In the manuscript the authors compare modeled and measured soil moisture in the context of landslide prediction in Switzerland. Measurements are available at 35 sites across Switzerland, while the 1D soil moisture transfer model CoupModel providing estimates of soil moisture is set up at 133 sites. The landslide prediction model used is based on different soil moisture metrics and optimized by using ROC-statistics.

The authors carry out different comparisons/experiments: comparing measured and modeled soil moisture over 14 reference sites, comparing performances of the landslide prediction model based on measured or modeled soil moisture, studying the impact of boundary conditions of the hydrological model, and the impact of soil parametrization (using soil samples, uniform texture sets, or soil properties obtained with pedotransfer functions and the SoilGrid database).

The authors find that modeled soil moisture is outperforming measured moisture, that the model is sensitive to boundary conditions, and performances worsen as the distance between soil moisture and landslide locations increases.

The manuscript is clear, well written and structured, and the topic addressed is relevant. Overall, the manuscript is worth publication in hess.

We thank the reviewer for the generally positive response and the constructive comments which we addressed below.

Nevertheless, there is one important aspect which is worth addressing and discussing more in details, concerning the choice and results of the hydrological model. It has been shown in previous studies that vertical flow is the dominant process leading to landsliding, compared to lateral flow (e.g., Iverson 2000), but lateral flow becomes essential for adequate description of initial soil moisture conditions (e.g., Mirus et al., 2017, Leonarduzzi et al., 2020). This idea and the fact that the model seem to reproduce mostly just event dynamics is confirmed by several of the results:

- Figure 4: the better R2 for shallowest depth (typically better matching the patterns of meteorological forcing)
- Underestimation of seasonal variations of soil moisture
- Line 382-383: "resulting even in a slight forecast goodness increase for extreme and normal coarse-grained uniform-texture profiles". Using a highly conductive soil which drains quickly, basically reduce the model to "get rid" of initial conditions and just represent the current infiltration event (i.e., your estimate of soil moisture is basically matching P-ET). But these soils are the one giving the worst match to measured soil moisture
- 9: modeled moisture outperforming measured moisture for event dynamics but not for antecedent condition metrics.

All these aspects, lead me to think that what is happening is that the hydrological model is actually just using the information in the recent meteorology (transformed into saturation estimate using soil parameters), while the "memory" component of saturation is not well represented/useful for landslide prediction. This is sort of the opposite of what one would expect in terms of information context in a "antecedent condition" metric, as typically saturation is considered a "cause", while recent rainfall the "trigger". The authors checked this by comparing the results to a simple rainfall-based prediction and indeed find similar performances. It would be worth exploring, or at least addressing, if using a combination of measured soil moisture (providing antecedent conditions) and rainfall event dynamics (possibly accounting also for soil properties), would actually lead to better landslide predictions (e.g., logistic regression using antecedent conditions saturation metrics measured/observed and rainfall event metrics). This would not invalidate the work presented or any of the findings but would definitely be a more complete/objective answer to the question the authors pose in the title: “Simulated or measured soil moisture: Which one is adding more value to regional landslide early warning?".

We acknowledge that the model is better at reproducing the event conditions and worse at characterizing initial saturated conditions. We addressed this in the discussion section and attributed the underrepresentation of the seasonal soil moisture cycle mainly to the definition of a common parametrization of the upper and lower boundary conditions (lines 435 – 455). We used a common parametrization set in order to be able to apply the model at sites where no site-specific calibration is possible (due to missing soil moisture measurements, soil moisture measured at distance from the meteorological site or located in the forest), which often is the case with landslide early warning systems where soil moisture is simulated. We agree that the use of a one-dimensional model which does not account for lateral water transport may add to the missing seasonal cycle too. We chose a 1D modelling approach due to computational restraints while still permitting a good representation of infiltration characteristics. We will discuss the motivation behind the common parametrization and the model choice in more detail in the revised paper.

