Quantifying the evidence of climate change in the light of uncertainty exemplified by the Mediterranean hot spot region

Heiko Paeth [a,*], Gernot Vogt [b], Andreas Paxian [a], Elke Hertig [c], Stefanie Seubert [c], Jucundus Jacobeit [c]

[a] *Institute of Geography and Geology, University of Würzburg, Germany*
[b] *German Weather Service, Offenbach/Main, Germany*
[c] *Institute of Geography, University of Augsburg, Germany*

A B S T R A C T

Climate change projections are subject to uncertainty arising from climate model deficiencies, unknown initial conditions and scenario assumptions. In the IPCC reports and many other publications climate changes and uncertainty ranges are usually displayed in terms of multi-model ensemble means and confidence intervals, respectively. In this study, we present a more quantitative assessment and statistical testing of climate change signals in the light of uncertainty. The approach is based on a two-way analysis of variance, referring to 24 climate models from the CMIP3 multi-model ensemble, and extents over the 21st century. The method also distinguishes between different climate variables, time scales and emission scenarios and is combined with a simple bias correction algorithm.

The Mediterranean region has been chosen as a case study because it represents an assumed hot spot of future climate change, where temperature is projected to rise substantially and precipitation may decrease dramatically by the end of the 21st century. It is found that future temperature variations are mainly determined by radiative forcing, accounting for up to 60% of total variability, especially in the western Mediterranean Basin. In contrast, future precipitation variability is almost completely attributable to model uncertainty and model internal variability, both being important in more or less equal shares. This general finding is slightly depending on the prescribed emission scenario and strictly sensitive to the considered time scale. In contrast to precipitation, the temperature signal can be enhanced noticeably when bias-correcting the models' climatology during the 20th century: the greenhouse signal then accounts for up to 75% of total temperature variability in the regional mean.

1. Introduction

The usage of models for complex systems is inevitably tied to uncertainties of different types and sources. Climate model projections for climate variations in the past and future represent a paradigm of such problems with uncertainties referring to practically all categories like parameter uncertainty, structural uncertainty, algorithmic uncertainty and experimental uncertainty (Palmer and Anderson, 1994; Palmer and Williams, 2008). In state-of-the-art general circulation models (GCMs), which provide the best tool to assess climate variability in a three-dimensional space (Murphy et al., 2004), the spread of projected climate changes among climate models mainly emanates from different model-specific climate sensitivities, i.e. the response of global mean temperature to a doubling in CO_2 concentrations (Sexton and Murphy, 2012). Recent studies have highlighted the role of feedbacks in the determination of climate sensitivity (Roe and Baker, 2007; Andrews et al., 2012), especially in the models' radiation schemes (Geoffroy et al., 2012) and, if incorporated in the model, the carbon cycle (Friedlingstein et al., 2014). Additional sources of uncertainty in climate model projections relate to the cycles and magnitudes of natural variability, e.g. in terms of solar and volcanic activity (Stott and Kettleborough, 2002), to scenarios of greenhouse gas emissions (Schenk and Lensink, 2007; Meinshausen et al., 2011), but also to inaccurate climate data, which are used to calibrate the models and to develop physical parameterizations (Hogan, 2005; Matthews et al., 2013).

As uncertainty is an intrinsic element of climate modeling, which, in either case, does not prevent us from climate mitigation (Lewandowsky et al., 2014), adaptation to future climate change has to be dimensioned against the background of more or less diverging climate model projections (Hawkins and Sutton, 2011). Nonetheless, even if we cannot reduce uncertainty beyond a given level, it must be quantified in an objective, reproducible and honest way in order to specify lower and upper limits and most probable ranges of future climate boundary conditions as a benchmark for adaptation and protection (Curry, 2011). Typically, the uncertainty of climate models is sampled by a large set of climate model experiments with different initial conditions, different physical parameterizations and grid resolutions, but identical changing boundary conditions, e.g. greenhouse gas concentrations, forming a

* Corresponding author at: Institute of Geography and Geology, University of Würzburg, Am Hubland, 97074 Würzburg, Germany.
E-mail address: heiko.paeth@uni-wuerzburg.de (H. Paeth).

multi-model ensemble like in the framework of the coupled model intercomparison projects in the second (Paeth et al., 2008), third (Meehl et al., 2007; Hawkins and Sutton, 2011) and fifth generation (Taylor et al., 2012). Climate change in the light of uncertainty is illustrated by means of changes in the multi-model mean and corresponding confidence intervals reflecting the spread across models. Prominent examples are given by the last IPCC reports (IPCC, 2007, 2013). Such probabilistic climate change assessments have been further developed, e.g. on the basis of Bayesian statistics (Tebaldi et al., 2005) and of models with perturbed physics (Collins et al., 2006; Paeth, 2015), and are available for climate impact research (Lewandowsky et al., 2014).

In this study, we present a more straightforward quantitative measure of the evidence of climate change. The main advantage is its comparability in a sense that it can be applied to any multi-model ensemble, emission scenario, region or time period, its plausibility and its normalized character. For this purpose, we differentiate the total variance of a given climate variable within a multi-model ensemble setting into four fractions: (1) the fraction arising from the common forcing, in this case changing atmospheric greenhouse gas and aerosol concentrations according to specific emission scenarios, (2) the portion related to systematic differences between the climate models, (3) the part coming along with different time structures in the response to radiative forcing, i.e. the way how quickly changes in climate variables occur over the 21st century in a specific climate model projection, and (4) the influence of unknown initial conditions. Fraction 1 is a quantitative indicator of the climate change signal, which is more or less blurred by uncertainties in the form of model uncertainty (fraction 2) and model internal variability (fraction 4). Compared with the similar approach by Hawkins and Sutton (2009), we rely on an analysis of variance, which, at the same time, allows for the quantification and the assessment of statistical significance of the individual contributions from climate change signals and sources of uncertainty to total variability. In addition, we differentiate between time scales and include a bias-correction algorithm. Analysis of variance has been successfully applied to issues of climate change assessment by Paeth and Hense (2002) for global temperature and precipitation based on a very small ensemble of CMIP2 simulations, by Wang and Swail (2006) for ocean wave heights and by Paeth and Pollinger (2010) for extratropical circulation modes.

