December 06, 2023

Differentiating between crop and soil effects on soil moisture dynamics

By Scholz et al.

Replies to comments from reviewers

Reviewer 1

This paper describes the application of the well-known principal component analysis method to disentangle effects of crops and soil properties on soil moisture dynamics using 64 soil moisture time series from an agricultural experiment with differently managed small plots. This study is based on a quite large data set of soil moisture measurements and is tangential to an important topic in environmental research. Unfortunately, the interpretations of the results are partly very speculative and difficult to comprehend. Furthermore, transferability of the results to other areas is very limited, as they are determined by the very specific conditions of the experimental study area. I recommend that the authors turn these weaknesses into strengths by arguing that homogeneous soil properties make it easier to study the effects of crop types on soil water balance. The manuscript is mostly well written but need to be checked by a native speaker. I have listed further limitations in my general and specific comments below.

We would like to thank the reviewer for the thorough review. We did our best to meet the comments and recommendations. We added more explanations and details to support the reader in comprehending the interpretation of the data. We agree that in our study soil texture exhibits little heterogeneity. After first submission of the manuscript additional soil data were analysed (see below). However, even that larger sample size did not exhibit clear correlation with principal components, which might partly at least be due to enhanced nugget effects, and partly due to soil structure effects that are not reflected by soil texture data. Thus our results in terms of soil heterogeneities as the main drivers on different loadings on single principal components are based only on indirect inferences.

General comments

The main goal of this study is to disentangle effects of crops and soil properties on soil moisture dynamics. However, the results cannot be generalized due to the peculiarities of the study area. On the one hand, the large vegetation effect observed in this study is due to very specific small-scale crop management with various crops in one field, which does not occur in regular agricultural systems. On the other hand, the soil texture of the studied plots is very similar, so that the minor soil effects on soil moisture found in this study are not representative for landscapes with more typical soil heterogeneity. The similarity in soil texture might also be the reason for the low influence of soil sensor depth and roots on the soil moisture time series.

We reworked the text to emphasize the peculiarities of the study on the one hand, and the wider applicability of the presented approach on the other hand, e. g. in line 368-369 in the Conclusions: *"Findings of this study highly depend on local conditions. However, we consider the presented approach generally applicable to a large range of site conditions."*

In terms of minor soil texture heterogeneity please see comment above.

For the reasons stated above, the title of the manuscript is not appropriate and should instead reflect the very specific conditions of the study area.

Please see comment above.

The data of the synthetic time series shown in Figures 4, 6, 8, and 10 as well as their interpretations are difficult to understand. To convince readers that the interpretation is robust, these data need to be explained and justified much better.

In the Methods section, we added to the elaboration of how these Figures are produced and how they can be interpreted as follows (line 180-187): *"The scores of the principal components constitute time series. Every observed time series can be presented at arbitrary precision as a combination of various principal components. When the data set consists of time series of the same observable measured at different locations, the first principal component describes the mean behaviour inherent in the data set. Subsequent principal components reflect typical modifications of that mean behaviour at single locations due to different effects. Thus, generating synthetic time series as linear combinations of the first PC and another additional PC helps to assign this additional PC to a specific effect. To that end, scores of that component have either been added to or subtracted from those of the first component using arbitrarily selected factors. The two resulting graphs show how the respective PC causes deviations from the mean behaviour of the data set."*

In the Results and Discussion sections, we added elaboration on how we interpreted the deviations from the mean behaviour as follows:

- line 211-213: *"As described in the Methods section, synthetic time series were generated as a linear combination of PC1 and PC2 (Figure 4). The graph resulting from applying a positive factor for PC2 represents a typical deviation from mean behaviour for sites that exhibit positive loadings, e.g., winter crops (blue line)."*
- line 217-218: *"In July and August, the approximately constant level of the blue curve indicates that only winter crops continue to consume water while summer crops are in their ripening phase and eventually harvested."*
- line 242-243: *"The most obvious difference between the orange line (negative loading on PC3) and the blue line (positive loading on PC3) during the first half of the study period is that the latter reaches a maximum of soil moisture after rainfall much earlier compared to the former (Figure 6)."*
- line 341-342: *"The blue line, representing sites with positive loadings on PC5 which is typical for sensors at greater depth (Figure 9), exhibits clearly reduced amplitudes compared to the orange line, that is, sensors at shallow depth (Figure 9, Figure 10)."*

This study uses data from an underground LoRa-based sensor network. The authors claim that this system is novel, but information on why it is novel is largely lacking.

More explanation on the novelty is added to the manuscript (line 70-73): *"The novelty of this Internet of underground Things (IouT) soil moisture monitoring network is characterized by its unique on-farm installation environment and the deployment of 180 sensors in up to 0.90 m soil depth, allowing for high spatio-temporal resolution wireless data transmission, and enabling conventional farming practices like machinery traffic, tillage and mechanical weeding."*

In addition, the soil moisture time series shows large data gaps. The authors provide some general information about data gaps, but do not go into technical detail (e.g. battery failure, transmission failure, sensor failure etc.), which would be interesting given the novelty of the wireless system.

More details are added to the manuscript (line 158-160): *"Transmission failures due to discharged batteries, signal disturbances in sinks after rainfall, patches with a high density of biomass (e.g. maize), and theft of parts of the monitoring system led to data gaps that amounted to 81 out of 257 days of the measuring period, which were therefore skipped for the analysis."*

The authors compare "conventional" with "reduced" cases, but in both cases weeds are being controlled. Therefore, not difference between both cases in terms of soil moisture can be expected.

