PUNI Handbook

Methods for Providing and Utilizing Uncertain Multi-model Based Information on Freshwater Related Hazards of Climate Change

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1. Introduction

Anthropogenic climate change will continue to happen in the future. This poses a multitude of risks for humans and other biota, in particular related to changes in the hydrological cycle. Risk assessment and thus identification of climate change adaptation measures is severely hampered by the considerable epistemic uncertainty about how climate and climate-related variables, including those describing the freshwater system, will develop. Where future human decisions are involved, uncertainty is deep (Döll and Romero-Lankao 2017). Deep uncertainty is best taken into account by generating plausible alternative scenarios. A scenario describes a potential future; it is not a prediction of what the future will be but rather a description of how the future might unfold. Scenarios cannot be characterized by a probability but should be equally plausible. An example for scenarios relevant for climate change assessments are the four greenhouse gas emissions scenarios (Representative Concentration Pathways or RCPs, Van Vuuren et al. 2011). There is only medium to deep uncertainty in our knowledge about the complex climate-water system (Döll and Romero-Lankao 2017), which makes it possible to quantify the uncertainty by probabilities of occurrence of certain futures at least approximately. It is recommended to describe future climate-change related developments - separately for each RCP - in a probabilistic manner. It is not informative to only provide one deterministic future under each emissions scenario, as it is not possible to predict, with a reasonable precision, the impact of a certain greenhouse gas emissions scenario on hydrological processes. Thus, for example, the hazard that domestic or irrigation water supply will be exposed to due to climate change can only be quantified with a large uncertainty. Consequently, decision making in the context of climate change is decision making under uncertainty (Cobb and Thompson, 2012; Jones et al. 2014). In particular, decision makers or stakeholders that are tasked with identifying and prioritizing suitable measures for adapting to climate change should fully embrace the knowledge about potential future hazards **and** their uncertainties, and integrate this knowledge in their decision process (Haasnoot et al. 2013; Dilling et al. 2015; Döll and Romero-Lankao 2017).

How large a climate change risk is depends 1) on the magnitude of the climate change hazard that is caused by potential changes of physical processes such as precipitation or groundwater recharge, 2) on the exposure of assets, humans and other biota to these changes and 3) on the specific vulnerability of the exposed system (IPCC 2014). The risk can also be determined by the probability of the hazard multiplied by the potential negative impact that would result if the hazard actually materializes (IPCC 2014), e.g. if groundwater recharge would actually decrease by 20% until 2050. Assuming a certain RCP, the probability distribution of the freshwater-related climate change hazard depends on the uncertainty of computing - by climate models -, the impact of greenhouse gas emissions scenarios on the future development of climate variables. Another source of uncertainty are the hydrological models that are necessary to translate climatic changes into hydrological changes. It is therefore state-of-the-art to rely on so-called multi-model ensembles (MME) for quantifying - for individuals RCPs - potential future changes in variables that are relevant for climate change risk assessments such as groundwater recharge or crop yield (Döll et al. 2015). These ensembles consist of the output of various models that are capable of computing the variable of interest. Each model has been driven by the output of a number of global climate models (general circulation models, GCMs) such that the models quantify the potential climate change hazards. Assuming that each model combination, i.e. each ensemble member, is equally likely, the multi-model ensemble can be used to roughly estimate the likelihood of certain future changes of the variable of interest. Given the uncertainties of the models, the resulting probability distribution is again uncertain (Döll et al. 2015), and MMEs may still underestimate the actual uncertainty, for example, if only a small number of GCMs were included.

In this handbook, we inform about provisioning and utilization of the MME-based global-scale quantitative estimates of freshwater-related hazards of climate change that are freely available on the CO-MICC portal (www.co-micc.eu). We refer to the corresponding methods as PUNI (**P**roviding and **U**tilizing e**N**semble **I**nformation) methods, which encompass appropriate ways for characterizing and dealing with the uncertainty of future hazards. A major goal regarding information provisioning is to represent uncertainty quantitatively in a way that is both scientifically correct and meaningful to the diverse users of the hazard information. A major goal regarding the utilization of the information is to identify approaches for integrating information with quantified uncertainty into (participatory) assessments of water-related climate change risks and adaptation options, also considering the rough representation of local conditions by global hydrological models (GHMs).

Ideally, local to regional climate change (CC) risk assessment would be supported by MMEs consisting of a number of local or regional hydrological models. If such alternative hydrological models are not available, as is the case almost everywhere around the globe, utilization of the MME output from GHMs is recommended. Even though a local hydrological model, which is calibrated to observations, is very likely to simulate observed historic water flows and storages better than any GHM, it is unlikely that such a model is capable of simulating future changes of water flows and storages with a low uncertainty. Calibration to observations does not ensure that the hydrological model is suitable for translating changes of climate variables such as precipitation and temperature into changes of runoff. For example, the choice of algorithm for computing potential evapotranspiration may strongly affect potential and thus actual evapotranspiration. Equally important, local hydrological models generally do not take into account the impact of changing atmospheric CO_2 concentrations as well as of climatic changes on vegetation dynamics and thus actual evapotranspiration, while some GHMs can do this. Therefore, to understand the range of plausible future changes at the local to regional scale, it is not sufficient to drive a local or regional hydrological model with the output of a number of global or regional climate models. To inform local to regional climate change risk assessments in the framework of climate change adaptation efforts, consequently, utilization of the MME of GHM output as provided by the CO-MICC portal is recommended. However, low spatial resolution (50 km) as well as insufficient representation of local conditions are an impediment to using CO-MICC portal data directly, and suitable methods for combining CO-MICC MME data with local data need to be applied.

In Chapter 2 of this handbook, we report how the MME was generated and how decisions about the optimized provisioning of model results on the portal were made in a co-design approach with experts and stakeholders. We also present the list of selected hazard indicators as well as their rationale and potential use for local to regional climate change risk assessment. In Chapter 3, methods for utilizing the information and data available on the CO-MICC portal are described. We distinguish utilization of the information for only small regions of the globe as required to support local to regional climate change risk assessments (Chapter 3.1) from utilization of the complete global-scale information by companies with globally spread production sites and supply chains (Chapter 3.2). We discuss in particular how the provided information on the uncertainty of the hazards can be used for decision-making.

2. Methods for *providing* uncertain multi-model based information on freshwater-related hazards of climate change

2.1 Generation of the multi-model ensemble

MMEs for estimating potential impacts of climate change have been generated in the framework of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) initiative (www.isimip.org). In the ISIMIP2b simulation round, a number of impact models (e.g. hydrological models among others) are driven by the bias-adjusted output of GCMs following a detailed simulation protocol (Frieler et al. 2017). For these outputs, each GCM had previously been run for a number of greenhouse gas emissions scenarios (RCP2.6, RCP4.5, RCP6.0 and RCP8.5). RCP2.6 represents an emissions scenario that is likely to constrain global warming to about 2 °C as compared to the pre-industrial period, while the RCP8.5 emissions lead to an approximate global warming of 4 °C by the end of the 21st century. RCP4.5 and RCP6.0 represent intermediate future emissions and thus intermediate degrees of climate change.

The CO-MICC portal provides information on potential future changes of a large number of hydrological variables under these four emissions scenarios (RCPs). These changes were computed by adapting the ISIMIP2b protocol and by using the available ISIMIP2b bias-adjusted output of four GCMs (see Appendix A) to drive three global hydrological models (GHMs): WaterGAP (Müller Schmied et al. 2021), LPJmL (Jägermeyr et al. 2015) and CWatM (Burek et al. 2020). All three GHMs provide their output at a spatial resolution of 0.5° geographical latitude by 0.5° geographical longitude, corresponding to a grid cell size of 55 km by 55 km at the equator. They take into account the impact of human water abstractions and man-made reservoirs on the natural water flows and storages on the continents. Only time series of monthly model output variables are taken into account for the CO-MICC portal, mainly due to the larger uncertainty of daily values. All GHMs provided output for the time period 1981-2099, with water abstractions and reservoirs held constant after 2005.

LPJmL differs from both WaterGAP and CWatM in that it can directly simulate the impact of changing atmospheric CO_2 concentrations as well as of climatic changes on evapotranspiration as it simulates vegetation processes such as the effect of CO_2 on photosynthesis, closure of stomata or plant growth. However, simulation of the vegetation response is uncertain, resulting in considerably varying effects on runoff and groundwater recharge among various GHMs that all simulate the vegetation response (e.g. Reinecke et al. 2021). Therefore, it is appropriate to include a range of hydrological models in the ensemble differing in their ability to simulate the vegetation response or in other process integrations, e.g. in the way potential evapotranspiration or runoff generation are computed, such as WaterGAP and CWatM. To cover a broader and more realistic uncertainty range, the CO-MICC MME does not only encompass the simulations of the three GHMs in their standard configuration but also simulations for each with alternative model variants where a key mechanism parameterization is altered. In the case of LPJmL, a run with an assumed constant atmospheric CO_2 concentration was added. For WaterGAP and CWatM, non-standard model runs were performed using an approach to mimic the vegetation response of global climate models with dynamic vegetation representations by altering the potential evapotranspiration mechanism (Milly and Dunne 2016; Yang et al. 2019; Peiris and Döll, in preparation). Thus, for each of the four RCPs, 4 (GCMs) x 3 (GHMs) x 2 (GHM variants) = 24 ensemble members are available.

As an example, we consider the relative change in groundwater recharge in the period around 2085: for each ensemble member, time series of monthly values of groundwater recharge between 1981-2099 are computed for 0.5° grid cells, which are then temporally aggregated to 30-year averages for the two time periods 1981-2010 and 2070-2099, with 1981-2010 being the reference period. Finally, the percent change of groundwater recharge between the reference period and the future period is computed for each ensemble member. Per RCP, this results in 24 equally likely potential changes of groundwater recharge in a grid cell. The probability distribution of relative groundwater recharge changes can then be quantified from this ensemble, for example, by its percentiles such as the median/50th percentile (which may experience, e.g. a 15% decrease) or the P10/10th percentile value that is exceeded by approximately 90% of the 24 ensemble members (which simultaneously may change differently, e.g. by -30%).

2.2 Co-design

For CO-MICC a data and knowledge portal is co-developed with stakeholders based on these global-scale multi-model simulations of hydrological variables. The aim of the co-design is finding out how to make the CO-MICC MME data optimally utilizable for climate change risk assessment and adaptation at different scales. In a participatory manner, we focused on (1) eliciting the relevant hydrological hazard indicators, (2) representing their uncertainty quantitatively in a way that is both scientifically correct and utilizable to the diverse users of the hazard information, and (3) creating guidance on how to integrate the uncertain global information into regional-scale assessments of water-related climate change risk and adaptation assessments. Adapting the tandem framework of the Swedish Environmental Institute (SEI, Daniels et al., 2019), participatory stakeholder dialogues including eleven workshops with stakeholders from focus regions in Europe and Northern Africa, and finally with globally-acting companies serve to iteratively integrate the various experiences, needs and expectations of various regions and users. Participants included local researchers, experts from meteorological services and decision-makers from regional and national hydrological administrations (water supply, irrigation, basin management). Co-development was structured through presentation, questionnaires and small discussion groups.

