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Mapping potential water repellency of Danish topsoil

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ABSTRACT

Soil water repellency (SWR) is a natural process and affects water dynamics from nano to ecosystem scales. However, the spatial distribution of SWR at the ecosystem scale, as well as the underlying drivers across diverse habitats, land uses and soil textures, remain underexplored. This study presents a comprehensive survey of SWR in Denmark and its predicted spatial distribution, using approximately 7,500 samples. We used digital soil mapping methods (Quantile Random Forest model) to map and identify the relationship between SWR and various environmental variables, including vegetation (via satellite imagery), soil properties (texture and soil organic carbon), and landforms (slope and wetness index). The predicted maps at 10 m resolution revealed that SWR varies across different land uses and vegetation types, with higher values in areas of natural vegetation (e.g., heathlands and coniferous forests) compared to grasslands and croplands (mostly hydrophilic). The analysis also identified soil organic carbon, Sentinel band 3 (Green band – Chlorophyll absorption) and soil texture as key drivers of spatial variation in SWR at the national extent. We found that soil texture influences SWR intensity, which generally decreases as clay content increases across most land use types, except for heathlands. While the predicted maps provided valuable insights into SWR distribution and its environmental drivers, further research is needed to explore the spatio-temporal dynamics of SWR within each habitat, particularly in relation to soil moisture changes. This study highlights the potential of combining machine learning and remote sensing to provide crucial spatial information for managing water resources and enhancing ecosystem resilience in the face of climate change.

1. Introduction

Soil water repellency (SWR) is a natural process and occurs at the nanoscale due to complex interactions between water and surface properties, chemical composition, biological communities and environmental conditions (Doerr et al., 2000a; Smettem et al., 2021). Moreover, it can significantly affect water dynamics at micro, pedon, and ecosystem levels (Mao et al., 2019). This phenomenon is present in a wide range of biomes globally (Doerr et al., 2000a), occurring in cold and wet regions (Fu et al., 2021; Hermansen et al., 2019; Weber et al., 2023) even though the majority of studies have focused on areas subject to forest fires and arid regions due to its pronounced negative impact on crop development and yields (Hall et al., 2010; Li et al., 2019). These adverse effects of SWR in agricultural areas are largely due to uneven soil wetting patterns and increased preferential flow, with water bypassing the root zone to deeper soil layers (Robinson, 1999). However, recent studies suggest that SWR may also have positive effects on water infiltration and evaporation dynamics (Bachmann et al., 2001; Imeson et al., 1992; Rye and Smettem, 2018), potentially as a result of the co-evolution of plants and microorganisms to enhance drought resilience (Seaton et al., 2019). Although contrasting findings regarding the benefits and adverse effects of SWR indicate the role of land use on SWR, its spatial assessment across diverse vegetation types and soil conditions remains limited (Seaton et al., 2019).

Soil water repellency is largely caused by hydrophobic compounds produced by plants and microorganisms, which coat soil mineral surfaces and prevent them from becoming wet (Bisdom et al., 1993; Giovannini et al., 1983) or are present as interstitial organic matter in the

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soil matrix (e.g. peat). It is well-known that plant cover affects the severity of SWR and is related to the biochemical quality of litter and root exudates (Popović and Cerdà, 2023). For example, *Eucalyptus* and *Pinus* species produce waxes and lipids that can cause severe SWR (Doerr et al., 1996; Hewelke et al., 2018; Martins et al., 2020). In agricultural areas, SWR has been recorded in grasslands (Gao and Yang, 2023), which can present superhydrophobic leaves (Barthlott et al., 2017). In addition to plant cover, SWR is also affected by the microbial community (Chai et al., 2022; Doerr, Shakesby, and Walsh 2000; Majid et al., 2023; Seaton et al., 2019) which is well-established for fungi (Hallett, Ritz, and Wheatley 2001; Unestam 1991; Unestam and Sun 1995).

The degree of SWR is affected by the composition and activity of the living microorganisms (Simpson et al., 2019) but also the microbial necromass which can represent a large proportion of the organic carbon content (Liang et al., 2019). The relationship between SWR and microorganisms is complex, as microorganisms can either decrease or increase the degree of SWR depending on whether they produce or degrade hydrophobic compounds (Chai et al., 2022; Seaton et al., 2019; Liu et al., 2013; Roper et al., 2005; Simpson et al., 2019). The production of hydrophobic compounds by the biological communities can be linked to water inundation or stress responses (Seaton et al., 2019).

Although the quality and quantity of organic matter is a determining factor in whether a soil can become water repellent, the type of soil minerals also play an important role (Doerr et al., 2000). For example, the clay and silt fractions are characterized by large specific surface areas (Petersen et al., 1996) when compared to the sand fraction. Therefore, a large amount of hydrophobic material is needed to cover conventionally hydrophilic clay mineral surfaces (van Oss and Giese, 1995) and render these water repellent as compared with coarse-textured soils with relatively small specific surface areas (Doerr et al., 2000a; Giovannini and Lucchesi, 1983). Thus, soil texture has an effect on SWR, but SWR is a complex phenomenon, and the effect of texture on SWR is not straightforward and has not been explored at a national level covering multiple vegetation types. For example, Jordán et al. (2009) and Mirbabaei et al. (2013) found positive correlations between SWR and sand content, while Doerr et al. (1996) found that SWR was associated with fine-grained soil fractions rather than coarse-grained fractions in pine and eucalyptus forests in northern Portugal.

