

Reply to Reviewer 2 comments

Manuscript number: hess-2013-221

Title of the manuscript: Distributed hydrologic modeling of a sparsely-monitored basin in Sardinia, Italy, through hydrometeorological downscaling.

Authors: G. Mascaro, M. Piras, R. Deidda and E. V. Vivoni.

Reply to Reviewer 2

First of all, we thank Reviewer 2 for the comments on our work. In the following, the comments raised by Reviewer 2 are split into parts and copied in bold fonts to facilitate understanding of our answers.

Reviewer 2 provides first a general comment.

The manuscript presents an investigation of climate change impacts for a Mediterranean basin, Rio Mannu, located in Sardinia. The study is based upon a set (four) of GCM-RCM combinations that in turn are used to drive a physically-based hydrological model, tRIBS, for past and future conditions under the A1B emissions scenario. Climate data are spatially and temporally downscaled and bias-corrected using statistical techniques whose skills have been exhaustively demonstrated in previous literature studies.

Overall, the study is well designed and the methodology is scientifically sound. The illustrations are all very high quality, and well organized. The issues discussed in this paper should be of interest to the scientific community, and is suitable for HESS. I recommend this manuscript being accepted with some minor/moderate revisions. Most of the issues that I have just need a bit clarification, with the first point listed below requiring the presentation of few additional simulation results.

We thank Reviewer 2 for this general summary and comment on the paper. In the following, we provide detailed answers to the specific comments.

1) I agree with authors that a reliable assessment of climate change impacts, especially in the Mediterranean area, depends on the use of high resolution information. In this sense, the novelty of the paper stems from the implementation of a downscaling procedure that generates an atmospheric forcing term on an hourly time step and over different points of the catchment. The improvement achieved with this setup, however, is not completely disclosed throughout the manuscript. Authors should therefore define a sort of base line simulation driving the hydrological model with spatially coarser (e.g., one point of the original RCM grid or a weighted average of the contributing points) and temporally (daily) constant climate information. To this aim, authors could arbitrary select one member of the ensemble and make a one-to-one (coarse vs high-resolution setup) comparison. This extra analysis will better highlight the value of the adopted methodology in reproducing changes in the different aspects of the hydrological response of the basin. This additional effort will eventually convey a stronger message to the scientific community.

We completely agree with Reviewer 2 on the importance of showing a comparison between model simulations forced by downscaled versus coarse-resolution forcings. However, we prefer to include this comparison in a future study that we are currently conducting with the aim of evaluating the impacts of climate change on extreme events in the Rio Mannu basin. We believe that differences between model outputs under downscaled versus coarse forcings will be particularly significant when focusing on

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extremes, because of the change in the runoff generation mechanism when rainfall intensity is changed from coarse to disaggregated products. We also point out that conducting a new set of simulations requires a significant amount of time and costs (for the simulations presented in this paper, 880 hours of CPU time over 64 processors were needed), in particular since the funding project of this study has concluded.

2) I found the analysis over the different sub-basins quite interesting. Some additional information, however, could improve the discussion. It is important to define the points of the atmospheric grid contributing to the response of each sub-basin. Indeed, considering their small size some of them are probably driven by the same atmospheric forcing term. In so doing, authors will be able to better distinguish their response in terms of soil properties and atmospheric variations. Moreover, to acknowledge the lack of the buffer effect due to a deeper groundwater table, it is necessary to inform the reader about the range of water table depth within the catchment and between the different sub-basins.

We thank Reviewer 2 for this useful recommendation. To address this comment, in Fig. A (this reply), we have reported the variation in the mean annual precipitation, ΔMAP , as a function of sub-basins contributing areas, A_c . It is apparent that the changes are quite similar among the different sub-basins (mean decrease of about -12%, as also reported in Table 2 of the manuscript for the entire watershed). This suggests that the change in sub-basins response is mostly due to their specific surface and subsurface properties, including the position of the groundwater table. To explore this last issue, Fig. B shows the mean depth of the water table, Nwt , in FUT period. Sub-basins 1–4 and 9, located in the northwest of the basin, have higher Nwt (i.e., deeper groundwater table) as compared to the rest of the sub-watersheds. This supports our interpretation on the reduced buffer effect due to a deeper groundwater table in this group of sub-basins (lines 2-3 on page 17).

Based on this, to address Reviewer's comment:

- 1) In lines 18-20, page 16, we added this sentence to report the similar variation in mean annual precipitation of all sub-basins:
“We first point out that the mean annual change in P is expected to be fairly constant in all sub-basins (not shown), suggesting that spatial differences may be mostly ascribed to surface and subsurface properties”. (We judged not necessary to show also Fig. A from this reply.)
- 2) We added the plot in Fig. B (this reply) in an additional panel in Fig. 7 to show the mean Nwt in the sub-basins and provided comments in the text (line 3 on page 17).

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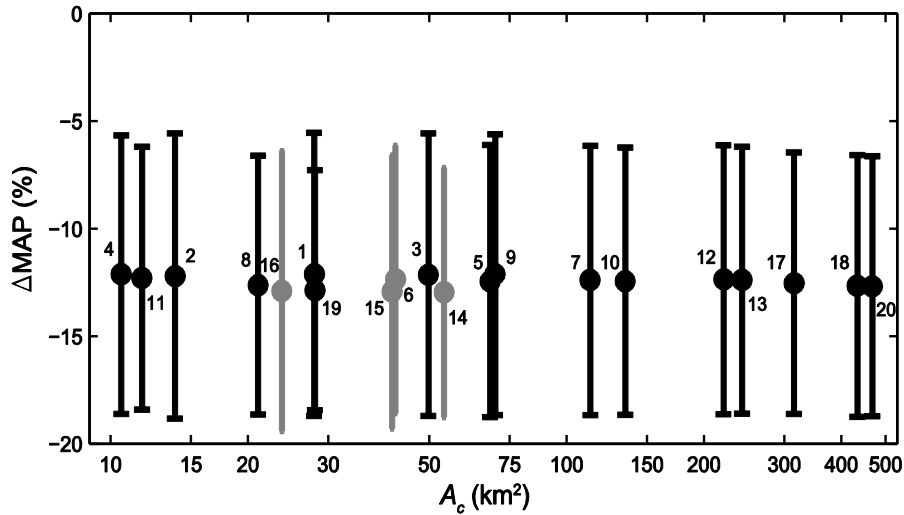


Fig. A. Relation between the change in annual MAP, ΔMAP , and sub-basin contributing area, A_c . Bars represent mean \pm standard deviation across the CMs. The number of each sub-basin as reported in Fig. 2b and Table 3 of the manuscript is also indicated.

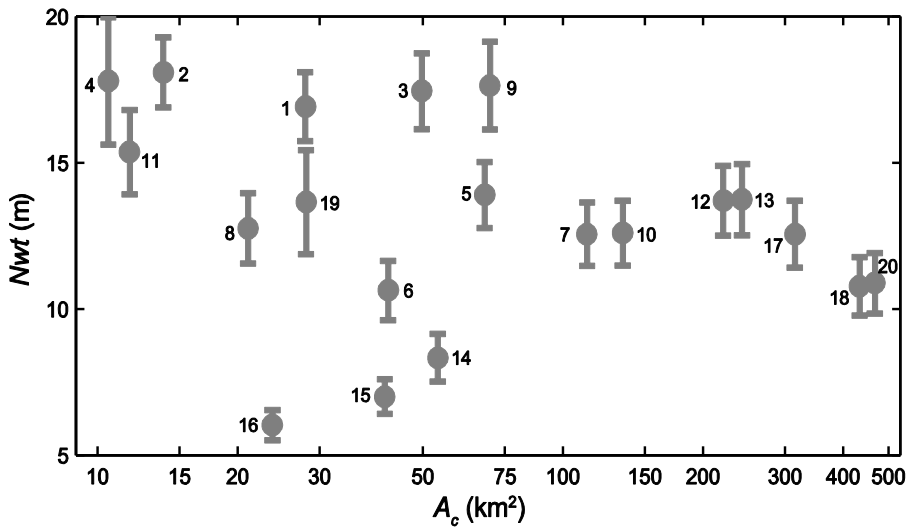


Fig. B. Relation between the mean groundwater table depth, Nwt , and sub-basin contributing area, A_c in the FUT period. Bars represent mean \pm standard deviation across the CMs. The number of each sub-basin as reported in Fig. 2b and Table 3 of the manuscript is also indicated.

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3) How do authors explain the consistent decrease in Q over winter months shown in Fig.6a without a significant decrease (increase) in P (ET_R) illustrated in Fig. 4a (Fig.12a)?

The percentage of variation in mean monthly Q during winter months is affected by the considered CM forcing, ranging from slightly positive (+8% in December for ECH-RMO) to highly negative (-56% in February for HCH-RCA). The reduction of Q occurring in winter months, despite the negligible change in P and ET_R , can be explained as follows. As shown in Fig. 8a of the paper, groundwater exfiltration (GE) runoff accounts for the largest percentage of the total Q . This is true for all months, including winter. Here, we have reported in Fig. C the monthly changes of each runoff type: the GE component is expected to decrease across all year. As a result, since this represents the largest component, the total Q also decreases. This result can be also interpreted as a consequence of the “memory” of the system. The marked decrease in P in all months except for winter leads to a gradual depletion of the groundwater table, which in turn causes a reduction of GE . The small variations predicted for P in winter are not able to affect this process. Thus, Q in winter diminishes as a consequence of what has been happening in the basin before and after the winter months.

To address this comment, in the new manuscript version, we have added this sentence in lines 12-14 on page 15:

“Note that the decrease of Q in months with little variation in P can be mostly ascribed to the diminution of the runoff portion due to groundwater exfiltration occurring throughout the year, as better illustrated below”.

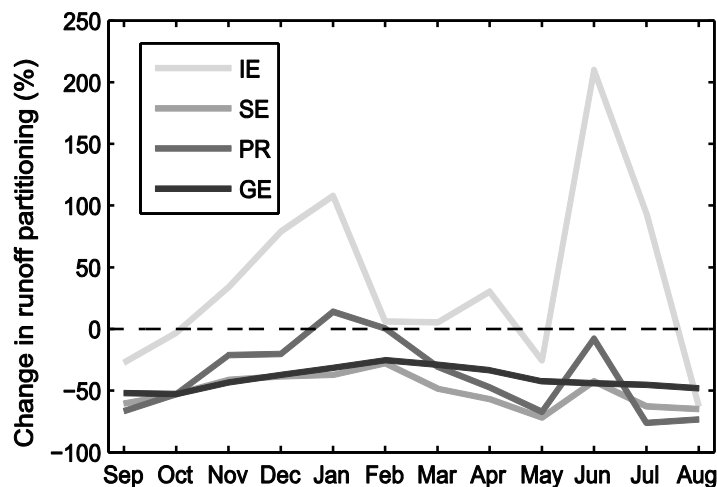


Fig. C. Monthly changes in partitioning of Q at the RMB outlet among the four runoff generation mechanisms. For each month, the mean of the four CMs is reported.

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4) The discussion around the groundwater dynamics seems a bit too short. Additional plots, showing for instance variations in the seasonal groundwater head values, could be useful and shed more lights on the involved processes.

As recommended by Reviewer 2, we inspected the monthly variation of the mean Nwt in the basin for each CM. Results are here reported in Fig. D. For each CM, it is clear that the drop of groundwater table is fairly stable for all months, with slight higher values in April and May. Clearly, each CM leads to different magnitudes of the drop, depending on the change in P . These considerations were added in the manuscript in lines 5-6 on page 21. We preferred not to add an additional figure due to the relatively limited information of Fig. D and the large number of figures (14) that are already part of the paper.

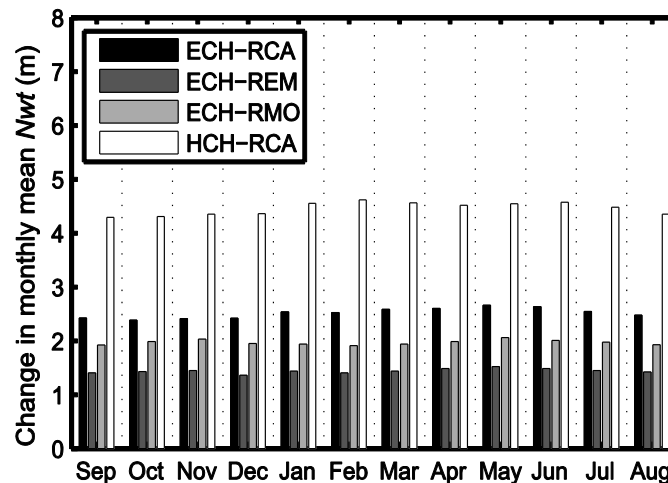


Fig. D. Relative change between FUT and REF periods in mean monthly Nwt .

5) In a similar vein to the previous comment, vegetation effect seems completely disregarded by authors. Some comments on this point will be useful as well.

