Water 2021 WEBINARS

Climate Change and Water Resources: Evidence, Impacts, Adaptation

07 OCTOBER 2021, 04:00 PM (CEST)

MDPI WEBINARS

Droughts, Climate Change and Water Resources Management in Mediterranean Areas

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SICILIAE STVDIVM GENERALE 1434

DICAR

Role of water engineers in dealing with floods and droughts

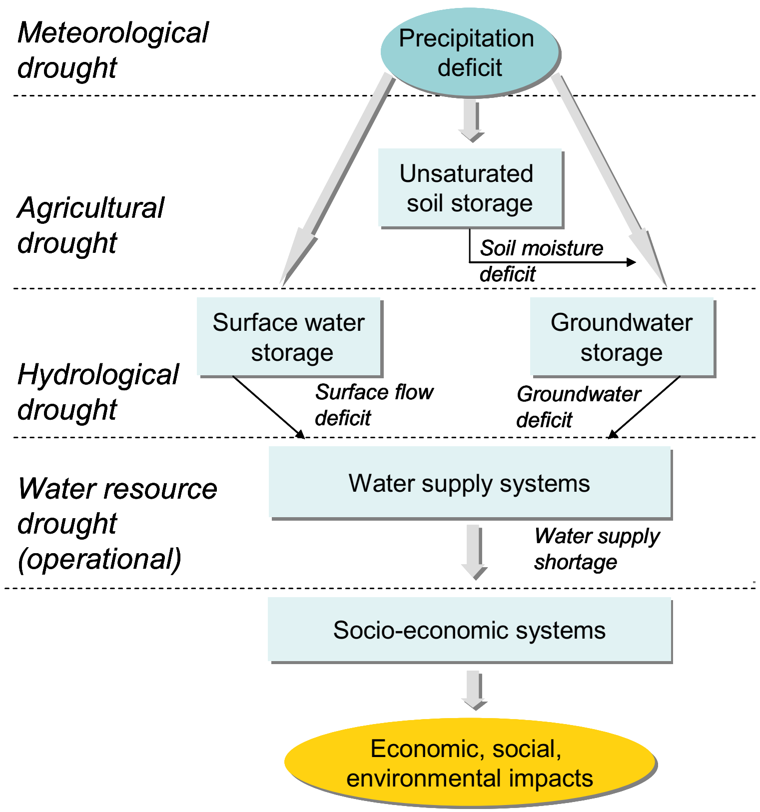
Then we'll act as guardians for all your crops and all your vines, making sure they're never harmed by drought or by a drenching rain.

Aristophanes, Clouds (first performed in 423 BC)

Sicily like tropics: here is the first coffee harvest from the world northernmost plantation

Droughts

- Elusive phenomenon
- Unlike other extreme events, difficult to define, characterize
- Despite its temporary nature, even onset and termination are not easily identifiable
    - Depends on the affected components of the hydrological cycle
    - Propagation of reduced precipitation over the different components is delayed
    - Creeping onset and long lasting effects before recovery
- Plethora of indices and indicators that attempt to identify droughts and assess its characteristics
- Interestingly enough, we often define droughts in terms of the index and not the other way around (as it should be)



Precipitation patterns

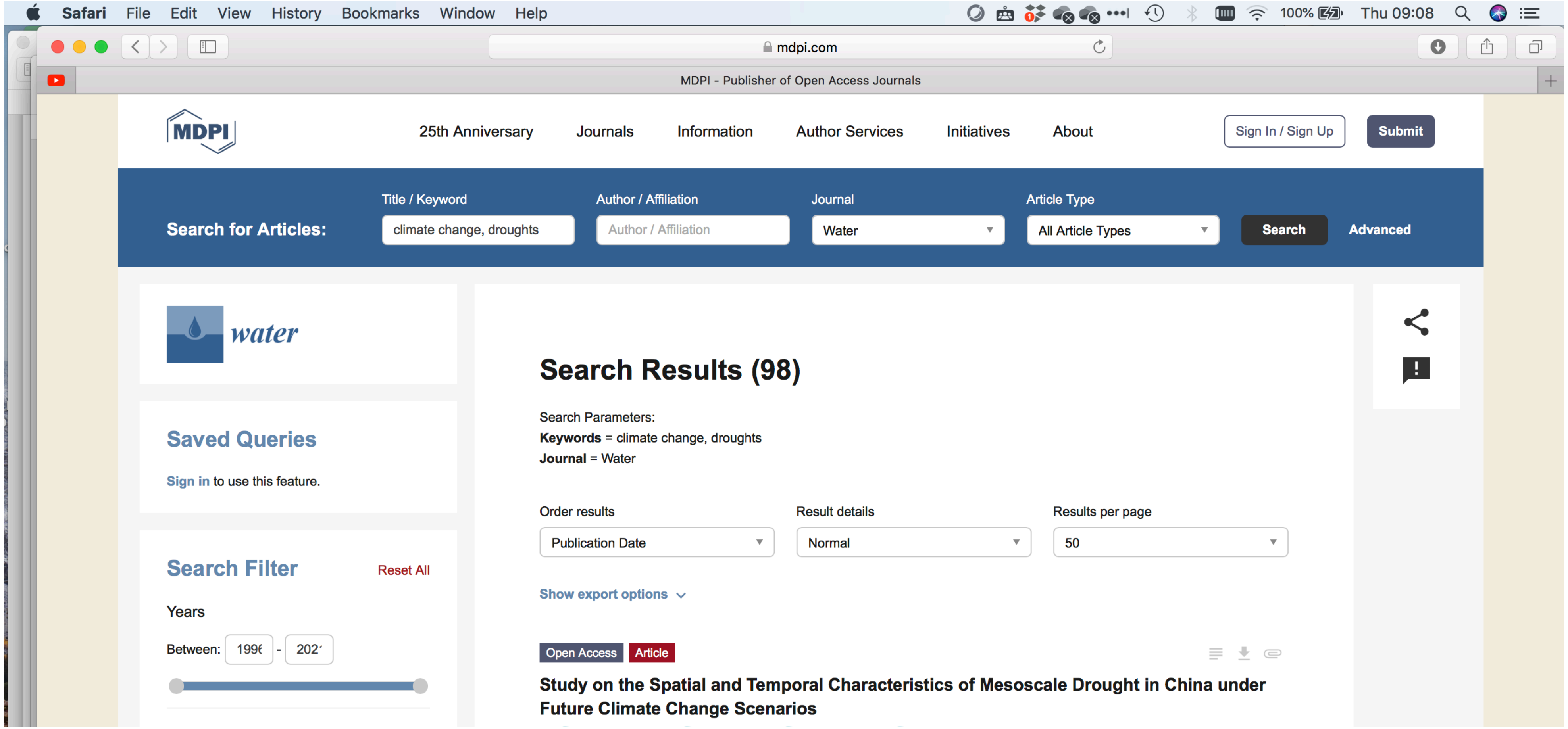
AED, ET

Land use

Water demands for the different uses

Other cuncurrent impacts

Droughts, climate change



Drought present trends

- Several indices adopted, baselines, etc., sometimes with disparate results, e.g.:

LETTERS
PUBLISHED ONLINE: 5 AUGUST 2012 | DOI: 10.1038/NCLIMATE1633
nature climate change

Increasing drought under global warming in observations and models

Aiguo Dai

?

LETTER
doi:10.1038/nature11575

Little change in global drought over the past 60 years

Justin Sheffield[1], Eric F. Wood[1] & Michael L. Roderick[2]

Drought is expected to increase in frequency and severity in the its ease of use and long history in agricultural applications. However,

Present trends

Received: 3 December 2019 | Revised: 12 June 2020 | Accepted: 18 June 2020 | Published on: 16 July 2020
DOI: 10.1002/joc.6719

RESEARCH ARTICLE

International Journal of Climatology RMetS

Long-term variability and trends in meteorological droughts in Western Europe (1851–2018)

Sergio M. Vicente-Serrano[1] | Fernando Domínguez-Castro[2] | Conor Murphy[3] | Jamie Hannaford[3,4] | Fergus Reig[1] | Dhais Peña-Angulo[1] | Yves Tramblay[5] | Ricardo M. Trigo[6] | Neil Mac Donald[7] | M. Yolanda Luna[8] | Mark Mc Carthy[9] | Gerard Van der Schrier[10] | Marco Turco[11] | Dario Camuffo[12] | Ivan Noguera[1] | Ricardo García-Herrera[13,14] | Francesca Becherini[12,15] | Antonio Della Valle[12] | Miquel Tomas-Burguera[16] | Ahmed El Kenawy[17,18]

reduction in the area affected by severe drought was detected, especially in winter.