Here, the method is exemplified by the Mediterranean region, where observational data foreshadow a substantial change towards higher temperatures and lower precipitation rates (IPCC, 2007, 2013; Seager et al., 2014). Indeed, the region has been identified as a hot spot of future climate change (Giorgi, 2006; Diffenbaugh and Giorgi, 2012), in terms of changes in mean seasonal climate features and extreme events (Paeth and Hense, 2005; Paxian et al., 2015). Therefore, we expect a relatively high evidence of climate change signals in temperature and precipitation, which may represent a benchmark for comparative studies with the same method in other regions of the globe.

In the following section the considered data sets and the statistical approach for the quantification of climate change signals from multi-model ensembles are presented. Section 3 is dedicated to the results, which are discussed in Section 4.

2. Data and methods

The evidence of temperature and precipitation changes in the Mediterranean region is derived from the CMIP3 multi-model ensemble (IPCC, 2007; Meehl et al., 2007). It is composed of 24 climate models, partly different versions of the same GCM, many of those providing several ensemble members with varied initial conditions. We consider the 20th-century experiments with observed greenhouse gas concentrations and scenario runs according to emission scenarios A1B, B1 and A2 until the end of the 21st century (Nakicenovic and Swart, 2000). The number of available runs differs among the scenarios with A1B being best represented. CMIP3 has been subject to numerous studies on future climate change (cf. IPCC, 2007) and constituted the state-of-the-art GCM data base for most climatological issues at the moment when our study began. In the meantime, CMIP5 as the next generation of coordinated multi-model ensembles has been made available (Taylor et al., 2012; IPCC, 2013). At the time of writing this manuscript, only a few CMIP5 models provided several ensemble members per scenario, which, however, is a basic requirement of the statistical method used in this study (see below). Although we could not yet consider CMIP5 in the framework of the project presented here, we see our analysis based on CMIP3 as a benchmark for further investigation of CMIP5. This is to assess whether the evidence of climate change in CMIP5 is more or less prevailing against the background of uncertainties compared with CMIP3 and what impact is imposed by the new emission scenarios (Meinshausen et al., 2011). However, note that Knutti and Sedláček (2013) have demonstrated that CMIP5 largely confirms CMIP3 with respect to rates of temperature change and model spread: the projected temperature rise in the Mediterranean is around 4 °C under comparable scenarios like A1B (IPCC, 2007) and RCP6.0 (IPCC, 2013).

During recent decades simulated temperature and precipitation changes from CMIP3 are compared with NCEP (Kistler et al., 2001) and ERA40 (Uppala and 45 co-authors, 2005) reanalyses. On the one hand, we want to evaluate to what extent simulated and observed trends agree across the Mediterranean basin, in the sense of model validation and confidence into future projections. On the other hand, we are interested in the conformity of trends among different observational data sets as a clue to experimental uncertainty (cf. Hogan, 2005; Matthews et al., 2013). For better comparison all model and reanalysis data sets are statistically interpolated to a regular $3° \times 3\times$ grid.

The statistical approach is based on a two-way analysis of variance (von Storch and Zwiers, 1999). A linear model is assumed, which splits up the total variance SS_T, indicated as sum of squares (SS), of a given variable at a given location into the so-called treatment effect SS_β of changing boundary conditions (in our case radiative forcing during the 21*st* century), the block effect SS_α (here the systematic difference between climate models), the unpredictable residual SS_ε (in our context model internal variability as imposed by varied initial conditions), and the interaction coefficient SS_γ (arising from different time structures in the emission scenarios). SS_β is a direct and quantitative measure of the evidence of climate change in the given variable. SS_α stands for model uncertainty and SS_ε for internal variability, both in quantitative terms as well. SS_γ can virtually be neglected, since the analysis of variance (ANOVA) is separately applied to model simulations of the same emission scenario. These four fractions of total variance can be determined from standard statistics based on means and standard deviations, for formulas see von Storch and Zwiers (1999); Paeth and Hense (2002) or Wang and Swail (2006). Statistical significance of SS_β and SS_α is estimated on the basis of a Fisher F test (von Storch and Zwiers, 1999) at an error level of 5%. SS_ε is not tested since it represents the residual, i.e. the null hypothesis. Note that the ANOVA requires several ensemble members per climate model and scenario, expulsing some single runs from the CMIP3 data base.

The innovative methodical aspect of this study consists in the combination of the standard ANOVA with an ex ante bias correction and in a closer look at the typical time scales, where climate change signals emerge. In contrast to more sophisticated approaches of bias correction, like e.g. model output statistics (Paeth, 2011), it is found that a simple postprocessing of model data is expedient: the climatology of each model simulation is brought to the same observed long-term mean, in this case the 1961–1990 time average of the ERA40 reanalysis as a plausible, but arbitrary choice. This type of bias correction has been combined with the ANOVA in order to assess in a quantitative sense, to what extent a simple postprocessing of model data based on available observations may enhance future climate change signals and, thus, provide a more confident landmark for adaptation measures. Throughout the paper, climate change is displayed as the linear change over a given period, i.e. the product of the univariate regression coefficient and the time interval. It is tested by means of a *t*-test at an error level of 5% (von Storch and Zwiers, 1999).