In our simulations, vegetation is involved in two processes: (i) rainfall interception, and (ii) calculation of actual evapotranspiration from potential evapotranspiration computed off-line (this procedure is described in sections 3.1.4 and 3.2). Vegetation parameters have been derived for the land cover classes of Fig. 2a of the manuscript, based on published values for similar land cover classes, including the study of Montaldo et al. (2008) in a similar landscape in Sardinia. This is described in Mascaro et al. (2013), where the parameter values are reported in Table 8.

These considerations were added in manuscript in lines 14-16 on page 12.

Technical corrections

- Please replace throughout the text “real evapotranspiration” with “actual evapotranspiration”

We substitute "actual evapotranspiration" throughout the revised manuscript.

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- Groundwater exfiltration and perched return flow seem more related to the conceptualization used in the model. Please try to define them (at least the first time in the text) in a more understandable way for the reader.

We provide a definition of the components groundwater exfiltration and perched return flow in paragraph 3.2 of the new manuscript version (lines 16-19 on page 11).

- Please check the y-label in Fig. 12a

We changed the label as “ ET_0 or ET_a (mm)”.

- Please check “Delrieu” citation.

We corrected this reference.

References

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7 **Quantification of hydrologic impacts of climate change in a Mediterranean**
8 **basin in Sardinia, Italy, through high-resolution simulations**
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1 **Abstract**

2 Future climate projections robustly indicate that the Mediterranean region will experience
3 a significant decrease of mean annual precipitation and an increase in temperature. These
4 changes are expected to seriously affect the hydrologic regime, with a limitation of water
5 availability and an intensification of hydrologic extremes, and to negatively impact local
6 economies. In this study, we quantify the hydrologic impacts of climate change in the Rio
7 Mannu basin (RMB), an agricultural watershed of 472.5 km² in Sardinia, Italy. To simulate the
8 wide range of runoff generation mechanisms typical of Mediterranean basins, we adopted a
9 physically-based, distributed hydrologic model. The high-resolution forcings in reference and
10 future conditions (30-year records for each period) were provided by four combinations of global
11 and regional climate models, bias-corrected and downscaled in space and time (from ~25 km, 24
12 h to 5 km, 1 h) through statistical tools. The analysis of the hydrologic model outputs indicates
13 that the RMB is expected to be severely impacted by future climate change. The range of
14 simulations consistently predict: (i) a significant diminution of mean annual runoff at the basin
15 outlet, mainly due to a decreasing contribution of the runoff generation mechanisms depending
16 on water available in the soil; (ii) modest variations in mean annual runoff and intensification of
17 mean annual discharge maxima in flatter sub-basins with clay and loamy soils, likely due to a
18 higher occurrence of infiltration excess runoff; (iii) reduction of soil water content and actual
19 evapotranspiration in most areas of the basin; and (iv) a drop in the groundwater table. Results of
20 this study are useful to support the adoption of adaptive strategies for management and planning
21 of agricultural activities and water resources in the region.

22
23 **Keywords:** Climate change, Mediterranean region, distributed hydrologic model, water
24 resources, statistical downscaling.

1 **1. Introduction**

2 Several studies using simulations of future climate robustly indicate the Mediterranean
3 area as one of the regions of the world to be most severely affected by global changes. This area
4 has in fact been classified by Giorgi (2006) as a primary hot spot most sensitive to climate
5 change based on an index that combines variations in precipitation and air temperature from a
6 multi-model ensemble of climate simulations. Specifically, the majority of climate projections
7 agree in the prediction of an increase in mean temperature and a reduction in mean precipitation
8 for the Mediterranean region. For example, climate simulations under the A1B emission scenario
9 (Nakićević et al., 2000; IPCC, 2007) predict a mean annual warming from 2.2°C to 5.1°C.
10 Christensen et al. (2008) found that mean annual precipitation is expected to decrease between
11 4% and 27%. Giorgi and Lionello (2008) provide a good synthesis of several climate simulations
12 conducted in the Mediterranean region that summarize these main results.

13 Mediterranean watersheds are characterized by high spatial heterogeneity of terrain and
14 surface properties. These features lead to a hydrologic response that is particularly sensitive to
15 current climate variability, which is characterized by a strong seasonality and large inter-annual
16 fluctuations, with alternations of dry and wet periods lasting several years. As a result, these
17 basins are prone to the occurrence of hydrologic extremes, including drought periods (Hoerling
18 et al., 2012) and floods and flash-floods (Delrieu et al., 2005; Borga et al., 2007; Silvestro et al.,
19 2012). Variations in future climate are expected to further impact Mediterranean watersheds at
20 various spatial and temporal scales (Frei et al., 2006; Beniston et al., 2007; Mariotti et al., 2008),
21 as also demonstrated through observed data (Mariotti, 2010; Hoerling et al., 2012). This, in turn,
22 is expected to affect important economic activities, especially those strongly dependent on water
23 resources such as agriculture and tourism. For example, a future reduction in crop production is

1 anticipated in southern Europe and Mediterranean regions due to decreasing water availability
2 and degradation of soil and water quality (Olesen and Bindi, 2002; Falloon and Betts, 2010).

3 Given the high sensitivity of Mediterranean basins to climate variability and its
4 socioeconomic impacts, a multi-institutional research project, named Climate-Induced Changes
5 on the Hydrology of Mediterranean Basins (CLIMB), was funded by the 7th Framework Program
6 of the European Union (Ludwig et al., 2010). The CLIMB project focused on seven study sites
7 encompassing different conditions. An approach based on simulations of various climate and
8 hydrologic models, analysis of environmental and economic data, field campaigns and
9 stakeholder engagement was adopted to: (i) reduce the uncertainty in the quantification of
10 climate-induced changes on hydrological responses, and (ii) develop projections and tools to
11 support planning and management of water resources and associated economic activities.

12 One of the CLIMB sites is the Rio Mannu basin (RMB, 472.5 km²) located in an
13 agricultural area in Sardinia, Italy. This basin has experienced multi-year drought periods (the
14 most recent during 1990-2000) that resulted in water restrictions for the agricultural and tourist
15 sectors and led to substantial financial losses. Despite this, no extensive study has been devoted
16 to evaluating the hydrological vulnerability of this and other Sardinian basins. In this paper, we
17 provide a contribution to address this issue by quantifying the hydrologic response of the RMB
18 to different climate change projections. For this aim, four bias-corrected climate forcings are first
19 set-up for a reference and a future period, using the best-performing combinations of global
20 (GCM) and regional (RCM) climate models selected by Deidda et al. (2013). These climate
21 forcings are used as input for the TIN-based Real-time Integrated Basin Simulator (tRIBS)
22 hydrologic model, which was calibrated and validated with reasonable accuracy as illustrated in
23 a previous study by Mascaro et al. (2013a). Since climate model outputs are provided at coarse

1 spatial (~25 km) and temporal (daily) scales while the hydrologic model requires hourly data,
2 proper downscaling tools are applied to increase their spatiotemporal resolution (up to 5 km, 1
3 h). Hydrologic model outputs under the four climate scenarios, including time series and spatial
4 maps, are then post-processed to (i) evaluate the impacts on water resources and hydrologic
5 extremes, and (ii) investigate possible changes on the dominant physical processes in the basin.

6 While the general approach adopted here has been used by other studies (Abbaspour et
7 al., 2009; Cayan et al., 2010; Liuzzo et al., 2010; Senatore et al., 2011; Montenegro and Ragab,
8 2012; Sulis et al., 2011, 2012; Camici et al., 2013; Trambly et al., 2013), our methodology has
9 novel contributions. First, most studies carry out hydrologic simulations at the daily scale. Here,
10 a process-based model at sub-daily (hourly) resolution is used to simulate the hydrologic
11 processes typical of Mediterranean basins (Moussa et al., 2007), which are characterized by short
12 response time and non-linear rainfall-runoff transformation resulting from different runoff
13 mechanisms (Pinol et al., 1997; Gallart et al., 2002; Beven, 2002). Second, procedures are
14 applied to downscale climate model outputs to smaller spatial and temporal scales required for a
15 reliable simulation of the hydrological processes in a medium-sized basin. Finally, the
16 uncertainty associated with different climate models is taken into account by using four scenarios
17 based on different combinations of GCMs and RCMs.

18 19 **2. Study Area**

20 The Rio Mannu di San Sperate at Monastir basin (RMB) is a medium-sized watershed
21 draining an area of 472.5 km², located in Sardinia, Italy (Fig. 1). It is a representative basin of the
22 Mediterranean region where the hydrologic response is affected by climate variability, with the
23 occurrence of multi-year drought periods affecting agricultural activities. In this watershed, the
24 Sardinian Agency for Research in Agriculture (AGRIS) manages an experimental farm of 436

1 hectares, where hydrometeorological data are collected and productivity of different crops is
2 monitored. The RMB contributes to the water supply system of Sardinia through a reservoir
3 located in proximity of the outlet (Fig. 1c). Topography of the RMB is gentle, with a minimum,
4 mean and maximum elevation of 66, 296 and 963 m.a.s.l. and a mean slope of 17.3%. The
5 western and central parts of the basin are relatively flat, while a mountain range lies in the
6 southeastern part. The climate is Mediterranean with a strong seasonality characterized by dry
7 summers (June to August) and rainfall during the rest of the year having a mean number of rainy
8 days per month between 6 and 12 days. Precipitation occurs almost always in form of rainfall
9 with a climatological annual mean of 680 mm. The annual average potential evapotranspiration
10 is 750 mm (Pulina, 1986). Streamflow is characterized by low flow conditions ($<1 \text{ m}^3 \text{ s}^{-1}$)
11 throughout the year, with a few flood events mostly caused by fall and winter frontal systems
12 (Chessa et al., 1999; Mascaro et al., 2013b). Land use information from the COoRdination de
13 l'INformation sur l'Environnement (CORINE) project shows that agriculture (~48%) and sparse
14 vegetation (~26%) are the dominant categories while other minor classes include olives, forests,
15 pastures, vineyards and urban areas (Fig. 2a). Soil texture includes mainly six classes: Clay loam
16 - Clay (37%), Sandy loam - Loam (32%) and Sandy loam - Sandy clay loam (20%) (Fig. 2b).

17

18 **3. Data and Methods**

19 The impacts on the hydrologic response due to changes in future climate were quantified
20 as follows. Outputs of different combinations of GCMs and RCMs were processed to create four
21 scenarios of hydrometeorological data in a reference (REF) time slice from 1971 to 2000 and a
22 future (FUT) period from 2041 to 2070. Changes in hydrologic response in terms of availability
23 of water resources and hydrologic extremes were quantified by comparing tRIBS outputs in REF

1 and FUT periods. Procedures to create the climate forcing for the hydrologic simulations are
2 discussed in section 3.1, while the main features of the tRIBS model are discussed in section 3.2.

3 4 **3.1. Generation of the Climate Forcing**

5 The procedure to create the high-resolution climate forcing in the REF and FUT periods
6 can be summarized in four steps: (i) selection of GCM-RCM combinations; (ii) large-scale bias
7 correction of climate model outputs; (iii) disaggregation in space and time of precipitation (P)
8 and local-scale bias correction; and (iv) computation of hourly potential evapotranspiration (ET_0)
9 from daily minimum (T_{min}) and maximum (T_{max}) temperature, as illustrated next.

10 11 **3.1.1. Selection of GCM-RCM Combinations**

12 Deidda et al. (2013) evaluated the performance of fourteen combinations resulting from
13 the coupling of six GCMs with six RCMs from the ENSEMBLES project ([http://ensembles-](http://ensembles-eu.metoffice.com)
14 [eu.metoffice.com](http://ensembles-eu.metoffice.com)) in some Mediterranean basins, including the RMB. The analysis was
15 restricted for the future period to the A1B emissions scenario, because (i) this is commonly
16 considered the most realistic, and (ii) the ENSEMBLES climate models have the most complete
17 dataset for this scenario. Model outputs at daily resolution in time and 0.22° (~ 25 km) in space
18 (see the grid in Fig. 1b) were compared against historical data of daily P and daily mean,
19 minimum and maximum temperature (T) from the CRU E-OBS dataset (Haylock et al., 2008),
20 available on the same spatial grid. In the RMB, four combinations of two GCMs and three RCMs
21 were found by Deidda et al. (2013) to be the most accurate: ECH-RCA, ECH-REM, ECH-RMO
22 and HCH-RCA (see Table 1 for model descriptions and acronyms). The selection of these GCM-
23 RCM combinations, hereafter simply referred as selected Climate Models (CMs), also obeys the
24 criterion of having at least two RCMs nested in the same GCM and two different GCMs forcing

1 the same RCM. The use of four climate scenarios permits characterizing, to a certain extent, the
2 uncertainties associated with different climate models and possible model combinations.