As the reviewer suggested, we fitted a landslide forecast model using antecedent saturation and event rainfall amount only using the same logistic regression model. We used both measured and simulated soil moisture and we compared these model fits to a landslide forecast model using rainfall information only (Figure S1). The analysis was conducted using all common sites and the same time periods (35 monitoring sites, 2008 – 2018), hence the lower number of infiltration events. Compared to using rainfall only, the forecast goodness increases at most forecast distances if antecedent soil moisture is used too, except for the 5 km forecast distance. This may be due to a low robustness of the statistical model fit at short forecast distances due to a low number of landslide triggering events. The forecast goodness improvement is more pronounced if measured soil moisture is used and it is only marginal if using simulated soil moisture, which is in line with the above discussion about the underrepresentation of the seasonal water storage. We will include this figure in the revised paper and expand the discussion.

As mentioned in the reviewer’s comment, in an applied context, soil moisture information will be used primarily as an antecedent metric to complement rainfall information. In that sense, the characterization of the antecedent saturation should be improved which could be achieved by the use of site-specific or regional-specific parametrization, or the use of more spatially integrated models. The objective of this paper however was not to produce specific soil moisture thresholds or an operationally applicable model, but rather to test the overall information content of soil moisture information and to highlight the differences between using simulated or measured soil moisture. We will clarify the objectives of this study in the revised paper.

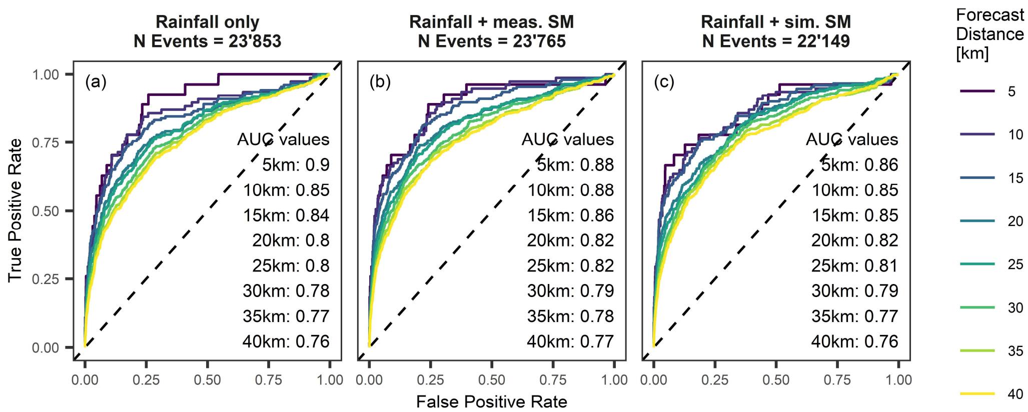

Figure S1 ROC curves and AUC values of model fits (a) using rainfall amounts only, (b) using antecedent saturation (measured and rainfall amounts and (c) using antecedent saturation (simulated) and rainfall amounts, for all 35 monitoring sites for the period of 2008 to 2018.

Finally, some minor comments:

- In Figure 5, are the lines showing the average across 14 sites for each depth?
  Yes, the lines show the average profile saturation across 14 sites, with the profile saturation being the mean saturation of all model depths or sensor depths. We will make this clearer in the revised manuscript.
- It could be interesting (although probably worth including only in the appendix), to see the trends of soil moisture observed and measured at different depths.
  We have added the measured soil moisture time series to the plot (Figure S2). Further, we have added a trend line to all time series. While a negative trend is visible at the measured time series, there is no apparent trend for the modelled time series which might be due to an underrepresentation of evapotranspiration in the model. However, the negative trend of the measurements might as well be influenced by non-stationary soil moisture measurement time series, e.g. due to compaction of the soil or enhanced root development around the sensors, as some of the sensors have been running for almost 10 years. Further, different numbers of sensors were integrated over different time periods as not all sensors have been installed at the same time which adds to the uncertainty of interpreting a long-term trend in this integrated signal. To assess the reasons for the trends in the measured time series, they could be compared to other long-term hydrological measurements such as ground-water or runoff time series from nearby stations, which would be needed if a site-specific calibration was conducted. In the revised paper, we will include the new figure and discuss the trend lines it in more detail.