Together, we co-produced 15 relevant model output variables, eliciting the time scales of interest and appropriate end-user products encompassing static and dynamically generated information for a data portal (see Chapters 2.3 and 2.4). The global-scale information products include interactive maps, diagrams, time series graphs and suitably co-developed statistics, with appropriate visualization of uncertainty, for which we provided example diagrams and collected valuable feedback in breakout groups. In complement, the knowledge tool provides transparent meta-information, tutorials and handbook guidelines to utilize the provided information in models of local participatory risk assessments.

Specific feature elements stem from the stakeholder dialogues and include, for example, explanations on the portal and the importance of transparently and clearly communicating the meaning and calculation basis of provided data in an understandable way. Both mouse-hover tip boxes and a glossary are part of the developed portal. Further features are the spatial aggregations for basin and country level, user selectable seasons, and download options.

2.3 Indicator list

The final list of indicators from the process is shown in Table 1, and structured into 15 variables and their specific indicators. On the CO-MICC data portal, we provide for most indicators in the table:

1. relative change (i.e. percent change) in a specified 30-year future time period as compared to the reference period 1981—2010 (for all ensemble members and emissions scenarios RCP)
2. absolute change, positive or negative (for all ensemble members and emissions scenarios RCP)
3. one reference value: median of ensemble members for the reference period 1981—2010

In general, relative changes can be computed more reliably than absolute changes and should therefore be applied for CC risk assessment. Only if relative changes are not available in a cell (because if the ensemble member value for the reference period is zero or very small, relative changes are not sensible, and the cell will be greyed-out), absolute changes should be considered. Simulated changes can be combined with the reference value to obtain a rough estimate of the indicator in future time periods. Preferably, a local estimate of the indicator during the reference period is used to obtain an estimate for the future.

Values are provided for all land areas of the globe (except Greenland and Antarctica).

The list in Table 1 also contains co-developed indications on the rationale and potential use of the indicators for local to regional climate change risk assessment.

Table 1: *Indicators for different hydrological variables computed by global hydrological models for 30-year periods. They are provided at annual time scale, for the four seasons or for each calendar month. CC abbreviates climate change.*

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
1. Blue water production BWP (Total runoff from soil and surface water bodies)	Annual	Mean	R: Total renewable water resources and the part of the precipitation that does not evapotranspire. Maximum amount of water available for management. U: Simulated change can be applied to local estimate of renewable water resources e.g. to compare to water demand or to serve as input to a local water allocation/supply model.
		Annual High (Q10)	R: The maximum amount of water available for management that is exceeded in only 1 out of 10 years, i.e. in a wet year.
		Annual Low (Q90)	R: The maximum amount of water available for management that is exceeded in 9 out of 10 years, i.e. in a dry year.
		Year-to-year variability: Standard deviation	R: The higher the standard deviation of annual BWP, the more difficult it is to reliably fulfil water demand (which is relatively constant from year to year or even higher in years with low BWP).
		Year-to-year variability: Coefficient of variation	R: Coefficient of variation = standard deviation/mean If both the standard deviation and the mean increase, the coefficient of variation may remain constant.

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
2. Streamflow	Annual	Mean	R: Simulated streamflow is, in contrast to BWP, affected by upstream human water use and man-made reservoirs (in most GHMs). Estimates for years after 2005 assume that water use and reservoirs remain at the 2005 level. U: Streamflow indicators based on annual streamflow (mean, annual high, annual low, interannual variability indicators) can be simulated more reliably by GHMs than indicators based on monthly or daily simulation results. This is particularly true for highly managed basins with reservoirs and high water use or even water transfers. U: To estimate the CC impact on reservoir inflow or the ability to transfer water, change of mean annual streamflow can be used. However, it is likely that streamflow downstream of significant water use, reservoirs or water transfers cannot be reliably computed by GHMs. In these cases, it is recommended to use either naturalized streamflow indicators at an upstream grid cell that is not affected by human impacts or BWP indicators as input to local risk assessments.
		Annual High (Q10)	R: Annual streamflow that is exceeded in only 1 out of 10 years, i.e. streamflow in a wet year.
		Annual Low (Q90)	R: Annual streamflow that is exceeded in 9 out of 10 years, i.e. streamflow in a dry year.
		Monthly High (Q10)	R: Monthly streamflow that is exceeded in only 1 out of 10 months (i.e. in 36 out of the 360 months of the 30-year period); a statistical high flow value. It is expected that monthly Q10 streamflow can be simulated reasonably well by GHMs.
		Monthly Low (Q90)	R: Monthly streamflow that is exceeded 9 out of 10 months (i.e. streamflow is lower only in 36 out of the 360 months of the 30-year period); a statistical low flow value. U: It is expected that monthly Q90 streamflow can be simulated reasonably well by GHMs.
		Year-to-year variability: Standard deviation	R: The higher the standard deviation of annual streamflow, the more difficult it is to reliably fulfil water demand (which is relatively constant from year to year or even higher in years with low streamflow).
		Year-to-year variability: Coefficient of variation	See standard deviation

		Calendar month with highest mean monthly flow	Only reference value and absolute change provided. R: Shift (in months: e.g. a shift by 1.7 month) indicates change in streamflow seasonality. U: To modify seasonality of locally quantified streamflow values.
		Calendar month with lowest mean monthly flow	Only reference value and absolute change provided. R: Shift (in months) indicates change in streamflow seasonality. U: To modify seasonality of locally quantified streamflow values.
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	R: Mean streamflow in March, April and May. U: Particularly in highly managed basins, seasonal streamflow simulated by GHMs may strongly differ from actual values
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	R: Mean streamflow in the calendar month January. U: Particularly in highly managed basins, monthly mean streamflow simulated by GHMs may strongly differ from actual values, even more than seasonal values.

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
3. Naturalized Streamflow	Annual	Mean	R: Streamflow simulated under the assumption that there are neither man-made reservoirs nor human water use. Simulated changes of naturalized streamflow are expected to differ insignificantly from simulated changes of (anthropogenically affected) streamflow except in highly managed basins. U: In highly managed basins, it is recommended to use either naturalized streamflow indicators at an upstream grid cell that is not affected by human

			impacts or BWP indicators as input to local risk assessments.
		Annual High (Q10)	see streamflow
		Annual Low (Q90)	see streamflow
		Monthly High (Q10)	see streamflow
		Monthly Low (Q90)	see streamflow
		(7-day low flow)	see streamflow
		Year-to-year variability: Standard deviation	see streamflow
		Year-to-year variability: Coefficient of variation	see streamflow
		Shift in high flow month	see streamflow
		Shift in low flow month	see streamflow
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	see streamflow
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October	see streamflow

		11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
4. PET	Annual	Mean	R: Potential evapotranspiration, i.e. evapotranspiration occurring in the cases of open water and very wet soils. U: Simulated change can be applied to local estimate of reservoir evaporation or PET estimates in models of irrigation water requirements.
		Year-to-year variability: Standard deviation	
		Year-to-year variability: Coefficient of variation	
		PET/Precipitation	R: Aridity indicator (the higher, the more arid)
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	R: Mean streamflow in March, April and May. U: Particularly in highly managed basins, seasonal streamflow simulated by GHMs may strongly differ from actual values
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	R: Mean streamflow in the calendar month January. U: Particularly in highly managed basins, monthly mean streamflow simulated by GHMs may strongly differ from actual values, even more than seasonal values.

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
5. AET	Annual	Mean	R: actual evapotranspiration from canopy, soil and surface water bodies
		Year-to-year variability: Standard deviation	
		Year-to-year variability: Coefficient of variation	
		AET/Precipitation	R: Fraction of precipitation that is actually evapotranspired
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
6. AET/PET	Annual	Mean	Note: AET and PET are computed as a mean over every grid cell which may consist of both surface water bodies and land. Therefore, the ratio of actual over potential evapotranspiration is not a measure of water stress of vegetation.

		Year-to-year variability: Standard deviation	
		Year-to-year variability: Coefficient of variation	
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
7. Groundwater recharge	Annual	Mean	R: Renewable groundwater resources, i.e. the maximum amount of groundwater that could be used without causing a continuing loss of groundwater storage and groundwater table decline. U: Percent change can be applied to local estimate of groundwater recharge from soil.

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
8. Soil moisture saturation	Annual	Mean	R: soil water content /maximum soil water content, a measure of water stress for vegetation.
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
9. Snow storage	Annual	Mean Storage	U: Mean annual snow water storage is not relevant for water supply; rather, change in snow storage at the end of the snow season is relevant. Seasonal or calendar month snow storage should be used.
		Number of months with snow	
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	

	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
10. Net irrigation requirement NIR	Annual	Mean	R: The mean amount of water that is additionally evapotranspired due to irrigation if enough water can be supplied to allow for optimal irrigation. Different GHMs assume different crops and growing periods. U: Simulated change can be combined with current, local estimates of NIR.
		Annual High (NIR10)	R: Annual NIR that is exceeded in only 1 out of 10 years, i.e. NIR in a dry year.
		Annual Low (NIR90)	R: Annual NIR that is exceeded in 9 out of 10 years, i.e. NIR in a wet year.
		Year-to-year variability: Standard deviation	R: An increase in standard deviation is likely to make a reliable water supply more difficult.
		Year-to-year variability: Coefficient of variation	See standard deviation

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
11. Temperature	Annual	Mean	

	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
12. Precipitation	Annual	Mean	
		Year-to-year variability: Standard deviation	
		Year-to-year variability: Coefficient of variation	
		Calendar month with highest mean monthly precipitation	Only reference value and absolute change provided. R: Shift (in months) indicates change in precipitation seasonality.
		Calendar month with lowest mean monthly precipitation	Only reference value and absolute change provided. R: Shift (in months) indicates change in precipitation seasonality.

		R95T	R: represents the contribution the heavy precipitation days generate to the total precipitation. Changes indicate a shift to more or less extreme precipitation patterns, i.e. where precipitation might concentrate in more intense events. U: to identify initial areas which could be prone to increased risk of flooding, and for which an in-depth flood risk assessment might be relevant.
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
13. Water scarcity	Annual	Mean	Absolute change and actual index value provided (and reference value). $Water\ scarcity = \frac{Water\ use\ (consumptive)}{Water\ availability}$
		Year-to-year variability: Standard deviation	
		Year-to-year variability:	

		Coefficient of variation	
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
14. Water stress	Annual	Mean	Absolute change and actual index value provided (and reference value). $Water\ stress\ = \frac{Water\ withdrawals}{Water\ availability}$
		Year-to-year variability: Standard deviation	
		Year-to-year variability: Coefficient of variation	
	Seasonal	Mean of 1 March to May 2 June to August	

		3 September to November 4 December to February	
	Calendar month	Mean of 1 January 2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December	

Variable	Time scale	Indicator	Rationale (R) and potential use for local to regional CC risk assessment (U)
15. Water availability	Annual	Mean	A cell's generated water (bwp or net cell runoff) plus accumulated inflow from upstream cells with already deducted upstream water use (anthropogenic streamflow) and incorporating an environmental flow requirement (80% of naturalized streamflow to remain in river)
		Year-to-year variability: Standard deviation	
		Year-to-year variability: Coefficient of variation	
	Seasonal	Mean of 1 March to May 2 June to August 3 September to November 4 December to February	
	Calendar month	Mean of 1 January	

	2 February 3 March 4 April 5 May 6 June 7 July 8 August 9 September 10 October 11 November 12 December

2.4 User interface of the data portal

The CO-MICC data portal is an interactive platform that offers the user a considerable degree of flexibility as to the hazard indicator selection, the definition of the MME and the type of visualization. As shown in Figure 1, it encompasses a menu bar on the left, a data viewer in the form of global maps and a tool for further data analysis in the form of various graphical representations (pop-up window hereafter called “raster cell box”).