3 4 **3.1.2. Large-scale Bias Correction**

5 Most climate models display some level of deficiencies in reproducing climatological
6 features and seasonality in large basins (Lucarini et al., 2007; 2008; Hasson et al., 2013; 2014).
7 In relatively small watersheds, these deficiencies are exacerbated. To reduce these well-known
8 discrepancies and better reproduce the observed seasonal statistics, a large-scale bias correction
9 of P and T fields predicted by the considered CMs was applied using the E-OBS dataset. For
10 this, the daily translation method was applied as it has demonstrated skill in prior studies (Wood
11 et al., 2004; Maurer and Hildago, 2008; Sulis et al., 2012). The method is based on computing
12 the monthly cumulative distribution functions (CDFs) of observed (F_{obs}) and simulated (F_{sim})
13 daily variables. For a given daily output variable of a climate model, x , the unbiased value, x^* , is
14 obtained as $x^* = F_{obs}^{-1}[F_{sim}(x)]$, where F_{obs}^{-1} is the inverse of F_{obs} . To reproduce the seasonal
15 cycles, F_{obs} and F_{sim} functions were derived on a monthly basis, i.e. pooling together all daily
16 observations (or simulated records) for each month. The procedure was applied to the daily P
17 and the daily mean, minimum and maximum T . In this effort, T was also corrected to account for
18 the different elevations adopted by CMs and E-OBS via a spatial and dynamic lapse rate.

19 20 **3.1.3. Precipitation Downscaling and Local-scale Bias Correction**

21 One source of uncertainty of climate models is related to the smoothing effect induced by
22 their coarse spatial (~25 km) and temporal (24 h) resolution (Wilby and Wigley, 1997; Maraun et
23 al., 2010; Bardossy and Pegram, 2011). This is especially true for P , which is characterized by
24 high intermittency and strong fluctuations in space and time, also affected by local orographic

1 effects. To reproduce this feature, we used the precipitation downscaling technique based on a
2 multifractal model (Space-Time Rainfall, STRAIN) that is able to recreate the scale invariance
3 and multifractal properties of precipitation fields observed from coarse to small spatiotemporal
4 scales (Deidda et al., 1999, 2000). This is achieved by means of a stochastic generator of
5 multiplicative multifractal cascades, whose parameters can be derived from the large-scale
6 rainfall amount, R (mm h^{-1}), according to empirical calibration relations. For the RMB, Mascaro
7 et al. (2013a) calibrated the algorithm with rainfall observations at 1-min resolution of 204
8 gages, collected in the period 1986-1996 in the coarse spatial domain of $104 \times 104 \text{ km}^2$ shown in
9 Fig. 1b. Here, the downscaling routine was applied by: (i) aggregating the bias-corrected daily P
10 outputs of the CMs in the coarse spatial domain to compute R , (ii) using the RMB calibration
11 relations to derive parameters conditioned on R , and (iii) applying STRAIN to downscale R to 5-
12 km and 1-h resolution. The disaggregated fields were also corrected for orographic effects using
13 the elevation modulation function described by Badas et al. (2006).

14 In principle, the statistically-based disaggregation technique requires the generation of an
15 ensemble of P downscaled fields, each representing an equally-probable realization of the coarse
16 condition. For example, Mascaro et al. (2013a) generated an ensemble of 50 P downscaled
17 members to calibrate and validate the tRIBS model. In this study, we only created a single
18 disaggregated realization for each selected CM for two main reasons. First, climate models do
19 not reproduce weather evolution in time according to deterministic rules, but rather reproduce the
20 statistical peculiarity of the climatic features (Lucarini, 2008). In other words, a one-to-one
21 correspondence between an observation and a climate model simulation does not exist for a
22 certain day. Second, the multi-decadal length of the REF and FUT periods (30 years) is large

1 enough to assure that the use of a single disaggregated member is able to capture a large portion
2 of the small-scale rainfall variability occurring within each time slice.

3 After the disaggregation, a last procedure for local-scale bias correction of P was applied
4 to correct residual biases mainly due to the coarseness of the rain gage network used for the E-
5 OBS dataset (Haylock et al., 2008), which may fail to reproduce the local features of P fields.
6 The procedure is illustrated in Fig. 3. The climatological monthly average of the mean areal
7 precipitation (MAP) in the RMB was first calculated using data observed by 13 gages within the
8 catchment over the period 1951-2008. In parallel, the same variable was computed for the
9 disaggregated fields from all selected CMs in the same period. The ratio between observed and
10 simulated mean monthly MAP was then used as a correction on the downscaled P fields to
11 eliminate the residual bias.

12 13 **3.1.4. Computation of Potential Evapotranspiration**

14 For each CM, we estimated the gridded ET_0 at hourly resolution starting from the bias-
15 corrected daily T_{min} and T_{max} . For this purpose, the T fields at ~ 25 -km resolution were first
16 interpolated in the same 5-km grid used for P as in Liston and Elder (2006), and then corrected
17 for elevation variations of the 5-km grid using a dynamic lapse rate. Then, the downscaling
18 technique proposed by Mascaro et al. (2013a) was applied to derive the maps of hourly ET_0 from
19 T_{min} and T_{max} . The method requires an estimate of the daily ET_0 by applying the Hargreaves
20 formula with T_{min} and T_{max} and a linear correction to derive the value returned by the Penman-
21 Monteith equation. Next, dimensionless functions that reproduce, for each month, the sub-daily
22 variability of ET_0 are used to derive the hourly ET_0 from the daily estimate. The procedure was
23 calibrated in the RMB using meteorological data (required to apply the Penman-Monteith
24 formula) observed in one station over 1995-2010.

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3.2. The Hydrologic Model

tRIBS is a physically-based, distributed hydrologic model that is able to continuously simulate the coupled water and energy balance (Ivanov et al., 2004a,b). Terrain is represented through Triangulated Irregular Networks (TINs) used to discretize the domain into Voronoi polygons. The use of TINs allows for computational savings as compared to grid-based models due to the multi-resolution domain representation (Vivoni et al., 2004; 2005). This feature is crucial for the feasibility of multi-decadal hydrologic simulations carried out in climate change studies. The spatially-distributed hydrologic response is reproduced by solving equations of the water and energy fluxes in each Voronoi polygon. In tRIBS, several hydrologic processes are represented, including canopy interception, infiltration and soil moisture redistribution, lateral water movement in the unsaturated and saturated zones, evaporation from bare soil and wet canopies, plant transpiration, overland flow in the hillslopes, and routing in the stream channel. The infiltration scheme allows for several configurations of soil moisture in the unsaturated and saturated zones. As a result, runoff generation is possible via four mechanisms: saturation excess, occurring when the single domain element is fully saturated from below; infiltration excess, occurring when the element is saturated from above by a high-intensity rainfall; perched return flow, occurring as lateral flow on the surface of a cell from a saturated layer in an upslope element; and groundwater exfiltration, occurring as lateral redistribution in the phreatic aquifer. The specific treatment of each process is described in detail by Ivanov et al. (2004a).

Model equations are parameterized through lookup tables and related spatial maps of soil texture and land cover. Precipitation can be provided as point time series or spatial grids. This last alternative is used in this study to force the model with gridded downscaled fields, as described in section 3.1.3. Computing actual evapotranspiration (ET_a) and its components

1 requires estimating ET_0 . This can be performed by applying the Penman-Monteith equation with
2 meteorological data or by forcing the model with ET_0 computed off-line, either in point or grid
3 format. Again, this last alternative is used in this study to provide downscaled ET_0 as described
4 in section 3.1.4. ET_a is then estimated as a fraction of ET_0 based on the available soil moisture
5 using a piecewise-linear equation (Mahfouf and Noilhan, 1991; Ivanov et al., 2004a). Model
6 outputs include time series of discharge at any location in the stream network and spatial maps of
7 hydrologic state variables and fluxes (e.g., evapotranspiration, soil water content at different
8 depths, ground water table position) at specified times or integrated over defined periods.

9 The model has been previously used in the areas of hydrometeorology (Mascaro et al.,
10 2010; Moreno et al., 2013), climate change (Liuzzo et al., 2010) and ecohydrology (Mahmood
11 and Vivoni, 2014). Recently, Mascaro et al. (2013a) calibrated and validated tRIBS in the RMB
12 against streamflow data. A TIN with 171,078 nodes was derived from a 10-m Digital Elevation
13 Model (DEM), retaining 3.6% of the DEM nodes and resulting in a vertical accuracy of 3 m.
14 Vegetation parameters, involved in the processes of rainfall interception and estimation of ET_a ,
15 have been derived for the land cover classes of Fig. 2a, based on values published in literature
16 for similar land cover classes. Despite the presence of several uncertainty sources, Mascaro et al.
17 (2013a) showed adequate performances in the RMB for the tRIBS model, which is used here
18 with the same parameterization.

19 20 **4. Results and Discussion**

21 In this section, we first analyze the monthly variability of the basin-averaged P and T
22 fields with the goal of highlighting the main climatological differences between the REF and
23 FUT periods. Subsequently, we present results of the hydrologic simulations forced with the
24 disaggregated P and ET_0 . Specifically, the changes on stream discharge (Q) are evaluated,

1 focusing on both water resources availability and hydrologic extremes. Finally, variations in
2 evapotranspiration (ET_a), soil water content (SWC), and ground water level are explored.

3 4 **4.1. Changes in Climate Forcing**

5 Fig. 4 reports different features of mean monthly variability of basin-averaged P grids for
6 the four CMs in the REF and FUT periods: mean areal precipitation (MAP; Figs. 4a,b), number
7 of rainy days (N ; Fig. 4c,d), and mean precipitation intensity in rainy days (I ; Figs. 4e,f). In the
8 left panels, the bars represent the mean \pm standard deviation across the four CMs of the 30-year
9 monthly average of each variable. Note that the months are ordered according to the water year.
10 For each CM, the relative monthly changes $\Delta\alpha$ (%) from REF to FUT, computed by the
11 following eq. (1) for a generic variable α , are plotted in the right panels:

$$12 \quad \Delta\alpha = \frac{\alpha_{FUT} - \alpha_{REF}}{\alpha_{REF}} \cdot 100, \quad (1)$$

13 where α_{FUT} and α_{REF} are the 30-year monthly mean of α in FUT and REF, respectively. Eq. (1)
14 is used in this paper for all variables, except for T for which the changes are calculated through
15 the simple difference between FUT and REF.

16 Fig. 4a shows that mean areal precipitation (MAP) is expected to decrease in FUT in all
17 months, except in winter (December to February) where mean values are similar. Negative
18 ΔMAP are predicted by all combinations in September, November, March, April, and May,
19 while in the other months the sign and magnitude of ΔMAP vary among the four combinations,
20 even significantly (e.g., October and December), suggesting higher uncertainty in climate
21 predictions (Fig. 4b). The mean annual MAP in REF and FUT periods and the relative changes
22 are reported in Table 2 for each combination: we can observe that the four CMs predict a
23 decrease in annual precipitation from -7% (ECH-REM) to -21% (HCH-RCA). These results are

1 consistent with a number of studies that analyzed climate projections in the Mediterranean region
2 under the A1B scenario (e.g., IPCC, 2007; Giorgi and Lionello, 2008; Senatore et al., 2011).

3 Similarly to MAP, the number of rainy days (N) is expected to decrease in FUT over the
4 year except for winter, where no significant variations are expected (Fig. 4c). Changes in N are
5 similar for the four CMs, indicating lower model uncertainty in predicting rainfall occurrence
6 (Fig. 4d). The projections for the mean precipitation intensity (I) are instead characterized by
7 high variability over the year and across the combinations. Fig. 4e shows that higher I is
8 predicted in FUT during the months with larger total precipitation (from October to December),
9 and most of the summer (June and July). The rainfall intensity in FUT will be lower from
10 January to May and in August and September. Fig. 4f shows that sign and magnitude of ΔI are
11 different in each month, highlighting a large uncertainty across the CMs. Since rainfall intensity
12 is a crucial variable influencing runoff, this underlines the importance of using multiple
13 combinations of GCMs and RCMs to account for climate model uncertainty in simulating
14 hydrologic responses.

15 The mean monthly T in REF and FUT periods is reported in Fig. 5a, while the relative
16 changes (ΔT) are shown in Fig. 5b. As found in previous works (e.g., Giorgi and Lionello, 2008),
17 the uncertainty in the prediction of future T is considerably reduced as compared to P . All
18 scenarios show a future increase of T for all months with a low standard deviation among the
19 combinations. Higher ΔT are expected in summer, with an average yearly variation from 1.87°C
20 (ECH-RCA) to 3.08°C (HCH-RCA), see Table 2 for more details. As for P , the HCH-RCA
21 combination predicts the largest variations in T . Overall, the monthly changes in P and T
22 predicted by the CMs are very similar to the forcing used in another Mediterranean climate
23 change study carried out by Senatore et al. (2011) in a watershed in southern Italy.