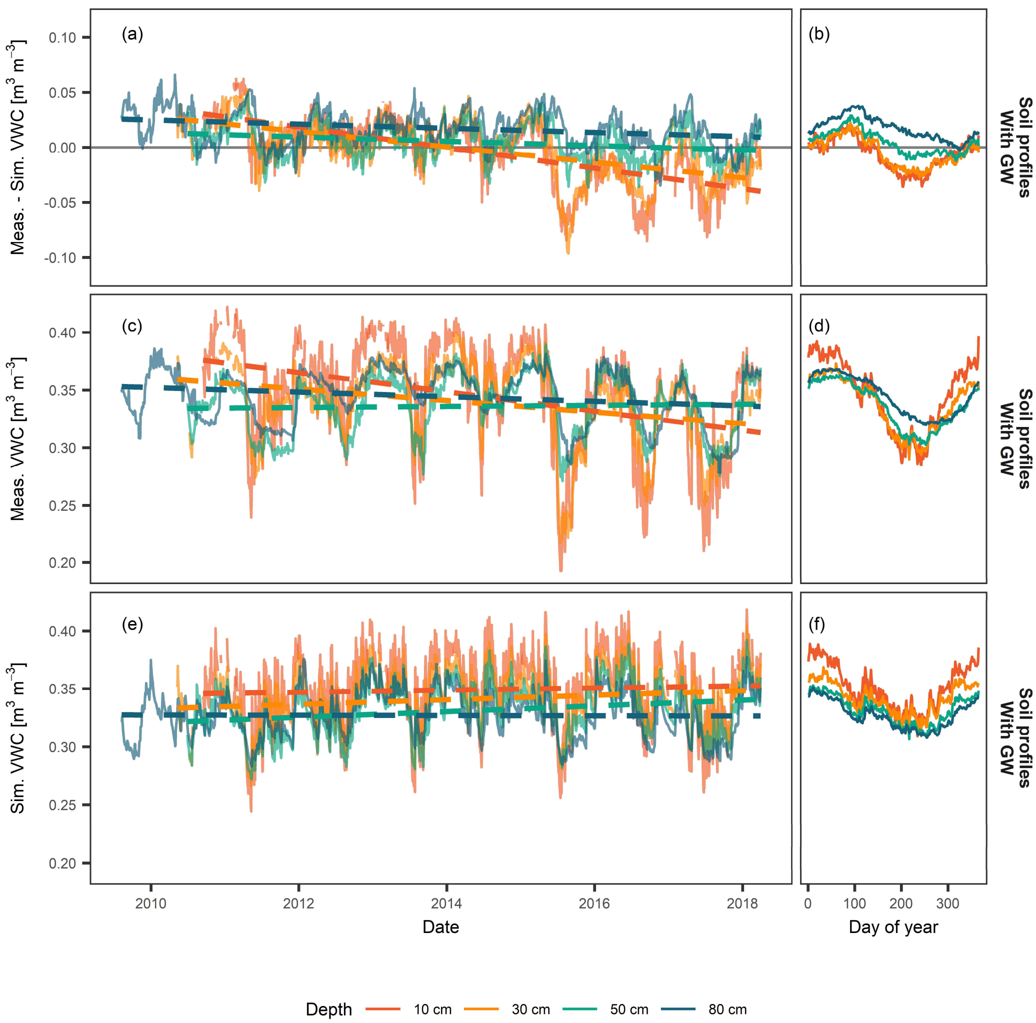

Figure S2 Temporal evolution and seasonal variation of mean daily residual VWC (a, b), i.e. deviation between simulated and observed soil water content, and mean daily measured (c, d) and simulated VWC (e, f) across all 14 reference sites by sensor depths (different colours) for a CoupModel set-up using soil hydrological properties derived from SoilGrids and a lower boundary condition with groundwater. Panels c and e include trend lines by sensor depth.

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