- With few exceptions, trends in droughts over Western Europe are statistically non-significant from a long-term perspective.
- Changes in droughts are spatially variable, especially on a seasonal basis. Therefore, detailed local and regional assessment of drought variability should be of

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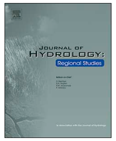
Contents lists available at ScienceDirect

Journal of Hydrology: Regional Studies

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



A new global database of meteorological drought events from 1951 to 2016

Jonathan Spinoni[a,*], Paulo Barbosa[a], Alfred De Jager[a], Niall McCormick[a], Gustavo Naumann[a], Jürgen V. Vogt[a], Diego Magni[b], Dario Masante[b], Marco Mazzeschi[c]

[a] *European Commission, Joint Research Centre (JRC), Ispra, Italy*
[b] *Arcadia SIT, Vigevano, Italy*
[c] *One Team, Milano, Italy*

- In this study, we have detected the following **drought hotspots** that have experienced a robust increase in drought frequency and severity between the periods 1951–1980 and 1981–2016: Patagonia, the **Mediterranean region**, the Sahel, the Congo River basin, north-eastern China, and (though not unanimously agreed by all indicators) central Asia and southern Australia. U

Drought present trends

- Most of the studies are based on traditional indices (PDSI, SPI, SPEI and variants) with some exceptions

water

MDPI

Article

Impact of Climate Change on Agricultural Droughts in Spain

María del Pilar Jiménez-Donaire [1,*], Juan Vicente Giráldez [1,2] and Tom Vanwalleghem [1]

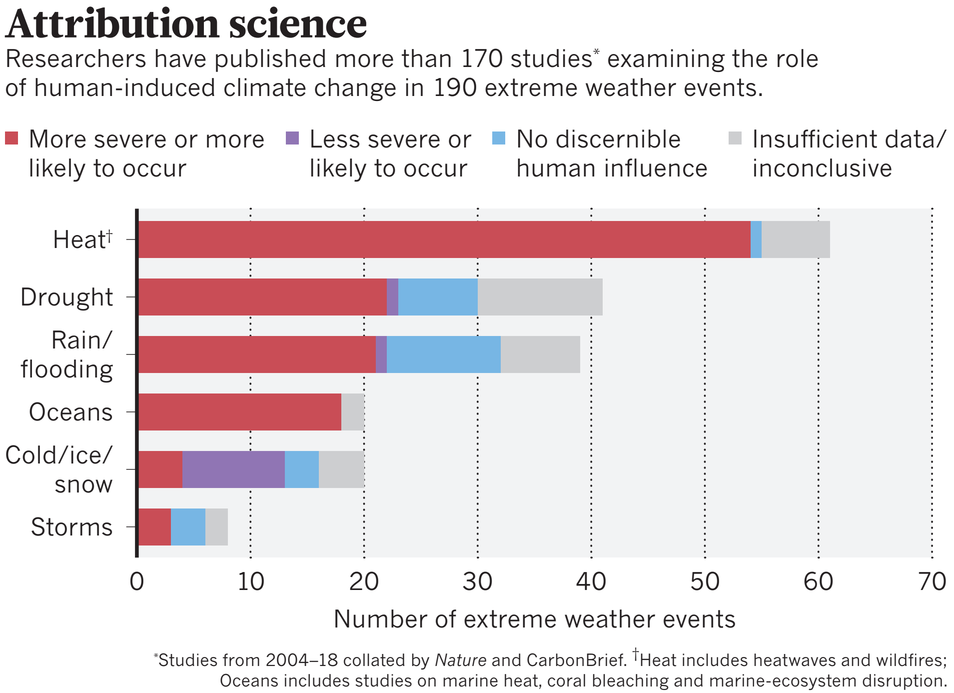
[1] Department of Agronomy, University of Córdoba, 14071 Córdoba, Spain; ag1gicej@uco.es (J.V.G.); ag2vavat@uco.es (T.V.)
[2] Institute for Sustainable Agriculture, CSIC, 14071 Córdoba, Spain
[*] Correspondence: g52jidom@uco.es

Received: 22 October 2020; Accepted: 12 November 2020; Published: 17 November 2020

check for updates

Attribution

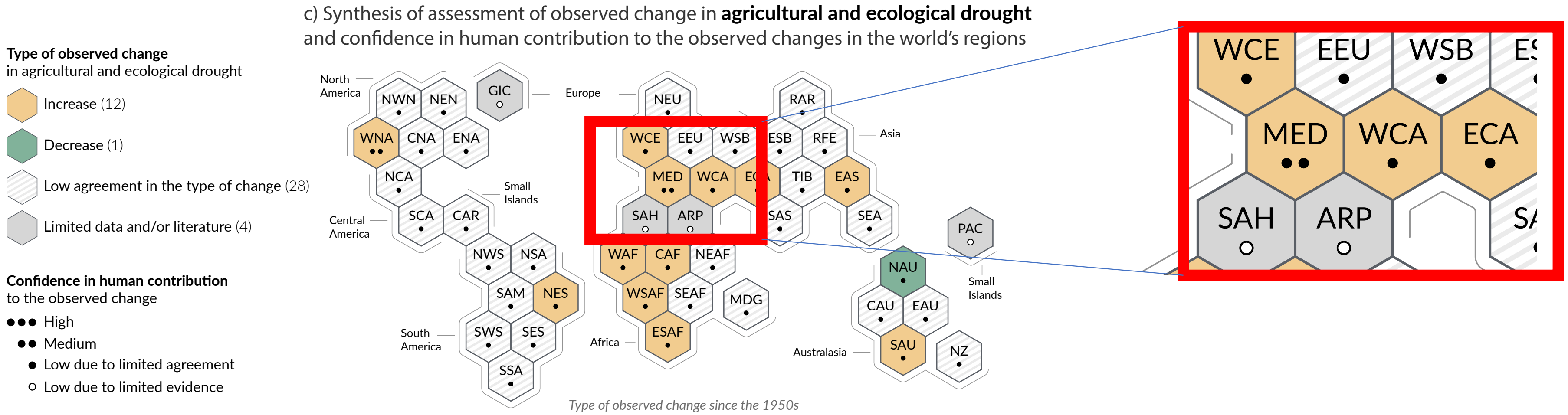
- In terms of attribution, there is no clear cut evidence (yet?) of human induced climate change in drought events



SCHIERMEIER , Nature 2018

Present trends…

- The draft of the 6th IPCC report concludes that:
  - *There is **low confidence** that human influence has affected trends in **meteorological droughts** in most regions, but **medium confidence** that they have contributed to the severity of some specific events. There is **medium confidence** that human-induced climate change has contributed to increasing trends in the probability or intensity of recent agricultural and ecological droughts, leading to an increase of the affected land area. {11.6.4}*



Received: 27 July 2019 | Revised: 26 November 2019 | Accepted: 29 November 2019
DOI: 10.1002/wcc.632

ADVANCED REVIEW

WIREs CLIMATE CHANGE WILEY

Unraveling the influence of atmospheric evaporative demand on drought and its response to climate change

Sergio M. Vicente-Serrano[1] | Tim R. McVicar[2,3] | Diego G. Miralles[4] | Yuting Yang[5] | Miquel Tomas-Burguera[6]

[1]Instituto Pirenaico de Ecología, Spanish National Research Council, Zaragoza, Spain
[2]CSIRO Land and Water, The Australian National University, Canberra, Australian Capital Territory, Australia
[3]Australian Research Council Centre of Excellence for Climate Extremes, The Australian National University, Canberra, Australian Capital Territory, Australia
[4]Laboratory of Hydrology and Water Management, Ghent University, Ghent, Belgium
[5]Department of Hydraulic Engineering, Tsinghua University, Beijing, China
[6]Estación Experimental de Aula Dei, Spanish National Research Council, Zaragoza, Spain

- The main differences relate to how different studies consider and parametrize key biophysical and hydrological processes, and atmospheric variables that contribute to drought severity, among them, arguably the role of the atmospheric evaporative demand (AED) is in the root of the debate.