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4.2. Changes in Stream Discharge and Runoff Mechanisms

The hourly gridded P and ET_0 from the four selected CMs were used to force the tRIBS model. A spin-up interval of two years was adopted before each 30-year run, totaling 256 years of simulation. This computational effort was carried out using the parallelized version of tRIBS (Vivoni et al., 2011), which took 880 hours of CPU time over 64 processors. Model outputs including time series at distributed locations and spatial maps of hydrologic fluxes and state variables were post-processed to quantify the changes from REF to FUT periods. Fig. 6 presents results for the mean monthly Q at the RMB outlet, according to Eq. (1). Despite no significant variation in MAP is anticipated during winter, Q is predicted to diminish in FUT for all months (Fig. 6a) and by all scenarios (Fig. 6b). A slightly positive ΔQ is only found in December and June in one of the combinations. Note that the decrease of Q in months with little variation in P can be mostly ascribed to the diminution of the runoff portion due to groundwater exfiltration occurring throughout the year, as better illustrated below. Table 2 shows the mean annual changes, which range from -17% (ECH-REM) to -50% (HCH-RCA). Note that the different percentages observed for each CM are related to the decrease in P .

The change in mean annual Q was further analyzed using the streamflow time series for the 20 sub-basins shown in Fig. 2b (sub-basin 20 refers to the entire RMB). The terrain, soil texture and land cover characteristics of the sub-basins are summarized in Table 3. The relation between ΔQ and the contributing area (A_c) is shown in Fig. 7a, in terms of mean and standard deviation across the CMs. Results indicate the presence of two groups of sub-basins. The first includes five sub-watersheds labeled as 1-4 and 9, with a slightly positive mean ΔQ ($\sim+8\%$) and higher standard deviation that suggests larger uncertainty due to the different climate forcings.

1 These sub-basins are located in the northwestern portion of the RMB and are characterized by
2 relatively low slope (mean of ~8%) and dominance of Clay loam – Clay soil texture (> 77%) and
3 Agriculture land use (> 71%). The second group includes all the other sub-basins and displays a
4 significant drop of Q (average of about -28%) and lower variability across the CMs.

5 To investigate the physical reasons underlying the changes in Q , we inspected the
6 variation in the dominant runoff mechanisms. The partitioning of Q at the RMB outlet into
7 infiltration and saturation excess (Q_{IE} and Q_{SE}), groundwater exfiltration (Q_{GE}) and perched
8 return flow (Q_{PR}) runoff is shown for each CM forcing in Fig. 8a for the REF period. The four
9 combinations indicate the dominance of Q_{GE} , followed by Q_{SE} , Q_{IE} and Q_{PR} . Fig. 8b presents the
10 change in the amount of total Q produced for each mechanism. All CMs predict a decrease in
11 Q_{SE} , Q_{GE} , Q_{PR} , which are the components controlled by water availability in the soil, while Q_{IE} is
12 expected to grow for all combinations except for ECH-RCA. This last runoff type occurs when
13 the rainfall rate exceeds the infiltration capacity, suggesting that a variation of Q_{IE} in FUT may
14 be due to a change in rainfall intensities during extreme events. To analyze this hypothesis, we
15 derived the mean of the annual maxima of hourly P over the 30-year records in FUT and REF
16 periods for each CM. Next, we computed the variation between these two average P maxima
17 from REF to FUT and we found a perfect correlation with the changes in Q_{IE} .

18 Modifications in runoff generation mechanisms within the basin were evaluated by
19 focusing on the sub-basins. We first point out that the mean annual change in P is expected to be
20 fairly constant in all sub-basins (not shown), suggesting that spatial differences may be mostly
21 ascribed to surface and subsurface properties. In sub-basins 1-4 and 9 located in the northwest
22 part of the RMB, Q_{SE} , Q_{GE} , Q_{PR} decrease considerably more than the rest of the watershed (mean
23 changes of -75%, -70% and -50%), while Q_{IE} slightly grows (mean change of +10%). For this set

1 of sub-basins, we can conclude that: (i) the small increase in Q is due to a growth in Q_{IE} ; (ii)
2 higher occurrence of Q_{IE} is due to more impermeable soils that make these sub-basins more
3 sensitive to changes in rainfall intensity; and (iii) higher occurrence of Q_{IE} and the reduced buffer
4 effect due to a deeper groundwater table (mean values shown in Fig. 7b for the FUT case) make
5 their runoff response more uncertain for the CMs. For the other set of sub-basins: (i) total Q
6 decreases due to a general reduction of all components; and (ii) the uncertainty in runoff
7 response is relatively lower, especially for increasing A_c .

8 9 **4.3. Changes in Hydrologic Extremes**

10 Changes in hydrologic extremes are investigated in terms of (i) low flow persistence,
11 which can be assumed as a proxy of drought periods, and (ii) occurrence of high flows. To
12 analyze the impacts on the first type of extremes, we computed Flow Duration Curves (FDCs)
13 for Q at the outlet. Fig. 9 clearly shows a downward shift in the FDCs over most exceedances,
14 consistent with the predicted reduction of total Q in the FUT period. To identify the low flow
15 conditions, we first calculated a threshold discharge, Q_{LF} , as the streamflow corresponding to the
16 70% percentage of exceedance for the REF period (circle in Fig. 9). Low flow conditions were
17 then defined as the periods during which $Q < Q_{LF}$. Fig. 10a shows that the monthly mean number
18 of low flow days is expected to increase in FUT for about 5 days for each month, implying more
19 frequent dry conditions. The annual average of the maximum consecutive length of low flow
20 days is reported in Fig. 10b. In current conditions, all combinations robustly simulate a value of
21 about 50 days occurring during the summer months. In the future, the length is expected to
22 increase from 19 to 52 days on average, depending on the CM, thus extending the low flow
23 conditions to spring and/or fall. This result confirms and further details previous findings on
24 future drought in the Mediterranean region (e.g., Beniston et al., 2007).

1 Concerning the second type of extremes, we used the time series of Q at the outlet and 19
2 internal sub-basins. For the REF and FUT periods: (i) the index-flood was obtained for each sub-
3 basin by averaging the corresponding 30 yearly Q maxima, and (ii) the ratio between the index-
4 flood and the corresponding A_c was computed. This ratio, labeled as μ_c , was found to remain
5 fairly constant as a function of A_c and, thus, was used to remove the effect of their size. We then
6 computed the changes $\Delta\mu_c$ from REF to FUT and explored their relation with terrain attributes
7 and soil texture. Results of this analysis are summarized in Fig. 11 where $\Delta\mu_c$ is plotted against
8 the mean sub-basin slope for each CM. Predictions under three combinations (ECH-REM, ECH-
9 RMO and HCH-RCA) indicate that the magnitude of the mean annual Q maxima will increase in
10 the FUT period as the basin slope decreases and when soils are dominated by clay and loam (Fig.
11 11b, c, and d). For the ECH-RCA case, a negative $\Delta\mu_c$ was instead systematically detected for all
12 sub-basin, without any clear link to soil type and basin slope (Fig. 11a). This behavior is again
13 explained with changes in the rainfall intensities of extreme events: for the first three CMs, the
14 mean of the annual maxima of hourly P is expected to increase in the future, while a reduction is
15 predicted for the latter CM. As previously discussed, this is reflected in similar changes in Q_{IE} ,
16 which is the dominant runoff mechanism during floods. It is worth noticing that the highest
17 positive $\Delta\mu_c$ in Figs. 11b-d are found for sub-basins 1-4 and 9, characterized by lower slope and
18 dominated by more impermeable soils (clay and loam), where a relatively higher increase in Q_{IE}
19 is expected.

20 21 **4.4. Changes in Evapotranspiration and Soil Water Content**

22 Fig. 12a shows time series of the mean and standard deviation of monthly average ET_0
23 and ET_a in the REF and FUT periods. As expected, projections of higher T in the future leads to
24 increasing ET_0 . In contrast, a reduced ET_a is simulated for most of the year, except for January,

1 May and November. This is mainly due to the reduction of soil water content (*SWC*) in the root
2 zone in the FUT period, which is related to the decreases of *P*. This is clearly shown by Fig. 12b,
3 where we can observe a marked reduction throughout the year of *SWC* and a negative change of
4 ET_a , despite a systematic positive variation of ET_0 . These findings are mostly in accordance with
5 Senatore et al. (2011) who found decreasing ET_a in winter and diminishing *SWC* across the year.

6 The feedbacks among changes in ET_a and *SWC*, and their relation with meteorological
7 forcing (*P* and *T*, and consequently ET_0) and basin characteristics (soil texture and topography)
8 were investigated using the spatial model outputs. As an example, Figs. 13 and 14 show maps of
9 ΔP , ΔSWC , ΔET_0 and ΔET_a in winter (December-February) and spring (March-May) seasons,
10 which are characterized by the smallest and largest ΔP and ΔET_0 in the ECH-RCA forcing. The
11 behavior found in the other seasons is similar to the dynamics in spring, while results derived for
12 other climate model combinations are not significantly different.

13 In winter, the basin-averaged changes in *P* are small ($\Delta P = -1.92\%$), limiting *SWC*
14 decreases and leaving enough soil water for evapotranspiration. A higher ET_0 ($\Delta ET_0 = +3.30\%$)
15 allows ET_a to rise slightly ($\Delta ET_a = +0.14\%$). The combined effect of decreasing water input
16 from *P* and higher ET_a causes a basin-averaged reduction of *SWC* of -3.66%. The pattern of
17 ΔSWC (Fig. 13b) is mostly influenced by soil texture and, to a less extent, by ΔP (Fig. 13a) and
18 ΔET_0 (Fig. 13c). Lower ΔSWC (from -2.0% to +0.9%) are found in the Sandy loam – Loam class
19 where ΔP is slightly negative to positive (indicated with L in Fig. 13b). In these regions, soil
20 water is available to be extracted at a higher rate (ΔET_0 varies from +3.1% to +4.0%), thus
21 causing ET_a to grow from +3% to +8%. *SWC* is expected to decrease more significantly (from -
22 3% to -20%) in areas of Clay loam – Clay and Sandy loam – Sandy clay loam (labeled H in Fig.
23 13b), where *P* decreases by up to -7% and ET_0 does not vary substantially (+2%). Note that this

1 area mostly contains sub-basins 1-4, and 9 that experience the highest reductions of Q_{SE} , Q_{GE} and
2 Q_{PR} . As expected, the spatial pattern of ΔET_a is highly correlated with ΔSWC (correlation
3 coefficient of 0.80), with a minor dependence on ΔET_0 , although its signature is also apparent.

4 In spring, P is predicted in FUT to be noticeably lower (basin-averaged $\Delta P = -28.37\%$)
5 and ET_0 higher ($\Delta ET_0 = +5.51\%$). As a consequence, the decrease in SWC is more significant
6 ($\Delta SWC = -7.13\%$) and the water available for evapotranspiration is limited, causing ET_a to
7 diminish ($\Delta ET_a = -2.12\%$), despite the positive trend of ET_0 . In most of the basin, ΔSWC ranges
8 from -6% to -7% (L areas in Fig. 14b), likely due to the relatively low spatial variability of ΔP
9 (Fig. 14a). Higher drops in SWC (up to -20%) occur in the areas dominated by Sandy loam –
10 Sandy clay loam where P decreases more (H areas in Fig. 14b). Topography also plays a role, as
11 reduced drops of SWC appear in areas of flow convergence close to streams. ΔET_a (Fig. 14d) is
12 still well correlated to ΔSWC (correlation coefficient of 0.75) and also affected by ΔET_0 (Fig.
13 14c). ET_a remains essentially constant in the areas labeled with L in Fig. 14d, characterized by
14 lower changes in SWC and relatively higher ΔET_0 . ET_a decreases instead significantly (up to -
15 12%; H areas) in the regions where the drop of SWC is the largest and changes in ET_0 are
16 modest. The effect of topography can be better appreciated in the map of ΔET_a : higher values
17 (+10%) are simulated in the areas close to the stream network with higher availability of water.

18 This analysis reveals that, despite higher ET_0 , the RMB will experience in the future a
19 decrease in ET_a in most areas and times of the year, due to the lack of soil water caused by lower
20 rainfall. The only season with a different behavior is winter, where P is expected to decrease to a
21 lesser extent or slightly increase, thus limiting the reduction in SWC and leading in certain areas
22 to higher ET_a . The patterns of SWC and ET_a are mainly controlled by soil texture and the
23 interaction of P and ET_0 . Terrain plays also a role when reductions of P are more significant.

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4.5. Changes in Groundwater

A last analysis was devoted to evaluate the impact of climate change on groundwater. For this aim, we computed the difference between the basin averaged groundwater level at the end of the 30-year simulation in FUT and REF periods. For all sets of climate forcing, we found a drop of the water table ranging from 1.0 to 4.6 meters, constant across the year. The amount of the drop simulated for each CM is linked to the corresponding diminution in P input (lowest for ECH-REM and highest for HCH-RCA). In fact, a decreasing rainfall input leads to a decrease of the soil water content in the unsaturated zone and reduces the recharge to the aquifer. This result is confirmed by the diminishing occurrence of Q_{GE} (Fig. 8b).