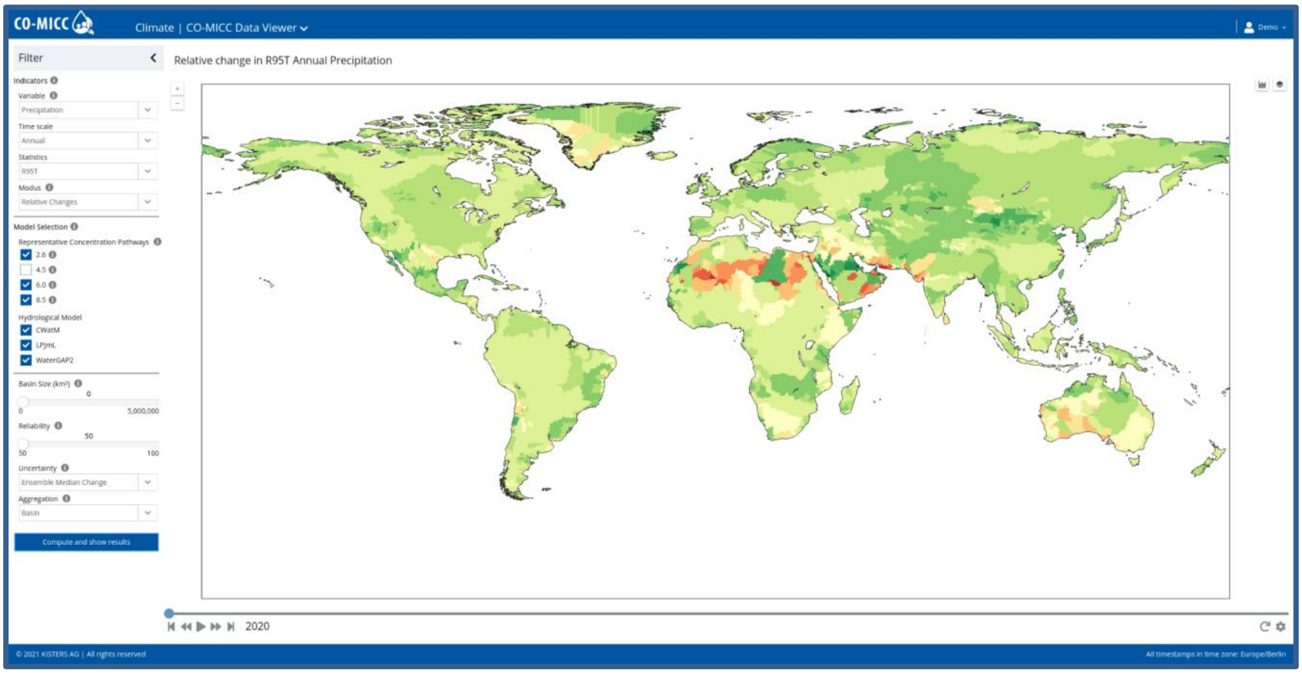


Figure 1: Frontend of the CO-MICC data portal: a menu bar on the left, and a data viewer with the global maps.

The hazard indicator is specified through the usage of four drop-down menus (Figure 2a) to select the hydrological variable, the time scale (annual, seasonal or monthly), and the statistic(s) to be calculated. Lastly, the modus can be changed (for most indicators, the choice can be made between relative and absolute changes as compared to the reference period). The definition of the MME is done by means of two selection menus (Figure 2b); one to specify the combination of RCPs and the other of GHMs. In both cases, all combinations are possible. By default, all possible GCMs and GHM variants are included (see Chapter 2.1).

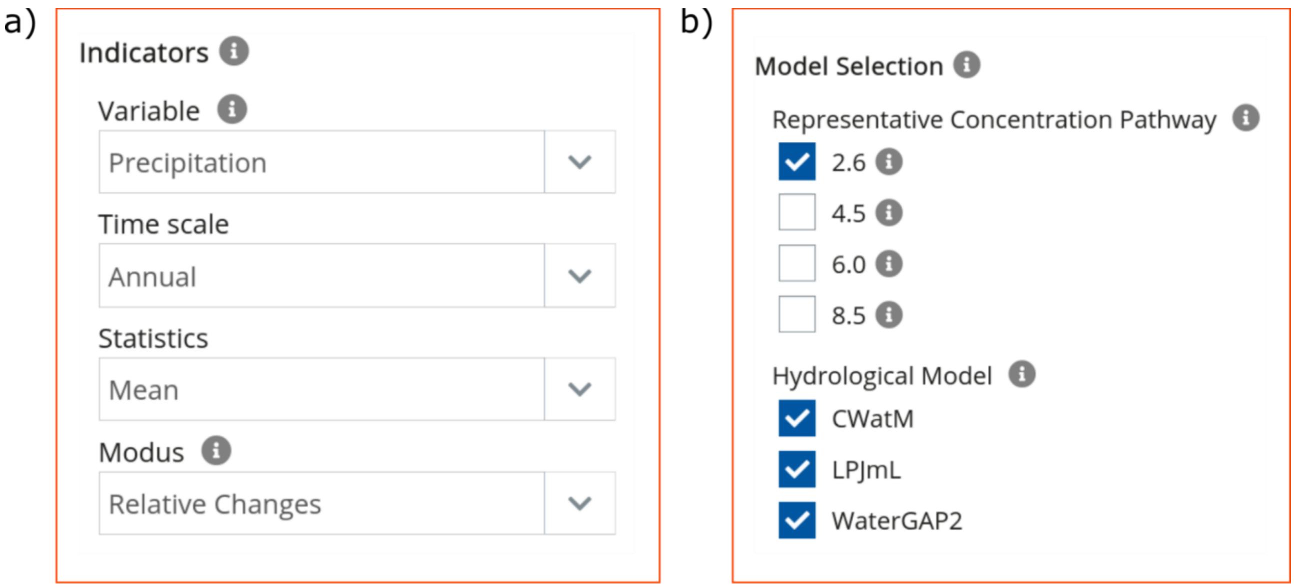


***Figure 2**: Menu options to select the hazard indicator and the multi-model ensemble. a) Drop-down menus for the selection of the hazard indicator. In the present example, the selected indicator corresponds to the relative change of mean annual precipitation between the reference and the future period. b) Menus for the*

selection of Representative Concentration Pathways (RCPs) and Global Hydrological Models (GHMs). In the present example, only one RCP, namely RCP2.6, and all three GHMs are selected to be part of the ensemble to be displayed.

By default, the data viewer displays the data corresponding to all grid cells globally. However, it can be the case that the user is only interested in the data in the cells corresponding to major basins. In that case, the user can define a minimum basin size by means of a slider, enabling in this way the selection of relevant basins (Figure 3).

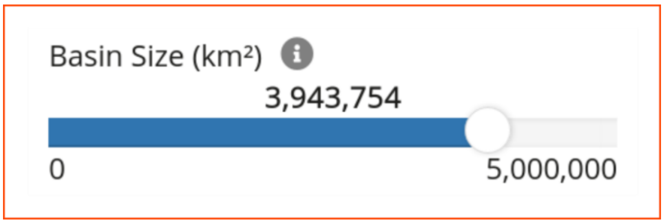


***Figure 3**: Slider to set a minimum threshold for basin size.*

Furthermore, the user has the choice between multiple spatial aggregation options. The selection is done through a drop-down menu (Figure 4). By default, the data viewer shows the data without any spatial aggregation, i.e. the data corresponding to each individual grid cell. In addition, the user can choose to have the data aggregated at the scale of predefined basins (approximately the largest 300 basins are included) or basins defined by each cell, i.e. corresponding to the upstream area of each cell.

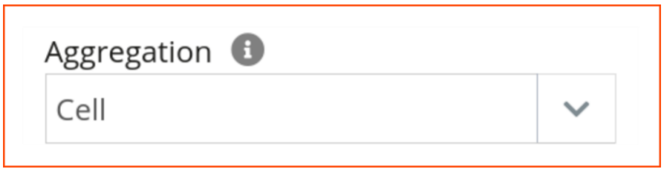


***Figure 4:** Drop-down menu to select the spatial aggregation of the data.*

The uncertainty of the MME data is represented in different ways in the portal, for both the map and cell displays. They therefore include several options in the left-hand-side menu as well as some of the diagrams available in the raster cell box. The visual representation of uncertainty is described in more detail in Chapters 2.4.1 and 2.4.2.

2.4.1 Data viewer

The maps show the selected hazard indicator by different colors according to a legend located in the bottom right corner of the data viewer. The legend is characterized by a diverging color scale with classes representing smaller numbers in light colors and classes representing larger numbers in dark colors. The range of the class containing the midpoint of the scale (i.e. zero) is deliberately small as it represents the case where there is no significant change or a very small change. The number of classes, which varies between 8 and 13, and the class breaks have been predefined after careful consideration by the modelers. The indicator values are provided for different spatial aggregations:

1) for each 0.5° grid cell
2) aggregated over countries, where each grid cell pertaining to a country shows the country average value of the indicator
3) aggregated over predefined basins (approximately the largest 300 basins are included), where each grid cell pertaining to a basin shows the basin average value of the indicator
4) aggregated over cell-specific basins (i.e. drainage basin of each cell), where each grid cell shows the upstream area (including the cell itself) average value of the indicator

When hovering with the mouse over a cell, a text box with the cell coordinates appears in the bottom left corner of the data viewer. Buttons to zoom in and out, to switch between different background layers and to download the data (as a CSV file) and map (as a PNG file) are also included. Furthermore, a time slider and animation option in the lower part of the data viewer allow the user to move through time.

Regarding the uncertainty of the MME data, some of the elements in the left-hand side menu have been explicitly designed to integrate this type of information in the map display. For instance, the “reliability” slider (Figure 5) allows the user to set a minimum threshold for the percentage of MME members agreeing on the sign of projected change (positive or negative), below which data in a cell is not displayed. For example, if the user sets the reliability slider to 75%, this means that at least three quarters of all MME members need to agree on the sign of change; the grid cells for which this condition is not met are filtered out in the data viewer. This option gives the user the freedom to set the condition that defines whether the forecast given by the selected MME is reliable or not. The filtered-out cells are considered to contain data that is too uncertain and thus unreliable.

