CEST 2017

15th International Conference on Environmental Science and Technology

Rhodes, Greece, 31 August to 2 September 2017

What is the optimum ensemble range of hydro-climatic simulations for impact modeling studies?

PECHLIVANIDIS I.G.[1*], GUPTA H.V.[2] and BOSSHARD T.[1]

[1] Swedish Meteorological and Hydrological Institute (SMHI), Norrköping, Sweden
[2] Department of Hydrology and Water Resources, University of Arizona, Tucson, Arizona, USA

*corresponding author
e-mail: ilias.pechlivanidis@smhi.se

Abstract.
Climate projections are associated with uncertainties both on the global and the regional scale, which are related to the different configurations of the modeling chain. Although a combination of numerous projections is usually needed to quantify the total uncertainty, practical impact modeling investigations can only handle a limited number of scenario combinations. Given the fact that all climate projections are subject to considerable uncertainty, it is crucial to know a representative, with regard to the information content, subset in an available ensemble. Here we propose a framework rooted in the concepts of information theory to identify a representative subset from a larger ensemble of climate projections. The Maximum Information Minimum Redundancy (MIMR) concept is used to identify the representative subset. The analysis is based on an ensemble of 16 climate projections for precipitation and temperature for the entire Sweden. The projections were further used to force the HBV hydrological model and simulate river discharge until the end of the 21st century. We identify the representative subsets for different statistical characteristics for precipitation, temperature and discharge and assess the sensitivity of the identification at different regions, seasons and future periods. Results show that a subset of 20-35% of the total available projections can represent a large fraction of the ensemble range of hydro-climatic changes highlighting the information redundancy in large model ensembles. Finally, the identified subsets are sensitive to the choice of variables, seasons and future periods, whilst the identification should not be solely based on climatic variables but rather consider hydrological information as well.

Keywords: Representative projections, information theory, climate change impacts, maximum information minimum redundancy

1. Introduction

The global climate change phenomenon is expected to have a strong impact on water resources at local, regional and global scales (Krysanova et al., 2017). Due to the inherent uncertainty of climate projections, projecting climate impacts on hydrological processes is often prone to considerable uncertainties (Pechlivanidis et al., 2017). Uncertainty about the future conditions is commonly described via a large ensemble of projections. Nevertheless, due to practical problems, the designing of impact modeling experiments can only make use of a low number of climate projections; limited available resources and communication of uncertainty between data providers (i.e. modelers) and users (i.e. water managers) are couple of the most common practical problems. It is hence apparent to derive methods and tools for the identification of optimised informative subsets of future conditions from a large available set of projections (Knutti and Sedláček, 2012).

Selecting optimized (in terms of information content) subsets from a large number of projections is not a straightforward task. Ideally, the optimized subset should maximize the diversity of modeled changes from the large available ensemble, and hence overcome artifacts by using a biased subset unable to represent the uncertainty in essential climate variables.

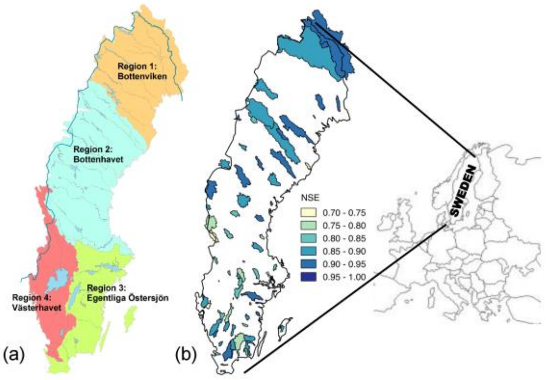

Figure 1. a) Sweden and its four climate regions, and b) NSE performance for the HBV model.

2. Study Area and Methods

The analysis was conducted in Sweden (450,000 km^2) which can be divided into four regions (Fig. 1) based on similarities in climate and morphology (Arheimer and Lindström, 2015). Here, we used 16 projections for precipitation, temperature and discharge, which differ in terms of emission scenarios (3 in total), GCMs (5), and RCMs (6) (see Table 1). Precipitation and temperature were firstly bias-adjusted applying the DBS method (Yang et al., 2010) against Sweden’s observation gridded (4x4 km) dataset for the 1981-2010 period. The HBV model (Lindström et al., 1997) was used to project discharge for the period 1981-2100. The model has a Nash-Sutcliffe Efficiency (NSE) greater than 0.70 at all 69 selected indicator basins (Fig. 1b).

In order to identify the optimum subset, we address this problem in a multi-objective optimization approach, in which redundant information from the subset should be minimized whilst its total information should be maximized. This concept has been named as Maximum Information Minimum Redundancy (MIMR) (Li et al., 2012).

Here we assess the information content of subsets in seasonal and annual scales and for the different variables of interest. The relative changes are the differences between the same statistics of the early (2036-2065) and mid (2056-2085) century, and the present period (1981-2010).

3. Results and Conclusions

The 16 available projections differ in terms of their information content and mutual information when paired, yet though a projection being informative for a single variable this does not necessarily ensure high information content for the other variables. We identified redundant information in the large ensemble and therefore, following the MIMR approach, we next sorted the hydro-climatic projections based on their importance/contribution to the total information of the available set. Fig. 2 shows that it is not straightforward to select a consistent subset, which is optimum for the selected variables, future periods and seasons. In particular, 80% of the total information seems to always be represented by a different optimum subset, highlighting the pre-requirement of a user driven objective to guide the selection procedure.

We next highlight the need to consider hydrological information in the selection procedure and not having it solely based on climatic variables. The pattern of identified projections contributing to a represention of more than 80% of the total information from the available set (red dots in Fig. 2) differs between precipitation, temperature and discharge.

