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CLIPC DELIVERABLE (D -N°: 6.3)

Future Tier-1 Climate Change Impact Indicator (CCII-T1) scenarios for Europe together with an assessment of CCII-T1 uncertainties and the developed representative reduced ensemble of future CCII-T1. Documented dataset.

Dissemination level: PU (public)

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Abstract

This report summarises work on transforming regional climate projections to Tier-1 climate change impact indicators (CCII T-1), as well as assessing the robustness of ensemble information and provide a method for subsampling ensemble data when necessary. Focus is on a creating a data set of CCII T-1s for use in the CLIPC prototype portal, as well as developing methods for and calculation of Tier-1 indicators and finding reduced ensembles. Expectations and requirements regarding climate data and information are different for different users and applications, and users' capacity to process climate data varies. We therefore focus on delivering flexible methods and tools. With the dual aim of testing the performance of the methods and tools and showcasing their applicability we have applied them in a series of case studies.

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CAPACITIES

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Executive Summary

This report documents the work on producing climate data that is focussing more on the needs of the impacts communities. The work has progressed along two main lines. Firstly, the development of methods and tools for processing the basic meteorological variables, like precipitation and temperature, to produce various impact-oriented measures or Tier-1 Climate Change Impact Indicators (CCII's). Tier-1 indicators are those that can be calculated from climate data only (i.e. commonly available data about the physical climate system). In the second line of work we have developed and applied a procedure for finding reduced representative ensembles.

The work on CCII-T1 has produced three main results: i) work towards a community standard (extending outside CLIPC) for metadata description of Tier-1 indicators. This work has been done in close collaboration with WP5, where the WP6 part concerns aspects that are closely related to the processing of the data. ii) a substantially extended and an updated processing tool, that also handles the stable components of the draft metadata standard. iii) production of a considerable ensemble of Tier-1 indicators, based on unadjusted as well as bias-adjusted regional projections and representing both RCP4.5 and RCP8.5. This ensemble is now available through the CLIPC portal.

At an early stage in the work on reduced ensembles it became clear, not least from interaction with stakeholders, that the requirements were so diverse so that it was not possible to develop one ensemble that would fit all purposes. Instead, we developed a tool that would be flexible enough to allow production of reduced ensembles tailored to the specific needs and applications. The procedure was tested in a range of different case studies. Assessment of the ensemble spread (aka 'uncertainty') were partly hampered by the fact that the ensembles of regional projections were rather small (about 10 members) and further reduced to 2-5 members only. We have applied the climate signal map approach to assessing the robustness of the full input ensemble, but this method is not applicable to smaller ensemble sizes. An objective method for assessing the robustness of such small ensemble sizes is presently not available.

This result highlights the fundamental guideline to avoid as far as possible to reduce the available ensemble size. While reducing the ensemble likely will reduce the calculated spread of the ensemble, it will not reduce the underlying uncertainty as such, only make it less visible and thus reduce the information regarding robustness of the results. Sometimes however the circumstances dictate that it is impossible to make use of the full ensemble, in which case the ensemble reduction method may provide a way forward.

1. Introduction

Tier-1 climate change impact indicators (CCII T-1) have a long history both in applications related to climate impacts, and as diagnostic measure of climate and climate change. They are commonly known as "climate indices". There is almost infinite possibilities to define specific indices, but the overall aim is to summarise climate data in a way that focusses on some specific sector, application or impact, rather than presenting general information about the average climate, or similar. Over the time there has been some convergence to define "core sets of indices". In particular two international expert teams have worked to standardise the set of climate indices. One is the joint CCl/WCRP/JCOMM Expert Team on Climate Change Detection and Indices, ETCCDI[1], the other one is the WMO/CCl Expert Team on Sector-specific Climate Indices, ET-SCI[2]. Both expert teams have published dictionaries of core climate indices, which partly overlap and complement each other. In this report we summarise the work on developing methods and a versatile tools used to in the production of a substantial ensemble of Tier-1 indicators.

For each generation of climate models and coordinated modelling experiments the total volume of climate projection data increases dramatically, now reaching several petabytes. The fundamental reason for this is the scientific quest within the climate modelling community to quantify the so-called uncertainty which is related to various modelling limitations, as well as the need to map out alternative future emission pathways and the fundamental uncertainty in the future development of the world. The well-established approach to analyse such huge multi-factor ensembles of projection data is to collect related projections into an ensemble and calculate statistics across the ensemble members, e.g. the ensemble average and ensemble spread. In particular, the spread carries information on the robustness of the ensemble mean, i.e. degree of agreement between the individual ensemble members. Essentially, the larger the ensemble is, the more representative the mean and spread becomes.

However, sometimes it is not possible to make use of the full ensemble that is available. The question then arises how best to select a reduced ensemble that still conveys as much as possible of the information available in the full ensemble. The ensemble reduction method described in this report provides an objective approach for answering this question.

2. Data and Methods

2.1. Overview of regional projections for Europe

CLIPC Deliverable D6.1[3] provides a general overview of Representative Concentration Pathway scenarios, global and regional climate projections. Here we focus on an overview of available datasets to serve as 'full' (input) ensembles to the ensemble reduction procedure. While the CMIP5 database of global projections is sizeable, the ensemble of dynamically downscaled projections is

[1] <http://www.wcrp-climate.org/unifying-themes/unifying-themes-observations/data-etccdi> (retrieved 2016-10-12)

[2] <http://www.wmo.int/pages/prog/wcp/ccl/opace/opace4/ET-SCI-4-1.php> (retrieved 2016-10-12)

[3] http://www.clipc.eu/content/content.php?htm=45(retrieved 2016-10-14)

comparatively very limited (Table 1). This is the real world situation with an imperfect and imbalanced RCM-GCM matrix resulting in a limited ensemble of opportunity. The reason for this is that only for a limited number of CMIP5 simulations the data necessary for performing dynamical downscaling were saved. For the Euro-CORDEX domain at least one regional projection is available for all possible global projections, i.e. for all global projections for which data required for dynamical downscaling is available. For the purpose of the prototype portal various sub-ensembles have been used in WP6. The details are provided in the relevant chapters, and Table 1 serves as a link to the overall availability of climate projections for Europe, even though this a moving target.

2.2. Metadata for Tier-1 indicators

The overall design criterion adopted by CLIPC is to use, as far as possible, the netCDF data file format[4] and the Climate and Forecasting (CF) convention[5] for metadata. There is currently no widely accepted metadata standard for Tier-1 indicators, but this is a necessary prerequisite for web-based processing of climate data to produce such indices. As the development of a metadata standard for Tier-1 indicators have ramifications well outside CLIPC it was decided to involve the larger community working on Tier-1 indicators in two hands on virtual workshop “CLIPC/IS-ENES2 Joint Workshop on Common CVs” in Toulouse 10-12 February 2016, and “2nd Joint CLIPC/IS-ENES2 Workshop on Metadata/DRS for climate indices” in Brussels 17 October 2016.

In CLIPC, work on Tier-1 metadata has been divided between Work Packages 5 and 6, where WP5 focusses on global metadata attributes necessary for searching/finding relevant datasets and for describing their temporal and spatial coverage, and the data provenance. WP6 focusses on metadata attributes for describing and characterising the data variable itself and the processing steps for creating the Tier-1 indicator from the basic model output or instrument observations. An outcome of the two workshops is that there now exist a first draft standard for metadata attributes for describing the Tier-1 indicator data variable. The work on specifying this draft standard is expected to continue beyond CLIPC and involve relevant international entities and networks (e.g. ET-SCI and ETCCDI).

2.3. Tools for producing Tier-1 indicators

There exists a wide range of software for producing Tier-1 indicators. Typically they have been developed to serve the needs of the specific work flow of a project or a research group. Only few software tools are aiming at a more general reach, and we choose to focus on a software tool, *icclim*[6], which as closely as possible follows the netCDF and CF standards, is geared towards integration in the CLIPC portal, and not least already integrated in the climate4impact portal.

[4] <http://www.unidata.ucar.edu/software/netcdf/> (accessed 2016-10-31)

[5] <http://cfconventions.org/> (accessed 2016-10-31)

[6] <http://icclim.readthedocs.org/en/latest/index.html> (accessed 2016-10-31)

Table 1. Overview of CMIP5 global climate projections that within the frame of the Euro-CORDEX collaboration have been dynamically downscaled at two resolutions, 0.44° and 0.11° (~50 km and ~12.5 km). Green/yellow/red lines indicate RCP2.6/RCP4.5/RCP8.5 forcing ('emission') scenarios. Snapshot of availability at ESGF as per June 2016, more regional simulations are planned or already on the way. For many of the GCM projections multiple realisations exist.

	CLMcom-CCLM4-8-17		CNRM-ALADIN53		DMI-HIRHAM5		IPSL-INERIS-WRF331F/P		KNMI-RACMO22E		MPI-CSC-REMO2009		SMHI-RCA4	
	0.11	0.44	0.11	0.44	0.11	0.44	0.11	0.44	0.11	0.44	0.11	0.44	0.11	0.44
ACCESS1-0														
BNU-ESM														
CCSM4														
CESM1-BGC														
CESM1-CAM5														
CESM1-WACCM														
CMCC-CESM														
CMCC-CM														
CMCC-CMS														
CNRM-CM5			X											
	X		X	X									X	X
	X		X	X									X	X
CSIRO-Mk3-6-0														
														X
														X
CanESM2														
														X
														X
EC-EARTH					X								X	X
	X				X	X			X	X			X	X
	X				X	X			X	X			X	X
FGOALS-g2														
FGOALS-s2														
GFDL-CM2p1														
GFDL-CM3														
GFDL-ESM2G														
GFDL-ESM2M														
														X
														X
GISS-E2-H														
GISS-E2-R														
HadCM3														
HadGEM2-CC														
HadGEM2-ES									X					X
	X								X				X	X
	X								X				X	X
IPSL-CM5A-LR														
IPSL-CM5A-MR														
							X	X					X	X
							X	X					X	X
IPSL-CM5B-LR														
MIROC-ESM														
MIROC-ESM-CHEM														
MIROC4														
MIROC5														X
														X
														X
MPI-ESM-LR											X	X		X
	X	X									X	X	X	X
	X	X									X	X	X	X
MPI-ESM-MR														
MRI-CGCM3														
NorESM1-M														X
														X
														X
bcc-csm1-1														
bcc-csm1-1-m														
inmcm4														

The *icclim* software has been substantially extended and upgraded both to expand its capability to compute a range of Tier-1 indicators and to automate the processing of global attributes and data variable metadata attributes. The new version of *icclim* substantially increases the number of indices that can be computed from ETCCDIO and ET-SCI lists of core indices, and updates the algorithm for calculating percentiles, which improves the accuracy of all indices based on percentiles. Furthermore, the new version enables users to define their own indices using a set of fundamental operations, as well as define their own seasons that go beyond the usual division into annual, the four standard seasons and monthly indices.