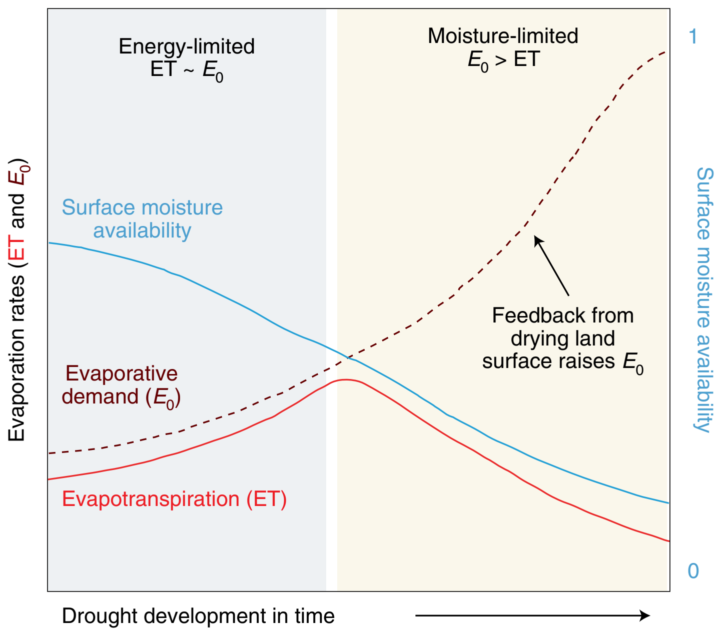


Fig. 3 | The response of evaporative demand and evapotranspiration to feedbacks from drying land. Schematic evolution of evaporative demand (E_0), evapotranspiration (ET) and surface moisture availability, starting from a wet (energy-limited, left side) state, which has enough water for ET to further increase if additional energy is added to the surface, and developing into a dry (water-limited, right side) state. Adapted with

nature climate change
PERSPECTIVE
https://doi.org/10.1038/s41558-020-0709-0
Check for updates

Flash droughts present a new challenge for subseasonal-to-seasonal prediction

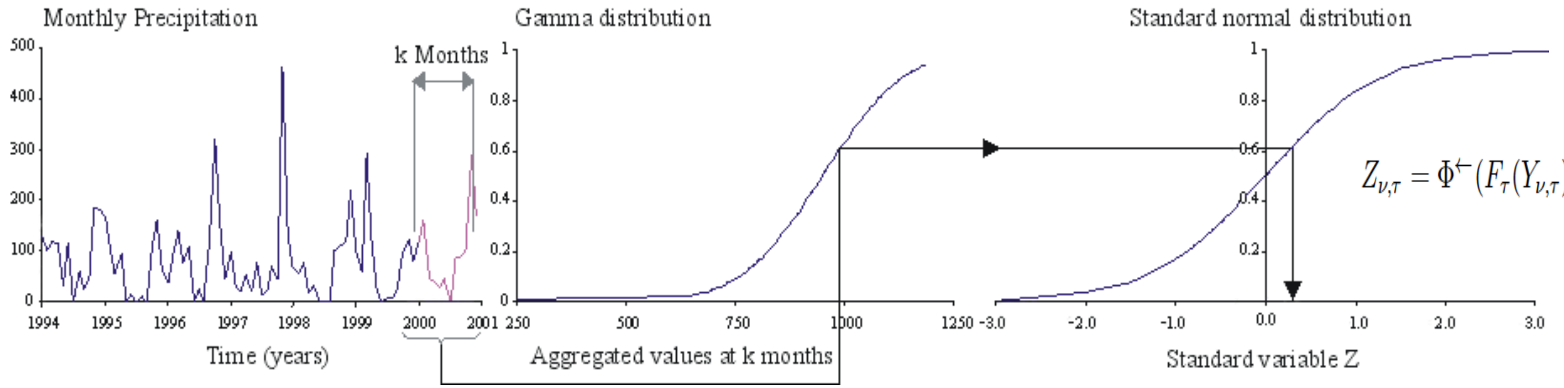
Angeline G. Pendergrass[1]✉, Gerald A. Meehl[1], Roger Pulwarty[2], Mike Hobbins[2,3], Andrew Hoell[2], Amir AghaKouchak[4], Céline J. W. Bonfils[5], Ailie J. E. Gallant[6,7], Martin Hoerling[2], David Hoffmann[6,7], Laurna Kaatz[8], Flavio Lehner[1], Dagmar Llewellyn[9], Philip Mote[10], Richard B. Neale[1], Jonathan T. Overpeck[11], Amanda Sheffield[12], Kerstin Stahl[13], Mark Svoboda[14], Matthew C. Wheeler[15], Andrew W. Wood[1] and Connie A. Woodhouse[16]

Drought indices

- Many (perhaps too many!)
- Differ for the hydrometeorological variable taken into account, time scales of application, standardization of results, etc.
- Measure negative deviations of one hydrological variable (or a a proxy of) with respect to some "normal" level (whatever that is…)
- Standardization of the deviations through a variety of more or less complex procedures, in order to compare drought conditions across different locations and seasons
- Duration, severity, intensity, etc. often making use of run theory (Yevjevich 1967)
- In a non stationary setting, this poses some questions: what is "normal" condition? How to standardize? How to take into account the presence of trends/shifts/cycles?

Standardized indices (*SPI, SPEI and all that*)

- Based on a backward aggregation over *k* time intervals (typically months, weeks) of some hydrological variable (or a proxy of) to reflect water availability in the past *k* intervals
- Such aggregated value is then standardized through an **equiprobability** transformation into a standard normal variable
- In essence, we define **droughts** in terms of **non exceedance probability** of the backward **aggregated values** of the hydrological variable of interest
- Thus, the resulting index is basically structured as a **moving average process** which *generally* exhibits:
  - strong autocorrelation structure (stronger as k increases)
  - apparent cycles, shifts, local trends, etc.

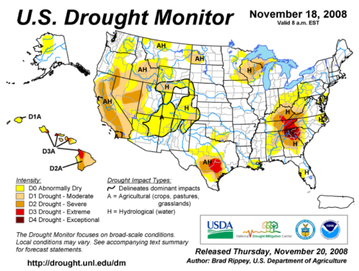


$$Z_{\nu,\tau} = \Phi^{\leftarrow}(F_\tau(Y_{\nu,\tau})) = \Phi^{\leftarrow}(F_\tau(\sum_{i=0}^{k-1} X_{\nu,\tau-i}))$$

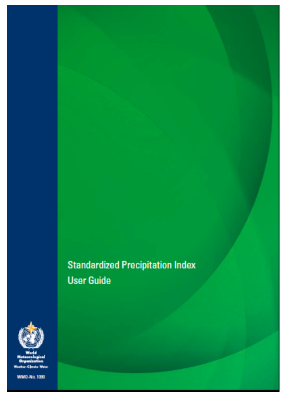
Standardized Precipitation Index

- Resolution 21 of the WMO XVI World Meteorological Congress (2011)

Requests “Members to ensure that all National Meteorological and Hydrological Services around the world use the Standardized Precipitation Index (SPI) to characterize meteorological droughts, in addition to other drought indices that are already in use in their service.”



- WMO Document 1090 “*Standardized Precipitation Index user guide*”, 2012



Stochastic characterization of SPI, SPEI, etc.

- It can be shown that standardized indices exhibit a stochastic structure that is compatible with a Periodic Autoregressive Moving Average process PARMA
- e.g. SPI aggregated precipitation normally distributed and uncorrelated: => PMA(0,*k-1*)

$$Z_{\nu,\tau} = \varepsilon_{\nu,\tau} - \sum_{i=1}^{k-1} \theta_{i,\tau}\varepsilon_{\nu,\tau-i} \qquad \theta_{i,\tau} = \frac{\sigma_{\tau-i}}{\sigma_\tau} \quad \text{with } i = 1,\ldots,k-1$$

- aggregated precipitation normally distributed and correlated: => PARMA(p,*q+k-1*)

k-1+ *q* MA polynomial

$$Z_{\nu,\tau} = \frac{1}{\sigma_\tau(y)} \frac{\Phi^*(B)\Theta_\tau(B)}{\Phi_\tau(B)} \varepsilon_{\nu,\tau}$$

