LSCE
LABORATOIRE DES SCIENCES DU CLIMAT & DE L'ENVIRONNEMENT

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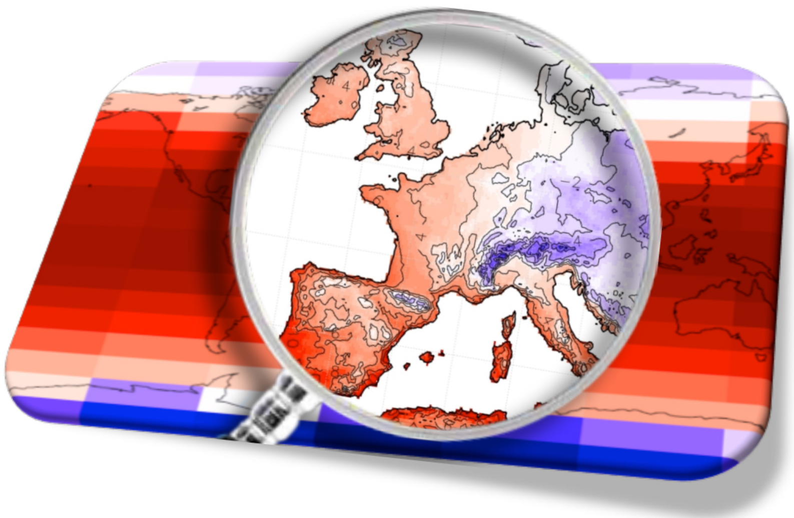
Sciences de l'environnement Institut Pierre Simon Laplace

Statistical downscaling & bias correction of climate simulations:
Main findings of the StaRMIP project



Mathieu Vrac

International MISTRALS workshop on "*Climate change impacts in the Mediterranean region*"
Montpellier, France, October, 16-18, 2017

Motivations

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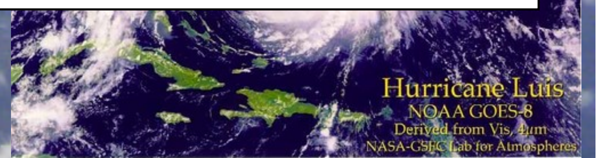
- **Downscaling**: To derive sub-grid scale (regional or local) weather or climate using General Circulation Models (GCMs) outputs or reanalysis data (e.g. NCEP)

- **Statistical Bias Correction** also often needed !!



How to downscale?: The basics

Coarse atmospheric data
Precipitation, temperature, humidity, geopotential, wind, etc.

≈ 250 km

How to use the **coarse simulations** to produce **regional/local** climate features?

?

Region, city, fields, station

Local variables (e.g., precip., temp.)
(small scale water cycle, impacts – crops, resources – etc.)

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- GCMs to drive regional models (5-50km) determining atmosphere dynamics
- Requires a lot of computer time and resources => Limited applications

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Statistical downscaling:

- Based on statistical relationships between large- and local-scale variables
- Low costs and rapid simulations applicable to any spatial resolution
- Uncertainties (results, propagation, etc)

Region, city, fields, station

Local variables (e.g., precip., temp.)
(small scale water cycle, impacts – crops, resources – etc.)

StaRMIP:

Statistical **R**egionalization (downscaling) **M**odels **I**ntercomparison and Hydrological Impacts **P**roject

Funded by ANR (French National Research Agency), 2013-2017

Goals (in a nutshell):

- Evaluation & intercomparisons of SDMs
- Developments of BC & SDMs

StaRMIP: Main goals & outline

Various evaluations

- **Intercomparisons** / Evaluations of SDMs
  - The **climate** point-of-view (Vaittinada Ayar et al., 2016)
  - The **hydrological** point-of-view (Grouillet et al., 2016)

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Developments

- "Spatial" (i.e. *field*) downscaling
  - Extreme fields of precipitation (SHD, Bechler et al., 2015)
  - Non-stationary spatial SWG for precipitation (See Pradeebane's prez)

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- Multivariate (multi-sites/variables) BC & SDMs
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Part 1

StaRMIP goal 1: Intercomparisons & guidelines

The climate point-of-view

Intercomparison of SDMs and RCMs in CORDEX

From

Vaittinada Ayar, P., Vrac, M., Bastin, S., Carreau, J., Déqué, M., Gallardo, C. (2016) *Intercomparison of statistical and dynamical downscaling models under the EURO- and MED-CORDEX initiative framework: Present climate evaluations*. Climate Dynamics, 46: 1301. https://doi.org/10.1007/s00382-015-2647-5

StaRMIP goal 1: Intercomparisons & guidelines

The climate point-of-view

- Main statistical approaches for downscaling

Coarse atmospheric predictors
Precip., temp., humidity, geopot., wind, etc.

Local variables (e.g., precip., temp.)
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StaRMIP goal 1: Intercomparisons & guidelines

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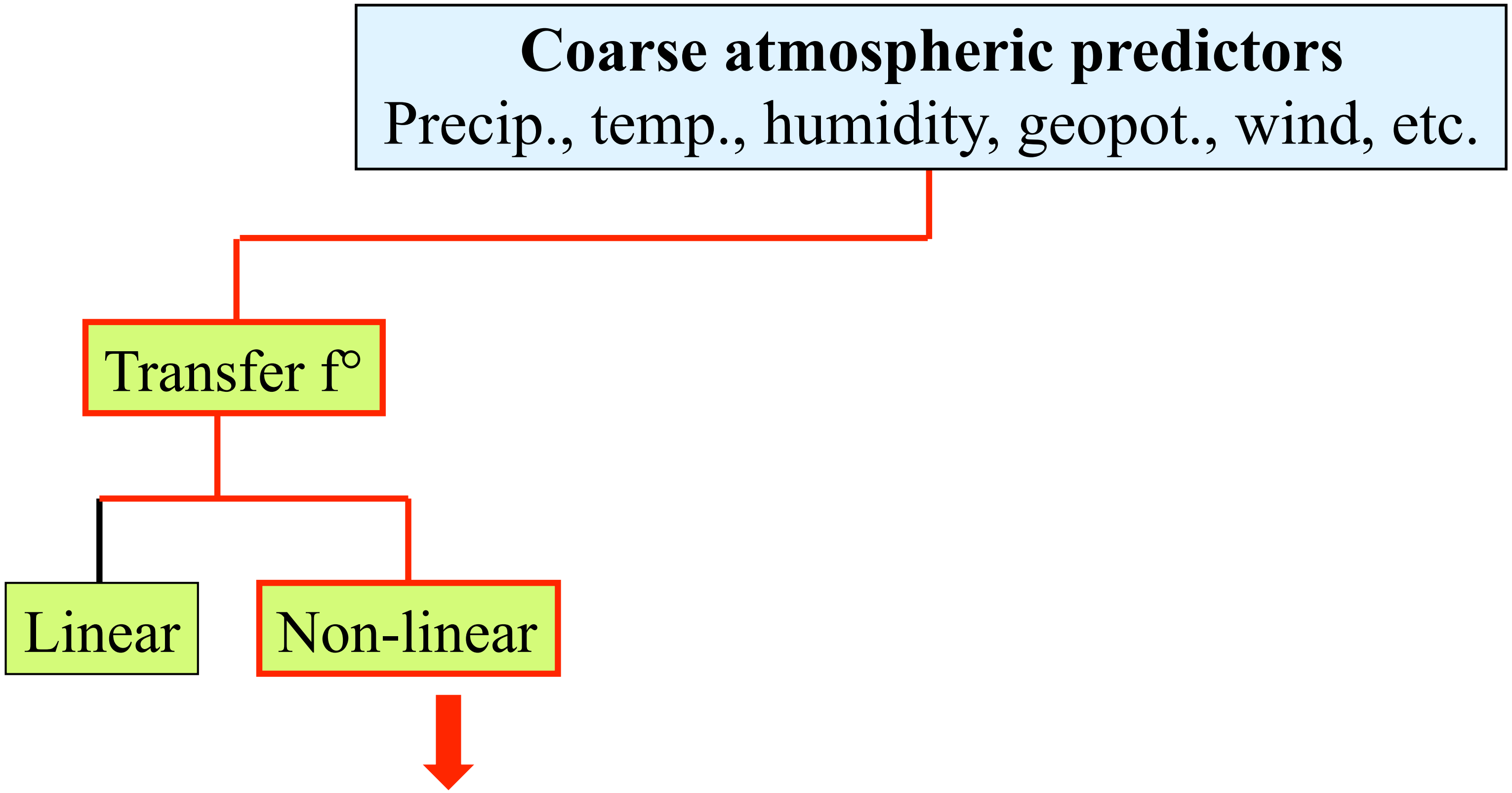

TF : Generalized Additive Models (GAM) [*Hastie and Tibshirani, 1990*]

$E(Y|X_1 \cdots X_p) = \sum_{j=1}^{p} f_j(X_j)$ with f_j **spline functions**

GAM (thresholded occurrence) / GAM-so (LR Eq. 1)

StaRMIP goal 1: Intercomparisons & guidelines

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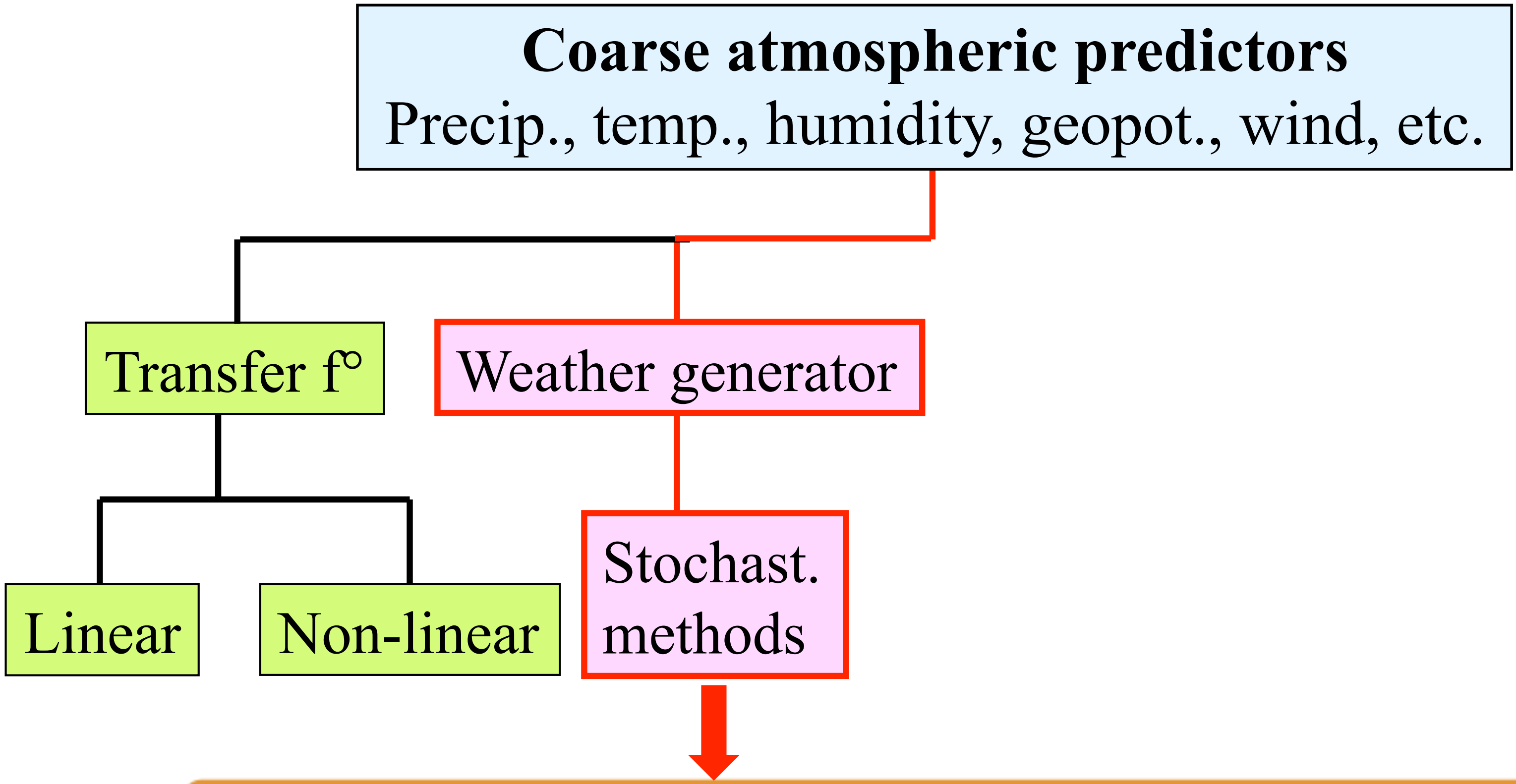

WG : VGLM [*Chandler and Wheater, 2002*]

- Rain occurrence : LR Eq. 1
- Rain intensity : **Gamma** $\Gamma_{\alpha,\beta}(\cdot)$: $\left[\ \alpha_i; \quad \beta_i\ \right] = \left[\ f_\alpha(X_{i,j}); \quad f_\beta(X_{i,j})\ \right]$

SWG (non-stationnary) / SWG-s (stationnary), constant occurrence probability (COP)

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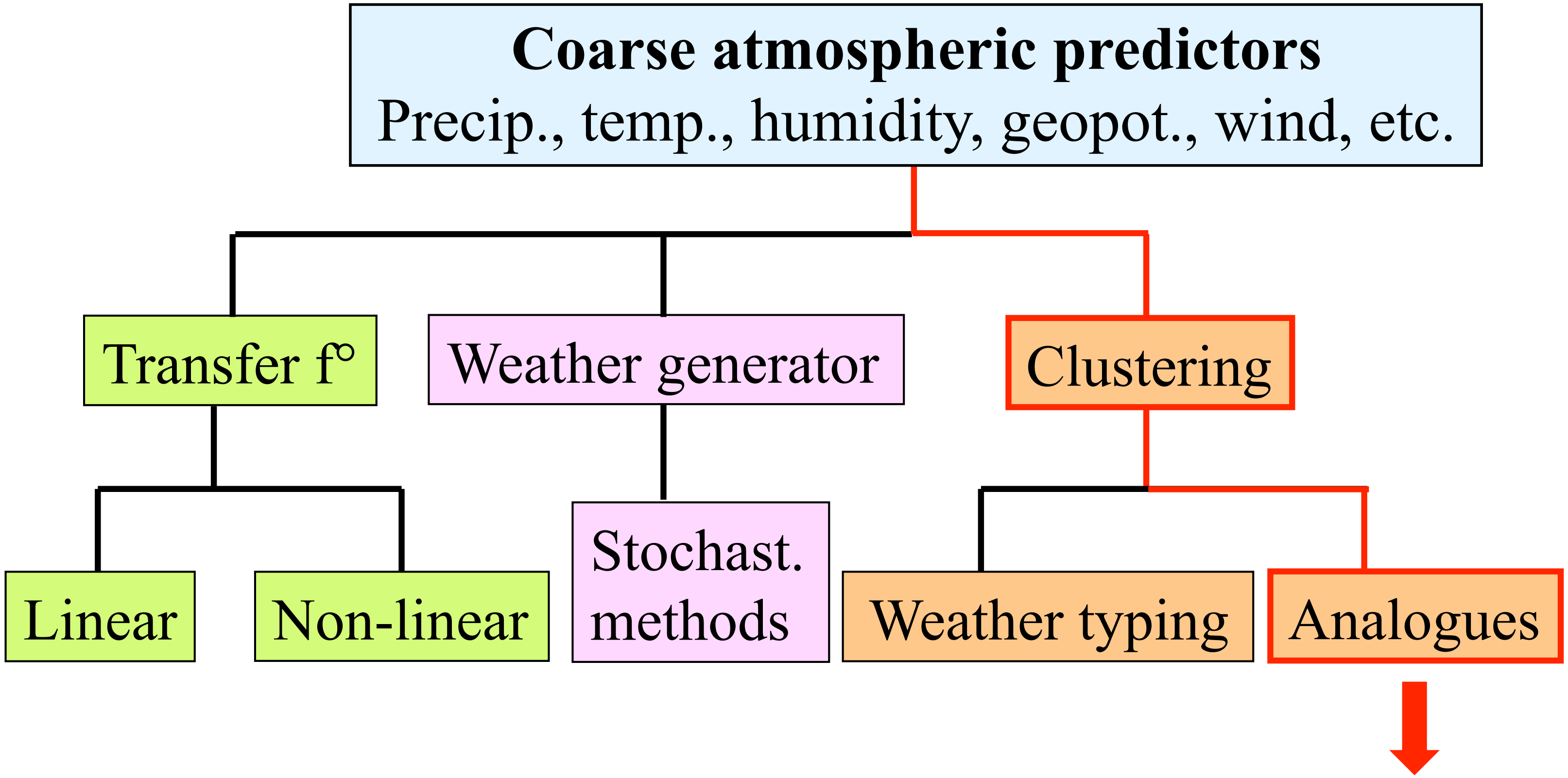

WT : Analogs of predictors anomalies [*Yiou et al., 2013*]

Resampled local-scale data : day minimizing **Euclidian distance** for large-scale data

ANALOG (thresholded)

