Response to Anonymous Referee #2

This paper conducts a series of model experiments using the JSM soil model to explore the response of modeled SOC to warming and drought, with specific focus to depolymerization terms and their temperature sensitivity.

To accomplish this, the authors impose several general warming and drought experiments. I think it would be useful to develop the model experiments following from a specific objective. For example, if the authors want to know how soils are likely to change with climate change in a given location, they may apply one or two warming scenarios using forcings derived from the Shared Socioeconomic Pathways (running the temperature and/or moisture changes over time rather than stepping up by a global average) at the site in Germany. While it is much more work to extract the appropriate forcing information, it gives a much more specific sense of what the model expects, and the potential to evaluate predictions.

There may be other objectives, such as to conduct a sensitivity analysis of JSM model parameters. With this objective, the authors could do a literature survey of possible parameter ranges and explore the SOC response space given systematic combinations of parameter values. Some attention needs to be given to the parameters chosen for analysis. Why were they chosen and not others? What physical or chemical significance do they have?

We thank reviewer #2 for their comments on our manuscript and helpful suggestions. We apologise for the unclear formulation of the scope and objectives for our study, and aim to improve their descriptions, especially in the introduction. Specifically, our study focuses on modelling the sensitivities of depolymerisation rates to changes in temperature and soil moisture changes. These are processes that have partially been overlooked in dynamic modelling studies before. In this work, we aim to study the effect of these temperature and moisture sensitivities parameterized based on data from a lab study by Allison et al. (2018).

For our model study, we do make use of scenario based estimates for climate change (4.5 degree warming by the year 2100 from RCP8.5). While this is different from the by the reviewer suggested warming scenario with gradual temperature increases over a 100 year period, our study does provide insight into the possible direction and magnitudes of change in SOC stocks following a temperature increase. Future soil moisture projections are highly variable in time, space, and very climate model-dependent (Berg et al., 2017), so that selecting one specific forcing dataset for our example site would not provide much new insights beyond what the existing forcing data and drought scenarios provide.

The choice of model parameters has been based on field and lab-based literature, and we will describe this more clearly in the methodology section of the paper. Several of these parameters have been tried and tested in the previous model studies by Yu et al. (2020, 2023) and Ahrens et al., (2015, 2020) and the ones that are newly introduced for this study (based on lab results from Allison et al. (2018)) received their own paragraph (2.3) in the methods section. The methodology will be revised to better convey this to the readers.

To understand how well JSM models the SOC response to temperature or soil moisture, authors could compare model output to data.

Given the long timeline of the simulations (100 years) and the novel focus of our study on the sensitivities of microbial processes to temperature and drought at different soil depths, we on the one hand see that such data is not readily available and therefore a comparison of the model outputs to observational data falls outside the scope of the study. In line with our reply to reviewer#1, we argue that on the other hand, available respiration data, for example, would only match the first few years of the simulations for the experiments and allow us to verify the bulk flux from the complete soil profile under 'ambient' climatic conditions (and not match the various the warming/drought experiments), and SOC measurements from warming/drought field experiments would be highly impacted by changes in plant productivity (litter inputs). A discussion of this study limitation is already part of the original manuscript. Please note that while JSM is a relatively new model, the processes and parameters for JSM and its predecessor COMISSION have been successfully tested against observations for various applications by Yu et al. (2020, 2023), Ahrens et al. (2015, 2020), and Fleischer et al. (in prep, but see https://meetingorganizer.copernicus.org/EGU22/EGU22-11276.html).

There are many options and I think this study could be quite interesting if expanded to fit into one of these frameworks, or a different one, as long as there is some clearer justification for the chosen experiments.

The kindly suggested options by the reviewer, as well as the comments by reviewer #1, indicate we were not successfully relaying the intended scope and objectives for our study in the original manuscript. We apologise for the unclear language and revise to make them more clear, alongside a better description of why the parameter values for the temperature sensitivities of the depolymerisation rates for litter and microbial residues were chosen from the lab-based study by Allison et al. (2018).

L46: I think there needs to be more description about what Km means in physical terms, and why it is important. As written, it seems a bit arbitrary to explore the temperature sensitive of a fairly abstract parameter in the kinetics equation and not the other sources of temperature sensitivity in the model.

*The half-saturation constant, Km, is the concentration (in this case of microbial biomass, Cb) where the depolymerization rate is 0.5*Vmax (Eq. 1). Km is not an abstract parameter at all, but an important determinant in the reaction rates of enzyme kinetics: A low half-saturation constant value would mean that the reaction rate is only limited at very low microbial biomass concentrations (e.g. in the subsoil). A high value means that the reaction rate will only be unlimited at very high microbial biomass concentrations (e.g. in the topsoil). The Km parameter for depolymerization can be viewed as the affinity of an enzyme to bind to different polymeric substrates for depolymerization, i.e. plant litter or microbial residues (Tang and Riley, 2019).*

The value of the half-saturation constant itself is sensitive to temperature and soil moisture and thereby has the potential of further accelerating or counteracting SOC decomposition rates in a warming climate (e.g. see Allison et al., 2018; Davidson and Janssens, 2006; Davidson et al., 2012). To our knowledge, this has not been explored in a dynamic modelling setting before, which makes this study very novel. Other temperature sensitivities, through the maximum reaction rates (Vmax) of the microbial depolymerisation and uptake rates, as well as the sorption and desorption rates, are also active in our study - these maximum *reaction rates are also affected by 4.5 degree warming through their respective Q10 values (listed in Table 1). These temperature sensitivities, however, are more well-established in the microbial-mineral SOC model literature (Wang et al., 2012, 2013) than the temperature sensitivities of the Km which were, with the interplay with soil moisture sensitivity, the focus of this study. These warming effects on SOC decomposition are presented and discussed at length in sections 3.1 and 4.1 of the manuscript.*

L193: I found the choices of Q10 parameter experiment a little confusing. Q10=1 and Q10=literature values makes sense, but I didn't quite understand the hypothesis underlying the choice to set both parameters to either litter or residue.

