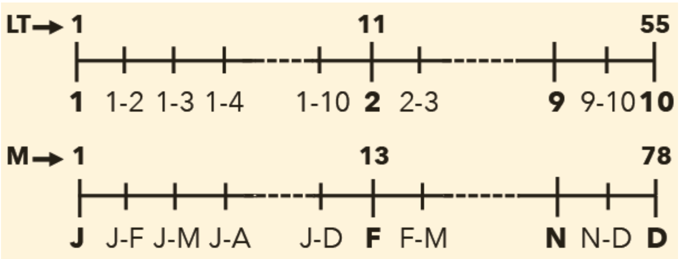


2. Systematic calculation the ACC and RMSE skill for all the possible combinations of:

- consecutive **months M**
- consecutive **lead-times LT**
- 26-yr **periods P** in [1960-2014]



3D matrix M x LT x P
120120 skill values
for each region

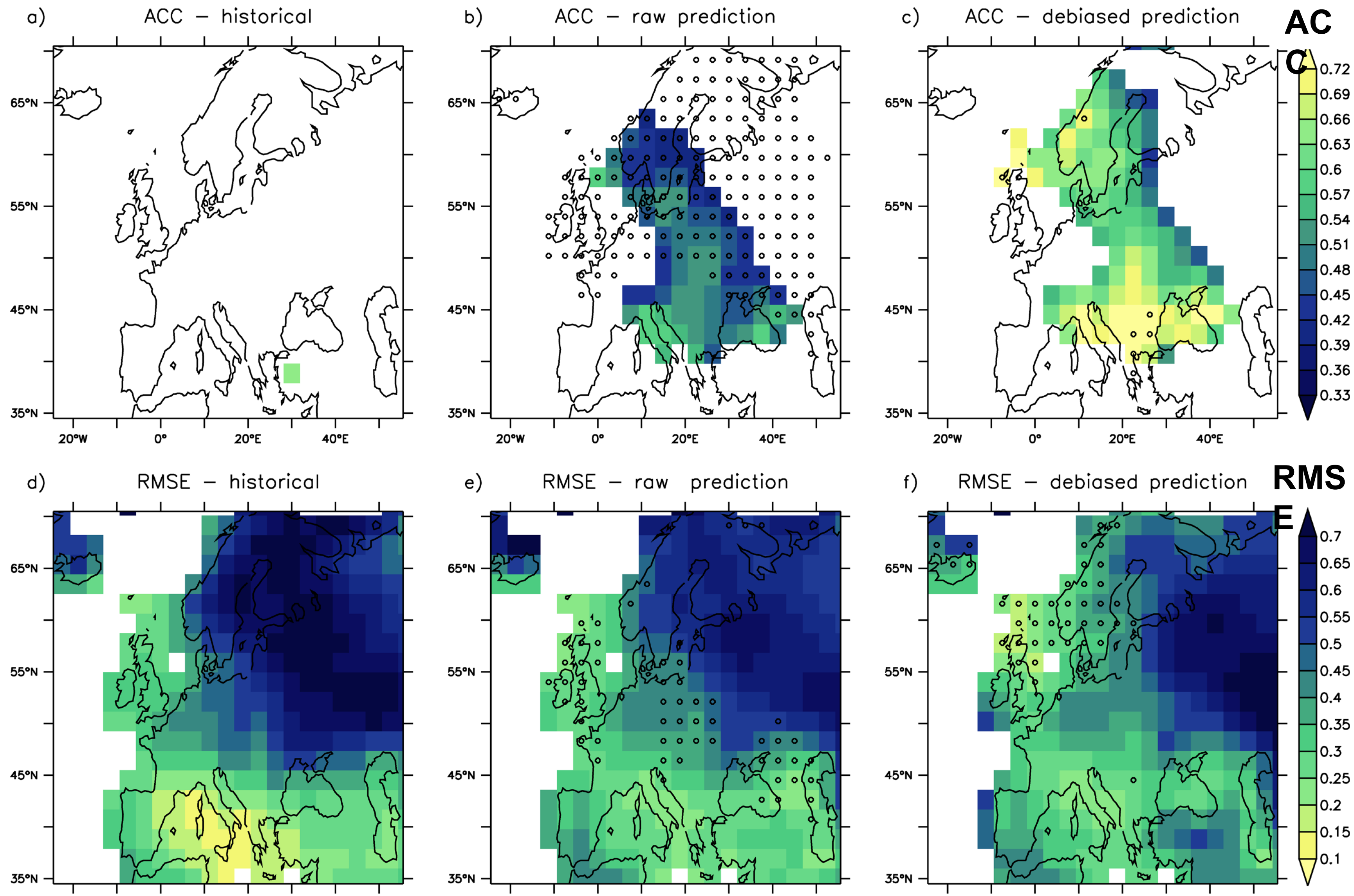


3. Analysis of the skill S at varying P, LT, M, i.e. **S=f(P, LT, M)** and identification of **skill opportunities** for Europe and its 7 sub-regions.

Reference context

P=1960-1985; LT=1-5 yr; M=Jan-Dec.

Skill for the reference context



O Statistically significant skill improvement the 95% confidence level have been displayed

N.B. For ACC, only correlations statistically significant at the 95% confidence level have been

03 Results

Reference context:
P=1960-1985; LT=1-5 yr; M=Jan-Dec.

For historical (left panels):

- **No significant ACC skill** although low RMSE over the Mediterranean Sector.