We provided a rationale in line 99-100 : *"Due to the potential impact of mechanical weeding on soil structure, i.e., on rainwater infiltration, soil evaporation and topsoil rooting intensity, we differentiate between these modes of weed control."*

The measured time series of soil moisture should also be presented in meaningful figures, since these form the basis for the statistical analysis. If the number of figures becomes too large, they can also be presented in an appendix.

The input data set is plotted in Figure 11 (Appendix A).

<u>Specific comments:</u>

L13-15: Combine sentences.

Adjusted in the manuscript (line 13 to 15) as follows: *"In this study, we apply a principal component analysis to a set of 64 soil moisture time series from a diversified cropping field featuring seven distinct crops and two management strategies."*

L42: All cited papers didn't use TDR, but capacitance probes etc.. These kind of low-cost soil moisture sensors are usually used in wireless sensor network applications (see e.g. Bogena et al., 2022). Therefore, I suggest using the more general term "electromagnetic soil moisture sensors".

We agree. The term was changed it accordingly in the manuscript (line 42-44).

L47: This study uses data from an underground LoRa-based sensor network. The authors claim that this system is novel, but information on why it is novel is largely lacking.

This is highlighted in the end of the introduction (line 70-73): *"The novelty of this Internet of underground Things (IouT) soil moisture monitoring network is characterized by its unique on-farm installation environment and the deployment of 180 sensors in up to 0.9 m soil depth, allowing for high spatio-temporal resolution wireless data transmission, and enabling conventional farming practices like machinery traffic, tillage and mechanical weeding."*

L66: Explain in more detail the novelty of this wireless soil moisture monitoring system (please note that are large number of similar systems already exist, see e.g. Bogena et al., 2022)

We thank the reviewer for the literature recommendation of Bogena et al. (2022) which we were not aware of as this manuscript was prepared before the publication of that paper.

The system is novel in terms of installation environment and number of installed sensors. Those wireless Lora systems may have been installed and used in the past in other ecosystems, but to the best of our knowledge we do not know about agricultural systems, and in particular one single field that is equipped with 180 sensors providing the information wirelessly in high temporal resolution and hence allow business as usual machine traffic and tillage. We added this justification in the introduction, as mentioned in the previous comment (on L47).

L83-84: Explain "yield potential zones".

We provided a short information on the cluster analysis carried out to define two different yield potential zones as follows (line 88-90): *"To that end, a cluster analysis was carried out based on soil maps and multi-year (2010 to 2019) yield data to identify high and low yield potential zones in the 70-ha large field (Donat et al., 2022)."*

L95: The "DriBox" is just the housing for the electronics. Please provide information on the manufacturer of the electronic parts.

We elaborated the technical section and provided all the hardware details (line 102-106): *"In each patch, one Dribox box was equipped with a SDI-12 distributer (serial data interface at 1200 baud rate, TBS04, TekBox, Saigon, Vietnam) connected to six TDR-sensors (TDR310H, Acclima, Meridian, USA) and attached to an outdoor remote terminal unit (RTU) fully LoRaWAN compliant (TBS12B: 4+1 channel analogue to SDI-12 interface for 24 Bit A/D conversion of sensor signals, TekBox, Saigon, Vietnam)."*

L97: Does this mean that you have dug 0.9 m deep trenches for the cables? Please explain the installation of the sensors in more detail.

We added a more comprehensive description about the sensor installation in the Methods section as follows (line 109-110): *"Soil sensors at 0.3 m were placed horizontally, while sensors at 0.6 and 0.9 m depth were placed vertically using auger-made tunnels and extension tubes for soil insertion. Driboxes were autarkic in terms of energy supply, and communication was wireless throughout. Thus no electric cabling except from connections between sensors and Driboxes was needed."*

L104: Why was only data from one drone campaign used in this study? Given the high temporal variability of plant and soil water status, the use of a single snapshot may not be sufficiently representative for the conclusions drawn in this analysis.

We included data from two additional dates (May 20, 2021, and July 06, 2021) into the analysis. Whereas correlations between loadings of PC2 and the data from May 20 are similar to ones from May 31, the correlations in July have opposite signs. We added findings in line 232-236): *"The results in July compared to those in May support the observation. At the time when the winter crops are already in the ripening phase and the summer crops reach high levels of evapotranspiration, the correlations are being reversed and negative loadings indicate above-average plant activity for summer crops. On July 06, highest Pearson correlations for NDVI are found for 0.6 m depth (r = -0.917)."*

L117: What is the accuracy of the soil texture prediction model? Please provide more information on the data processing in the appendix.

To clarify the accuracy of the soil texture prediction model using the Geophilus system, the following sentences were added in line 152 to 155 in the Methods section: *"A non-linear regression model was applied. The RMSE of sand content (5.7%) was considerably smaller than the standard deviation of the sand content in the first layer from the manual soil texture analysis (11.9%), indicating a satisfactory prediction performance. The γ-sensor was used to minimize uncertainties, being less sensitive to soil moisture than the ERa readings (Bönecke et al., 2021)."*

L118: What do you mean with "gamma sensor" and how does it reduce uncertainty?

The gamma sensor is used to detect the natural gamma radiation emitted by the ground. It is emitted mainly by uranium and thorium particles and thus reflects the proportion of potassium-rich minerals in the clay and silt fraction. Therefore, the measured gamma activity is proportional to the clay content. Because the γ-radiation is less sensitive to soil moisture than the ERa readings, the ratio between the γ-activity and the ERa of the array with the smallest electrode spacing (investigation depth: 0–0.25 m) represents the influence of the soil water on the ERa readings (Bönecke et al., 2021).

L123: Please describe in more detail the technical problems (e.g. transmission failure etc.).