Soil water repellency is also a transient soil property. The severity of SWR can vary according to, e.g., soil water content (de Jonge et al., 1999; Doerr et al., 2000b; Karunarathna et al., 2010; Regalado et al., 2008), pH (Diehl et al., 2010a; Graber et al., 2009b; Hermansen et al., 2019), temperature (Graber et al., 2009b; King, 1981), and ambient relative humidity (Doerr et al., 2000b; Roy and McGill, 2002a). Soil water content, in particular, can affect the severity of SWR since SWR varies nonlinearly with this parameter, and the exact same soil can change from being hydrophilic to becoming extremely hydrophobic with only small increments in soil water content (Hermansen et al., 2019; Regalado et al., 2008). Although it is well-known that SWR varies as a function of water content, it is extremely time-consuming to measure SWR versus water content curves, which causes this approach to be inappropriate for large-scale SWR surveys. Dekker and Ritsema (1994) introduced the term 'potential' SWR, referring to an SWR measurement on soils heat-pretreated at 60 °C, and the approach of measuring potential SWR after heat pretreatment of 60–65 °C has been applied in other studies as well studies (Bisdom et al., 1993; Dekker et al., 2001; Müller et al., 2010). Assessing the severity in SWR using 'potential' SWR has previously been referred to as an appropriate parameter for the intercomparison of soils regarding the severity in SWR (Dekker et al., 2001; Dekker and Ritsema, 1994a).

There are several common methods for measuring the severity of SWR. Some of the most applied methods for assessing SWR are the measurement of SWR persistence following the water drop penetration time (WDPT) method (King, 1981) and the measurement of the degree of SWR with the molarity of an ethanol droplet (MED) test (King, 1981; Roy and McGill, 2002a). The WDPT gives a measure of how long water repellency persists on a soil surface, whereas the MED test gives an indirect measure of the soil surface tension since it gives a measure of how strongly a droplet of water is repelled by the soil surface (Doerr, 1998). Both methods are well-suited for large amounts of soil, but the WDPT test has the disadvantage that long persistence times can cause this method to be very laborious (Doerr, 1998; Wallis and Horne, 1991).

The development of digital soil mapping (DSM) has enabled the spatial assessment of soil properties and the identification of the main drivers at different scales (McBratney et al., 2003). Over the last three decades, fundamental soil properties, such as soil texture components and soil organic carbon (SOC), have been mapped from the field (Guo et al., 2020; Møller et al., 2021) to global scales (Hengl et al., 2017; Poggio et al., 2021). DSM uses geostatistical and machine learning models to capture the linear and non-linear relationships between target variables and explanatory variables and make predictions in space. For instance, the Quantile Random Forest is a commonly used approach and has the advantage of retrieving the predictions quantiles (Meinshausen, 2006; Poggio et al., 2021). Although DSM techniques have proven highly useful for mapping soil properties that exhibits little temporal variation (such as soil texture and SOC), mapping dynamic soil properties that vary greatly in space and time and represent soil functions (e.g., water infiltration/water regulation) remains a challenge (Gomes et al., 2023). The constraints in mapping soil functions lie in the fact that they are processes influenced by dynamic soil properties and environmental conditions (e.g., climate, vegetation). Dynamic soil properties have high potential as indicators for soil health assessment, but the absence of maps hinders their use across large areas by farmers and policymakers. SWR is a prime example of a soil process/property that is time-consuming to measure and is influenced by biotic and abiotic factors that vary in space and time. Despite some efforts to map SWR in grassland areas in China (Gao and Yang, 2023) and New Zealand (Bayad et al., 2020), comprehensive national spatial assessments covering different agricultural and natural habitats are unprecedented. Understanding the spatial distribution of SWR across large areas with diverse vegetation types and soil conditions could provide valuable insights into its significance for different land uses/ land cover at a national level.

Although SWR is not a major problem in Denmark, it has been recorded in agricultural (de Jonge et al., 2007), forest areas (Wahl, 2008), and numerous natural and semi-natural habitat types (Danielsen et al., 2023; Danielsen et al., 2025). A better understanding of SWR across different habitats and its links with soil and vegetation factors can provide important insights into its potential benefits for infiltration and drought resistance (Robinson et al., 2010), which are important in the context of climate change. Therefore, this study aims to (i) conduct a national potential SWR survey across all habitats, land uses, and soil types in Denmark; (ii) map the potential SWR on a national scale; and (iii) identify the main drivers of SWR and their effects.