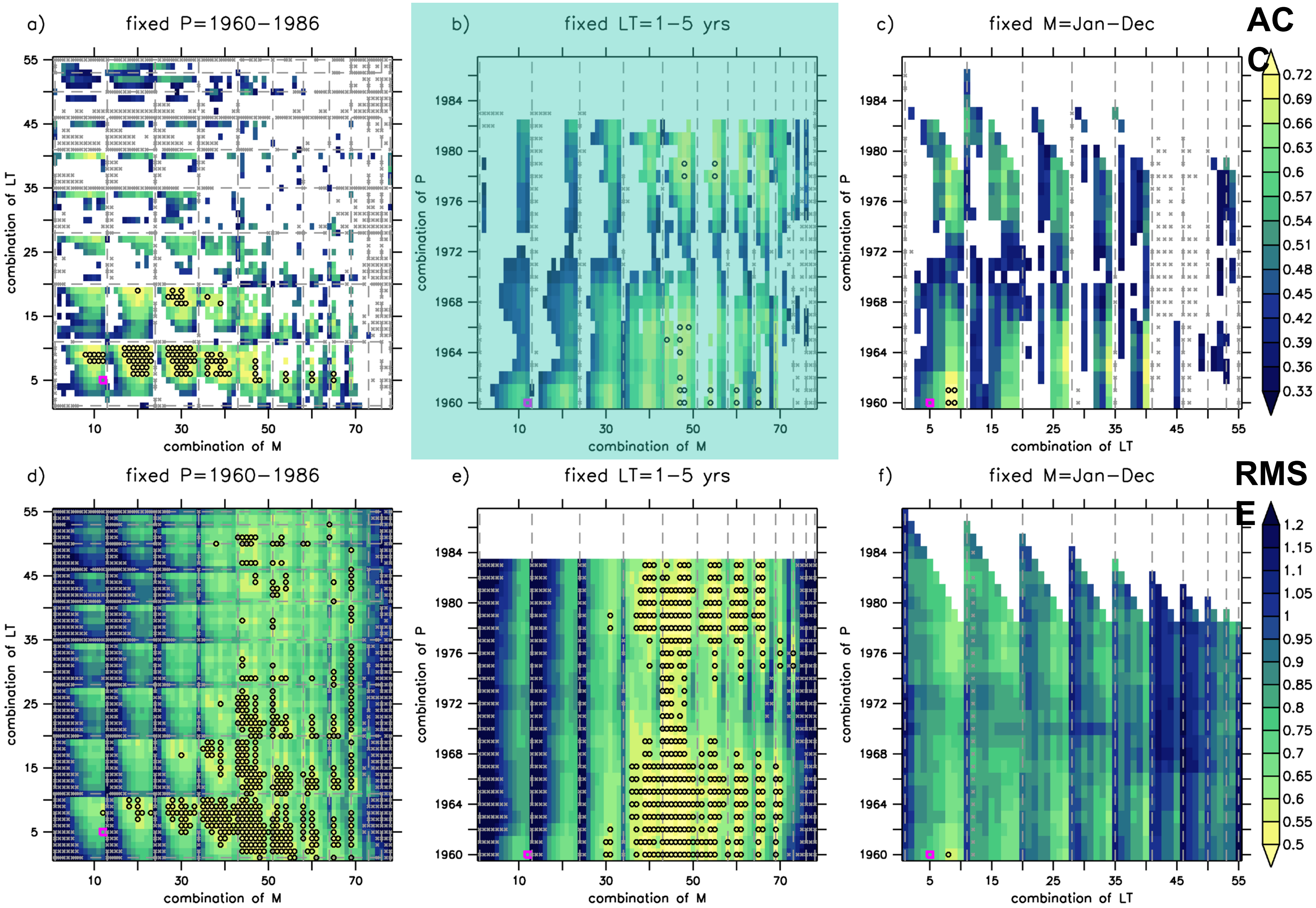
For raw hindcast (central panels):

- **General skill improvement**, notably north of 45ºN for ACC.
- Statistically **significant ACC** over the central part of Europe.

For de-biased hindcast (right panels):

- **Further skill improvement**, which are significant over

Skill at varying two independent variables



O Statistically significant skill improvement with respect to the standard context (violet square)

X Statistically significant skill decrease with respect to the standard context (violet square)

N.B. For ACC, only correlations statistically significant at the 95% confidence level have been

03 Results

We analyse: **S = f (P, LT, M)** in raw DCP for temperature averaged over Europe.

Behaviour along P:

- Two main epochs characterised by higher skills: before about 1970s and after about 1980s.

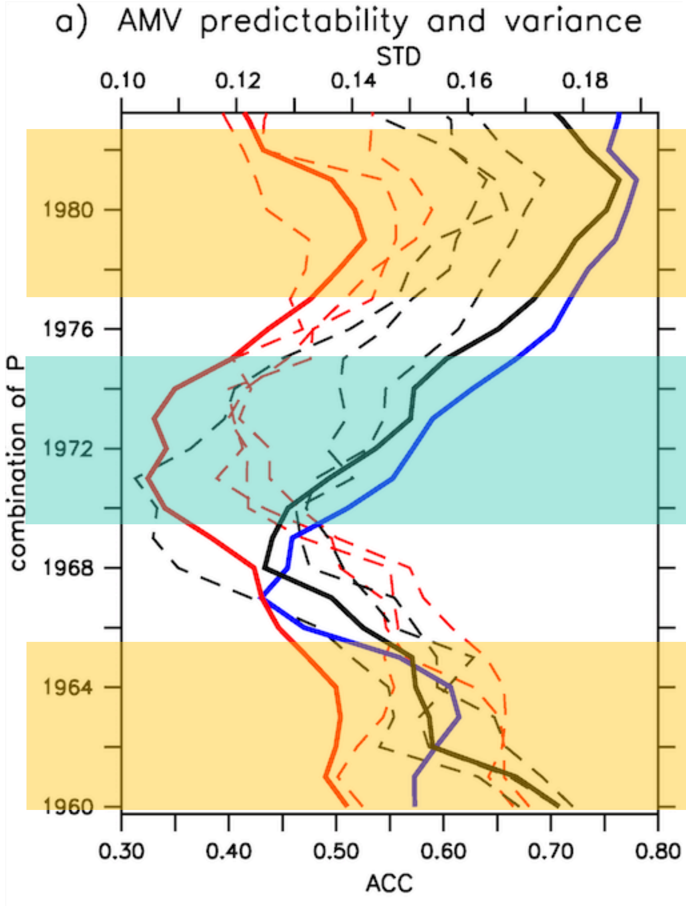
Behaviour along LT:

- Better skills for **longer forecast periods**, and/or **short lead-times**.

