HydroSciences
Montpellier

Institut de Recherche pour le Développement
FRANCE

Montpellier, 30/11/2020

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Dear Markus Hrachowitz,

Please find enclosed the revision of our manuscript entitled “Modeling the response of soil moisture to climate variability in the Mediterranean region”.

We carefully addressed all of the reviewer comments, that were constructive to improve the quality of the manuscript. In particular, we re-processed the whole modelling chain according to the comments of reviewer n°1, Guillaume Evin. The approach suggested, to re-calibrated the stochastic generator for each scenario, was tested but did not provide satisfactory results, we explain why in the response to his comments. However, we did improve the calibration of the generator according to his recommendations. Overall, the new results do not change the main conclusions.

Following the response to the reviewer comments, a manuscript with the changes marked is provided.

On behalf of the authors, I would like to thank you for handling this manuscript.

YVES TRAMBLAY

Reviewer 1, Guillaume Evin

I thank the authors for this interesting paper on the relationship between meteorological forcings and soil moisture in the Mediterranean region. The manuscript is well written, well organized and the different modelling tools are adequately applied. The first important result is that the increase in temperature is not the main driver of the changes in soil moisture, but seems to be precipitation characteristics. The second important contribution is methodological since this study shows how a soil moisture model and meteorological scenarios can be used to assess the sensitivity of the soil moisture to these forcings. I have two major comments (see below) regarding how rainfall scenarios are generated. The authors simulate changes of intermittency using the parameter lambda of the Neyman-Scott model. This lambda parameter is the master Poisson process parameter and is directly related to the frequency of rainfall events. I think that the interpretation of 'intermittence' is misleading, which is annoying since the main results of the paper rely on this interpretation. My main recommendation is thus to change the way rainfall scenarios are generated. In my opinion, the best option for the generation of scenarios would be to recalibrate the NSRP model for each set of rainfall statistics (the observed ones + the perturbed ones). In the current version of the manuscript, it must be clearly understood that when one parameter (e.g. lambda) is modified, it affects all rainfalls statistics, which complicates the interpretation of the main factors leading to changes in the soil moisture.

Thank you for this in-depth review of the manuscript and in particular of the stochastic generation method applied in our work.

We acknowledge the concerns raised by the approach considered. While it is true that some authors applied this re-calibration of the rainfall generator after the modification of rainfall statistics (Burlando and Rosso, 2002; Bordoy and Burlando, 2014), other studies considered a similar approach as ours, by modifying directly the parameters of interest in the rainfall generator (Onof and Wheater, 1994; Wasko et al., 2015).

We tested the approach proposed, based on the recalibration of the generator, but this approach did not provide satisfactory results. We also improved the calibration of the rainfall generator. Please find a more detailed response below.

Burlando, P. and Rosso, R.: Effects of transient climate change onbasin hydrology, 1. Precipitation scenarios for the Arno River Basin, central Italy, Hydrol. Process, 16, 1151–1175, 2002.

Bordoy, R. and Burlando, P.: Stochastic downscaling of climate model precipitation outputs in orographically complex regions: 2. Downscaling methodology. Water Resources Research, 50(1), 562–579. https://doi.org/10.1002/wrcr.20443, 2014

Major comments:

#1 Due to its structure, the different parameters of the Neyman-Scott rectangular pulse model are not directly interpretable in terms of rainfall statistics. In the current version of the manuscript, parameters lambda and xi are loosely interpreted in terms of "intermittence" and "mean intensity". In my opinion, this interpretation is incorrect and misleading: - The parameter lambda, which governs the master Poisson process, represents the rate of rainfall events (storms). As such, the mean intensity (for any aggregation duration) is linear in lambda (Eq. 2.5 in Cowpertwait, 1998). It is also true for the covariance for any lag (Eq. 2.6 in Cowpertwait, 1998). This means that when lambda decreases (in this paper the inverse of the storm frequency), the mean rainfall intensity increases in proportion. - The parameter xi is the parameter of the exponential distribution for rain cell intensity. The mean rainfall intensity (for any aggregation duration) is linear in lambda. When xi increases, the mean rainfall intensity increases in proportion (Eq. 2.5 in Cowpertwait, 1998). An augmentation of 50% in lambda is directly compensated by an augmentation of 50% in xi, which is indicated in Section4.1 (l. 20). However, an increase of xi with the same increase in lambda leads to the same annual rainfall but also to an increase of the mean intensity of the rainy days (which is indicated at l. 21 but not clearly since the authors refer to the "mean rainfall intensity"), and to an increase of the number of dry days. - Intermittency is not clearly defined in the paper. I strongly suggest proposing a definition in terms of rainfall statistics. A stronger intermittence could be, for the same annual rainfall, a higher number of dry days. It could be parametrized with lambda and xi, but also with the other parameters. Note also that the theoretical proportion of dry days can be easily obtained with the NSRP model (see Eq. 9a-9b in Cowpertwait, 1991), using a numerical integration. The two quantities that would be perturbed could thus be "the total annual rainfall" and "the proportion of dry days" (or equivalently the number of dry days), which would have a direct interpretation. - As said above, in my opinion, the only valid option for the generation of scenarios is to recalibrate the NSRP model for each set of rainfall statistics (the observed ones + the perturbed ones). When lambda or xi is modified, it affects many rainfalls statistics at the same time, which complicates the interpretation of the main factors leading to changes in the soil moisture. As the proportion of dry days is

important in this study, it should also be included in the set of rainfall statistics used to estimate the parameters. Cowpertwait, Paul S. P. 1991. "Further Developments of the Neyman-Scott Clustered Point Process for Modeling Rainfall." Water Resources Research 27 (7): 1431–38. https://doi.org/10.1029/91WR00479. Cowpertwait, Paul S. P. 1998. "A Poisson-Cluster Model of Rainfall: High-Order Moments and Extreme Values." Proceedings: Mathematical, Physical and Engineering Sciences 454 (1971):885–98.

We implemented the approach proposed, by first modifying the rainfall statistics, and then recalibrating the rainfall generator based on the modified rainfall statistics.

Figure 1 shows that the characteristics of the generated rainfall time series after the perturbation of the rainfall statistics and recalibration are not consistent with the perturbation of the observed rainfall statistics. For instance, for an increase in precipitation intensity and no change in precipitation intermittence, some stations (Lez, Nar, Pez, Vil) do not show any increase in total precipitation (Fig 1 upper panel).

And regarding the impact on soil moisture, Figure 2 shows that, with this method, an increase in precipitation intensity leads to a decrease in the median soil moisture for most of the stations, which seems unrealistic.

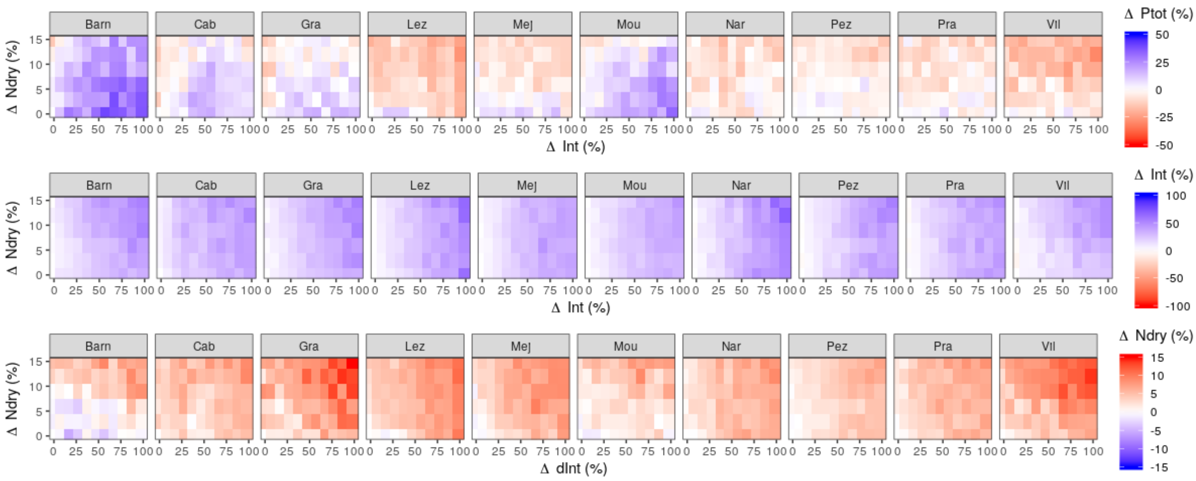


Fig 1: Change in annual precipitation (upper panel), daily rainfall intensity (middle panel), and annual number of dry days (lower panel) obtained after perturbating the rainfall statistics and recalibrating the rainfall generator.

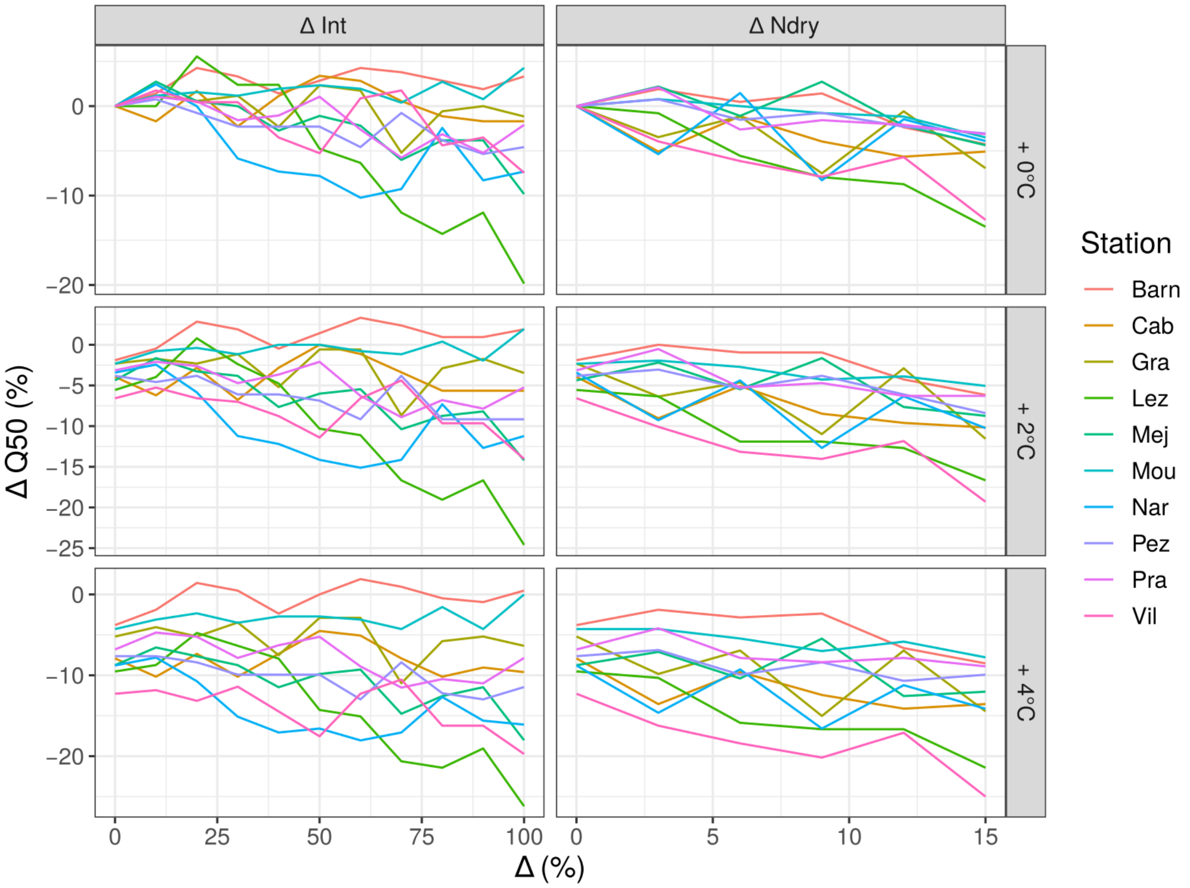


Fig 2: Sensitivity of the median of the simulated soil moisture to an increase of the mean daily rainfall intensity (left panel), and to an increase of mean number if dry days (right panel) under different temperature scenarios (+0 °C, +2 °C, +4 °C)

Consequently, since this approach is not satisfactory in our case, most probably due to the interdependence of different parameters in the Neyman-Scott model (as noted by the reviewer) that is probably amplified when conducting many re-calibration procedures, we kept the initial approach of perturbing the rainfall generator parameters.

But we added Figures 3 and 4 into the manuscript to show the relation between the perturbation of the parameters λ and ξ the change in the number of dry days and precipitation intensity of the generated rainfall series. Figure 3 shows that the perturbation of the parameter ξ is equivalent to perturbating the mean rainfall intensity. There is also a clear relation between the modified value of the λ parameter and the mean number of dry days. An increase of 100% of the λ parameter leads to an increase ranging between 10 and 18 % of the number of dry days depending on the station.

