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Soil moisture-vegetation interaction from near-global *in-situ* soil moisture measurements

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Abstract

Although the interactions between soil moisture (SM) and vegetation dynamics have been extensively investigated, most of previous findings are derived from satellite-observed and/or model-simulated SM data, which inevitably include multiple sources of error. With the effort of many field workers and researchers in *in-situ* SM measurement and SM data integration, it is now possible to obtain the integrated *in-situ* SM dataset in the global range. Here we used the *in-situ* SM dataset of the International Soil Moisture Network to analyze the anomaly correlation between SM and leaf area index (LAI). We found that positive (negative) correlations exist between SM (LAI) and temporally lagged LAI (SM). The peak correlation and lagging time to reach it (often less than 3 months) depends on climate, land cover and rooting depths. The high SM-LAI anomaly correlation prevails in water-limited regions, e.g. dryland, where plant physiology has strong sensitivity to subsurface water stress. Dynamics of vegetation with deeper maximum rooting depths are not always correlated with SM in deeper soil layers, and vegetation dynamics with shallower maximum rooting depth may strongly correlate with SM in deeper soil layers. Overall, we highlight the potential of the global *in-situ* SM observation network to analyze the interactions between SM and vegetation dynamics.

1. Introduction

Vegetation dynamics has an important role in changing the climate. Over half of the global vegetation dynamics are accounted by hydrological processes, especially over drier regions (Heimann and Reichstein 2008, Chen et al 2014). Specifically, soil moisture (SM) can directly associate with vegetation dynamics and shape the local-scale vegetation distribution (Miralles et al 2010). The interaction between SM and vegetation dynamics is crucially important in numerous aspects (Van der Molen et al 2011, Bolten and Crow 2012) such as drought monitoring (Mo et al 2011, Hao et al 2014, Sawada 2018), cropland security (Bolten et al 2010, Asoka and Mishra 2015), land carbon cycles (Trugman et al 2018) as well as climate modeling (Dirmeyer et al 2018, Gallego-Elvira et al 2019). One critical feature of the SM-vegetation interaction is the time lag effect, i.e. local SM (vegetation)

might have a stronger connection with the temporally lagged vegetation (SM) (Adegoke and Carleton 2002, Ji and Peters 2003, Vicente-Serrano *et al* 2013). In the light of it, some early warning systems have been built to monitor drought and vegetation growth, so as to minimize losses in food production and better manage water resources during the stress conditions (Funk and Brown 2006, Asoka and Mishra 2015). Nevertheless, at the global scale, the knowledge on the relevance, timing, and conditions regulating the SMvegetation interactions is still lacking.

Owing to the merits of their extensive spatialtemporal coverage, high availability and affordability, the current analyses on the correlation between SM and vegetation are mostly derived from satellite observation and/or numerical simulation of land surface models (Seddon *et al* 2016, Madani *et al* 2017, Stocker *et al* 2018, Walther *et al* 2019, Stocker *et al* 2020, Li *et al* 2021). However, nonnegligible biases are included in satellite observation and land surface models. On the one hand, satellite sensors operate at coarse spatiotemporal resolutions, which inevitably interferes the accurate SM measurement (Srivastava *et al* 2013, Dorigo *et al* 2017). In addition, only few centimeters' sensing depth of satellite sensors makes it difficult to detect SM in the deep soil layer (Ulaby 1982, Albergel *et al* 2008, Brocca *et al* 2011, Dorigo *et al* 2015). On the other hand, the land surface models have been widely recognized to suffer from the uncertainty in model parameters, model structure and forcing data, which degrades the accuracy of the SM estimation (Vrugt and Sadegh 2013, Dumedah and Walker 2014, Fang *et al* 2016).