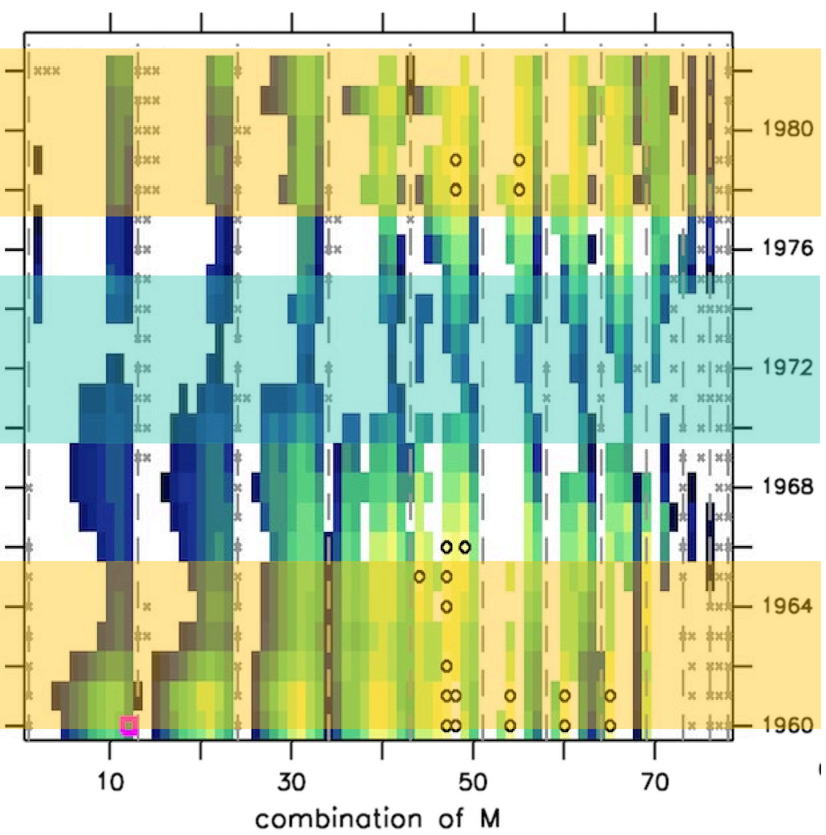
Behaviour along M:

- Higher skills for those combinations including the central months of the year, i.e. from mid—spring to early autumn (**extended summer**)

Link with the predictability of the AMV



ACC for LT=1-5 yr over Europe



— ACC skill in predicting AMV
— AMV variance in OBS
— AMV variance in DCP

N.B.: **AMV** = 5-yr low-pass filtered annual mean temperature averaged over the North Atlantic basin (80W-0W, 0N-65N)

O Statistically significant skill improvement with respect to the standard context (violet square)

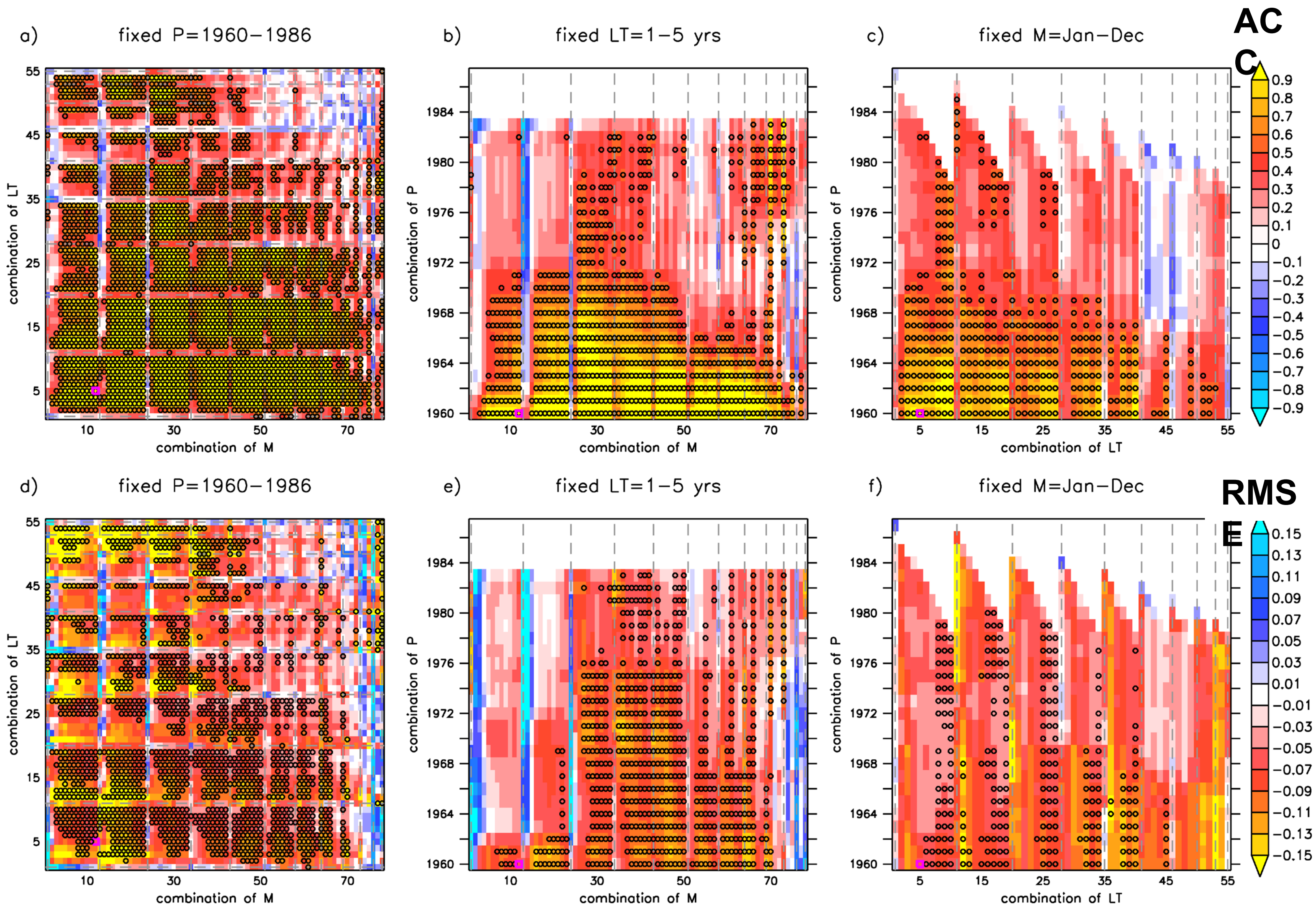
X Statistically significant skill decrease with respect to the standard context (violet square)