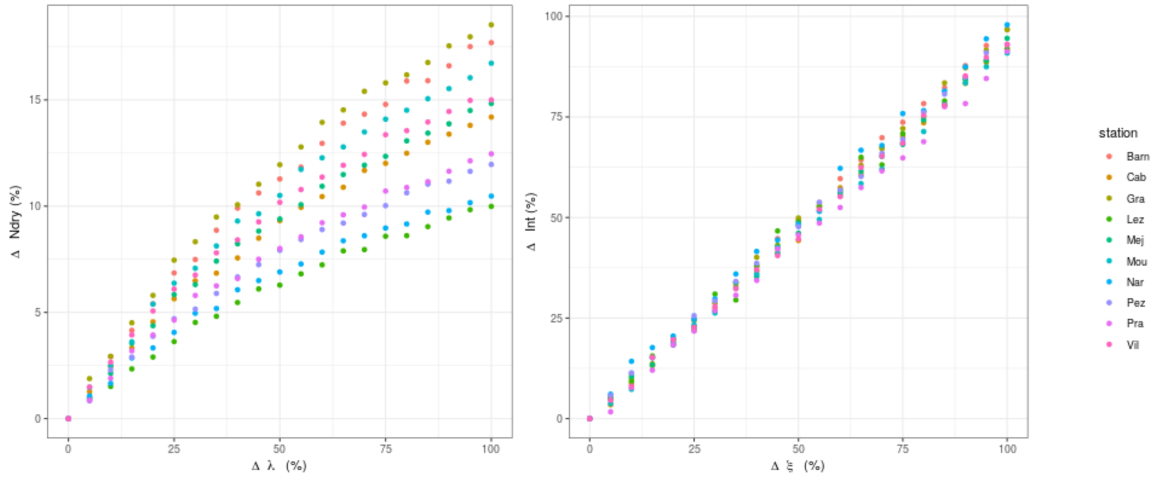


Figure 3: Change in the number of dry days (left panel) and rainfall intensity (right panel) when perturbing the λ and ξ parameters of the rainfall generator.

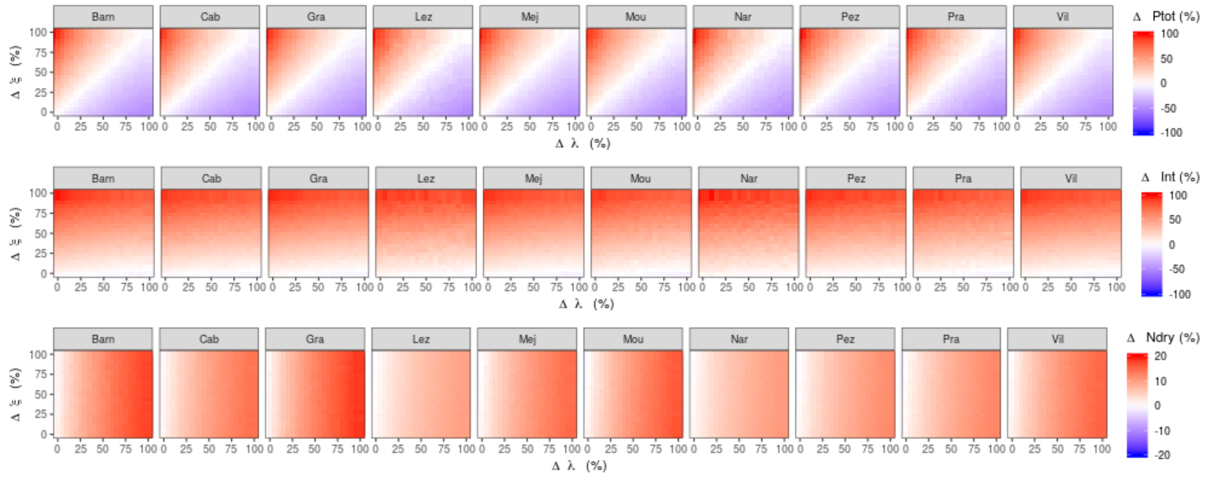


Figure 4: Change in the rainfall characteristics (upper panel: mean annual precipitation, middle panel: mean daily rainfall intensity, lower panel: mean number of dru days) of the generated rainfall time series when increasing the λ and ξ parameters from 0 to +100%.

In the initial manuscript we considered perturbations of the parameters up to +50%, which were equivalent to an increase up to 50% of the mean daily intensity and an increase up to 10% of the mean number of dry days. These values might be in fact too low to analyse the impact of extreme changes in rainfall patterns to soil moisture, that is why we extended the range of perturbation of the parameters up to +100%.

All the figures of the manuscript were updated in the revised manuscript. The general results and main conclusions remain the same as the ones in the submitted manuscript.

#2 Many parameter estimates seem to indicate a failure of the estimation method. For eta, the rain cell duration parameter, many zero

values appear (e.g. Pezenas, June to August) associated to very high values of xi and 1 for beta (the initial value of the optimization I guess). In Pezenas, in September, eta reaches the highest value of10 I guess, and lambda is very high (666.7). It affects maybe 10 months for all the stations, but the problem should be addressed. I cannot trust these simulations with these unrealistic parameter estimates. Possible solutions are: 1. Try different starting values for the optimization, 2. Change the objective functions (weighted sums, relative/absolute differences between observed and simulated statistics), 3. Smooth the estimation from one month to another, there is no strong reason to have a big difference between two consecutive months

We tried applying different starting values for the optimization, with a monthly variation to have a smoother variability between two consecutive months. Results show that the different calibration strategies we tested in order to modify the initial values for the calibration do not significantly reduce the unrealistic parameters values obtained and give very similar results in terms of rainfall intensities.

We kept in the revised manuscript the calibration results that yielded the most realistic values for the rainfall generator parameters. We also checked carefully the rainfall intensities generated to make sure we did not produce strongly biased values. The figure 5 below shows very similar rainfall intensities obtained with the different calibration strategies.

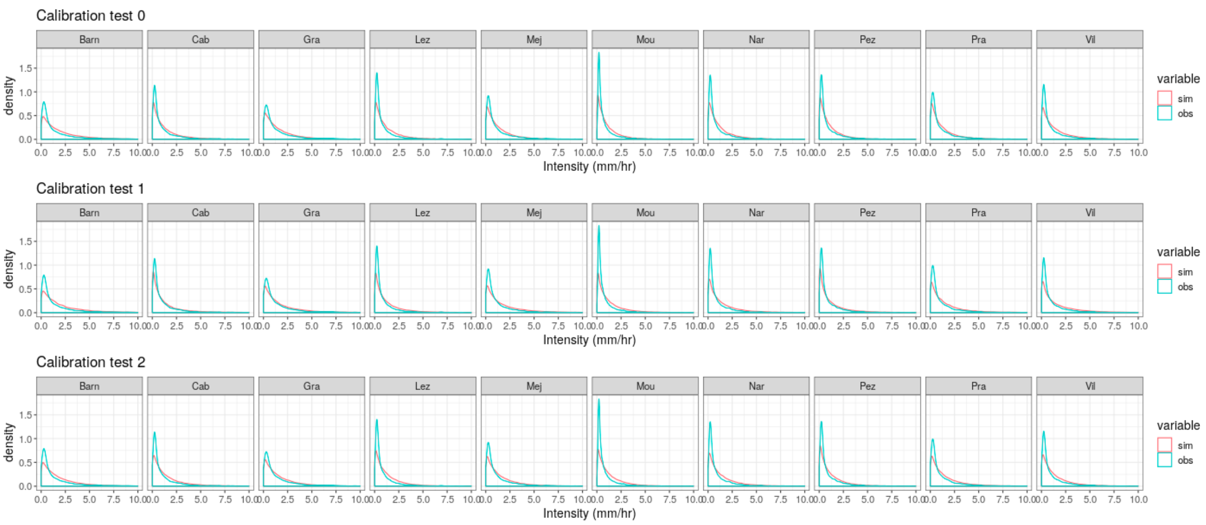


Figure 5: Density plot of observed (green) and simulated (red) hourly rainfall intensities

Minor comments:

p.2, l.14: Repetition of “soil moisture”, “For soil moisture” could be removed.

removed

p.2, l.32: For your information, a recent reference of scenario neutral approaches is “Keller, Luise, Ole Rössler, Olivia Martius, and Rolf Weingart-ner. 2019. “Comparison of Scenario-Neutral Approaches for Estimation of ClimateChange Impacts on Flood Characteristics.” Hydrological Processes 33 (4): 535–50.https://doi.org/10.1002/hyp.13341”.

we added this reference page 2, line 32

p.3, l.5: with -> and.

Replaced

Figure 1: Missing labels (Lon-gitude / Latitude).

Added

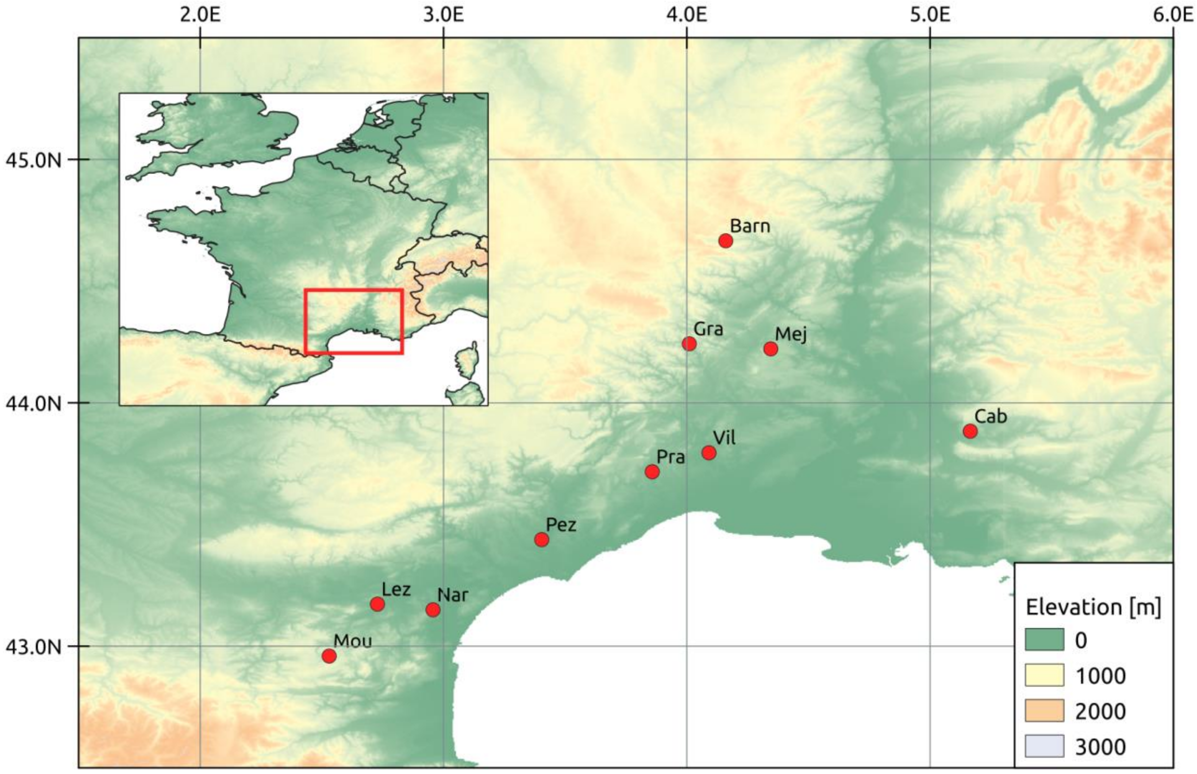


Figure 6: Localisation of the study sites in southern France

Figure 2: Please increase the font size.

Modified

p.7, l.3: “of” should be removed.

Removed

p.7, l.4-8: I think it would be fair to indicate that it is the standard version of the NSRP model, many more elaborate versions have been proposed in the last decades.

We added “the standard version of ..” ”

p.7: The mean number of raincell per storm is often denoted by the Greek letter nu, as is actually done in the manuscript in Section 3.4.1.

We replaced by Greek nu to be consistent with section 3.4.1.

p.8, l.1: I suggest indicating the statistical properties used for the estimation of the parameters. For these statistics at least, we should have a good agreement between the observations and the simulated values.

We added the rainfall properties:
“The statistical properties of rainfall included in the objective function to calibrate the model are: hourly mean, hourly variance, daily variance, lag1 autocorrelation of daily data, hourly skewness, daily skewness and the percentage of dry days.”

p.8, l.11: +4C the symbol “degree” is missing.