3. Results

3.1. Past changes

Fig. 1 depicts the changes in annual, winter (December–February) and summer (June–August) 2-meter temperature over the 1961–2000 period as indicated by NCEP reanalyses, ERA40 reanalyses and the CMIP3 multi-model mean. The entire Mediterranean region is considered expanding from 20 °W to 45 °E and from 26 °N to 45 °N. At first sight, all three data sets differ noticeably: NCEP mainly exhibits a warming pattern, but also reveals a cooling tendency in parts of northern African, eastern Turkey and Southeast Europa, especially in winter. The cooling is yet barely statistically significant. In contrast, ERA40 is characterized by a higher and mostly significant warming rate. The CMIP3 models indicate a weak, but spatially coherent and significant warming pattern in all seasons. Its lower amplitude is mainly due to the fact that it refers to the mean over many individual realizations. There is also one feature where reanalyses and climate models basically agree, that is to say the pronounced temperature rise in summer. In the observations it partly exceeds 2 °C over 40 years, which is more than twice as much as on global average since the late 19th century and has been one reason for identifying the Mediterranean region as a hot spot of climate change (Diffenbaugh and Giorgi, 2012). The striking discrepancies between NCEP and ERA40 shed light on the problem of experimental uncertainty (cf. Hogan, 2005; Matthews et al., 2013) and are quite alarming in a region, which, in a global context, is relatively well represented by station observations. The differences between reanalyses and CMIP3 can partly be explained by different cycles of decadal variability in observations and uninitialized climate model simulations, impeding the validation of simulated climate trends over short time intervals (cf. Lu et al., 2014; Paxian et al., 2014).

The agreement between ERA40 and NCEP tends to be higher in terms of precipitation changes during the late 20th century (Fig. 2): annual precipitation amount decreases in most parts of the Mediterranean domain with highest amplitudes over southern Europe and the central basin. Drying prevails in all seasons, especially in winter where rainfall peaks during the seasonal cycle. In contrast, some parts of northern Africa and the eastern North Atlantic have experienced a slight and statistically insignificant increase of precipitation. The CMIP3 multi-model ensemble mean also denotes a drying pattern, but with very low amplitudes and only sporadic significance. However, this should not be over-interpreted for the reasons mentioned above. Altogether, the data sets draw a rather consistent picture of aridification in the Mediterranean region as reported by several other studies (e.g. IPCC, 2007, 2013; Seager et al., 2014).

3.2. Future changes

The temperature changes over the 21st century as projected by the CMIP3 multi-model ensemble mean are displayed in Fig. 3 for the A1B emission scenario. Annual, winter and summer trends exhibit a similar pattern with higher warming rates over land masses and higher magnitudes in summer compared to winter. The temperature rise is everywhere statistically significant and extends from below 2 °C over the North Atlantic to about 5 °C over southwestern and southeastern Europe by the end of this century. Note that global-mean warming under A1B emissions scenario amounts to 2.5 °C over the same period (IPCC, 2007), highlighting the prominence of the Mediterranean region in the global warming context. Under the assumption of B1 scenario the Mediterranean temperature change does not exceed +3 °C until 2100, while it reaches up to 6.5 °C under A2 (not shown). From a regional perspective, this reflects an enormous margin and, likewise, a strong motivation for climate mitigation measures.

The drying tendency of the late 20th century appears to continue until the year 2100 with a reduction of annual precipitation of more than 100 mm (Fig. 4). In many subregions of the Mediterranean basin the aridification is in the order of more than 25% of present-day precipitation totals. In summer the decrease is more expressed over southern Europe, in winter over the eastern Mediterranean and the Near East with a slight and insignificant increase along the northern borders of the basin. Notably striking is the negative trend over the Iberian Peninsula. B1 emission scenario is coming along with a less pronounced reduction of precipitation amount, whereas the drying is much more dramatic under A2 with values beyond −150 mm per year in most parts of the Mediterranean region (not shown). This indicates again a large scope of action for climate protection.

In summary, current climate models obviously tend to project a much warmer and dryer climate evolving over the 21st century. Thus, from a global perspective future climate change appears to be particularly evident in the Mediterranean region. However, the illustrations in Figs. 3 and 4 do not reveal anything about the uncertainty of these projections, lurking within the CMIP3 multi-model ensemble. In the next subsection, the future temperature and precipitation changes are