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5. Conclusions

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In this study, we quantified the impacts of climate change on water resources and hydrologic extremes in an agricultural Mediterranean basin of 472.5 km² located in Sardinia, Italy. For this aim, the tRIBS model was used to simulate the hydrologic processes occurring in Mediterranean areas. The high-resolution (5-km, 1-h) forcing in reference (1971-2000) and future (2041-2070) period were provided by outputs from four combinations of GCMs and RCMs, bias-corrected and downscaled in space and time through statistical tools. Outputs of the hydrologic model were then compared in the reference and future periods to quantify the changes in several variables. The main results of this study are summarized below.

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At annual scale, all CMs predict decreasing P (mean of -12.70%) and increasing T (mean +2.18°C), leading to a significant diminution of Q (-32.55%) at the basin outlet. The changes in future climate will mostly lead to a reduction of those runoff generation mechanisms that depend on water available in the soil, namely Q_{SE} , Q_{PR} and Q_{GE} . A higher degree of uncertainty across

1 the climate model combinations was found while predicting the variation in Q_{IE} , which depends
2 on the combined effect of rainfall intensities and soil hydraulic properties.

3 Changes in annual Q were also investigated at distributed locations, finding two sets of
4 sub-basins with different behavior. In the northwest region, characterized by flatter terrain and
5 clay-loam soils, the mean Q is expected to increase somewhat in the future. Specifically, a small
6 growth in Q_{IE} is anticipated, while Q_{SE} , Q_{PR} and Q_{GE} will have the largest reduction over the
7 basin. Hydrologic responses in this area under different CMs are affected by higher uncertainty,
8 due to the higher occurrence of the faster runoff component (Q_{IE}) and the lower contribution of
9 slower subsurface components (Q_{PR} and Q_{GE}) that tend to attenuate the variability of the climate
10 forcing. In contrast, for other sub-basins in the RMB, Q is anticipated to diminish with relatively
11 low uncertainty across the four CMs, due to a decreasing contribution of all runoff components.

12 At basin scale, the combined effect of lower P and higher T leads to increasing ET_{θ} and
13 decreasing SWC throughout the year, and diminishing ET_a over all months except for winter. The
14 spatiotemporal analysis of the interactions between SWC and ET_a reveals that: (i) in most areas
15 and times of the year, negative changes of P lead to a reduction in ET_a , because there is not
16 enough soil water to sustain the higher evaporative demand; (ii) in winter, some areas experience
17 a modest decrease or a slight rise of P , leading to local growth in ET_a ; (iii) soil texture controls
18 the amount of the variations in SWC , with higher drops in the Sandy loam – Sandy clay loam
19 class; and (iv) topography also plays a role with positive changes in SWC and ET_a found in areas
20 of flow convergence near the stream network.

21 To our knowledge, this is the first climate change study conducted in Sardinia at the
22 watershed scale. Results suggest that the basin hydrologic regime will be significantly impacted
23 by variations in future climate. The diminution in annual Q at the outlet implies that: (i) the

1 inflow at the reservoir located in proximity of the outlet will be reduced, and (ii) more frequent
2 and longer low flow conditions, which are an indication of hydrological drought, are expected. In
3 addition, agricultural areas are anticipated to experience the largest drop in *SWC* in the root zone
4 (mean of -6%) among all land cover classes. This finding, in conjunction with the decreasing *P*,
5 may have important impacts on the crops (especially the rainfed areas) that are currently grown
6 in the basin. As a result, the implications of this study are useful to support the selection of
7 adaptive strategies for water and crop management and planning under climate change, as well
8 as to quantify the social and economic vulnerability of the region. Future work will be devoted to
9 the comparison of outputs from different models applied in the RMB by several research groups
10 in the context of the CLIMB project, thus addressing the uncertainty of hydrologic models.

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1 **Table Captions**

2 **Table 1.** List of the Global Climate Models (GCMs) used as drivers of ENSEMBLES Regional
3 Climate Models (RCMs) considered in this study together with corresponding climatological
4 center and model, and acronyms adopted. The four GCM-RCM combinations used in this study
5 are ECH-RCA, ECH-REM, ECH-RMO and HCH-RCA.

6
7 **Table 2.** Mean annual values of MAP, T and Q in the RMB in REF and FUT periods with
8 relative changes for each CM. The mean and standard deviation (Std) are also reported.

9
10 **Table 3.** Terrain, soil texture and land cover characteristics of the RMB sub-basins shown in Fig.
11 2b, including: contributing area (A_c), slope, and length of the main channel (L); percentages of
12 Sandy loam - Sandy clay loam (SL-SCL), Clay loam – Clay (CL-C), Sandy loam – Loam (SL-
13 L); and percentages of Agriculture (A), Sparse Vegetation (SV), and Olives (O).

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15

	Climatological center and model	Acronym
Global Climate Models, GCMs	Hadley Centre for Climate Prediction, Met Office, UK HadCM3 Model	HCH
	Max Planck Institute for Meteorology, Germany ECHAM5 / MPI Model	ECH
Regional Climate Models, RCMs	Swedish Meteorological and Hydrological Institute (SMHI), Sweden RCA Model	RCA
	Max Planck Institute for Meteorology, Hamburg, Germany REMO Model	REM
	Koninklijk Nederlands Meteorologisch Instituut (KNMI), Netherlands RACMO2 Model	RMO

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Table 1. List of the Global Climate Models (GCMs) used as drivers of ENSEMBLES Regional Climate Models (RCMs) considered in this study together with corresponding climatological center and model, and acronyms adopted. The four GCM-RCM combinations used in this study are ECH-RCA, ECH-REM, ECH-RMO and HCH-RCA.

Climate Model Combination	Mean annual MAP			Mean annual T			Mean annual Q		
	REF (mm)	FUT (mm)	Δ MAP (%)	REF (°C)	FUT (°C)	ΔT (°C)	REF (mm)	FUT (mm)	ΔQ (%)
ECH-RCA	570.93	502.81	-11.93	16.85	18.72	1.87	107.39	71.90	-33.05
ECH-REM	559.71	519.18	-7.24	16.77	18.68	1.91	86.74	71.87	-17.14
ECH-RMO	542.80	487.87	-10.12	16.83	18.72	1.89	91.30	67.87	-25.66
HCH-RCA	575.06	453.19	-21.19	16.52	19.59	3.08	107.96	53.71	-50.24
Mean	562.13	490.76	-12.70	16.74	18.93	2.18	98.35	66.34	-32.55
Std	14.42	28.12	6.03	0.15	0.44	0.60	10.93	8.63	14.07

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2 **Table 2.** Mean annual values of MAP, T and Q in the RMB in REF and FUT periods with
3 relative changes for each CM. The mean and standard deviation (Std) are also reported.

4

Sub-basin	A_c (km ²)	Slope (%)	L (km)	Main soil texture classes			Main land cover classes		
				SL-SCL	CL-C	SL-L	A	SV	O
1	28.00	10.43	14.60	9.35	88.33	0.00	87.01	7.21	0.84
2	14.82	9.03	7.15	5.05	89.98	0.00	71.81	3.48	17.34
3	50.17	8.96	16.55	7.44	89.02	0.00	82.38	5.31	5.71
4	10.78	5.56	8.09	17.40	77.35	0.00	90.83	0.00	4.44
5	68.10	13.79	18.36	18.72	60.89	15.98	67.74	10.46	6.77
6	42.67	22.93	16.51	3.37	26.98	69.05	31.33	39.13	5.82
7	113.51	16.98	20.06	12.79	49.09	34.89	54.20	20.70	6.69
8	20.95	16.59	13.55	0.00	58.55	31.52	30.34	25.43	16.77
9	70.16	7.70	19.55	8.09	88.09	0.00	84.90	4.12	5.31
10	135.01	16.89	21.07	10.85	50.38	34.38	50.68	21.43	8.16
11	11.54	7.46	8.11	23.14	65.28	0.00	74.95	7.07	4.02
12	221.99	13.71	27.40	11.46	60.65	21.49	60.65	16.19	7.67
13	244.99	13.14	30.55	13.30	60.05	19.60	61.96	15.40	7.26
14	58.18	19.05	22.43	21.42	3.28	42.32	25.05	47.24	8.86
15	41.99	33.82	13.43	0.81	0.00	93.06	4.70	67.23	0.00
16	23.96	34.58	10.76	5.57	0.09	94.18	2.44	74.56	4.35
17	315.75	13.77	34.77	15.83	48.48	23.39	55.95	20.67	7.41
18	436.41	16.67	25.45	19.25	35.63	34.06	45.39	28.16	8.54
19	28.59	6.35	15.09	27.73	58.31	0.77	76.55	2.35	4.53
20-Outlet	472.50	17.30	38.75	19.61	36.67	31.91	47.43	26.38	8.21

1
2 **Table 3.** Terrain, soil texture and land cover characteristics of the RMB sub-basins shown in Fig.
3 2b, including: contributing area (A_c), slope, and length of the main channel (L); percentages of
4 Sandy loam –Sandy clay loam (SL-SCL), Clay loam –Clay (CL-C), Sandy loam –Loam (SL-L);
5 and percentages of Agriculture (A), Sparse Vegetation (SV), and Olives (O).

6

1 **Figure Captions**

2 **Fig. 1.** Location of the RMB within (a) Italy and (b) the island of Sardinia. (c) DEM of the RMB
3 in UTM coordinates. In (b) and (c), crosses are centroids of the 25-km grid of the RCMs, and the
4 black square is the 104-km x 104-km coarse-scale domain for the precipitation downscaling
5 scheme. In (c), the circles are the centroids of the 5-km grid of the disaggregated precipitation
6 products, and the triangles are the rain gages used to perform the local-scale bias correction.

7
8 **Fig. 2.** (a) Land cover and (b) soil texture maps used as input for the tRIBS model. In (b), the
9 boundaries of 20 sub-basins are also reported along with the stream network.

10
11 **Fig. 3.** Illustration of the local-scale bias correction. Black line: climatological monthly average
12 of the mean areal precipitation (MAP) in the RMB observed by 13 rain gages over 1951-2008.
13 Black dashed line: MAP averaged across the four CMs during the same period before the bias
14 correction. Gray shades continuous lines: MAP of the four CMs after removing the bias.

15
16 **Fig. 4.** (a) Mean monthly MAP in the RMB in REF (black) and FUT (gray). Bars are mean \pm
17 standard deviation across the CMs. (b) Relative change between FUT and REF periods in mean
18 monthly MAP (Δ MAP). (c)-(d) Same as (a)-(b), but for the mean monthly N . (e)-(f) Same as (a)-
19 (b), but for the mean monthly I .

20
21 **Fig. 5.** Same as Fig. 4, but for the mean monthly T .

22
23 **Fig. 6.** Same as Fig. 4, but for the mean monthly Q at the RMB outlet.

24
25 **Fig. 7.** (a) Relation between the change in annual runoff, ΔQ , and sub-basin contributing area,
26 A_c . (b) Relation between the mean level of the groundwater table, N_{wt} , in the FUT period and A_c .

1 Bars represent mean \pm standard deviation across the CMs. The number of each sub-basin as
2 reported in Fig. 2b and Table 3 is also indicated.

3
4 **Fig. 8.** (a) Partitioning of Q at the RMB outlet in the REF period among the four runoff
5 generation mechanisms: infiltration excess (Q_{IE}), saturation excess (Q_{SE}), perched return flow
6 (Q_{PR}), and groundwater exfiltration (Q_{GE}) runoff components. (b) ΔQ for the runoff mechanisms.

7
8 **Fig. 9.** FDCs computed from the discharge at the RMB outlet. Continuous (dashed) lines are
9 used for REF (FUT). Circle shows the threshold discharge, Q_{LF} , used to identify low flow
10 conditions.

11
12 **Fig. 10.** (a) Mean monthly number of low flow days (LFDs) in REF (black) and FUT (gray).
13 Bars are mean \pm standard deviation across the CMs. (b) Mean annual maximum consecutive
14 length of LFDs in REF (black) and FUT (gray) periods.

15
16 **Fig. 11.** Relation between the change in the mean of the annual maximum Q , $\Delta\mu_q$, and the
17 corresponding mean slope. Black (gray) circles indicate sub-basins dominated by the Clay loam
18 – Clay (Sandy loam – Loam) class; a cross is used to indicate sub-basins 1-4 and 9. Each panel
19 refers to results obtained for each CM.

20
21 **Fig. 12.** (a) Mean monthly ET_0 (dashed lines) and ET_a (continuous lines) plotted as mean \pm
22 standard deviation of the four CMs in REF (black) and FUT (gray); (b) Mean across the CMs of
23 the relative changes of ET_0 , ET_a , and SWC .