2.4. Bias-adjustment of regional projections

Since publication of CLIPC Deliverable D6.1 further work has been ongoing within WP5 and WP6, together with the European project IS-ENES2 and a wider community to publish bias-adjusted (Euro-)CORDEX data onto the ESGF system of nodes. This involves endorsement by the WCRP and the Scientific Advisory Team for CORDEX of the meta-data standards and associated controlled vocabularies developed in CLIPC. This was recently concluded and the bias-adjusted data that previously were available through interim web services set up for CLIPC Deliverable D6.1 is now widely available under the ESGF Project “CORDEX-Adjust”.

While bias-adjusted RCM projection data is often preferred, in particular for calculation of Tier -1 CCIs involving thresholds or other non-linearities, and sometimes even necessary for certain applications, it is not uniformly superior. It depends on the application. Hence, the WCRP web page[7] introducing the bias-adjusted CORDEX data prominently displays the following cautionary note

> “Note that even if bias adjustment (or bias correction) is widely used it is still a controversial approach with its own pros and cons. Bias-adjusted CORDEX simulations should be used carefully with full understanding of all potential limitations of the bias adjustment approach.”

And the text on the web page goes on to strongly recommended to read a short report produced by an IPCC Expert Group (IPCC, 2015)

2.5. Ensembles of Tier-1 indicator for Europe

A set of 15 Tier 1 climate indicators was calculated using *icclim* (version 4.2.3) from an ensemble of 10 regional projection, where 10 different global projections were downscaled by the regional model SMHI-RCA4 (Table 2) covering the EUR-44 domain (~50 km resolution) covering the ‘historical’ period 1970-2005 and the scenario period 2006-2099 using RCP4.5 and RCP8.5. Both unadjusted and bias-adjusted versions of all projections were employed. The selection of Tier 1 indicators covers the four most often used meteorological parameters (daily total precipitation, mean, maximum and minimum daily temperature). The individual ensemble indicators together with the ensemble statistics

[7] http://www.cordex.org/index.php?option=com_content&view=article&id=275&Itemid=785 (accessed 2016-11-16)

(median, 20th and 80th percentile) of each indicator are available via the CLIPC portal[8]. A subset of the calculated indicators was used to generate the climate signal maps, together with the calculated indicators for EUR-11 domain. A complete set of indices and models presented in the CLIPC portal are described in Table 3. Following users' requests, the raw input used to calculate the set of Tier 1 indicators was also provided via the portal. Complementary work was dedicated to incorporate the metadata of the generated netCDF files storing the indices. This work was carried out in parallel with the development of the DRS checker in WP5. A git repository[9] is available online containing the workflow for calculating the provided indices and adjustment of the metadata for full CLIPC DRS compliance.

Table 2. CMIP5 GCMs that have been used to provide boundary conditions for the RCA4 regional projections making up the input (full) ensembles.

Modelling centre	*Model name*
Canadian Centre for Climate Modelling and Analysis	CanESM2
Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique	CNRM-CM5
EC-EARTH consortium	EC-EARTH
NOAA Geophysical Fluid Dynamics Laboratory	GFDL-ESM2M
Met Office Hadley Centre	HadGEM2-ES
Institut Pierre-Simon Laplace	IPSL-CM5A-MR
Atmosphere and Ocean Research Institute (The University of Tokyo), National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology	MIROC5
Max Planck Institute for Meteorology	MPI-ESM-LR
Norwegian Climate Centre	NorESM1-M
CSIRO Marine and Atmospheric Research / Queensland Climate Change Centre of Excellence	CSIRO-Mk3-6-0

2.6. Method for producing representative reduced ensembles

Based on the model simulation selection method of Mendlik and Gobiet (2015) an improved variant was developed (Wilcke and Bärring, 2016). Figure 1 shows the selection process for climate projection ensembles. The procedure is divided into five steps: 1) identify user requirements (climate variables, climate indices, study regions, seasons, etc.) that form the basis for the input variables; 2) calculate the climate change signal (i.e. for each input variables/Tier-1 indicators take the difference between a future period and a reference period) and transform these differences into orthogonal (uncorrelated) variables using EOF/PCA/SVD; 3) calculate the optimum number of clusters (average silhouette widths) as recommendation for the impact modeller; 4) use hierarchical clustering to

[8] http://www.clipc.eu/ (accessed 2016-11-16)

[9] https://github.com/KNMI/Indices_icclim_ClipC (accessed 2016-11-16)

group the simulations; and finally 5) select the simulation closest to each group's mean as the most representative ensemble member.

Table 3. Overview of produced CCII-T1 and derived statistics for the historical (1970-2005) and projections RCP4.5 & RCP8.5 EUR-44 ensemble, including both bias-adjusted and unadjusted regional projections produced by the SMHI-RCA4 regional model. In total for EUR-44, 900 files were generated for individual model indices and 90 files for derived statistics of the indices. Tmin/Tmean/Tmax is the daily minimum/mean/maximum temperature. The boldfaced part of CCII-T1 names identifies a commonly used short name.

Climate model		**Name of the CCII-T1 (climate index)**	**Acronym**	**(unit)**
Regional	**Global**			
SMHI-RCA4	CanESM2 CNRM-CM5 EC-EARTH GFDL-ESM2M HadGEM2-ES IPSL-CM5A-MR MIROC5 MPI-ESM-LR NorESM1-M CSIRO-Mk3-6-0	Number of wet days (precip ≥ 1mm)	r1mm	(days)
		Maximum daily precipitation	rx1day	(mm)
		Total precip. during wet days (precip≥ 1mm)	prcptot	(mm)
		Number of days when precip. > climatological 95th percerntile	r95p	(days)
		Number of **Ice Days** (Tmax < 0°C)	id	(days)
		Number of **Frost Days** (Tmin < 0°C)	fd	(days)
		Number of days with precipitation ≥ 10 mm	r10	(days)
		Number of days with precipitation ≥ 20 mm	r20	(days)
		Number of **Summer Days** (Tmax > 25°C)	su	(days)
		Number of **Tropical Nights** (Tmin > 20°C)	tr	(days)
		Maximum **Consecutive Wet Days** (≥1 mm)	cwd	(days)
		Maximum **Consecutive Dry Days** (<1mm)	cdd	(days)
		Heating Degree Days (Tmean >17°C)	hd17	(K)
		Mean Tmax	tx	(K)
		Mean Tmin	tn	(K)
Ensemble statistics		**For each CCII-T1**	Median 20th percentile 80th percentile	

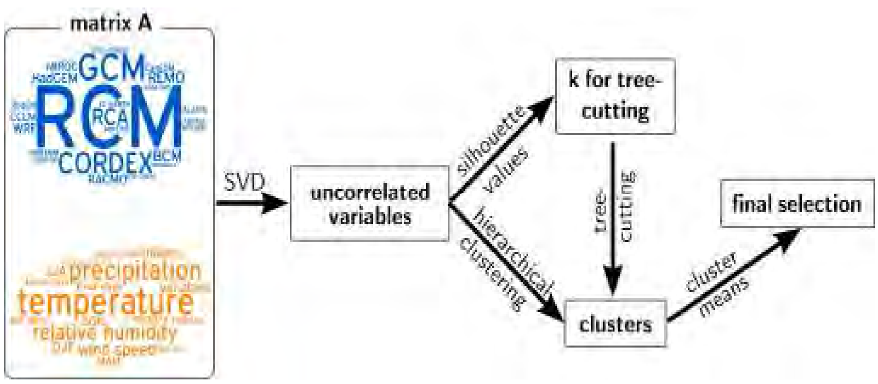

Figure 1. Schematic of the selection process from climate model output (orange) and climate model ensemble (blue) via the hierarchical clustering to the selection (Fig. 2 in Wilcke and Bärring, 2016).

Essentially, the method clusters the climate change 'signal' of key variables in an input ensemble of climate projections and suggests how to select one representative member from each cluster of the projection ensemble. The selected ensemble members thus make up the reduced projection ensemble. The procedure involves four key design criteria to consider:

i. the size of the available input (full) ensemble,
ii. which are the key variables to use as input for calculating the climate change signal,
iii. the desired size of the output (reduced) ensemble,
iv. which regions to average over.

The first criterion is typically the externally determined 'ensemble of opportunity' of climate projections available to the analyst through services like the CLIPC portal and other data providers. The other three criteria are internally determined by the specific requirement of each individual application. For example, some applications targets summer climatic conditions, where the key variables may be seasonal averages of temperature, degree days, and total effective precipitation (i.e. precipitation minus evaporation). Other applications may target short-term extremes, such as maximum total precipitation over one or a few days, or dry spells length, in combination with humidity and heat waves. Yet other applications focus on winter climatic conditions or conditions over some other specific period.

Thus it is not possible to provide one final and best reduced ensemble that fits all purposes. In chapters 3.1-3.5 we present some test cases that serve the dual purpose of illustrating how the reduction procedure can be applied and the interpretation of results, and the procedure's sensitivity to input data.

2.6.1. Sensitivity study

In order to analyse and document the performance of the reduction procedure in relation to various combinations of input data we carried out a sensitivity study (Wilcke and Bärring, 2016). The input data consisted of various combinations of seasonal averages of temperature, precipitation, wind and relative humidity, as well as a range of different climate indicators (based on the same meteorological parameters) that were selected represent various applications. The basic input projection ensemble were drawn from (at the time) available Euro-CORDEX 0.44° (~50 km) RCM projections of RCP8.5. In total 11 projections were used, of which 9 were produced by the RCA4 model. The conclusion was that the method is sensitive to the selection of input data, which region is in focus, etc. If input variables based on temperature are present they have a strong tendency to dominate the results because the temperature change signal is strong and most consistently represented by different models compared to other variables.

The fundamental cause for this sensitivity is of course that the climate change signals in the different input variables and Tier-1 indices exhibit different characteristics and inter-variable correlation in different regions This is a clear indication that one reduced ensemble cannot uniformly provide an optimal representation of the climate change signal in various regions and independent of input data selection.

2.7. Assessment of robustness in ensemble climate change signals

Climate projection ensembles consisting of different model simulations and/or different scenarios span a wide range of possible climate changes. It is, however, not always directly evident from the range of possible climate changes whether robust information can be derived from the data.

To evaluate the robustness of the projected changes in climate projection ensembles and to make the results of such evaluations quickly comprehensible and spatially visible, the climate signal map method was developed (Pfeifer et al., 2015). "Robust" is thereby defined as the agreement of simulations toward the projected changes as well as with the portion of the simulations that project statistically significant changes. To avoid overwhelming the user with the richness of information, only condensed, tailored information of the climate projection ensemble is selected for the visualisation. Only one direction of change is always examined, either the increase or decrease of a variable.

A three-fold colour code with individual thresholds is assigned to demonstrate the robustness of the climate change signal. These thresholds are based on expert judgment and practical relevance and categorise the climate change signal into a low, medium or strong magnitude depending on the purpose of the climate signal map. For example, if we are interested in the change in tropical nights for Europe, we select the increase in tropical nights because the more often occurrence of tropical nights in the future would require adaptation activities. In the case that for a region no robust information can derived from the ensemble of model projections, the region is marked in grey. Regions in white are those areas in which the climate ensemble would project the opposite direction of the climate change signal. Following the example of displaying the increase of tropical nights, areas with a decrease of tropical nights get the colour white assigned to.