Information is now provided in the manuscript (line 158-160): *"Transmission failures due to discharged batteries, signal disturbances in sinks after rainfall, patches with a high density of biomass (e.g. maize), and theft of parts of the monitoring system led to data gaps that amounted to 81 out of 257 days of the measuring period, which were therefore skipped for the analysis."*

L125: Could you explain why these sensors show frequent malfunctioning (e.g. do to the sensors itself or do the wireless system)?

To provide more detail about the sensor functions and the frequency of malfunctioning due to multiple reasons, additional explanations were added in line 158-160 in the Methods section (see reply to comment above).

L125: Define "short".

Details were added to the manuscript (line 162-164): *"Of all 20,668 interpolated gaps, 96% were shorter than two hours, 3 % between two and six hours and 1 % longer than six hours. In 26 cases, the gap exceeded the duration of one day."*

L140-141: Was this the case in this study? Otherwise, delete.

All analysed PC had an eigenvalue greater than one (see Table 4).

L143: Please explain "local effects".

This part of the methodology was not necessarily important for the manuscript and was therefore deleted.

L158-160: The interpretation that the first PC shows the control of atmospheric forcing should be better justified. For instance, the time series of scores could be correlated with P-ET time series.

The following sentences were added in line 200-201 in the Results section*: "The correlation between the scores and the cumulative water balance (P – ETp) was -0.969 ($p < 0.01$)."*

L169-173: Move to "Methods" section and expand explanation (e.g., arbitrary factors).

Moved to the Methods section and expanded explanation added in the manuscript in Methods section as follows (line 180-187): *"The scores of the principal components constitute time series. Every observed time series can be presented at arbitrary precision as a combination of various principal components. When the data set consists of time series of the same observable measured at different locations, the first principal component describes the mean behaviour inherent in the data set. Subsequent principal components reflect typical modifications of that mean behaviour at single locations due to different effects. Thus generating synthetic time series as linear combinations of the first PC and another additional PC helps to assign this additional PC to a specific effect. To that end scores of that component have either been added to or subtracted from those of the first component using arbitrarily selected factors. The two resulting graphs show how the respective PC causes deviations from the mean behaviour of the data set."*

L174-177: These interpretations of Fig. 4 are not clear to me. Maybe I have too little experience with PCA, but I think that other readers see it similarly and also need more explanation.

We added some explanations in the Methods (see comment above) to facilitate interpretations. We also modified the line 211-213 in the Results section for a better understanding of the interpretation: *"As described in the Methods section, synthetic time series were generated as a linear combination of PC1 and PC2 (Figure 4). The graph resulting from applying a positive factor for PC2 represents a typical deviation from mean behaviour for sites that exhibit positive loadings, e.g., winter crops (blue line)."*

Furthermore, more information was added in line 217-218: *"In July and August, the approximately constant level of the blue curve indicates that only summer crops continue to consume water while winter crops are in their ripening phase and eventually harvested."*

L186: The direct use of surface temperature (Ts) may not be a very good proxy for ETa. Typically, energy balance models or the warming rates from diurnal Ts measurements are used to infer ETa from Ts (e.g. Panwar et al., 2019). In addition, it is evident from Table 2 that Ts is strongly anticorrelated with NDVI, indicating that the two variables are not independent.

Diurnal data were not available as the drone images provided only a single snapshot in time. Instead, the spatial pattern of surface temperature was deemed to be related to that of actual evapotranspiration in a monotonic, although not necessarily linear way. Close anti-correlation of the resulting pattern with that of NDVI provided some evidence that this approach was justified. In addition, we added observations from another two drone surveys which support our inference in that that the relationship of winter and summer crops with PC2 reversed in the July survey compared to the surveys in May (line 232-236): *"The results in July compared to those in May support the observation. At the time when the winter crops are already in the ripening phase and the summer crops reach high levels of evapotranspiration, the correlations are being reversed and negative loadings indicate above-average plant activity. On July 06, highest Pearson correlations for NDVI are found for 0.6 m depth (r = -0.917)."*

L193: What is meant by this? The soil map does not show any relevant structures.

We clarified the statement (line 239-241): *"The location of the patches roughly follows an east-west direction, which, however, cannot be assigned to topography or structures apparent on the topsoil map."*

L194-195: These interpretations are too speculative.

We rephrased to better describe the effect (line 242-244): *"The most obvious difference between the orange line (negative loading on PC3) and the blue line (positive loading on PC3) during the first half of the study period is that the latter reaches a maximum of soil moisture after rainfall much earlier compared to the former (Figure 6)."*

Thereby, in combination with additional elaboration in the Discussion section, we hope to support the reader in comprehending the interpretation of this PC (line 328-332): *"Loadings on the third principal component were not related to crop types. In contrast, a spatial pattern emerged: Only sensors from 0.9 m depth from six adjacent patches exhibited strongly negative loadings (Figure 2) whereas all other sensors showed minor positive or negative loadings. This points to an effect of subsoil substrates, that is, higher clay content and consequently higher water holding capacity. That would be consistent with delayed response to seepage fluxes and reduced desiccation in the vegetation period (Figure 6)."*

L206-209: These interpretations are not clear to me. Furthermore, the soil texture in the study area is extremely homogeneous, which is why any interpretation of soil effects seems to me to be exaggerated.