Added

p.10, l.4: there is a space after “+4” that should be removed.

Removed

p.10, l.11: There is a slight overestimation of the annual number of dry days for some stations (e.g. Barn), it could be noticed.

Added

p.12:m3.m-3 seems to be a strange unit (adimensional actually), is it correct

It is the standard unit for soil moisture measurements, so it is also the unit of the RMSE values computed.

<u>Reviewer 2</u>

I am very excited to see a manuscript that (finally) shows changing rainfall intermittency is important for soil moisture and hence flooding. This is very important and timely work. I can only expect (and look forward to) seeing the follow up work to this study involving the impact on flooding. Please see my minor (and bordering on pedantic) suggestions below.

We would like to thank you for your positive appraisal of our manuscript. Please find below the answer to your comments.

I am not sure on the format of HESS – but the "Annexe" references didn't quite match the SI for me.

We modified the format of supplementary materials.

I am not sure I saw a reference to the full calibration parameters?

We added page 10, line 14: "(see supplementary material S2 for the calibrated NSRP parameters)".

Page 1, Line 6: "on a 10 year time period" -> "for a 10 year time period"

Changed

Page 2, Line 4: I would appreciate Wasko and Nathan (2019) to be cited along side these as, though similar to Bennett et al (2018), it goes beyond to quantify the impact of soil moisture changes with flood recurrence.

We added this reference page 2 line 4

Page 1, Line 9: Just wonder if the following also supports the drying trend you are referring to. Rodell, M., Famiglietti, J. S., Wiese, D. N., Reager, J. T., Beaudoing, H. K., Landerer,F. W., & Lo, M. H. (2018). Emerging trends in global freshwater availability. Nature,557(7707), 651–659. https://doi.org/10.1038/s41586-018-0123-1

Indeed, but this paper refers to groundwater dynamics, where in this section we are mentioning trends in atmospheric water supply.

Page 1, Line 20: Obviously I am more familiar with Australian references, but the following evaluates in-situ soil moisture. I would

make the point that one issue with evaluation is the different depths that are measured and modelled by all products.
Holgate, C. ., De Jeu, R. A. M., van Dijk, A. I. J. ., Liu, Y. ., Renzullo, L. J., Vin-odkumar, et al. (2016). Comparison of remotely sensed and modelled soil moisture data sets across Australia. Remote Sensing of Environment, 186, 479–500.https://doi.org/10.1016/j.rse.2016.09.015

We added this reference page 2, line 22. The issue of evaluation at different depths is mostly valid for remote sensing data, able to measure soil moisture for the surface only, when in climate models the land surface scheme is capable of reproducing also the root zone soil moisture.

Page 3, Line 2: Please have a look at the following as I think it is also looking at soil moisture using a scenario-neutral approach: Stephens, C. M., Johnson, F. M., & Marshall, L. A. (2018). Implications of future climate change for event-based hydrologic models. Advances in Water Resources, 119, 95–110.

We added this reference page 2, line 31.

Figure 1: If it isn't too much of a hassle it would be nice to see Figure 1 include an inset of the study site in the context of the greater region (as I am not familiar with the study region). But this is only a suggestion and I don't mind if this isn't performed.

We added a small map of France in the top left corner to locate the region of interest (see our response to reviewer 1, Figure 6)

Page 7, Line 2: "series"

Changed

Page 8, Line 5: I recognize studies often change all the parameters in the NSRP model for downscaling (e.g. Bordoy and Burlando, 2014). If you are looking for examples of where a parameter is fixed in stochastic generation based on, for example, physical intuition you can see Wasko et al (2015) and Onof and Wheater (1994).
Bordoy, R., & Burlando, P. (2014). Stochastic downscaling of climate model precipita-tion outputs in orographically complex regions: 2. Downscaling methodology. WaterResources Research, 50(1), 562–579. https://doi.org/10.1002/wrcr.20443
Wasko, C., Pui, A., Sharma, A., Mehrotra, R., & Jeremiah, E. (2015). Representing low-frequency variability in continuous rainfall simulations: A hierarchical ran-dom Bartlett Lewis continuous rainfall

generation model. Water Resources Research,51(12), 9995–10007. https://doi.org/10.1002/2015WR017469
Onof, C., & Wheater, H. S. (1994).Improvements to the modelling of Britishrainfall using a modified random parameter Bartlett-Lewis rectangular pulse model.Journal of Hydrology, 157, 177–195. https://doi.org/http://dx.doi.org/10.1016/0022-1694(94)90104-X

Following the recommendations of Reviewer 1, Guillaume Evin, we also tested a different approach by recalibrating all the parameters of the rainfall generator after modifying the rainfall statistics (similar to Bordoy and Burlando 2014), see our response. Since this approach did not work well, we kept our original approach, similar to the two references you mentioned. We added the two references proposed.

Page 8, Line 14: "resumes" -> "presents"

Changed

Page 8, Line 21: where you say the modelling chain is processed 20 times, I think you mean to say "stochastic replicates" or "simulated ensembles" – this terminology I think is clearer.

Changed to "a simulated ensemble of 20 stochastic replicates is generated"

Page 9, Line 8: A typo has occurred. Remove "the)"?

Changed

Section 4.1: These increases of say 432mm, is this for one site in particular? Or across all the sites on average? I am a bit confused here.

We added: across all sites on average

Page 10, Line 9, 12: "The" NSRP model?

Added

Page 10, Line 18: "Opposite" -> "Alternatively"

Changed

Page 15, Line 1: "The Figure" -> "Figure"

Changed

Page 15, Lin 9: “became” -> “be”

Changed

Figure 9, 11, 12 captions: I think these say “extreme” drought while in other parts of the manuscript you just say “drought”. I would stick to the terminology “drought”.

We removed “extreme” in the figure captions

Page 17, Line 7: Can you mention in the text what the blue and red symbols in Figure10 are and maybe specifically mention how the RCP changes predicted are at the “extreme” ends of your scenario space. If I have interpreted the results correctly his point was lost on me but is very important to highlight I think?

We added this information about the symbols in the text page 17, line 7 and 8.

Page 21, Line 2: The following manuscript is one of the few manuscripts demonstrating how drier soils interact with higher precipitation intensities. Wasko, C., & Nathan, R. (2019).Influence of changes in rainfall andsoil moisture on trends in flooding.Journal of Hydrology, 575, 432–441.https://doi.org/10.1016/j.jhydrol.2019.05.054

We added this reference in the introduction.

<u>**Reviewer 3: Ryan Teuling**</u>

The manuscript by Mimeau et al. addresses the important issue of changes in soil moisture conditions in the Mediterranean. The stochastic approach is a nice addition to existing studies, and the main findings are important. The topic also fits very well in the special issue. However I have some concerns regarding details in the Methods, the use of literature on stochastic approaches to soil moisture dynamics, and the presentation of the results. These are discussed below. I believe the concerns are best addressed in a major revision.

Thank you for the revision of our manuscript. Please find below a point-by-point response to your comments and the modifications made to the revised manuscript.

Introduction "Only a few studies attempted to validate the soil moisture simulated by the GCM or RCM land surface schemes" -> Maybe, but other studies (such as Stegehuis, GRL,2013, doi.org/10.1002/grl.50404) have used flux observations which should have the same, if not better, effect.

We note that in Stegehuis et al 2013, there is no evaluation of simulated soil moisture but only sensible heat flux at the surface and the 2-m mean temperature.

"This is particularly true for the Mediterranean regions . . . land surface models" -> Ok, but next you claim this can be solved by using a simplified model. So are the other models all worse than the simple model used here? Or is the lack of calibration of higher importance than model structure?

We do not claim that the large variability between climate model simulations of soil moisture can be solved with a simpler model than the land-surface schemes of the climate models. We just state that there are obvious discrepancies in soil moisture simulated by these different models, so we prefer to rely on a bottom-up approach based on observed data to estimate the sensitivity of soil moisture to changes in climate characteristics. We added: "As a consequence, the direct use of soil moisture from climate models may not be the best option to assess small scale soil moisture variability in relation with climate conditions."

"The only study that applied this method to soil moisture" -> There are at least several others, such as Teuling et al. (GRL 2007, doi:10.1029/2007GL031001), and Calanca et al. (WRR 2004, doi:10.1029/2004WR003254)

Literature: In general, I miss a discussion on the previous use of stochastic approaches in soil moisture modeling. These include for instance the work by Milly (WRR 2011,doi:10.1029/2000WR900337), Laio et al. (AWR 2001, 24, 707-723), and Rodriguez-Iturbe (1999, Proc R Soc Lond A 455: 3789-805). These (analytical) approaches use a more basic description of the precipitation process, so it should be motivated why a more complex Neyman-Scott representation is needed to address the research question.

Thank you for these additional references. We modified this section to include the proposed references, and provide a better review of previous studies applying stochastic methods to soil moisture. We do not think that a complex stochastic generator is necessarily required. For instance, Zhu et al 2020 used a rather simple elasticity approach or Guo et al 2018 applied a simpler weather generator to achieve satisfactory results. We used a Newman-Scott model to represent distinctly the changes in precipitation intermittence and intensity at the hourly time step but other approaches can be equally valid too, as soon as they are able to represent changes in these rainfall properties.

Method

Table 2 mentions the "Monthly potential evaporation coefficient L". What is the role of this parameter, and how is it different from the coefficient for evapotranspiration Kc?

L is the monthly percentage of total daytime hours out of total daytime hours of the year. This fixed parameter, computed based on the station's coordinates, enables to represent the monthly variations of the potential evaporation. The values of L are not calibrated.

Kc is a correction factor that is calibrated for each station to adjust evapotranspiration.

Brocca, L., Camici, S., Melone, F., Moramarco, T., Martínez-Fernández, J., Didon-Lescot, J.-F., & Morbidelli, R. (2013). *Improving the representation of soil moisture by using a semi-analytical infiltration model. Hydrological Processes, 28(4), 2103–2115.* doi:10.1002/hyp.9766

"a linear relationship between actual and potential evapotranspiration" -> Please provide more information. Is this linear between field capacity and wilting point? If so, this is a big simplification. Many other studies have shown that there is a considerable range in soil moisture over which ET is potential (above the critical moisture content), and that this unstressed soil moisture range is in fact required to explain observed soil moisture and vegetation dynamics and features such as strong

bimodality (Salvucci, 2001 WRR 37(5), 1357–1365, Teuling et al. GRL 2005 doi:10.1029/2005GL023223,Denissen et al. JGR 2020, doi:10.1029/2019JD031672). It should be better motivated why this gross simplification is justified, and what the potential implications are for the simulated soil moisture dynamics (for instance, the higher stress could explain why most lines in Fig5 are above the 1:1 line around 20 Vol%)

This was an error in the model description. It is not a linear relation between actual and potential evapotranspiration but a linear relation between potential evapotranspiration and soil saturation, that is used to compute actual evapotranspiration. See equation 7 of Brocca et al., 2008. This formulation is quite standard and many models use it.

We modified the text to remove this error, thank you for noticing this mistake.

"two additional calibrations were performed on subperiods . . . in order to analyze the stability of the calibration" -> For the stability it is more important to consider the variability in optimum parameters than the model performance itself (that is listed in Table3). Please also provide the parameters for periods 1 and 2 so that the robustness of the calibration can be better assessed.

We added the calibrated parameters (soil moisture model) on the 2 periods, see table below. It can be seen that the parameters values are within the same order of magnitude for the three calibration periods, with a stronger variability of the Ks compared to the two other parameters.

	Barn	Cab	Gra	Lez	Mej	Mou	Nar	Pez	Pra	Vil
					Calibration on the total period					
K_s (mm.hr^{-1})	38.1	34.3	35.9	23.1	28.8	36.2	51.1	14.6	59.6	6.9
m	17.6	15.6	10.9	14.1	16.4	23.0	15.9	12.8	11.89	38.2
K_c	1.17	1.43	1.74	1.22	1.81	0.94	1.26	1.99	1.32	1.63
NSE	0.76	0.77	0.93	0.85	0.9	0.63	0.91	0.789	0.65	0.9
					Calibration on the first sub-period					
K_s (mm.hr^{-1})	26.9	52.0	56.2	41.6	24.6	22.5	52.0	24.0	61.9	22.6
m	17.8	15.8	11.3	15.4	14.7	17.8	17.5	21.0	10.5	40.0
K_c	1.28	1.49	1.95	1.30	1.76	1.02	1.31	1.86	1.31	1.63
NSE	0.6	0.72	0.86	0.87	0.80	0.69	0.87	0.31	0.64	0.87
					Calibration on the second sub-period					
K_s (mm.hr^{-1})	29.6	23.7	43.9	40.8	45.6	77.4	43.1	6.4	71.4	2.7
m	23.2	17.1	11.3	14.8	18.9	22.4	13.5	5.5	13.0	39.9
K_c	1.09	1.42	1.53	1.11	1.87	1.32	1.19	1.97	1.31	1.56
NSE	0.71	0.75	0.87	0.78	0.91	0.04	0.912	0.60	0.57	0.86

Table 3. Calibrated parameters of the SM model and NSE validation values while calibrating on the total period, the first and second sub-periods of the in situ data series.