03 Results

We compare **AMV predictability** and **variance** with **S = f (P, M)** over Europe for LT=1-5yr.

- **AMV Predictability** is **phased** with the **observed AMV variance.**
- **AMV variance** in DCP is **underestimated** and does not exactly phase with the observed AMV variance.
- However, the **peaks of maximum AMV variance** in the model coincides with those in observations.
- The behaviour of **ACC skill** in predicting air temperature over Europe is phased with the modeled **AMV variance**

Added value due to initialisation

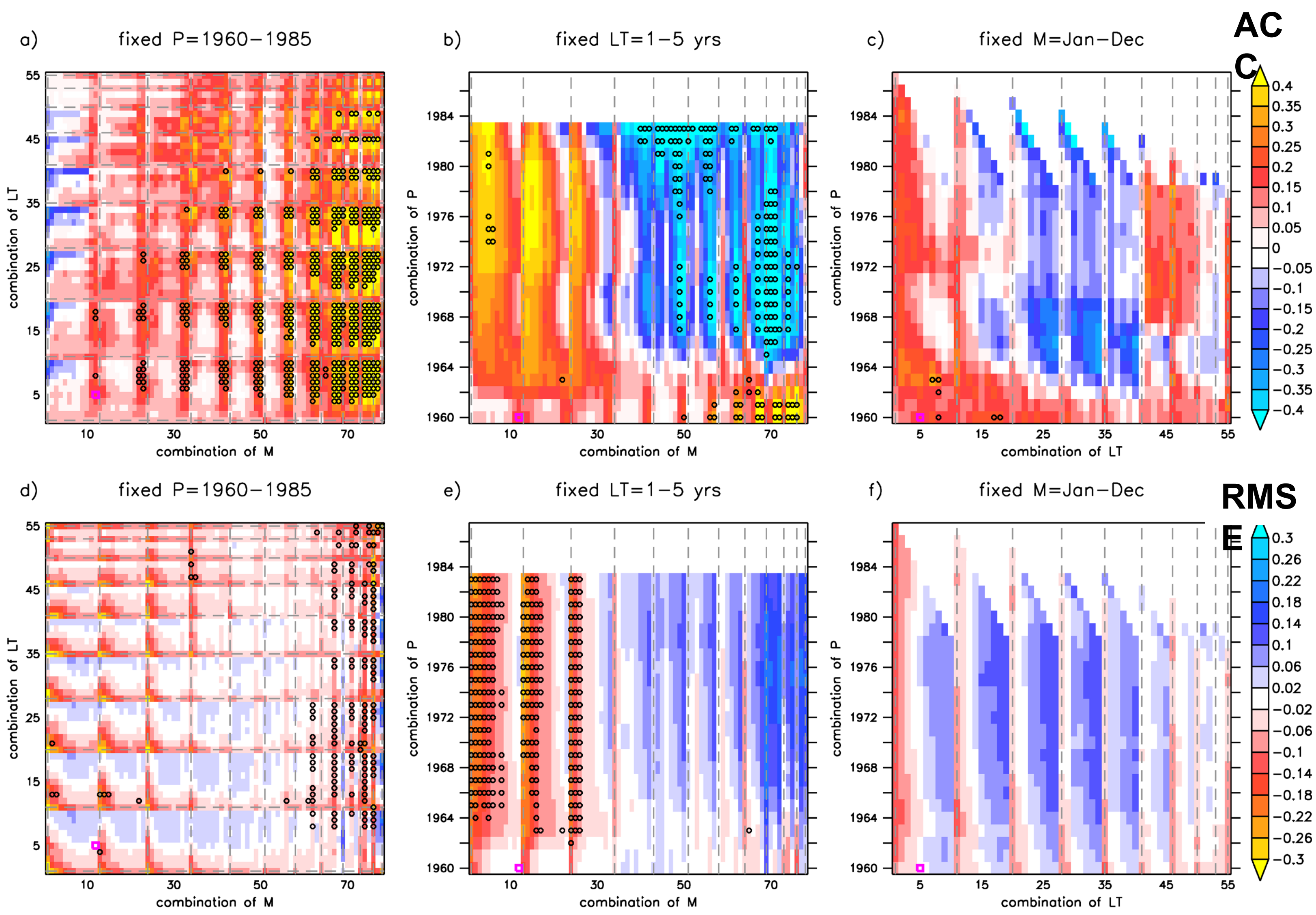


O Statistically significant skill change with respect to the HIS experiment.

We systematically analyse:
$\Delta S = S_{DCP}$ (P, LT, M) - S_{HIS} (P, LT, M) over Europe.

- Initialisation implies a general improvement of both ACC and RMSE skills.
- Skill increases more consistently for 26-yr time windows starting prior to the 1970s.
- Initialisation is beneficial notably for short lead-time
- Over M axis, uniform improvement.
- In total, improvement in about 67% of the 120,120 contexts.

Effect of de-biasing on skill score



O Statistically significant skill change with respect to the DCP experiment.