The statement has been refined (line 253-257) to clarify our interpretations: *"Figure 8 illustrates the effect of the fourth PC on time series. A positive factor would be typical for more sandy soils and for patches with fallow in autumn and winter (blue line). In contrast the orange line depicts behaviour in more loamy soils and for winter crops. The latter line exhibits slightly more delayed responses to rainstorms and subsequent less steep recovery as would be expected for more loamy soils. However, it is not clear how winter crops on the one side and fallow on the other side could induce such a different behaviour."*

As mentioned before, we consider PCA as a tool to discover effects on soil moisture variability driven by even small variations of specific parameters, in this case texture. We therefore consider it justified to interpret little texture variabilites as a decisive factor in the soil moisture variability.

After first submission of the manuscript additional the auger data including those from greater depth were analysed. Unfortunately, there is a high level of uncertainty in transferring the information on texture from the auger sampling points to the location of the sensors (distances between sampling and sensor points: around 0.8 to 2.5 m). The auger data were collected with the aim of obtaining a spatial picture of texture variability of the entire landscape laboratory area. Small scale variability was not the aim of the campaign. Due to the distance of approximately 5 m between the sampling points, the transferability of the information from auger sampling point to sensor location is highly uncertain. Great nugget effects confirm this. Furthermore, we do not have auger data for four out of twelve studied patches.

L222-223: This statement is not clear to me. Please explain in more detail.

The statement has been re-formulated (line 271-273). *"The first five principal components described about 97% of the variance of the data set, which consisted of observed time series from 64 soil moisture probes and revealed various effects of weather, soil texture, soil depth, crops and management schemes (Table 1)."*

L239-240: Please explain in more detail how you arrive at 61%.

We added additional explanations (line 289-291): *"When not considering the temporal component reflected by PC1 and thus only looking at the spatial variability, 61% of the remaining variance (attributed to PC2 to PC64) is caused by the vegetation effect reflected by PC2."*

L253-254: This statement needs to be better justified.

To further clarify this, the following sentences were added in line 302 to 305: *"The scores are time series and reflect the effect size of a particular process represented by the respective PC. The more the scores of a certain PC deviate from zero during specific periods, the stronger the respective effect is. Consequently, the time series of PC2 scores indicates that the effect of vegetation on total variability varies by time."*

L258-259: Too speculative.

We elaborated a little bit more on that but emphasizing that these are very preliminary inferences, based on own observations and similar observations made by other colleagues (e.g., Döring et al., in preparation). To further clarify, following sentences were added in line 321 to 324: *"Usually, such effects are assumed to occur only at larger time scales, which is closely related to problems of detecting changes soil organic carbon quantity or quality. So far there is only anecdotal evidence for rather short-term soil organic carbon quality affecting soil hydraulic properties even at smaller time scales."*

L262-263: Too speculative.

See reply to comment above (on L258-259).

L265-268: These interpretations are implausible because the aforementioned effects on soil organic matter take many years to occur.

See reply to comment above (on L258-259). We think more research is needed here, including but not being restricted to indirect methods like that used in our studies.

L272: In this case crop management shapes the environment.

We agree and we adjusted the respective phrase in the manuscript as follows: *"If it were to be confirmed, it would be a good example for how crop management shapes soil properties."*

L285: Figure 9.

Thank you, Figure 9 is now referenced.

L286: It is not clear to me why positive loadings should indicate a damped behavior of soil moisture.

The statement has been further elaborated as follows (line 340-343*): "Loadings on this component are clearly related with depth (Figure 9). Strong positive loadings indicate a strongly damped behaviour of soil moisture time series: The blue line, representing sites with positive loadings on PC5 which is typical for sensors at greater depth (Figure 9) exhibits clearly reduced amplitudes compared to the orange line, that is, sensors at shallow depth (Figure 9, Figure 10)."*

In combination with information on how Figures 4, 6, 8, and 10 (see also third general comment) are derived and how they can be interpreted, we hope that readers can now follow our interpretations.

L294: In my opinion, this research is not an indispensable prerequisite for tailored field and crop management. In fact, modern sensor-based agricultural techniques allow for a tailored crop management already (e.g. Chamara et al., 2022).

The statement relates to disentangling and quantifying different effects in general, not specifically to the suggested approach. We consider the latter very helpful in addition to modern sensor systems. To further clarify, we added the following sentences to the Conclusion (line 353-354): *"Principal component analysis is a step further to meet these challenges although not entirely without problems. In this study which focuses on the interplay between crops and soil heterogeneities in terms of soil moisture dynamics, the strength of the methodology in contributing to disentangling different effects of complex spatially and temporally diversified cropping systems based on a comprehensive real-world data set is presented."*

Figures

Fig. 1: Please add horizontal bars for each patch to the figure to make the vegetation stages of the patches easier to understand. In addition, potential ET should be plotted, which is a better proxy for actual ET then air temperature.

We added bar plots, showing periods at what time which crops were present at patches.

Figs. 3 and 7: Use same color scheme as in Fig. 5 to better differentiate the different sensor depths.

The figures were adjusted accordingly.

References

Bogena, H.R., A. Weuthen and S. Huisman (2022): Recent developments in wireless soil moisture sensing to support scientific research and agricultural management. Sensors 22: 9792. DOI: 10.3390/s22249792

Chamara, N., Islam, M. D., Bai, G. F., Shi, Y., & Ge, Y. (2022). Ag-IoT for crop and environment monitoring: Past, present, and future. Agricultural systems, 203, 103497.

Panwar, A., Kleidon, A., & Renner, M. (2019). Do surface and air temperatures contain similar imprints of evaporative conditions?. Geophysical Research Letters, 46(7), 3802-3809. https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019GL082248

Reviewer 2

Summary

In the study “Differentiating between crop and soil effects on soil moisture dynamics” by Helen Scholz et al. 64 soil moisture time series covering eight months are evaluated by a principal component analysis. The data have been measured in three depths at a site in Eastern Germany with a wireless network of TDR sensors. The resulting components were interpreted based on supporting information about (i) precipitation and temperature, (ii) crop rotation, (iii) sand content in the upper 25 cm, and (iv) NDVI and surface temperature. A share of 97 % of total soil moisture variance could be described by the first five components and has been assigned to meteorological conditions (27%), the cropping system (17 %), soil properties (6,3 %), and signal damping (1.7 %).