p AR polynomial

- Most importantly, SxxI exhibit strong **autocorrelation !!!**

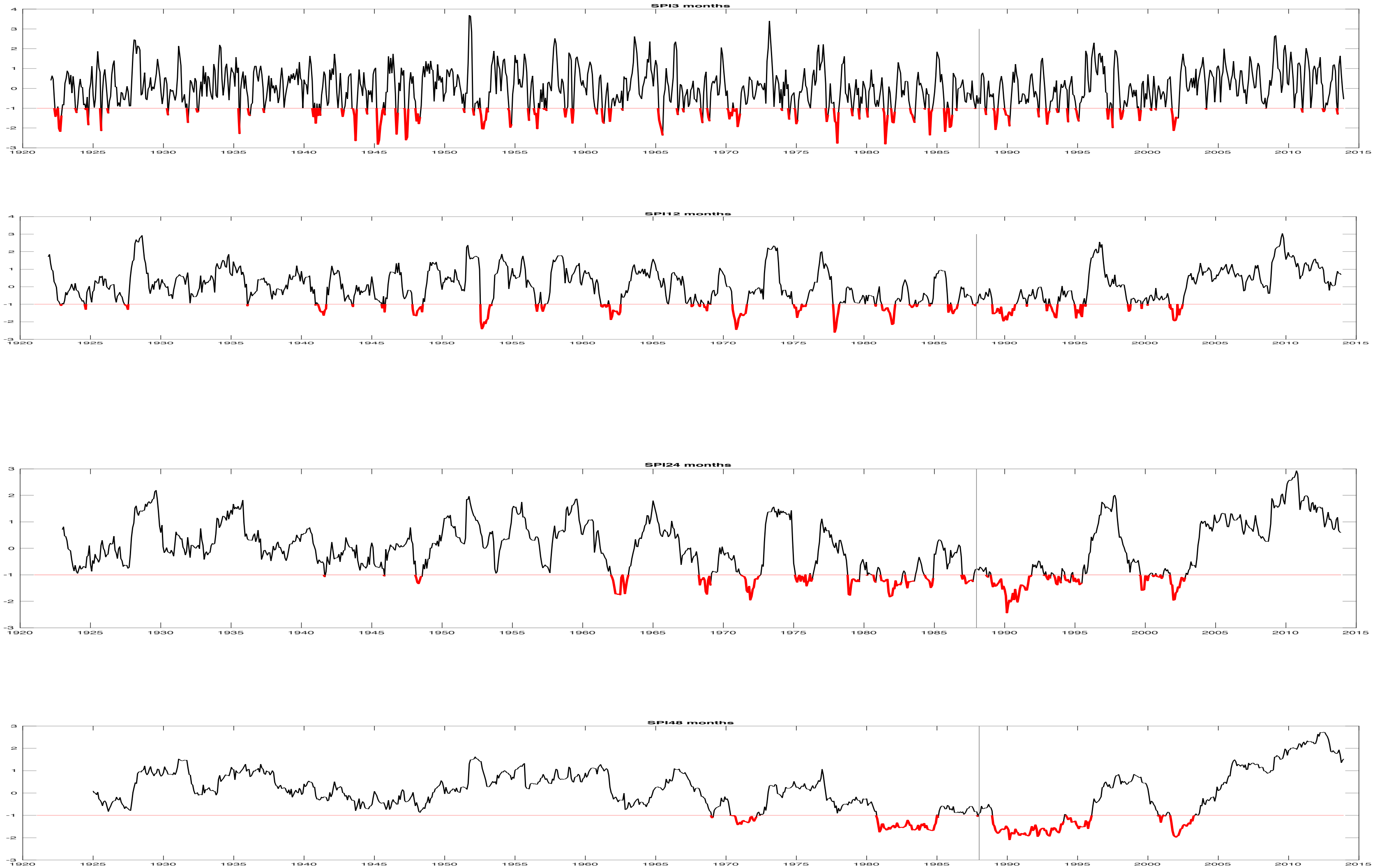
Average precipitation Simeto watershed at Barca (Sicily, Italy)

SPI 3 months

SPI 12 months

SPI 24 months

SPI 48 months



Slutzky (1937), *Econometrica*

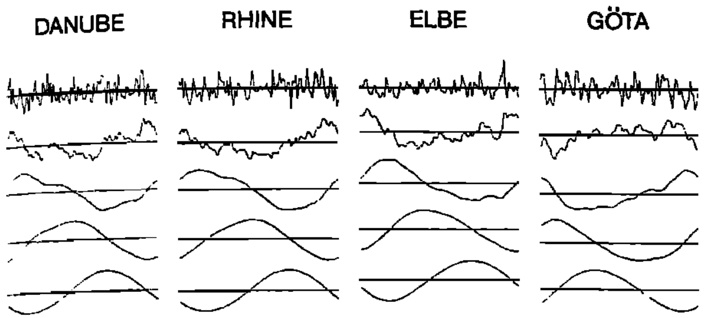
THE SUMMATION OF RANDOM CAUSES AS THE SOURCE OF CYCLIC PROCESSES*

By Eugen Slutzky

I. SCOPE OF THE INVESTIGATION

Almost all of the phenomena of economic life, like many other processes, social, meteorological, and others, occur in sequences of rising and falling movements, like waves. Just as waves following each other on the sea do not repeat each other perfectly, so economic cycles never repeat earlier ones exactly either in duration or in amplitude. Nevertheless, in both cases, it is almost always possible to detect, even in the multitude of individual peculiarities of the phenomena, marks of certain approximate uniformities and regularities. The eye of the

Moran, P. A. P. (1950, April). The oscillatory behaviour of moving averages.
In *Mathematical Proceedings of the Cambridge Philosophical Society*



Klemes and Klemes (1988), *WRR*

WATER RESOURCES RESEARCH, VOL. 24, NO. 1, PAGES 93–104, JANUARY 1988

Cycles in Finite Samples and Cumulative Processes of Higher Orders

Vít Klemeš

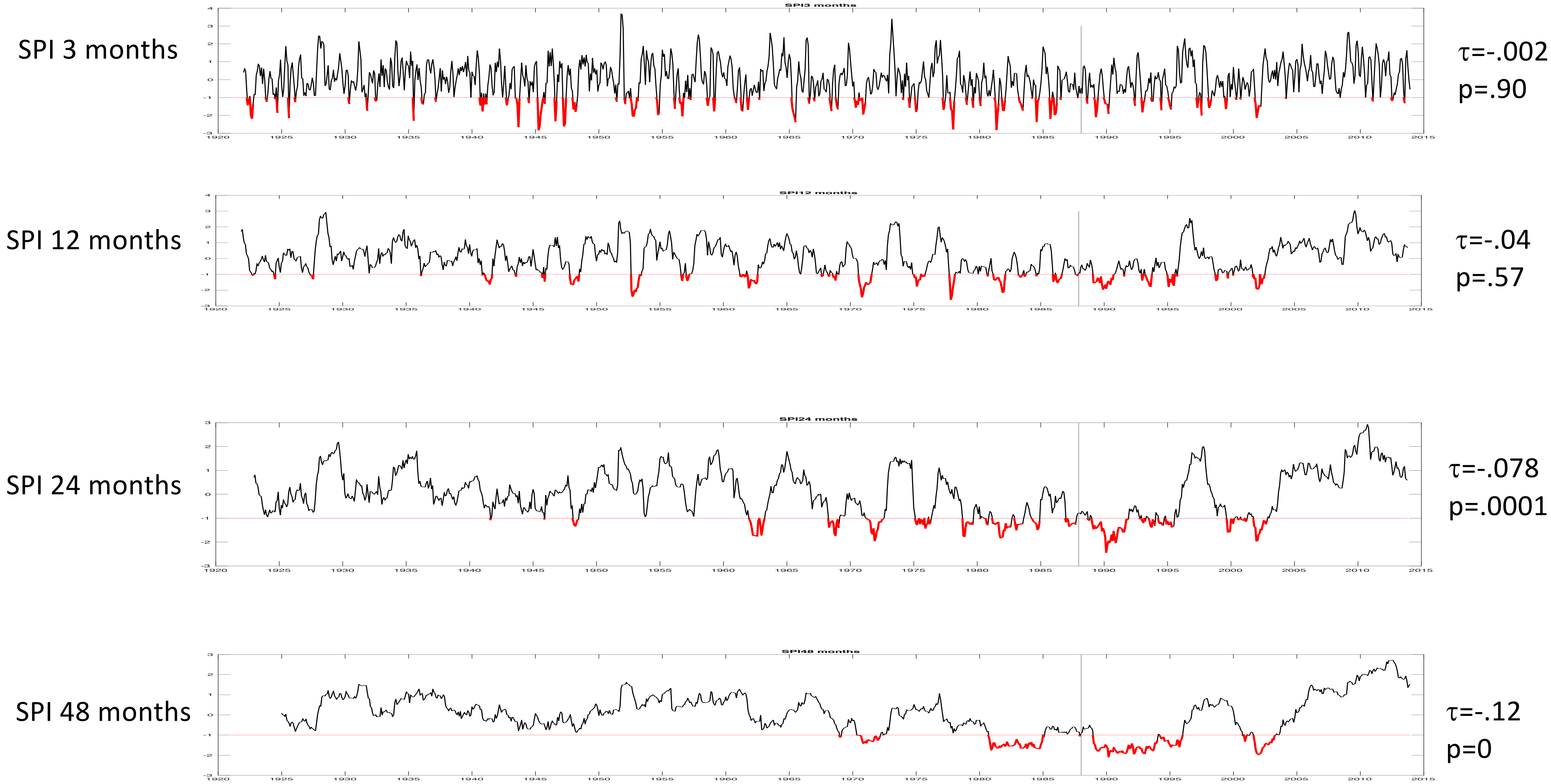
National Hydrology Research Institute, Department of Environment, Saskatoon, Saskatchewan

Ivo Klemeš[1]