In the method, it is mentioned that the rainfall parameters are estimated for each month of the year. I assume that this also means that the model is run for every month separately? This is not mentioned. If so, this has some implications for the results, because in this way one doesn't account for the month-to-month carry-over of soil moisture memory (i.e. going into summer the soil moisture will be slightly higher at the beginning of each month because of the on average wetter previous month). Please explain and discuss the potential impacts this approach has on the results.

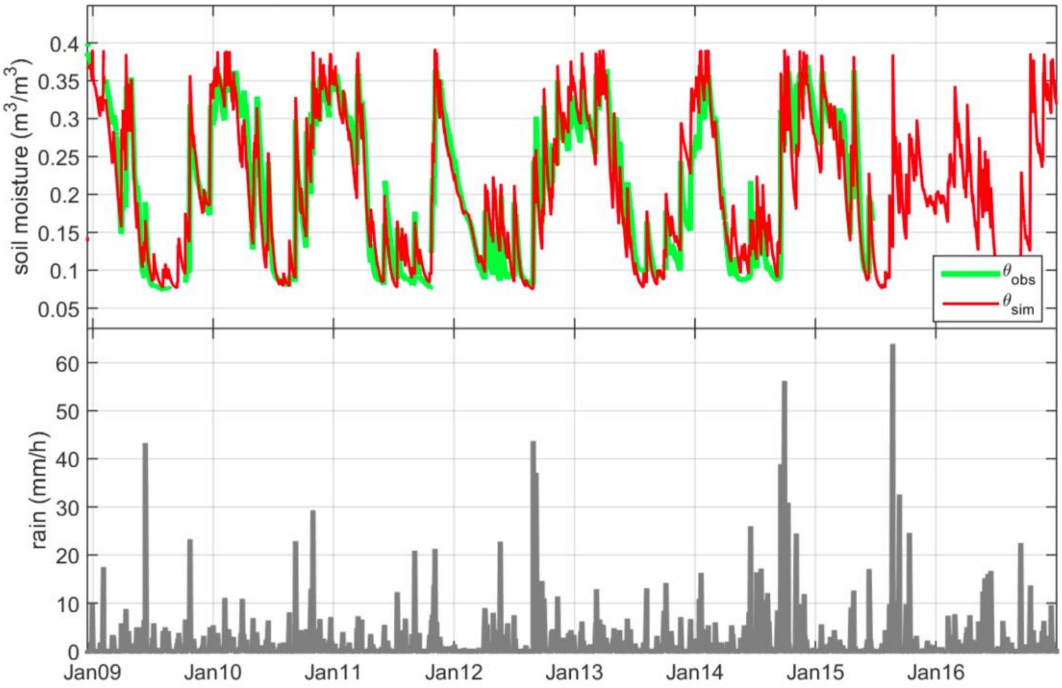
The NSRP model (the rainfall generator) is applied to each month separately, since the distribution of rainfall needs to be homogeneous (the distribution of hourly rainfall is obviously not the same in December or in August in these Mediterranean areas). This is a very standard practice when using this type of rainfall generator. If the distributions are estimated for each month, the generator then simulates continuous rainfall series, to be used as inputs in the soil moisture model and provide time series across all months/years.

We added page 8, line 2: "Once the model parameters estimated for each month, it is run to produce continuous simulations.".

Results

I miss an illustration of model performance, for instance a modeled and simulated time-series at one of the stations so that model performance can be visually checked (NSE tends to be high by default in strongly seasonal climates, so this alone might not be a good indication).

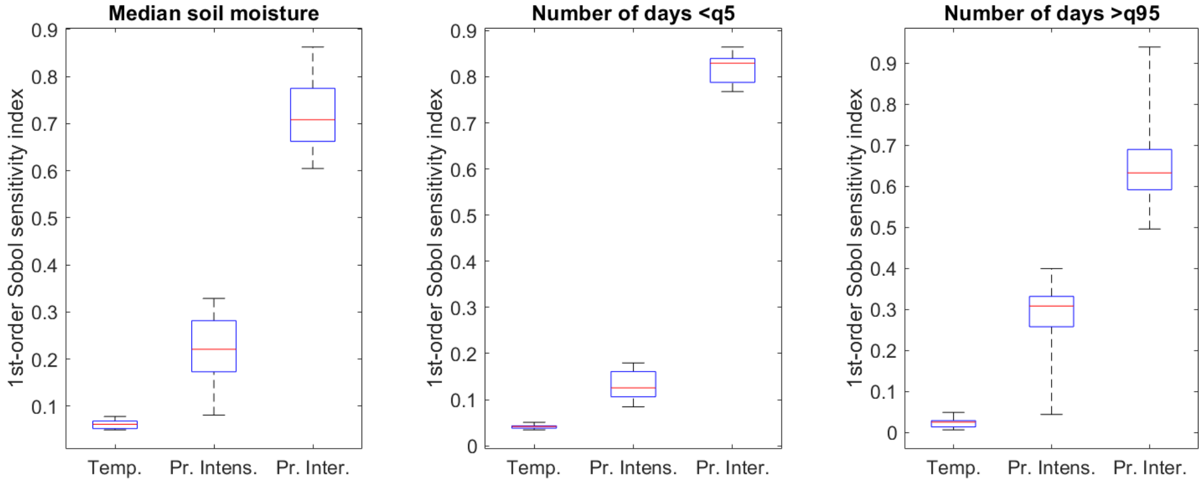
We added a new figure with the observed and simulated time series of soil moisture.



Simulated (green) and observed (red) soil moisture at the Villevieille station

Figure 8: This is an important figure, but I find it difficult to extract any relevant information other than that intermittence is the most sensitive factor. This could more easily be shown by first averaging over all stations, and only show the stations if there a story to it. The most important aspect now is the comparison between the different rows, and this is not easy because the reader has to guess the values and compare visually. Consider plotting the differences more explicit if this is where conclusions are based on.

The fact that intermittence is the key factor is indeed the main message of this figure. We modified the figure according to your recommendation, showing boxplots of the Sobol indices for Temperature (Temp.), Precipitation intensity (Pr. Intens.) and Precipitation Intermittence (Pr. Inter.), see the new figure below:


Median soil moisture
Number of days <q5
Number of days >q95
1st-order Sobol sensitivity index
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
Temp.
Pr. Intens.
Pr. Inter.

Modeling the response of soil moisture to climate variability in the Mediterranean region

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Abstract. Future climate scenarios for the Mediterranean region indicate a possible decrease in annual precipitation associated with an intensification of extreme rainfall events in the coming years. A major challenge in this region is to evaluate the impacts of changing precipitation patterns on extreme hydrological events such as droughts and floods. For this, it is important to understand the impact of climate change on soil moisture since it is a proxy for agricultural droughts and the antecedent soil moisture condition plays a key role on runoff generation. This study focuses on 10 sites, located in Southern France, with available soil moisture, temperature, and precipitation observations for a 10 year time period. Soil moisture is simulated at each site at the hourly time step using a model of soil water content. The sensitivity of the simulated soil moisture to different changes in precipitation and temperature is evaluated by simulating the soil moisture response to temperature and precipitation scenarios generated using a delta change method for temperature and a stochastic model (Neyman-Scott rectangular pulse model) for precipitation. Results show that soil moisture is more impacted by changes in precipitation intermittence than precipitation intensity and temperature. Overall, increased temperature and precipitation intensity associated with more intermittent precipitation leads to decreased soil moisture and an increase in the annual number of days with dry soil moisture conditions. In particular, a temperature increase of +4 °C combined with a decrease of annual rainfall between 10 and 20 %, corresponding to the current available climate scenarios for the Mediterranean, lead to a lengthening of the drought period from June to October with in average +28 days of soil moisture drought per year.

1 Introduction

The Mediterranean region is a transitional zone between dry and wet climates and in these semi-arid areas the direct evaporation from the soil plays an important role on the surface energy balance, with evapotranspiration strongly dependent on available soil moisture (Koster et al., 2004; Seneviratne et al., 2010; Taylor, 2015). Consequently, the Mediterranean has been identified as a region with a strong coupling between the atmosphere and the land surface, with feedback effects of soil moisture on temperature and also precipitation (Seneviratne et al., 2010; Knist et al., 2017; Hertig et al., 2019). Indeed, soil moisture is a key variable in the hydrological cycle for the partitioning of rainfall into infiltration and runoff and also for the mass and energy balance between land surface and the atmosphere (Seneviratne et al., 2010; Brocca et al., 2017). The water contained in the unsaturated, or vadose zone, is an important driver for floods with soils close to saturation having more probability to produce runoff when subjected to precipitation inputs (Zehe et al., 2005; Ivancic and Shaw, 2015; Woldemeskel and Sharma, 2016; Bennett et al., 2018; Wasko and Nathan, 2019). This is particularly true in the Mediterranean context where several studies have shown the strong influence of soil moisture on flood generation processes (Brocca et al., 2008; Penna et al., 2011; Tramblay et al., 2010; Uber et al., 2018; Tramblay et al., 2019). Similarly, the soil moisture is an important parameter for drought analysis, since low soil moisture content is a good proxy for drought impacts on agriculture or wildfires occurrence (Vidal et al., 2010; Ruffault et al., 2013).

There is a climatic trend towards a drying of the Mediterranean region, both during the historical period but also in future climate scenarios, showing a decrease in precipitation amounts and occurrence, associated with an increasing frequency of drought episodes (Hoerling et al., 2012; Polade et al., 2014, 2017; Hertig and Tramblay, 2017; Lionello and Scarascia, 2018; Tramblay et al., 2020). For a RCP8.5 emission scenario, Giannakopoulos et al. (2009) and Polade et al. (2014) both estimate a mean decrease up to -30 % of the annual precipitation in the Mediterranean region by the end of the century and increase of dry days ranging between +1 to +3 weeks per year. The precipitation decrease associated with higher temperatures leading to stronger evaporation rates is causing a decrease in soil moisture for large parts of the Mediterranean (Vidal et al., 2010; Vicente-Serrano et al., 2014; Hanel et al., 2018). Samaniego et al. (2018) and Grillakis (2019) provided future projections of soil moisture for Europe using different combinations of climate scenarios from General Circulation Models (GCM), Regional Climate Models (RCM), hydrological and land surface models, showing a clear climate signal towards a future decrease in soil moisture content and consequently increase in agricultural droughts for Mediterranean regions.

Only a few studies attempted to validate the soil moisture simulated by the GCM or RCM land surface schemes, probably due to the lack of sufficient networks with in situ soil moisture measurements, which show high spatial variability (Brocca et al., 2007; Crow et al., 2012; Holgate et al., 2016). Yuan and Quiring (2017) validated ensemble of Coupled Model Intercomparison Project Phase 5 (CMIP5 GCMs) over North America with in situ and satellite soil moisture observations. Knist et al. (2017) evaluated the Coordinated Regional Climate Downscalling experiment (CORDEX) regional climate models over Europe using GLEAM (Global Land Evaporation Amsterdam Model) and FLUXNET reference data. Hertig et al. (2019) tested the ability of two GCMs (CNRM-CM5 and MPI-ESM-MR) from CMIP5 to reproduce soil moisture dynamics as modelled by the Global Land Data Assimilation System (GLDAS) over Europe. If the main patterns of seasonal soil moisture were found adequately represented from climate models, these studies also pointed out the large multi-model variability in particular in the transitional climate zones. Indeed, many studies reported a high model dependence of soil moisture simulations (Koster et al., 2009; Berg et al., 2017). This is particularly true for the Mediterranean regions, due to structural uncertainty, different process representation, soil depths and interactions with vegetation that are not currently adequately reproduced by land surface models (Knist et al., 2017; Quintana-Seguí et al., 2019). As a consequence, the direct use of soil moisture from climate models may not be the best option to assess small scale soil moisture variability in relation with climate conditions.