We systematically analyse:
$\Delta S = S_{deb}$ (P, LT, M) - S_{DCP} (P, LT, M) over Europe.

- De-biasing implies both improvement or degradation of skills.
- No coherent structure in the distribution of improvement.
- In total, ***for ACC skill***:
  - improvement in about 2% of the 120,120 contexts.
  - degradation in about 2% of the 120,120 contexts.
- ***For RMSE***:
  - around 2% of the contexts characterised by skill improvement
  - no significant degradation

04 Conclusions

Main outcomes

- The skill of the IPSL-CM5A DCP system in predicting air temperature over Europe appears to be dependent on **(1)** the season, **(2)** the forecast time, **(3)** the period and **(4)** the specific region considered.
- The **intermittence** in time of the performance of the prediction appears to be linked with the simulated variance of the **AMV**.
- The **de-biasing** procedure implies a **significant skill improvement** of about **2%** of the 120,120 contexts analysed.
- Overall, we evidenced the concrete **existence of skill opportunities**.

Possible implications

- Our systematic approach may be easily applied to different DCP systems and for their ensemble mean, and/or for different variables.
- It can be seen as a **prototype for preparatory analyses** for the development and optimisation of **decadal prediction services**, e.g. viticulture

Reference

Sgubin G. , Swingedouw D., Borchert L. F, Menary M. B., Noel T., Loukos H., Mignot J. (2021) Systematic investigation of skill opportunities in decadal prediction of air temperature over Europe. ***Climate Dynamics***, DOI10.1007/s00382-021-05863-0.

Thank you!

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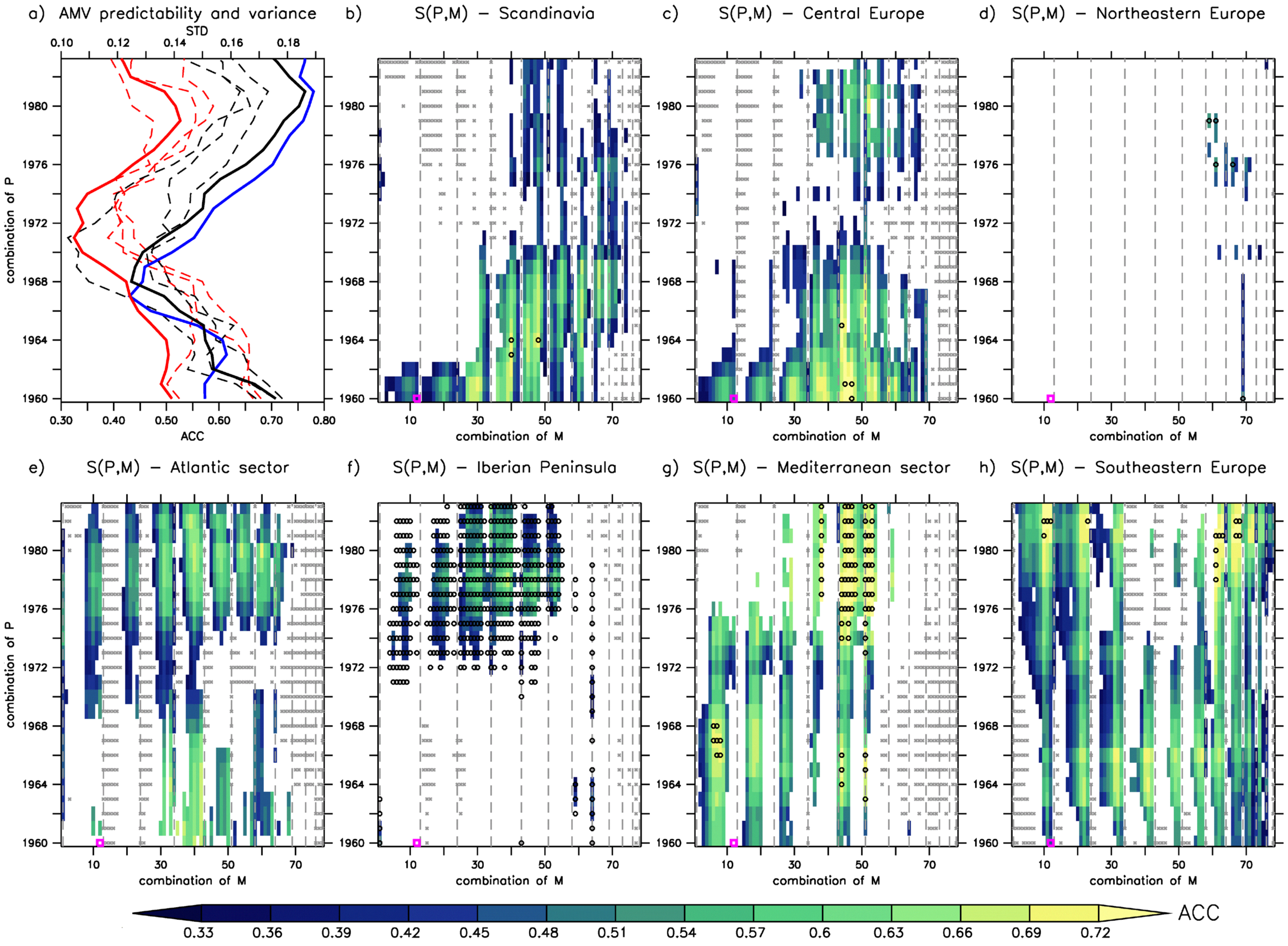
Link with the predictability of the AMV



O Statistically significant skill improvement with respect to the standard context (violet square)