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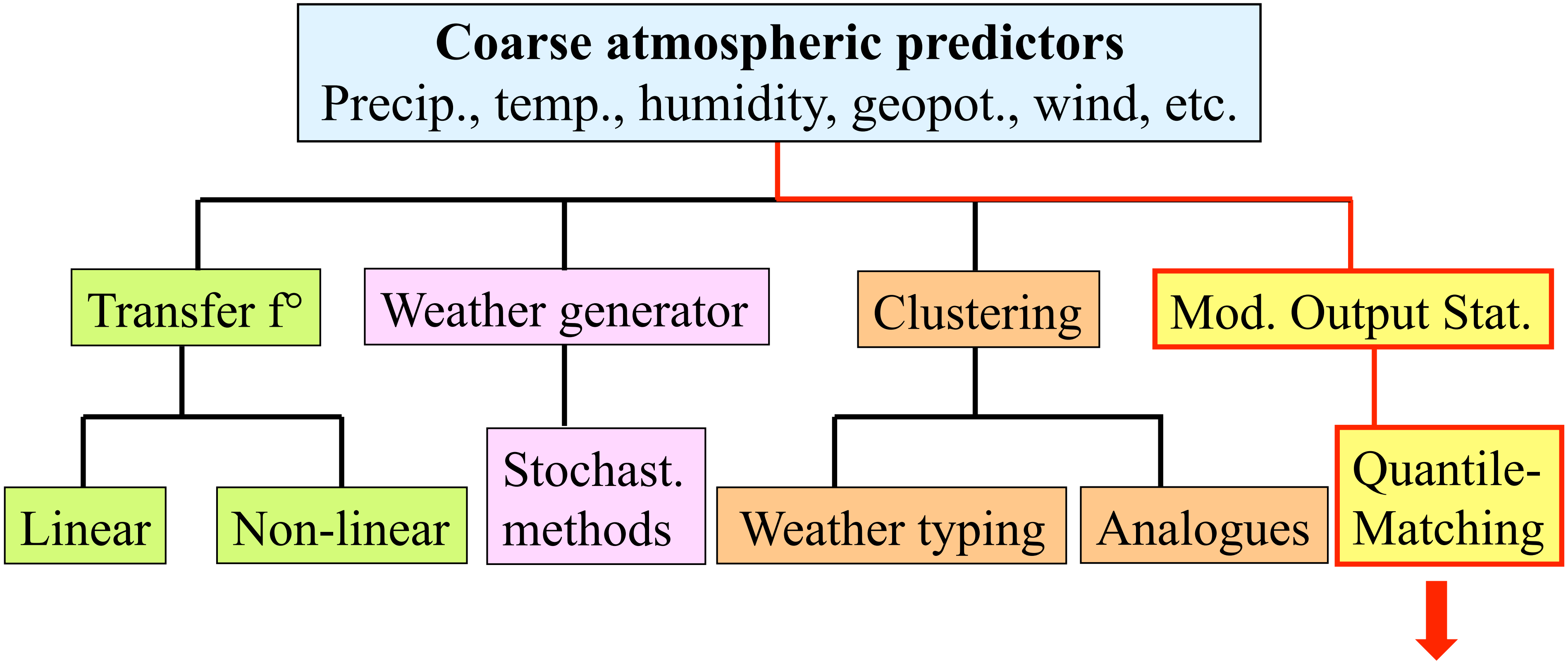


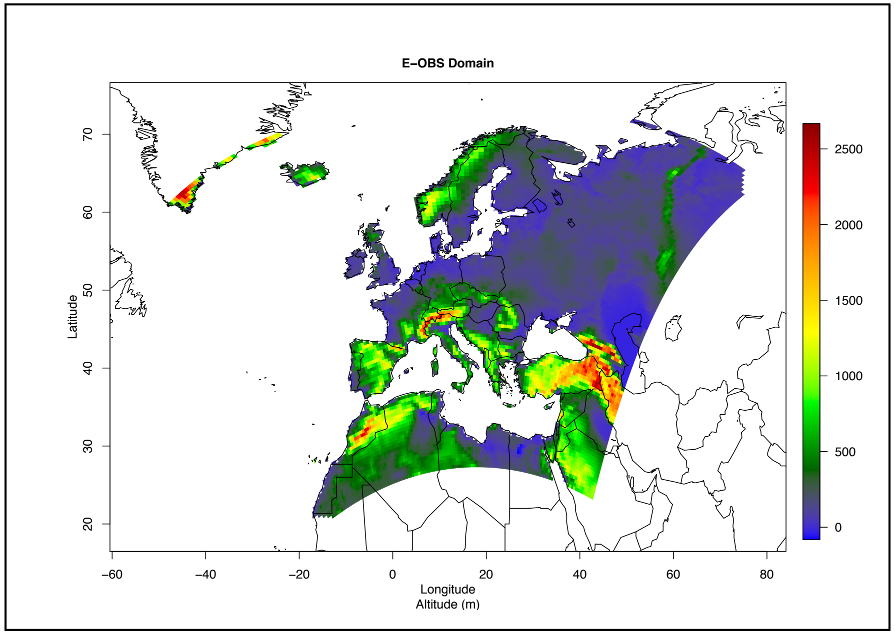
Bias Correction / MOS : CDFt [*Vrac et al., 2012*]

Quantile Mapping taking into account the Climate Change signal

CDFt-so (LR Eq. 1)

Cross-validation set-up

- Reference & predictand E-OBS (Haylock et al., 2008) precipitation at 0.44° resolution



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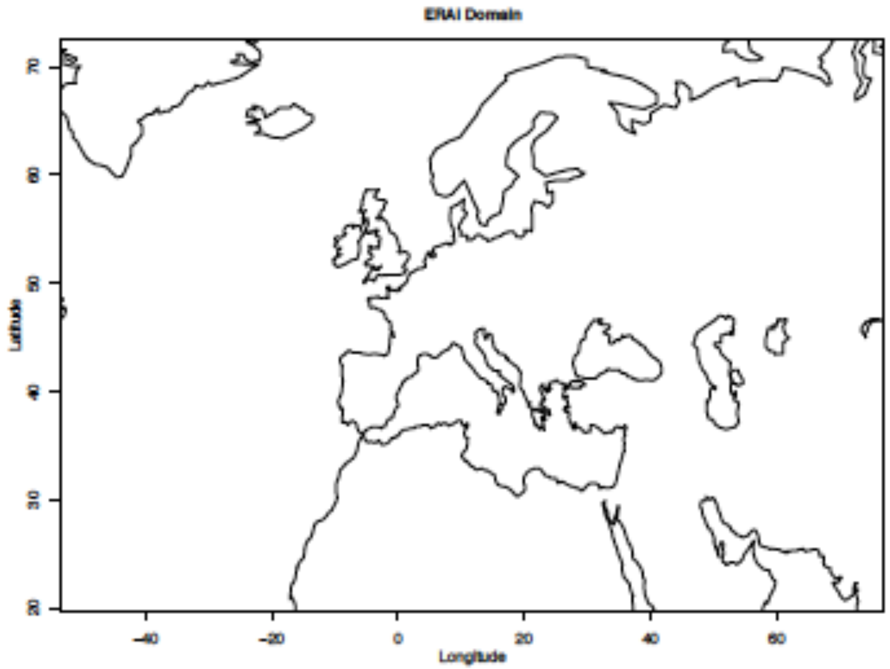

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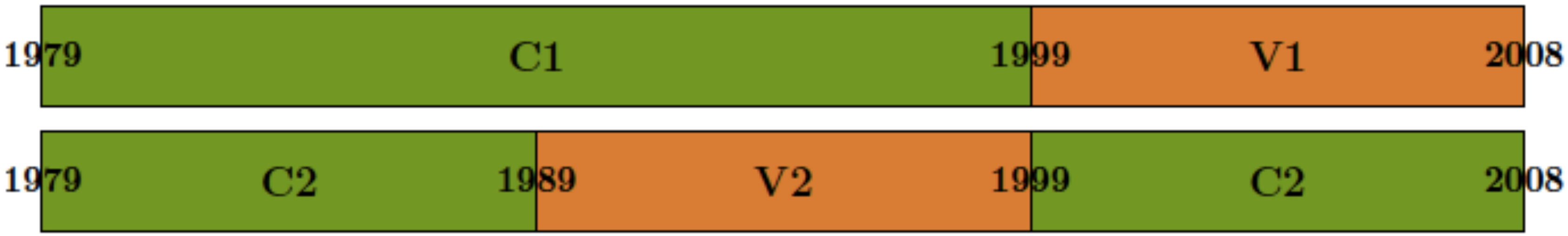

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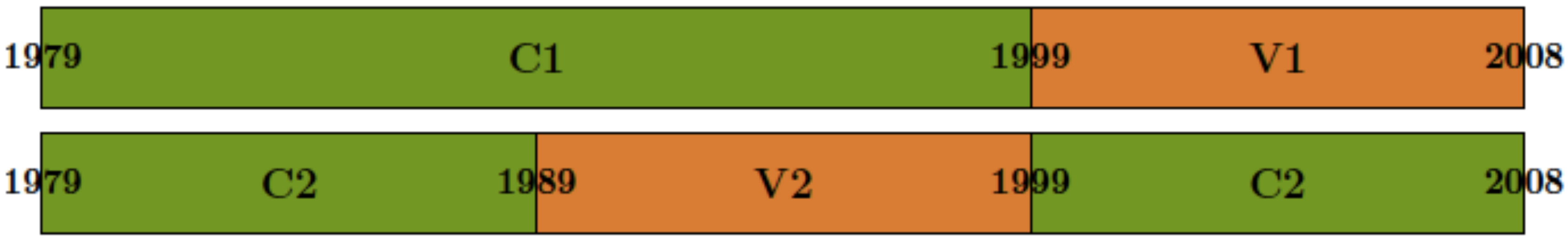


- 6-month "summer" (15 Apr.-14 Oct.)
- 6-month "winter" (15 Oct.-14 Apr.)
- Occurrence threshold = 1mm/day

StaRMIP goal 1: Intercomparisons & guidelines

The climate point-of-view

Six SDMs at 0.44° resolution

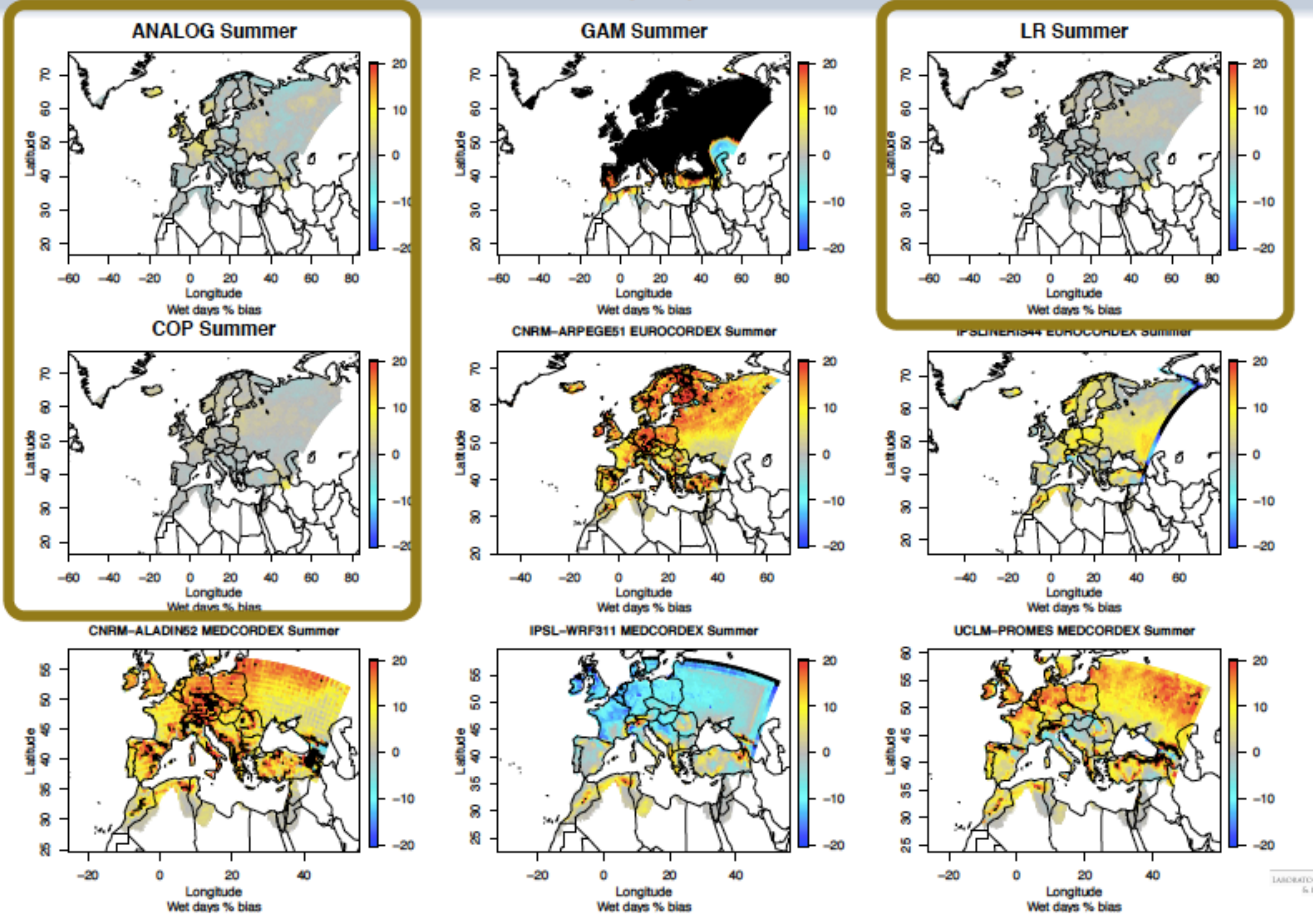
- Transfer Functions : GAM, GAM-so,
- Weather pattern-based : ANALOG,
- Stochastic Weather Generators : SWG, SWG-s,
- Bias Correction/Model Output Statictics (MOS) : CDFt-so.

Five RCMs at 0.44° resolution

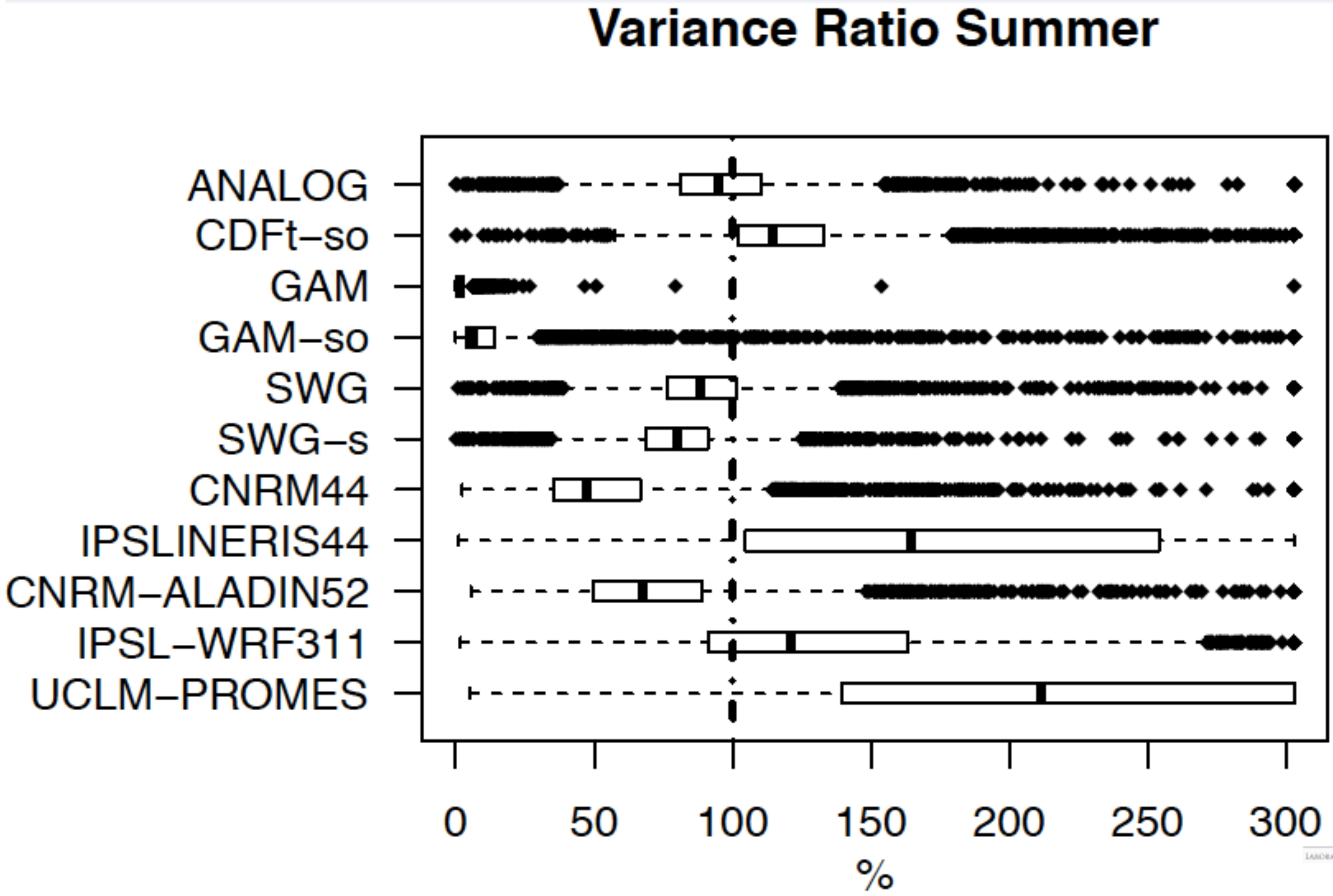
1. MED-CORDEX [*Drobinski et al., 2014*] :
   - IPSL-WRF311,
   - CNRM-ALADIN52,
   - UCLM-PROMES
2. EURO-CORDEX [*Vautard et al., 2013*] :
   - WRF-IPSL-INERIS44,
   - ARPEGE-CNRM44