Table 4. T-1 indicators used to produce the climate signal maps, indicating the shorthand name of the Tier-1 indicator (cf. Table 3), the historical and the future period under RCP4.5, and the ensemble statistics for both EUR-44 and EUR-11 domain. The number of files reflects the number of ensemble members used for each domain (10 for EUR-44 and 15 for EUR-11).

Harmonised Tier1 ensemble data set for EUR-44 and EUR-11		**Number of files**	
	r1mm r10mm fd su id tr hd17	EUR-44	EUR-11
Past (1970-2005)	Yearly (every member)	10	15
	Median	1	1
	20th percentile	1	1
	80th percentile	1	1
Future (2006-2099)	Yearly (every member)	10	15
	Median	1	1
	20th percentile	1	1
	80th percentile	1	1
Total		182	252

There are several ways to spatially visualise the climate signal maps. They can be represented on various types of regions depending on the purpose for which the maps are produced, for example by administrative units, such as countries, states or physical regions. The method can of course also be applied on the original model grid (in the case that the simulations are done with similar horizontal grid resolutions) or on a common grid to which all simulation results are mapped. For more information about the digital application of the climate signal maps see Deliverable 8.4[10].

All in all, climate signal maps have been produced for the Tier-1 indices listed in Table 4.

3. Case studies

In five case studies we provide examples of how the methods and tools have been used for various applications. The aim is both to show a few hands-on applications using various, and widely different, types of data and give some guidance as to the interpretation of the results. Case study 1 outlines the workflow envisaged in the CLIPC portal for applying the climate signal map methodology to full ensembles, and for producing reduced ensembles. Moreover, impact of bias-adjustment is illustrated. Case study 2 summarises an application of the ensemble reduction method is used in the context of impact modelling research. Case study 3 draws on external requirements imposed in another EU project to briefly show that the ensemble reduction procedure allows the size of the reduced ensemble to be prescribed rather than automatically (and optimally) determined by the silhouette value. Moreover, this case study involved testing the robustness of the reduced ensemble by varying the input variables. In case study 4 three alternative definitions of tailored cold wave indices are applied to GCM data. Finally, in case study 5 a comparatively large ensemble of CMIP5 global projections data for Europe is used to calculate the same Tier-1 indicators (FD and SU) as in case study 1. This ensemble data is then subjected to the ensemble reduction procedure to test its performance.

3.1. Case study 1: European Summer days and Frost days

CLIPC targets the European region and to meet users' demand for detailed spatial information the focus here is on dynamically downscaled projections using regional climate models from the Euro-CORDEX collaborative network.

To define the input (full) ensemble of regional climate projections for this demonstrator dataset we identified several desirable properties:

- For many applications and users – but not all – it is advantageous to use bias-adjusted regional climate projections rather that unadjusted ('raw') ones. We therefore want to explore and highlight the effect of bias-adjustment by applying the procedure to both a bias-adjusted and an unadjusted version of the ensemble.
- A range of alternative combinations of input variable and seasons were analysed by Wilcke and Bärring (2016), and they concluded as expected that variables related to temperature

[10] http://www.clipc.eu/project-information/deliverables-and-milestones

dominated the results. For this generic demonstrator dataset we highlight both summer and winter conditions related to temperature. To go beyond the traditional seasonal means as input variables we select the annual number of Frost Days (FD) and Summer Days (SU) to capture changes during both winter and summer.

- To get a clear picture of how the reduced ensemble is able to represent the climate change signal we calculate the climate change signal (i.e. difference) between the averages for the periods 1981-2010 and 2070-2099.
- Future pathways of greenhouse gas emissions and other anthropogenic factors are represented by Representative Concentration Pathways, RCPs. Rather than mixing different RCPs we envision that users want to explore the effect of selecting alternative scenarios of future development. Therefore, we produce separate ensembles for the different RCP scenarios.
- In the current implementation the ensemble reduction procedure focusses on input variables based on spatial averages, which typically are some regions of interest to the impact scientists/users. As we are producing a generic demonstrator dataset we draw on the widely used 'Prudence regions' (Figure 2 and Table 5), that divide large parts of Europe into broadly homogeneous regions.
- For practical reasons, as well as data availability at the time of this work, in combination with the requirements detailed in the points above, we make the following restrictions:
    - Focus on the coarse-resolution 0.44° Euro-CORDEX projections to limit the data volume.
    - Focus on the RCP4.5 and the RCP8.5 scenarios as Table 1 shows that only very few regional scenarios exist for RCP2.6.
    - It is preferable to use data from a reasonably balanced set of different RCMs. However, as is seen from Table 1 this is not straightforward. For this particular work, an additional limitation was that some data were still in production and thus not yet available. We therefore take the alternative approach and focus on regional projections downscaled by one single RCM, namely RCA4.

Table 5. Geographic boundaries of the 'Prudence regions'.

Acronym	*Region*	*Longitude (° East)*		*Latitude (° North)*	
		W	*E*	*S*	*N*
BI	British Isles	−10	2	50	59
ME	Mid Europe	2	16	48	55
AL	Alps	5	15	44	48
FR	France	−5	5	44	50
MD	Mediterranean	3	25	36	44
EA	Eastern Europe	16	30	44	55
IP	Iberian Peninsula	−10	3	36	44
SC	Scandinavia	5	30	55	70

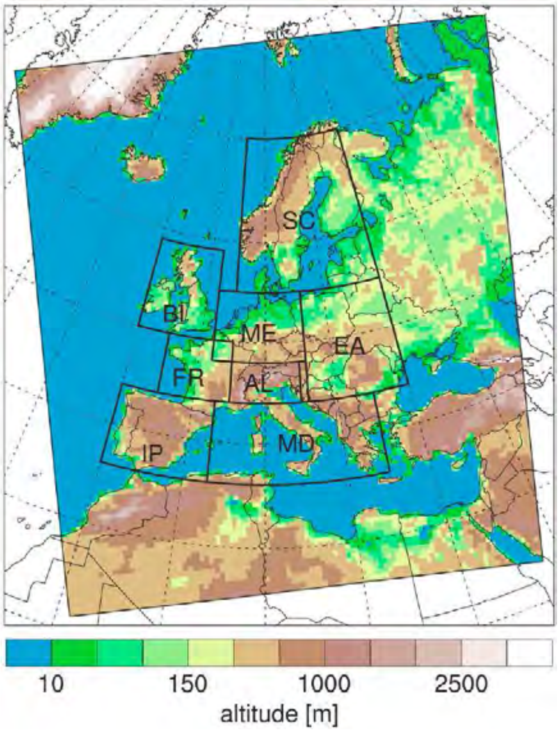

Figure 2. The 'Prudence regions' commonly used in analysis of regional climate projections for Europe (Bellprat et al., 2012).

These requirements resulted in four alternative input (full) ensembles crossing RCP4.5 and RCP8.5 with unadjusted and bias-adjusted projections. These four ensembles of regional projections are based on the same CMIP5 global models (Table 2) downscaled by RCA4. In the following the individual ensemble members will be identified by the GCM name shown in the right column of Table 2.

3.1.1. Assessment of robustness using climate signal maps

Application and interpretation

The statistically method behind the climate signal maps requires comparatively large climate data ensembles, which in practice has shown to be as a rough rule-of-thumb are a minimum of least ten members. Thus, in the context of CLIPC it is just possible to apply the method to the full 'raw' unadjusted and full bias-adjusted ensembles (see Table 3), but not to the representative reduced ensembles. Within CLIPC we adapted and extended the method underneath the climate signal maps in order to publish the produced climate signal maps in the CLIPC portal. All input climate simulations were on the EUR-44 grid, i.e. in ca. 50 km resolution. To meet users' demand on detailed spatial information, we have chosen to calculate the climate signal maps on the original grid and visualised this information as colour-filled circles.

The input ensemble is the full ensemble based on the RCA4 climate simulations with 10 members and the bias-adjusted RCA4 simulation with 10 members (see Table 3), each ensemble for RCP4.5 and RCP8.5. The climate change signal is calculated based on 30-year periods for current and future conditions (2070-2099 minus 1971-2000). The climate signal map is a measure to present the robustness of an ensemble of climate projections. Shown are the climate signal maps for the non-bias adjusted RCA4 ensemble and the bias-adjusted version of it. As mentioned earlier in this deliverable, bias-adjusted simulations are required by some impact modellers in order to be able to use climate model data as input to simulate the impact of climate change.

The climate signal maps have been implemented in the CLIPC portal for a series of climate impact indicators. Here in this study the scope is to analyse the robustness of climate projection ensembles of the non-bias adjusted RCA4 ensemble (left column of Figure 3 and Figure 4) and compare this briefly to the robustness of the bias-adjusted RCA4 ensemble (right column of Figure 3 and Figure 4). This comparison is exemplarily done for two climate impact indicators and helps to interpret the potential changes of the bias adjustment on the climate change characteristics not only of the individual model simulations but on the characteristics of the whole ensemble.

Decrease frost days RCP4.5 and RCP8.5 for the full RCA4 ensemble

The thresholds for the magnitude of the decrease in frost days is for a weak decrease by less than 15 days (yellow) and a strong decrease by more than 40 days (red) and in between presents a medium change (orange). The climate signal maps for both RCP4.5 and RCP8.5 depict a robust decrease in frost days all over Europe towards the end of the next century. The strongest decrease with more than 40 days is shown for Scandinavia (SC) and the alpine region (AL) for both RCPs whereas this strong decrease is extended towards the south to the regions mid Europe (ME) and Eastern Europe (EA) for RCP8.5. For all other regions, a robust but rather medium decrease in frost days is depicted. Only for the coastal regions of the Iberian Peninsula (IP) and the Mediterranean regions (MD) close to the Mediterranean Sea the simulations indicate a weak but still robust decrease in frost days.

Increase in summer days RCP4.5 and RCP8.5 for the full RCA4 ensemble

The magnitude of the increase in summer days is defined for a weak increase by less than five days (yellow) and a strong increase by more than 30 days (red) and a medium increase between five and 30 days (orange). A robust increase in summer days is shown for both RCPs, expect from northern British Isles (BI) and Scandinavia (SC). In general, the climate signal maps for both RCP4.5 and RPC8.5 depict somehow the opposite picture than that of the frost days, with regions having a strong decrease in frost days showing a strong increase in summer days. Whereas the RCP4.5 ensemble depicts a mostly medium increase in summer days and only at the Mediterranean coast a strong increase, the RCP8.5 ensemble indicates a strong increase of summer days over south and mid Europe expect from the Alps and the Baltic Sea coast.

The regions British Isles (BI) and Scandinavia (SC) show a weak to medium increase in summer days. The RCP4.5 ensemble displays a not robust signal or even a decrease in summer days for the northern parts of BI and SC. This feature is less dominant for the RCP8.5 ensemble.