Thanks for the comprehensive and in-depth review.

General comments

Objectives of the study:

The research question addressed in the study (L66-70) is generally relevant and also interesting for the readers of HESS. It should be defined more precisely what exactly is meant by “highly diversified fields” in this study. It might also be unclear at first what “quantify the drivers of soil moisture” really means. The readers might first think about quantifying the individual components of the hydrological water balance by absolute values. However, due to the z-transformation, this cannot be achieved with a PCA. The objectives should be formulated more precisely.

In patchCROP we combined both and designed a cropping system design with a high level of diversification in terms of crops, soil management zones, field size and land use intensity (in terms of plant protection). The changing soil-hydrological dynamics in such complex diversified agricultural systems with increasing heterogeneity and site-specific adjustment of crops, soil types and field management have hardly been studied so far.

We did our best to clarify information on the objectives of the study and on diversification, e. g.:

- Details on diversification were added to line 73-74 in Introduction: *“The main objective of this study was to identify the drivers of soil moisture variability in a diversified cropping field in terms of crop selection, soil type and field management by applying PCA.” With re-formulating this sentence we also hope to clear up misunderstandings about “quantifying soil moisture variability drivers”.*
- To further clarify that the main objective is to interpret patterns in soil moisture dynamics, line 74-75 in Introduction was modified as follows: *“Special focus was put on the interpretation of spatial and temporal effects of crop diversification and of soil heterogeneities on soil moisture dynamics.”*
- We added to the Methods section the limitations of the analysis of z-transformed data sets regarding absolute values (line 167).
- For more details, please see our replies to specific comments.

Methods:

PCA of soil moisture time series is a promising approach to identify the dominating factors of soil moisture dynamics and assess the strength of their effects. It is not a new approach, since some very similar studies already exist, where a PCA has been applied to soil moisture time series. However, this should not be a problem for a publication in HESS, because we can still learn a lot from repeating the analyses at new sites. The main methodological problem I see in the study is that extensive and robust data are needed to identify interpretable patterns with the PCA approach, which are important to draw valid conclusions about thematic research questions. Unfortunately, quite limited data were considered in this study.

We agree that long and gapless time series would be ideal for any in-depth analysis. However, such data sets are often not available. Fortunatley though PCA can be applied and the results be interpreted despite data gaps. We added about that in line 365-367 as follows: *"It has been shown that principal component analysis has a high value for the application in environmental sciences, as it allows to draw conclusions about variabilities in large data sets from real-world monitoring setups despite gaps in time series."*

Analysed Data:

Only a very short period of eight months of soil moisture measurements have been analyzed. These time series additionally contained large data gaps, unfortunately during interesting times: (i) the period during steady rain mid of May, and (ii) the three weeks after the strong rain in July. Unfortunately, the data gaps meet particularly interesting situations where soil moisture information would have been very important to learn about the hydrological functioning at the site. The study would be improved strongly, when soil moisture data for a longer time period could be included. Maybe moisture time series of higher quality have been measured in the subsequent growing period.

We agree in terms of the detrimental long data gap. Still, other important and characteristic time periods of the year were covered, such as the moist winter months with subsequent rain falls in end of January and in February and the dry weeks in June. For modifications in the manuscript, see comment above.

The available soil texture information only contains sand contents in the upper 25 cm derived from geoelectric exploration. This information is poorly suited for process interpretations, because the sand content at the TDR-sensor positions varies in a very small range of only 3 % (between 77.9% and 80.7% ,Table 1), which might even be close to the uncertainties of the geoelectrical method. There are a lot of other potential factors determining the soil hydraulic properties (e,g, clay content, bulk density, organic carbon content, etc.), which have not been taken into account in this study. I think that this marginal variance in sand content cannot be used alone to explain the soil moisture patterns identified by principal components. When single components shall be related to soil texture, more texture information from all considered soil depths is needed. Therefore, I highly recommend going back to the field, taking new soil samples (e.g with a small hand auger or a gouge auger) and determining their sand silt and clay contents.

In the meantime, additional data were provided. They are manual soil auger results until 1 m depth available from project activities in the DFG excellence cluster PhenoRob for eight out of twelve analysed patches. However, even that larger sample size did not exhibit clear correlation with principal components, which might partly at least be due to enhanced nugget effects, and partly due to soil structure effects that are not reflected by soil texture data. Thus our results in terms of soil heterogeneities as the main drivers on different loadings on single principal components are based only on indirect inferences.

Regarding data on organic carbon, we assume that rather the quality than the measured quantity plays a role, as elaborated in the Results and Discussion Section on PC4. See comment below for further explanations.

Findings, interpretations and conclusions:

The 1st, 2nd and 5th principal components could be related to reasonable controlling factors and the process interpretations also seem plausible. This does not apply to the third and fourth components. The interpretations of these components are not based on solid data.

I assume that either the information actually needed to interpret these PCs is not available, or that the PCA fails to provide clearly interpretable components here. The weak interpretation of the third and fourth components should be discussed in more detail. In general, there should be more discussion of the suitability of the available data for principal component interpretation.

We elaborated and refined our reasoning in terms of the third and fourth component. We agree that these arguments are far from unequivocal proofs. But we consider it worthwhile to consider even unexpected results. E.g., the interpretation of the fourth principal component is consistent with own observations and similar observations made by other colleagues (e.g., Döring et al., in preparation).