=> 11 models

Wet Days Frequency Bias (%)



Variance Ratio (%)



Summary

Model	ANALOG	CDFt-so	GAM	GAM-so	SWG	SWG-s	EURO-CNRM	EURO-IPSL	MED-CNRM	MED-IPSL	MED-UCLM	ERA-I
Wet days % bias	-1.04(3)	-0.29(2)	32.87(9)	-0.29(2)	-0.29(2)	0.02(1)	10.75(7)	4.10(5)	11.19(8)	-2.80(4)	8.33(6)	3.66
Wet mean persistence	-0.09(2)	-0.50(5)	9.01(9)	-0.50(5)	-0.50(5)	-0.66(6)	0.72(8)	-0.02(1)	0.66(6)	-0.17(3)	0.34(4)	0.24
Dry mean persistence	-28.13(8)	-14.97(2)	286.75(9)	-14.97(2)	-14.97(2)	6.28(1)	-25.98(5)	-26.38(6)	-27.37(7)	-21.57(4)	-16.70(3)	-16.17
Brier Score	0.26(6)	0.14(1)	0.37(9)	0.14(1)	0.14(1)	0.16(3)	0.28(8)	0.26(6)	0.23(4)	0.15(2)	0.24(5)	0.14
Total Rank Occurrence	19	**10**	36	**10**	**10**	11	28	18	25	13	18	-
Mean bias mm	-0.26(6)	1.18(9)	-3.74(11)	-0.15(3)	0.16(4)	-0.01(1)	-1.08(8)	0.33(7)	-1.26(10)	-0.06(2)	0.19(5)	-1.47
Variance Ratio%	88.45(2)	146.71(7)	2.65(11)	42.09(10)	98.93(1)	82.79(3)	80.56(4)	166.53(8)	75.52(5)	140.27(6)	224.06(9)	76.97
Q99 bias mm	-2.57(2)	4.00(7)	-21.90(11)	8.45(9)	0.17(1)	-3.01(5)	-2.85(3)	5.23(8)	-3.18(6)	2.85(3)	10.99(10)	-4.04
Total Rank Intensity	10	23	33	22	**6**	9	15	23	22	11	24	-
EOF1	1	2	4	11	2	11	6	6	6	5	10	-
Spatial pattern correlation	0.23(8)	0.27(8)	0.32(6)	0.28(7)	0.19(10)	0.11(11)	0.36(4)	0.36(4)	0.49(2)	0.62(1)	0.41(3)	0.53
Total Rank Spatial	9	10	10	18	12	22	10	10	8	**6**	13	-
Cor. Annual Amount	0.26(9)	0.46(4)	0.34(7)	0.27(8)	0.20(10)	-0.10(11)	0.43(5)	0.37(6)	0.58(2)	0.63(1)	0.50(3)	0.69
Cor. Seas. Cycle	0.80(3)	0.81(2)	0.87(1)	0.75(5)	0.80(3)	0.58(9)	0.58(9)	0.61(7)	0.61(7)	0.49(11)	0.68(6)	0.85
AR1 (E-OBS :0.38)	0.31(6)	0.12(7)	0.68(10)	0.11(8)	0.10(9)	0.00(11)	0.46(5)	0.41(4)	0.37(2)	0.39(2)	0.38(1)	0.52
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Wet mean persistence	-0.09(2)	-0.50(5)	9.01(9)	-0.50(5)	-0.50(5)	-0.66(6)	0.72(8)	-0.02(1)	0.66(6)	-0.17(3)	0.34(4)	0.24
Dry mean persistence	-28.13(8)	-14.97(2)	286.75(9)	-14.97(2)	-14.97(2)	6.28(1)	-25.98(5)	-26.38(6)	-27.37(7)	-21.57(4)	-16.70(3)	-16.17
Brier Score	0.26(6)	0.14(1)	0.37(9)	0.14(1)	0.14(1)	0.16(3)	0.28(8)	0.26(6)	0.23(4)	0.15(2)	0.24(5)	0.14
Total Rank Occurrence	19	**10**	36	**10**	**10**	11	28	18	25	13	18	-
Mean bias mm	-0.26(6)	1.18(9)	-3.74(11)	-0.15(3)	0.16(4)	-0.01(1)	-1.08(8)	0.33(7)	-1.26(10)	-0.06(2)	0.19(5)	-1.47
Variance Ratio%	88.45(2)	146.71(7)	2.65(11)	42.09(10)	98.93(1)	82.79(3)	80.56(4)	166.53(8)	75.52(5)	140.27(6)	224.06(9)	76.97
Q99 bias mm	-2.57(2)	4.00(7)	-21.90(11)	8.45(9)	0.17(1)	-3.01(5)	-2.85(3)	5.23(8)	-3.18(6)	2.85(3)	10.99(10)	-4.04
Total Rank Intensity	10	23	33	22	**6**	9	15	23	22	11	24	-
EOF1	1	2	4	11	2	11	6	6	6	5	10	-
Spatial pattern correlation	0.23(8)	0.27(8)	0.32(6)	0.28(7)	0.19(10)	0.11(11)	0.36(4)	0.36(4)	0.49(2)	0.62(1)	0.41(3)	0.53
Total Rank Spatial	9	10	10	18	12	22	10	10	8	**6**	13	-
Cor. Annual Amount	0.26(9)	0.46(4)	0.34(7)	0.27(8)	0.20(10)	-0.10(11)	0.43(5)	0.37(6)	0.58(2)	0.63(1)	0.50(3)	0.69
Cor. Seas. Cycle	0.80(3)	0.81(2)	0.87(1)	0.75(5)	0.80(3)	0.58(9)	0.58(9)	0.61(7)	0.61(7)	0.49(11)	0.68(6)	0.85
AR1 (E-OBS :0.38)	0.31(6)	0.12(7)	0.68(10)	0.11(8)	0.10(9)	0.00(11)	0.46(5)	0.41(4)	0.37(2)	0.39(2)	0.38(1)	0.52
Total Rank Temporal	18	13	18	21	22	31	19	17	11	14	**10**	-

Summary

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- No model really takes the advantage on the others
- Ranking is indicator-dependent and therefore depends on end-users needs !
- This work provides
  - ⇒ SDMs simulations within the EURO- & MED-CORDEX initiative
  - ⇒ a methodology to select the most suited simulations/models for end-users needs.

  (Philosophy similar to the COST Action VALUE)

Part 2

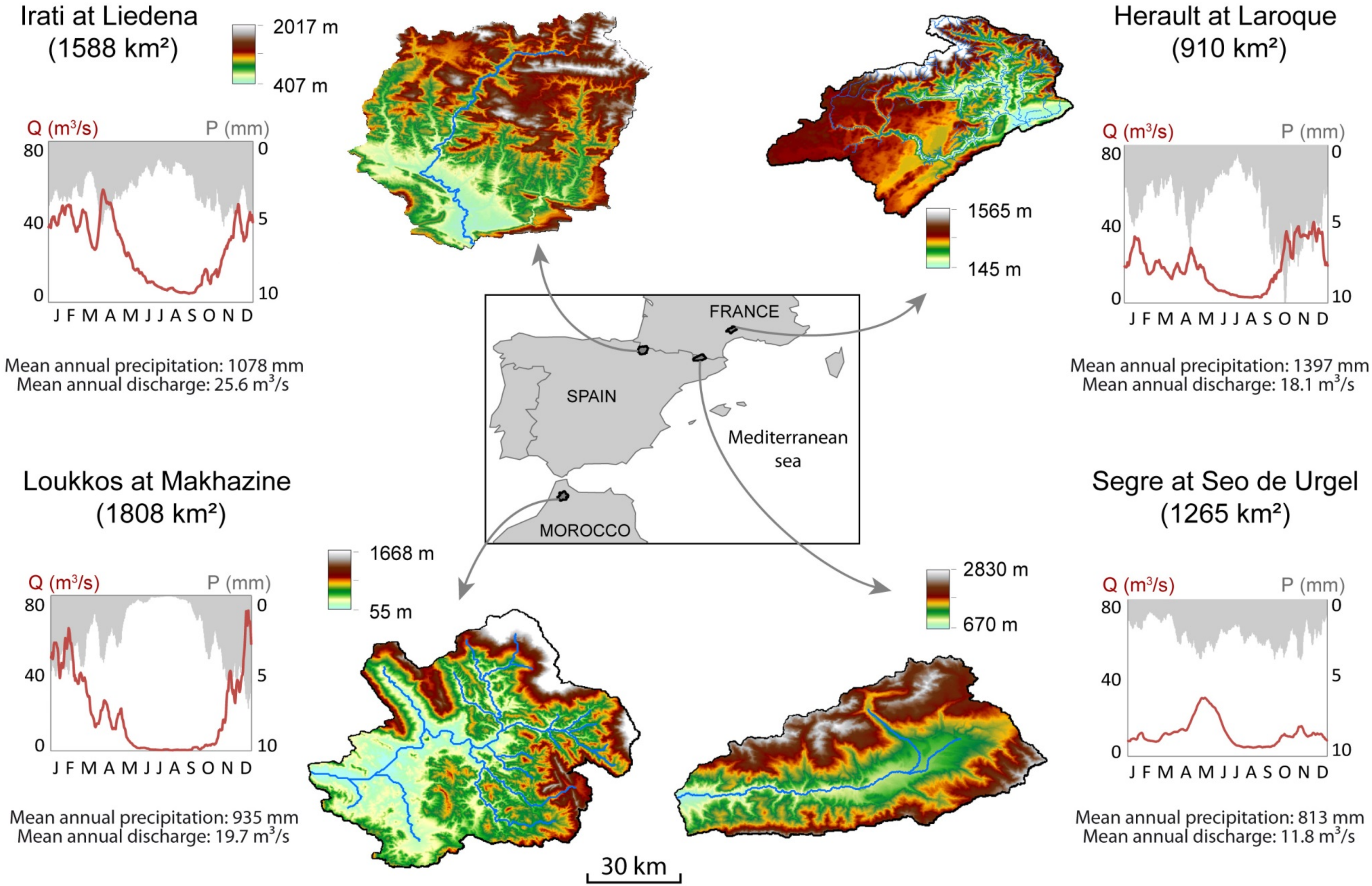
StaRMIP goal 2: Intercomparisons & guidelines

The hydrological point-of-view

From

Grouillet, B., Ruelland, D., Vaittinada Ayar, P. & Vrac, M. (2016).
Sensitivity analysis of runoff modelling to statistical downscaling methods in the western Mediterranean.
Hydrol. & Earth Syst. Sci., 20, 1031–1047.

Evaluation on 4 Mediterranean non-influenced basins



Low resolution climate data

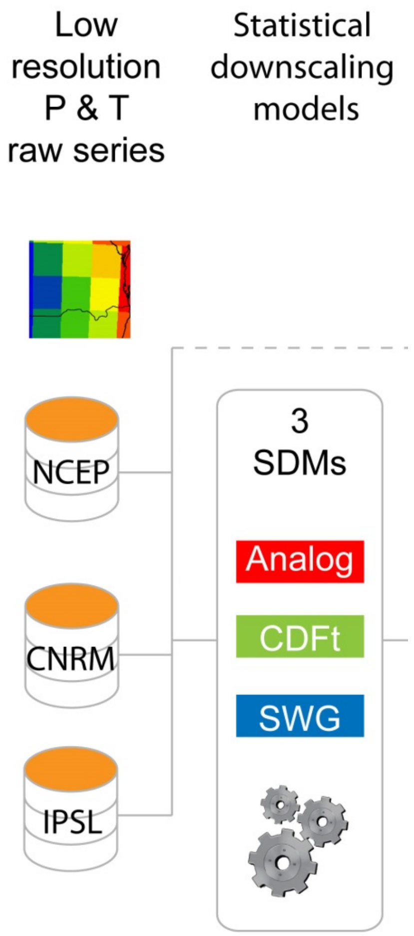
Low
resolution
P & T
raw series

- NCEP/NCAR daily reanalysis data with a 2.5° spatial resolution
  (Kalnay *et al.*, 1996)

- CNRM-CM5 GCM, regridded at a 2.5° spatial resolution
  (Voldoire *et al.*, 2013)

- IPSL-CM5A-MR GCM, regridded at a 2.5° spatial resolution
  (Dufresne *et al.*, 2013)

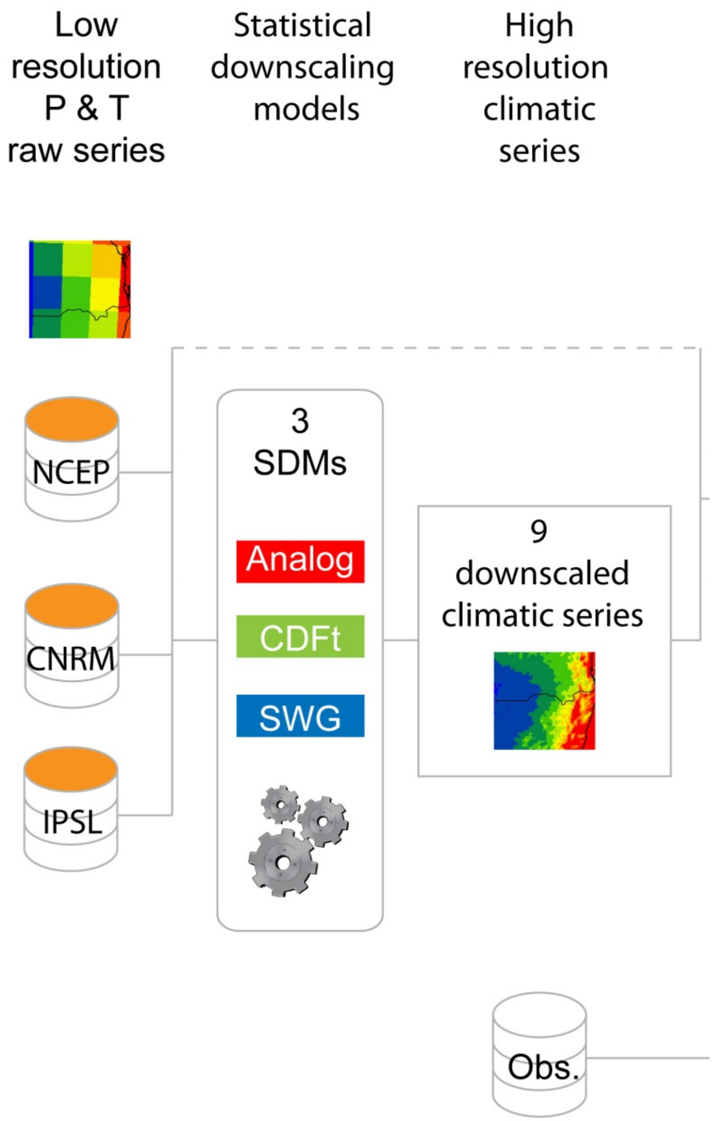
Statistical downscaling models (SDMs)



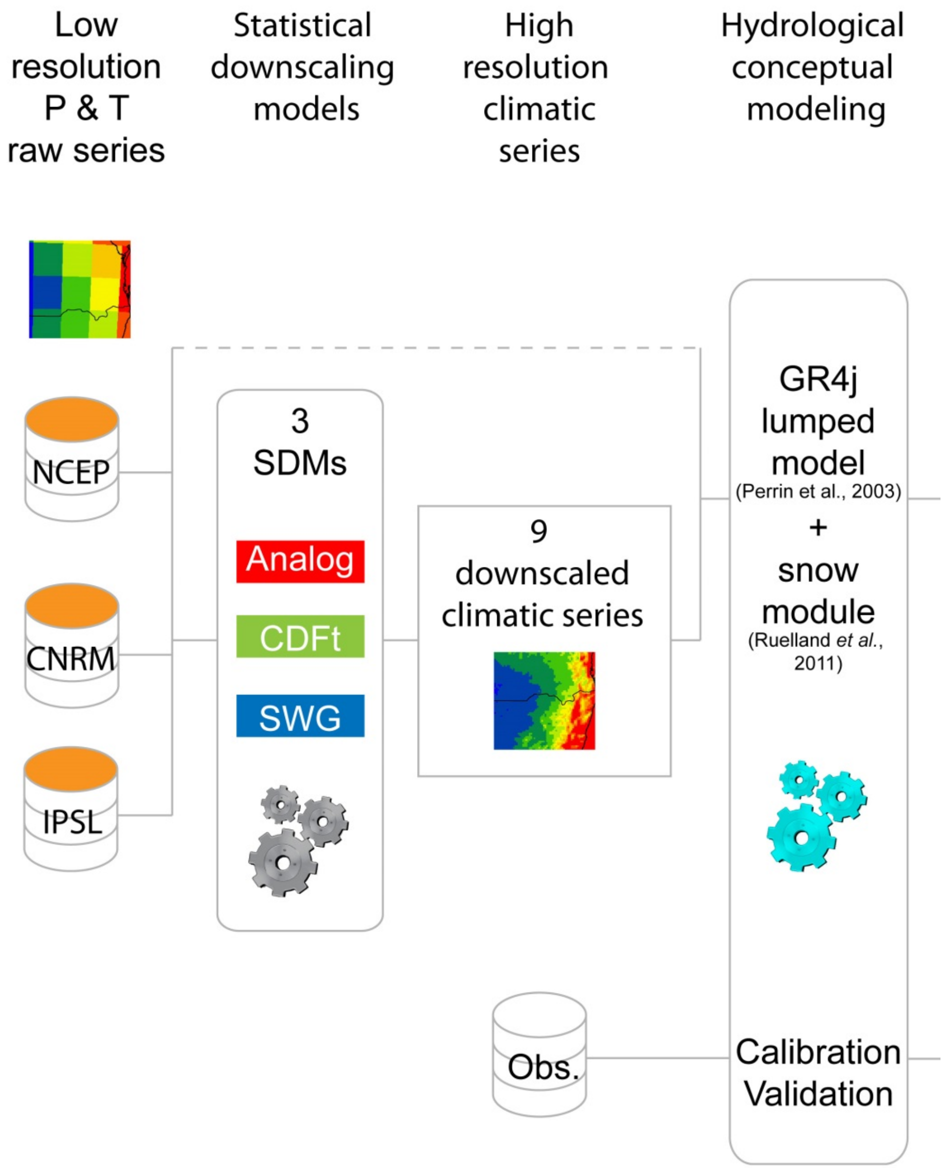
Representing the main families of SDMs:

- analogs of atmospheric circulation patterns (Analog)
- the "Cumulative Distribution Function - transform" approach (CDFt)
- a stochastic weather generator (SWG)

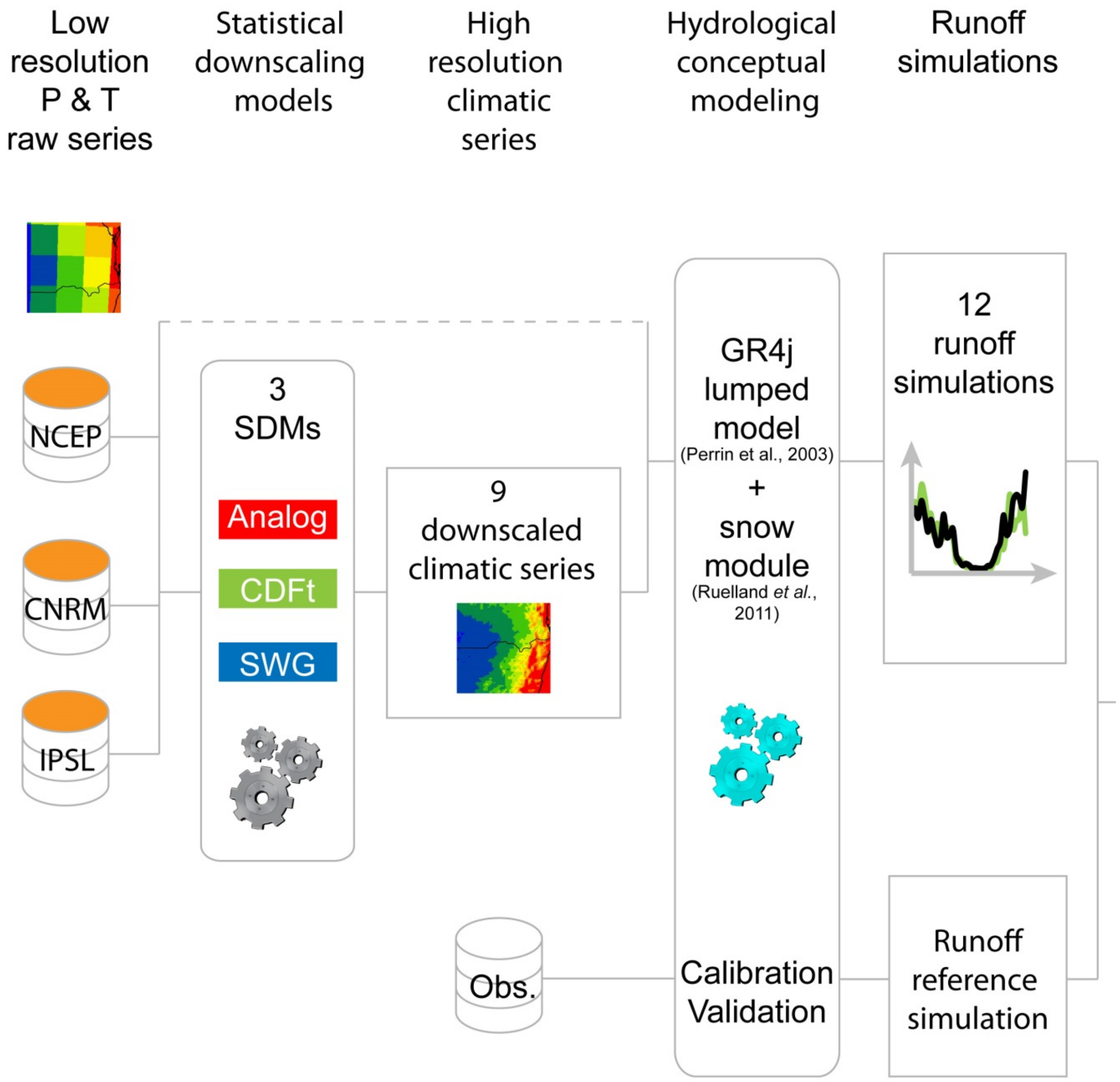
High resolution climate series



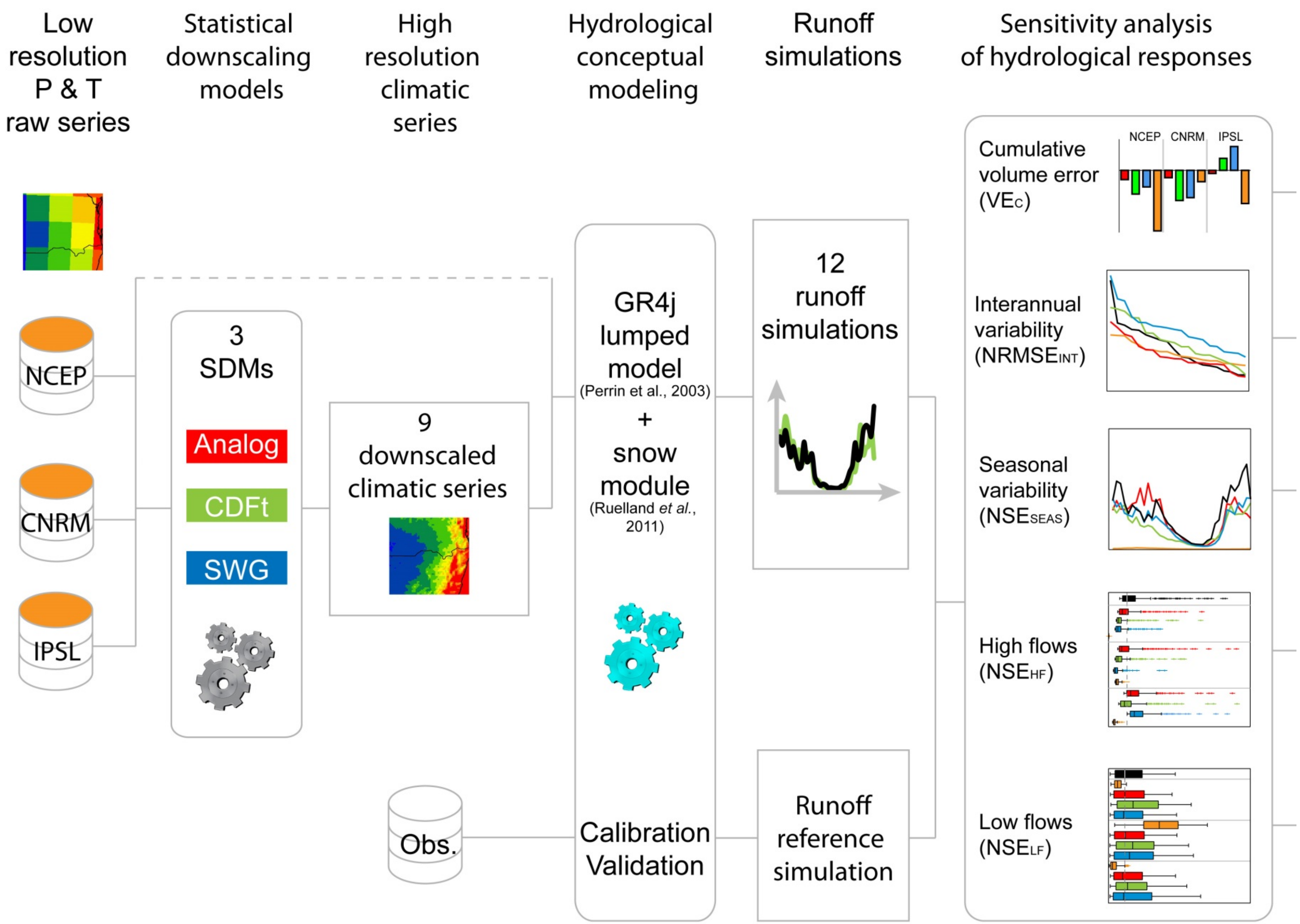
Hydrological modeling



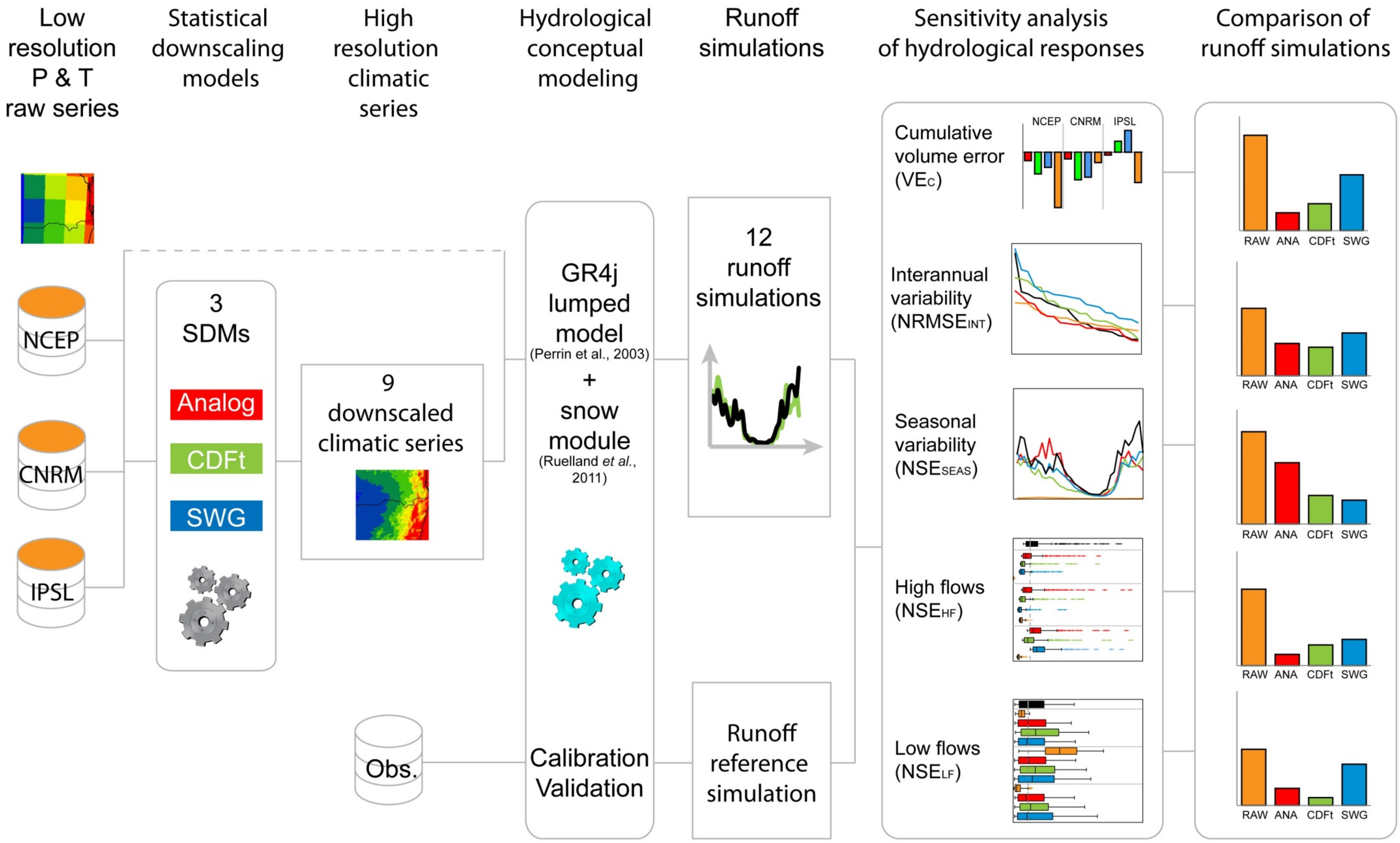
Runoff simulations



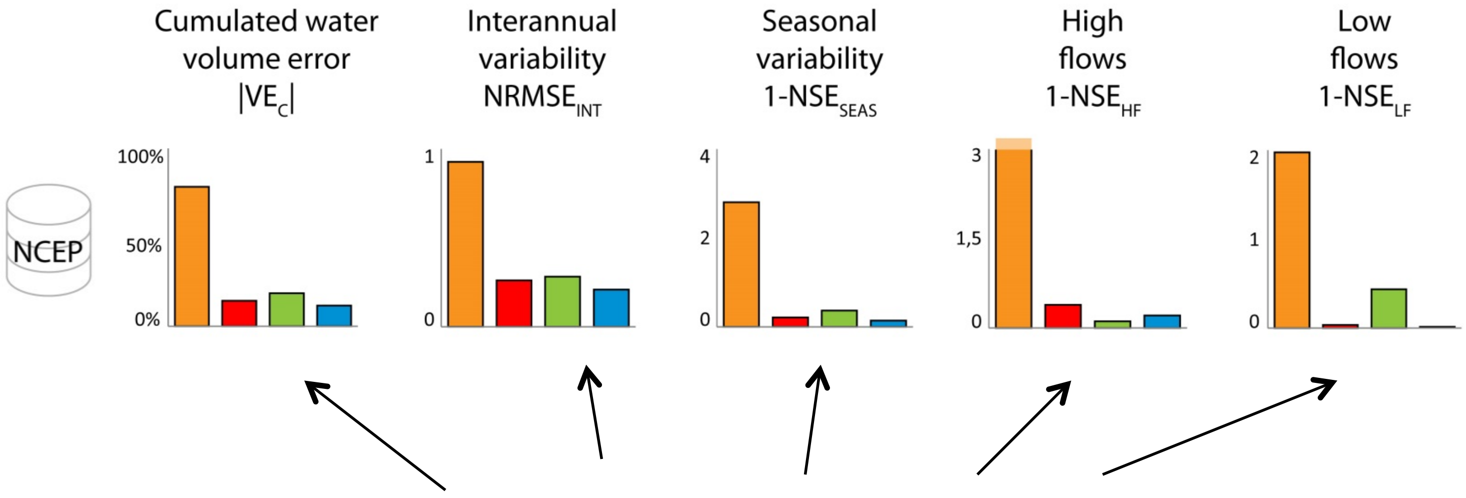
Sensitivity analysis of hydrological responses