Robustness modification of the climate change signal in the bias-adjusted ensemble

It is known that bias-adjustment can alter the climate change signal. This can happen when the bias of the input simulations is not constant for all values in the reference period, and the distribution of climatologies changes in the projection period. For example, if a simulation has large biases for warm

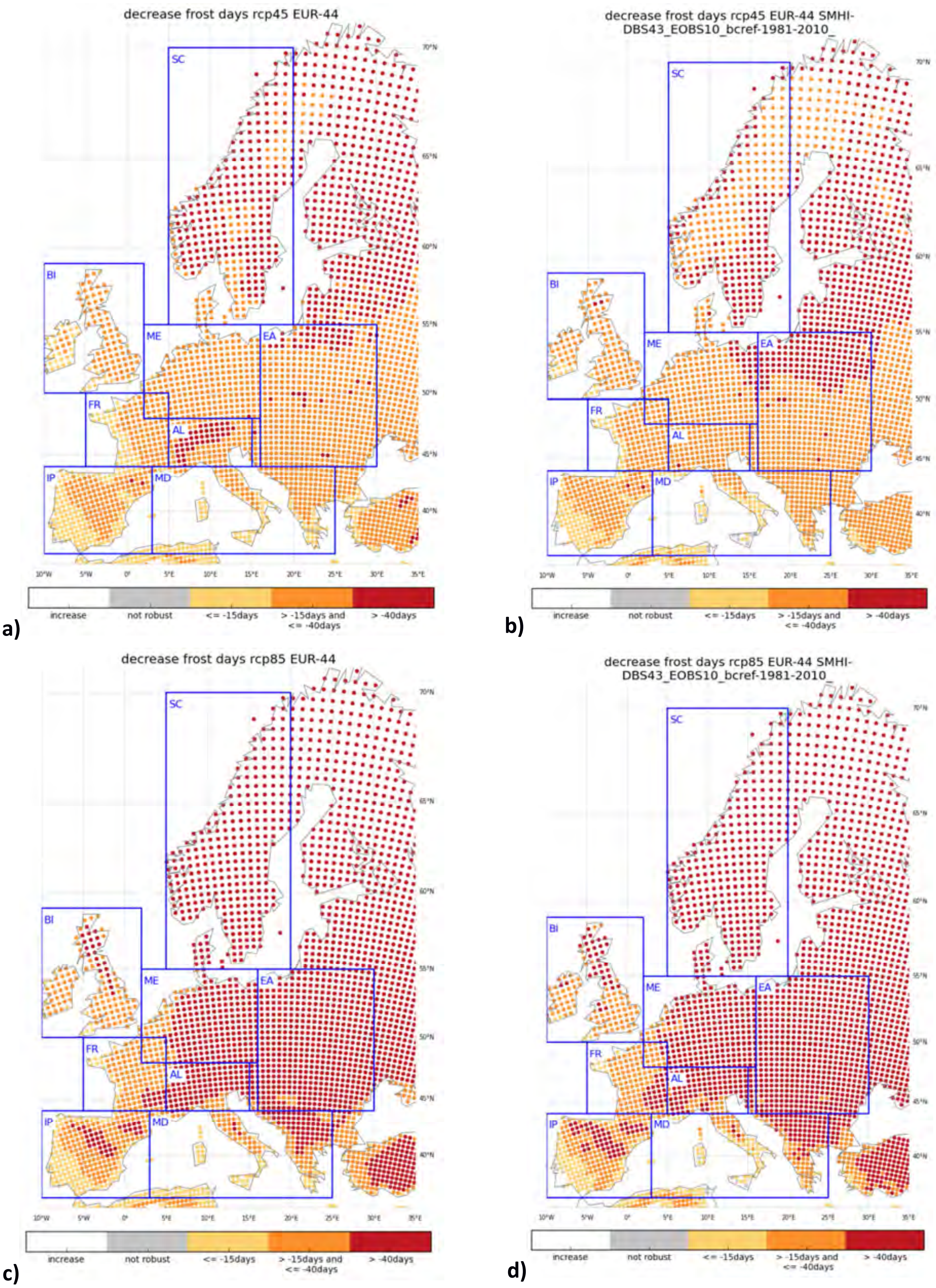

Figure 3. Climate signal maps for Frost Days.The upper (lower) row shows results for the RCP4.5 (RCP8.5) ensembles, and the left (right) column shows results for the unadjusted (bias-adjusted) version ensemble of the ensembles. The blue boxes indicate the boarders of the PRUDENCE regions (Table 5). Each dot corresponds to one gridcell.

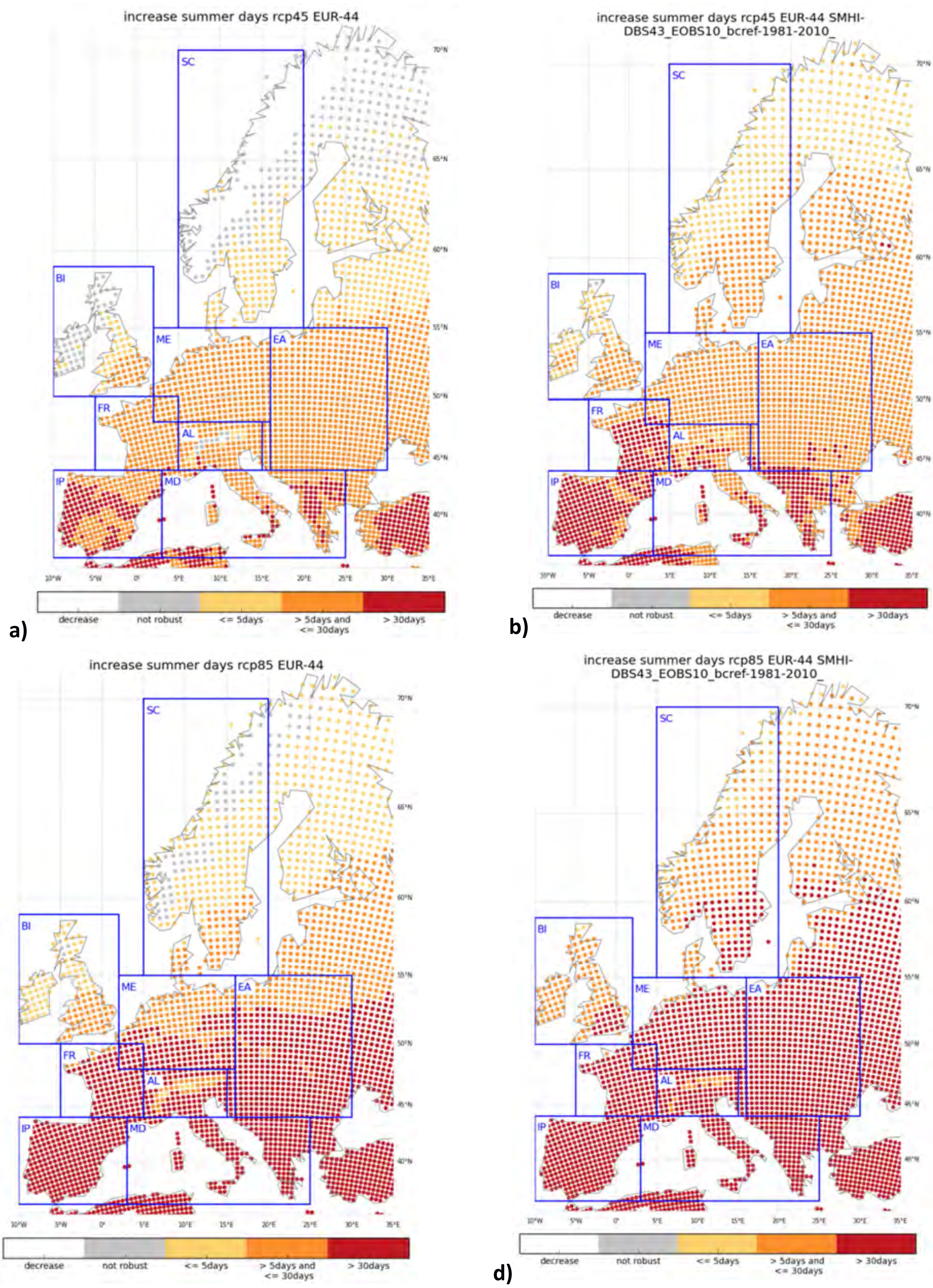

Figure 4. Same as Figure 3 but for Summer Days.

days, then for future warming hot days will occur more often and so those high biases are summed to occur more often as well. This leads to a stronger correction in the projection period than in the reference period and thus the climate change signal is altered (Boberg et al., 2012; Dosio et al., 2012). For details of the applied bias correction method see section 2.4 in this deliverable. In the following the differences in the climate signal maps based of the bias adjusted when compared to the non-bias adjusted ensembles are discussed.

Decrease bias-adjusted frost days

As for the non-bias adjusted ensemble the bias adjusted signal maps depict a robust decrease in the number of frost days for all of Europe. The main differences that stand out in the signal maps based on the bias adjusted and non-bias adjusted ensembles is the modification of the climate change signal for the bias-adjusted ensemble in Scandinavia (SC) and the Alp region (AL) with a change from a strong to a medium decrease in frost days (Figure 3, upper right). This effect, however, is not present for the RCP8.5 bias-adjusted ensemble.

When analysing the bias in the underlying daily minimum temperature (not shown) it becomes clear, that all models have a cold bias (when compared to EOBS12) in the daily minimum temperature over the alpine region as well as over large parts of Scandinavia. Bias adjustment therefore leads to a decrease in the number of frost days for the historical period but also for the scenarios, although not in the same magnitude. Additionally, due to the application of fixed thresholds in the climate signal maps some changes are leading to a jump from the strong to the medium class, whereas similar changes some are just “hidden” within a class. Hence, the bias adjustment seems to weaken the climate change signal for frost days over the alpine region and for Scandinavia for RCP4.5; whereas due to the generally larger magnitude, no effect is observed for RCP8.5, although in the same bias adjustment is applied to the data as for the RCP4.5.

Increase in bias-adjusted summer days

In contrast to the frost days, the bias adjustment for the increase in summer days effects the robustness of the projected changes. The climate signal maps of both bias-adjusted RCP4.5 and RPC8.5 ensembles (Figure 4, right column) show for Scandinavia a shift from a not-robust signal towards a rather robust increase in summer days. While in the non-bias adjusted ensemble no summer days are present in almost all individual model simulations over this region for neither current nor future condition. This effect changes after bias-adjustment. As for the minimum temperature also in the maximum temperature a general cold bias (when compared to EOBS12) is present in all of the RCA4-simulations. The combination of bias-adjustment and the general warming tendency projected for the future leads to the occurrence of a few summer days in the future in almost all model simulations. As the change occurs from no summer days to a few robust summer days, from a statistical point of view significant both robustness criteria are fulfilled and the change is marked to be robust in the signal maps.

Nevertheless it has to be noted, that the discussion on the robustness of the bias-adjusted climate change signal is challenging and does not lead to a final interpretation. In addition to the robustness testing of the bias-adjusted climate change signal, the assessment of the robustness should be extended to the output of climate impact models that apply bias-adjusted climate data.