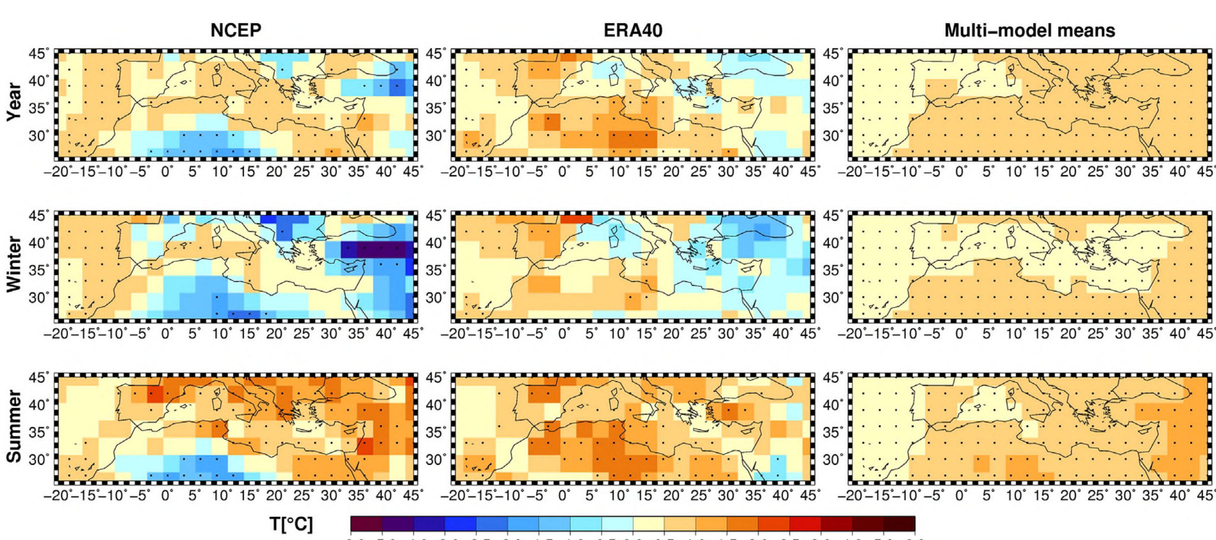

Fig. 1. Changes in annual, winter and summer near-surface temperature over the 1961–2000 period from NCEP and ERA40 reanalyses and CMIP3 multi-model mean. Black dots indicate statistical significance at the 5% level.

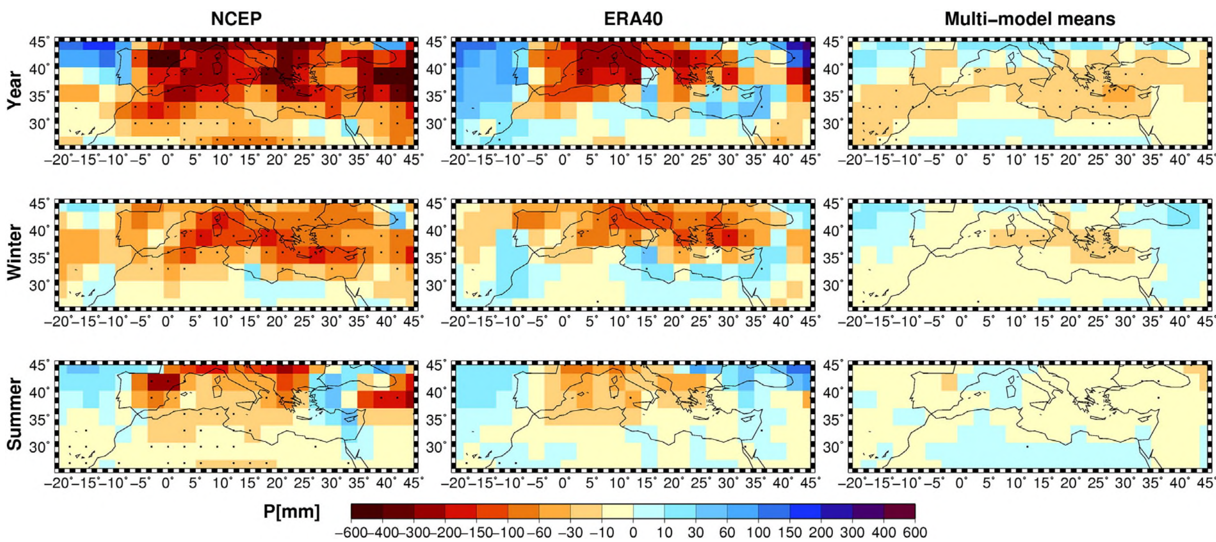

Fig. 2. Same as Fig. 1, but for precipitation.

quantified and evaluated in the light of model uncertainty and internal variability.

3.3. Quantification of climate change signals and uncertainties

Based on the climate changes under A1B scenario as indicated by Fig. 3, the total variance of annual-mean near-surface temperature over the 2001–2098 period and over all ensemble runs of the CMIP3 multi-model data set is split up into the fraction related to the common climate change signal over all simulations (β in Fig. 5), the contribution by model uncertainty (α in Fig. 5) and the component of model internal variability (ε in Fig. 5). As the fourth fraction, that is to say the interaction coefficient, can be neglected in our experimental setting (see Section 2), these three portions sum up to nearly 100% of total temperature variance. Interestingly, the pattern of variance explained by radiative forcing (Fig. 5, top) is inverse compared with the pattern of future temperature changes (Fig. 3, top): the evidence of projected warming is higher over the ocean surface, but its magnitude is higher over land. The climate change signal is statistically significant in all grid cells and accounts for up to 60% of total temperature variance in the western Mediterranean region and over the North Atlantic. In contrast, with up to 80% of total temperature variance model uncertainty prevails over northern Africa and the Near East and is also significant across the entire Mediterranean basin (Fig. 5, middle). Internal variability is most pronounced in the northern-most part of the basin and, especially, over the eastern North Atlantic (Fig. 5, bottom) where mid-latitude cyclonic activity during winter leads to stronger high-frequency variability (cf. Paeth and Pollinger, 2010). With less than 20% of explained variance internal variability is relatively weak, making near-surface temperature a robust detection variable of future climate change (cf. Paeth and Hense, 2002).