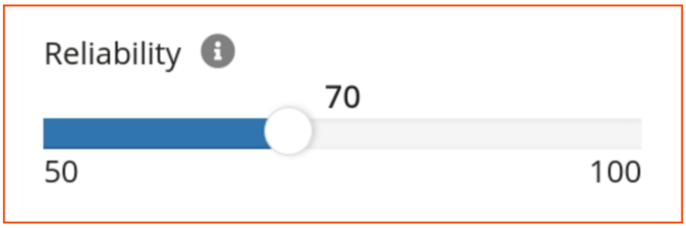


Figure 5: *Slider to set a minimum threshold for the percentage of multi-model ensemble members agreeing on the sign of change.*

Moreover, instead of only one type of value describing the MME change, the user can choose between displaying the ensemble median (default option), the ensemble 10th percentile or the ensemble 90th percentile by the means of a drop-down menu (Figure 6). In this way, the user can get a picture of the MME data uncertainty.

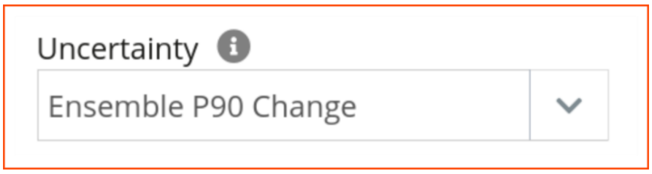


Figure 6: *Drop-down menu to select the multi-model ensemble value to be displayed.*

2.4.2 Raster cell box

The raster cell box is displayed over the data viewer when clicking on a specific location. A menu on the left of the box offers a selection of different graphical representations that the users can choose from, depending on the type of information that they wish to visualize (temporal evolution, comparison between different RCPs or GHMs, probabilities etc.) and how they want it to be displayed (e.g., time series, box plots). These graphical representations can be classified into three chart type categories: curves, box plots and tables. As for maps, it is also possible to download the graphs (as PNG files) and related data (as CSV files) generated with the raster cell box.

By default, the data is displayed in the form of a time series (curve chart) with the y-axis representing the relative (or absolute) change and the x-axis the climate period centre (Figure 7). Each data point corresponds to the change averaged over the 30-year period defined by its centre year. For example, the year 2030 actually refers to the climate period 2015-2044. The MME median is represented as a line. Furthermore, two levels of shading around the curve are given; the darker shading represents the spread of the individual solutions between the 25th and 75th percentiles, and the lighter shading the spread between the 10th and 90th percentiles. In this type of representation, information about the uncertainty is given by the shaded areas.

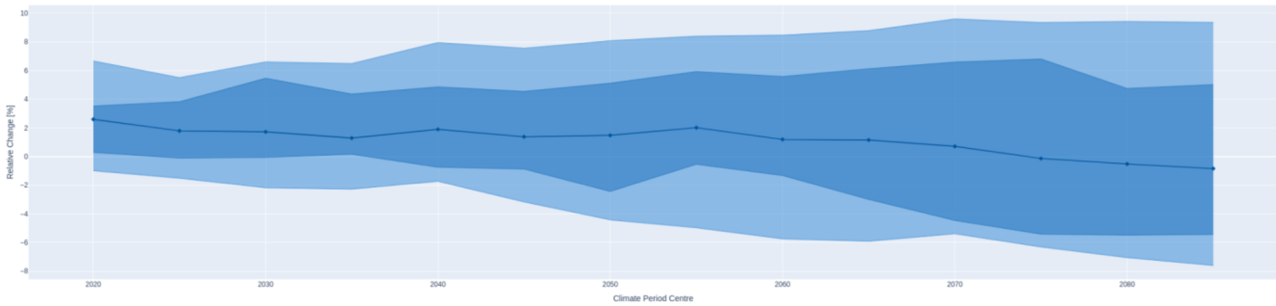


Figure 7: *Time series displayed in the raster cell box.*

Another option to display the data is a chart type called "box plot". Box plots are useful to compare the distribution of multiple sets of data. The user can choose to display box plots to compare the distribution of MMEs corresponding to different RCPs or to different GHMs (Figure 8). In this way, it is possible to visualize the uncertainty related to the choice of RCP and to the choice of GHM.
A box plot shows the distribution of the values of a given data set. It is composed of a box and two whiskers (i.e. lines extending from the box). The box gives a three-number summary of the distribution, namely the median (or 50th percentile), and the 25th and 75th percentiles (or first and third quartiles). In a box plot drawn vertically (a box plot can also be drawn horizontally), the bottom and upper ends of the box represent the 25th and 75th percentiles, respectively, and the median is represented as a dark bar within the box. The bottom and upper whiskers show the 10th and 90th percentiles, respectively.

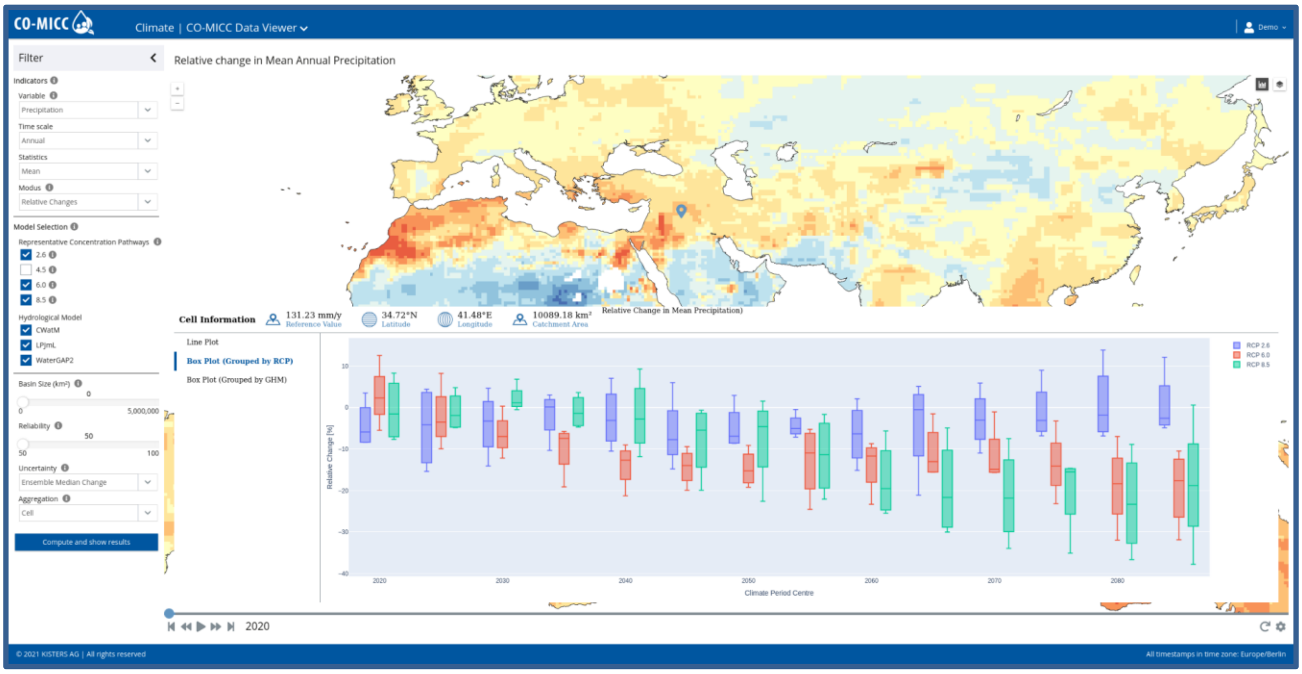


Figure 8: Boxplots displayed in the raster cell box.

Moreover, the MME data can also be visualized in the form of a table. Three types of value are given in the table, namely the median and the 10th and 90th percentiles. Values are given for all projected 30-year periods and for all RCPs individually, showing in this way the uncertainty related to the choice of RCP.

3. Methods for *utilizing* uncertain multi-model based information on freshwater-related hazards of climate change

According to IPCC (2014, p. 9), "assessment of the widest possible range of potential impacts, including low-probability outcomes with large consequences, is central to understanding the benefits and trade-offs of alternative risk management actions". Therefore, not only multi-model ensemble means should be analyzed but also less likely outcomes with a high risk, i.e. outcomes that may have strong negative impacts. MMEs can inform stakeholders with different degrees of risk aversion or "safety requirements" (Crosbie et al. 2013). For example, in a case where a certain decrease in a statistical low streamflow (e.g. monthly Q_{90}) would put the production of safe drinking water at risk and require investment in additional water supply infrastructure, stakeholders with a high safety requirement may decide in favour of the investment even if only 10% of the ensemble runs project such a decrease over the design period, while stakeholders with a low safety requirement may only invest if at least 50% of the runs do this.

A first step in climate change risk assessment is the definition of relevant risks, with the formulation of the specific risks of what and for whom. For example, a risk for water supplier could be formulated as the risk of certain increases in the frequency of water use restrictions caused by a lack of water supply in a changing climate, e.g. from 1-in-10 years to 1-in-5 years, as suggested by Borgomeo et al. (2016, 2018) in a case study of water supply in the British Thames river basin. In the next step, risk was quantified by using a sophisticated water supply model that was driven by an ensemble of climate scenarios as well as scenarios of water demand. Then, adaptation measures such as the construction of water reservoirs were implemented in the model to see their effect. Finally, the cost of adaptation measures could be related to their risk-reducing effect, i.e. to what extent they could reduce the otherwise increased frequency of water use restrictions. A more simple risk metric is, for example, the ratio of water demand over water resources. Even hazard indicators such as the change in statistical low streamflow values (e.g. indicator Q_{90}, Chapter 2.3) can be used as a risk metric for the well-being of the exposed freshwater biota.

To guide the user optimally, in this chapter we distinguish utilization of the information into two broad categories, specifically utilization of information for small regions as compared to utilization of the complete global-scale information. Both are associated with different target user groups, associated methods and support different kinds of risk assessments, and are described in the respective subsections in this chapter.

3.1 Local to regional climate change risk assessments

Once the relevant local freshwater-related risks of climate change have been formulated, including the causative changes in specific water flows (e.g. streamflow) and storages (e.g. soil moisture), suitable hydrological hazard indicators need to be determined. For example, the change of mean streamflow during the summer season might be critical for a specific risk. Then, as indicated in Chapter 1, local climate change risks assessment and management would ideally be informed by the mean summer streamflow changes as projected by a MME consisting of various local (or basin-scale or regional) hydrological models that are fed by climate change scenarios from a range of global (and possibly regional) climate models. If such MMEs are not available, there are methods of utilizing the information provided on the CO-MICC portal in local to regional freshwater-related climate change risk assessment.