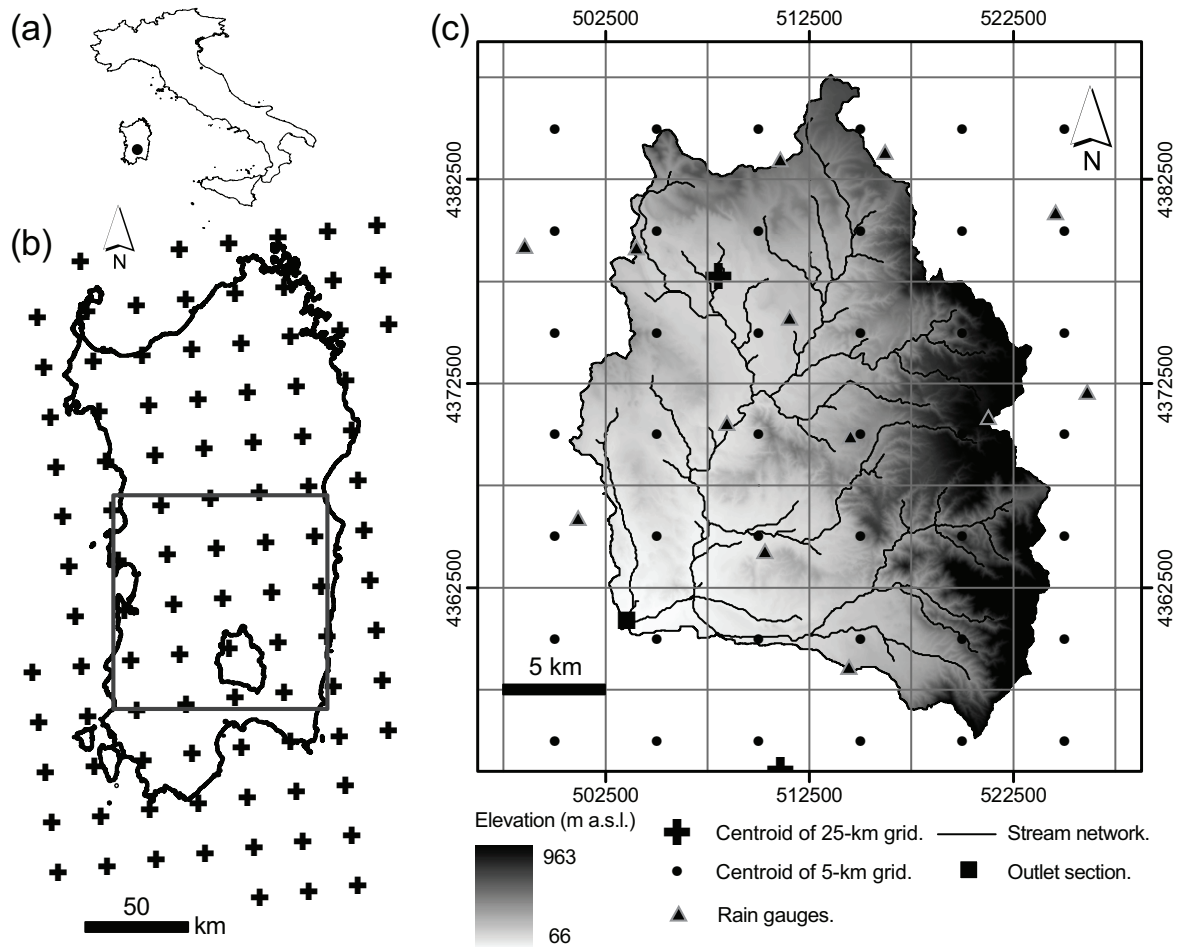
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25 **Fig. 13.** Changes between REF and FUT periods averaged over the winter season (December-
26 February) for (a) P , (b) SWC , (c) ET_0 , and (d) ET_a under the ECH-RCA combination. In (b),

1 areas where the variables are characterized by positive or lower negative changes are indicated
2 with L, while regions with higher negative changes are indicated with H.

3
4 **Fig. 14.** Same as Fig. 13, but for the spring season.

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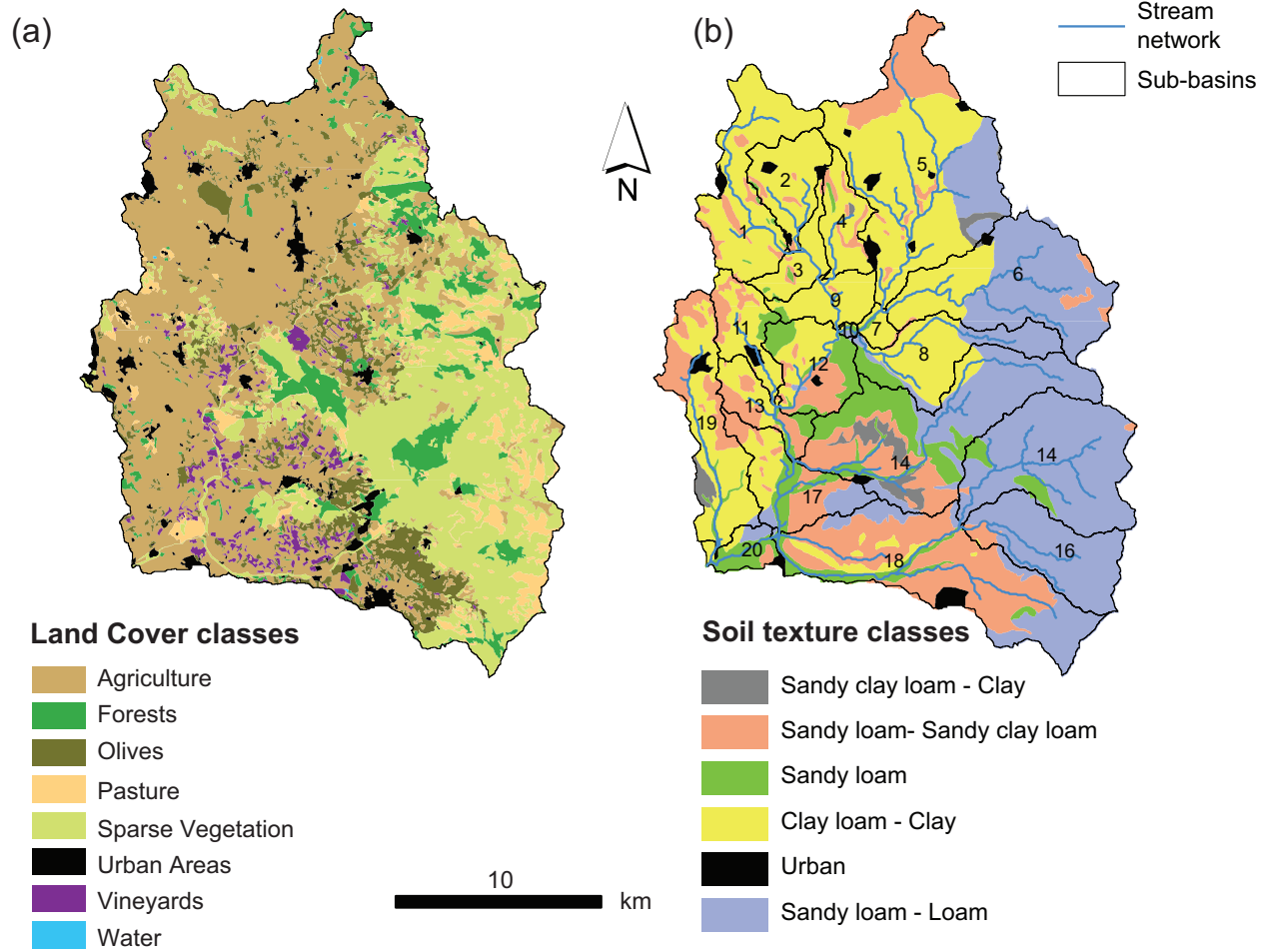
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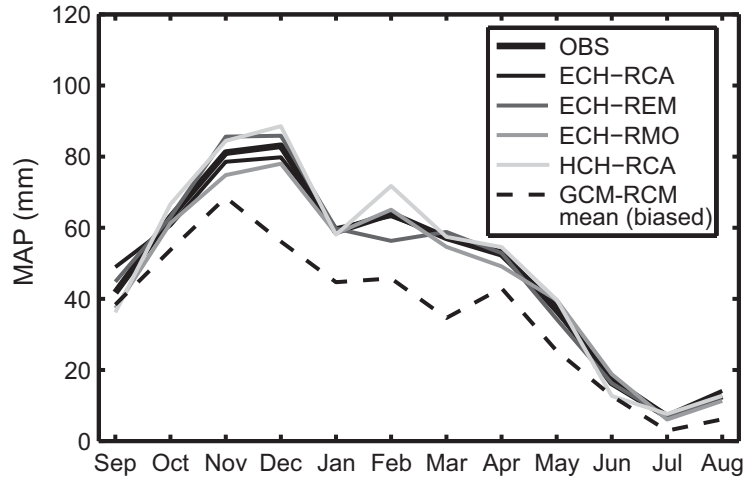
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 5 the black square is the 104-km x 104-km coarse-scale domain for the precipitation downscaling
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 7 products, and the triangles are the rain gauges used to perform the local-scale bias correction.

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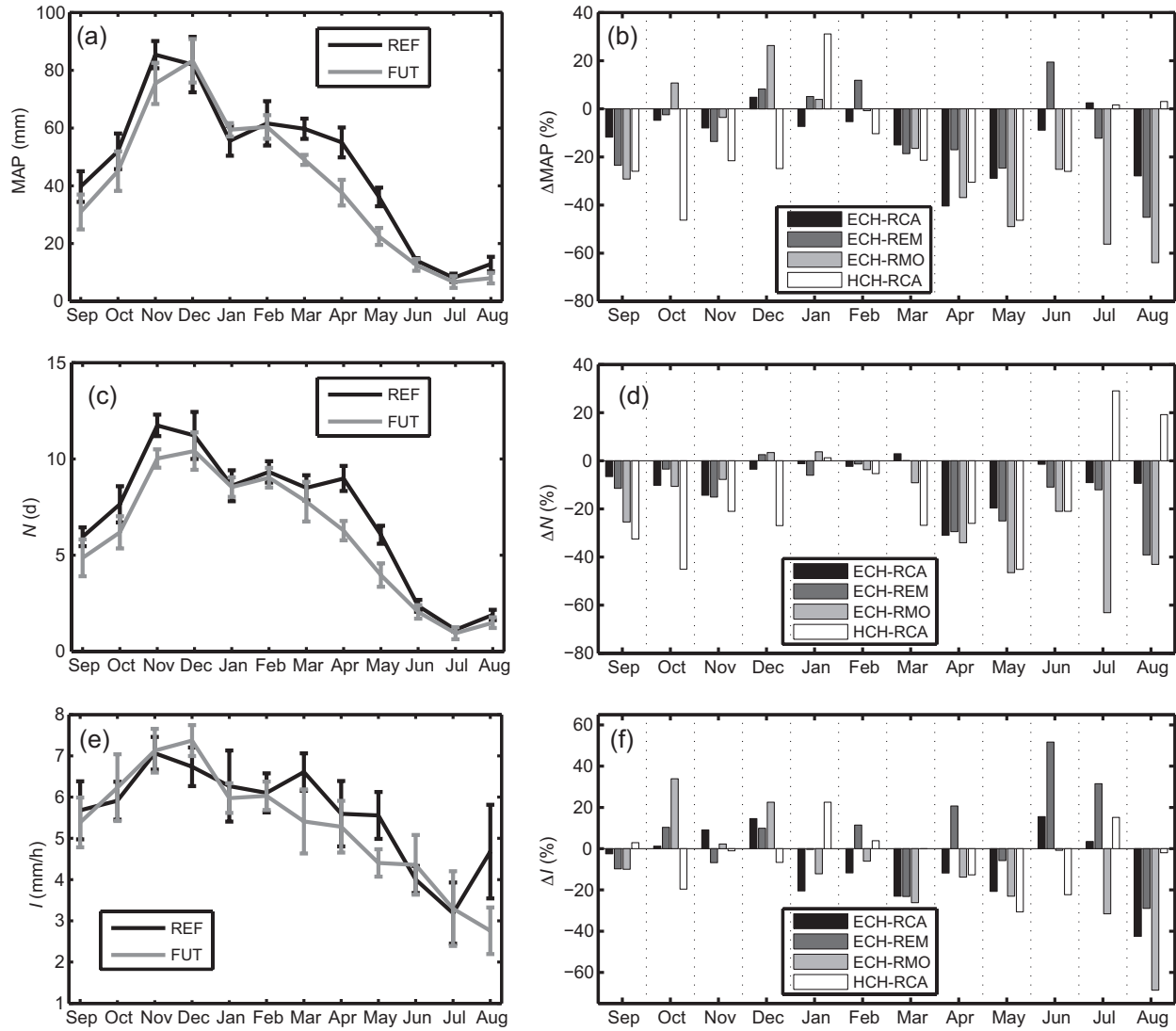
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Fig. 2. (a) Land cover and (b) soil texture maps used as input for the tRIBS model. In (b), the boundaries of 20 sub-basins are also reported along with the stream network.