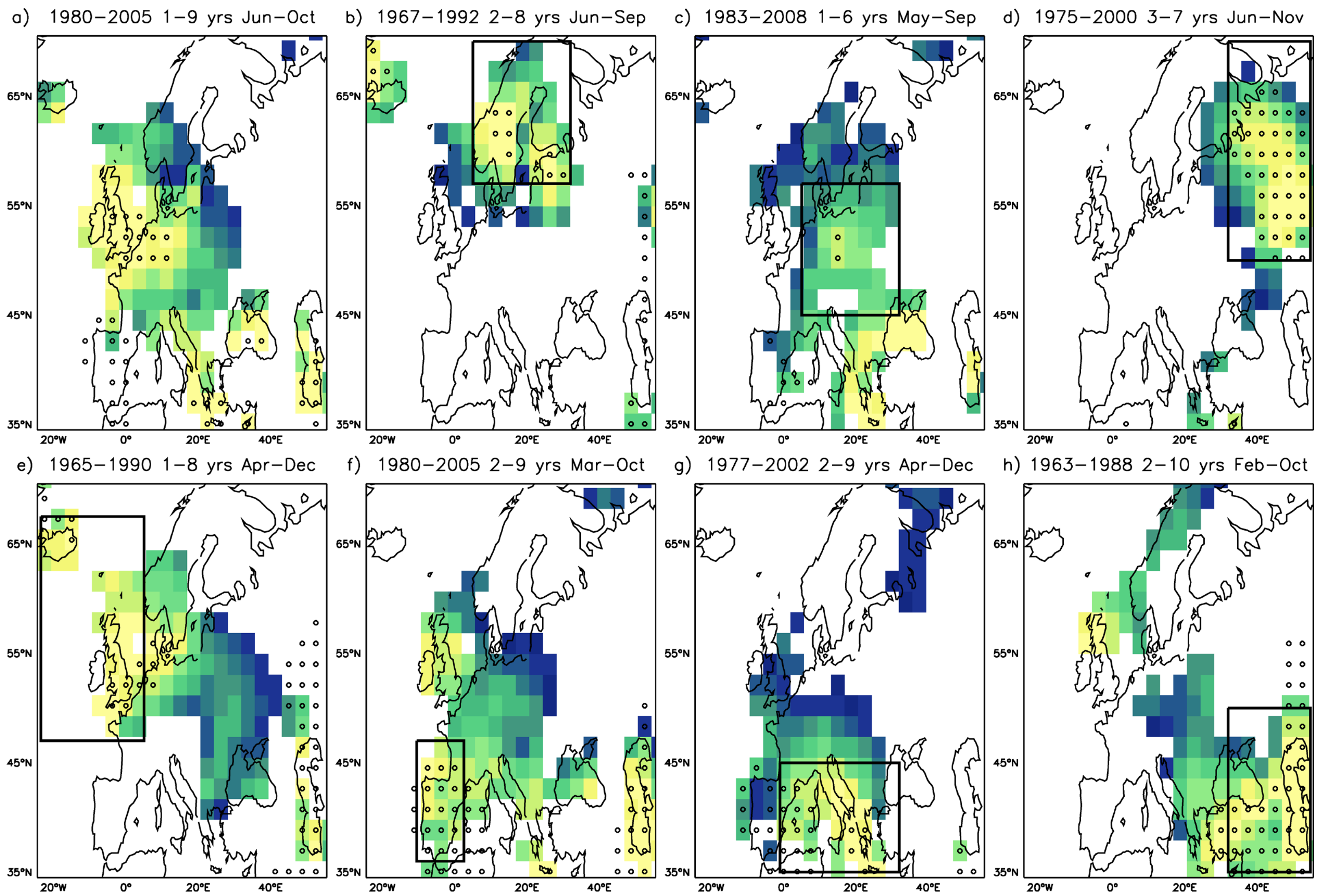
X Statistically significant skill decrease with respect to the standard context (violet square)

N.B. For ACC, only correlations statistically significant at the 95% confidence level have been

We compare **AMV predictability** and **variance** with **S = f (P, M)** over 7 European sub-regions for LT=1-5yr.

- For all the regions, lowest skills correspond to the period of lowest simulated AMV variance.
- Southernmost (Northernmost) sectors show the highest skill for predictions after (prior to) the 1970s.
- Skill variability is weaker for the Eastern regions suggesting a lower impact of AMV.
- The **variance of the predicted AMV** may be a **potential indicator of future windows of opportunity** in the decadal prediction of air temperature

Conditions for best ACC skill over Europe



O Statistically significant skill improvement the 95% confidence level have been displayed

N.B. For ACC, only correlations statistically significant at the 95% confidence level have been

We extract the **conditions of best performance** in the 3D matrix and analyse the spatial pattern.

- Some common features.
- Best performances coincide with:

1. prediction of **summer months**.
2. forecast periods averaged at least over 5 years and/or including the first lead-time years

- No common feature along P.
- There exist skill opportunities for all the sub-regions.

04 Conclusions

A concrete example

agronomy

MDPI

Article

The Impact of Possible Decadal-Scale Cold Waves on Viticulture over Europe in a Context of Global Warming

Giovanni Sgubin [1,*], Didier Swingedouw [1], Iñaki Garcia de Cortázar-Atauri [2], Nathalie Ollat [3] and Cornelis van Leeuwen [3]

Contents lists available at ScienceDirect

Agricultural and Forest Meteorology

journal homepage: www.elsevier.com/locate/agrformet

ELSEVIER

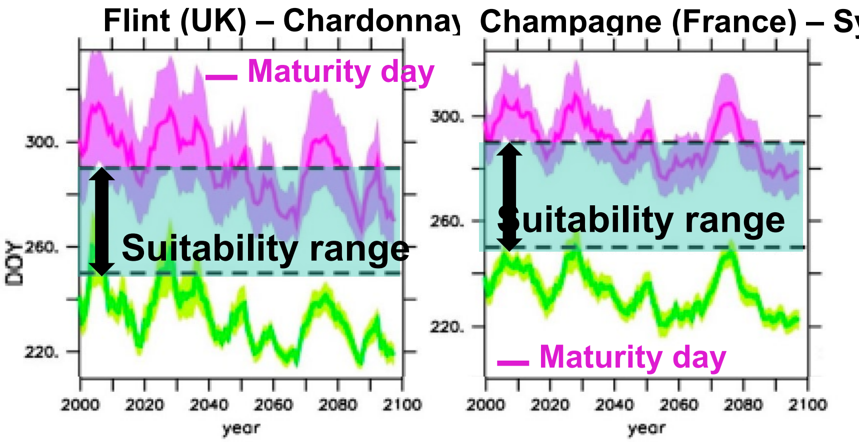
The risk of tardive frost damage in French vineyards in a changing climate