If there is very little local information available, which is often the case in particular regarding hydrological variables such as soil moisture or groundwater recharge, direct use of the 0.5° grid scale percent changes of hydrological variables as provided by the CO-MICC ensemble provides informative input to local to regional climate change risk assessments. However, it is preferable to combine the spatially coarse and non-local data available at the CO-MICC portal with local information and data in a meaningful way. Chapter 3.1.1 describes how this can be achieved in a simple way. In Chapter 3.1.2, more sophisticated and costly options are presented. In Chapter 3.1.3, we present how CO-MICC MME data can be utilized by Bayesian Belief Network (BN) modeling for local (to regional) risk assessments. With this approach, local climate change risks can be estimated in a probabilistic manner, thus explicitly taking into account uncertainty. We provide a specific example of how the CO-MICC MME data can be integrated into the BN to compute climate change risks for water supply. This example is applicable in case there is no local or regional hydrological model available.

3.1.1 Simple approaches for combining CO-MICC MME data with local data

Values of hydrological variables, computed by driving GHMs by GCM output, such as, for example, of streamflow during the reference period, in most cases do not fit well to local-scale observations. One reason is that due to the stochastic and chaotic character of weather, it is impossible for GCMs to simulate the historic weather exactly. Other reasons are model uncertainties of GCMs and GHMs. Even after bias-adjustment of GCM output (daily temperature, precipitation, etc.) using observation-based historic climate time series, the historic time series of simulated climate variables of a certain GCM may differ appreciably from both observations and the output of other GCMs. GHMs driven by climate scenarios can provide, however, robust information on hydrological changes due to climatic (and other) changes, with relative changes likely being more robust than absolute changes, as the absolute values during the reference period differ among GCMs and from observations. To estimate a plausible range of future values of hydrological indicators, we therefore recommend combining the best local estimates of hydrological indicators (HIs) of interest (e.g. mean groundwater recharge, snow storage in March, net irrigation requirement in the summer season or the annual streamflow that is exceeded in 1 out of 10 years) with percent changes of these indicators from the CO-MICC MME. Applying each of the e.g. 24 estimates of percent change in hydrological indicator HI (one per ensemble member) separately, the ensemble of future local HI is calculated as:

HI_local (future time period) (ensemble member i) = HI_local (reference time period best local estimate) * (1 + percent change of HI of ensemble member i / 100)   (Eq. 1)

However, this approach may not lead to meaningful information for all hydrological hazard indicators. For example, GHMs cannot simulate well the seasonality of streamflow in highly managed basins with large water abstractions and man-made reservoirs, or even water transfers out of the basin. In this case, the MME percent changes of e.g. streamflow in May should not be used for local risk assessments. To assess season-specific hydrological changes in such basins, it is required to use a local hydrological and water supply model to translate MME changes to changes in local dynamics.

3.1.2 More sophisticated and costly options

In many catchments or river basins, there exists a good local hydrological and/or water supply system model that takes into account the management of reservoirs, water abstractions and water transfers. In this case, there are many options for combining information from the CO-MICC MME with the local model. The choice of option depends on the model and the local conditions. Downscaling of the 0.5° output of the CO-MICC ensemble with a local hydrological model can be achieved by using CO-MICC MME percent changes of annual "blue water production" (BWP, equivalent to the total runoff generation from soil and surface water bodies) (see Chapter 2.3). The total runoff estimates of the local model within each 0.5° grid cell for the reference period can be scaled with the 0.5° percent changes of the CO-MICC MME, such that for each ensemble member and 0.5° grid cell, the percent change of the mean annual total runoff of the local model is equal to the value of the corresponding CO-MICC ensemble member. In this way, a major signal of climate change that is known to vary widely among GCMs and GHMs is represented by the local model simulations. However, changes in seasonality and other temporal variabilities as driven by climate change are not taken into account. Alternatively, changes in mean monthly naturalized streamflow in 0.5° grid cells (12 values per grid cell) could be utilized for scaling time series of temporally and spatially more highly resolved streamflow that is computed by the local model for the reference period. Then, the local supply model would be run for the whole reference period with implementation of the scaling factors from each CO-MICC ensemble member. This will produce a number of local model results for the selected future time period, one for each CO-MICC ensemble member, and thus a range of potential futures of streamflow at the spatial and temporal resolution of the local model.

If there is a local water supply system model that simulates the operation of reservoirs and water abstraction, MME data on changes of mean monthly naturalized streamflow upstream (see Chapter 2.3) of the most upstream reservoir and of significant surface water abstraction can be used as input to the local water supply system model. To compute future hydrological conditions, the inflow into the most upstream reservoir simulated by the local model for the reference period could be scaled, separately for each calendar month, with percent changes of mean monthly naturalized streamflow of each CO-MICC ensemble member individually, according to Equation 1. For each calendar month of the time series, the same change factor is applied. This generates six local streamflow time series for each future time period and RCP that then serve as input to the local water supply system model. In case of irrigation water use, the percent change of net irrigation requirement of the CO-MICC ensemble could also be taken into account to scale water abstractions or consumptive irrigation use as computed by the local model. Then, the local supply model would be run for the whole reference period, driven by the scaled inflow (and irrigation water abstractions). This will produce local model results over the selected future time period for each CO-MICC ensemble member, i.e. an ensemble of local model runs for the future time period and a range of potential futures of e.g. reservoir outflow or water demand coverage.

A popular water supply or rather water allocation model is the WEAP (Water Evaluation and Planning) software (www.weap21.org), partly because it is free-of-charge for low-income countries and relatively easy to set up. WEAP requires upstream streamflow data (monthly time series) and then computes the demand coverage of water demand sites that are distributed along the stream network, also taking into account reservoirs. To estimate the impact of climate change on water demand coverage, the local best estimate time series of upstream streamflow for the reference period is modified using the percent changes of mean monthly naturalized streamflow to generate local streamflow time series for a future time series. This approach is the same as suggested in the last paragraph for application with local water supply system models.

3.1.3 Bayesian Belief Network Modelling

Local climate change risk assessments are best supported by a quantitative integration of physical hazards, exposures and vulnerabilities that includes the characterization of uncertainties. Using Bayesian Networks (BNs) for this task is a suitable approach as the available MME output can be integrated into BNs, in order to probabilistically assess risks for, e.g., water supply.

Bayesian Networks are a cutting-edge integrated modelling approach (Terzi et al., 2019; Düspohl et al., 2012) to deal with uncertain and complex domains such as climate change by estimating probabilities of risks (Phan et al., 2016; Sperotto et al., 2017). BNs are a formal representation of the joint probabilistic behavior of a system conditioned by deeply uncertain but potentially useful information about the future (Lempert, 2004; Taner et al., 2019). They can (1) combine quantitative multi-model output data and qualitative expert knowledge, (2) inherently deal with uncertain multi-model ensemble projections and other system variables through their representation with probability distributions, (3) include multiple stressors and endpoints, (4) compute alternative scenarios for water availability and demand, and (5) take into account the effect of adaptation policies on climate change risks (Sperotto et al., 2017). In the past two decades the use of Bayesian Networks in many environmental fields with a risk assessment perspective has been exponentially growing (Phan et al., 2016) and Bayesian networks are increasingly being integrated with other modeling constructs and tools (Marcot and Penman, 2019). Phan et al. (2016) found 111 original, peer-reviewed papers published from 1997 to 2016 dealing with Bayesian Networks in the field of water resources. Sperotto et al. (2017) reviewed 22 publications dealing with Bayesian Networks for climate change risk (or impact) assessments and management.

In this chapter we use an example of a co-developed Bayesian Network Model from a stakeholder dialog with water experts from the Maghreb countries (Chapter 2.2) to show how such a BN can be set up. This focuses on how to integrate CO-MICC MME data into a BN to obtain a state-of-the-art representation of climate change hazards and their uncertainties, and the involvement of experts in the BN development. For the example, projected relative changes in runoff, groundwater recharge and net irrigation requirement from the MME were processed using MATLAB, taking into account local information on historic water availability and use. Probability distributions of risk levels under historic and future climate and water use were co-developed with experts from the Maghreb, who positively evaluated the BN application for local climate change risk assessments. The presented approach is thus suitable for application in the many local climate change risk assessments necessary for successful adaption to climate change world-wide.

3.1.3.1 Method and co-design

A linked chain of models informed by the MME output, literature data and local expert knowledge and literature data can be used to assess the probabilistic risk of climate change for water supply from groundwater and from surface water (Figure 9). Our method consisted of six steps: (1) co-defining the real-world problem, the key risks, the structure of the system to be modeled including its boundaries and its spatio-temporal extents and resolution as well as the system variables, (2) co-developing causal networks, (3) co-developing the Bayesian Network model structure including gathering data from literature and our multi-model ensemble, (4) setting up the Bayesian Network model based on computations with the software tools MATLAB and Netica, and (5) simulating the Bayesian Network model with Netica under reference and future conditions, computing risks under different climate change and water use scenarios.

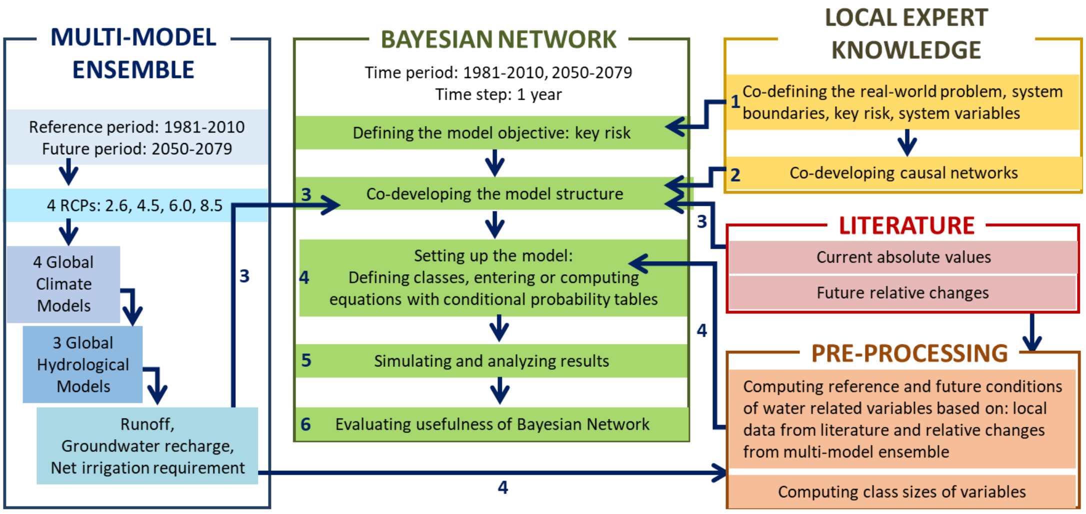


Figure 9: *Steps 1 to 6 (blue numbers) of local climate change risk assessments by BN modeling, with the three knowledge sources local expert knowledge, multi-model ensemble and literature.*

Local expert knowledge is integrated in steps 1, 2, 3 and 6 in our participatory process (Figure 9). It was elicited during individual interviews and two expert workshops with scientific presentations, guided discussions and break-out groups (**Table 2**).