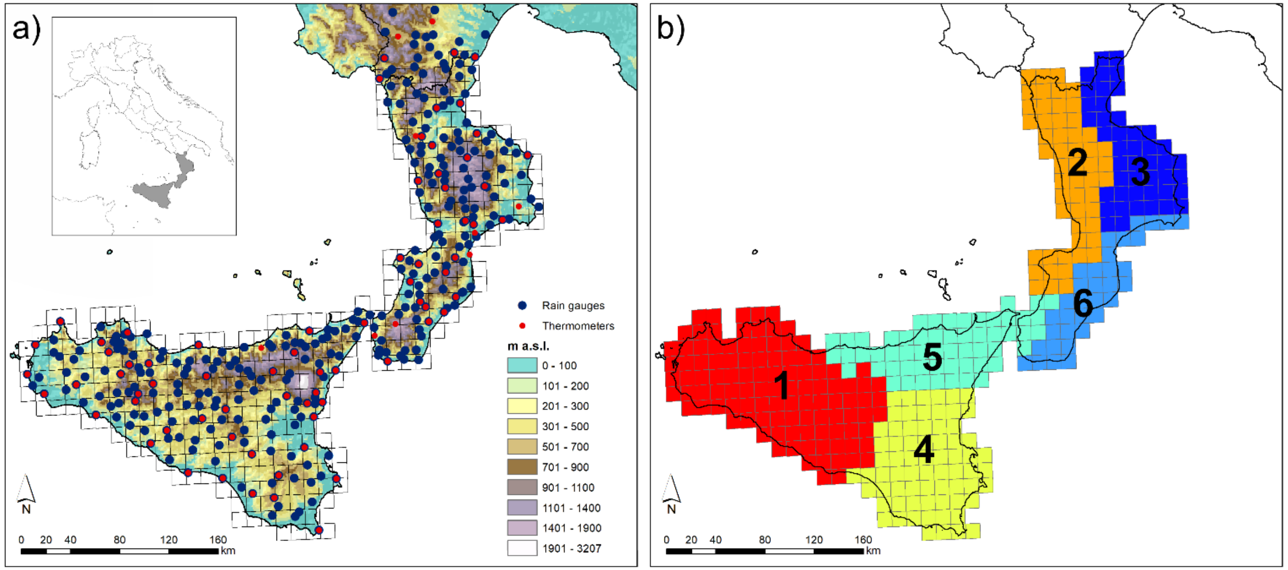
Department of Mathematics, University of British Columbia, Vancouver

The process formed by a sequence of cumulative departures from the mean or from some other constant (residual mass curve, cusum chart) is a popular tool for the representation and analysis of time series in many sciences, for example, in hydrology, climatology, economics, game theory. In these and other natural and social sciences, similar cumulative processes also often arise naturally; examples include fluctuations of storage in a dam with a constant release rate, lake levels, volume of glaciers, biomass, inventories, and bank accounts. Moreover, many natural economic and other phenomena may

Average precipitation Simeto watershed at Barca (Sicily, Italy)



EuroCordex models vs. observations (Southern Italy)



- 84 temperature stations
- 335 precipitation stations
- 19 combinations of GCM-RCM models
- 6 climatic zones identified by PCA

Nat. Hazards Earth Syst. Sci., 20, 3057–3082, 2020
https://doi.org/10.5194/nhess-20-3057-2020

Natural Hazards and Earth System Sciences

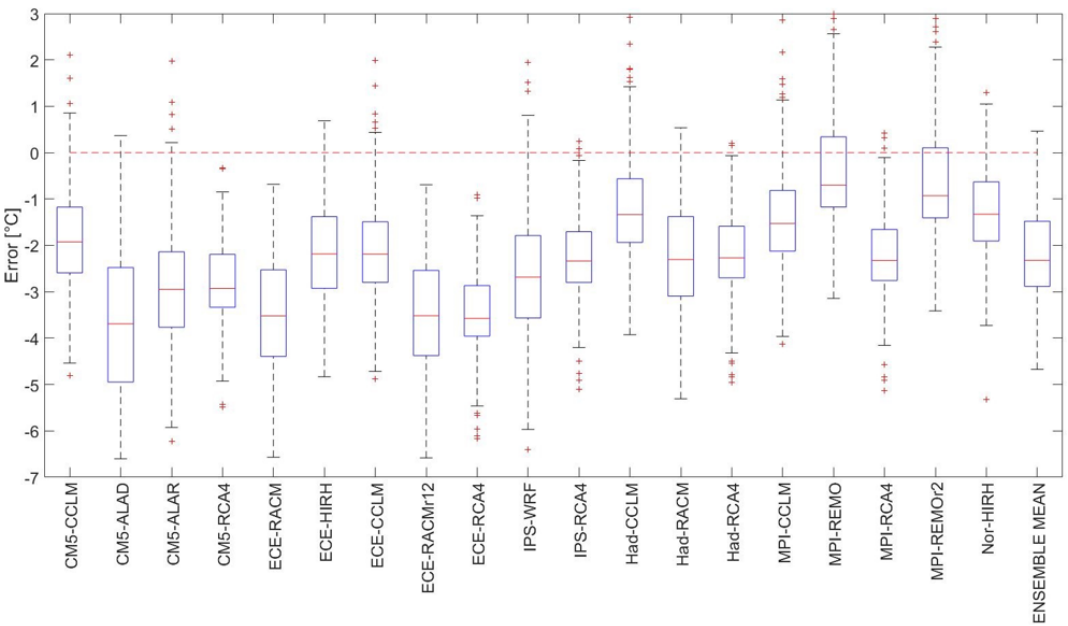
Evaluation of EURO-CORDEX (Coordinated Regional Climate Downscaling Experiment for the Euro-Mediterranean area) historical simulations by high-quality observational datasets in southern Italy: insights on drought assessment

David J. Peres[1], Alfonso Senatore[2], Paola Nanni[1], Antonino Cancelliere[1], Giuseppe Mendicino[2], and Brunella Bonaccorso[3]

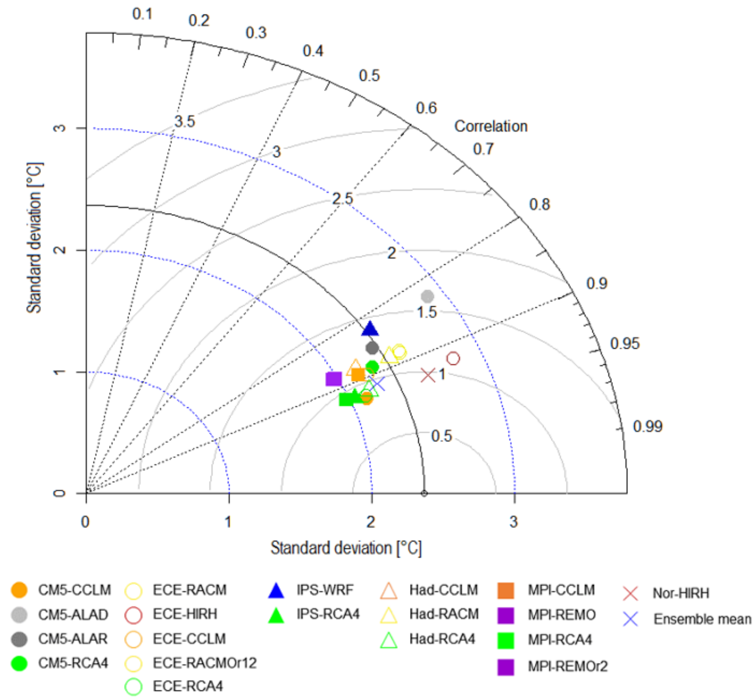
	CNRM-CERFACS-CNRM-CM5	ICHEC-EC-EARTH	IPSL-IPSL-CM5A-MR	MOHC-HadGEM2-ES	MPI-M-MPI-ESM-LR	NCC-NorESM1-M
CNRM-ALADIN53	CM5-ALAD	–	–	–	–	–
RMIB-UGent-ALARO-0	CM5-ALAR	–	–	–	–	–
CLMcom-CCLM4-8-17	CM5-CCLM	ECE-CCLM	–	Had-CCLM	MPI-CCLM	–
DMI-HIRHAM5	–	ECE-HIRH	–	–	–	Nor-HIRH
KNMI-RACMO22E	–	ECE-RACM*	–	Had-RACM	–	–
SMHI-RCA4	CM5-RCA4	ECE-RCA4	IPS-RCA4	Had-RCA4	MPI-RCA4	–
MPI-CSC-REMO2009	–	–	–	–	MPI-REMO*	–
IPSL-INERIS-WRF331F	–	–	IPS-WRF	–	–	–

Results – Air temperature

- Annual variability: the overall tendency of the models is to underestimate temperatures as the medians are negative. Errors are predominantly between the values -5 and -1°C, thus implying that the models underestimate up to 5°C.