Beside the use of climate models, scenarios neutral approaches are increasingly employed to assess the vulnerability of water resources under different climate change scenarios (Prudhomme et al., 2010; Guo et al., 2017; Stephens et al., 2018;

Keller et al., 2019). The approach is similar to a sensitivity analysis aiming at quantifying the changes in a given hydrological variable for a plausible range of changes in hydrometerological conditions. Several studies have previously used stochastic approaches to investigate the sensitivity of soil moisture to precipitation patterns, with various levels of complexity in the representation of precipitation properties and soil moisture dynamics (Rodriguez-Iturbe et al., 1999; Milly, 2001; Calanca, 2004; Laio et al., 2001; Teuling et al., 2007; Zhu et al., 2020). This type of approach can provide useful information to identify the hydro-meteorological parameters that have the greatest impact on a given response variable. Guo et al. (2018) provided an example of such a scenario-neutral approach based on a stochastic weather generator to explore possible rates of changes in rainfall intermittence and extremes in Southern Australia. Yoo et al. (2005) coupled a stochastic generator of rainfall to a soil moisture model in the Walnut Gulch experimental watershed in southeastern Arizona to estimate soil moisture changes due to rainfall variability. They found that rainfall arrival rates was the most sensitive parameter, with decreasing soil moisture content and increasing rain intermittence, even without a decrease of the total volume of rainfall. Yet, this type of approach needs to be applied to other land regions and different sites in order to evaluate the possible spatial variability in addition to the temporal variability of rainfall. These bottom-up approaches are complementary to the modelling chains linking climate and land surface models, and document the most relevant process leading to soil moisture changes than in turn can be used to improve the land surface schemes.

The objective of this study is to analyze the variability of soil moisture for a set of Mediterranean sites according to changes in precipitation and temperature. The method relies on the use of a stochastic precipitation generator coupled with the soil moisture model proposed by Brocca et al. (2008). The scientific questions addressed in the present work are: which precipitation characteristics (intermittency, intensity) do influence soil moisture changes, in conjunction with changes in temperature as a proxy for evapotranspiration changes? And how this response of soil moisture to changes in climate drivers varies in space for a range of different locations with different topographical and soil properties?

The paper is structured as follows: Sect. 2 describes the study area and collected datasets; Sect. 3 provides a description of the soil moisture and stochastic rainfall models (Sect. 3.1 to 3.3), and of the experimental design for the simulation of the soil moisture scenarios (Sect. 3.4); Sect. 4 presents the validation of stochastic rainfall model (Sect. 4.1) and soil moisture model (Sect. 4.2) after calibration and the sensitivity analysis of the median (Sect. 4.3) and extreme soil moisture (Sect. 4.4) to precipitation and temperature variations; Sect. 5 discusses the results and summarises the main conclusions of the paper.

2 Data

This study uses soil moisture, precipitation and temperature in situ data from 10 stations of the SMOSMANIA network (Calvet et al., 2007; Albergel et al., 2008) located in the French Mediterranean region (Fig 1).

Stations all present a characteristic Mediterranean precipitation seasonal cycle with a hot and dry summer followed by heavy precipitation between September and November (Fig 2). This precipitation cycle directly impacts soil moisture with lower soil moisture values during summer and higher values during winter. Although all stations are located in the French Mediterranean region, they differ in altitudes, ranging from 30 (Pezenas) to 538 m.a.s.l. (Mouthoumet), in mean annual precipitation, ranging

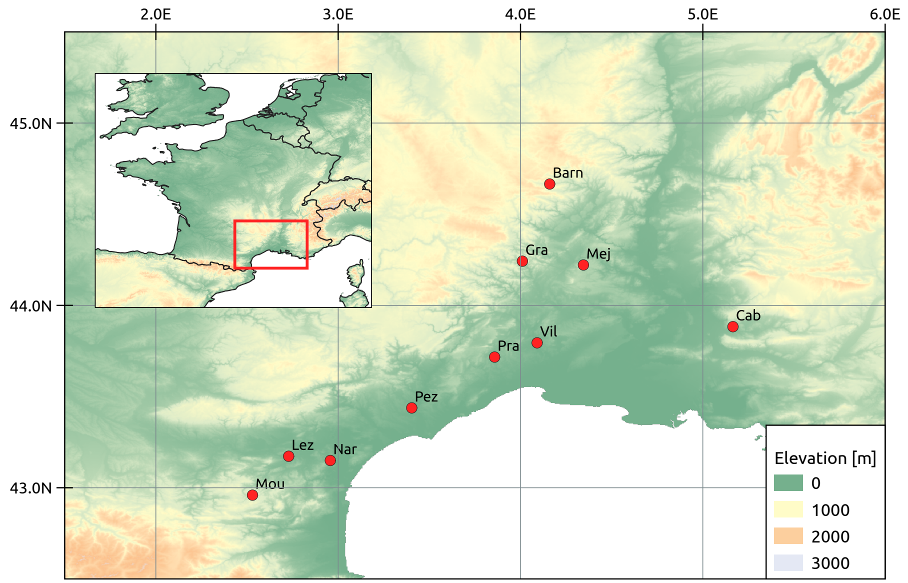

Figure 1. Localisation of the study sites in southern France.

from 500 mm (Lézignan Corbières, Pézenas) to 1734 mm (Barnas), and in soil characteristics (Table 1). The station altitude is correlated to mean annual precipitation (r=0.7), except for the station Mouthoumet with lower annual precipitation than stations with comparable altitude (if this station is removed, r=0.92 between altitude and mean annual precipitation).

In-situ data is collected at hourly time step and covers a period starting in 01/01/2007 to 31/12/2016. Soil moisture data series used in this study are computed from measurements at four different depths (5, 10, 20, and 30 cm) as the weighted average as a function of soil layer depth. The integration of the measurements at various depths enables to have a representation of the average soil moisture in the root zone layer.

3 Method

3.1 Soil moisture model

The soil moisture model developed by Brocca et al. (2008) is used to simulate present soil moisture and soil moisture response under different climate scenarios. The soil moisture model (SMmodel) incorporates a Green-Ampt approach for infiltration, a gravity-driven approximation for drainage, and a linear relationship between potential evapotranspiration and soil saturation to estimate actual evapotranspiration. The SMmodel simulates the hourly temporal evolution of soil moisture and actual evapotranspiration. Hourly precipitation and air temperature are used as input into the SMmodel, potential evapotranspiration is computed from air temperature through the Blaney and Criddle approach. Details on the model equations can be found in

						Soil properties				
Code	Name	Lat [°]	Lon [°]	Altitude [m]	Precipitation [mm/yr]	Clay [%]	Sand [%]	Silt [%]	Soil class (ISSS)	Landcover
Barn	Barnas	44.666	4.16	480	1734	9.5	77.3	13.2	Sandy loam	Tree cover
Cab	Cabrieres d'Avignon	43.884	5.165	142	697	24.2	47.6	28.2	Clay loam	Cropland
Gra	La Grand Combe	44.243	4.01	499	1412	12.9	73.2	13.9	Sandy loam	Urban areas
Lez	Lezignan Cor- bieres	43.173	2.728	60	502	27.3	44	28.7	Light clay	Urban areas
Mej	Mejannes-le- Clap	44.222	4.345	318	992	16.2	45.5	38.3	Clay loam	Grassland
Mou	Mouthoumet	42.96	2.53	538	689	29.4	42	28.6	Light clay	Grassland
Nar	Narbonne	43.15	2.957	112	530	46.4	26.2	27.4	Heavy clay	Cropland
Pez	Pezenas	43.438	3.403	30	508	17.5	50.6	31.9	Clay loam	Cropland
Pra	Prades-le-Lez	43.717	3.858	85	816	31.1	27	41.9	Light clay	Cropland
Vil	Villevielle	43.795	4.091	41	756	13.6	65.7	20.7	Sandy loam	Cropland

Table 1. Stations characteristics

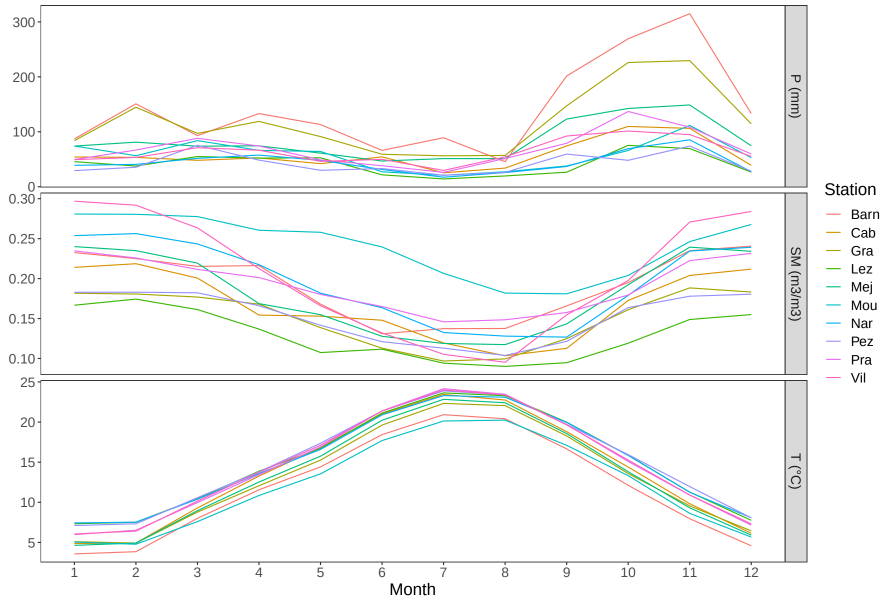

Figure 2. Observed seasonal cycle of precipitation, soil moisture, and air temperature at stations.

Fixed parameter	Value
Wetting front soil suction head ψ	-155.0 mm
Initial condition θ_0	0.2 m^3/m^3
Saturated soil moisture θ_{sat}	max of observed soil moisture
Residual soil moisture θ_{res}	min of observed soil moisture
Monthly potential evaporation coefficient L	0.208 0.234 0.266 0.300 0.329 0.345 0.339 0.314 0.282 0.248 0.218 0.201
Soil layer depth Z	300 mm
Calibrated parameter	**Range**
Hydraulic conductivity K_s	0.01 $< K_s <$ 100 mm/h
Exponent of drainage m	1 $< m <$ 45
Evaporation coefficient K_c	0.5 $< K_c <$ 2

Table 2. Fixed parameters values and ranges of calibrated parameters of the soil moisture model. Fixed parameter L is calculated as the monthly percentage of total daytime hours out of total daytime hours of the year.

Brocca et al. (2008) and Brocca et al. (2014). The model has been applied at multiple sites in Italy and Europe (e.g., Brocca et al. (2014)) with satisfactory results.

3.2 Soil moisture model calibration

The SMmodel uses fixed and calibrated parameters. The fixed parameters values (Table 2) were estimated based on the observed soil moisture and geographic location of the stations. Three parameters were calibrated: hydraulic conductivity K_s, root zone depth Z, exponent of drainage m, and coefficient for evapotranspiration K_c (calibration ranges in Table 2). These parameters are calibrated for each station using the total period of observed data, but two additional calibrations were performed on sub-periods (first half and second half of the total period) in order to analyze the stability of the calibration. For the calibration process, missing precipitation and temperature data are reconstructed by replacing missing precipitation with an intensity of 0 mm/hr, and by linearly interpolating temperature data for gaps of less than 3 hours or using the climate mean otherwise. Time steps with reconstructed precipitation and temperature are not taken into account in the calculation of the NSE coefficient used as optimization criterion for the calibration (Nash and Sutcliffe, 1970). Details on missing data at each stations are presented in Table S1 (Supplementary Material).

3.3 Generation of temperature and rainfall scenarios

For each station, a 20 years temperature data series is generated by repeating the hourly climatic mean. Temperature scenarios are generated by applying a delta ranging between +0°C and +4°C.

The stochastic weather generator, the standard version of the Neyman-Scott rectangular pulse model, NSRP (Cowpertwait et al., 1996) is used to generate 20 series of hourly rainfall data time series. The peculiarity of the model lies in its capability to preserve the statistical properties of benchmark rainfall time series over a range of time scales. As the model has been extensively described in previous papers (e.g. Cowpertwait et al., 1996; Camici et al., 2011) here only a brief discussion is given.

The NSRP model has 5 parameters:

- λ: mean waiting time between adjacent storm origins [hr].
- β: mean waiting time between raincell origins after storm origins [hr],
- ν: mean number of raincell per storm,
- η: mean duration of raincell [hr],
- ξ: mean intensity of raincell [mm/hr]

A Poisson process with parameter λ controls the generation storm origins. For each storm origin, a random ν number of raincell origins are generated displaced from the storm origin according to a β parameter exponentially distributed process. Duration and intensity of each raincell are expressed by two other independent random variables assumed exponentially distributed with parameter η and ξ respectively. These parameters are estimated, for each month of the year, by minimizing an objective function evaluated as the weighted sum of the normalized residuals between the statistical properties of the observed time series and their theoretical expression derived from the model. The statistical properties of rainfall included in the objective function to calibrate the model are: hourly mean, hourly variance, daily variance, lag1 autocorrelation of daily data, hourly skewness, daily skewness and the percentage of dry days. Once the model parameters estimated for each month, the NSRP model is run to produce continuous rainfall simulations.