Table 2*: Expert involvement.*

Type of interaction	Number of local experts	Location	Duration	Date	Topic
Semi-structured expert interviews	13	Tuni (Tunisia) Algiers (Algeria) Marrakesh, Beni Mellal, Casablanca (Morocco)	10 days, 2 hours per interview	May 2018	1) Tasks, responsibilities and challenges of expert's organization 2) Expert's problem perception of the situation and challenges in the country 3) Co-development of causal networks representing the situation 4) Information needs to support the country in climate change adaptation in the water sector 5) Data availability and needs, time frame for planning of the organization
Workshop I	6	Le Mans (France)	1.5 days	November 2018	1) Presentation of causal networks 2) Introduction to Bayesian Networks and presentation of first Bayesian Network structure 3) Agree on expert's input for knowledge and data provisioning
Workshop II	7	Tunis (Tunesia)	2 days	October 2019	1) Presentation of further developed Bayesian Network 2) Co-development of possible risk indicators, further variables and qualitative classes

3.1.3.2 Co-developing causal networks

During expert interviews, causal networks or influence diagrams were created as perception graphs regarding climate change impacts on water from the point of view of the expert's organization (Düspohl and Döll, 2016). They are useful during the interviews in elucidating the perception of each expert in a concrete way and visualize it. All causal networks taken together were translated into a Bayesian Network structure (next section) taking also into account the most important factors and relationships reported in literature.

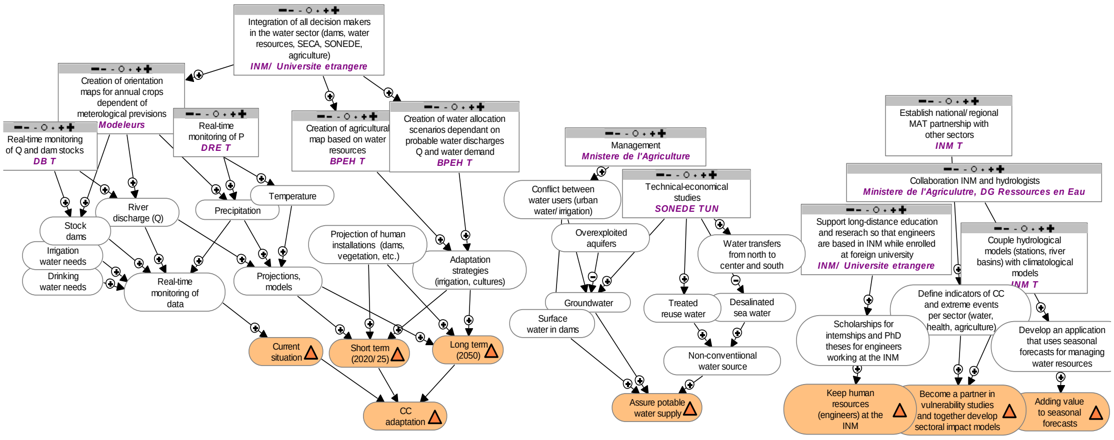


***Figure 10**: Causal networks of three experts, depicting actions (rectangles), factors (oval, non-colored boxes) and goals (oval, colored boxes).*

3.1.3.3 Co-developing the Bayesian Network structure

A BN model is a probabilistic graphical model for which a graph expresses the conditional dependence structure among variables. It consists of two main components: (1) the structure of the Bayesian Network, i.e. a directed acyclic graph that consists of a set of nodes representing the system variables and a set of arrows indicating the relationships between the system variables (Phan et al., 2016), and (2) conditional probability tables or deterministic expressions that represent how one system variable depends on the state of another variable, thus quantifying the links in the graph (Phan et al., 2016). Each variable is described by distinct classes of values or states and the probability of the variable belonging to each class. For Bayesian Network modelling we used the software Netica (http://www.norsys.com/netica.html).

The developed Bayesian Network model structure with variables, classes and links is shown in Figure 11. Two risk nodes are placed at the bottom of the net (red boxes) and were defined for groundwater and for surface water as “risk level of groundwater scarcity” and “risk level of surface water scarcity”, respectively. The qualitative risk nodes only depend on quantitative groundwater and surface water scarcity indicators, respectively (pink boxes). The groundwater scarcity indicator is computed as the ratio of annual groundwater abstractions (under long-term mean annual climate) to long-term mean annual groundwater recharge. The surface water scarcity indicator is computed as the ratio of surface water abstractions (under long-term mean annual climate) to long-term mean runoff. Given the high uncertainties of runoff and groundwater recharge estimates for the particular basin in the reference period, and to keep the complexity of the BN low, we assumed that mean annual surface water availability is equal to mean annual runoff and did not take into account that it may be reduced due to a decrease of groundwater discharge that is caused by groundwater use.

The water scarcity indicators are the child nodes of nodes representing physical hazards (blue boxes) as well as vulnerabilities and exposures (yellow and green boxes). The three hazard nodes are: Net irrigation requirement change due to CC, groundwater recharge change due to CC and runoff change due to CC. The yellow nodes are root nodes that representing water use-related vulnerabilities and exposures which require input from experts, while the green ones are child nodes computed by the BN model. The model structure comprises two decision nodes: “Time period and RCP” (orange box at the top of the net) and “Allocation ground- and surface water”, which need to be set by BN user to yield computations for the specific time period and RCP and a specific ration of groundwater to surface water use. Except for these two, all other nodes are probabilistic nodes.

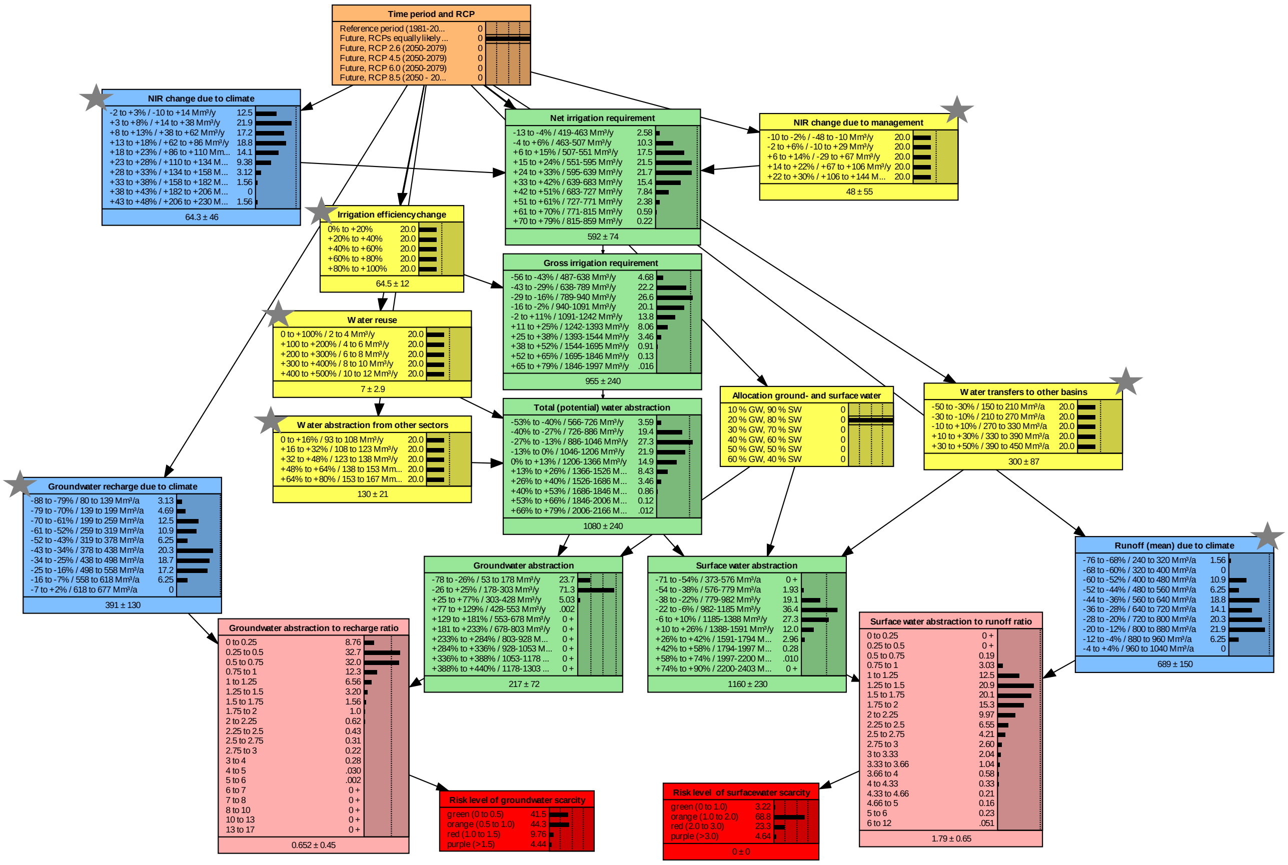


***Figure 11**: Bayesian Network model with nodes representing: 1) RCP and future time period (orange box), 2) physical hazards (blue boxes, informed by multi-model ensemble), 3) exposures and vulnerabilities, developed from expert knowledge and literature (yellow boxes), 4) computed intermediate variables representing water use (green boxes), 5) key risks indicators (pink boxes) and qualitative risk levels (red boxes). CC denotes climate change. Stars denote the root nodes for which absolute values for the reference period need to be specified to allow computation of the key risk indicators (see section 3.1.3.4). These nodes require an absolute value [m³] for the reference period. The child nodes do not require a probability table, just an equation is entered.*

3.1.3.4 Setting up the Bayesian Network model

As input for the Bayesian Network model we used data from a MME (Chapter 2) and data from literature and expert knowledge.

Regarding the latter, input of the water supply risk BN encompassed data on water resources, water demand and management in the study area during the reference period. A literature review and knowledge of local experts served to provide absolute values of all BN variables for the reference period, as these are required to compute the two selected key risk indicators, 1) a groundwater scarcity indicator, the ratio of groundwater abstractions to long-term mean annual groundwater recharge and 2) a surface water scarcity indicator, the ratio of surface water abstractions to surface water availability. In addition, published expectations of change for management and water demand nodes were reviewed as the basis for plausible ranges of change in the designed scenarios.

Setting up a BN model requires input information for each node in two steps: (i) defining the classes of each node and (ii) entering the probability distribution either directly (for root nodes) or – where it depends on the parent nodes – in the form of conditional probability tables (CPTs) for child nodes. Defining classes includes extracting lower- and upper-class boundaries and a uniform class size, based on the occurring range of values for the respective variable. This range can be either defined by the given input data from the multi-model ensemble or from literature, or by the passed down, combined ranges of parent nodes. Therefore, the required information and our process below differs slightly for the different types of nodes in the network.