2. Material and methods

2.1. Study area and sampling

Denmark covers approximately 43,000 km2 and has a climate classified as warm temperate humid, according to the Köppen-Geiger classification. The country's mean annual temperature ranges from 6 to 10 °C, with an average annual precipitation of 780 mm. The land use in Denmark is primarily agricultural, covering about 60 % of the land surface, followed by forests (14 %) and other natural areas such as wetlands (2 %; Levin and Gyldenkærne (2022)). The predominant soil types in Denmark are Luvisols, Arenosols, and Cambisols (Adhikari et al., 2014). Soil texture varies across the country, with low clay content (0–5 %) in the west, where Arenosols dominate, and higher clay content in the east, where Luvisols are prevalent. There are also small areas with very high clay content (28–63 %) in the southwest (Fig. 1a).

To capture the diversity of agricultural and natural habitats, we collected around 7,500 soil samples across Denmark in the period from

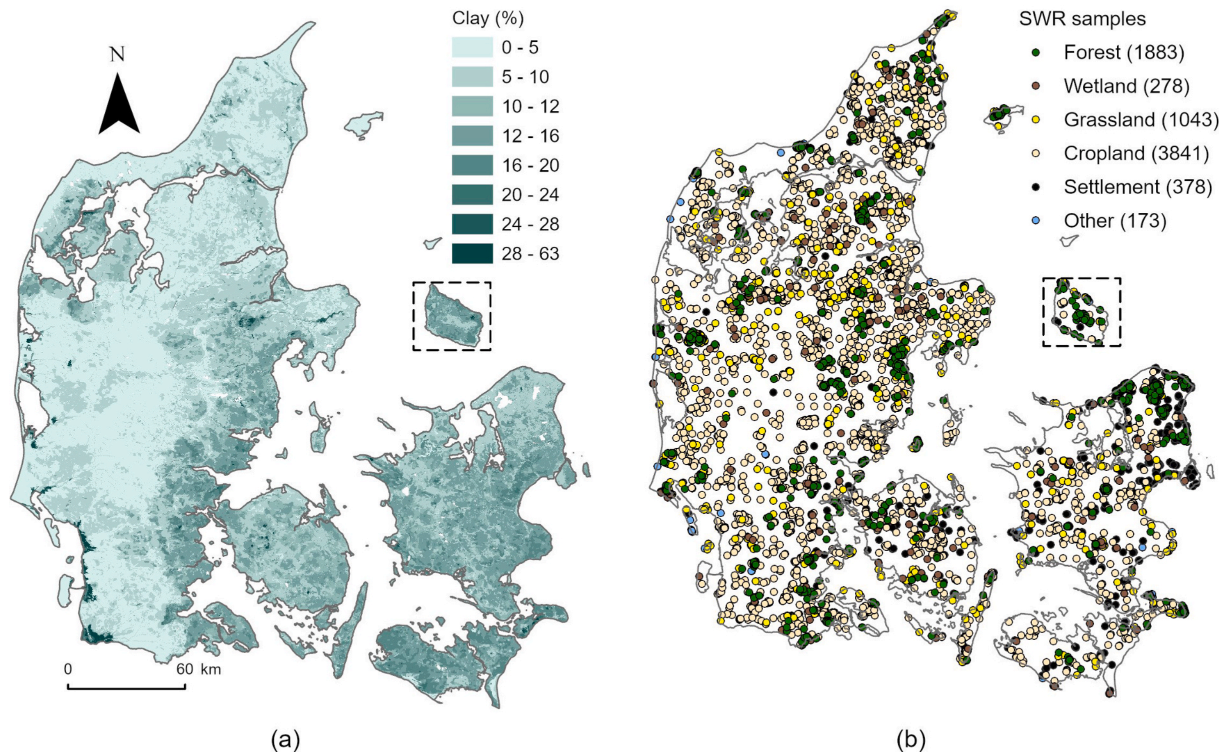

Fig. 1. Clay content map (%, a) and the distribution of soil water repellency sampling points (b) within the different land use cover classes in Denmark. Clay map adapted from Adhikari et al. (2013).

2021 to 2023, covering all land uses and a wide range of soil organic carbon contents as well as soil texture groups (Fig. 1b). All samples were collected from the topsoil (0–20 cm) with the majority sampled in agricultural areas (3,841 samples), followed by forests (1,883 samples) and grasslands (1,043 samples), according to the Danish land use classification (Levin and Gyldenkærne, 2022). The forest areas were well-represented in the sampling to cover different forest types, which is evident from the clustered samples (green) shown in Fig. 1b. In the Danish land use classification, the grassland category encompasses a broad range of habitats, including managed and natural grasslands, where the vegetation is dominated by grasses and forbs, as well as heathlands. To analyze the results of this study, we distinguished between agricultural grasslands (hereafter referred to as grasslands) and heathlands.

2.2. Soil water repellency measurements

The degree of SWR was measured with the molarity of an ethanol droplet (MED) test (Roy and McGill, 2002b) on air-dried and 2-mm sieved soil samples which, prior to SWR measurement had been heat-pretreated in the oven at 60 °C, and thereafter kept at lab conditions (20 °C) for 48 h to equilibrate. Thus, as in previous studies (Dekker and Ritsema, 1994b; Deurer et al., 2011) a measure of the 'potential' SWR was obtained by measuring SWR after heat-pretreatment at 60 °C.