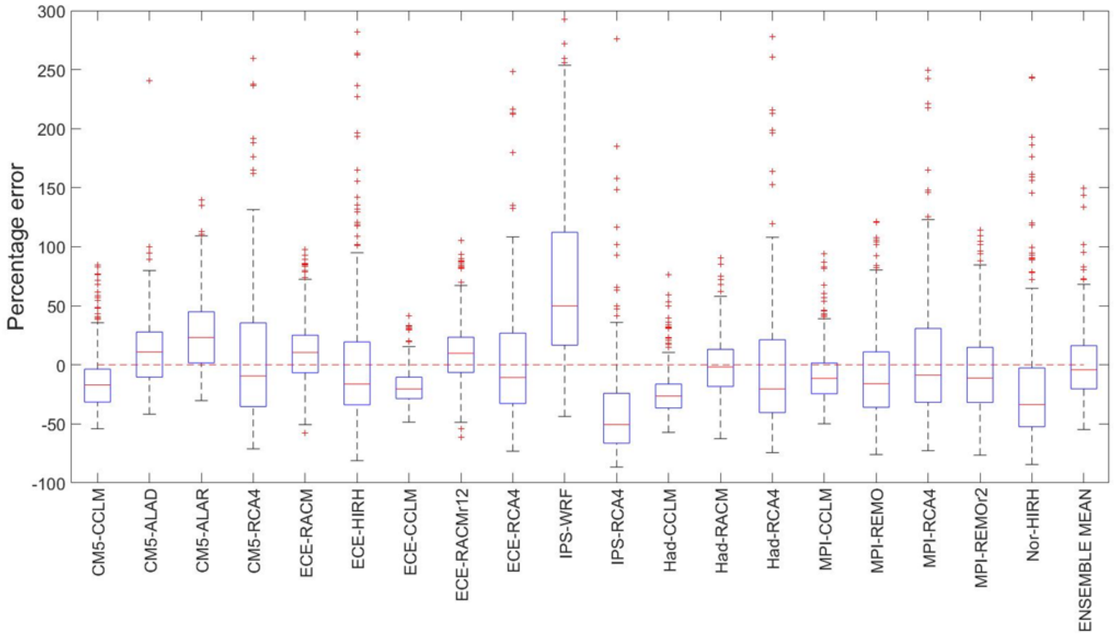
a)



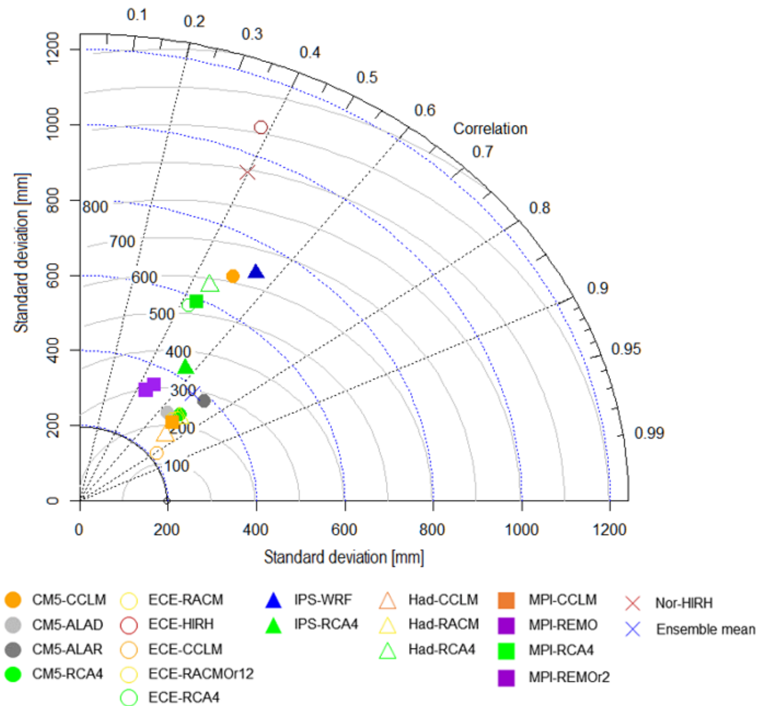
b)

Results - Precipitation

- Annual variability: Had-RACM and ECE-CCLM as the best combinations for the entire area. CM5-ALAD works well for the whole area. IPS-WRF, IPS-RCA4, Nor-HIR, and CM5-RCA4 are the worst models.

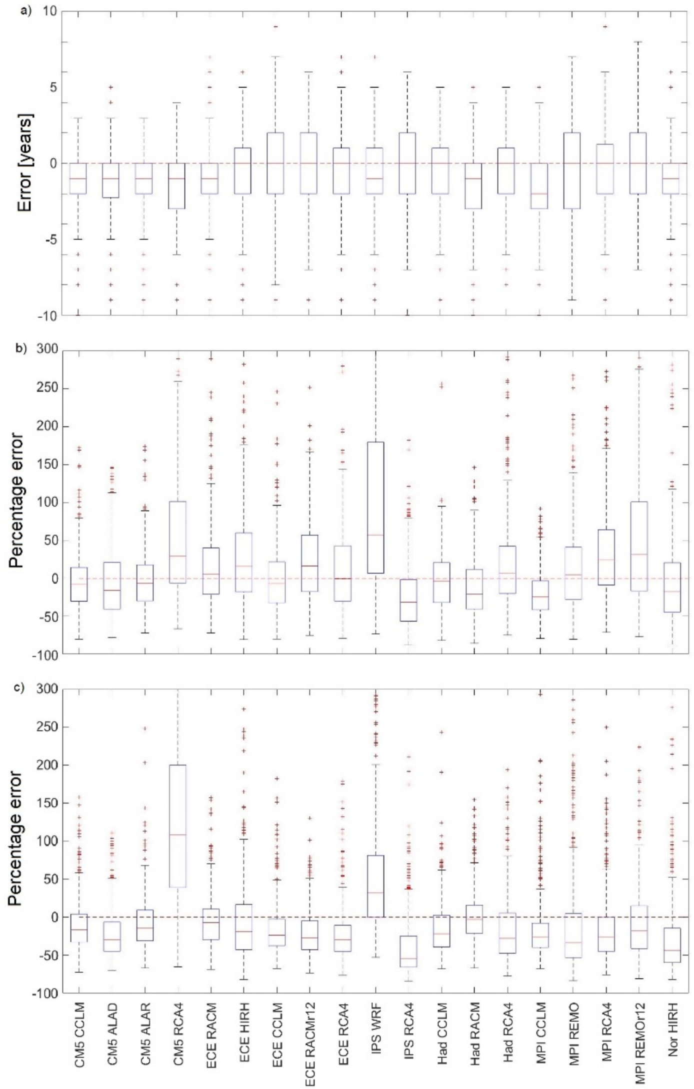


a)



b)