Giovanni Sgubin [a,*], Didier Swingedouw [a], Gildas Dayon [b], Iñaki García de Cortázar-Atauri [c], Nathalie Ollat [d], Christian Pagé [b], Cornelis van Leeuwen [d]

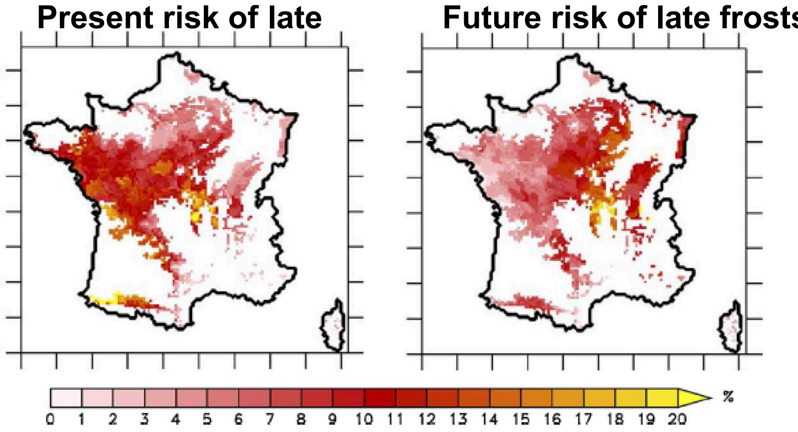
Two potential applications of DCP for **climate services for viticulture**:

1) Grapevine growing climatic suitability
2) Risk of late frost for grapevine

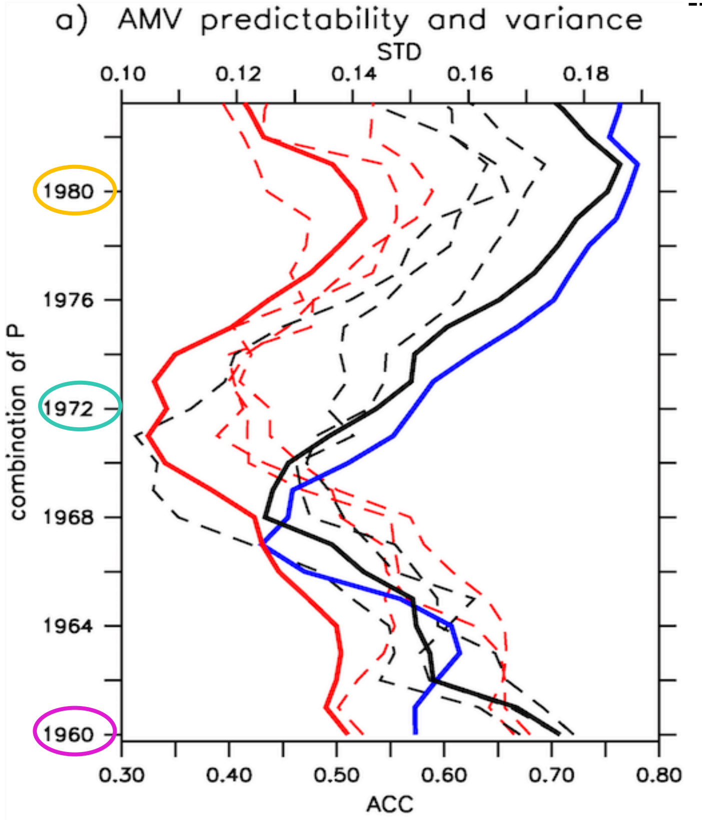
1) Assessment relying on simulated **dates of maturity,** in turn primarily relying on simulation of **late spring-to-early autumn** air temperature.