Following the approach outlined in Hermansen et al. (2019) and Weber et al. (2021), droplets of 60 μL (ethanol solution concentrations within a concentration range of 0 to 0.80 cm^3 cm^3) were placed on the soil surface. The resulting degree of SWR (Liquid Surface Tension − LST (mN m^{-1})) was derived from the highest ethanol concentration, which did not infiltrate within 5 s (Roy and McGill, 2002b).

Water-repellent soils exhibit a lower surface tension than hydrophilic soils. Increasing concentrations of ethanol gradually decrease the liquid surface tension of the droplets placed on the soil surface. Using the equation given in Roy and McGill (2002) to convert between molarity and liquid surface tension of ethanol, pure water with a concentration of 0 cm^3 cm^3 ethanol corresponds to a liquid surface tension of 71.276 mN m^{-1} and characterizes hydrophilic soil, whereas surface tensions below 71.276 mN m^{-1} characterize an increasing severity of SWR with decreasing liquid surface tension. In reality, the liquid surface tension of water at 25 °C is 72.75 mN m^{-1} (Doerr et al., 2000), but for consistency we applied the value of 71.276 mN m^{-1} to define hydrophilic soil.".

The severity in SWR was divided into five categories. The upper level of SWR severity was defined as extreme SWR, based on the definition of 40.9 mN m^{-1} given in Doerr et al. (2000a). Thus, three SWR categories were created with an equal span in surface tension: high (40.9 – 51.0 mN m^{-1}); moderate (51.0 – 61.1 mN m^{-1}) and mild (61.1 – 71.27 mN m^{-1}). Hydrophilic soil (No SWR) was characterized by a surface tension of 71.27 mN m^{-1}.

2.3. Digital soil mapping and covariates

We applied the DSM approach (McBratney et al., 2003) to predict SWR across Denmark using the Quantile Random Forest (QRF) model (Meinshausen and Ridgeway, 2006). The QRF model allows us to retain predictions from all trees (quantiles), providing a measure of uncertainty within the model. Here, we selected the 0.1, 0.5 and 0.9 quantiles to produce the median values (q0.5) and the prediction interval (q0.1 to q0.9). We split the dataset into 75 % for training and 25 % for testing, using the test set as external validation. However, random selection of data for training and testing can affect the results, so to mitigate this issue, we ran the model 50 times, each time creating different training and test datasets. We used a 10-fold cross-validation with ten potential values for tuning hyperparameters to optimize the model.

The models' performance was assessed using test data and evaluated with five statistical metrics. The mean absolute error (MAE) and root mean squared error (RMSE) summarize the residuals and describe the absolute accuracy of the models, indicating how close the predicted values are to the actual values. The coefficient of determination (R2) indicates the proportion of variance in the target variable that the model explains, showing how much the model improves predictions compared to simply using the mean of the observed target variable as the prediction. Lin's concordance correlation coefficient (LCCC) evaluates the agreement between the observed and predicted values, assessing both the precision and accuracy of the predictions (Khaledian and Miller, 2020). As an additional validation, we applied the "Null" MAE and "Null RMSE" by calculating these metrics for a null model that uses the mean observations as predictions. Using "Null" models is a good strategy to establish thresholds and evaluate the "badness" of the models, allowing for comparison with a model where the predictors are set to 0 (null).

To predict topsoil water repellency, we used covariates related to soil properties, landscape, and vegetation. We used soil organic carbon and soil texture maps from Denmark (Møller et al., 2024). Slope and the SAGA wetness index were calculated from a Digital Elevation Model (DEM) and used to represent the landforms. The vegetation covariates were derived from Sentinel-2 images taken during the spring season (01/03 – 31/05) from 2019 to 2023 and compiled into a composite image. All bands were used, and the vegetation indices Normalized Vegetation Index (NDVI) and Normalized Moisture Index (NDMI) were calculated. We selected images from the spring season due to the availability of cloud-free data. All covariates were at a 10 x 10 m resolution. Given the lack of a significant gradient in air temperature across Denmark, we decided not to use climate-related covariates to predict SWR.

3. Results and Discussion

3.1. Soil water repellency

Soil water repellency (SWR) was observed in 50.7 % of soil samples, with the SWR severity (LST < 45 mN m^{-1}) predominant found in the western regions and specific locations in the eastern parts of Denmark (Fig. 2). A substantial number of samples (3,716) were classified as hydrophilic (LST $\geq$ 71.276 mN m^{-1}) and were distributed throughout Denmark, with the majority associated with cultivated cropland areas (Fig. 3) such as spring barley and winter rape under tillage systems. Natural habitats exhibited the highest severities in SWR, with a decreasing gradient observed from forests and wetlands, followed by grasslands (agricultural and heathland) and croplands (Fig. 3). Our findings support the notion that SWR is more the norm than the exception (Doerr and Ritsema, 2006). Studies conducted in similar humid climates to Denmark have reported varying degrees of water repellency, with 63 % (Doerr et al., 2006) and 92 % (Seaton et al., 2019) of samples showing some level of water repellency. These studies also observed higher severities in SWR in natural habitats compared to agricultural areas.