In contrast, in-situ SM observation has relatively limited bias, especially in small spatial scales (Famiglietti et al 2008, Gruber et al 2013). In many in-situ SM observation sites, the subsurface SM data can be obtained (e.g. from surface to 1-2 meters in the soil), where water amount variation and rooting dynamics are active. While the satellite-observation can only infer them from surface SM, the in-situ observations can directly 'see' the critical dynamics. With the rapid growth of ground-based observation networks, the in-situ SM data are recently better maintained and organized in the global scale than in the past (Dorigo et al 2011, 2021), covering a wide range of climate and land cover regions. Despite the varying quality, spatial sampling densities, and uneven overall distribution of in-situ SM stations over the globe (Babaeian et al 2019), it provides a unique opportunity for the SM and vegetation correlation analysis in different soil depths and under various conditions.

Despite a lot of efforts in analyzing the SMvegetation interaction at the global range, no studies fully used the high potential of the global in-situ SM observation network. We aim to quantify the relevance, timing, and conditions regulating the SMvegetation interactions at near-global range using insitu SM observations. Thus, in this paper we will answer the following scientific questions: In a nearglobal range, (a) How does the *in-situ* observed SM correlate with leaf area index (LAI) when the timelagged effect is considered? (b) How different the insitu observation-based SM-LAI anomaly correlations are in the different soil depths? (c) How different are the correlations across different climate and land cover conditions, and ecosystems with different rooting depths?

2. Data and methods

2.1. Data

2.1.1. SM and LAI data

In this study, the *in-situ* SM data of the International Soil Moisture Network (ISMN) were used (Dorigo *et al* 2011, 2021). In ISMN, the *in-situ* SM measurements from operational networks and validation campaigns are collected, harmonized, and made available after quality examination. The ISMN's hourly observed SM record, which spans from 1952 to present, includes 2678 stations in 65 networks over the globe. Figure 1 shows the global available stations and networks during 2000–2015.

As a proxy of vegetation dynamics, the LAI data are derived from the globally re-processed moderateresolution imaging spectroradiometer (MODIS) dataset by Ichii *et al* (2017). In the processed dataset, the MODIS LAI data are retrieved every 8 d ranging from 2000 to 2015, with spatial resolutions of ranging from 500 m to 30 km.

2.1.2. Climate and land cover maps

To analyze the spatial distribution of the SM-LAI correlation, we classified the *in-situ* SM stations into different groups based on climate and land cover maps.

We used the Koppen-Geiger climate map of the present day (1980–2016), which includes up to 30 climate classes (Beck *et al* 2018). The 4 broad definitions of climate classifications, i.e. humid, temperate, dry and cold were considered for analysis, so as to include the sufficient number of the *in-situ* SM observations in each climate classification.

For land cover types, we used the yearly land cover map of the International Geosphere-Biosphere Programme (IGBP) class from MODIS (Friedl and Sulla-Menashe 2015). We selected the land cover map in 2008 since it is in the middle of our study period (2000–2015). Despite the fine classification scheme in the original map (16 land cover types), the *in-situ* SM stations were classified into the five broad land cover groups: forest, savanna, shrub, grass and crop.

2.2. Method

2.2.1. Quality control

Although the *in-situ* SM data in ISMN have been carefully examined, additional quality control was performed to investigate the long-term interactions between SM and LAI. To have sufficient SM and LAI data points for comparison, *in-situ* SM observations were used only if completely continuous SM timeseries lasted for longer than 5 years in the study period (2000–2015). As a result of quality control, data duration longer than 10 years exists in approximately half of the total grid cells (figure 1).