3.1.2. Reduced ensemble based on area averages across European regions

Table 6 gives an overview of the outcome of reduction procedure for each ensemble. For all four ensembles the two first principal components (PC1 and PC2) together explains more that 75% of the total variance and reaches 80% for three of them. This is considered to be enough for not including more PCs. The peak value (Table 6, column SV1) of the silhouette plots (Figure 5 – *Figure 8*) is used as a guideline for objectively choosing the number of clusters. With the exception of the unadjusted/RCP8.5 ensemble, the silhouette plots do not show a distinct peak, which indicates that there is no unequivocal answer to the question as to how many clusters are needed. Therefore, as a preliminary measure we explore the clustering into the number of groups suggested by the highest and second highest silhouette value (SV1 and SV2). For all but one ensembles, 3 and 4 clusters are optimal and second best. Only for the unadjusted/RCP4.5, 2 clusters come out as second best after 3 clusters.

Table 6. Overview of the outcome of the ensemble reduction procedure. Column "PC1+PC2" gives the % explained variance by the first two principal components. Columns "SV1" and "SV2" give the highest and second highest silhouette value, and columns "N1" and "N2" gives the corresponding number of clusters.

Ensemble		*PC1+PC2*	*SV1*	*N1*	*SV2*	*N2*
Unadjusted	RCP4.5	80%	0.41	3	0.40	2
	RCP8.5	80%	0.53	4	0.49	3
Bias-adjusted	RCP4.5	78%	0.49	3	0.48	4
	RCP8.5	84%	0.40	4	0.38	3

Table 7. List of the members for the different representative reduced ensemble alternatives. For each of the four ensembles the best and second best alternatives are listed.

Ensemble		*Alternative*	*Selected members*
Unadjusted	RCP4.5	1	HadGEM2-ES, GFDL-ESM2M, EC-EARTH
		2	HadGEM2-ES, NorESM1-M
	RCP8.5	1	CanESM2, MPI-ESM-LR, CNRM-CM5, EC-EARTH
		2	MIROC5, MPI-ESM-LR, CanESM2
Bias-adjusted	RCP4.5	1	IPSL-CM5A-MR, MPI-ESM-LR, MIROC5
		2	IPSL-CM5A-MR, MPI-ESM-LR, CNRM-CM5, EC-EARTH
	RCP8.5	1	IPSL-CM5A-MR, NorESM1-M, CNRM-CM5, CanESM2
		2	HadGEM2-ES, NorESM1-M, CNRM-CM5

Table 7 lists the representative reduced ensembles for each of the full ensembles. The dendrograms and biplots in Figure *5*-Figure 8 provide a more detailed picture of how each of the selected members in the representative reduced ensembles relate to the groups they represent.

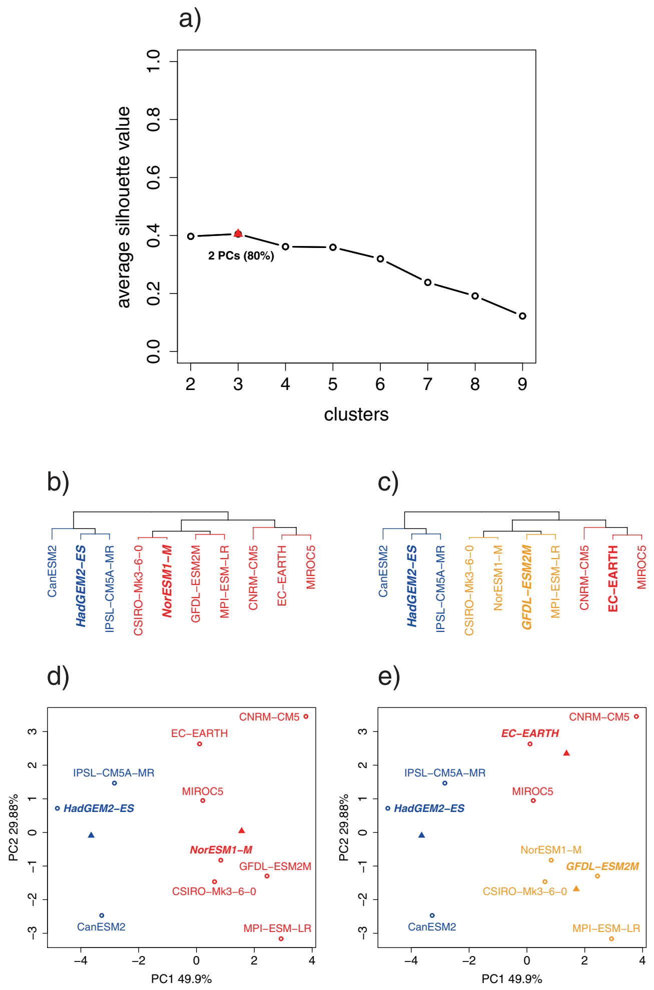

Figure 5. Illustrations for the reduced ensembles of unadjusted RCP4.5 regional scenarios. a) silhouette plot showing that 3 clusters are optimal (red triangle) closely followed by 2 clusters. b) and c) dendrograms showing the structure for 2 and 3 cluster. d) and e) biplots of PC1 and PC2 with the within-cluster mean indicated by triangles and where the boldfaced and italicised projection is selected to represent the cluster in the representative reduced ensemble.

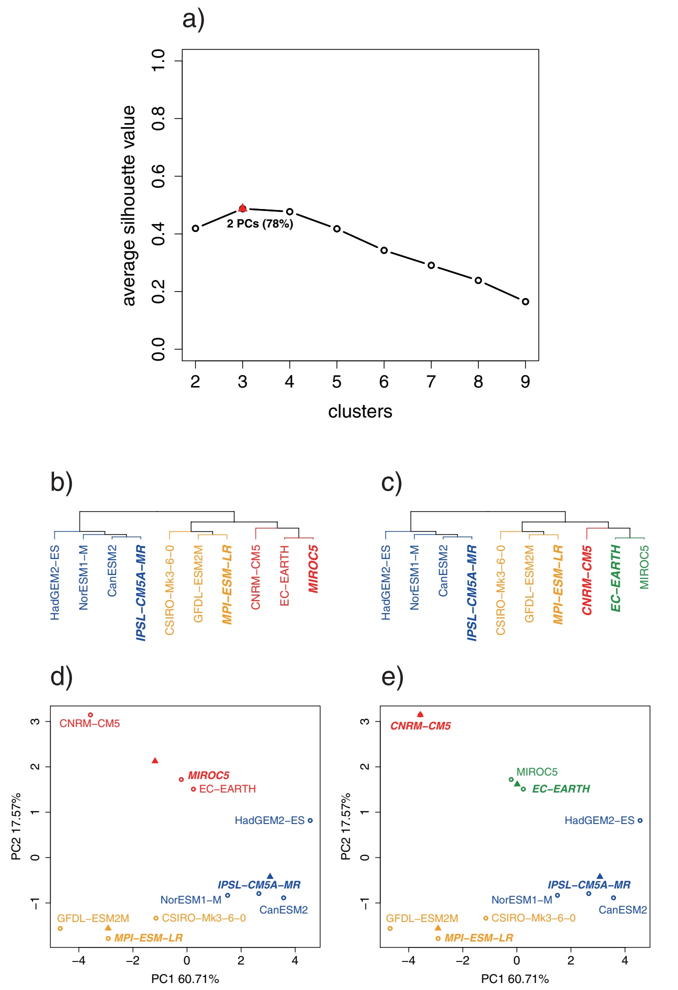

Figure 6. Same as Figure 5 but for bias-adjusted RCP4.5. Panel a) shows that 3 clusters are optimal (red triangle) closely followed by 4 clusters.

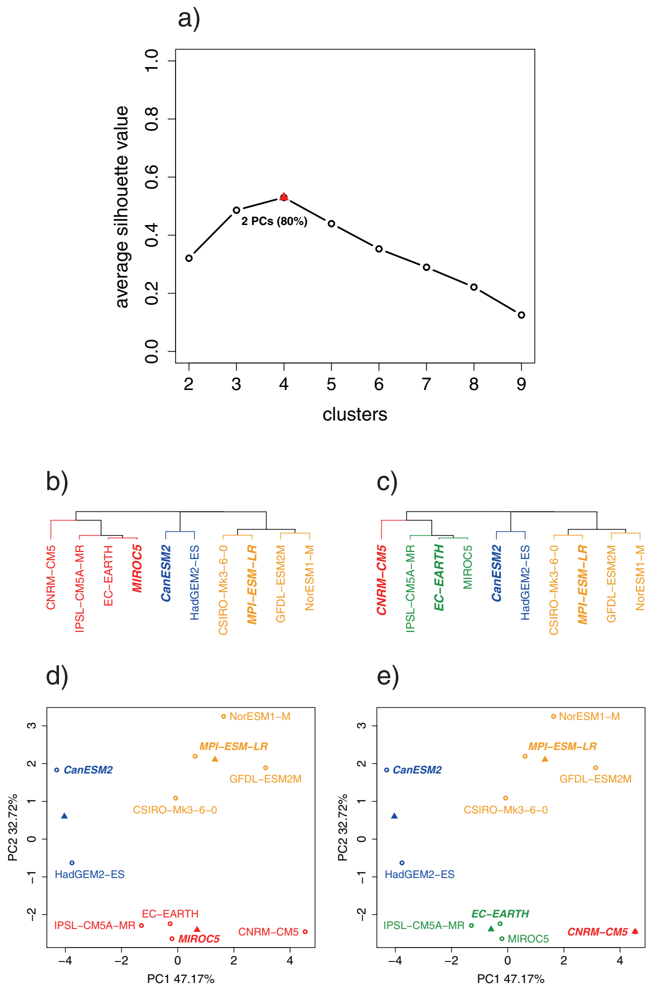

Figure 7. Same as Figure 5 but for unadjusted RCP8.5. Panel a) shows that 4 clusters are optimal (red triangle) followed by 3 clusters.

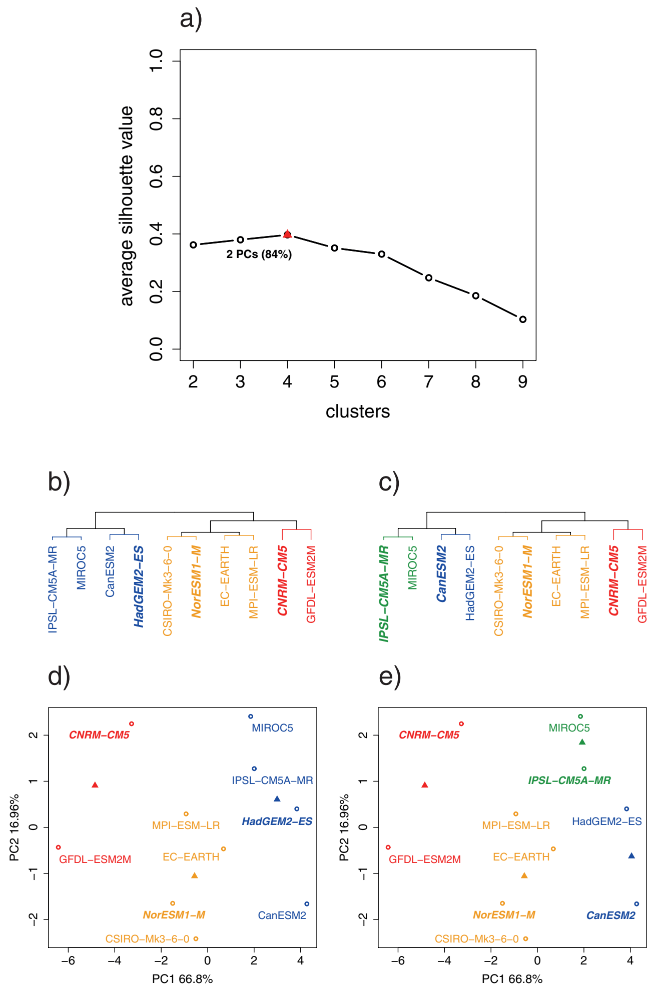

Figure 8. Same as Figure 5 but for bias-adjusted RCP8.5. Panel a) shows that 4 clusters are optimal (red triangle) closely followed by 3 clusters.