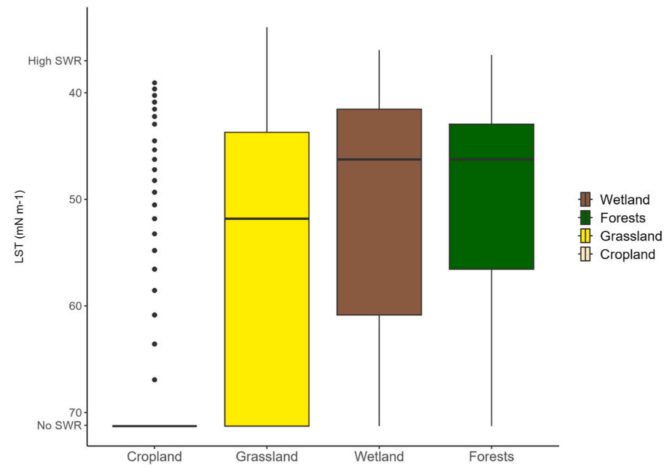

Fig. 3. Soil water repellency (SWR; Liquid Surface Tension –LST (mN m^{-1})) in the different land use/cover in Denmark. The grassland class here covers agricultural grasslands and heathlands.

The differences in SWR between natural habitats and agricultural areas can be attributed to the presence and quality of organic matter

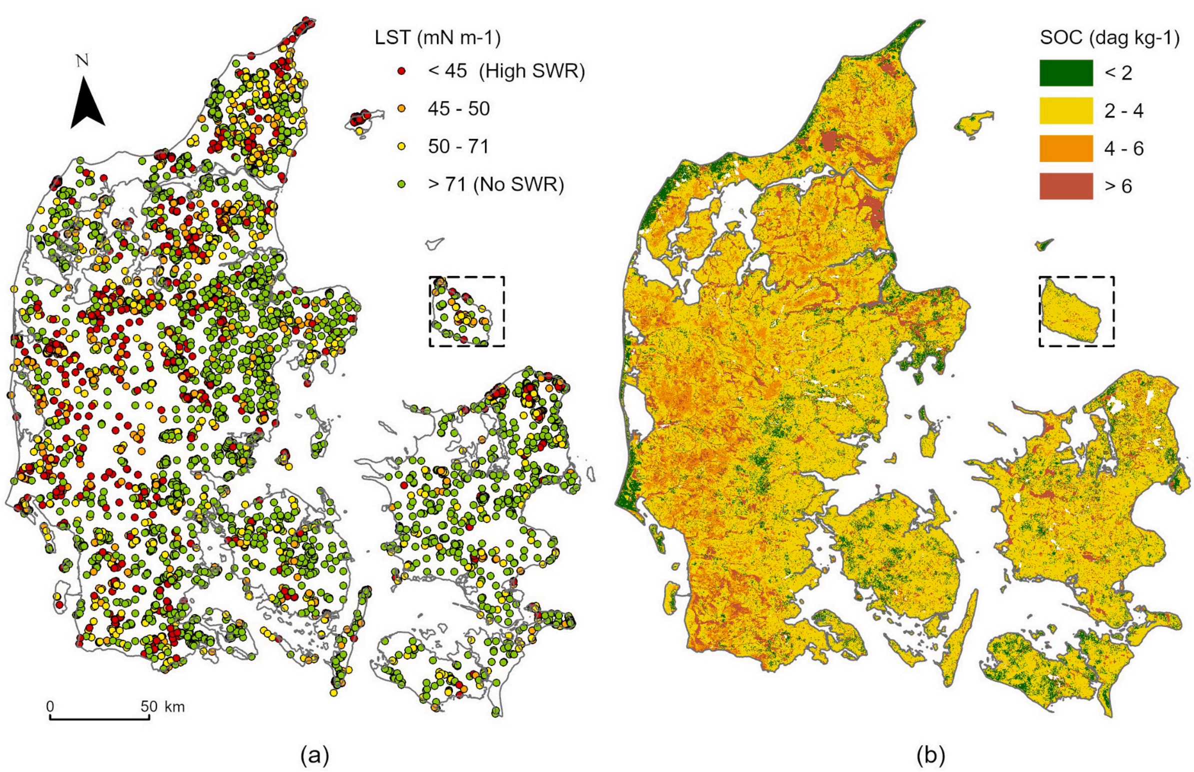

Fig. 2. Soil water repellency samples (SWR, Liquid Surface Tension –LST (mN m^{-1})) (a), and soil organic carbon (SOC) map (b) from Denmark. SOC map adapted from Adhikari et al. (2014b).