2.2.2. Grid map coordination

Since MODIS LAI is the grid-based data and the ISMN *in-situ* SM is the point-based data, they are not straightforward to be directly compared. However, many studies found that *in-situ* SM observation can, to some extent, represent its surrounding SM condition (Brocca *et al* 2007, Famiglietti *et al* 2008, Brocca *et al* 2010, 2012,). For the SM-LAI comparison, the *in-situ* SM data have been upscaled to match



Figure 1. Global distribution of available grid cells over four soil layers for the SM-LAI interaction analysis, with a close-up view of the densely clustered grid cells in North America (there are no valid cells in South America). Data duration in each cell is represented by the depth of red color. In each soil layer, inset bar plot shows the grid cell number in 2 categories: data duration ranging (a) from 5 to 10 years and (b) from 10 to 15 years.

the grid-based LAI data by (a) defining a global gridded map that corresponds to the coordinate system of the LAI data, (b) assigning each *in-situ* SM observation station to its nearest grid cell and (c) calculating the grid-averaged *in-situ* SM as the representative value for each grid cell, if there are a plural number of stations in the specific cell. Here *in-situ* SM data are rescaled to the 500 m grid cell, i.e. the highest spatial resolution of the LAI data, which minimizes the scaling errors. It has been shown that a single *in-situ* SM station in ISMN has the accurate representation of areal data with the spatial resolution of up to 50 kilometers (Nicolai-Shaw *et al* 2015), which can therefore be used as a reference for coarse-scale mean SM (Jackson *et al* 2010, Albergel *et al* 2012). Based on these findings, *in-situ* SM data upscaled to 500 m resolution should have high spatial representativeness and reliably represent the areal SM in the grid cell. In total, discarding overlapping grid cells in different layers, 733 valid cells are generated and available for subsequent analyses, most of which located in North America, Europe, Africa and Australia (figure 1).

2.2.3. Soil layer stratification

In ISMN, the measurement depths substantially vary among observation stations (Dorigo et al 2011). To analyze the contributions of SM in the different depths to the SM-LAI interactions, we categorized the measurement depths of the different stations. According to the measurement depths of the networks in ISMN, we discretized the subsurface soil profile into 4-layer: 1st layer (0-0.1 m), 2nd layer (0.1-0.5 m), 3rd layer (0.5–1 m) and 4th layer (soil below 1 m). SM measured at different depths was assigned to these four corresponding layers. If more than one SM observations are categorized in a single layer, the averaged SM in each layer was calculated and recognized as the representative SM value in that layer. Figure 1 shows a sufficient distribution of available in-situ SM observations in upper soil layers, despite the relatively small number of observations in the deepest layer (figure 1(d)).

In addition, we explored how SM-LAI interaction varies for vegetation with different rooting depths, i.e. the deepest soil depth reached by the roots of individual plant (Schenk and Jackson 2002). The maximum depth of root water uptake dataset generated by Fan *et al* (2017) was used as the proxy of rooting depth. Using an inverse model, Fan *et al* (2017) derived the rooting depth by estimating root wateruptake depths at 1-km global grids with observed vegetation productivity and atmosphere data, which highlights the plant-water feedback pathway. The *insitu* SM stations were classified into four groups by rooting depth, corresponding to the four soil layers defined earlier.

2.2.4. Time lagged anomaly correlation

To remove seasonal cycles, the anomaly correlation between SM-LAI was used. Due to the lower dynamic range of anomalies, the scaling error in the anomaly correlation is expected to be lower than that in the absolute values of SM (Gruber *et al* 2013). The anomaly correlation between SM and LAI $r_{SM,LAI}$ was calculated as follows:

$$r_{SM,LAI} = \frac{\sum_{t=1}^{T} (SM_t - \overline{SM}) (LAI_t - \overline{LAI})}{\sqrt{\sum_{t=1}^{T} (SM_t - \overline{SM})^2} \sqrt{\sum_{t=1}^{T} (LAI_t - \overline{LAI})^2}}$$

where *T* denotes the length of the temporal range in 8 d, SM_t and LAI_t denotes 8-daily time-series of normalized SM and LAI anomalies, \overline{SM} and \overline{LAI} denotes multiyear averaged 8 d value of normalized SM and LAI anomalies, respectively.