3.1.3. Reduced ensembles for the individual European subregions

To complement the European scale analysis of the average condition in the eight regions we independently repeated the same analysis for each individual region. The same data, Frost Days and Summer Days were used without averaging across the region (i.e. full gridcell resolution). As is evident from Table 8 the structure and composition of the clusters varies substantially for the

Table 8. Cluster structure for the reduced ensembles derived independently for each individual region.

	RCP4.5		RCP8.5	
	bias-adjusted	**unadjusted**	**bias-adjusted**	**unadjusted**
France	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	GFDL-ESM2M	CanESM2	GFDL-ESM2M	GFDL-ESM2M
	CNRM-CM5	Cluster 2	CNRM-CM5	NorESM1-M
	Cluster 2	GFDL-ESM2M	NorESM1-M	CanESM2
	NorESM1-M	Cluster 3	Cluster 2	MPI-ESM-LR
	MIROC5	NorESM1-M	MIROC5	IPSL-CM5A-MR
	CSIRO-Mk3.6.0	MPI-ESM-LR	CSIRO-Mk3.6.0	Cluster 2
	CanESM2	Cluster 4	CanESM2	CNRM-CM5
	EC-EARTH	HadGEM2-ES	EC-EARTH	MIROC5
	HadGEM2-ES	Cluster 5	HadGEM2-ES	CSIRO-Mk3.6.0
	IPSL-CM5A-MR	IPSL-CM5A-MR	IPSL-CM5A-MR	EC-EARTH
	MPI-ESM-LR	CSIRO-Mk3.6.0	MPI-ESM-LR	HadGEM2-ES
		Cluster 6		
		CNRM-CM5		
		Cluster 7		
		EC-EARTH		
		MIROC5		
Alps	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	CanESM2	CanESM2	GFDL-ESM2M	GFDL-ESM2M
	HadGEM2-ES	HadGEM2-ES	NorESM1-M	NorESM1-M
	IPSL-CM5A-MR	IPSL-CM5A-MR	Cluster 2	Cluster 2
	Cluster 2	Cluster 2	CNRM-CM5	CSIRO-Mk3.6.0
	GFDL-ESM2M	MPI-ESM-LR	MIROC5	MPI-ESM-LR
	MPI-ESM-LR	GFDL-ESM2M	CSIRO-Mk3.6.0	Cluster 3
	Cluster 3	EC-EARTH	CanESM2	HadGEM2-ES
	CNRM-CM5	CNRM-CM5	EC-EARTH	IPSL-CM5A-MR
	Cluster 4	CSIRO-Mk3.6.0	HadGEM2-ES	CanESM2
	MIROC5	MIROC5	IPSL-CM5A-MR	Cluster 4
	EC-EARTH	NorESM1-M	MPI-ESM-LR	CNRM-CM5
	Cluster 5			Cluster 5
	NorESM1-M			MIROC5
	CSIRO-Mk3.6.0			EC-EARTH
British Isles	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	CanESM2	CanESM2	CanESM2	CanESM2
	EC-EARTH	CSIRO-Mk3.6.0	Cluster 2	HadGEM2-ES
	HadGEM2-ES	HadGEM2-ES	EC-EARTH	Cluster 2
	Cluster 2	Cluster 2	HadGEM2-ES	MIROC5
	GFDL-ESM2M	EC-EARTH	Cluster 3	CSIRO-Mk3.6.0
	MPI-ESM-LR	IPSL-CM5A-MR	GFDL-ESM2M	EC-EARTH
	CSIRO-Mk3.6.0	CNRM-CM5	Cluster 4	IPSL-CM5A-MR
	NorESM1-M	Cluster 3	MPI-ESM-LR	MPI-ESM-LR
	MIROC5	MPI-ESM-LR	CSIRO-Mk3.6.0	GFDL-ESM2M
	CNRM-CM5	GFDL-ESM2M	NorESM1-M	CNRM-CM5
	IPSL-CM5A-MR	MIROC5	Cluster 5	NorESM1-M
		NorESM1-M	MIROC5	
			IPSL-CM5A-MR	
			CNRM-CM5	
Eastern Europe	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	CanESM2	HadGEM2-ES	MIROC5	CanESM2
	MIROC5	IPSL-CM5A-MR	HadGEM2-ES	HadGEM2-ES
	HadGEM2-ES	CanESM2	CanESM2	Cluster 2
	IPSL-CM5A-MR	Cluster 2	IPSL-CM5A-MR	IPSL-CM5A-MR
	NorESM1-M	CNRM-CM5	Cluster 2	MIROC5
	Cluster 2	MIROC5	CSIRO-Mk3.6.0	EC-EARTH
	MPI-ESM-LR	CSIRO-Mk3.6.0	EC-EARTH	Cluster 3
	GFDL-ESM2M	EC-EARTH	MPI-ESM-LR	CSIRO-Mk3.6.0
	Cluster 3	MPI-ESM-LR	GFDL-ESM2M	MPI-ESM-LR
	EC-EARTH	GFDL-ESM2M	CNRM-CM5	NorESM1-M
	CNRM-CM5	NorESM1-M	NorESM1-M	Cluster 4
	CSIRO-Mk3.6.0			GFDL-ESM2M
				CNRM-CM5

	RCP4.5		RCP8.5	
	bias-adjusted	**unadjusted**	**bias-adjusted**	**unadjusted**
Iberian Peninsula	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	HadGEM2-ES	HadGEM2-ES	GFDL-ESM2M	CNRM-CM5
	CanESM2	CanESM2	CNRM-CM5	Cluster 2
	NorESM1-M	IPSL-CM5A-MR	Cluster 2	IPSL-CM5A-MR
	Cluster 2	Cluster 2	HadGEM2-ES	MIROC5
	CNRM-CM5	CNRM-CM5	CanESM2	EC-EARTH
	MIROC5	EC-EARTH	Cluster 3	HadGEM2-ES
	CSIRO-Mk3.6.0	Cluster 3	MPI-ESM-LR	Cluster 3
	GFDL-ESM2M	MPI-ESM-LR	EC-EARTH	CanESM2
	EC-EARTH	CSIRO-Mk3.6.0	IPSL-CM5A-MR	Cluster 4
	IPSL-CM5A-MR	MIROC5	CSIRO-Mk3.6.0	GFDL-ESM2M
	MPI-ESM-LR	NorESM1-M	MIROC5	CSIRO-Mk3.6.0
		GFDL-ESM2M	NorESM1-M	MPI-ESM-LR
				NorESM1-M
Mediterranean	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	CNRM-CM5	CanESM2	HadGEM2-ES	CNRM-CM5
	Cluster 2	IPSL-CM5A-MR	CanESM2	Cluster 2
	GFDL-ESM2M	HadGEM2-ES	MPI-ESM-LR	GFDL-ESM2M
	MPI-ESM-LR	Cluster 2	MIROC5	MPI-ESM-LR
	Cluster 3	EC-EARTH	IPSL-CM5A-MR	NorESM1-M
	EC-EARTH	CNRM-CM5	Cluster 2	Cluster 3
	NorESM1-M	NorESM1-M	CNRM-CM5	HadGEM2-ES
	Cluster 4	MIROC5	NorESM1-M	CanESM2
	CanESM2	Cluster 3	CSIRO-Mk3.6.0	CSIRO-Mk3.6.0
	HadGEM2-ES	MPI-ESM-LR	GFDL-ESM2M	Cluster 4
	IPSL-CM5A-MR	GFDL-ESM2M	EC-EARTH	IPSL-CM5A-MR
	Cluster 5	CSIRO-Mk3.6.0		Cluster 5
	CSIRO-Mk3.6.0			EC-EARTH
	MIROC5			MIROC5
Middle Europe	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	CanESM2	GFDL-ESM2M	CanESM2	CNRM-CM5
	HadGEM2-ES	MPI-ESM-LR	EC-EARTH	Cluster 2
	IPSL-CM5A-MR	NorESM1-M	HadGEM2-ES	MIROC5
	NorESM1-M	Cluster 2	IPSL-CM5A-MR	EC-EARTH
	Cluster 2	CNRM-CM5	MIROC5	CSIRO-Mk3.6.0
	MPI-ESM-LR	Cluster 3	Cluster 2	IPSL-CM5A-MR
	GFDL-ESM2M	EC-EARTH	CSIRO-Mk3.6.0	Cluster 3
	Cluster 3	CSIRO-Mk3.6.0	CNRM-CM5	CanESM2
	EC-EARTH	MIROC5	NorESM1-M	HadGEM2-ES
	CNRM-CM5	CanESM2	GFDL-ESM2M	Cluster 4
	CSIRO-Mk3.6.0	HadGEM2-ES	MPI-ESM-LR	GFDL-ESM2M
	MIROC5	IPSL-CM5A-MR		MPI-ESM-LR
				NorESM1-M
Scandinavia	Cluster 1	Cluster 1	Cluster 1	Cluster 1
	CSIRO-Mk3.6.0	HadGEM2-ES	GFDL-ESM2M	HadGEM2-ES
	GFDL-ESM2M	Cluster 2	MPI-ESM-LR	MIROC5
	MPI-ESM-LR	CNRM-CM5	CSIRO-Mk3.6.0	CanESM2
	Cluster 2	NorESM1-M	Cluster 2	Cluster 2
	CNRM-CM5	CanESM2	CanESM2	EC-EARTH
	NorESM1-M	EC-EARTH	NorESM1-M	IPSL-CM5A-MR
	CanESM2	CSIRO-Mk3.6.0	Cluster 3	Cluster 3
	EC-EARTH	IPSL-CM5A-MR	EC-EARTH	NorESM1-M
	HadGEM2-ES	MIROC5	CNRM-CM5	CNRM-CM5
	IPSL-CM5A-MR	GFDL-ESM2M	MIROC5	GFDL-ESM2M
	MIROC5	MPI-ESM-LR	HadGEM2-ES	MPI-ESM-LR
			IPSL-CM5A-MR	CSIRO-Mk3.6.0

different regions. Within each region there is no consistency between the RCP and between unadjusted and bias-adjusted data. Sometimes the unadjusted data result in a simpler structure (fewer clusters) than for the bias-adjusted data, and sometimes it is the other way around. To identify the underlying causes of these differences more detailed studies are needed that go beyond the focus of the CLIPC project.

These results may at first sight seem contrary to the Climate Signal Maps (Figure 3-Figure 4) that show a consistent and large scale signal in the ensemble means. But the two procedures do in fact complement each other and address different questions. The climate signal maps are used to assess the robustness in the climate change signal as quantified by the ensemble mean, and the ensemble reduction procedure addresses the question how best to reduce a specific given ensemble while still represent as good as possible the ensemble mean and spread.