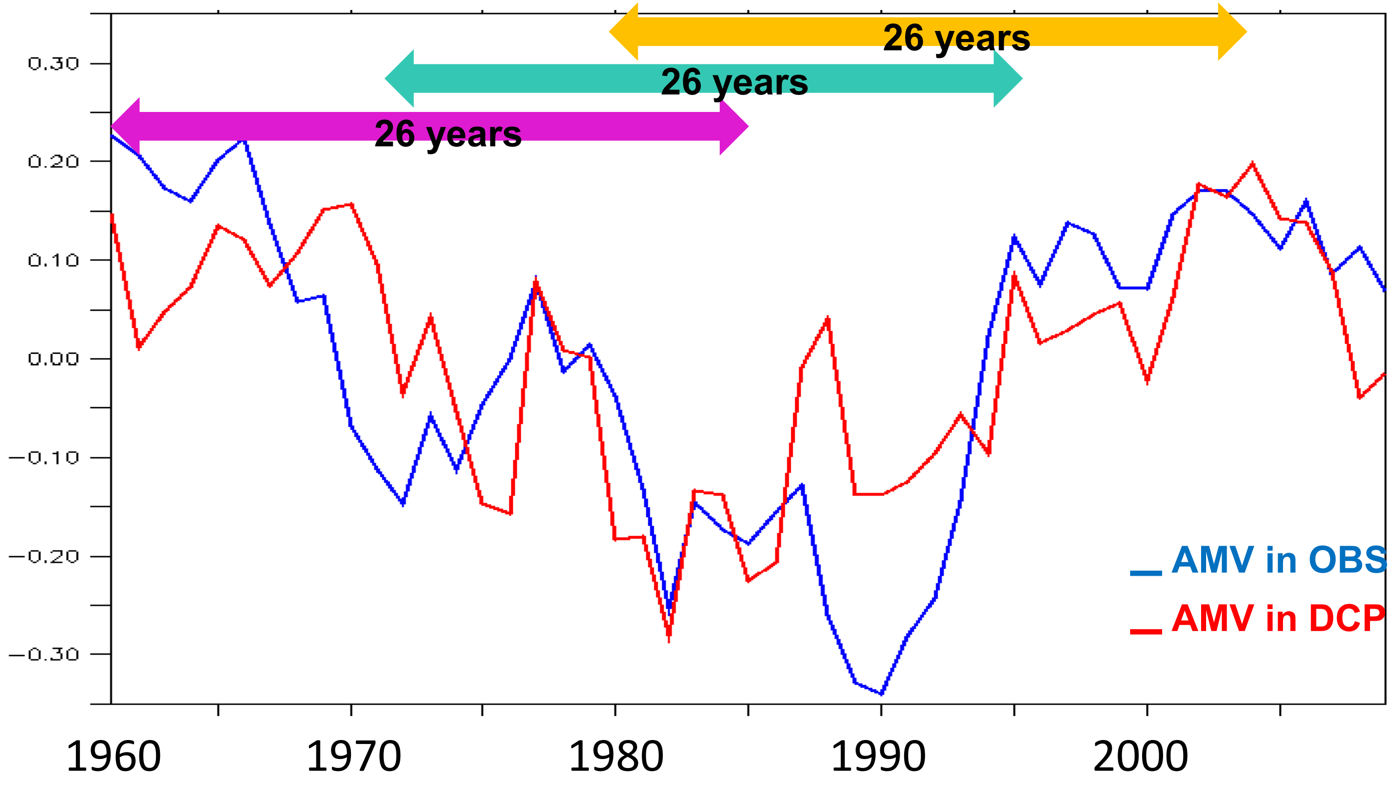


2) Assessment relying on simulated **dates of budburst,** in turn primarily relying on simulation of **winter-to-early spring** air temperature.



IPSL-CM5A-LR DCP potentially more reliable for impact studies on grapevine growing suitability


a) AMV predictability and variance
STD
0.10
0.12
0.14
0.16
0.18
1980
1976
1972
1968
1964
1960
combination of P
0.30
0.40
0.50
0.60
0.70
0.80
ACC


26 years
26 years
26 years
0.30
0.20
0.10
0.00
−0.10
−0.20
−0.30
1960
1970
1980
1990
2000
AMV in OBS
AMV in DCP

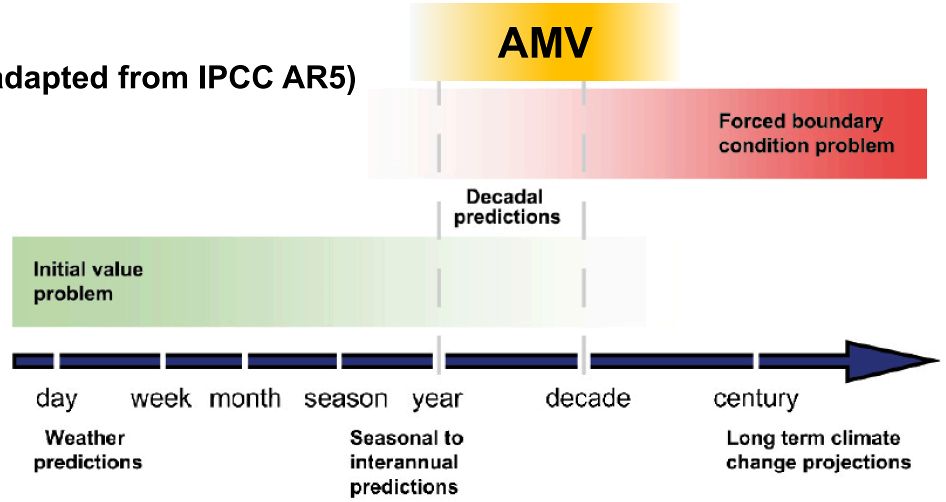
01 Rationale

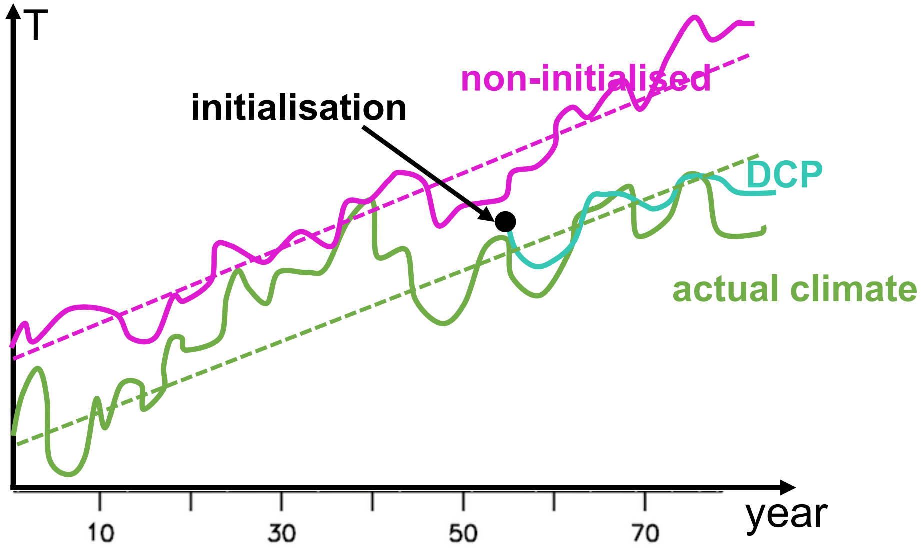
Background

- **Decadal Climate Predictions** (DCP) are simulations of the climate evolution over a time horizon of 1-10 years.

External forcing
+
Un-forced internal variability
(e.g. **AMV**[1] for temperature over Europe)

(adapted from IPCC AR5)





- DCP relies on the synchronisation between model initial conditions and the real climate (**initialisation**).
- Initial conditions are obtained by **assimilating** a set of observational data.

[1] **AMV**=Atlantic Multi-decadal Variability