Generally, wetter soils can induce greater subsequent vegetation growth while denser vegetation can lead to greater transpiration and thus less subsequent SM (D'Odorico *et al* 2007, Wu *et al* 2015). To explicitly demonstrate the time lag effect as well as the simultaneous SM-LAI anomaly correlation, we calculated the anomaly correlation coefficients between SM and LAI that lagged for $n \times 8$ d (integer n ranges from 1 to 12). Similarly, we calculated the anomaly correlation coefficients between LAI and SM that lagged for $n \times 8$ d (integer *n* ranges from 1 to 12). The SM-LAI anomaly correlation coefficients calculated under the different lagged times will be compared and analyzed to reveal the magnitude of the time lag effect.

Further, the Wilcoxon signed-rank test has been conducted to evaluate the statistical significance of median value of anomaly correlation at different soil layers and time lags.

3. Result

Throughout all climate classes and soil layers, there are substantial differences between the SM-LAI anomaly correlations when LAI lags behind SM and those when LAI leads SM (figure 2). In most cases, there is no significant correlation if the lag time exceeds 3 months. According to figure 2, the highest SM-LAI anomaly correlation exists in the dry region when LAI lags behind, which indicates the strongest response of vegetation dynamics to SM variation in the water-limited ecosystems. In temperate and dry regions, the anomaly correlation reaches peak value when LAI lags behind SM by 8 d and 16 d, respectively. However, it takes approximately 1 month for LAI to respond to the advanced variation of SM in cold regions. In other words, vegetation greening responding to SM changes in temperate and dry regions needs shorter time than in cold regions. In addition, when LAI leads SM, strong negative correlation is found in cold regions, which takes about 8 d to reach peak value in upper soil layers. In temperate region, when LAI leads SM, the correlation shows weak statistical significance despite the sufficient available grid cells in the categories, which indicates that vegetation growth will less likely cause SM reduction. For the humid region, the anomaly correlation shows widespread statistical insignificance in deeper layers and when LAI leads SM, which is very likely due to the small amount of available data (figure 2). Generally, figure 2 indicates weaker SM-LAI anomaly correlation in deeper soil layers \overline{U}^{2} primary coupling between vegetation dynamics and \overline{U}^{2} SM in the shallower soil laws SM in the shallower soil layers.



Figure 2. SM-LAI anomaly correlation (median value) throughout four simplified climate classes (from Köppen-Geiger climate classifications), 4 soil layers considering different time lag scenarios is presented as heatmaps (left) and string diagrams (right), respectively. *x* axis in two diagrams denotes the temporal length that LAI lead SM in timeseries (negative value means LAI is temporally lagged). The hatched blocks in heatmap and hollow dots in string diagrams represent statistically insignificant SM-LAI anomaly correlation with a 95% significance level. The inset bar plots are attached to the heatmaps to show the number of available grid cells for each soil layer. Since the median value of SM-LAI anomaly correlation is closely fitted to the mean values (figure S2), we choose median value as the proxy to represent the average correlation. More detail information for the correlation is shown in figure S2 in the supporting information.

The time lag effect on the SM-LAI anomaly correlation can also be found when the in-situ observation stations are classified into the five land cover types (figure 3). The higher SM-LAI anomaly correlation exists in ecosystems of crop and grass (high correlation in shrub ecosystem are overall statistically insignificant and will not be discussed here). When timeseries of LAI lags behind, SM-LAI anomaly correlation has higher peak value and shorter response time (8 d to 1 month) to reach it in crop and grass ecosystems than in forest and savanna ecosystems. It indicates greater sensitivity of vegetation growth to SM variation in crop and grass ecosystems than that in forest and savanna ecosystems, especially over shallow soil layers. On the other hand, when LAI leads SM, it takes short time (8–24 d) to reach maximum negative correlation in most regions except for area where crop grows. In addition, in the deep soil layer the response of SM to LAI variation is negative in forest ecosystems but positive in crop and grass ecosystems. That is to say, the growth of grass and crop do not reduce SM in the deep soil layer.