We apologise for this confusion and will further expand the motivation for this choice in sections 2.3 and 2.4 of the methodology, where we refer to the lab-based measurements of Allison et al. (2018). Setting these values to either all litter or all microbial residues was done to showcase the effects of an overall Q10,KM of 1.3 and a Q10,Km of 0.7. Setting both parameters to either litter or residue was hence not based on a mechanistic hypothesis but rather as an exploration of the edge cases of all Q10,KM below 1 and all Q10,Km above 1. We will make clearer that this was intended as a sensitivity study and model experiment rather than testing a specific hypothesis.

L223: Rather than visual inspection to determine steady state, you could set some quantitative measure such as <1% change in stock (or a moving average) over the last 100 years.

We used linear regression to determine the steady-state assumptions and will mention this in the methods.

L230: Sulman et al. 2018 (https://link.springer.com/article/10.1007/s10533-018-0509-z) demonstrated that different soil C models had widely different assumed temperature sensitivities of mineral associated carbon. Can you make a compelling case that MAOM is less temperature sensitive than microbial processes?

Yes, in a review article on uncertainty in soil C feedbacks, Bradford et al. (2016) recognize the important role that microbes play in the stabilisation and formation of stabilised SOC, which is less sensitive to warming (Fig. 3 in Bradford et al. (2016), and see Tang and Riley (2015)). We will include these references in the manuscript.

The five models analysed in Sulman et al. (2018) contain four models that include microbially mediated decomposition rates (CORPSE, MIMICS, RESOM and MEND), of which only one (the MEND model) has non-linear representations of mineral SOC protection, comparable to JSM, which can be decomposed by microbes (not possible in RESOM). Therefore, the widely-ranged values reported for the other four models reflect the differences in model structure, as each value must be somehow calibrated to fit inside its specific model framework, rather than reflect values which are process-based as is the case in the MEND model and JSM.

In our study, we make use of the values reported by Wang et al. (2013) for the temperature sensitivity of sorption and desorption parameters $Q_{10,adsorption}$ and $Q_{10,desorption}$ (Table 1). In this study (for the MEND model), Wang et al. (2013) developed and tested parameter values for *explicitly modelling the desorption and adsorption of SOC to mineral surfaces based on literature (reported in Table 3 of Wang et al., 2013). An application for JSM (with its predecessor model, COMISSION) has been successfully reported by Ahrens et al. (2015, 2020).*

L267: Define here which pools you consider to be in POC vs MAOC. I think this may be the first occurrence of the abbreviation so you should define the terms as well.

We apologise for the late definition in the original manuscript (L.357-358). We will change this and add it to section 2.5.

Figures 5 seems very similar to Figure 4, and not additive to the effect of temperature shown in Figure 3 – yellow line. Why is that? Does this imply that SOC in JSM is more sensitive to soil moisture than temperature?

The figures indeed look similar, because the effect of drought and warming on SOC stocks through the half-saturation constant, Km, as shown in Fig. 5 is of a much smaller magnitude than the effect of drought + warming (Fig. 4, without temperature sensitivity of Km). Drought rapidly increases the amount of POC in the topsoil as litter inputs accumulate over the simulation period (Fig. A2, 0–6 cm orange and pink lines), which makes the temperature effect on Km very small. The temperature effect can be better observed in the deep soil layer, as Km becomes more important at lower microbial biomass concentrations (Fig. 1, Eq. 3).

We would like to point out that the results shown in Figure 4 also include the effects of soil warming by 4.5 degrees, as is the case in ALL model experiments (but not in the ambient model run, dark blue line Fig. 3). We colour coded the lines in Figs 3 – 5 for easy visual comparison between figures: In Figure 3 and 4, the purple lines are identical, and in Fig. 3 and 5, the yellow lines are identical. We apologise for not clarifying this better in the text and figure captions, and will improve this in the revised version of the manuscript. We could also, for example, revise Figure 5 to only show the differences between these model runs and the ones shown in Fig. 4, to highlight that the effects of Q10,Km are stronger in the subsoil than the topsoil – i.e. visualising the % SOC changes listed in Table 2 and reporting in section 3.3 (L. 290 – 316).

L334: The temperature sensitivity of adsorption and desorption seems like potentially important parameters.

Yes, they play a role in explaining the overall lower SOC losses from the subsoil in response to soil warming, as the amount of adsorbed carbon is larger in the subsoil (Fig A1). The MAOC pool is not directly affected by microbial depolymerisation (Fig. 2), but temperature does affect the desorption rates of MAOC into the DOC and microbial residues pool. As a result, the lower temperature sensitivities of adsorption and desorption contribute to the overall lower apparent temperature sensitivity of the total SOC pools when the ratio of MAOC:POC is high. We discuss this in lines 341 – 358, but will mention this important distinction earlier on in the manuscript.

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