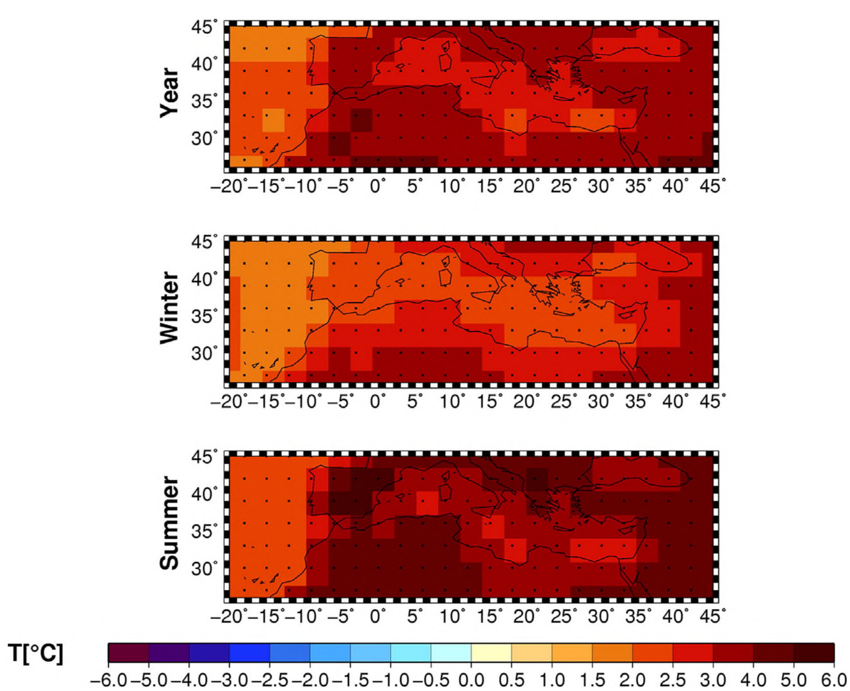

Fig. 3. Changes in annual, winter and summer near-surface temperature over the 2001–2098 period from CMIP3 multi-model mean under A1B emission scenario. Black dots indicate statistical significance at the 5% level.

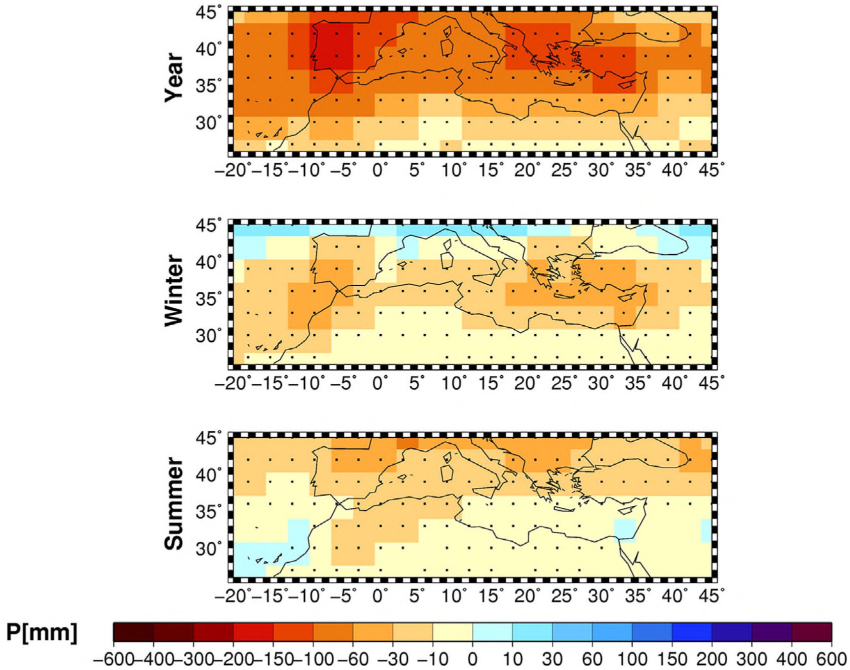

Fig. 4. Same as Fig. 3, but for precipitation.

In terms of future precipitation changes a completely different picture is drawn (Fig. 6): almost none of the total variance can be attributed to a common climate change signal. Instead, precipitation changes within the CMIP3 multi-model ensemble are almost entirely governed by the spread among different climate model projections and internal variability at interanual to decadal time scales. Both sources of uncertainty range in the same order of magnitude with model uncertainty prevailing over the land masses, particularly over North African dry areas, and internal variability being more pronounced over the sea surface.

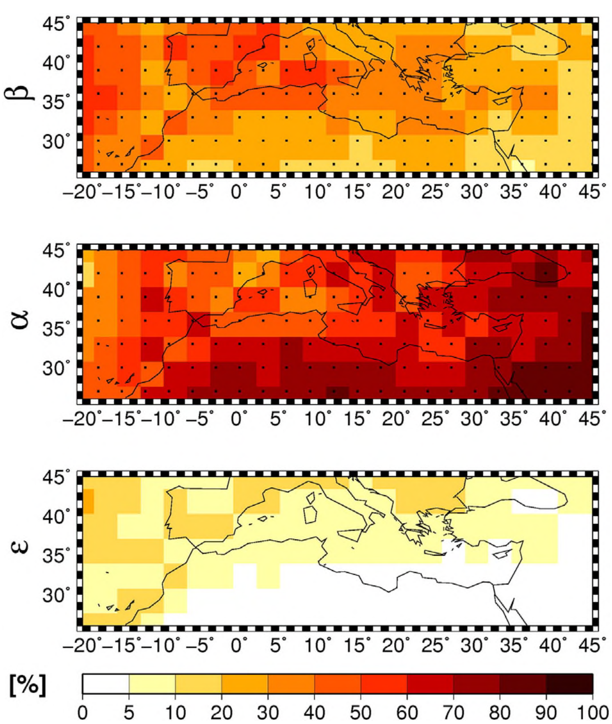

Fig. 5. Portions of total variance of annual near-surface temperature explained by common climate change signal (top), by model discrepancy (middle) and by model internal variability (bottom) over the 2001–2098 period from CMIP3 multi-model ensemble under A1B emission scenario. Black dots indicate statistical significance at the 5% level.