Results – Drought characteristics

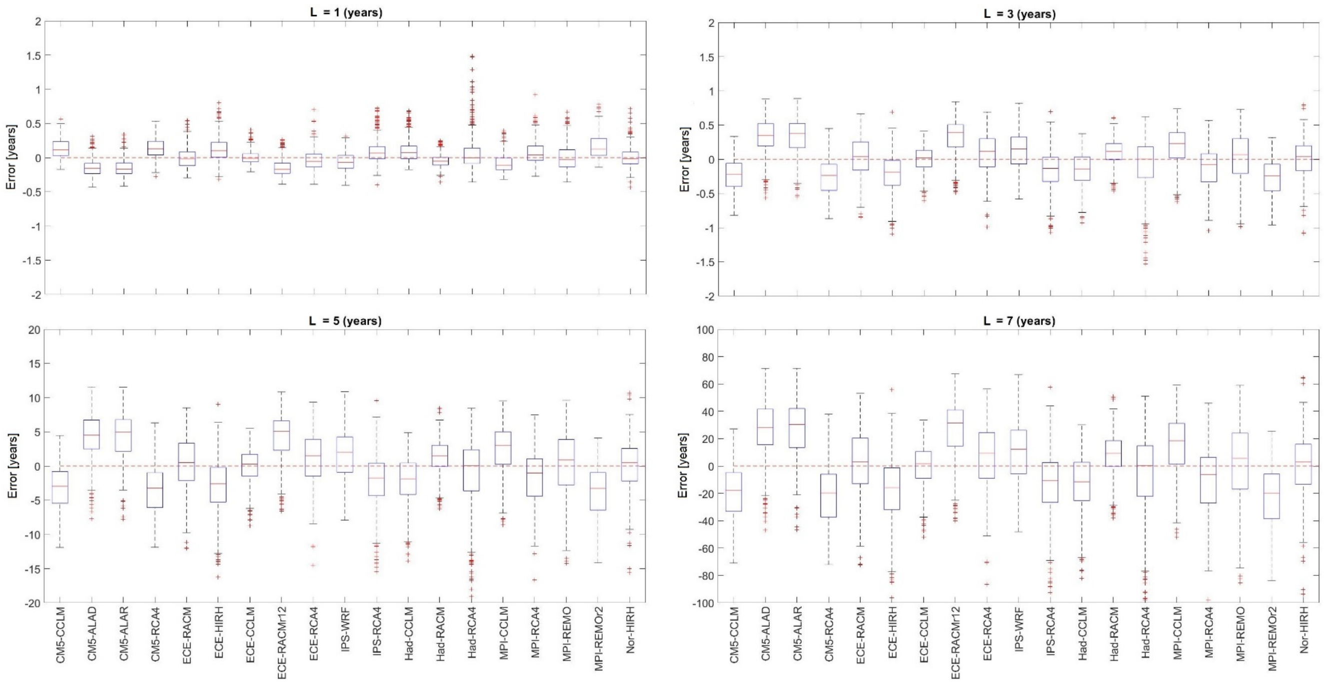


Maximum duration

Maximum accumulated deficit

Maximum intensity

Results – Drought characteristics



Ranking of GCM-RCM models

$$\varepsilon_m = \sqrt{\sum_{k=1}^{S}\left(\frac{\sum_{j=1}^{P} E_{k,m}(j)}{\sum_{m=1}^{M}\sum_{j=1}^{P} E_{k,m}(j)}\right)^2},$$

Annual mean temperature

	Total Area	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6
CM5-CCLM	6	7	7	4	6	5	6
CM5-ALAD	19	18	19	19	17	17	18
CM5-ALAR	14	15	13	15	13	13	15
CM5-RCA4	15	14	14	12	16	15	13
ECE-RACM	16	16	15	17	14	14	16
ECE-HIRH	10	10	11	9	10	9	10
ECE-CCLM	8	8	8	8	7	8	9
ECE-RACMr12	18	19	18	18	18	18	19
ECE-RCA4	17	17	17	16	19	19	17
IPS-WRF	12	13	12	14	12	6	11
IPS-RCA4	4	5	4	1	4	7	1
Had-CCLM	3	2	3	3	3	4	5
Had-RACM	11	11	10	11	9	10	12
Had-RCA4	7	6	6	5	8	11	8
MPI-CCLM	1	3	1	2	1	1	3
MPI-REMO	2	1	2	6	2	2	2
MPI-RCA4	9	9	9	7	11	12	7
MPI-REMOr2	5	4	5	10	5	3	4
Nor-HIRH	13	12	16	13	15	16	14

Annual mean precipitation

	Total Area	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6
CM5-CCLM	7	2	12	4	6	9	4
CM5-ALAD	3	5	4	5	11	2	1
CM5-ALAR	9	13	3	9	4	7	12
CM5-RCA4	17	16	14	16	15	18	19
ECE-RACM	5	3	1	14	8	5	8
ECE-HIRH	15	11	13	15	18	17	18
ECE-CCLM	2	4	6	1	1	1	6
ECE-RACMr12	4	6	5	6	5	4	3
ECE-RCA4	11	9	10	12	14	11	11
IPS-WRF	19	19	19	11	12	19	15
IPS-RCA4	16	18	17	19	17	10	14
Had-CCLM	6	8	7	2	3	6	7
Had-RACM	1	1	2	3	2	3	2
Had-RCA4	14	12	15	17	16	14	17
MPI-CCLM	8	7	9	8	7	8	5
MPI-REMO	12	14	16	10	9	15	9
MPI-RCA4	13	10	8	13	13	12	13
MPI-REMOr2	10	15	11	7	10	13	10
Nor-HIRH	18	17	18	18	19	16	16

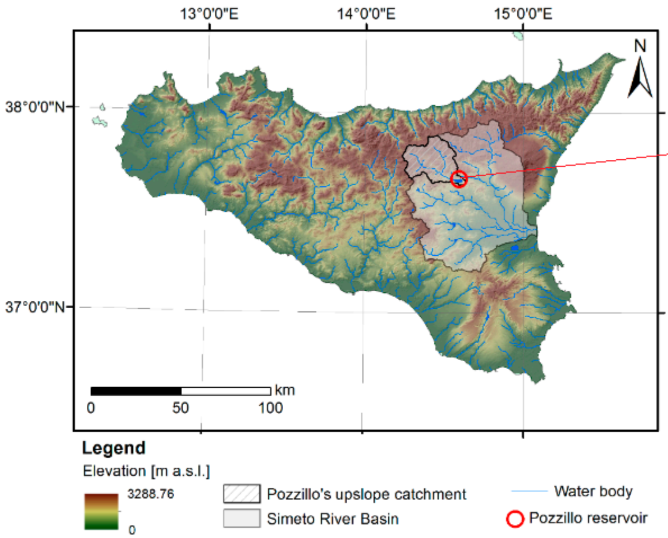
Drought characteristics

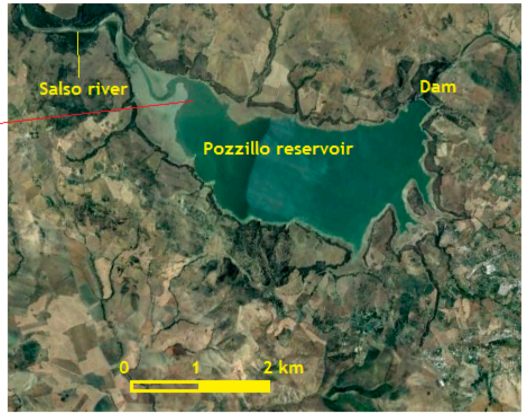
	Total Area	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6
CM5-CCLM	5	3	5	10	13	12	6
CM5-ALAD	16	16	17	6	14	8	10
CM5-ALAR	15	17	16	1	8	9	13
CM5-RCA4	19	19	19	19	19	19	19
ECE-RACM	3	11	2	13	2	1	7
ECE-HIRH	12	8	9	14	17	14	17
ECE-CCLM	1	1	4	3	3	2	1
ECE-RACMr12	17	18	18	4	6	15	4
ECE-RCA4	6	9	11	9	5	10	9
IPS-WRF	18	12	14	7	10	18	12
IPS-RCA4	13	14	12	17	16	11	8
Had-CCLM	4	4	3	11	15	4	5
Had-RACM	2	2	1	2	1	3	3
Had-RCA4	9	6	6	18	9	6	15
MPI-CCLM	7	15	15	5	4	7	2
MPI-REMO	14	7	8	8	12	17	16
MPI-RCA4	8	13	7	16	7	5	11
MPI-REMOr2	11	5	13	12	18	16	18
Nor-HIRH	10	10	10	15	11	13	14

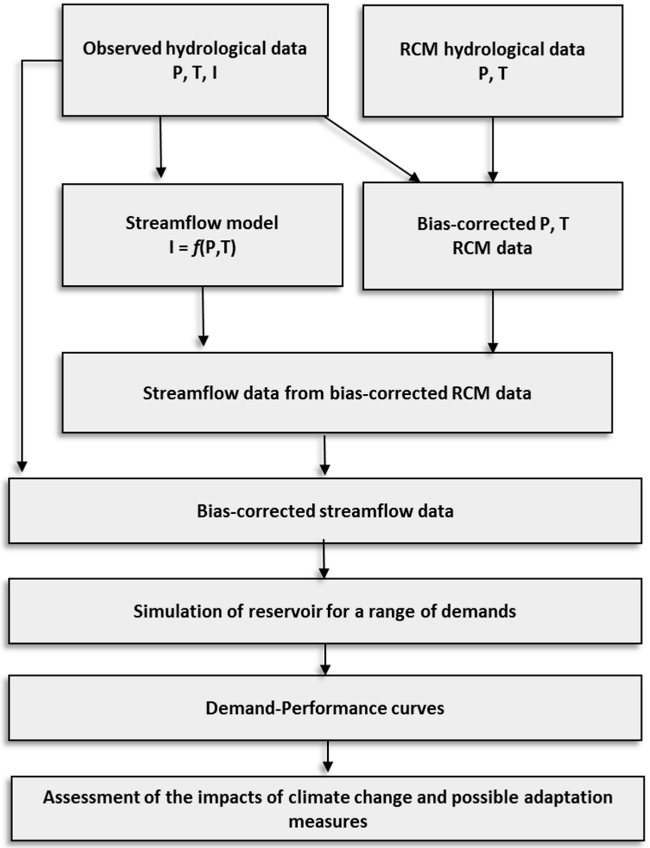
Article

Assessing Future Impacts of Climate Change on Water Supply System Performance: Application to the Pozzillo Reservoir in Sicily, Italy