We added elaborations on our interpretations about soil organic carbon in line 321-324 in the Discussion section for our readers: *"Usually, such effects are assumed to occur only at larger time scales, which is closely related to problems of detecting changes soil organic carbon quantity or quality. So far there is only anecdotal evidence for rather short-term soil organic carbon quality affecting soil hydraulic properties even at smaller time scales. Although this effect constituted only a minor share of soil moisture variance (Table 4), it was clearly discernible as a separate principal component. This effect would be worth to be tested in more detailed studies."*

Minor comments

L30-32: Please, provide some more references for the effects listed.

Additional references were included:

- Fischer, C., Roscher, C., Jensen, B., Eisenhauer, N., Baade, J., Attinger, S., Scheu, S., Weisser, W. W., Schumacher, J., Hildebrandt, A.: How Do Earthworms, Soil Texture and Plant Composition Affect Infiltration along an Experimental Plant Diversity Gradient in Grassland?, PLos ONE, 9, 6, https://doi.org/10.1371/journal.pone.0098987, 2014.
- Koudahe, K., Allen, S. C., Djaman, K.: Critical review of the impact of cover crops on soil properties, International Soil and Water Conservation Research, 10, 343-354, https://doi.org/10.1016/j.iswcr.2022.03.003, 2022.
- Nunes, M. R., van Es, H. M., Schindelbeck, R., Ristow, A. J., Ryan, M.: No-till and cropping system diversification improve soil health and crop yield, Geoderma, 328, 30-43, https://doi.org/10.1016/j.geoderma.2018.04.031, 2018.

L33: What is exactly meant by "complexity of the assessment and monitoring". What shall be assessed and why?

We revised the phrase as follows: *"However, as the diversity of independent variables in agricultural systems increases, demands for frequency and spacing of soil moisture measurements and related data interpretation grow".*

L47-50: "Soil moisture variograms" are a poor example for "sophisticated data analysis approaches", because they are very simple. Please rephrase or find another example.

We rephrased the formulation: *"Methods include geostatistical analysis (Vereecken et al., 2014) or data driven approaches (Hong et al., 2016)."* Examples for more sophisticated approaches are given in the following sentence.

L55-57: The concept of "temporal stability" was introduced by Vachaud (1985) (https://doi.org/10.2136/sssaj1985.03615995004900040006x) which should be acknowledged with a citation. The review by Vanderlinden et al. (2012) (https://doi.org/10.2136/vzj2011.0178) also seems to be a very suitable reference here.

Thank you for the valuable note, the references were added to the manuscript.

L64: The term "highly diversified fields" should be defined more exactly.

The term has been defined more clearly in line 73-74 as follows: *"The main objective of this study was to identify the drivers of soil moisture variability in a diversified cropping field in terms of crop selection, soil type and field management by applying PCA".*

L83-84: What is a "yield potential zone"?

We added elaborations in line 88-90: *"To that end, a cluster analysis was carried out based on soil maps and multi-year (2010 to 2019) yield data to identify high and low yield potential zones in the 70-ha large field (Donat et al., 2022)."* Details can be found in the given reference.

Table 1: What is meant by "treatment"? Readers might think about pest control or soil tillage. Maybe you can find another term.

We decided to re-name this column to "crop groups". This was further clarified in the following sentences in line 94 to 95: *"In the cropping season 2020/2021, seven different main crops were grown, for subsequent data interpretation, crops have been grouped into A) winter crops, B) fallow, followed by summer crops and C) cover crops, followed by summer crops."*

Table 1: The "highly heterogeneous soils" (L75) are not reflected in the sand content listed in the Table. They vary only in a range of 3%. Therefore, I expect that they cannot explain large parts of the soil moisture variance. The clay content would be much more interesting here.

The sand content in the upper layer at the study site varied between 69 % and 81 % according to the analysed Geophilus data. However, the variability in the analysed patches was indeed low.

The mentioned data from augers show that texture variability increases over depth. However, the sampling size is relatively small and the data show considerably high nugget effects. Thus, the data could not be used to represent the subsurface structure of the soil sufficiently and were not included into further analysis.

L94-98: The technical description should be improved. What do the "node boxes do"? How are the TDR sensors connected to the node boxes?

We elaborated the technical description of the sensor system and provide all hardware details in lines 102 to 107 as follows: *" In each patch, one Dribox box equipped with a SDI-12 distributer (serial data interface at 1200 baud rate, TBS04, TekBox, Saigon, Vietnam) connected to six TDR-sensors (TDR310H, Acclima, Meridian, USA) and attached to an outdoor remote terminal unit (RTU) fully LoRaWAN compliant (TBS12B: 4+1 channel analogue to SDI-12 interface for 24 Bit A/D conversion of sensor signals, TekBox, Saigon, Vietnam) was installed. The Dribox was deployed at least 0.3 m below ground to allow normal field traffic and soil tillage."*

L102: How have the meteorological data been measured?

This information has been added in lines 116 to 119 in the Methods section as follows: *"Precipitation and temperature data (Fig. 1) were obtained from two weather stations located in the Eastern and Western end of the main patchCROP field with a 15 min temporal resolution. Climatic water balance was calculated from precipitation and potential evapotranspiration, both measured at the climate station by the German Weather Service in Müncheberg (DWD Climate Data Center (CDC), 2021)."*

L111: Which physical variable is meant by "near infrared" and the red band? The intensity? or a relative share?