As studies on future precipitation patterns in the Mediterranean region predict an increase of the dry days frequency associated with an intensification of extreme precipitation events (Paxian et al., 2015; Polade et al., 2017; Tramblay and Somot, 2018; Chan et al., 2020; Pichelli et al., 2020), we generate precipitation scenarios with increasing precipitation intermittence and increasing mean intensity by applying deltas from +0 to +100 % on the λ and ξ parameters (see details in Sect.3.4). It should be noted that in some studies all the parameters of the rainfall generator are re-calibrated after the perturbation of rainfall statistics according to a climate change signal (Bordoy and Burlando, 2014). Other authors fixed some parameters while allowing others to change according to climate variability (Wasko et al., 2015). This is the latter approach adopted herein, since preliminary experiments based on the re-calibration of the NSRP generator were not satisfactory, due to the parameters instability when performing multiple model calibration procedures. For each precipitation scenarios produced by the modification of the NSRP model parameters λ and ξ, 20 precipitation data series are generated with the NSRP model over a 20 years period and used as input of the soil moisture model.

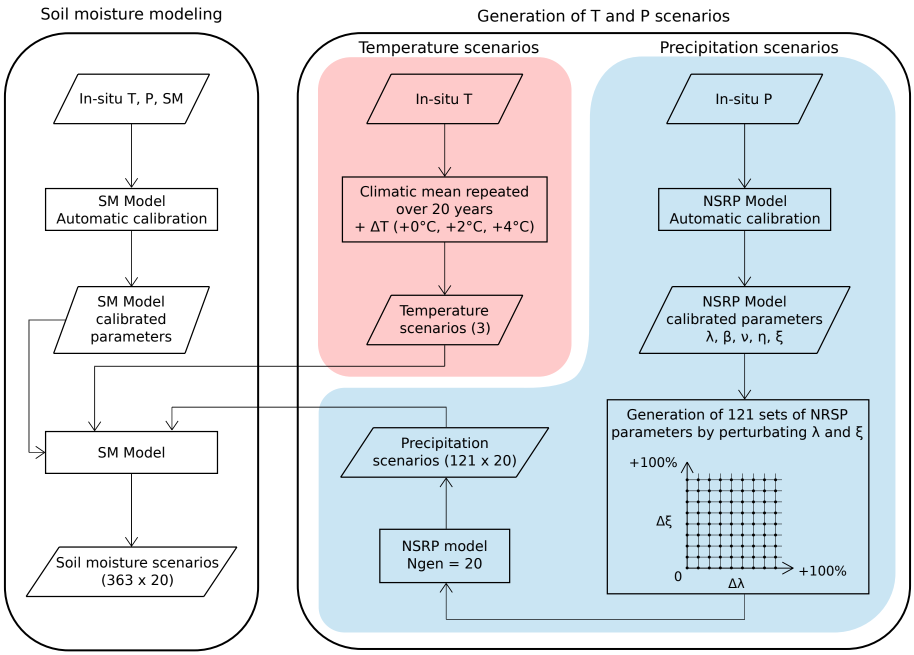

Figure 3. Flowchart of the experimental design for the simulation of the soil moisture scenarios.

3.4 Sensitivity analysis of the simulated soil moisture to precipitation and temperature changes

3.4.1 Direct analysis

We first analyze the sensitivity of the simulated soil moisture for specific changes in temperature and precipitation. We consider three temperature scenarios with $\Delta T = +0°C, +2°C, +4°C$, and 121 precipitation scenarios with $\Delta\xi$ and $\Delta\lambda$ regularly spaced between +0 and +100 % with a 10 % step. The soil moisture model is then run for each precipitation and temperature scenarios (i.e. 363 scenarios per stations) to analyze the sensitivity of the simulated soil moisture to temperature and precipitation changes. Figure 3 presents the process for the simulation of the soil moisture scenarios. The simulation with no change in temperature and precipitation intensity and intermittence is called the reference scenario and is used to represent soil moisture conditions under present climate. The evolution of extreme soil moisture events is evaluated by estimating the mean number of days per year under soil water excess, and drought. We consider episodes of soil water excess as consecutive days with a daily soil moisture above the reference scenario 95$^{\text{th}}$ percentile, and drought episodes as days with soil moisture below the 5$^{\text{th}}$ percentile. Considering the modeling chain as *(i)* the NSRP model (depending on the calibrated values of β, ν, η, λ and ξ and the applied perturbations $\Delta\lambda$ and $\Delta\xi$); *(ii)* the temperature scenario generation perturbed of ΔT and *(iii)* the SM model, for a given set of parameters, a simulated ensemble of 20 stochastic replicates is generated. Quantiles and annual numbers of days under drought or soil water excess are computed for each of the 20 corresponding soil moisture results and then averaged to produce a unique scenario.

3.4.2 Global Sensitivity Analysis

A Global Sensitivity Analysis (GSA) (Saltelli et al., 2008; Pianosi et al., 2016) assess the model behavior (model output sensitivity to the input parameters) in the whole parameter space using a variance decomposition method. Considering $Y = f(\underline{X})$ with Y the output of the model f to a set of parameters $\underline{X} = (X_1, X_2, ..., X_N)$. A functional ANOVA decomposition is applied to Y (e.g. (Sobol, 1993; Saltelli et al., 2010)) :

$$V(Y) = \sum_{i=1}^{N} V_i + \sum_{i=1}^{N} \sum_{j>i}^{N} V_{i,j} + ... + V_{1,2,...,N}$$

where N represents the number of sampled parameters. $V(Y)$ is the total variance of the model output, V_i the first order variance of Y due to parameter X_i, V_{ij} the second order variance (covariance) of Y due to X_i and X_j the higher order variance due to more than 2 parameters. A first-order Sobol index S_i corresponds to the ratio of the corresponding variance V_i to the total variance $V(Y)$: $S_i = V_i / V(Y)$ and is thus always between 0 and 1. The sum of all the (first and higher order) Sobol indices is equal to unity.

Assuming that the changes in temperature and precipitation are stochastic variables, the first-order Sobol indices are computed using the state dependent parameter modelling proposed by (Ratto et al., 2007). For the Global Sensitivity Analysis, a different set of 1000 sets of temperature and precipitation changes, generated randomly in the range of values presented in section 3.3, is used in order to cast continuously the range of values ($\Delta T = [+0; +4°C]$, $\Delta\lambda = [0; +100\%]\,\lambda$ and $\Delta\xi = [0; +100\%]\,\xi$). The objective of this sensitivity analysis is to estimate the relative influences of changes in temperature and precipitation characteristics on soil moisture.

4 Results

4.1 NSRP model calibration and generated rainfall scenarios

Rainfall series generated with the NSRP model for the reference scenario show good agreement with the observed rainfall characteristics. Figure 4a shows that the mean annual amount of rainfall is well reproduced by the model (r2=0.99) and that the range of values of annual amount of rainfall is also comparable to the range of observed values. The mean annual number of dry days (i.e. days with precipitation below 1 mm) is similar to observations reproduced (r2=0.71) but with a bias going from -11 days (Cabrieres d'Avignon station) to +10 days (Mouthoumet station) (Fig. 4b). NSRP model tends to slightly overestimate lower values of the daily intensities distribution (Fig. 4c), but overall, the simulated distributions are in good agreement with observed distributions (see supplementary material Fig. S1 for the calibrated NSRP parameters).

The perturbation of the NSRP parameters ξ, and λ, from +0 to +100 %, enables to produce rainfall scenarios with different patterns in annual rainfall, mean daily intensity and annual number of dry days (Fig 5). An equal perturbation of ξ, and λ leads to an unchanged annual rainfall, with an increase in rainfall intensity and increased intermittence compared to the reference scenario. A perturbation of +100 % of the ξ parameter with no perturbation on λ parameter leads to an increase of 100% the annual rainfall across all sites, associated with an increase of mean rainfall intensity of wet days of +9.5 mm/day (+83 % of

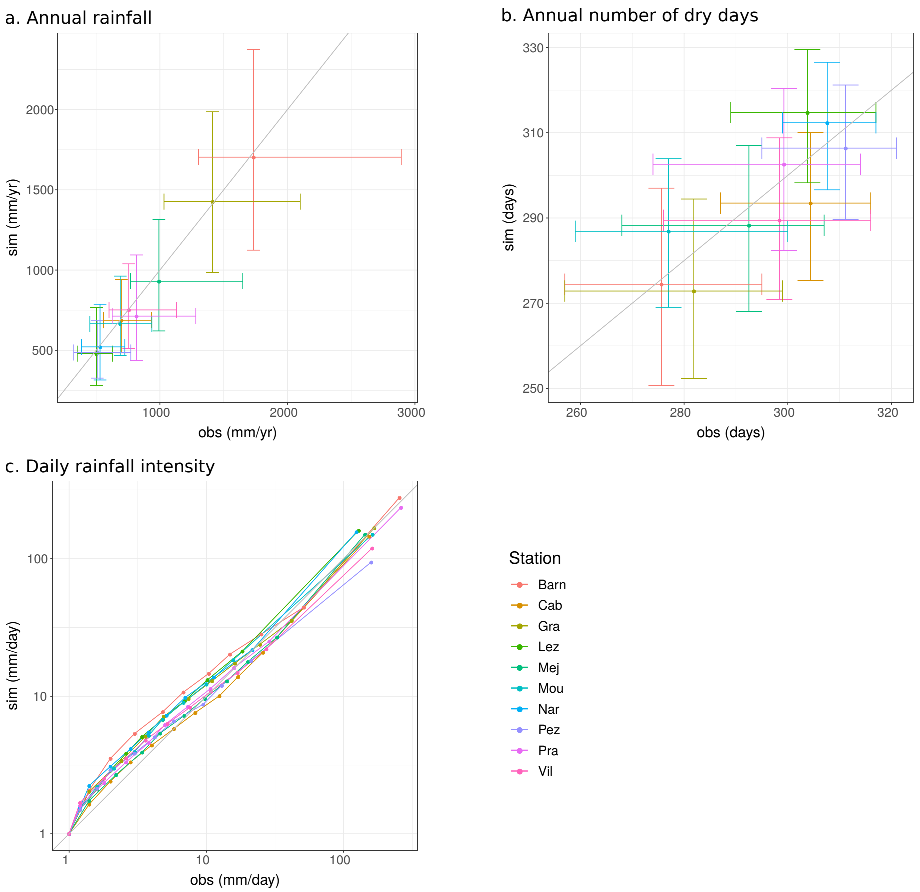

Figure 4. Characteristics of simulated rainfall with NSRP model for the reference scenario and observed rainfall. Comparison of simulated and observed a) annual rainfall b) annual number of dry days (dots represent mean values and bars the range from minimal to maximal simulated or observed values). c) Q-Q plot of daily rainfall intensities (dots represent deciles values).

original rainfall intensity). Alternatively, an increase of +100 % of the lambda parameter with an unchanged value of ξ leads to a mean decrease of of the annual rainfall of 50 % and an increase of +34 days/yr of dry days (+11 %). However, some stations are more sensitive to the perturbation of parameters than others. Figure 5d shows that the change in the annual number of dry days for $\Delta\lambda$ =100 % ranges between +8 and +16 %.

4.2 SM model calibration

Table 3 presents the calibrated parameters of the SMmodel and NSE values after calibration. The NSE values for the calibration on the total period are all above 0.6, and 9 stations out of 11 have a NSE value above 0.75. RMSE values range from 0.015 to 0.032 m^3.m^{-3}. Calibrations on the sub-periods (first and second halves of each station time series) lead to similar parameters (see Table S2) and NSE values on both sub-periods, showing that the calibration is stable for the selected period. Lower NSE

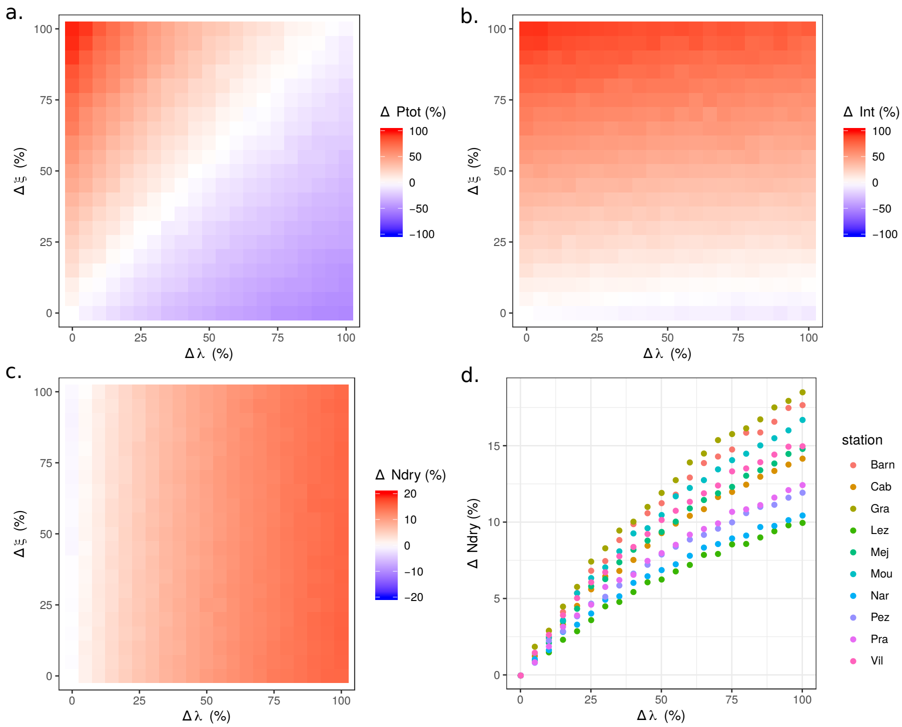

Figure 5. Impact of the perturbation of NSRP parameters $\Delta\lambda$ and $\Delta\xi$ on a) the total annual precipitation, b) the mean daily precipitation intensity, c) the annual number of dry days. a, b, and c show averaged results for the 10 study sites, d shows the relation between the perturbation of λ and the change in number of dry days for each station when $\Delta\xi = 0$.