Fig. 7 reveals that the evidence of future temperature and precipitation changes is an unmistakable function of emission scenario. Under A2 the fraction of total annual temperature variance accounted for by radiative forcing reaches up to 70% and is 20–30% higher in all grid boxes compared with B1 (left panels), A1B being just in the middle of this range. Nonetheless, the temperature signal is significant under all emission scenarios. Concerning precipitation, there is no distinct evidence of future climate change under B1, but some explained variance of 5–20%

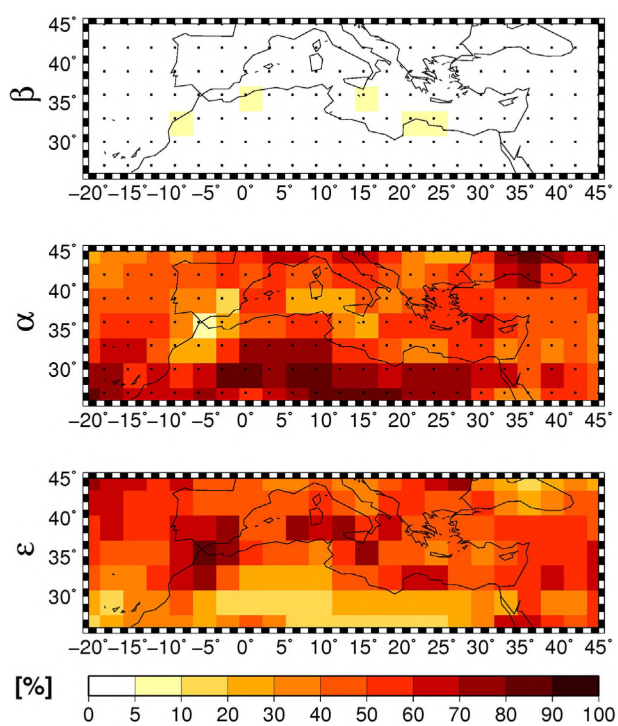

Fig. 6. Same as Fig. 5, but for precipitation.

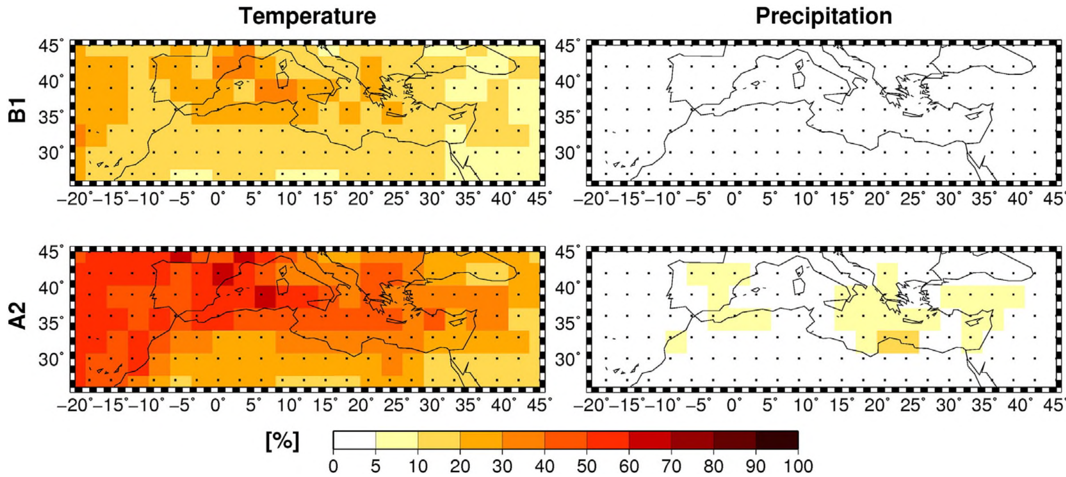

Fig. 7. Portion of total variance of annual near-surface temperature (left) and annual precipitation (right) explained by common climate change signal over the 2001–2098 period from CMIP3 multi-model ensemble under B1 (top) and A2 (bottom) emission scenarios. Black dots indicate statistical significance at the 5% level.

over the southeastern Mediterranean Sea under A2 (right panels). Obviously, the strength of the climate change signals is proportional to the amount of emitted greenhouse gases.

Fig. 8 provides insight into the sensitivity of the climate change signals to the considered time scale and into their temporal structure. For this purpose, regional-mean time series of annual temperature (left panels) and precipitation (right panels) are built for the entire Mediterranean domain and the ANOVA is applied to running 30-year (top panels) and 60-year (bottom panels) time windows over the 1900–2098 period. 30-year intervals have been chosen because they are mainly characterized by interannual and decadal variability, while 60-year periods are more marked by long-term trends (cf. Lu et al., 2014; Paxian et al., 2014). At both time scales, the temperature signal emerges in the late 20th and over the entire 21st century (cf. Maraun, 2013), but it is clearly more evident over 60-year periods, exceeding 20% of explained variance. This happens at the expense of lower model uncertainty, whereas internal variability is equally pronounced over 30-year and 60-year time intervals. Thus, the model spread within CMIP3 is larger at the interannual to decadal rather than at the multi-decadal time scale because the latter is more affected by the radiative forcing, which is common to all model projections. With regard to annual precipitation, the forcing component occurs in none of the considered time periods. Total variability is rather arising from systematic model differences and internal noise. The considered time scales hardly affect the relative contributions to total precipitation variance, but the time series are smoother for 60-year periods because the time windows overlap more extensively. In general, model uncertainty is the most dominant factor accounting for almost two third of total variance.