The MIMR approach resulted in a representative subset which includes two emission scenarios, three GCMs and 3 RCMs, highlighting the general presence of redundant information in the setups and structure of the climate models.

Table 1. Climate projections used, with a 50x50 and 25x25 km spatial resolution for (*) and (**) RCMs respectively.

ID	Emission scenario	GCM	RCM (Resolution)
1	A1B	ECHAM5r1	SMHI-RCA3 (*)
2	A1B	ECHAM5r2	SMHI-RCA3 (*)
3	A1B	ECHAM5r3	SMHI-RCA3 (*)
4	A1B	ECHAM5r3	SMHI-RCA3 (**)
5	B1	ECHAM5r1	SMHI-RCA3 (*)
6	A1B	ARPEGE	SMHI-RCA3 (*)
7	A1B	CCSM3	SMHI-RCA3 (*)
8	A1B	ARPEGE	ALADIN (**)
9	A1B	ECHAM5r3	KNMI-RACMO (**)
10	A1B	ECHAM5r3	REMO (**)
11	A2	ECHAM5r3	SMHI-RCA3-C4I (**)
12	A1B	HadCM3Q0	HadRM3 (**)
13	A1B	HadCM3Q16	SMHI-RCA3-C4I (**)
14	A1B	BCM	DMI-HIRHAM (**)
15	A1B	HadCM3Q0	DMI-HIRHAM (**)
16	A1B	ECHAM5r3	DMI-HIRHAM (**)

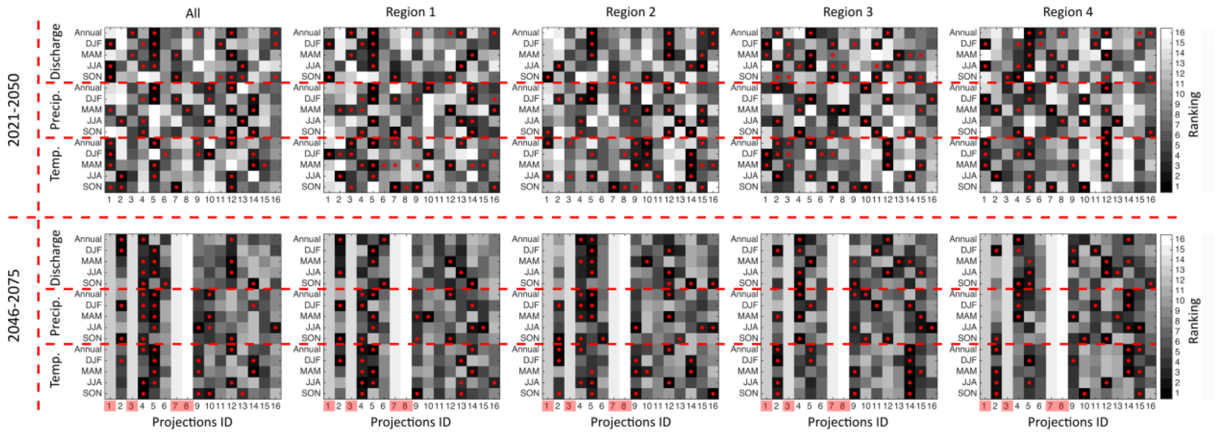

Figure 2. Ranking of simulations using the MIMR approach (16 being the least important) for different periods of interest, variables, seasons, and regions. Note that the projections highlighted with pink color are not available for the mid-century.

References

Arheimer, B., Lindström, G., 2015. Climate impact on floods – changes of high-flows in Sweden for the past and future (1911–2100). Hydrol. Earth Syst. Sci. 19, 771–784. doi:10.5194/hess-19-771-2015

Knutti, R., Sedláček, J., 2012. Robustness and uncertainties in the new CMIP5 climate model projections. Nat. Clim. Chang. 3, 369–373. doi:10.1038/nclimate1716

Krysanova, V., Vetter, T., Eisner, S., Huang, S., Pechlivanidis, I.G., Strauch, M., Aich, V., Arheimer, B., Chamorro, A., Gelfan, A., van Griensven, A., Kumar, R., Kundu, D., Lobanova, A., Mishra, V., Plötner, S., Reinhardt, J., Seidou, O., Wang, X., Wortmann, M., Zeng, X., Hattermann, F.F., 2017. Intercomparison of regional-scale hydrological models in the present and future climate for 12 large river basins worldwide - A synthesis. Environ. Res. Lett. 12, 105002. doi:10.1088/1748-9326/aa8359

Li, C., Singh, V.P., Mishra, A.K., 2012. Entropy theory-based criterion for hydrometric network evaluation and design: Maximum information minimum redundancy. Water Resour. Res. 48, WR011251. doi:10.1029/2011WR011251

Lindström, G., Johansson, B., Persson, M., Gardelin, M., Bergström, S., 1997. Development and test of the distributed HBV-96 hydrological model. J. Hydrol. 201, 272–288.

Pechlivanidis, I.G., Arheimer, B., Donnelly, C., Hundecha, Y., Huang, S., Aich, V., Samaniego, L., Eisner, S., Shi, P., 2017. Analysis of hydrological extremes at different hydro-climatic regimes under present and future conditions. Clim. Change 141, 467–481. doi:10.1007/s10584-016-1723-0

Yang, W., Andréasson, J., Graham, P.L., Olsson, J., Rosberg, J., Wetterhall, F., 2010. Distribution-based scaling to improve usability of regional climate model projections for hydrological climate change impacts studies. Hydrol. Res. 41, 211–229. doi:10.2166/nh.2010.004