SM-LAI anomaly correlation is also compared across ecosystems with different vegetation maximum root water uptake (figure 4). Vegetation whose maximum rooting depths is within the 1st soil layers may primarily uptake SM in the 1st layers. However, LAI of ecosystems with near surface roots are highly correlated with SM in the 1st, 2nd and 3rd soil layers when SM leads LAI by 16 d to 1 month. When SM lags behind LAI, there is no significant correlation between them. In general, unlike shallow root vegetation, in ecosystems with deeper roots LAI can lead to significant reduction in SM across upper layers. Nevertheless, the growth of deep root vegetation is less sensitive to SM variation when SM leads.

We further compare SM-LAI anomaly correlation across four climate classes and ecosystems with different vegetation rooting depths to reveal their differences in different time lags (figures 5 and S5). In temperate region, when LAI lags behind, it shows stronger positive anomaly correlations in the shallow root ecosystems than in the deep root ecosystems, especially for surface SM. In cold region, the growth of vegetation with deeper root has stronger negative impacts on subsequent SM by consuming more subsurface water resources. This trend is pronounced for shallow SM, while in deep soil layer the vegetation growth and SM variation shows little relevance due to the statistical insignificance. Deep root vegetation is dominant in dry region (figure S6). The growth of deep root vegetation positively correlates with SM



across different soil layers when LAI lags behind SM, especially in upper layer. Similar to temperate region, vegetation growth has little impact in SM reduction in dry region, indicating a less important role of vegetation growth in influencing SM variation there.

4. Discussion

This study reveals the SM-LAI interaction in various climate and land cover regions. Even though the in-situ SM sites are unevenly distributed in the globe (many of them are located in North America), the validity of the results is less affected because of their sufficient coverage of a wide variety of climates and land covers (figures 2-4). Based on the in-situ SM observations, the SM-LAI anomaly correlations found in our analyses are dominant with short time lag, which is in line with the published knowledge of regional studies (Adegoke and Carleton 2002, Ji and Peters 2003, Musyimi 2011, Chen et al 2014, Asoka and Mishra 2015, Sawada 2018). Our finding is also consistent to Miguez-Macho and Fan (2021), who clarified that nearly 90% of plant transpiration rely on the current month and pre-month atmospheric water input. In addition, the highest

SM-LAI anomaly correlation is found in the drier region because plant physiology has strong sensitivity to subsurface water stress under moisture-limited conditions (Stocker *et al* 2018, 2020, Jiao *et al* 2021). Further, SM variation can significantly influence the growth of vegetation with small biomass such as grass and crop, while large biomass plant like tree and savanna tends to consume more subsurface water to sustain its growth above ground (figure 3). The results confirm the different strategy towards SM variation adopted by herbaceous and woody vegetations (Anderegg *et al* 2019, Carminati and Javaux 2020). Nevertheless, despite the consistencies, some critical questions in the SM-LAI interaction remain unanswered by previous works.

Existing studies mainly addressed the SM-LAI interaction at the monthly scale, and the temporal extent of the response time in the SM-LAI interaction has not yet been fully clarified. We find that in temperate and dry regions, vegetation dynamics can quickly respond to SM variation in upper soil layer in as short as 8 and 16 d, respectively (figure 2). This study also thoroughly compares between the asymmetric responses of SM to LAI and LAI to SM, whereas previous studies mainly investigated









the effect of anomalous SM variation on vegetation growth (Chen *et al* 2014, Asoka and Mishra 2015). Our results indicate that vegetation growth will lead to quick (8–24 d) reduction in subsurface water for cold climate. On the other hand, there is no significant SM reduction in regions such as temperate area. Another finding is the quicker response of vegetation to SM in temperate and dry regions than that in cold regions (figure 2). This is probably because low temperature in cold regions freezes SM and prolongs the response time (Beck *et al* 2018, Li *et al* 2021).