Comparison of runoff simulations to provide guidelines

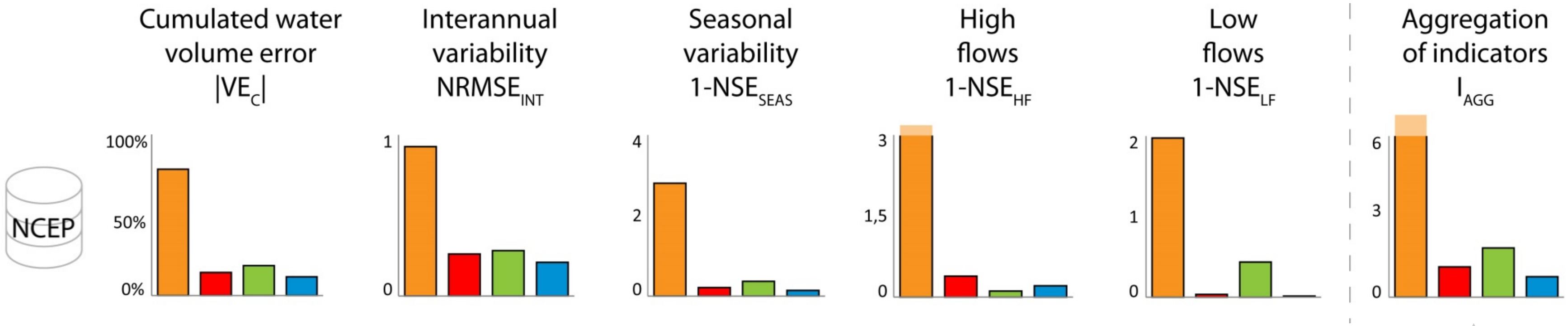


Guideline to select SDMs from a hydrological point of view



Median of the criterion values from the four basins

Guideline to select SDMs from a hydrological point of view



$$I_{AGG} = |VE_C| + NRMSE_{INT} + (1 - NSE_{SEAS}) + (1 - NSE_{HF}) + (1 - NSE_{LF})$$

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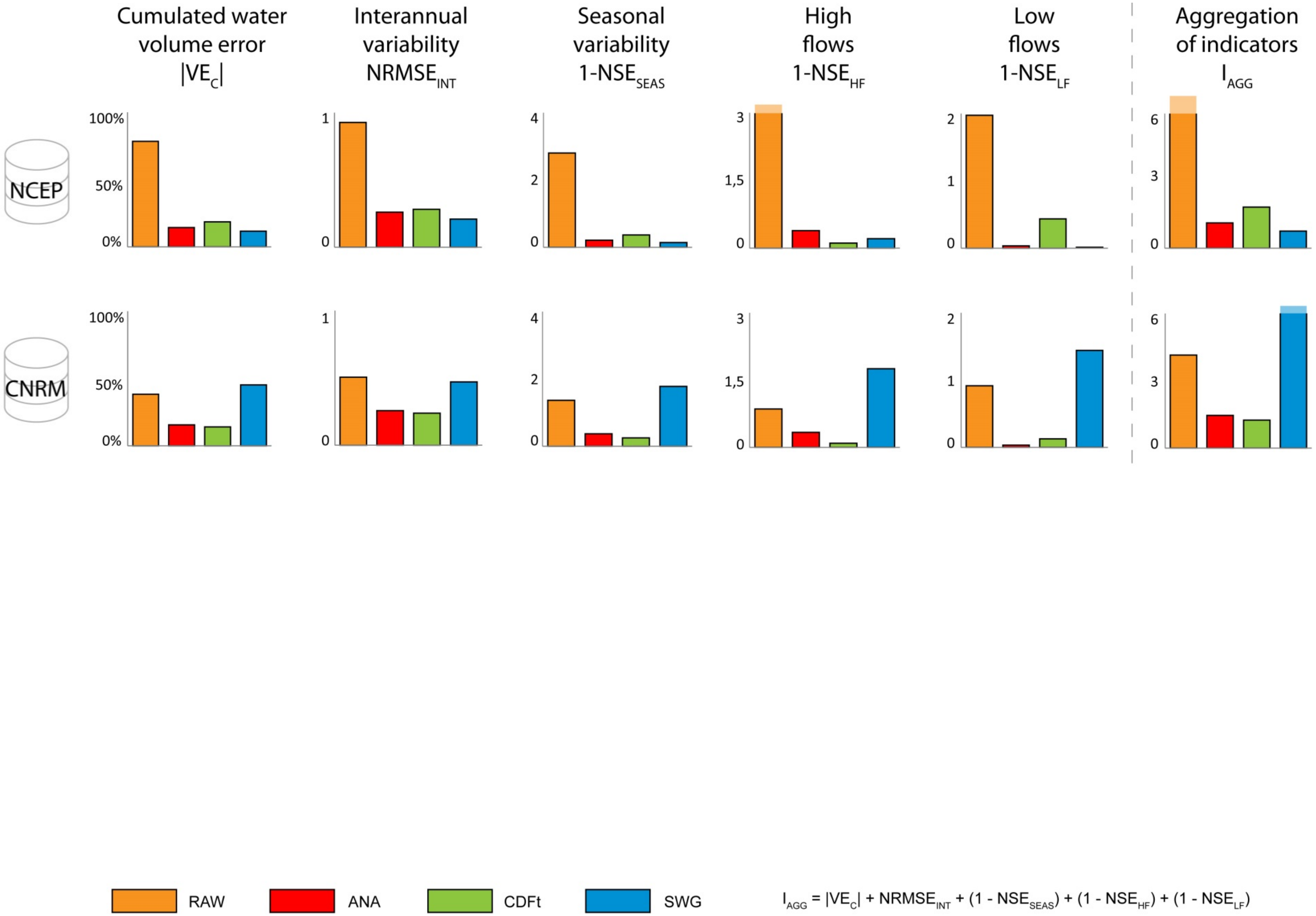

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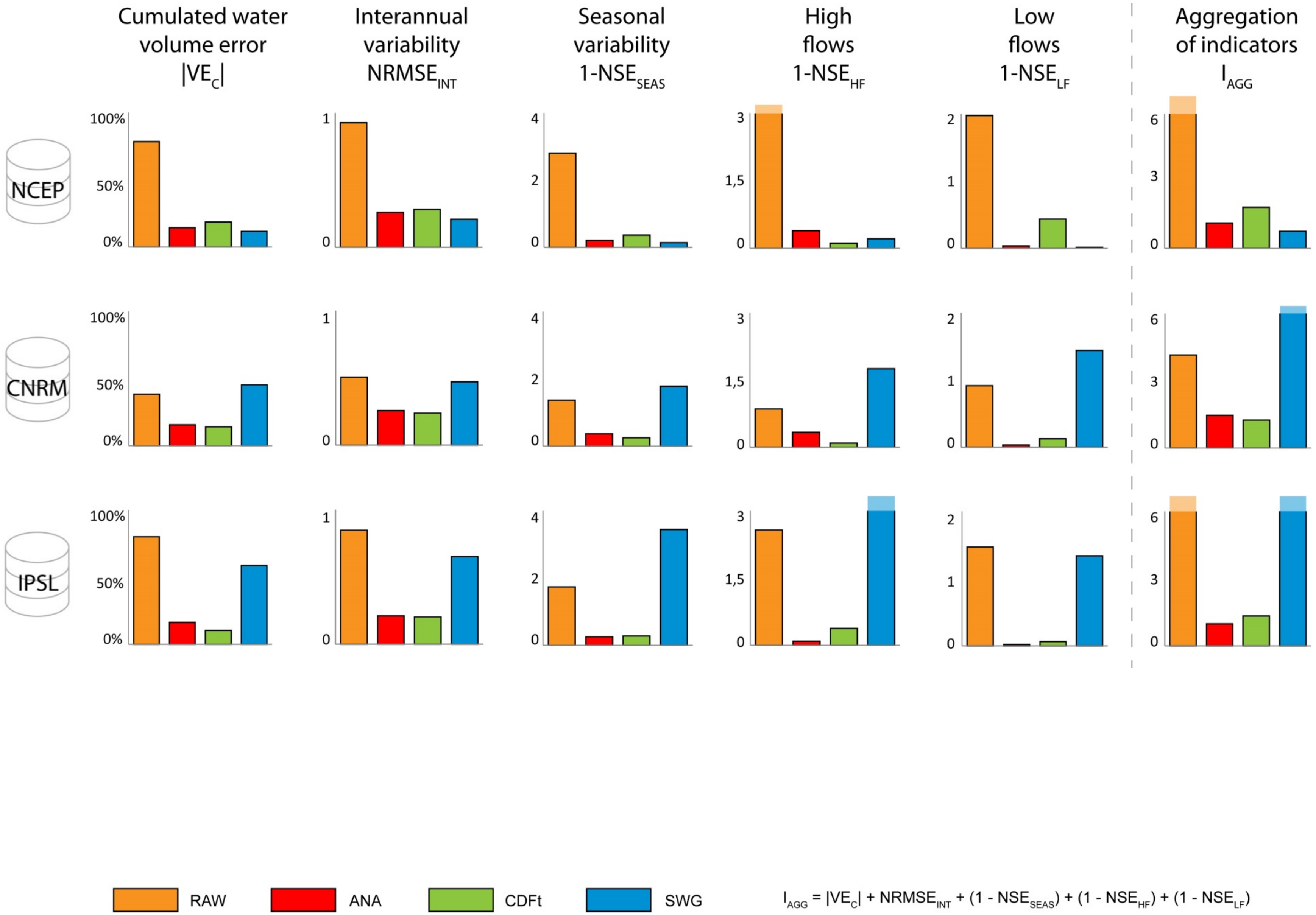

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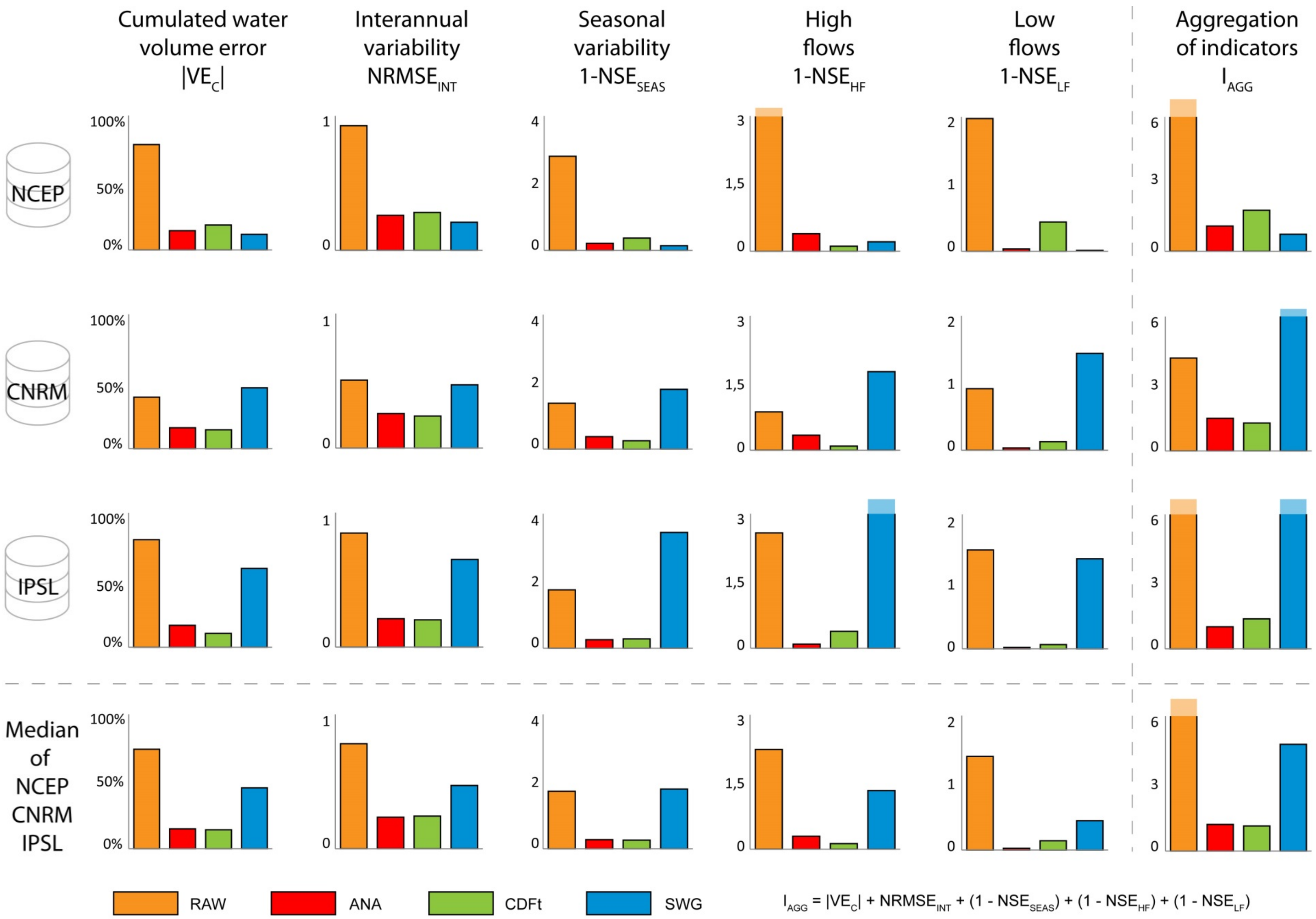
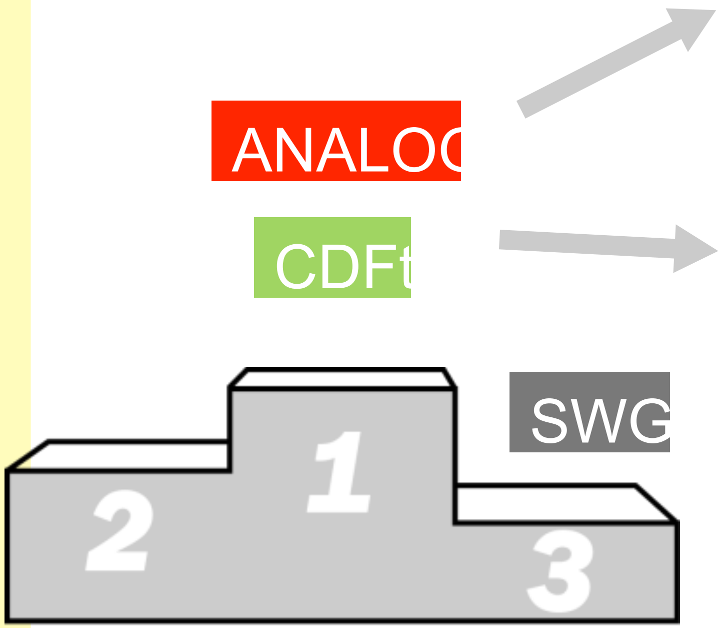


Outcome



Best results but never supplies downscaled values out of the range of the calibration reference dataset

Good performance and could be improved with additional covariates as predictor

Reduce downscaling uncertainty in climate scenarios

Uncertainty of 12 runoff simulations over the 2041–2060 period based on :

- **2 GCMs**
  CNRM / IPSL
- **2 RCPs**
  RCP4.5 / 8.5
- **3 SDMs**
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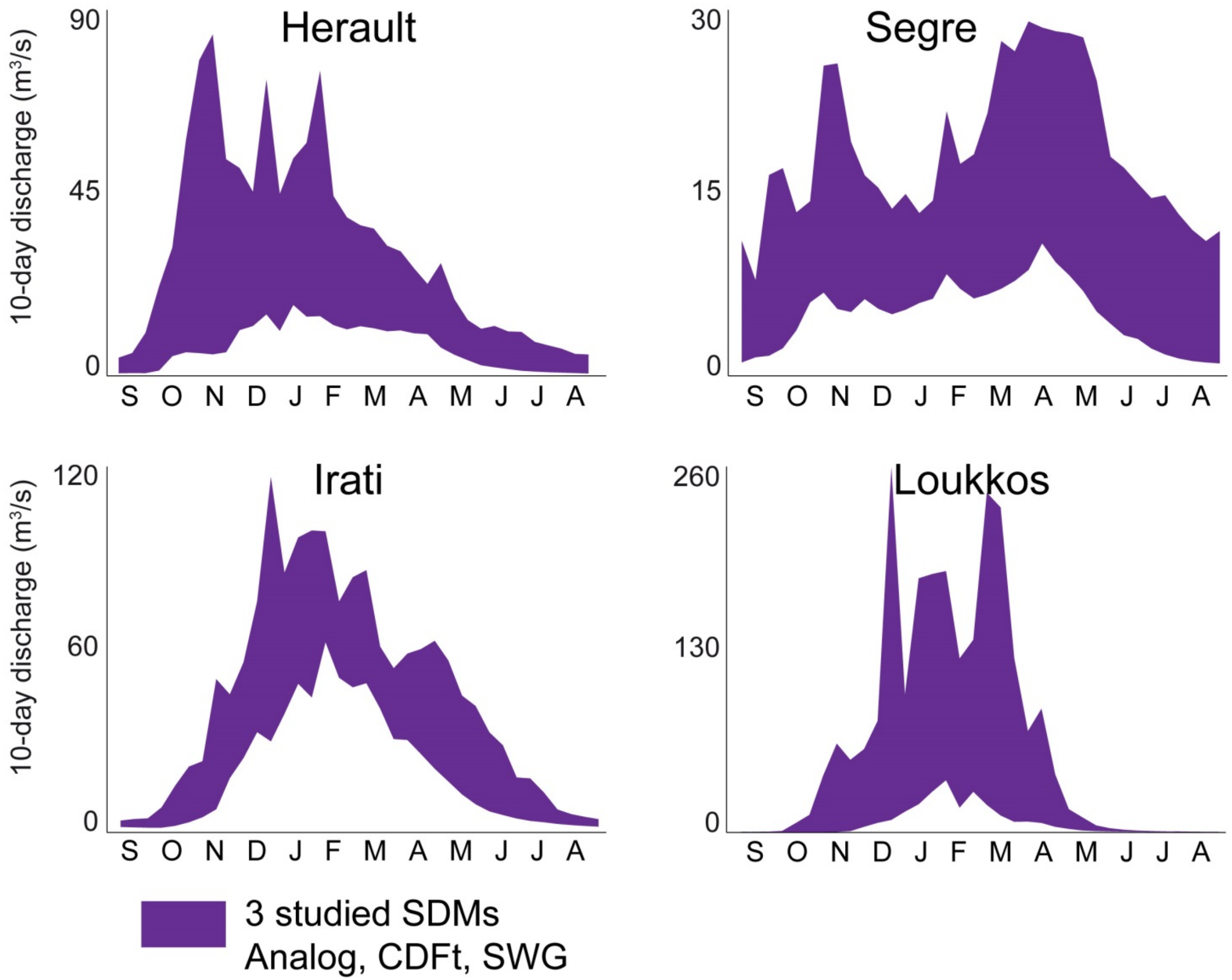