In Section 2, fraction α was defined as an indicator of systematic differences between the various climate models in the CMIP3 data base. It

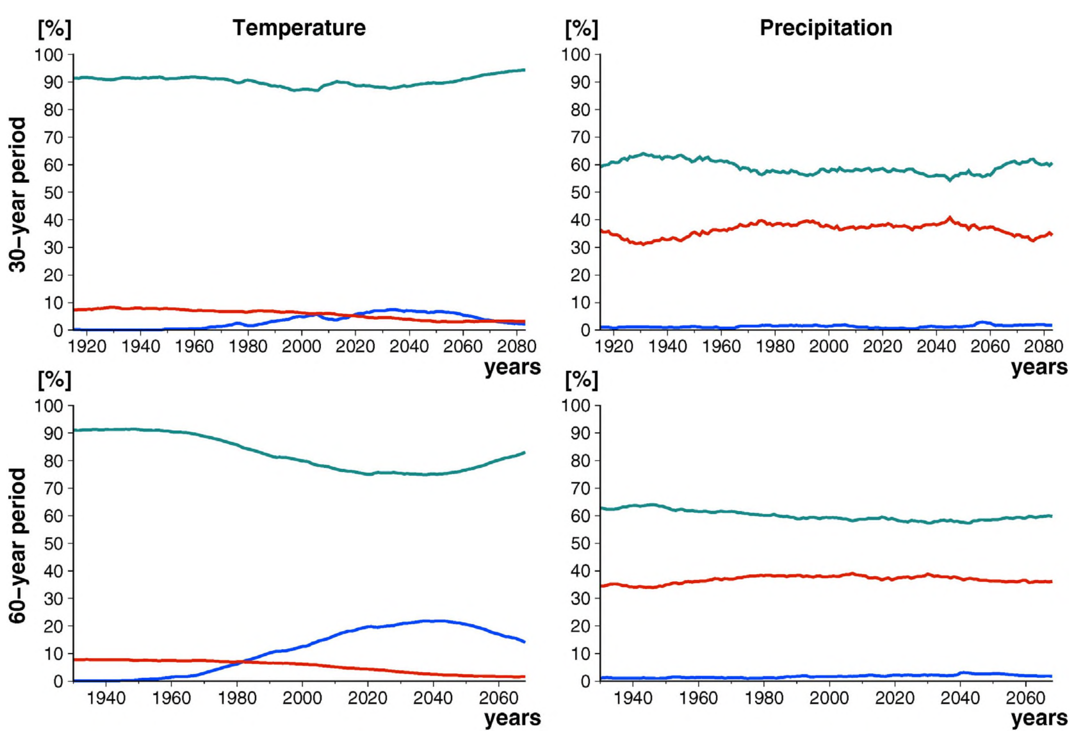

Fig. 8. Portion of total variance of regional-mean annual near-surface temperature (left) and annual precipitation (right) explained by common climate change signal (blue lines), by model discrepancy (green lines) and by model internal variability (red lines) over sliding 30-year (top) and 60-year (bottom) periods from CMIP3 multi-model ensemble under A1B emission scenarios. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

partly reflects different model climatologies during the 20th century, which more or less deviate from given observations. Thus, one option to reduce the model spread of future climate projections may consist in a correction of model biases over past time periods, for which observational data for calibration are available. Here, temperature and precipitation means over the 1961–1990 reference period from all considered model experiments are adapted to the corresponding ERA40 climatology. In contrast to more sophisticated model output statistics (e.g. Paeth, 2011), this simple bias correction allows for retaining the interannual to centennial variability of each individual model run. This is crucial in order to avoid that model internal noise is partly suppressed after bias correction. Fig. 9 illustrates that bias correction has a remarkable effect on the evidence of future temperature changes over 60-year sliding time windows in the Mediterranean region (left panel): the portion of temperature variance explained by the common radiative forcing increases from less than 25% in the original CMIP3 multi-model ensemble to more than 70% after calibration. Nonetheless, internal variability accounts for a slightly larger portion of total variance and model uncertainty still increases towards the end of the 21st century. In contrast, the bias correction barely affects the precipitation signal. It now becomes apparent, but does not exceed 10% of total variance. Instead, model differences as one source of uncertainty are replaced by internal variability as another source of uncertainty. Like for temperature the model spread slightly increases over the 21st century. Consequently, the effectiveness of bias correction in the assessment of future climate change signals depends on the considered climate variable.

4. Summary and conclusions

This study was dedicated to a quantitative assessment of climate change signals and uncertainties in future projections of near-surface temperature and precipitation in the Mediterranean region. The aim was to provide comprehensible and comparative measures of forcing effects, model uncertainty and model internal variability, which can be applied to arbitrary climate variables, regions, time slices, scenarios and multi-model ensembles. The Mediterranean basin has been chosen as a test case because previous studies have identified this region to be a hot spot of climate change (Giorgi, 2006; Diffenbaugh and Giorgi, 2012). Climate models and various reanalyses indicate a warming and drying tendency over recent decades, although all data sets differ noticeably at the seasonal and sub-regional scale. This suggests some important experimental uncertainty in the observational data, even in a region, where data coverage is relatively high. In the CMIP3 multi-model ensemble mean a substantial warming and drying is projected over the 21st century. The temperature rise under a given emission scenario is far beyond the global-mean warming rate and precipitation decrease is among the most pronounced around the globe (cf. IPCC, 2007, 2013; Seager et al., 2014). This is basically supportive of the idea of a climate change hot spot.