In general, standard Bayesian Network software such as Netica is not suited to extract information for defining classes of a root node from a given multi-model ensemble or other data source. Instead, Netica requires this information to be entered manually. Nor is it able to calculate down the graph the optimal class boundaries of nodes depending on the ranges of values in the parent nodes. Therefore, we used the software MATLAB for calculating the required input into Netica for the different node types:

- *Root nodes (representing physical CC hazards, derived from multi-model ensemble output):* Based on the ensemble of future relative change values from the multi-model output and the absolute reference value from literature, uniform class boundaries were calculated in the form of relative changes and of absolute values for input into Netica. In addition, the probability distribution of changes in the three hydrological variables was computed for each RCP (orange box in Figure 11): for future periods the probability distribution was calculated for each individual RCP and for all RCPs mixed together, assuming that each GCM-GHM model combination is equally likely. For this, each output value of the multi-model ensemble members was assigned to its corresponding class and the probability for multi-model ensemble members to be in one class was calculated (e.g. a result of 8 out of 64 ensemble members in one class represented a 12.5% probability). For the reference period the distribution was manually set to 100% in the class of zero change.
- *Root nodes (exposure/vulnerability, starred yellow nodes):* Based on the absolute reference value and respective scenario ranges of relative change, class boundaries were calculated in the form of relative changes and of absolute values as well.
- *Child nodes (green nodes):* Based on the minimum and maximum class boundary, the absolute reference value of each parent node and the quantitative relationship between the parent nodes, the absolute reference value for the reference period of the child node and the class boundaries were calculated.
- *Risk indicator nodes (pink):* Class boundaries and absolute reference values were calculated as for other child nodes. In addition, the uniform class boundaries over the range of occurring values obtained by MATLAB were manually adjusted to reflect details around actual critical thresholds after assessing the occurring values. Adjustment included the number of classes and non-uniform class sizes.
- *Risk nodes (red):* For the actual risk node, a meaningful aggregation of the risk indicator classes was performed, to enable effective risk management and decision-making. Four classes (green, orange, pink, red) reflected the user's specific view of the actual thresholds between acceptable and unacceptable performance; the assigned thresholds defined the class boundaries.

For each node type, we selected an appropriate number of classes (blue: 10, yellow: 5, green: 10, pink: 20, red: 4) considering data availability and detail needed. In general, the more precise the knowledge, the more refined the resolution in a node.

The MATLAB result for probability distributions of blue and yellow root nodes (Figure 11, marked by stars) was then transferred into the conditional probability table of the respective node in Netica. Each climate scenario (reference period, future periods with RCPs individually or equally likely) yielded a row in the table; here, the current period was set manually to 100% in the class of zero change. The probability distribution of all down-graph child nodes (variables computed from other variables, i.e., green nodes in Figure 11) is given in conditional probability tables. These were computed by Netica based on specific equations describing the quantitative relationship (e.g. additive, subtractive, etc.) between the parent nodes which were entered into the software. For the risk nodes (red), the conditional probability tables comprised an aggregation of the values from the risk indicator node (pink) into the four classes. The Netica computation of the CPTs was based on 10^6 samples per cell.

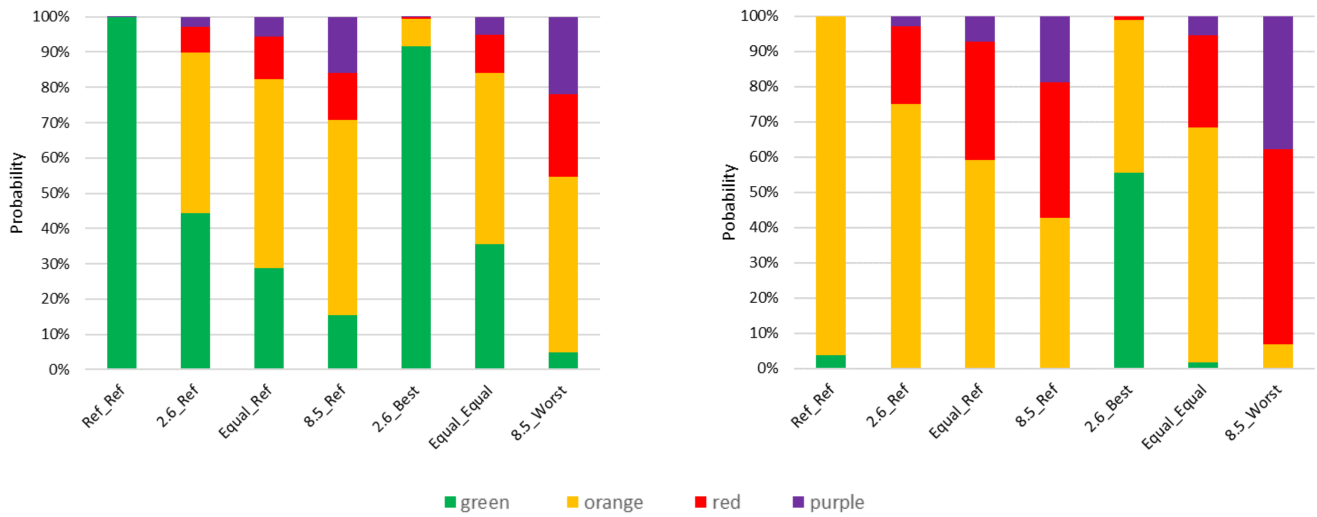
3.1.3.5 Simulations and probability distributions of risk levels

The Bayesian Network model was first used to determine probability distribution of the groundwater and surface water scarcity and thus the respective water supply risks. Specifically, seven scenarios and what-if cases were calculated, combining different RCP scenarios in the orange selector node and water use scenarios selected in the yellow root nodes – either deterministically or equally likely (see **Figure 12**). Comparing the risks between the reference period and the future period for the six scenarios enables to understand how risks for water supply may develop in case the different scenarios became true.

	1	2	3	4	5	6	7
Name	Ref_Ref	2.6_Ref	Equal_Ref	8.5_Ref	2.6_Best	Equal_Equal	8.5_Worst
Period	Reference	Future	Future	Future	Future	Future	Future
Climate	Reference (RCPs equally likely)	RCP 2.6	RCPs equally likely	RCP 8.5	RCP 2.6	RCPs equally likely	RCP 8.5
Water use	Reference	Reference	Reference	Reference	Best case	Equally likely	Worst case

***Figure 12**: Scenarios generated in this study combining different scenarios of climate change between the reference period 1981-2010 and the future period 2050-2079 with reference water use and with changing water use scenarios. "Scenario 1" is not an actual scenario but represents the conditions during the reference period.*

Results of probability distributions are shown for the two risk level nodes of the Bayesian Network (Figure 13). Results show the change in the probability range for the future scenarios compared to the reference scenario (Ref_Ref). The BN could further be used to determine the impact of a certain action of policy measure on risk, by assessing the impact on risk from a change in a specific node.



(a) risk of groundwater scarcity (b) risk of surface water scarcity

***Figure 13:** Cumulative probability distributions of risk levels for the nodes (a) risk of groundwater scarcity and (b) risk of surface water scarcity for seven scenarios.*

3.2 Global-scale climate change hazard and risk assessments

The CO-MICC portal provides data and visualizations for 0.5° grid cells or aggregations of these cells (Chapter 2.4). These data and visualizations can be directly used without any downscaling to fulfill various information needs. Scientists and educators are potential users of the information on the wide variety of freshwater-related hazards of climate change provided on the CO-MICC portal. Companies with globally-spread production sites and supply chains can use the information for their water footprint and life cycle analysis.

3.2.1 Utilizations by educators, hydrological consultants and scientists

Those wishing to educate others about freshwater-related hazards of climate change in their country or world-wide can select hydrological variables of interest such as soil moisture or groundwater recharge and then zoom into the region of interest. They can then download the visualization shown on the screen and use the graphics in their educational efforts.

Hydrologists working e.g. as consultants or engineering firms may prefer to download the MME values of freshwater-related climate change hazards directly, to use them for their professional purposes. Scientists outside of hydrology are also likely to download the values for specific variables of interest to them. Examples are freshwater ecologists, who require information on potential streamflow changes as this affects suitability of streams as habitat for freshwater biota. Terrestrial ecologists interested in riparian vegetation would also download streamflow data, while those interested in forests and other vegetation would like to analyze soil moisture changes. Groundwater recharge changes are of interest to global energy modelers who want to assess the potential for the production of hydrogen, while streamflow changes are of interest for hydropower production.

3.2.2 Utilization by global companies

3.2.2.1 Introduction

With climate change being considered as one of the most prominent challenges the world is facing today, global companies have the responsibility to act as well as a need to prepare. Act to mitigate the adverse effects of global warming, and the need to prepare for the future impacted by changing climate. That includes performing risk assessments, developing climate strategies as well as reporting on the current performance and on future climate risks through well-established frameworks such as CDP (formerly Carbon Disclosure Project) or TCFD (Task Force on Climate-related Financial Disclosures). The goal of the global stakeholder dialogue was to co-design methods

The CDP (formerly the Carbon Disclosure Project) is an international non-profit organization that runs the global disclosure system for investors, companies, cities, states and regions to disclose and manage their environmental impacts. Its aim is to make environmental reporting and risk management a standard business practice, driving disclosure, insight, and action towards a sustainable economy. Current areas of focus include climate change, water and forests (CDP2020).

The Task Force on Climate-Related Financial Disclosures (TCFD) is an organization that was established by the Financial Stability Board with the goal of developing a set of voluntary climate-related financial risk disclosures to help identify the information needed by investors, lenders, and insurance underwriters to assess and price climate-related risks and opportunities. The Task Force developed widely adoptable recommendations on climate-related financial disclosures that are applicable to organizations across sectors and jurisdictions (TCFD2020).

3.2.2.2 Co-design

In a stakeholder dialog with two multinational companies, two PUNI methods were co-designed for optimally providing information from multi-model ensembles on freshwater-related climate change risks including their uncertainties to world-wide operating industries, in order to increase availability and applicability of salient and credible information. Therefore, research on industry needs and state of the art as well as interviews and workshops with world-wide operating industries were facilitated to bridge the worlds of science and industry.

3.2.2.3 Identified water-related risks

2,114 companies disclosed their water-related information through CDP in 2018, currently representing over 50% of global market capitalization (CDP2018). The number of participants grows every year, across different programs (climate change, water and forests). Table 3 displays the A-list (highest scored) companies in the water program. Participation of some of the world’s largest companies provides a sound basis for a preliminary identification of water-related risks industries face, but also highlights the need for robust methods for conducting water-risk assessments (CDP2018).

Table 3: Highest scored companies (A-list) in the water program of the CDP (CDP2018).

ACCIONA S.A.	Ford Motor Company	LG Innotek
Altria Group, Inc.	Galp Energia SA	LIXIL Group Corporation
Asahi Group Holdings, Ltd.	Gap Inc.	L'Oréal
AstraZeneca	General Mills Inc.	Metsä Board
Bayer AG	International Flavors & Fragrances Inc.	Microsoft Corporation
Braskem S/A	KAO Corporation	Mitsubishi Electric Corporation
Brembo SpA	Kirin Holdings Co Ltd	Nabtesco Corporation
CNH Industrial NV	Klabin S/A	Stanley Black & Decker, Inc.
Coca-Cola European Partners	Las Vegas Sands Corporation	Suntory Beverage & Food
Diageo	LG Display	Toyota Industries Corporation
FIRMENICH SA		

Using the CDP database[1], the following water-related risks (**Table 4**) and impacts were identified, along with the primary response to those risks. It can be seen from the initial analysis that water-related risks can be disruptive to companies' operations and threaten their longevity. It is paramount that companies have the tools to respond to them and to prepare their adaptation strategies.