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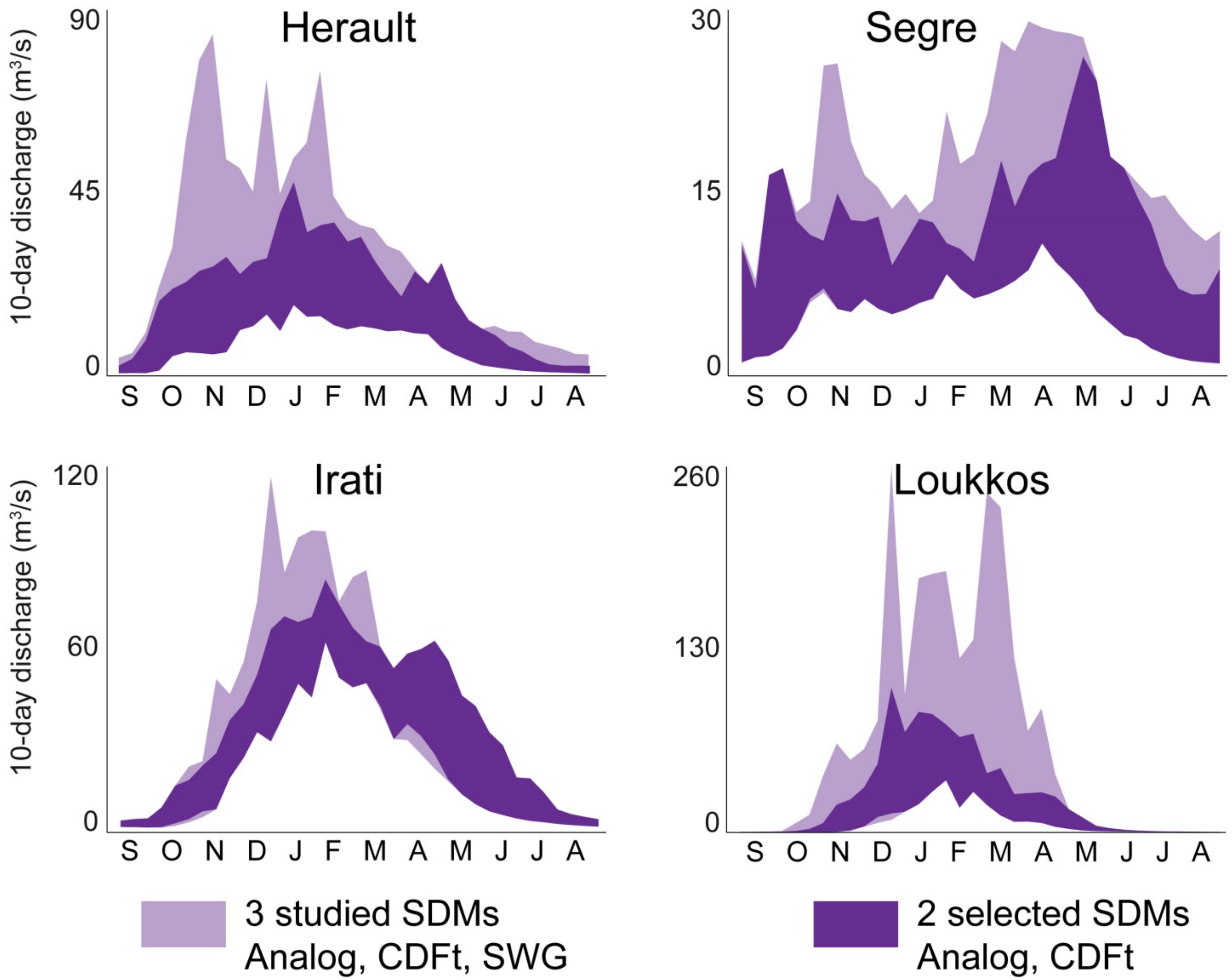

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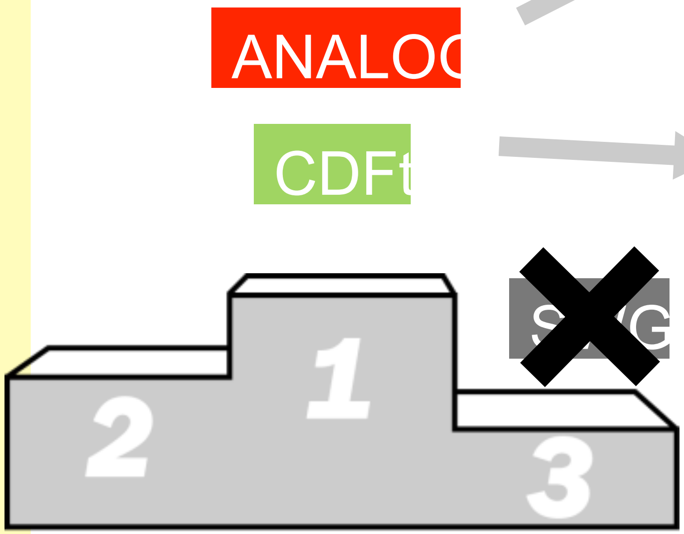

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Good performance and could be improved with additional covariates as predictor

Unsuitable as is **because of the biases between NCEP/NCAR (calibration) and GCMs predictors**.

<u>One solution</u> : correction of the GCMs predictors

Combining BC & SDMs

What is the influence of bias correcting predictors on statistical downscaling models ?

From

Vrac, M. and P. Vaittinada Ayar (2017)
Influence of Bias Correcting Predictors on Statistical Downscaling Models.
J. Appl. Meteor. Climatol., **56**, 5–26, https://doi.org/10.1175/JAMC-D-16-0079.1

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Multivariate bias correction

2 main philosophies

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Parallel correction of
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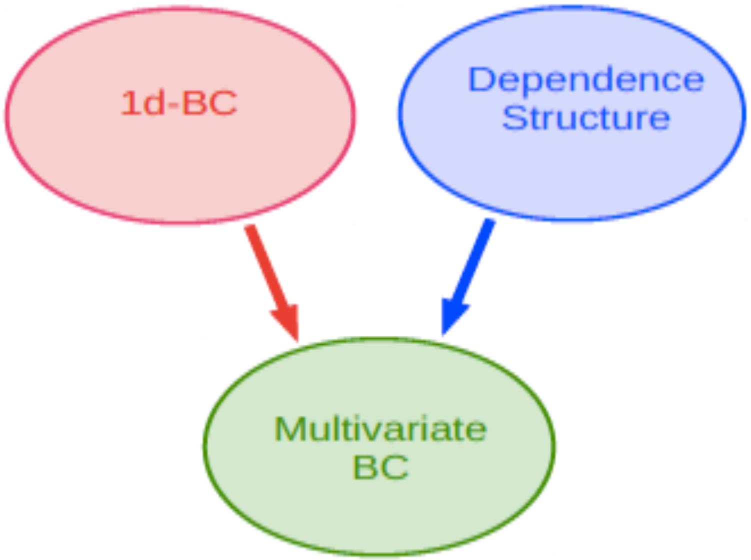

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- etc.

Multivariate bias correction

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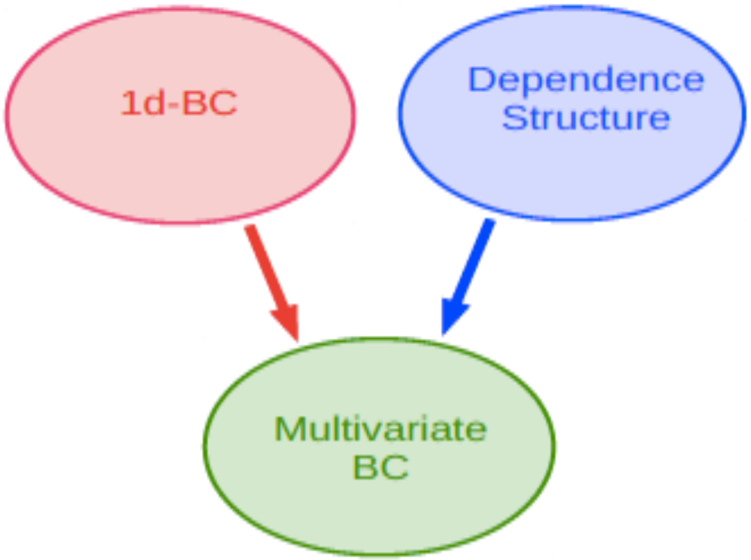

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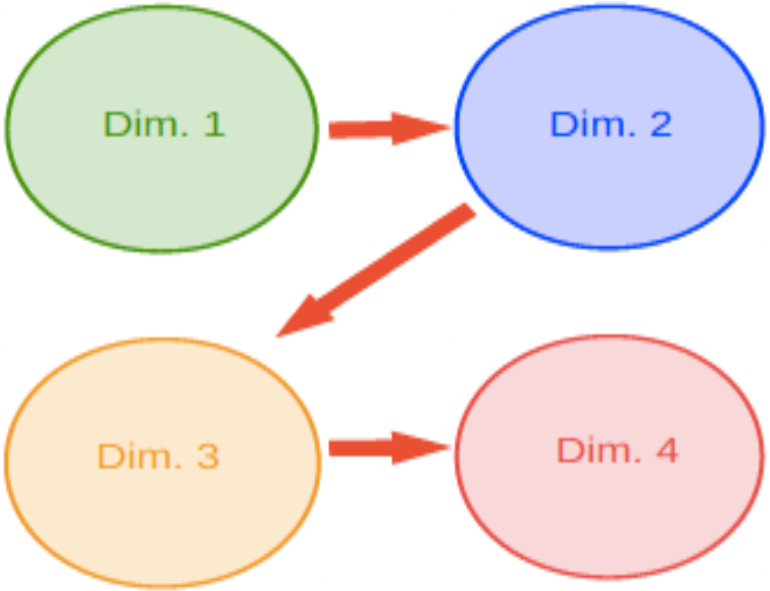
Successive conditional corrections



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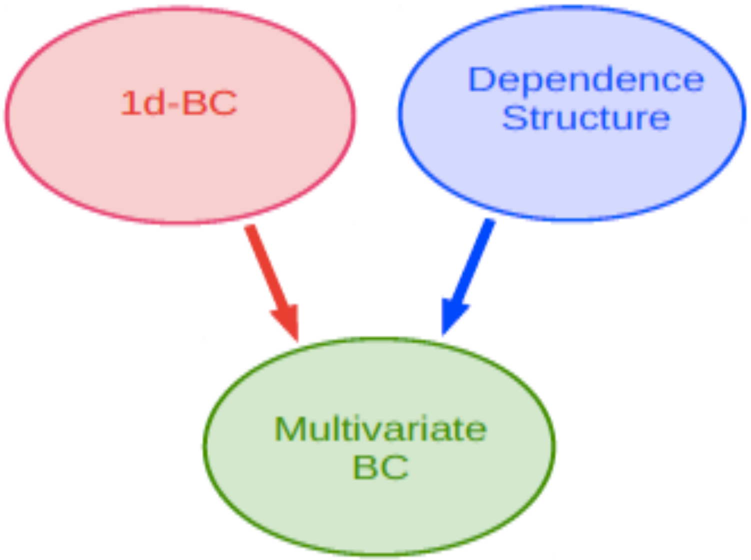

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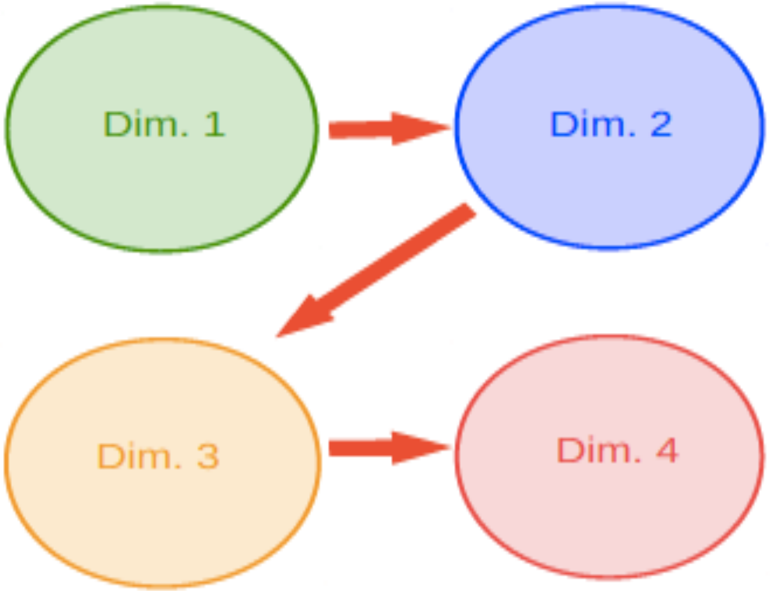

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$x_T^{(i)}$	$k(x_T^{(i)})$	$y_T^{(i)}$	$k(y_T^{(i)})$	$x_P^{(i)}$	$k(x_P^{(i)})$	$y_P^{(i)}$	$k(y_T^{(i)})$
0.3	1	1.1	1	0.7	3	1.3	2
0.5	2	1.7	3	0.5	2	1.8	4
0.9	4	1.2	2	0.2	1	1.1	1
0.8	3	1.9	4	0.9	4	1.4	3

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0.5	2	1.7	3	0.5	2	1.8	4
0.9	4	1.2	2	0.2	1	1.1	1
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Multivariate Empirical Copula – Bias correction (EC-BC)

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  Multivariate – Inter-variable, spatial and temporal – bias correction

1. Univariate (classical, 1d) bias correction (BC) w.r.t. reference (training) data
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0.3	1	1.1	1	0.7	3	1.3	2	0.2	1	1.1	1
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- **Multivariate** – temporal, inter-var. & spatial – **properties are reconstructed** !!

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- **Multivariate** – temporal, inter-var. & spatial – **properties are reconstructed** !!
- Applicable to any of your favourite 1d-BC or DS method !!

Data & Calibration/Projection

- **Reference** data = **SAFRAN** dataset (S-E of France), 8km x 8km
- **Model** data to be corrected = **ERA-I**nterim reanalyses, 0.75°x0.75°

- Calibration = 1980-1994
- Projection = 1995-2009

One "summer" season
(15 Apr. – 14 Oct.)

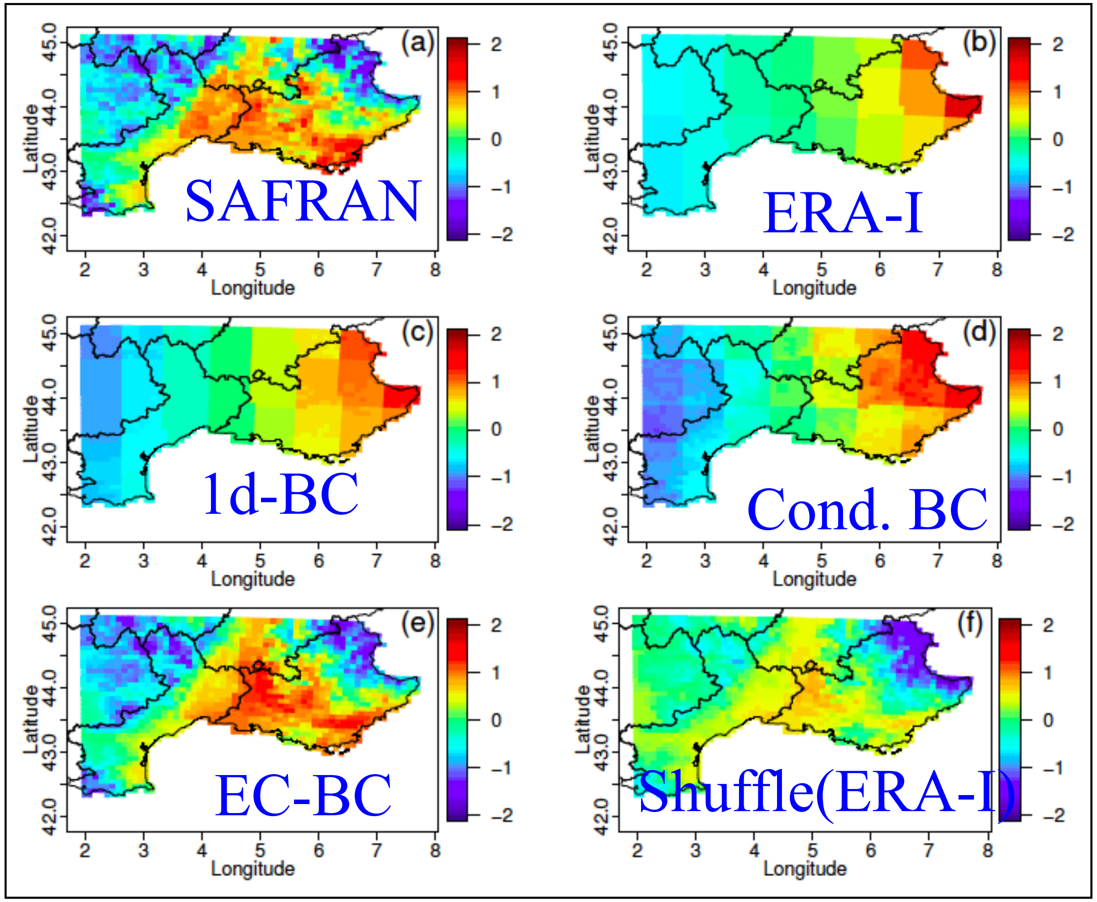
One "winter" season
(15 Oct. – 14 Apr.)

1d-BC vs. Cond.BC(2d) vs. EC-BC(3012d) vs. ERA-I vs. Shuffle(ERA-I)
vs.
SAFRAN(proj)

The "winter" results are shown next
(but equivalent results for summer)

EC-BC : spatial evaluation (illustration on T2)

FIG. 4. First EOF of 2m temperature for (a) reference, (b) ERA-I, (c) independent bias correction, (d) conditional approach, (e) MBC and (f) Schaake shuffle on ERA-I without BC.