From a simple comparison of the cluster structure and composition of the independent regional reduced clusters (Table 8) with the one obtained in the pan-European (Table 7) analysis, it is clear that the ensemble reduction procedure is sensitive both to spatial scale and region.

3.2. Case study 2: Potato crop and pests

An early 'real-world' application of the ensemble reduction procedure was carried out in collaboration with climate impact modellers at Lund University, Sweden (Pulatov et al., 2016). The same ensemble as was used in the sensitivity study (Chapter 2.6.1) of Euro-CORDEX 0.44° projections were used here. The climate projections' daily temperature data were bias-adjusted and a set of tailored degree-day indices were calculated. These indices were used in two climate impact models, one for potato annual phenology and growth and the other for the Colorado potato beetle, which is a severe pest on potatoes. These tailored indices are highly application specific and designed to address specific climate change impacts. Full details of the study are found in Pulatov et al. (2016).

3.3. Case study 3: Reduced ensembles for basin scale hydrological modelling

In the European funded project GLOBAQUA there are four case study regions studies (Adige, northern Italy; Ebro, eastern Spain; Evrotas, Greece; and Sava, Balkan region). For these regions all CORDEX EUR-11 simulations under the RCP8.5 scenario available in spring 2016 (Table 9) were utilised. The following variables, all averaged over the four canonical seasons, are utilised: 2m temperature, precipitation, 2m relative humidity, 10m wind, short wave incoming radiation at the surface, evapotranspiration and total runoff. The ensemble reduction is based on the climate change signal calculated as the difference between the scenario (2036-2065) and the reference (1981-2010) periods chosen in GLOBAQUA.

Results of the selection can be sensitive to different combinations of the above input and a number of sensitivity experiments excluding one case study and one or few variables were run giving in total

21 selections. GLOBAQUA activities required always using 3 Euro-CORDEX simulations. For that reason the automatic selection of ensemble size based on silhouette value was bypassed and three clusters were always enforced, even if it may be not the optimal choice for some of the combinations of input parameters. After running 21 selections a skill score showing how many times each individual simulation was selected is assigned to all RCM simulations (Table 9). Based on the skill score one can see that there are three clear favourites: SMHI-RCA4(HadGEM2-ES), KNMI-RACMO22E(EC-EARTH-r1) and CLMcom-CCLM4-8-17 (EC-EARTH-r12) and these three simulations have been selected.

Table 9. The ensemble of Euro-CORDEX simulations (regional models and their driving global models) at 12 km resolution available in spring 2016 and counts of how many times simulations has been selected.

RCM	GCM	Total score (21 max)
SMHI-RCA4	CNRM-CM5	**4**
	HadGEM2-ES	**14**
	EC-EARTH-r12	**4**
	MPI-ESM-LR	**1**
	IPSL-CM5A-MR	**3**
DMI-HIRHAM5	EC-EARTH-r3	**2**
KNMI-RACMO22E	**EC-EARTH-r1**	**12**
	HadGEM2-ES	**2**
CLMcom-CCLM4-8-17	CNRM-CM5	**0**
	HadGEM2-ES	**5**
	EC-EARTH-r12	**14**
	MPI-ESM-LR	**2**

3.4. Case study 4: Alternative frost indices for France derived from GCM data

For this case study we tested the ensemble reduction procedure for three different cold wave indices definitions. The idea was to see how alternative definitions of a Tier-1 indicator for ‘cold waves’ influences the sub-sampling result, which highlights that a reduced ensemble is case study as well as based on the selected Tier-1 indicators. The three cold waves indices were defined based on the SECIF-ANR French project (Cordero-Llana et al., in prep.). Each Tier-1 indicator represents one French energy sector. These criteria was applied to the full CMIP5 ensemble for both historical and future periods and compared with observations. The clustering method was applied to each of the cold wave indices (see Figure 9).

The aim of this study was to better understand the ensemble spread in the projections of future cold waves. Therefore the different sources of ensemble spread were included in the study and the clustering algorithm applied for all the cases. The different sources studied were the influence of climate Tier-1 indicator, scenario, near-future versus future predictions of cold waves and model runs. It seems that the major difference appears when we used different cold wave indices, as it can be seeing in Figure 9. Interesting results were found when estimating cold wave events for the near future (2041-2070) instead of the period 2071-2100. For the latter many models predict zero events, which could be due to the fact that the climate is changing too rapidly and therefore the cold wave definitions should be redefined for the future climate.

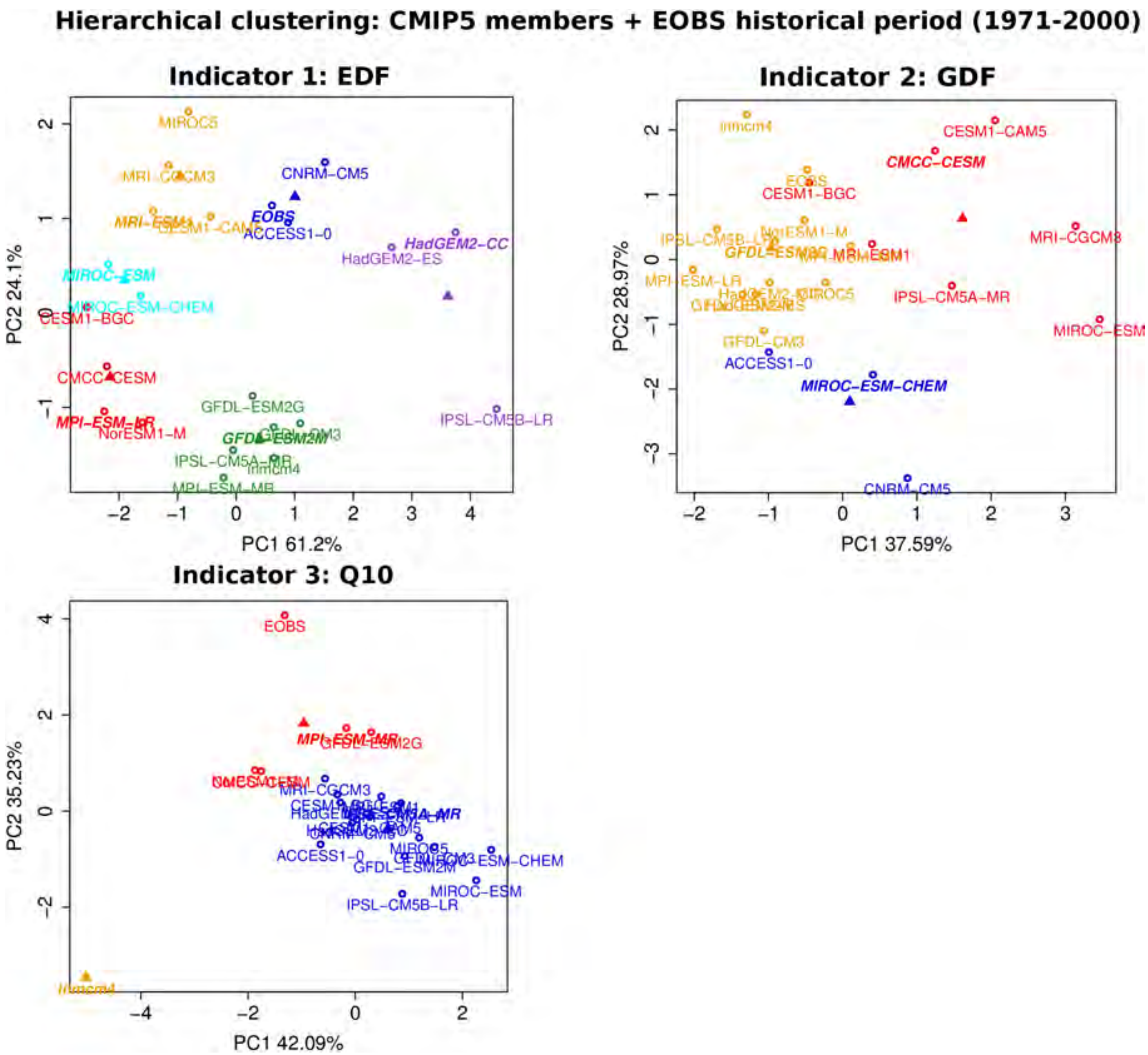

Figure 9. Hierarchical clustering results for the three cold waves indices (normalised) for the historical period 1971-2000), EOBS is also included for comparison.

3.5. Case study 5: GCM scenarios for Europe

The ensemble reduction method has been applied to global projections. In this application we focussed on seasonal mean temperature and total precipitation averaged oved the Prudence regions (Figure 2). In total, 98 projections the CMIP5 archive were used in the total ensemble, of which 27 were forced by the RCP2.6 scenario, 35 by RCP4.5, and 36 by RCP8.5 (Table 10).

Table 10. List of the global scenarios from the CMIP5 archive. In total 98 projections were used, 27 representing RCP2.6 (green), 35 representing RCP4.5 (yellow), and 36 representing RCP8 (red).

model	RCP	code	model	RCP	code	model	RCP	code
ACCESS1-0	4.5	1B	FIO-ESM	2.6	10A	IPSL-CM5A-LR	2.6	18A
ACCESS1-0	8.5	1C	FIO-ESM	4.5	13B	IPSL-CM5A-LR	4.5	25B
ACCESS1-3	4.5	2B	FIO-ESM	8.5	14C	IPSL-CM5A-LR	8.5	25C
ACCESS1-3	8.5	2C	GFDL-CM3	2.6	11A	IPSL-CM5A-MR	2.6	19A
CanESM2	2.6	4A	GFDL-CM3	4.5	14B	IPSL-CM5A-MR	4.5	26B
CanESM2	4.5	5B	GFDL-CM3	8.5	15C	IPSL-CM5A-MR	8.5	26C
CanESM2	8.5	5C	GFDL-ESM2G	2.6	12A	IPSL-CM5C-LR	4.5	27B
CCC-CSM1-1	2.6	2A	GFDL-ESM2G	4.5	15B	IPSL-CM5C-LR	8.5	27C
CCC-CSM1-1	4.5	3B	GFDL-ESM2G	8.5	16C	MIROC5	2.6	20A
CCC-CSM1-1	8.5	3C	GFDL-ESM2M	2.6	13A	MIROC5	4.5	28B
CCC-CSM1-1-M	2.6	1A	GFDL-ESM2M	4.5	16B	MIROC5	8.5	28C
CCSM4	2.6	5A	GFDL-ESM2M	8.5	17C	MIROC-ESM	2.6	22A
CCSM4	4.5	6B	GISS-E2-H	2.6	14A	MIROC-ESM	4.5	30B
CCSM4	8.5	6C	GISS-E2-H	4.5	18B	MIROC-ESM	8.5	30C
CESM1-CAM5	2.6	6A	GISS-E2-H	8.5	19C	MIROC-ESM-CHEM	2.6	21A
CESM1-CAM5	4.5	8B	GISS-E2-H-CC	4.5	17B	MIROC-ESM-CHEM	4.5	29B
CESM1-CAM5	8.5	8C	GISS-E2-H-CC	8.5	18C	MIROC-ESM-CHEM	8.5	29C
CESM1-CGC	4.5	7B	GISS-E2-R	2.6	15A	MPI-ESM-LR	2.6	23A
CESM1-CGC	8.5	7C	GISS-E2-R	4.5	20B	MPI-ESM-LR	4.5	31B
CMCC-CESM	8.5	9C	GISS-E2-R	8.5	21C	MPI-ESM-LR	8.5	31C
CNRM-CM5	2.6	7A	GISS-E2-R-CC	4.5	19B	MPI-ESM-MR	2.6	24A
CNRM-CM5	4.5	9B	GISS-E2-R-CC	8.5	20C	MPI-ESM-MR	4.5	32B
CNRM-CM5	8.5	10C	HadGEM2-AO	2.6	16A	MPI-ESM-MR	8.5	32C
CNU-ESM	2.6	3A	HadGEM2-AO	4.5	21B	MRI-CGCM3	2.6	25A
CNU-ESM	4.5	4B	HadGEM2-AO	8.5	22C	MRI-CGCM3	4.5	33B
CNU-ESM	8.5	4C	HadGEM2-CC	4.5	22B	MRI-CGCM3	8.5	33C
CSIRO-Mk3-6-0	2.6	8A	HadGEM2-CC	8.5	23C	MRI-ESM1	8.5	34C
CSIRO-Mk3-6-0	4.5	10B	HadGEM2-ES	2.6	17A	NorESM1-M	2.6	27A
CSIRO-Mk3-6-0	8.5	11C	HadGEM2-ES	4.5	23B	NorESM1-M	4.5	35B
EC-EARTH	4.5	11B	INM-CM4	4.5	24B	NorESM1-M	8.5	36C
EC-EARTH	8.5	12C	INM-CM4	8.5	24C	NorESM1-ME	2.6	26A
FGOALS-g2	2.6	9A				NorESM1-ME	4.5	34B
FGOALS-g2	4.5	12B				NorESM1-ME	8.5	35C
FGOALS-g2	8.5	13C						