	Barn	Cab	Gra	Lez	Mej	Mou	Nar	Pez	Pra	Vil
K_s (mm.hr^{-1})	38.1	34.3	35.9	23.1	28.8	36.2	51.1	14.6	59.6	6.9
m	17.6	15.6	10.9	14.1	16.4	23.0	15.9	12.8	11.89	38.2
K_c	1.17	1.43	1.74	1.22	1.81	0.94	1.26	1.99	1.32	1.63
NSE	0.76	0.77	0.93	0.85	0.9	0.63	0.91	0.789	0.65	0.9

Table 3. Calibrated parameters of the SM model and NSE validation values while calibrating on the total period.

values for the calibration on sub-periods are due to missing observed data unevenly distributed over the total period. These results show that the SMmodel is able to simulate soil moisture accurately in the present period 2007-2016. Calibrated values of K_s are consistent with the range of hydraulic conductivities for natural soils. (Angerer et al., 2014) (Table S3). Figure 6 shows an example of soil moisture simulation after calibration at Villevielle station.

The calibrated parameters are then used to simulate soil moisture under different scenarios of temperature and precipitation. Figure 7 compares the distributions of observed daily soil moisture with simulated daily soil moisture forced with the reference scenario. Results show that in the reference scenario soil moisture distribution is in very good agreement with the distribution

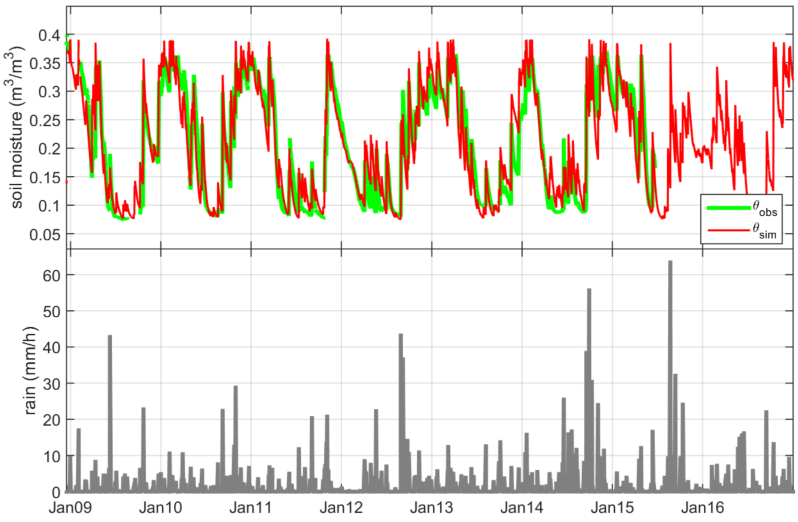

Figure 6. Soil moisture simulation at the Villevielle station.

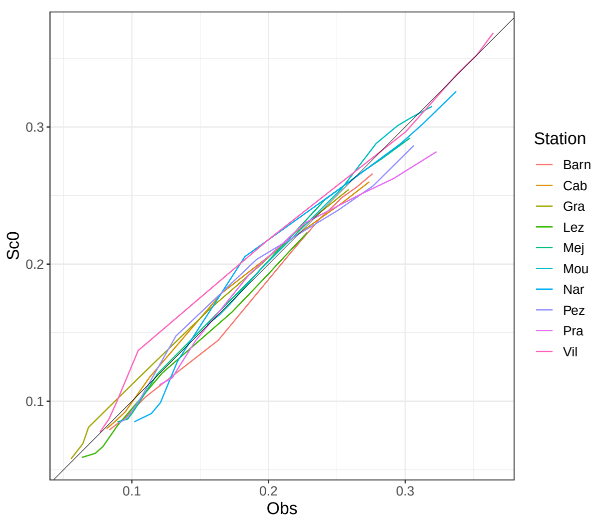

Figure 7. Q-Q plot of simulated (reference scenario) and observed daily soil moisture.

of observed soil moisture. The bias between the mean soil moisture from the reference scenario and the mean observed soil moisture is low and ranging from -0.006 to 0.01 m^3.m^{-3} all sites considered.

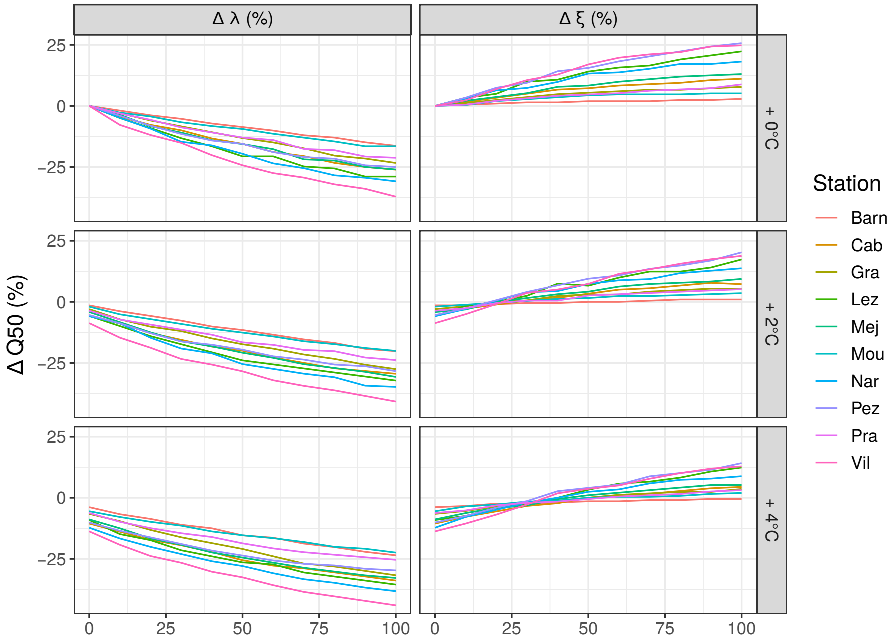

Figure 8. Sensitivity of the median of the simulated soil moisture to an increase of the precipitation intermittence (left panel), and to an increase of mean precipitation intensity (right panel) under different temperature scenarios (+0°C, +2°C, +4°C)

4.3 Sensitivity of soil moisture to precipitation and temperature changes

Figure 8 shows the sensitivity of the median simulated soil moisture to changes in precipitation patterns. Results show that the median soil moisture is more sensitive to changes in precipitation intermittence ($\Delta\lambda$) than to changes in precipitation mean intensity ($\Delta\xi$). For the +0°C scenario, an increase of the precipitation intermittence of +100 % leads to a decrease between -16 and -37 % on the median soil moisture, whereas an increase of 100 % in the precipitation mean intensity only leads to an increase of the median soil moisture ranging between +3 and +26 %. Results also show that stations have different sensitivity to precipitation and temperature changes. Stations such as Villevielle, Narbonne, and Lézignan seem to be more sensitive to climate variability, whereas Barnas, La Grand-Combe, Mouthoumet and Prades-le-Lez stations show a lower impact of changing precipitation patterns and temperature on the median soil moisture. The sensitivity of soil moisture response to changes in temperature and precipitation pattern seems to be correlated to the station local temperature and also to local precipitation to a lesser extent (Fig. 9). Southern stations presenting a warmer and dryer climate seem to be more impacted by changes in precipitation and temperature than northern stations located in the Cevennes mountain range with a colder and wetter climate. No correlation was found between the soil moisture response and the NSRP model and SM model parameters values, meaning that the observed variability between station is independent from the models calibrations.

Figure 10 presents the distribution for the 10 stations of the 1st-order Sobol indices of the median soil moisture (resp. number of days under drought or excess condition) to the parameter change (temperature, precipitation intensity and precipitation

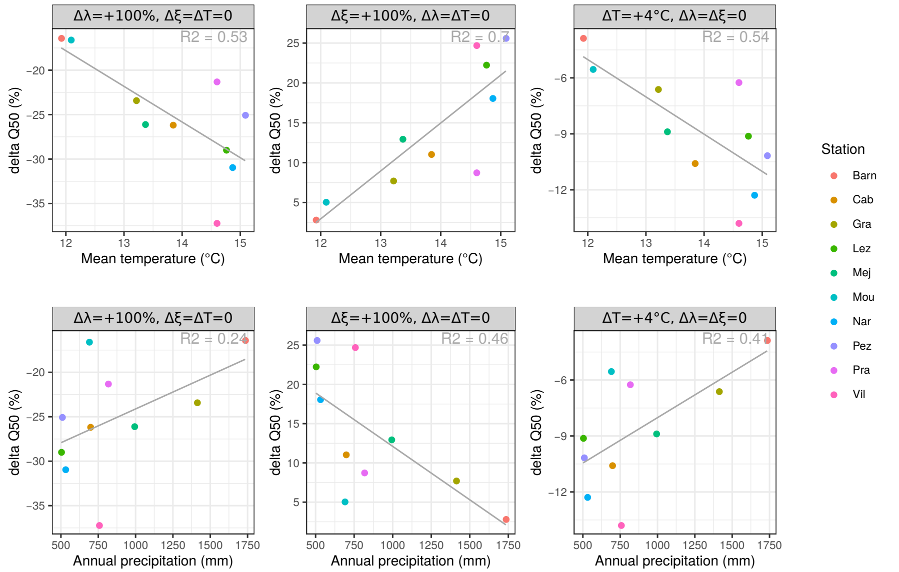

Figure 9. Sensitivity of the median of the simulated soil moisture to precipitation and temperature scenarios (Δ: precipitation intensity scenario, $\Delta\lambda$: precipitation intermittence scenario, ΔT: temperature scenario) related to the observed mean annual a) temperature b) precipitation.

intermittence). For instance, the Sobol index of the soil moisture to a parameter is the percentage of the soil moisture variance explained by the considered parameter. Over all the stations, the sum of the 1st-order Sobol indices are between 0.99 and 1.003, this indicates that the GSA is based on a sufficient number of simulations. The Sobol sensitivity analysis shows that soil moisture variance is more impacted by changes in precipitation intermittence than changes in precipitation intensity and temperature, especially for the median soil moisture and the number of days with drought (i.e. low soil moisture values). Changes in precipitation intensities have a larger impact on higher soil moisture values and can be almost equivalent to the changes in precipitation intermittence, as for example in the Pezenas station. There is a link with the mean precipitation and Sobol indices related to changes in precipitation intermittence and intensity. Indeed, the smaller the annual precipitation, the higher the Sobol index to the precipitation intermittence is for the median and 95th percentile of soil moisture (with correlations equal to respectively r=-0.71, r=-0.56). It is the opposite relationship between annual precipitation and precipitation intensity (with correlations equal to r=0.77 for median soil moisture, r=0.33 for the 5th percentile and r=0.74 for the 95th percentile). This indicates that changes in precipitation intermittence are more strongly impacting soil moisture in locations with low annual precipitation.