with hydrophobic compounds produced by local plants and microorganisms (Cesarano et al., 2016; Mao et al., 2015). Plants in natural habitats often retain evolutionary traits, such as the production of hydrophobic compounds like cutin and suberin, which enhance their ability to withstand various environmental stresses, including water stress, insect damage, and pathogen attacks (Popović and Cerdà, 2023). For instance, coniferous trees are known to produce litter with a high concentration of hydrophobic compounds (Jetter et al., 2006). Conversely, agricultural areas in humid climates generally exhibit lower SWR severities or no repellency as compared to natural areas, consistent with previous studies conducted in the UK (Doerr et al., 2006; Seaton et al., 2019). The difference between agricultural and natural habitats may result from crop types that produce less hydrophobic material (Miller et al., 2019) and agricultural management practices such as intense tillage, which can deplete soil organic carbon, a key source of hydrophobic compounds and a factor highly correlated with SWR. In addition, the croplands are mainly located in areas with higher clay content and lower SOC (eastern region), which contribute to the differences in SWR compared with natural habitats. Soil pH management may also be a factor and remains to be explored further (Diehl et al., 2010b; Graber et al., 2009a). Grasslands exhibited the greatest variation in SWR (Fig. 3), likely due to differences between heathlands and agricultural grasslands. The grasslands also span a wide pH gradient, which may further contribute to the observed variation in SWR. Additionally, many managed grasslands contain up to 50 % clover, potentially influencing the production of hydrophobic compounds.

3.2. Spatial distribution of soil water repellency

The predictive model demonstrated good performance on the test dataset, achieving mean values of $R^2 = 0.58$, LCCC = 0.72, MAE = 5.6 mN m^{-1} and MAE_NULL = 11.7 mN m^{-1}, considering mapping activities in large areas (Chen et al., 2022). The spatial distribution of predicted SWR mirrored the trends observed in the soil samples (Fig. 4). Higher severities in SWR are observed in the western part of Denmark (Central Jutland) and the northern and southwestern coastal regions, while lower or no water repellency is found in the eastern part of Denmark. In general, agricultural areas, primarily croplands, show no SWR, whereas natural areas such as forests and heathlands exhibit higher SWR severity. A detailed examination of SWR distribution within these natural areas reveals variations between habitat types (Fig. 5). For instance, the model effectively distinguishes between coniferous and deciduous trees (Fig. 5). A closer look at a peatland area in northern Denmark indicates that bogs and grasslands have higher SWR compared to peatlands under intensive agriculture. Additionally, spatial variation in SWR within heathland areas likely relate to the density of different plant species in these habitats (Fig. 5).

The uncertainty of predictions, based on the 80 % prediction interval, was higher for coarse-textured soils in the west than in fine-textured soils in the east (Fig. 4b). Specifically, the model performed well in predicting high values of SWR and hydrophilic soils, with cropland areas located mainly in the loamy soils in the east presenting low uncertainty ($<$ 5 mN m^{-1}). The same was observed for coniferous forests, with higher SWR values but lower uncertainty compared with deciduous forests (Fig. 5). The lower uncertainty in the extreme values of SWR gradient can be attributed to the role of satellite images, which is powerful to capture cropland and the uniformity of coniferous trees.

The use of Sentinel images with a 10 m resolution enabled detailed observations related to SWR across various land uses and within natural areas. Bayad et al. (2020) used time-series Sentinel images and machine learning models to predict SWR occurrence in grasslands in New Zealand. Although our study did not identify SWR in croplands, higher variation was found in grasslands. These findings highlight the potential of remote sensing images to monitor SWR occurrence. This capability is valuable not only for natural areas but also for agricultural settings, where it can be used to identify critical zones for targeted interventions. It may also be of high value for identifying inclined forested areas prone to overland flow and flash floods, particularly in relation to forest fires.

3.3. Main drivers of SWR

Analysis of the observed SWR from soil samples revealed that while vegetation type is a key driver of SWR, soil texture also significantly modifies its intensity in natural habitats (Fig. 6). SWR generally