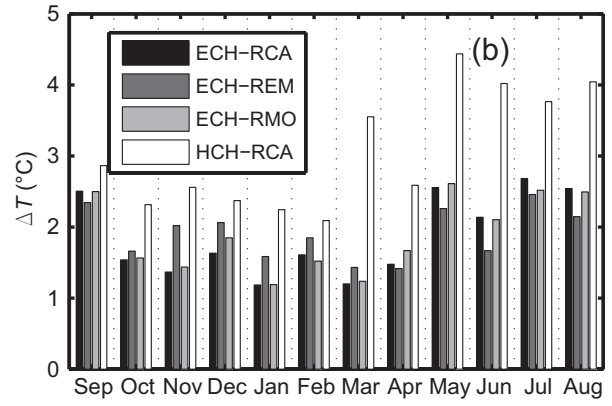
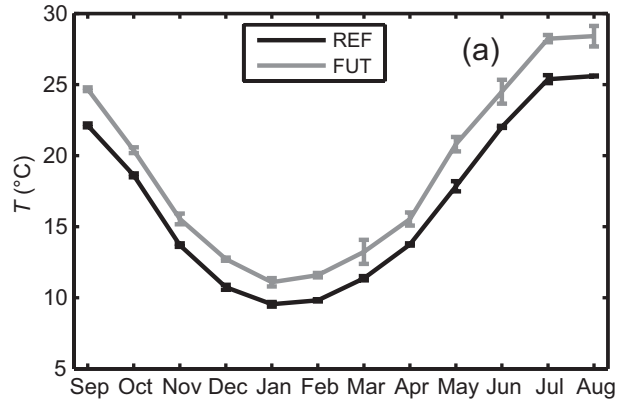
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Fig. 3. Illustration of the local-scale bias correction. Black line: climatological monthly average of the mean areal precipitation (MAP) in the RMB observed by 13 rain gages over 1951-2008. Black dashed line: MAP averaged across the four CMs during the same period before the bias correction. Gray shades continuous lines: MAP of the four CMs after removing the bias.



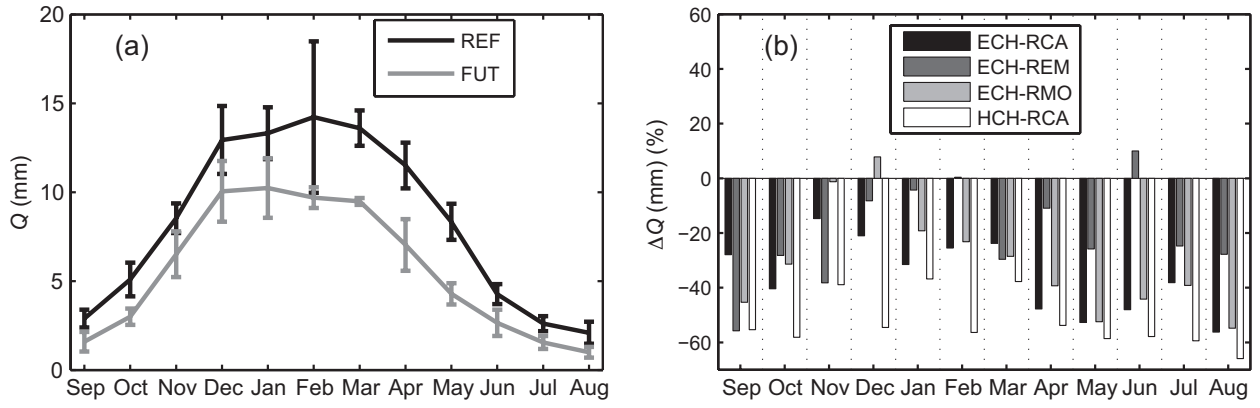
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 2 **Fig. 4.** (a) Mean monthly MAP in the RMB in REF (black) and FUT (gray). Bars are mean \pm
 3 standard deviation across the CMs. (b) Relative change between FUT and REF periods in mean
 4 monthly MAP (Δ MAP). (c)-(d) Same as (a)-(b), but for the mean monthly N . (e)-(f) Same as (a)-
 5 (b), but for the mean monthly I .

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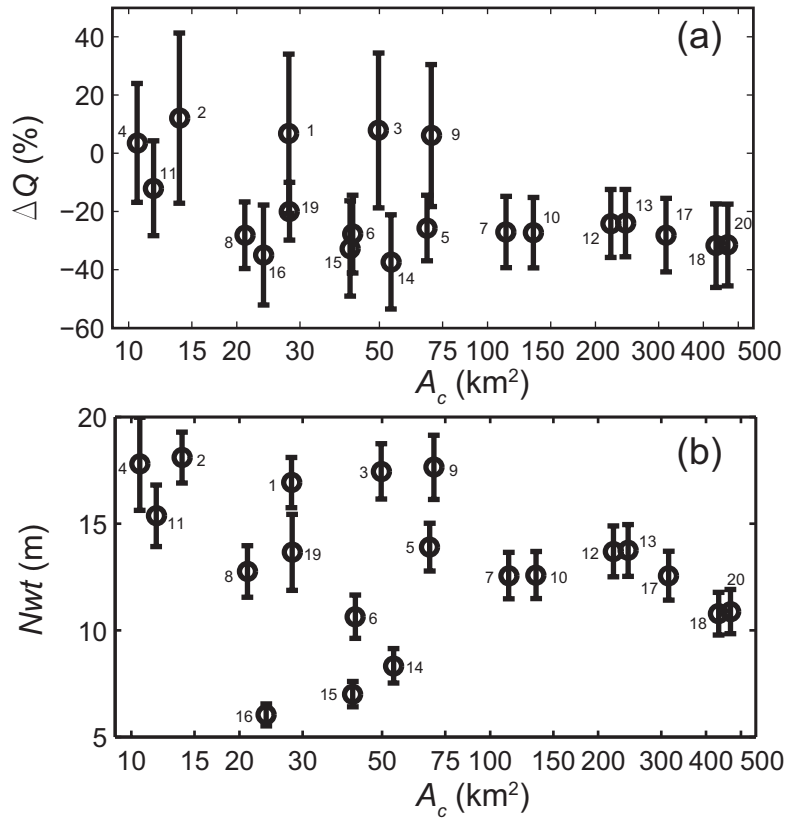
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Fig. 5. Same as Fig. 4, but for the mean monthly T .



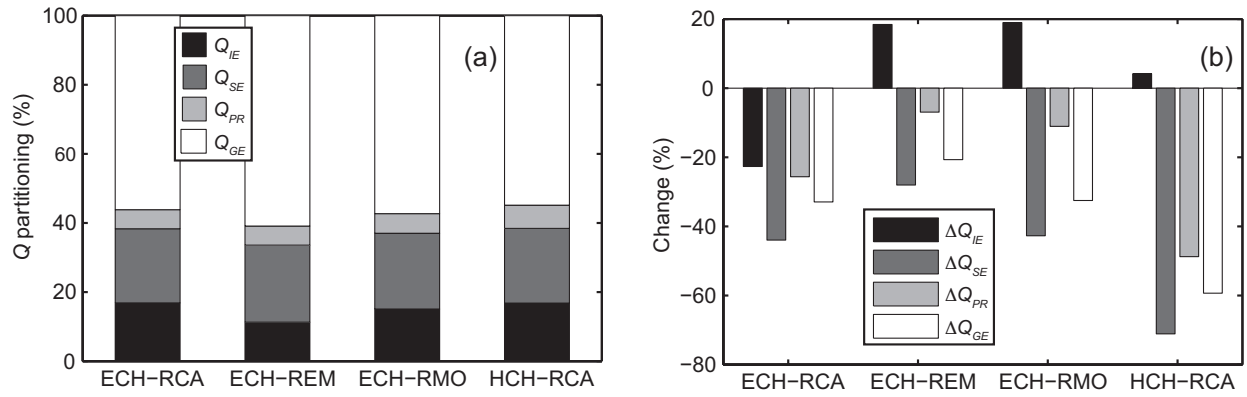
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Fig. 6. Same as Fig. 4, but for the mean monthly Q at the RMB outlet.



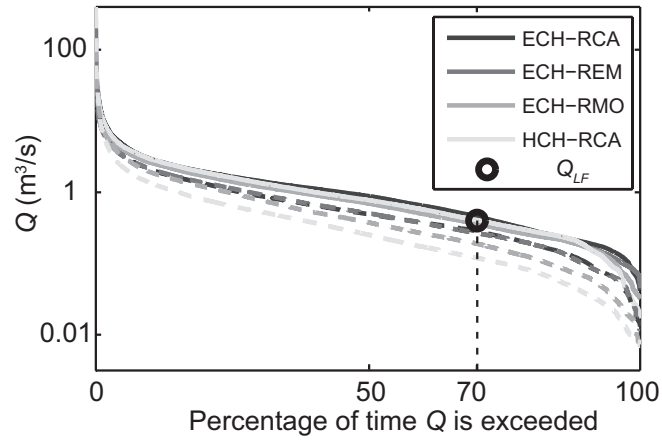
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3 **Fig. 7.** (a) Relation between the change in annual runoff, ΔQ , and sub-basin contributing area,
4 A_c . (b) Relation between the mean level of the groundwater table, Nwt , in the FUT period and A_c .
5 Bars represent mean \pm standard deviation across the CMs. The number of each sub-basin as
6 reported in Fig. 2b and Table 3 is also indicated.

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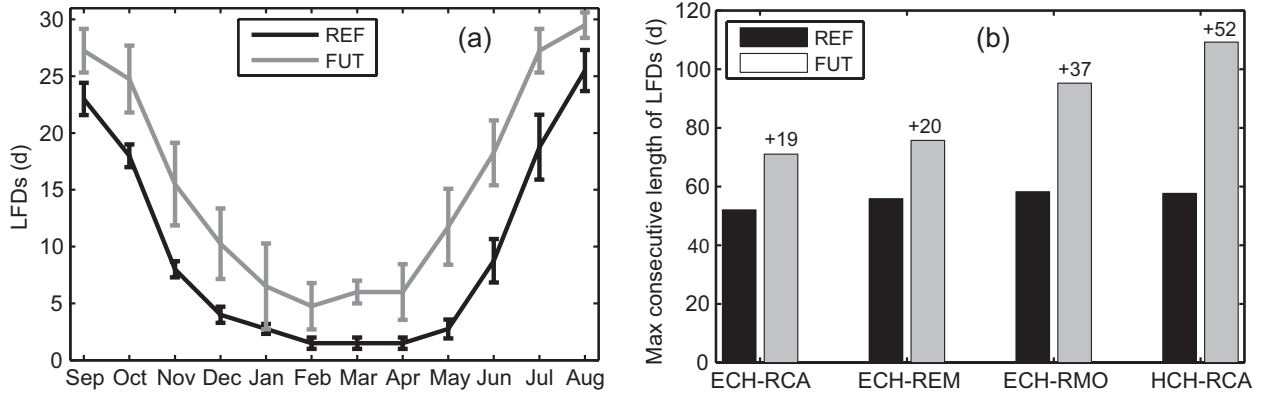
Fig. 8. (a) Partitioning of Q at the RMB outlet in the REF period among the four runoff generation mechanisms: infiltration excess (Q_{IE}), saturation excess (Q_{SE}), perched return flow (Q_{PR}), and groundwater exfiltration (Q_{GE}) runoff components. (b) ΔQ for the runoff mechanisms.