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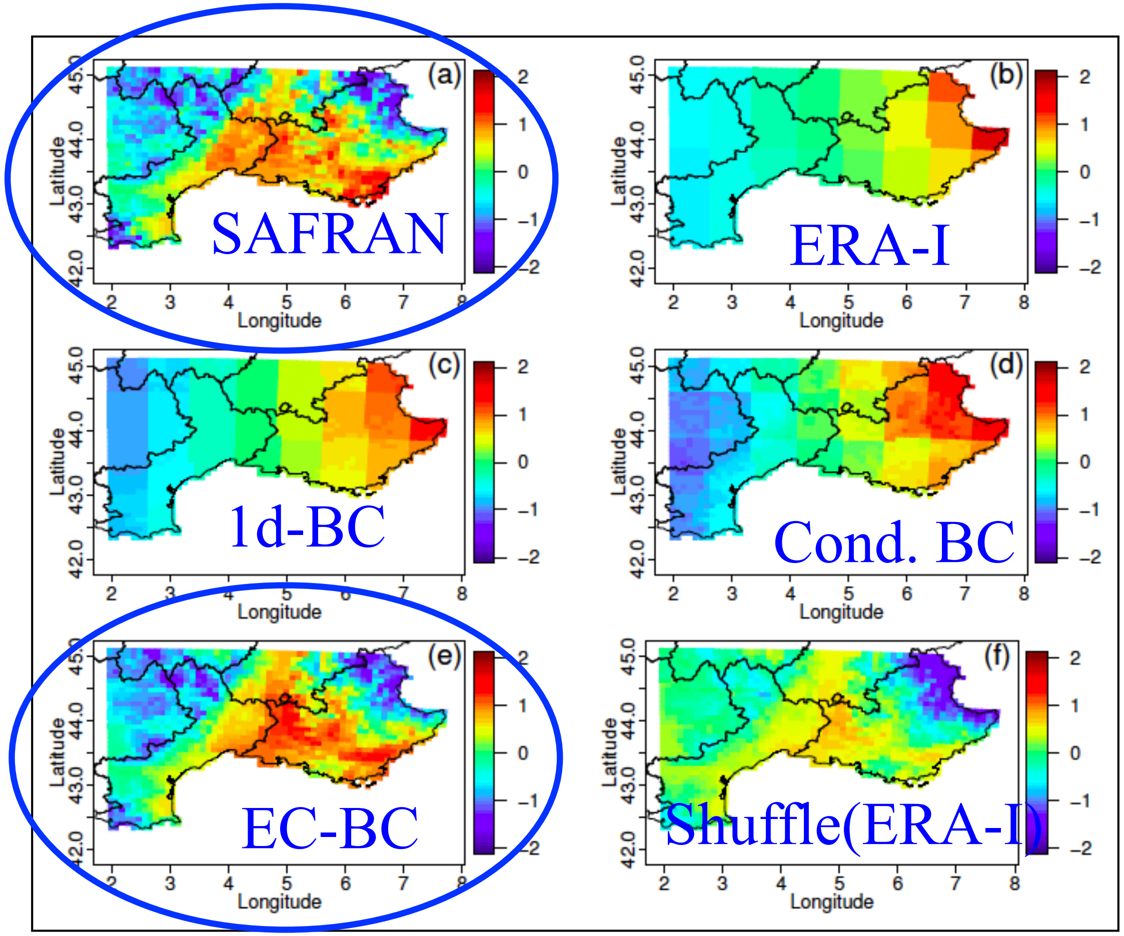

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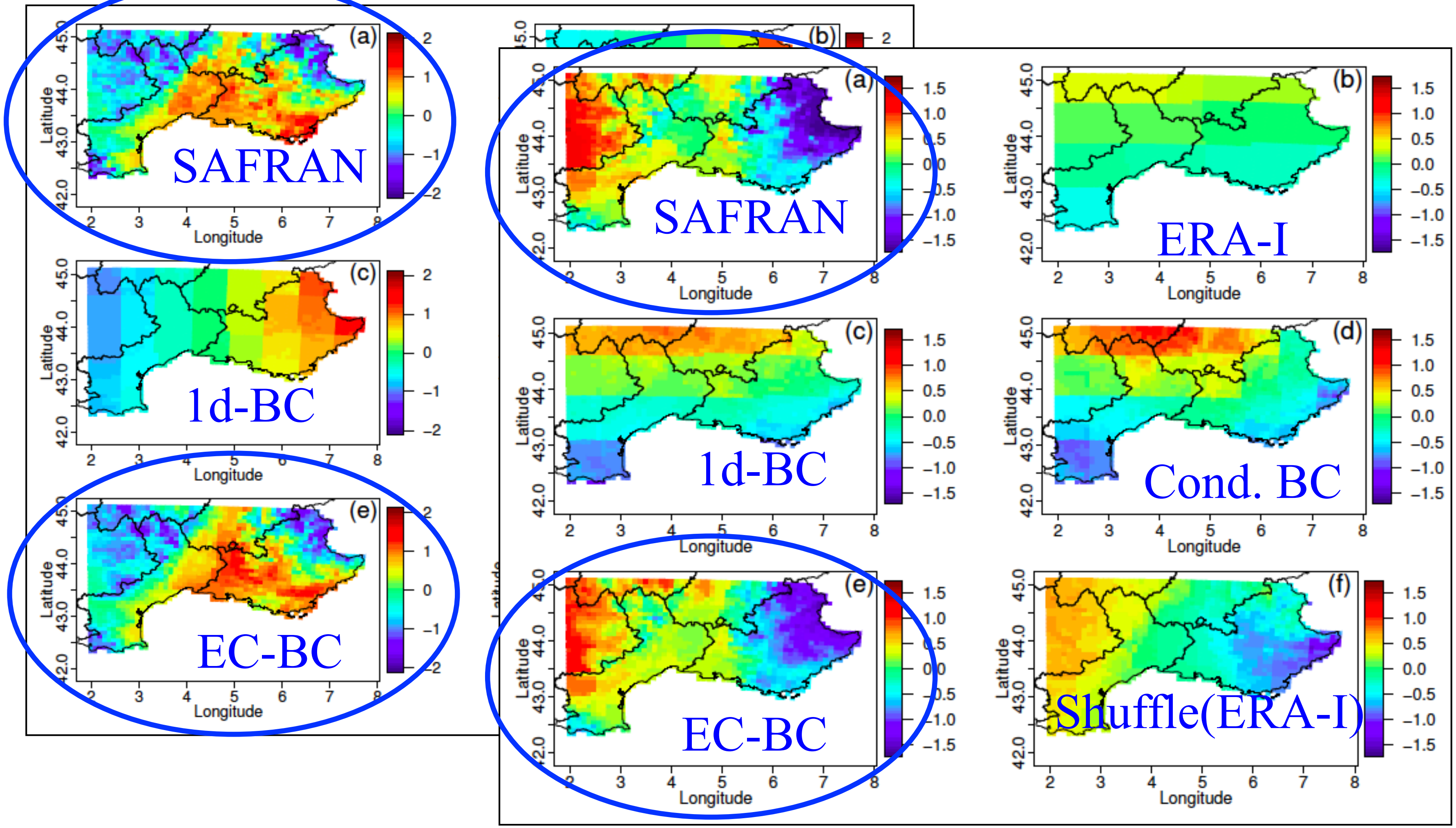

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EC-BC : Inter-variable (PR-T) evaluation

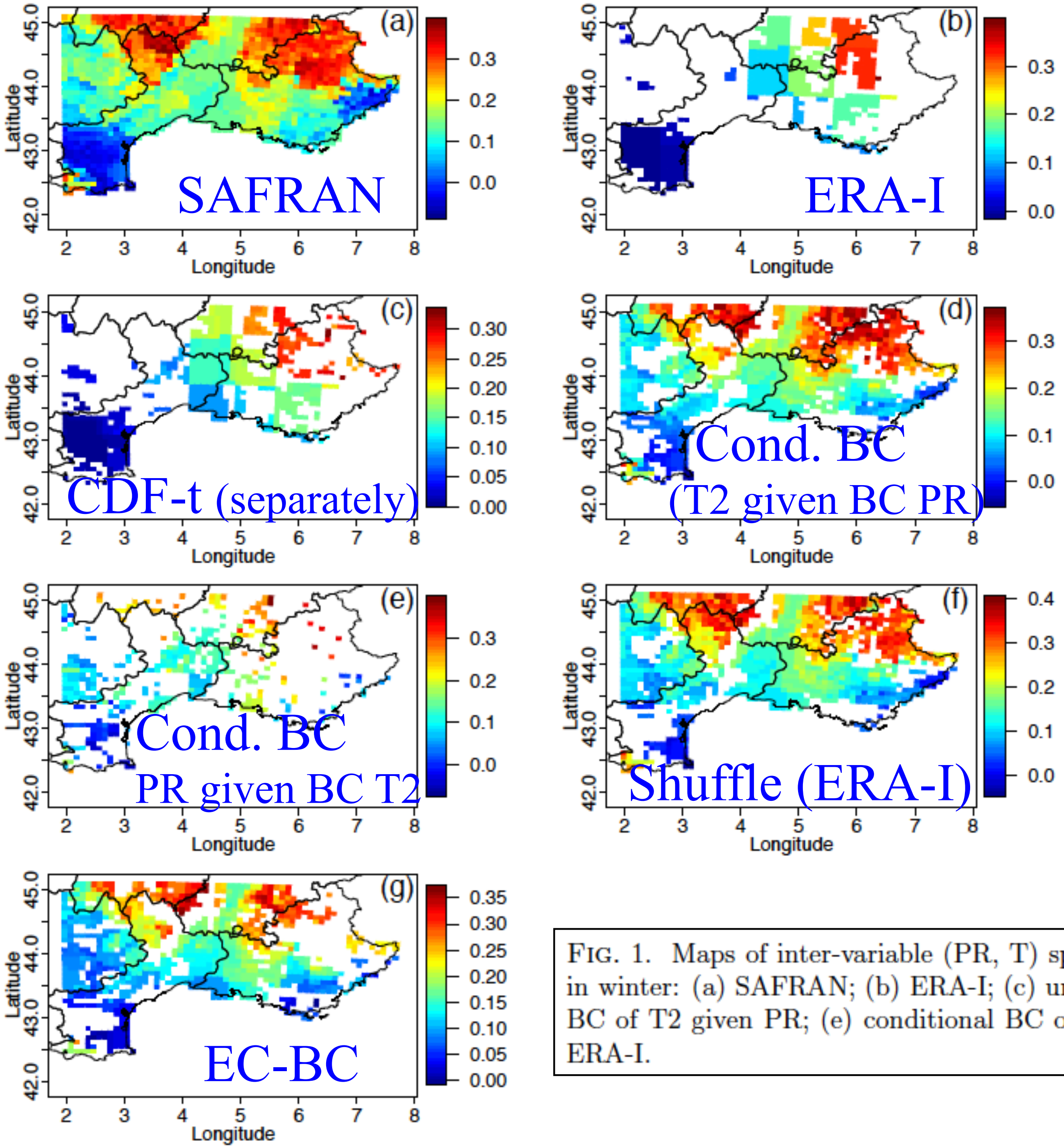

FIG. 1. Maps of inter-variable (PR, T) spearman correlations for the different approaches in winter: (a) SAFRAN; (b) ERA-I; (c) unconditional BC (through CDFt); (d) conditional BC of T2 given PR; (e) conditional BC of PR given T2; (f) MBC; (g) Schaake shuffle on ERA-I.

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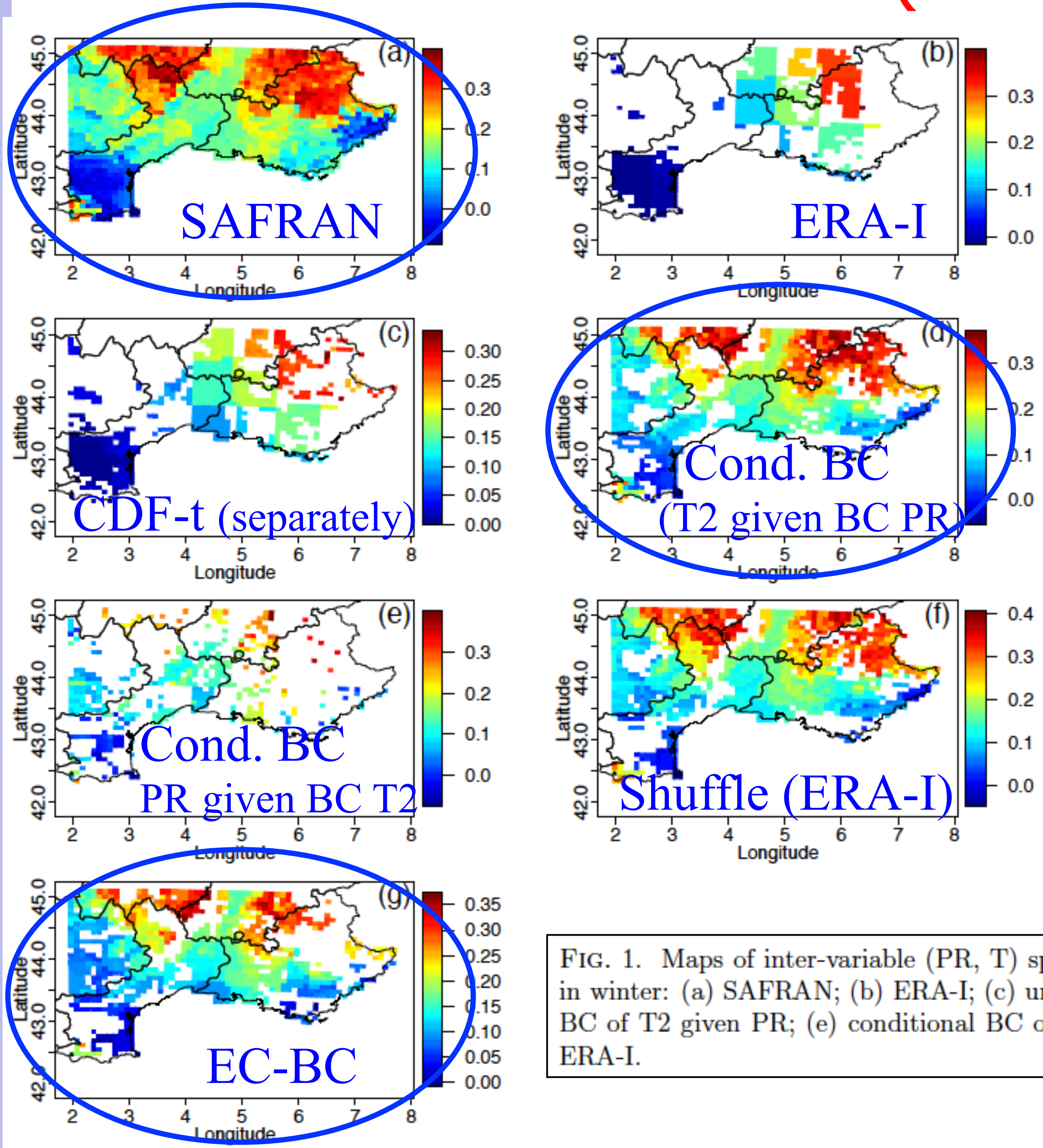

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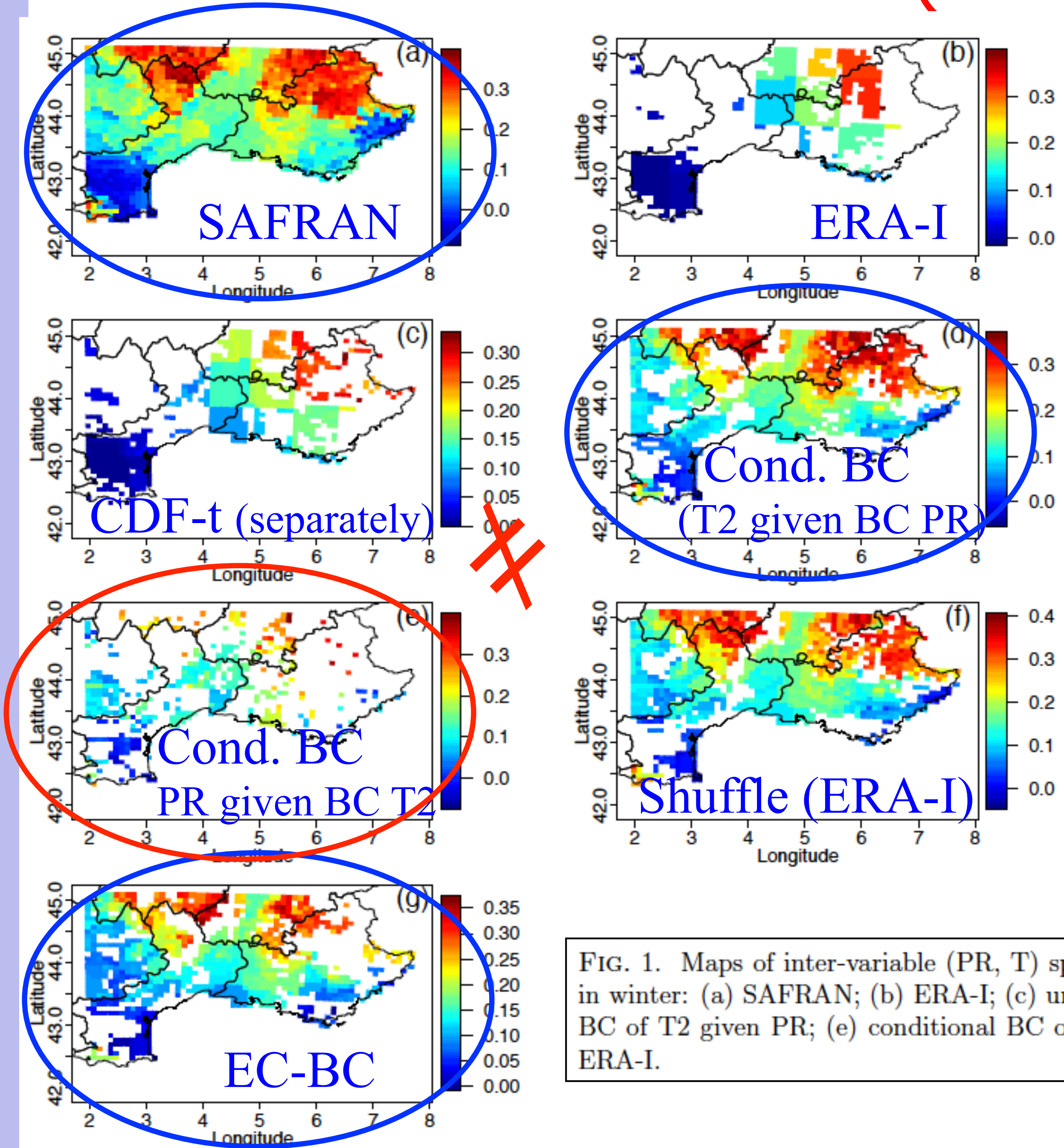