Details were added in line 129-130 as follows: *"in which NIR is the intensity of reflected near-infrared light (reflected by vegetation) and Red the intensity of reflected red light (absorbed by vegetation)."*

L124: I really regret (i) that the considered time periods are so short and (ii) that the data gaps occur during the most interesting periods. I see this as one of the biggest problems in this study. Is it possible to extend the period or maybe use other data from the following growing period?

We agree in terms of the detrimental long data gap. Still, other important and characteristic time periods of the year were covered, such as the moist winter months with subsequent rain falls in end of January and in February and the dry weeks in June. We added in line 365-367: *"It has been shown that principal component analysis has a high value for the application in environmental sciences, as it allows to draw conclusions about variabilities in large data sets from real-world monitoring setups despite gaps in time series."*

On the other hand, though, considering longer time series beyond the length of a single cropping period would cause another problem inasmuch as effects of different crops would mix up in the soil moisture readings of single sites. Thus, identification of crop-related effects would hardly be feasible.

L128-130: Please explain the implications of the z-transformation. Readers have to know that the z-transformation has to be kept in mind when interpreting the scores of a PC.

To further clarify this aspect, the following sentence was added in line 167: *"As a consequence, differences of absolute values were not considered by the further analysis."*

L140-141: Please rephrase the explanation of the criterion by Kaiser (1960). Eigenvalues greater than one indicate that a PC explains more variance than one input time series can contribute to the total variance of the entire input data set.

To further clarify this aspect, the following sentence was added in line 176-177: *"Eigenvalues greater than one indicate that a PC explains more variance than a single input time series could contribute to the total variance of the entire input data set (Kaiser, 1960)."*

L143-145: I don't understand what has been done here and why. Please provide more information.

This part of the methodology was not necessarily important for the manuscript and was therefore deleted.

L156-161: Please mention in half a sentence why the scores and loadings of the first PC are not shown here in the manuscript.

Since the loadings on the first PC were all one-directional, and the first PC does not indicate more than the degree of similarity with mean behaviour at the site the graphic was not shown. However, it is provided in the appendix (Figure 12, Appendix B).

L183-189: It is very difficult to follow and to understand the effects and potential causal relations that are described here. For example: Soil temperature is negatively correlated with the loadings of PC 2 which in turn indicate a negative (summer crops) and positive (winter crops) correlation between the moisture time series and the scores of PC 2. I am sure that most readers (including me) need a better explanation of these dependencies. They need to be better guided in order not to get lost.

The paragraph has been re-formulated (line 227-231): *"At the end of May, the NDVI, as a proxy for photosynthesis potential, was positively correlated with the loadings (Table 3). Surface temperature exhibited a negative correlation. The spatial pattern of surface temperature is assumed to be inversely related to that of actual evapotranspiration. Thus, both proxies, NDVI and surface temperature, support the inference that positive loadings on this principal component represent sites with above-average plant activity and root water uptake by the end of May."*

Figure 4: What about harvesting? In August the winter crops (blue line) have constant scores (indicating stopped transpiration after harvesting?) while the scores describing moisture dynamics for summer crops (red line) are still decreasing (ongoing transpiration?). Unfortunately there is a data gap.

We agree, this effect can be attributed to the earlier harvesting of winter crops. We added this observation to the description of the Figure as follows (line 217-218): *"In July and August, the approximately constant level of the blue curve indicates that only winter crops continue to consume water while summer crops are in their ripening phase and eventually harvested."*

190-195: It is hard to follow the description of the third PC. I have the feeling that in the third PC the effects of several factors interact. Perhaps the relevant supporting information to understand PC 3 is simply not known. If the authors are really confident in their interpretation of the third PC, they should describe the relationships more clearly. If they are skeptical, as I am, they should discuss these problems in detail.

Further explanation on how to read Figure 6 is given in the Methods section in line 180-187 as follows: *"The scores of the principal components constitute time series. Every observed time series can be presented at arbitrary precision as a combination of various principal components. When the data set consists of time series of the same observable measured at different locations, the first principal component describes the mean behaviour inherent in the data set. Subsequent principal components reflect typical modifications of that mean behaviour at single locations due to different effects. Thus generating synthetic time series as linear combinations of the first PC and another additional PC helps to assign this additional PC to a specific effect. To that end scores of that component have either been added to or subtracted from those of the first component using arbitrarily selected factors. The two resulting graphs show how the respective PC causes deviations from the mean behaviour of the data set."*

We added details on the interpretation of Figure 6 in the Results section in line 242-244: *"The most obvious difference between the orange line (negative loading on PC3) and the blue line (positive loading on PC3) during the first half of the study period is that the latter reaches a maximum of soil moisture after rainfall much earlier compared to the former (Figure 6)."*

Due to the local, non-systematic occurrence of particularly pronounced loadings we attribute this PC to soil properties. We hope that the changes, together with the lines 333-338 in the Discussion section, allow the reader to follow our interpretations: *"Loadings on the third principal component were not related to crop types. In contrast, a spatial pattern emerged: Only sensors from 0.9 m depth from six adjacent patches exhibited strongly negative loadings (Figure 2) whereas all other sensors showed minor positive or negative loadings. This points to an effect of subsoil substrates, that is, higher clay content and consequently higher water holding capacity. That would be consistent with delayed response to seepage fluxes and reduced desiccation in the vegetation period (Figure 6). Data on the texture at the sensor location in deeper layers can help to confirm the assumptions."*

L203-205: Are the correlations with the sand contents not shown? As mentioned earlier, I don't think that the sand content can explain any variance due to its small variation.