4.4 Impact of changing precipitation and temperature on extreme soil moisture

In this section we analyse the response of extreme soil moisture to the precipitation and temperature scenarios. Figure 11 shows the relative change of the mean annual number of days under saturation or drought conditions with respect to the reference

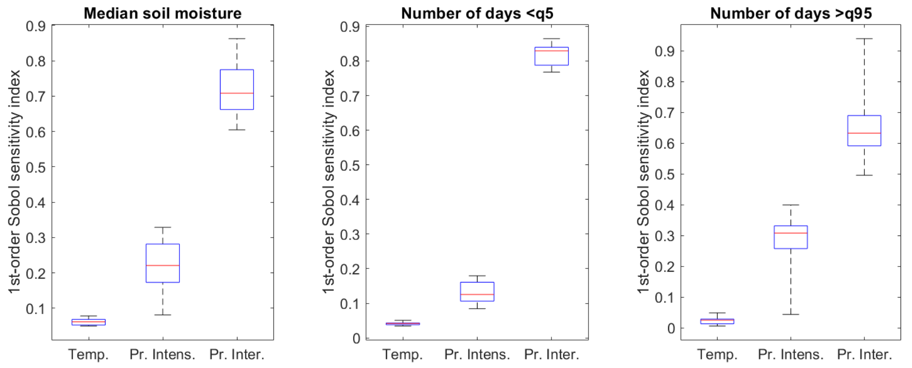

Figure 10. First order Sobol sensitivity index of median soil moisture (left panel), the number of days under drought conditions (center panel), and the number of days with water excess (rigth panel) to temperature, precipitation intensity and precipitation intermittence changes. Boxplots represent the distribution of the 1st-order Sobol indices for the 10 stations.

scenario for the Barnas and Pezenas stations (complete results are presented in supplementary material). Days under saturation (drought) conditions are defined as days with a daily soil moisture above the 95th (below the 5th) percentile of the reference scenario.

There is a large variability in the evolution of the mean annual number of days with wet conditions with results ranging from -16 to +30 days per year for the +2 °C scenario and from -17 to +22 days per year for the +4 °C scenario (Fig. 11a). For the +2 °C scenario, only 24 % of the scenarios result in an increase of annual days with wet conditions in average for the 10 stations. On average, an increase in dry days (i.e days with no precipitation) above +16 days/yr results in a decrease of the number of days with saturated soil moisture condition, regardless the increase in precipitation intensity. Regarding the +4 °C scenario, only 18 % of the scenarios result in an increase of the number of days with wet soil moisture condition, and all scenarios with an increase of dry days above +13 days/yr result in a decrease of the period under saturated soil moisture condition. Scenarios similar to the RCP8.5 scenario of Polade et al. (2017) (i.e. scenarios corresponding to a decrease of annual precipitation ranging between -10 and -20 % and a +4 °C temperature increase, red triangles on Fig 12) lead to an average of 10 days per year with wet conditions, i.e. a decrease of 8 days per year relatively to the reference scenario (blue dots on Fig 12).

Concerning the impact of changing precipitation and temperature on dry soil moisture conditions, Figure 11b shows that changes in precipitation and temperature have a strong impact on droughts as almost all scenarios lead to an increase of dry soil moisture conditions. RCP8.5 scenarios show a mean number of days with dry soil moisture condition ranging between 37 and 55 days/yr, corresponding to a mean increase of +28 days per year comparing to the reference scenario (Fig 12). This increase of dry days mainly impacts the summer and autumn seasons from June to October (Fig. 13). None of the stations show an increase of extreme dry days during winter. These results show that agricultural drought events in the Mediterranean region are likely to be more intense with longer episodes extending until the months of October and November.

Overall, results show that changes in precipitation patterns and temperature have a larger impact on lowest range of the soil moisture distribution than on the highest. This means that climate change is very likely to have a major impact on agricultural

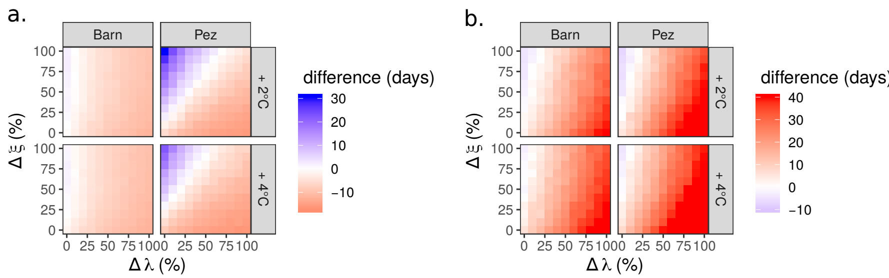

Figure 11. Sensitivity of the annual number of days (a) with saturated soil (i.e. with soil moisture above the observed 95th percentile) and (b) under drought conditions (i.e. with soil moisture below the observed 5th percentile), according to changes in precipitation intensity (y axis), precipitation intermittence (x axis) and temperature, for the Barnas and Pezenas stations.

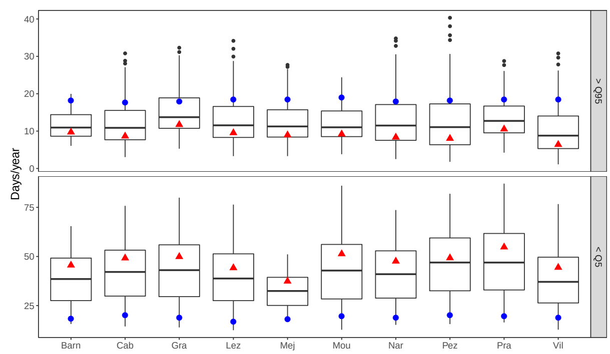

Figure 12. Variability of the annual number of days under saturated condition (SM above the observed 95th percentile, upper panel) and under drought conditions (SM below the observed 5th percentile, lower panel) at each station for a +4°C temperature scenario. Boxplots represent the results for all precipitation scenarios with increasing precipitation intensity and intermittence. Blue dots represent the reference scenario, with no change in temperature or precipitation pattern. Red triangles represent the mean of the scenarios with a decrease of annual precipitation between -10 and -20% (corresponding to scenario RCP8.5 Polade et al. (2017).

droughts with dryer soil moisture and longer drought events. Regarding the impact on flood events, it is difficult to make conclusions based on the results of this study as we do not simulate runoff generation. Our results show a decrease of the median soil moisture for most of the considered scenarios as well as a decrease of days under saturated conditions suggesting a higher infiltration capacity of the surface soil layer with a potential lower runoff generation.

5 Discussion

One of the main limitations to this study lies in the constant soil moisture model parameters under different climate scenarios. The use of constant parameters implies that processes such as the adaptation of vegetation to soil water stress or the impact of rising CO_2 on the vegetation physiology, which may have a sensitive impact on evapotranspiration and thus soil moisture

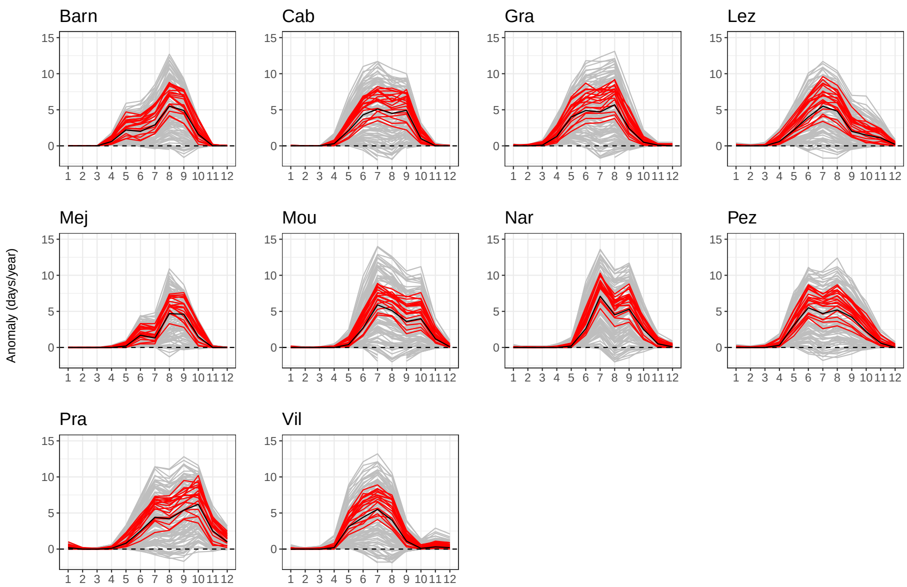

Figure 13. Monthly anomaly of days under extreme drought for a +4°C temperature scenario. Grey lines represent the results for all precipitation scenarios with increasing precipitation intensity and intermittence. Black lines represent the median of the scenarios ensemble. Red lines represent the change of drought days for the scenarios with a decrease of annual precipitation between -10 and -20% (corresponding to scenario RCP8.5 Polade et al. (2017).

(Berg and Sheffield, 2018), are not taken into account in this study. To avoid this issue, it would be required to consider land surface modelling schemes that are able to take into account the feedback effects between vegetation and land surface processes (Albergel et al., 2017). In addition, offline computation of potential evapotranspiration with standard formulas such as the Blaney and Criddle or Penman-Monteith equations can be problematic since it neglects several factors, in particular the surface conditions (Barella-Ortiz et al., 2013). The impact of different formulations of potential evapotranspiration on soil moisture changes needs also to be investigated, since simple temperature-based formulas may overestimate the temperature effects on evapotranspiration (Sheffield et al., 2012; Vicente-Serrano et al., 2019).

Another source of uncertainties is related the selection of temperature and precipitation scenarios, while currently the majority of available climate simulations are at the daily time step. The projected changes on hourly climate characteristics remains largely unknown, and this is why we adopted a stochastic simulation approach to encompass the plausible range of future scenarios. However, convection-permitting regional climate models (CPRCM) are increasingly being implemented over Europe during the last years to reproduce hourly changes in precipitation (Coppola et al., 2018) and these simulations should be considered in future experiments. Similarly, the approach considered in the present paper is based on distributional changes, while the impact of possible changes in the seasonal to inter-annual variability of precipitations on soil moisture cannot be taken into account. This issue could be also resolved by using CPRCM simulations instead of a stochastic rainfall generator to simulate the soil moisture response to various changes in precipitation including seasonal and inter-annual variability.

Finally, this study relies on a set of soil moisture observations from different sites located in Southern France and, despite different annual precipitation and temperature patterns, the vegetation at the different locations belongs to the same biome. It would be interesting to perform this type of analysis on a larger set of sites located in various Mediterranean environments, including North Africa and the Middle East with more arid climate conditions, to investigate the possible relationships between soil moisture dynamics and soil types, vegetation cover and climate characteristics for different degrees of aridity. Indeed, the Mediterranean region includes a great variety of types of vegetation, forming mosaic patterns created by variations in soil, topography, climate, fire history and human activity (Geri et al., 2010). Therefore, it would be very useful to produce a typology of the sensitivity of soil moisture changes for a variety of Mediterranean landscapes.

6 Conclusions

Soil moisture is an important variable to consider in a climate change context since its strongly influences agricultural droughts and flood generation processes. Future climate scenarios for the Mediterranean indicate an increase in temperature, associated with an increased frequency of dry days but also an intensification of extreme rainfall events. This study considered soil moisture monitored at 10 plots located in southern France, in a modelling framework aiming at estimating its sensitivity to changes in precipitation and temperature. For that purpose, a range of precipitation and temperature variations coherent with current climate scenarios available for the Mediterranean region have been generated with a stochastic model to investigate the response of soil moisture to these climatic changes. The main result of this study shows that the sensitivity of soil moisture to changes in precipitation and temperature is similar at the different sites, with a higher sensitivity of soil moisture to intermittent precipitation and the number of dry days rather than their intensity or the temperature increase. However, these changes are modulated by the climate characteristics of the different stations, with a higher sensitivity of soil moisture to precipitation intermittence in locations with dryer and warmer climate characteristics. Overall, it is observed that changes in precipitation and temperature have a greater impact on low soil moisture values than on conditions close to soil saturation. This implies that the current climate change scenarios may induce longer periods of depleted soil moisture content, corresponding to agricultural drought conditions. About the potential impacts of soil moisture changes on flood generation, more research is needed to better understand the joint influence of lower antecedent soil moisture conditions associated with higher rainfall intensity on flood magnitude and occurrence.

Data availability. The computed indices are available upon request to the corresponding author

Author contributions. TEXT

LM and YT designed the experiments, performed the analyses and wrote the paper, LB, CM and SC contributed to soil moisture modelling and climate scenarios, P F-G contributed to the sensitivity analysis. All authors helped the interpretation of results and revised the paper.

Competing interests. TEXT

Nothing to declare.

Acknowledgements. This work is a contribution to the HYdrological cycle in The Mediterranean EXperiment (HyMeX) program, through INSU-MISTRALS support. The authors would like to thank Météo-France for providing precipitation and temperature data, the soil moisture from the SMOSMANIA network has been downloaded from the International Soil Moisture Network (https://ismn.geo.tuwien.ac.at/en/). This work has been realized with the support of the High Performance Computing Platform MESO@LR (https://meso-lr.umontpellier.fr/), financed by the Occitanie / Pyrénées-Méditerranée Region, Montpellier Mediterranean Metropole and the University of Montpellier. The authors wish to thank the three reviewers, Guillaume Evin, Ryan Teuling and an anonymous reviewer.

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