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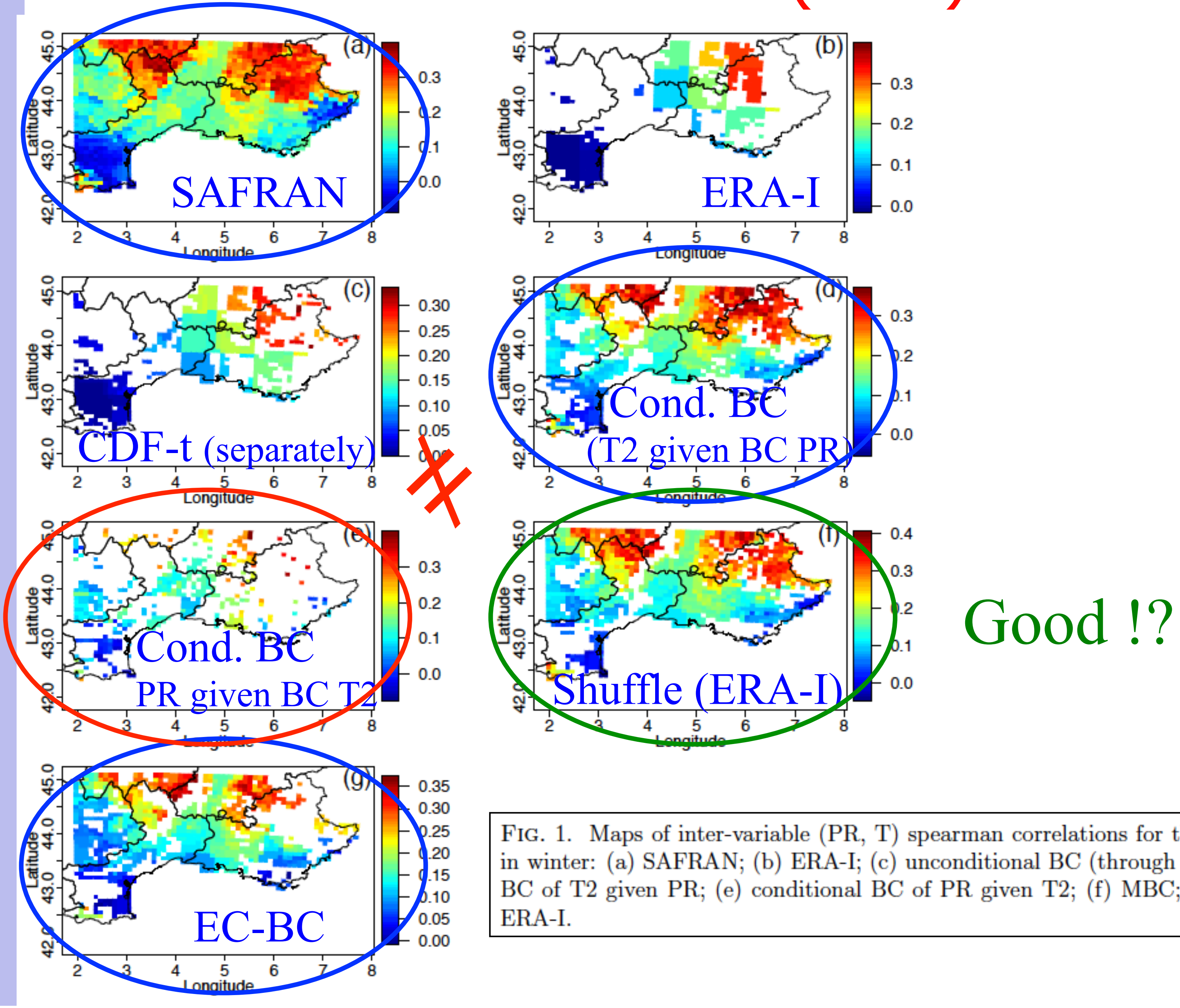

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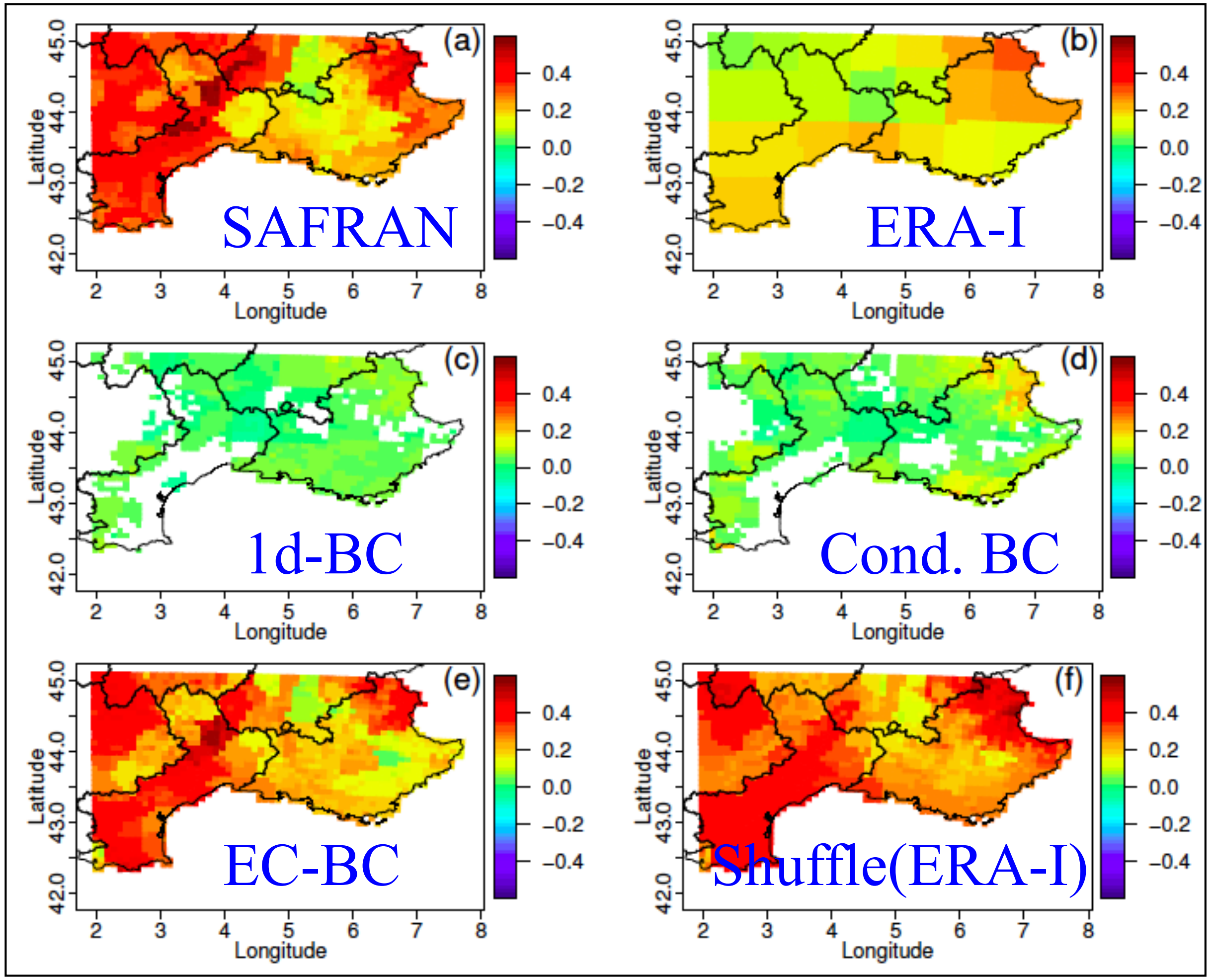
EC-BC : Temporal evaluation (illustration on PR)

FIG. 10. First coefficient of AR(2) process fitted to precipitation for (a) reference, (b) ERA-I, (c) independent bias correction, (d) conditional approach, (e) MBC and (f) Schaake shuffle on ERA-I without BC.



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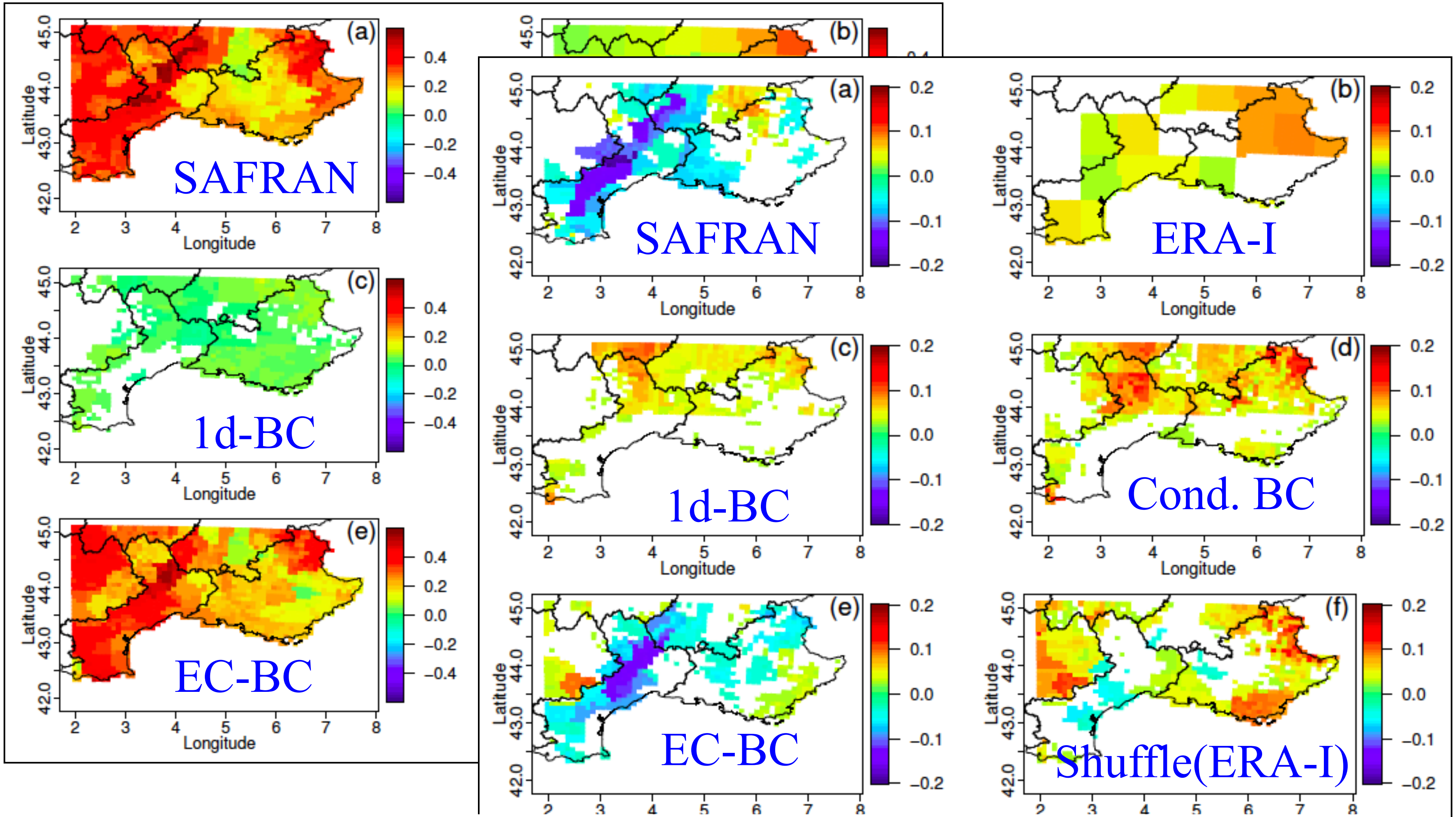

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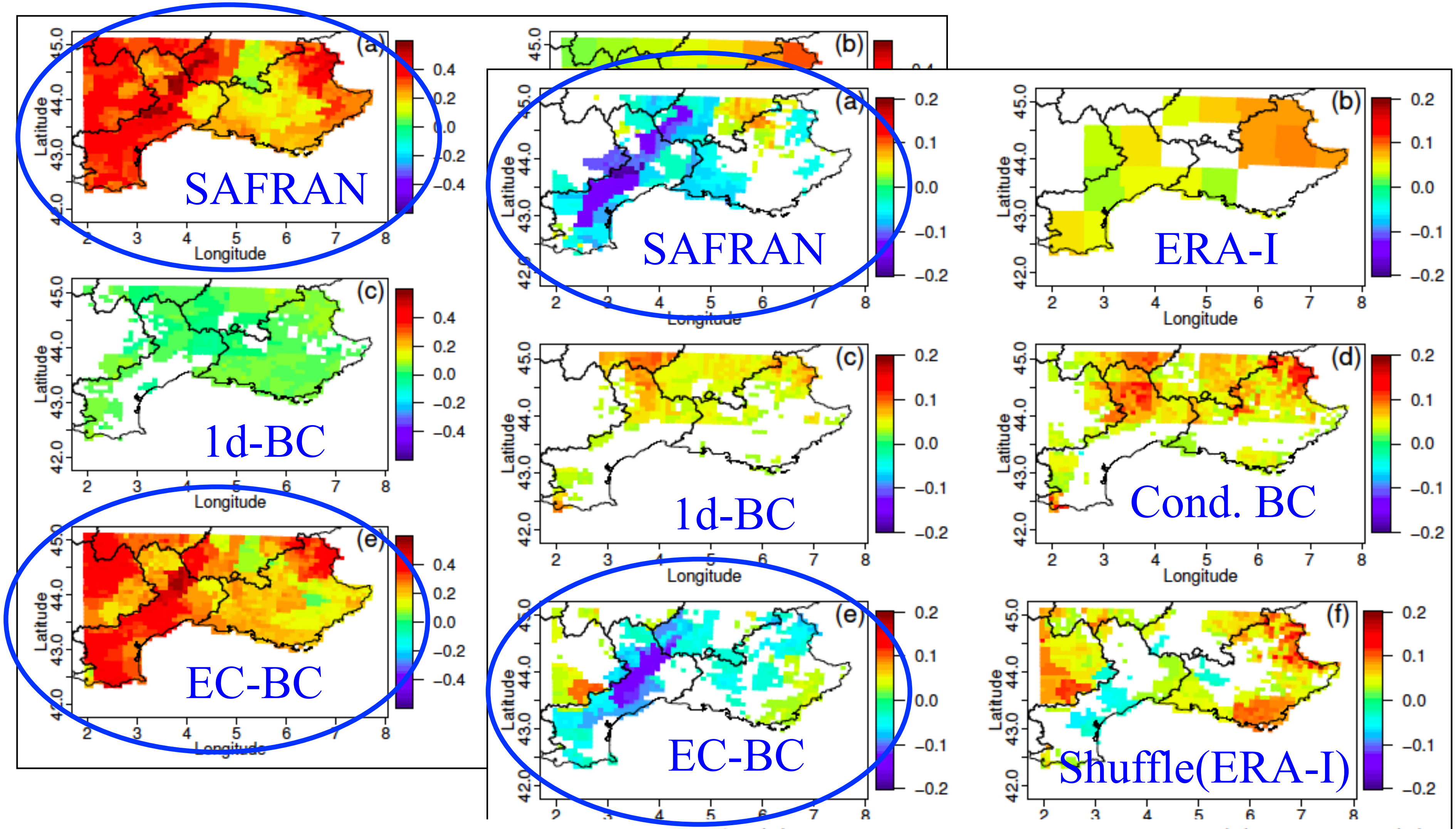

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More evaluations in Vrac and Friederichs (2015, JClim):

Vrac, M., and Friederichs, P. (2015).
Multivariate – Intervariable, Spatial, and Temporal—Bias Correction.
J. Climate, **28**, 218–237.
doi: http://dx.doi.org/10.1175/JCLI-D-14-00059.1

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- **1d-BC** methods (CDF-t/QM) **not able** to produce multi-dimensional properties
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- **Flexibility**: EC-BC is applicable with **any 1d-BC or 1d-SDM** !!!
- Easiness of coding + flexibility + fast application + quality
  - = EC-BC is a good candidate for many (multivariate) BC applications
- **Package R** (ECBC) already **available** (upon request to me)

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- **GCMs/RCMs** instead of reanalyses
- **Ensemble** (i.e., multiple models) approaches
  - ✓ Multi-1d-BCs / Multi-MBCs/ Multi-RCMs
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  - ⇒ Variants (R^2B^2) of EC-BC (Vrac, in prep.)
  - ⇒ Different approach(es): "Optimal" BC (Robin et al., in prep.)

Thank you

& many thanks to the StaRMIP team

Sophie Bastin (LATMOS)

Julie Carreau (HSM)

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Pradeebane Vaittinada Ayar (LSCE)

Benjamin Grouillet (HSM)