For interpretations of the sand content, we refer to our comment above (General Comments, Reviewer 1): "We agree that in our study soil texture exhibits little heterogeneity in the first layer and thus the results allow only limited inferences on soil heterogeneity effects. After first submission of the manuscript additional soil data were analysed. However, even that larger sample size did not exhibit clear correlation with principal components, which might partly at least be due to enhanced nugget effects, and partly due to soil structure effects that are not reflected by soil texture data. Thus our results in terms of soil heterogeneities as the main drivers on different loadings on single principal components are based only on indirect inferences.

L203-209: It is rather difficult to interpret the effects of two different factors (cropping system and sand content of upper 25 cm) in PC 4, which explains only 2.2% of the total variance.

The results of the PCA show that a large part of the variance results from the meteorological signals. Another substantial part stems from the difference between summer and winter crops. We therefore interpret the results in such a way that the part of the variance that lies on PC4 does not cover the entire effect of the cropping system, but only a partial aspect.

For our interpretations on the effect of the cropping system on PC4, please see the comment on general comment of Reviewer 2 on findings, interpretations and conclusion: “We agree that our arguments are far from unequivocal proofs. But we consider it worthwhile to consider even unexpected results. Our preliminary interpretation of the fourth principal component is consistent with own observations and similar observations made by other colleagues (e.g., Döring et al., in preparation). Effects of changing soil organic carbon quantity and quality are assumed to occur only at larger time scales which is closely related to the problem of detecting respective changes within shorter periods. However, that might be more a problem of detectability rather than a sound disproof of the suggested mechanism. We think more research is needed here, including but not being restricted to indirect methods like that used in our studies.”

L217: Please check if it should be lupine instead of sunflower.

Thank you for the valuable remark. It is indeed lupine as was modified accordingly in the respective line of the manuscript.

L222-223: I don’t really know what is meant here. Is redundancy here the correct term?

We revised the wording as follows (line 271-273): *“The first five principal components described about 97% of the variance of the data set, which consisted of observed time series from 64 soil moisture probes and revealed various effects of weather, soil texture, soil depth, crops and management schemes.”*

L232: “quantification of the strength of these effects” might be more precise

We revised the wording into *“quantification of the impact of these effects.”*

L247-250: Please check if Yang et al. (2015) have also z-transformed their data. If not it might be difficult to compare their findings with those of this study.

Since no z-transformed data set was used in the reference and the type of vegetation in the referenced study also differed, we decided not to make a comparison to the results of this study.

L265: What do you mean by loamy soils? I think that all soils at the site are sandy soils.

The phrase has been re-formulated (line 315-316): *“According to this component, soil moisture dynamics at the fallow patches resembled more the typical behaviour one would expect for sandy soils, and that of winter crop patches more a more damped behaviour typical for more loamy soils.”*

L265-267: Very speculative. I think that an increase of carbon stock happens at larger time scales and can unlikely explain the moisture patterns explained by PC 4.

For our interpretations on the effect of the cropping system, please see the comment on general comment of Reviewer 2 on findings, interpretations, and conclusion:

We elaborated and refined our reasoning in terms of the third and fourth component. We agree that these arguments are far from unequivocal proofs. But we consider it worthwhile to consider even unexpected results. E.g., the interpretation of the fourth principal component is consistent with own observations and similar observations made by other colleagues (e.g., Döring et al., in preparation).

We added elaborations on our interpretations about soil organic carbon in line 321-325 in the Discussion section for our readers: *"Usually, such effects are assumed to occur only at larger time scales, which is closely related to problems of detecting changes soil organic carbon quantity or quality. So far there is only anecdotal evidence for rather short-term soil organic carbon quality affecting soil hydraulic properties even at smaller time scales. Although this effect constituted only a minor share of soil moisture variance (Table 4), it was clearly discernible as a separate principal component. This effect would be worth to be tested in more detailed studies."*

L274-291: I can imagine that soil texture is an important factor controlling soil moisture dynamics at the investigated site. However, as mentioned before, more information about the depth distribution of soil texture is needed. If it is planned to run the "patchCROP" experiment for longer, it is really worth going back to the field, collecting soil samples at each TDR sensor position in 30, 60, and 90 cm depth and performing a texture analysis.

As described, data on soil texture in different depths are available for the majority of the analysed patches, which show that the variability is high, at least in deeper layers. However, it was decided not to use these for correlations with the loadings, as the transferability from the sampling point to the sensor point is not certain (see also reply to comment on L206-209 by Reviewer 1).

L296: I agree that it is important to study the interaction of different factors in their effect on soil moisture dynamics. Unfortunately, in these interactions, the patterns identified by a PCA often become blurred, making interpretation difficult with the usually limited supporting information available.

We consider PCA a powerful tool in this regard, although only just another step on the way to develop diagnostic tools for complex real-world systems. We added a corresponding statement (line 353-354): *"Principal component analysis is a further step to meet these challenges although not entirely without problems."*

L304-305: I agree, but is that conclusion really founded on the findings of this study? The sentence could also be shifted to the introduction.

The phrasing was revised to highlight the connection between the study and this statement (line 362-363): *"In particular, the plant-induced effects on soil hydraulic properties would be worthwhile to be studied in more detail. Knowledge from data-driven approaches can support adequate crop selection as a management option to encounter the increasing drought risk in the study region."*

L307-309: This paragraph might be shifted to the discussion section.

The phrasing was revised to highlight the potential of such analyses as one of the conclusions drawn from this study (line 367-370): *"Information from this study will contribute to elucidate management effects as well as to develop both parsimonious and tailored mechanistic models. Findings of this study highly depend on local conditions. However, we consider the presented approach generally applicable to a large range of site conditions. In this regard, principal component analysis of soil moisture time series performed as a powerful diagnostic tool and is highly recommended."*