David J. Peres *, Rosario Modica † and Antonino Cancelliere







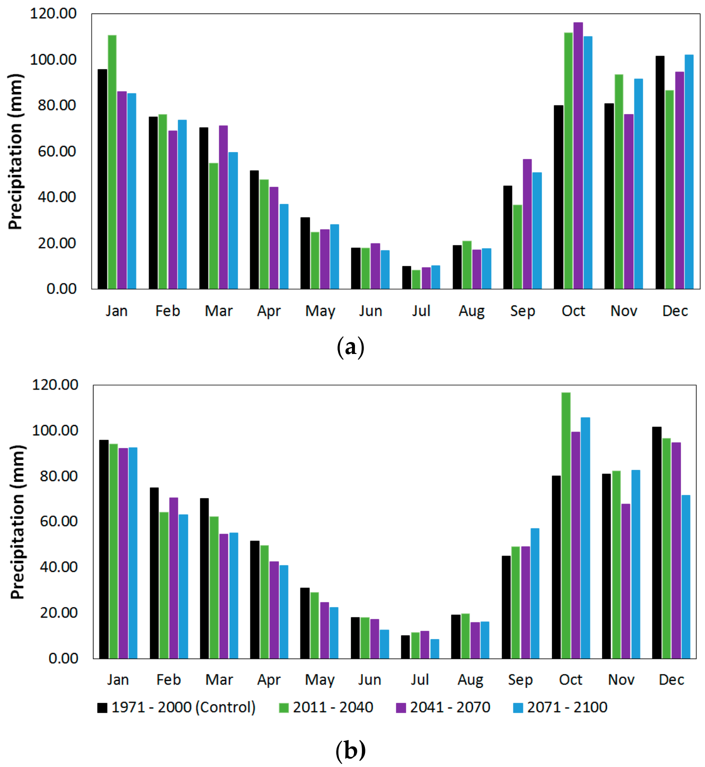


Figure 4. Future vs. control mean monthly precipitation for two climate change scenarios: (**a**) RCP4.5 and (**b**) RCP8.5.

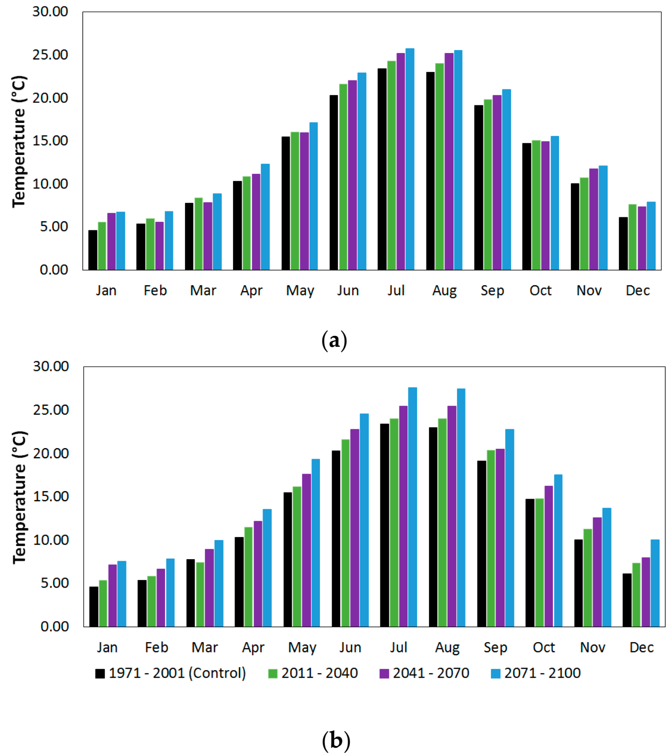


Figure 5. Future vs. control mean monthly temperature for two climate change scenarios: (**a**) RCP4 and (**b**) RCP8.5.

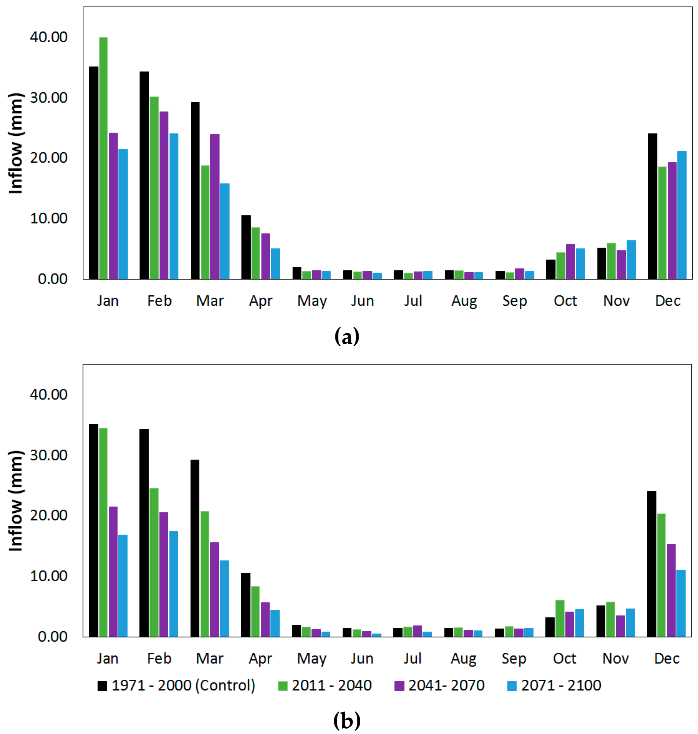


Figure 6. Future vs. control mean monthly reservoir inflow for two climate change scenarios: (**a**) RCP4.5 and (**b**) RCP8.5.

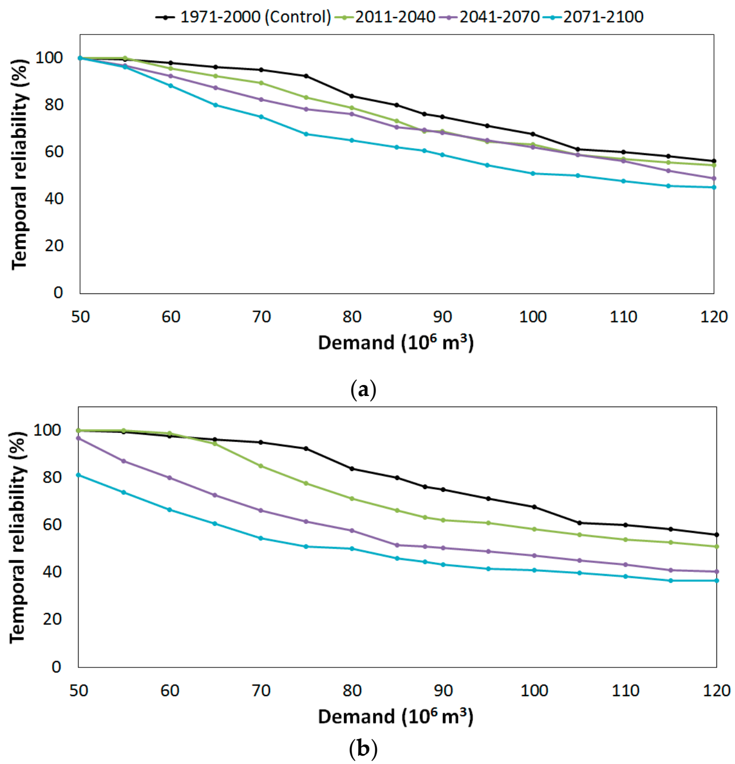


Figure 7. Future vs. control mean monthly Pozzillo's reservoir temporal reliability for two climate change scenarios: (**a**) RCP4.5 and (**b**) RCP8.5.

Table 3. Future demands corresponding to the performances in the control period. In brackets, the variations respect to the demand in the control period. Values in bold indicate maximum negative variations.

Period	$D(R_T)$ (hm^3)		$D(R_V)$ (hm^3)		$D(I_B)$ (hm^3)	
	RCP4.5	RCP8.5	RCP4.5	RCP8.5	RCP4.5	RCP8.5
2011–2040	82.5 (−6.3%)	**76.3 (−13.4%)**	**78.0 (−11.3%)**	77.4 (−12.0%)	78.7 (−10.5%)	77.1 (−12.4%)
2041–2070	80.0 (−9.1%)	62.7 (−28.8%)	**73.8 (−16.2%)**	**60.9 (−30.8%)**	75.8 (−13.9%)	62.0 (−29.5%)
2071–2100	68.9 (−21.7%)	53.5 (−39.2%)	**67.8 (−23.0%)**	**49.2 (−44.1%)**	68.2 (−22.4%)	50.0 (−43.2%)

Conclusive remarks

- No strong evidence of changes in drought characteristics at global scale
- Some hot spots (including Mediterranean area)
- Care should be exercised when analysing standardized drought indices
- Preliminary screening of GCM-RCM models can help to reduce uncertainty (or perhaps lose confidence on them….)