Indeed, the ANOVA approach has revealed that the future temperature increase clearly stands out from model uncertainty and internal variability, while the latter is a less important source of uncertainty. The pattern of variance assigned to the common radiative forcing is inverse to the pattern of the magnitude of future temperature changes. This implies that ocean surfaces are characterized by a smaller temperature increase than land masses, but its evidence from the CMIP3 multi-model ensemble is higher. Over the land masses, this relationship is inverse. Paeth and Hense (2002) have also concluded that tropical and subtropical oceans exhibit a weak, but particularly robust climate change signal. However, in contrast to temperature precipitation change is almost entirely blurred by model spread and internal noise, leaving no room for a robust interpretation of projected future trends. Thus, previous works can be confirmed, stating that temperature is a much better detection variable of climate change than precipitation (e.g. Paeth and Hense, 2002). This must be taken into account when defining hot spot regions of climate change. Model uncertainty is generally higher over land masses, especially in dry regions, than over the oceans, where internal variability tends to be more pronounced.

Our study has also demonstrated that the strength of climate change signals is a function of the emission scenario, pleading for timely climate mitigation measures, and of the considered time scale: 30-year time intervals are too short to identify climate changes against the background of high-frequency components of climate variability (cf. Hawkins and Sutton, 2011; Lu et al., 2014). Indeed, climate models strictly diverge at interannual to decadal time scales, which are mainly affected by the choice of initial conditions (Paxian et al., 2014). This is particularly evident for precipitation, where internal variability over 30 years is almost as high as model uncertainty. Over 60-year periods, the temperature signal clearly emerges from the 1980s onward, whereas precipitation variability in the CMIP3 data base must still be assigned entirely to model discrepancies and internal noise.

Finally, a simple algorithm of bias correction during the 20th century has an appreciable impact on the temperature signal: the portion of variance arising from the radiative forcing increases from below 30% to above 70%, although the model spread becomes more and more apparent over the second half of the 21st century. No such positive effect can be obtained for precipitation: a reduced contribution by model uncertainty is replaced by an enhanced influence of internal variability. This has also been suggested by Hawkins and Sutton (2011) and Rowell (2012).

Compared to other regions of the globe, it is likely that the climate change signal of temperature in the Mediterranean basin is quite distinct. Based on a large number of ensemble members from the same climate model Deser et al. (2012) have highlighted that uncertainty arising from internal variability may substantially blur the greenhouse

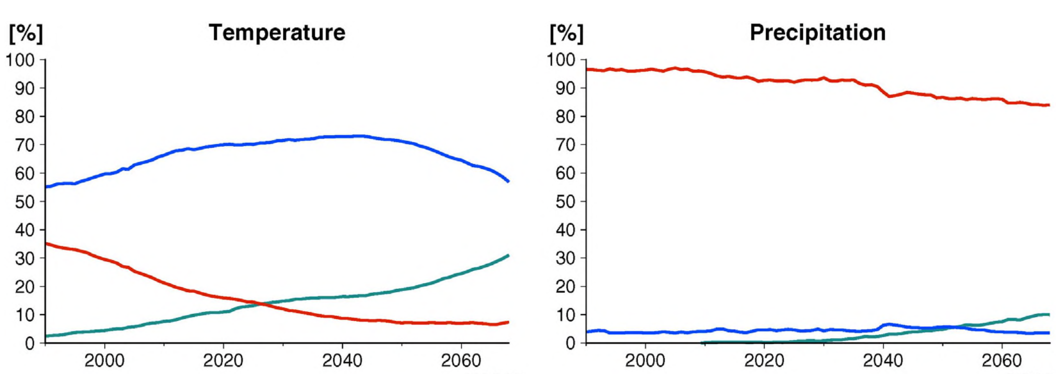

Fig. 9. Same as Fig. 8, but for sliding 60-year periods only and for bias-corrected model climatologies during the 1961–1990 period.

gas induced warming signal across North America, even at the scale of larger regional means. Extratropical regions may be more concerned by this signal deterioration than tropical and subtropical areas, as also reported by Paeth and Hense (2002).

Based on these findings, the next steps are quite obvious: for comparison the ANOVA approach should be applied to other regions and, in particular, to the CMIP5 data base. CMIP5 represents the latest version of multi-model ensembles, providing an even larger number of future climate projections (Taylor et al., 2012; IPCC, 2013) under a new set of emission scenarios (Meinshausen et al., 2011). Nevertheless, it is not necessarily expectable that climate change signals in CMIP5 and CMIP3 basically differ from each other, since Knutti and Sedláček (2013) pointed out that both data sets are quite similar in terms of future warming rates and model spread. However, their projections, being composed of climate change signals and internal variations, may still be very different, given their specific cycles of internal variability – especially for precipitation.

A constraint of our approach is given by the fact that climate change signals may be exaggerated and sources of uncertainty underestimated when the underlying multi-model ensemble does not reflect a realistic range of possible future pathways of climate. In fact, some authors argue that climate models in the CMIP framework are not independent of each other and, hence, model spread is systematically underestimated (Curry, 2011; Hawkins and Sutton, 2009, 2011; Sanderson and Knutti, 2012). It has also been suggested that model ensembles with perturbed physics (Collins et al., 2006) or even stochastic climate models (Palmer and Williams, 2008) may give a more appropriate insight into real model uncertainty. While this is essential ongoing research, Collins et al. (2011) have shown that the model spread from CMIP3 is comparable with the spread from an ensemble with perturbed physics using the HadCM3 climate model. Thus, CMIP3 appears to be appropriate for quantifying climate change signals against the background of uncertainties.

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