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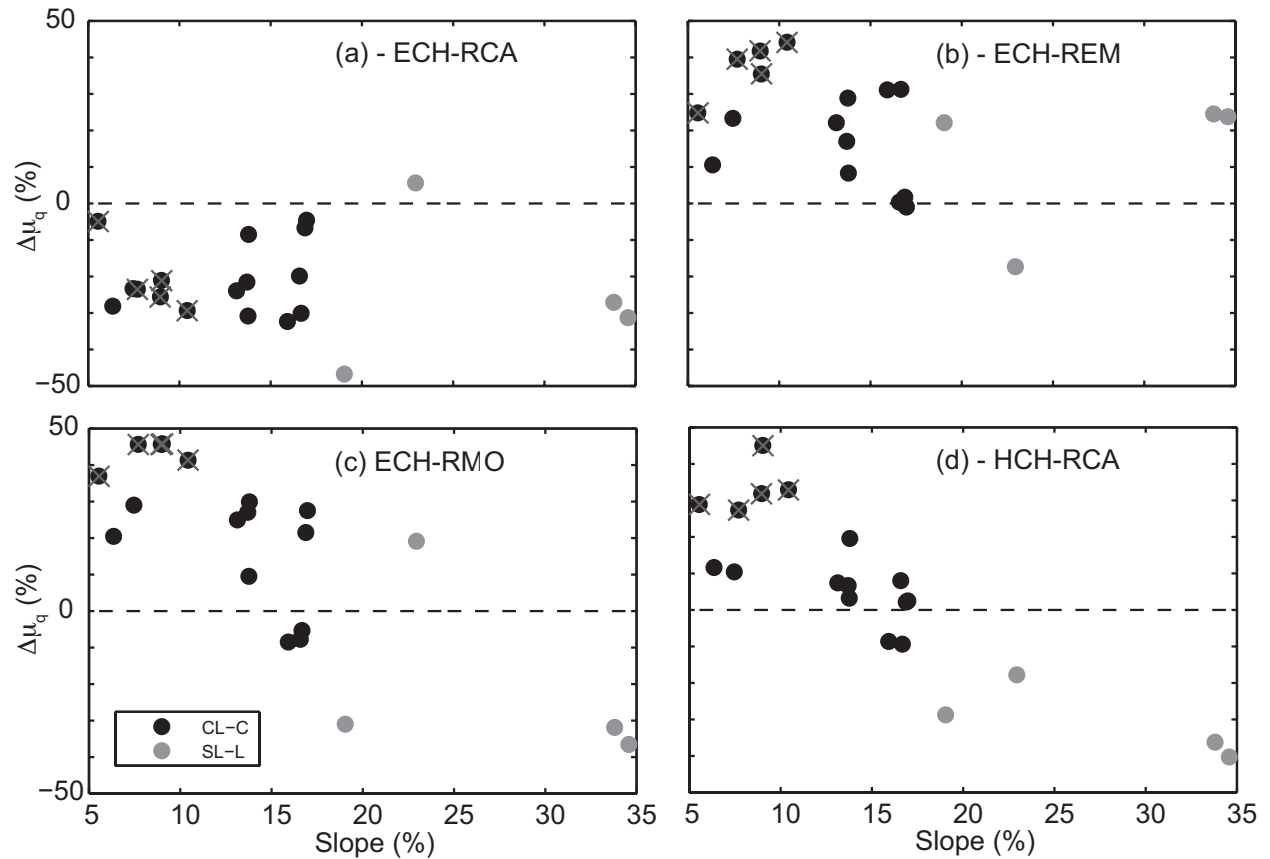
3 **Fig. 9.** FDCs computed from the discharge at the RMB outlet. Continuous (dashed) lines are
 4 used for REF (FUT). Circle shows the threshold discharge, Q_{LF} , used to identify low flow
 5 conditions.

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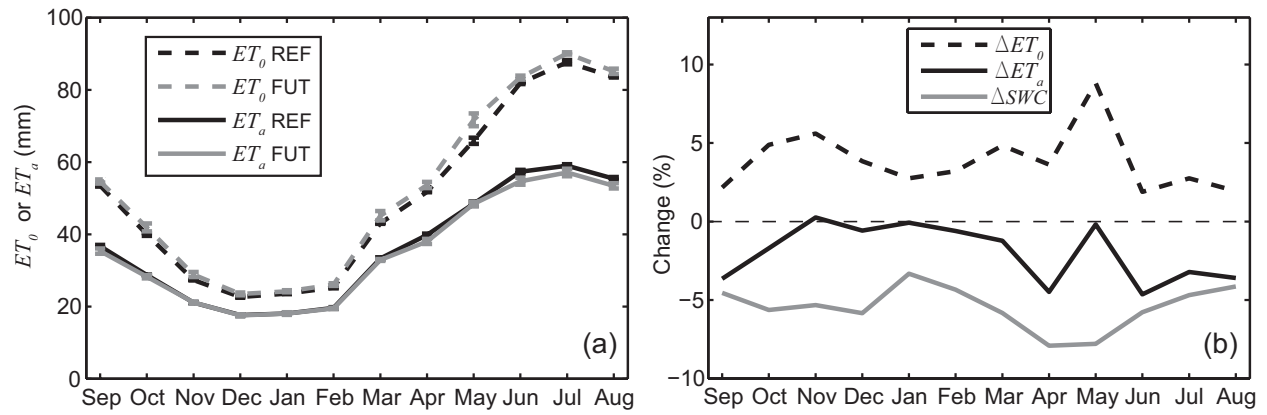
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Fig. 10. (a) Mean monthly number of low flow days (LFDs) in REF (black) and FUT (gray). Bars are mean \pm standard deviation across the CMs. (b) Mean annual maximum consecutive length of LFDs in REF (black) and FUT (gray) periods.



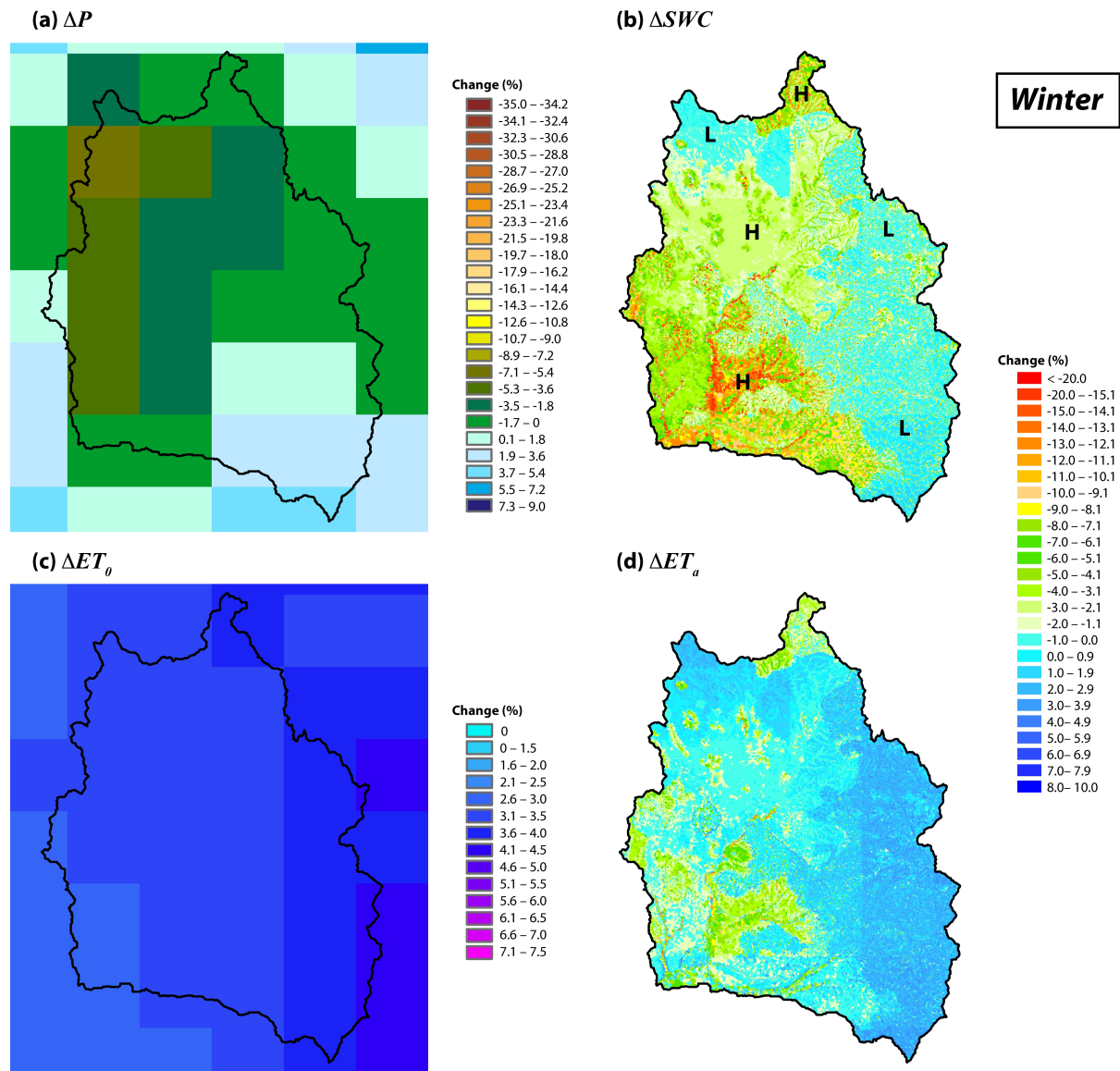
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Fig. 11. Relation between the change in the mean of the annual maximum Q , $\Delta\mu_q$, and the corresponding mean slope. Black (gray) circles indicate sub-basins dominated by the Clay loam – Clay (Sandy loam – Loam) class; a cross is used to indicate sub-basins 1-4 and 9. Each panel refers to results obtained for each CM.



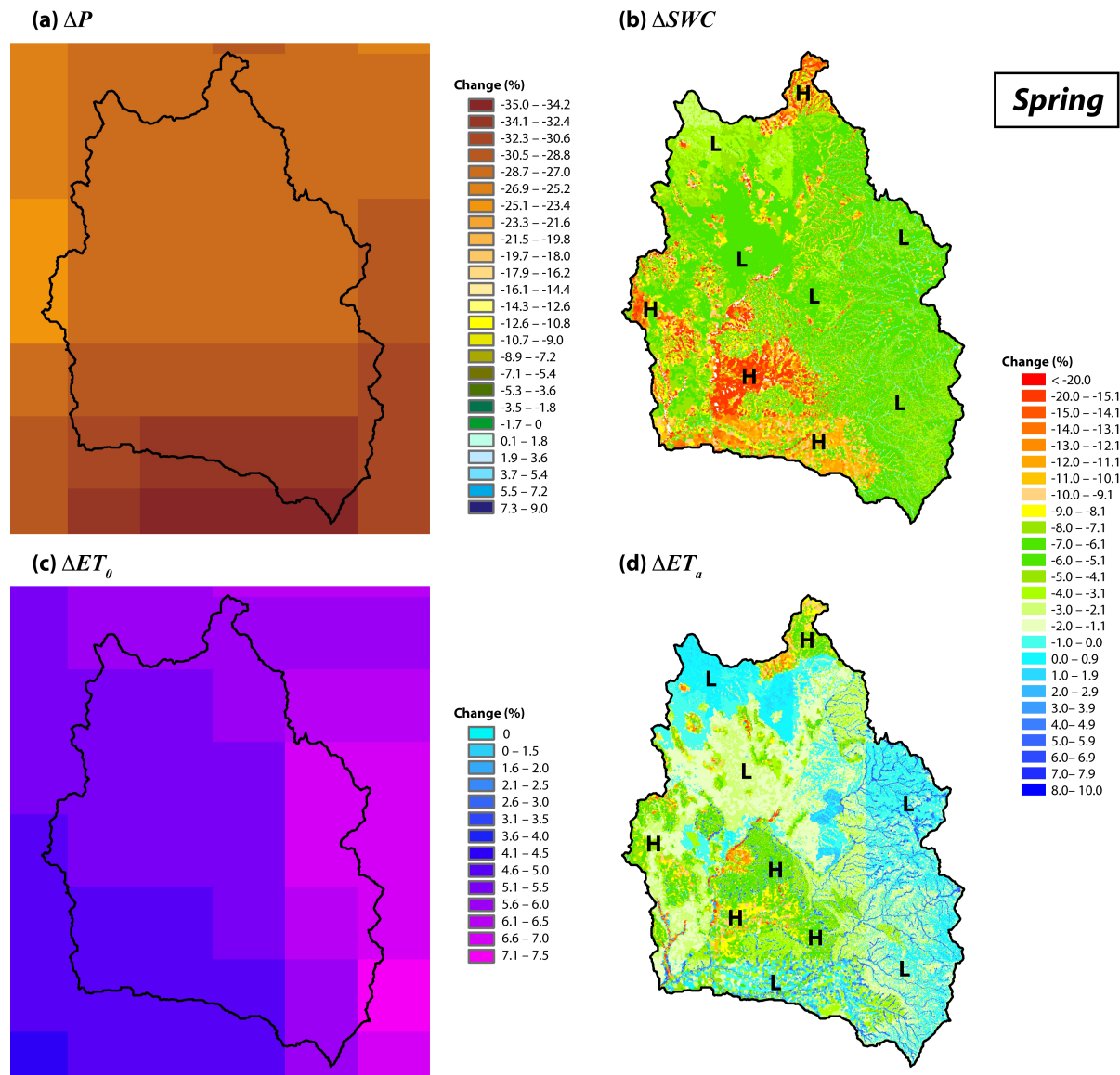
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 2 **Fig. 12.** (a) Mean monthly ET_0 (dashed lines) and ET_a (continuous lines) plotted as mean \pm
 3 standard deviation of the four CMs in REF (black) and FUT (gray); (b) Mean across the CMs of
 4 the relative change of ET_0 , ET_a , and SWC .

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 3 **Fig. 13.** Changes between REF and FUT periods averaged over the winter season (December-
 4 February) for (a) P , (b) SWC , (c) ET_0 , and (d) ET_a under the ECH-RCA combination. In (b),
 5 areas where the variables are characterized by positive or lower negative changes are indicated
 6 with L, while regions with higher negative changes are indicated with H.

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3 **Fig. 14.** Same as Fig. 13, but for the spring season.