Table 4: Water-related risks together with potential impact and response to those risks (CDP2018 and related individual company reports).

Primary risk driver	**Primary potential impact**	**Primary response to risk**
Increased water stress	● Increased operating costs ● Disruption to sales due to value chain disruption ● Reduction or disruption in production capacity	● Establish site-specific targets ● Work with supplier to engage with local communities ● Secure alternative water supply ● Adopt water efficiency, water re-use, recycling and

[1] Based on water-related information disclosed through CDP by Volkswagen, Bayer, L'Oréal, General Mills Inc., Diageo, FIRMENICH SA, Gap, International Flavors & Fragrances Inc., Stanley Black & Decker, Inc. in 2018 (CDP2018 and related individual company reports)

		conservation practices ● Water-related capital expenditure ● Supplier diversification
Increased water scarcity	● Reduction or disruption in production capacity ● Supply chain disruption ● Increased operating costs	● Increase investment in new technology ● Detailed diagnostic today and future ● Alliance for Water Steward Standard ● Water-related capital expenditure
Drought	● Reduction or disruption in production capacity ● Increased production costs	● Increase investment in new technology ● Engage with NGOs/special interest groups
Flooding	● Supply chain disruption	● Amend the Business Continuity Plan
Severe weather events	● Increased production costs due to changing input prices from supplier	● Certification, collaborative actions
Declining water quality	● Increased operating costs	● Engage with NGOs/special interest groups ● Alliance for Water Steward Standard
Inadequate infrastructure	● Reduction or disruption in production capacity	● Adopt water efficiency, water re-use, recycling and conservation practices
Rationing of municipal water supply	● Reduction or disruption in production capacity ● Increased operating costs	● Establish site-specific targets ● Increase investment in new technology

3.2.2.4 Existing tools and methods concerning water-related risks

Companies report the use[2] of the following tools and methods (**Table 5**) to identify and assess water-related risks:

[2] Based on water-related information disclosed through CDP by Volkswagen, Bayer, L'Oréal, General Mills Inc., Diageo, FIRMENICH SA, Gap, International Flavors & Fragrances Inc., Stanley Black & Decker, Inc. in 2018 (DP2018 and related individual company reports)

***Table 5**: Water-related risks together with potential impact and response to those risks (CDP2018 and related individual company reports).*

WRI Aqueduct	IPCC Climate Change Projections
WWF-DEG Water Risk Filter	Environmental Impact Assessment
Life Cycle Assessment	FAO/AQUASTAT
Water Footprint Network Assessment tool	Ecolab Water Risk Monetizer
WBCSD Global Water Tool	Alliance for Water Stewardship Standard
COSO Enterprise Risk Management Framework	Regional government databases
Maplecroft Global Water Security Risk Index	National-specific tools or standards
Ceres AquaGauge	Internal company methods
ISO 31000 Risk Management Standard	External consultants

WRI (World Resources Institute) Aqueduct Water Risk Atlas, WWF-DEG (World Wide Fund for Nature and German finance institution (Deutsche Investitions- und Entwicklungsgesellschaft)) Water Risk Filter and Life Cycle Assessment (AWARE (Available WAter REmaining) methodology) were selected for further evaluation due to their widely-adopted use by the industry in risk assessments, and due the shared similarities in relation to the intended purpose of the tools.

WRI Aqueduct Water Risk Atlas is an online tool to access water-related risks. The tool compiles advances in hydrological modeling, remotely sensed data, and published data sets into a freely accessible online platform. Is it primarily a prioritization tool and should be augmented by local and regional deep dives. The tool covers physical, regulatory and reputational risks across 13 indicators (WRI2019).

WWF-DEG Water Risk Filter is an online tool developed by WWF and the German Development Finance Institution DEG to explore, assess, and respond to water risks. Users can assess basin risks by entering information on the sector and locations of its facilities. Based on the Water Risk Filter's 32 water risk data sets and pre-selected industry weightings, basin risk scores at the facility and for the entire portfolio are generated. It covers physical, regulatory and reputational risks across 32 indicators (WWF2020).

The AWARE method is commonly used for assessing water scarcity as one of the results of the application of the life cycle assessment (LCA) method. AWARE is used as a midpoint indicator related to water use and representing the relative Available WAter REmaining per area in a watershed, after the demand of humans and aquatic ecosystems has been met (AWARE2019).

3.2.2.5 Utilization methods

To address the variation of challenges faced by different stakeholders, two complementary PUNI-methods to present the data from the multi-model ensemble were developed:

- Method 1: Production Site Granular Level Risk Assessment
- Method 2: High-Level Supply/Value Chain Risk Assessment

Both methods were presented and discussed in the first phase of the stakeholder dialogue with the world's leading companies in the automotive and in the chemical sector (Section 3.2.2.8).

3.2.2.6 PUNI Method 1: Production Site Granular Level Risk Assessment

- **Goal**: the selected indicators and diagnostics of Method 1 shall directly support the definition of decisions and action.
- **Applicability**: this method is applicable for all companies operating their own production sites worldwide. It is particularly relevant for companies operating at an early stage of global value chains – for example, those companies producing commodities such as in the chemical or metal and mining industry. In such settings water risk assessments at production-site level is common practice. However, there is currently a lack of a) globally consistent data including uncertainties for future water hazards and b) linking water hazards to climate adaptation analysis.
- **Desktop research**: industry pre-assessment suggested an alignment between the industry needs and the originally proposed CO-MICC indicators and diagnostics.

3.2.2.7 PUNI Method 2: High Level Supply/Value Chain Risk Assessment

- **Goal**: identification of main risks and prioritization of actions within the companies' supply/value chains
- **Applicability**: this method is applicable for all companies operating at the "end" of world-wide supply chains, such as OEMs (e.g. automotive industry) and consumer goods (e.g. apparel industry). It is particularly relevant for companies with complex supplier networks, where high-level screening assessments are needed in order to prioritize actions within the supply chain. Those could include informing selected suppliers and requesting more detailed analysis with the aim to define concrete actions.
- **Desktop research**: the need for additional high-level indicators was established. Those indicators include water stress and water scarcity, which are common in the life cycle assessment method, widely applied by globally operating companies.

3.2.2.8 Extended interviews

An integral part of the co-design efforts was the global stakeholder dialogue, during which interviews with global companies were conducted. The purpose of the interviews was to:

a. build on the industry pre-assessment conducted in the earlier stages and further explore (i) the water-related risks that companies face, (ii) future assessment needs, (iii) tools, methods and data currently used by industry for high-level strategic water risk assessment;
b. map the findings against possible project outcomes;
c. confirm relevance of PUNI Methods 1 and 2.

3.2.2.9 Outcome of the stakeholder dialogue

The main outcomes of the interviews included further insight into the current practices by globally operating companies in relation to water challenges and climate change adaptation; confirmation of the importance of the proposed indicators and diagnostics; confirmation of the relevance of two PUNI methods proposed; and specification of modelling requirements for users and modelers.

The global stakeholder dialogue confirmed the need for globally consistent data including uncertainties of future water hazards, and for linking water hazards to climate adaptation analysis. The PUNI methods presented to the companies were perceived as relevant and important, and as a result these indicators were added to the portal:

- Water scarcity (based on Mesfin2016)
- Water stress (based on Mesfin2016)
- Water availability

The brief comparison of CO-MICC to the other three selected tools used by the industry, focusing on the added value that CO-MICC could provide, illustrates the increase in knowledge through the project. WRI Aqueduct Water Risk Atlas, WWF-DEG Water Risk Filter and Life Cycle Assessment (AWARE methodology) and the CO-MICC portal attempt to assist with identifying current and future water-related risks, but differ in terms of indicators covered, underlying models, timeframe, and among other aspects. WRI Aqueduct and WWF-DEG Water Risk Filter cover the period until 2040 and 2050, respectively, in ten-year increments, while CO-MICC MME data provides data up until 2099 with five-year intervals. The longer time period is intended to assist companies with long-term climate adaptation preparedness.
In terms of output variables as far as physical risks are concerned, both WRI Aqueduct and WWF-DEG Water Risk Filter provide future projections for four variables, whereas CO-MICC MME data provides future projections for all 15 variables covered by the project. A broad coverage of indicators is intended to help global stakeholders assess climate change-related impact on water resources against multiple risk criteria. It is also intended to provide the right level of granularity and transparency, and support companies in deployment of the PUNI methods.
Regarding the RCPs for which future projections are provided, WRI Aqueduct centers the models around RCP4.5 and RCP8.5, while WWF-DEG Water Risk Filter modelling is in line with RCP4.5 and RCP6.0. CO-MICC MME data, on the other hand, incorporates all original RCPs – RCP2.6, RCP4.5, RCP6, and RCP8.5 for an increased variety of future projection options. It is supposed to help companies prepare for a varied degree of future scenarios.

A powerful addition offered by CO-MICC portal is the inclusion of uncertainties in future projections. As opposed to the median, the outputs on the CO-MICC portal include uncertainty ranges. This is intended to help the users assess their risks on a multiple scenario basis and prepare action plans reflecting the uncertainty associated with future projections. In addition, the uncertainty ranges enable companies to develop worst- and best-case scenarios with the risks assessments.

In life cycle assessment (AWARE methodology), characterization factors are derived using water availability and water demand. While being a useful concept, it is somewhat limited in that future climate change-related projections are not taken into account. CO-MICC MME data aims to address this gap, basing output variables on both hydrological and climate change models. Since AWARE characterization factors are calculated using a number of variables that are also covered by CO-MICC MME data (such as runoff, precipitation, evapotranspiration), there is scope for the AWARE method to utilize the CO-MICC outputs.

Appendix

Appendix A: Specification of the multi-model ensemble (MME) runs

- Land mask used
    - WATCH-CRU land mask and DDM30 drainage map, consistent with ISIMIP simulations.
- Climate input data
    - Climate input data based on ISIMIP2b is used to force the hydrologic models. Bias-adjusted to the EWEMBI (http://doi.org/10.5880/pik.2016.004) data set at daily temporal and 0.5° horizontal resolution using updated versions of Fast-Track methods (see bias-correction Fact Sheet at www.isimip.org and Lange (2018) for methods description and further references).
        - Daily time step, 0.5° horizontal resolution
        - Historical (1861-2005) and future (RCP2.6, RCP4.5, RCP6.0 and RCP8.5) conditions provided based on CMIP5 output of:
            - IPSL-CM5A-LR 15
            - GFDL-ESM2M
            - MIROC5
            - HadGEM2-ES
- Land-use input data
    - Land-use (like human influences below) is kept at 2005 levels.
    - Vegetation is kept at what it is (except in LPJmL).
- Human influences:
    - Human influences should be fixed at 2005 levels (**2005soc**), in all simulations: Reservoirs, dams, water abstraction, irrigation water extraction are simulated consistently to ISIMIP: see section 2.5 in ISIMIP2b modelling protocol
- Lake specifications
    - Consistent with ISIMIP2b simulations: see section 2.7 in ISIMIP2b modelling protocol (https://www.isimip.org/documents/345/ISIMIP2b_protocol_AllSectors_fxQe9G5.pdf)

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