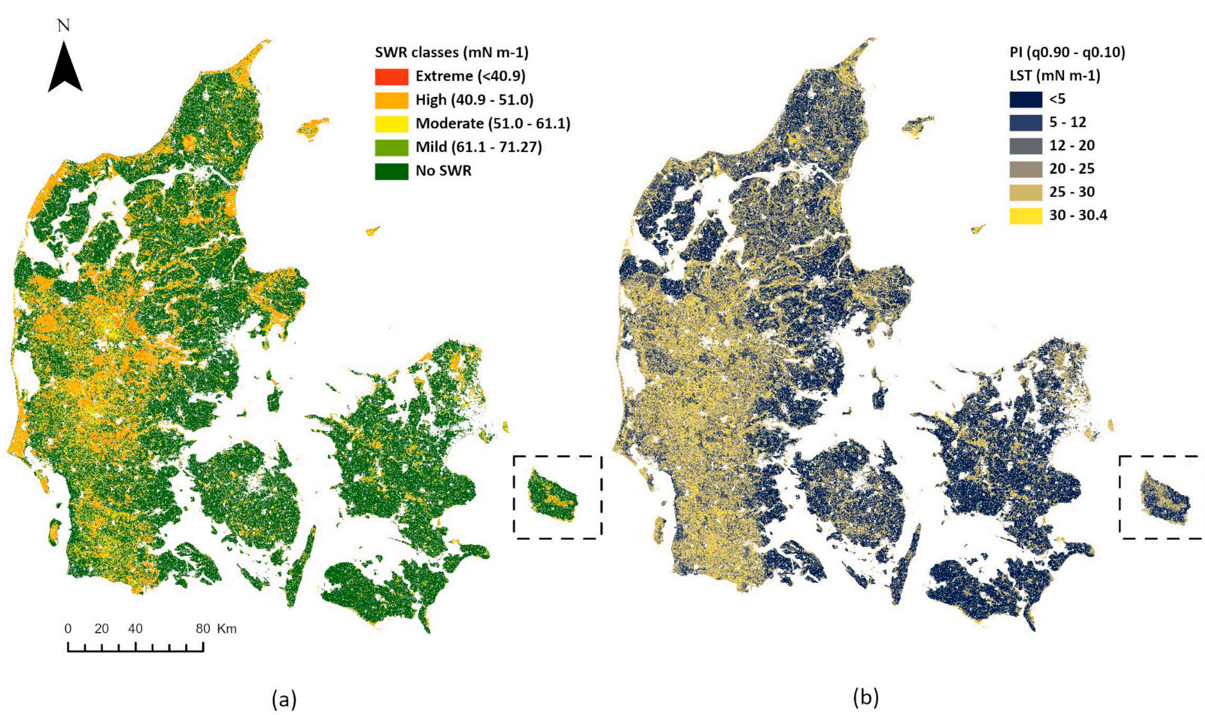

Fig. 4. Predicted map of soil water repellency (SWR, Liquid Surface Tension –LST (mN m^{-1})) (a) and the uncertainty map (PI –prediction interval) in Denmark (b). The quantiles q0.10 and q0.90 represent the 80% prediction interval.