By fully leveraging *in-situ* SM data synthesis, the straightforward comparison between SM-LAI coupling and estimated plant rooting depth could be implemented. The dominant vegetation type in arid region of our ISMN sites commonly has deeper root (figure 5), so previous studies revealed that they can easily tap into soil water in deep soil layers to adapt to the water scarce condition on surface (Neill et al 2013, Fan et al 2017, Li et al 2021). This study shows that they consume subsurface water in upper soil layers more often. This might be because some vegetation biomes have a larger portion of roots in the shallower depth than the maximum rooting depth (Jackson et al 1996), so that there is stronger SM-LAI coupling in shallower soil layers. Figure 4 shows the strong anomaly correlation between LAI and SM in subsurface soil layers even for shallow root vegetation. This can be expected as many empirical evidences point out that surface SM are typically correlated to some degree with changes in subsurface SM (Albergel et al 2008, Short Gianotti et al 2019).

Actually, the satellite and *in-situ* SM data are different in many manners such as extent, depth and preciseness and hence do not measure the same water volume (Gruber *et al* 2013, McColl *et al* 2014, Gruber *et al* 2020). Although previous works on the SM and vegetation interactions relied on satellite observed and/or model simulation data, we open the door to use the *in-situ* SM data to analyze the interactions.

In the meanwhile, the scaling error caused by aligning point-based SM to grid-based LAI data may still, to some extent, dampen the analyses (Gruber *et al* 2013). To enhance the validity of the conclusion, more sophisticated upscaling method is expected in the future as an avenue to minimize the scaling error.

5. Conclusions

Here we analyze the interactions between SM and vegetation dynamics in the near-global scale by maximizing the potential of the existing *in-situ* SM observation networks. The *in-situ* SM data from worldwide available networks organized by ISMN are used to analyze the anomaly correlation between SM and LAI. We reveal how the interaction between SM and LAI differs in different climate, land cover conditions, and vegetation rooting depths. To sum up, our results indicate that:

- (a) SM or LAI can respond to their counterpart's variation when it lags by a relatively short term, but they can hardly respond to changes with a lag of more than three months.
- (b) Generally, the highest SM-LAI anomaly correlation is found in the region with dry climate.
- (c) Dynamics of vegetation with deep root is not always correlated with SM near rooting depth and it may consume SM from upper soil layers, and shallow root vegetation may strongly correlate with SM from deeper layers.

Under the continuous impact of climate change, the spatial distribution of climate and land cover classifications is assumed to be changed in the coming century (Beck *et al* 2018). It is also predicted that drying trend will continuously dominate and amplify climate change impact (Deng *et al* 2020, Li *et al* 2022). The pattern of the SM-LAI interaction in different regions is expected to change due to the shift in climate and land cover types. In this context, our results not only provide critical insights into the relationship between SM and vegetation dynamics but also useful benchmark for future large-scale modeling studies.

Data availability statement

The ISMN *in-situ* SM data are, after registration of an account in the platform, freely accessible through www.geo.tuwien.acat/insitu/data_viewer/. The MODIS LAI data are obtained from ftp://modis.cr.chiba-u.acjp/ichii/DATA/MODIS/GLO BAL/tmp/. The Koppen-Geiger climate map is available at www.gloh2o.org/koppen/. The IGBP land cover map is available at https://e4ftl01.cr.usgs.gov/ MOTA/MCD12C1.006/2008.01.01/. The maximum rooting depth data are available from https://wci. earth2observe.eu/thredds/catalog/usc/root-depth/ catalog.html. The processed data are available at https://doi.org/10.5281/zenodo.6815593. All links are valid as of Oct 14th, 2022.

The data that support the findings of this study are openly available at the following URL/DOI: www. geo.tuwien.ac.at/insitu/data_viewer, https://doi.org/ 10.5281/zenodo.6815593.

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Conflict of interest

The authors declare no conflict of interest.

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