The silhouette plot (Figure 10a) indicates that 4 clusters are optimal, with secondary peaks at 13, 19 and 34/36 clusters. While a reduction of the ensemble size from 98 to 34/36 is substantial, we argue that if ensemble reduction is at all necessary a reduced ensemble size of 34 or 36 would very likely be too large. Therefore, we here focus on the alternative smaller ensemble sizes.

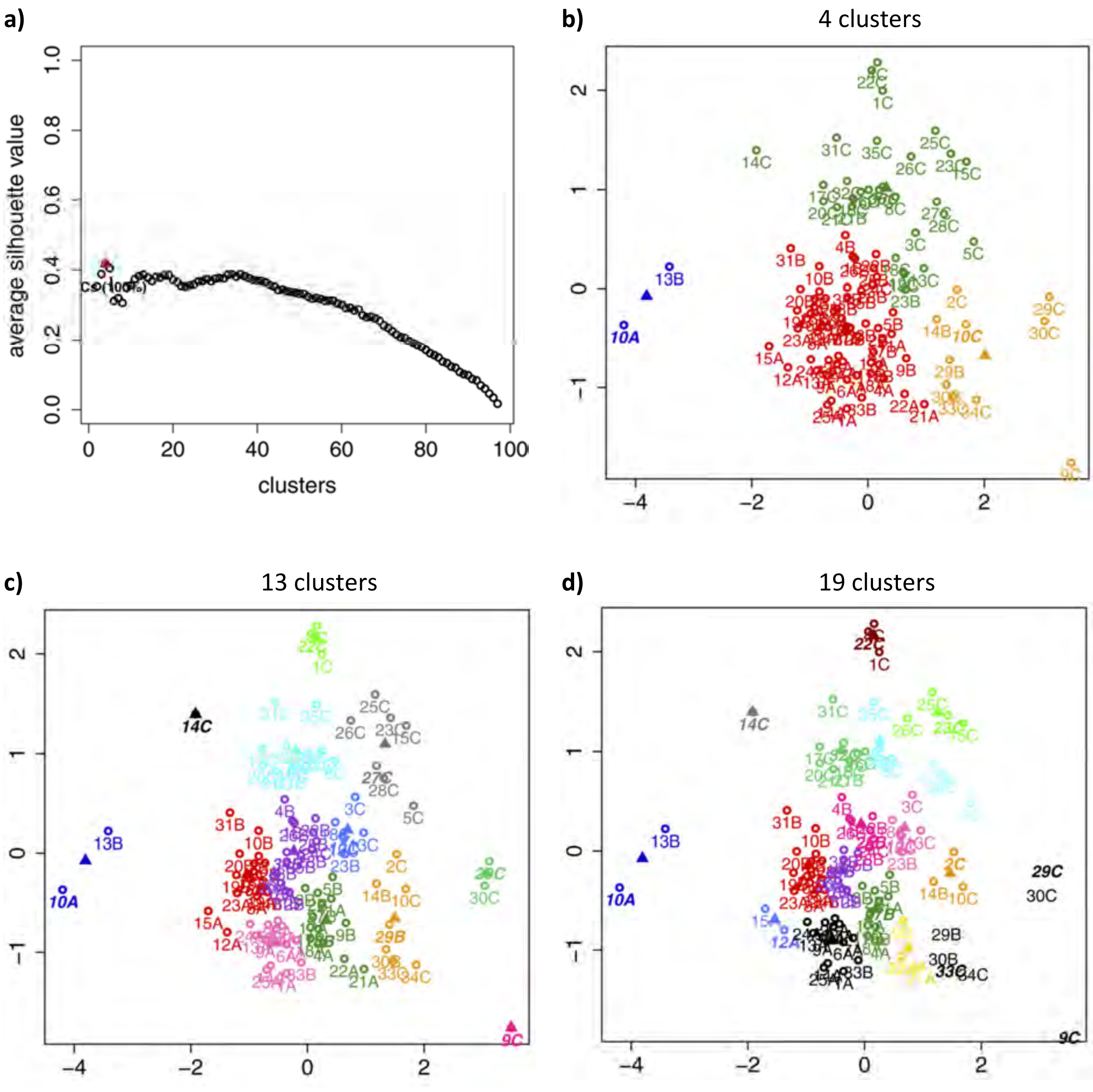

Figure 10. Results of subsampling the overall ensemble of 98 CMIP5 projections. Note that in panel d) some colour are reused for several clusters because the number of clusters is larger than the number of available colours.

As is evident from the bi-plots in Figure 10b-d the hierarchical clustering results in a successively more detailed division of the initial four groups. The 4 cluster solution (Table 11)results in two large groups where one (cluster #2, red) is a mixture of projections representing RCP2.6 and RCP4.5, and one (#4, green) representing RCP8.5. When going from 4 clusters to 13 clusters, these two clusters are successively divided. To interpret these results one may look at the climate sensitivity of the individual models, as well as the genealogy models. This is however beyond the scope of this report.

Table 11. List of the individual members of the four clusters shown in Figure 10b. The colour coding in the header is the same as in the plot, and the colour code of the individual members follows Table 10; green for RCP2.6, yellow for RCP4.5, and red for RCP8.5

Cluster							
1	**2**				**3**	**4**	
10A	10B	18B	25A	3A	10C	11C	23C
13B	11A	19A	25B	3B	14B	12C	25C
	11B	19B	26A	4A	29B	13C	26C
	12A	1A	26B	4B	29C	14C	27C
	12B	1B	27A	5A	2C	15C	28C
	13A	20A	27B	5B	30B	16C	31C
	14A	20B	28B	6A	30C	17C	32C
	15A	21A	2A	6B	33C	18C	35C
	15B	22A	2B	7A	34C	19C	36C
	16A	22B	31B	7B	9C	1C	3C
	16B	23A	32B	8A		20C	4C
	17A	24A	33B	8B		21B	5C
	17B	24B	34B	9A		21C	6C
	18A	24C	35B	9B		22C	7C
						23B	8C

4. Concluding remarks

The technical work for developing the metadata standards and processing tools for producing Tier-1 climate change impact indicators has greatly facilitated the production of the demonstrator dataset for the CLIPC portal. For some Tier-1 indicators the processing time is short enough for enabling online (real-time) calculation, for other Tier-1 indicators this is currently not possible, which means that pre-computed datasets are needed. Irrespective of whether the data is pre-calculated or on demand stable and widely accepted metadata standards are required. The CLIPC has initiated this work and made substantial progress in achieving a standard that is accepted by the wider international community. It is envisioned that this work will continue beyond CLIPC.

The Bias Correction Inter-comparison Project (BCIP) has resulted in publication of a ground-breaking dataset of bias-corrected Euro-CORDEX projection. This dataset covers alternative formulations belonging to the quantile mapping approach for bias adjustment. This rich dataset is currently analysed and used in several projects and is thus already an important contribution to the climate science and climate impact activities.

Early on in the CLIPC project it became clear that users' requirements on representative reduced ensembles could not be met by one pre-calculated dataset. Instead the work has been focussed on developing a methodology and procedure that was flexible enough to allow calculation of reduced ensembles tailored to specific requirements of various users and applications. This procedure has been tested in a number of case studies focussing of a range of applications and involving different input datasets (i.e. global and regional projections over Europe, bias-adjusted and unadjusted regional data, a range of different Tier-1 indicators, etc.). The procedure performed as expected in all cases but one, in which the input data were bias-adjusted and unadjusted data, and RCP4.5 and RCP8.5, for 8 standard regions in Europe. The procedure produced useful and consistent results if the input data were averaged within each of the 8 regions and then used together as input to the reduction procedure. But if the each of the eight regions were analysed separately without spatial averaging of the gridcell data, the procedure still produced a reduced ensemble. But the results were not consistent when comparing bias adjusted and unadjusted results, and/or results for RCP4.5 and RCP8.5. The underlying reason for this is not clear, and requires further investigation beyond the scope of CLIPC.

Case study 1 outlines the workflow in the CLIPC portal is utilised, and is used to produce several of the demonstrator datasets used in the portal. The ensemble of opportunity of regional projections the climate signal map methodology to be used for assessing the robustness. But the reduced ensembles were too small (at least 10 members are required). Thus we here summarise the robustness assessment for the full ensembles.

For large areas of Europe robust increase in summer days and robust decrease in frost days is simulated. This effect is more pronounced for RCP8.5 driven climate projection ensemble than for the RCP4.5 ensembles.

The selection of the climate projection ensemble for calculation the climate signal maps has to be done with care. This needs to take into account the underlying scenario assumptions and the imperfectness of the ensemble in terms of sampling errors, model interdependencies and the coverage of the full bandwidth of possibilities. The interpretation of the robustness of bias-adjusted climate projection ensembles is challenging and should be done with utmost caution.

The resulting robustness of the climate signal maps should always be done context-specific. The climate signal map method allows the user to adjust parameters, such as the classification of the magnitude of the climate change signal into weak, medium and strong, the significance level of the significance test or the fraction of simulations that have to agree on the direction of changes or that have to pass the significance test. The adjustment of these parameters depends on the application of the climate signal map and on the basis of the input data, i.e. the chosen climate projection ensemble.

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