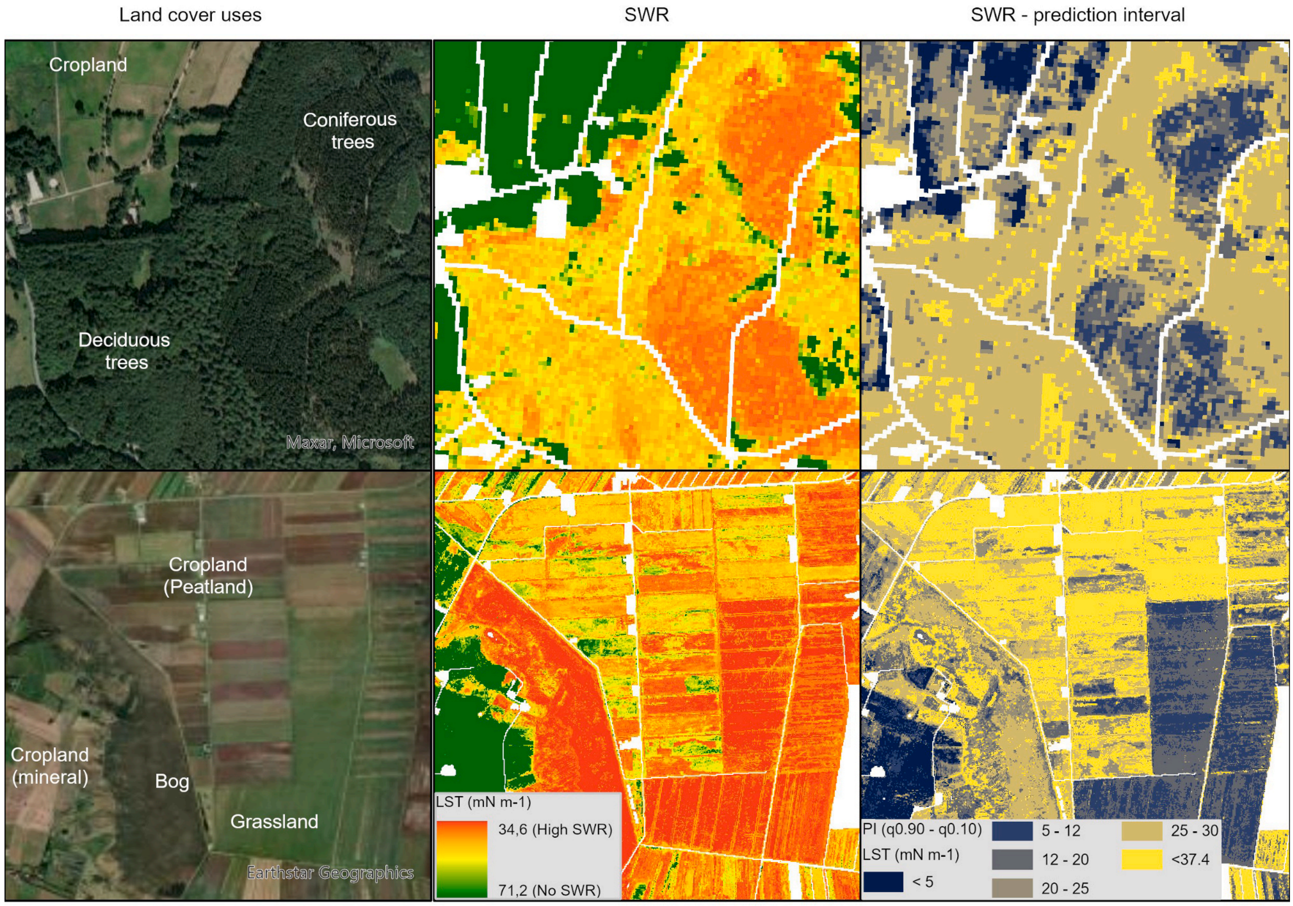

Fig. 5. Detailed visualization of predicted soil water repellency (SWR; Liquid Surface Tension –LST (mN m^{-1})) and the uncertainty (PI- prediction interval) for different land uses/covers in Denmark.

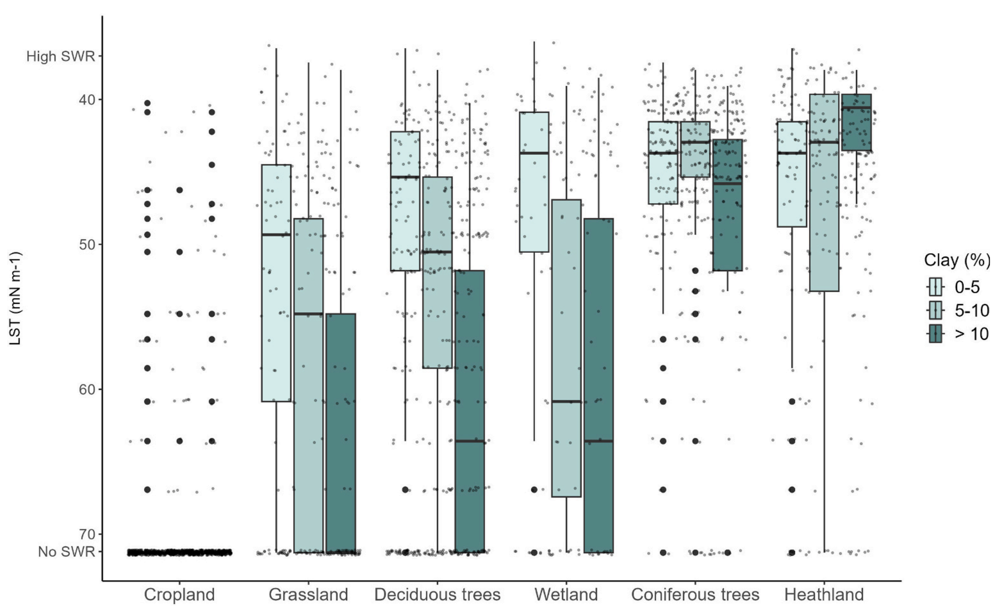

Fig. 6. Soil water repellency (SWR, LST – Liquid Surface Tension (mN m^{-1})) in Denmark's specific land uses/habitat types grouped by clay content (%). More information about the land uses can be found in Table S1.

decreases with higher clay content (>10 %) across most habitat types, except for heathlands. In heathlands, soils with higher clay content exhibited the highest severities in SWR. The observed increase in SWR with higher clay content in heathlands may be attributed to three factors. First, heathlands represent one of the last frontiers in agricultural conversion in Denmark (Lohrum et al., 2024), and many of these areas may only be used for grazing, thereby preserving the natural vegetation for long periods. Second, the plant species in heathlands produce hydrophobic compounds with high carbon-to-nitrogen (CN) ratios (Strandberg et al., 2018), which tend to accumulate in the soil over time. These hydrophobic compounds may create coatings around aggregates, which ultimately decrease the specific surface area needed to be covered by hydrophobic material to render the soil water-repellent (Doerr et al., 2000a). Third, some of the heathlands are burned (controlled fires), which may enhance SWR. Consequently, the combination of high production of hydrophobic compounds and their prolonged presence can lead to increased SWR, even in soils with high clay content. For example, SWR has been detected in soils with clay contents as high as 34 % (Wijewardana et al., 2016) and 60 % (Dekker and Ritsema, 1996).

Our results also reveal the effect of clay content on the severity of SWR varies between different habitat types. For example, the impact of increasing clay content on SWR is less pronounced in coniferous forests compared to deciduous forests (Fig. 6). This variation is likely related to the quality of litter and hydrophobic compounds produced by different forest types (Cools et al., 2014). For instance, coniferous trees produce litter with more recalcitrant compounds (e.g., lignin) compared with deciduous trees (Berg and McClaugherty, 2008). Lorenz and Thiele-Bruhn (2019) identified high SOC stocks under coniferous trees compared to deciduous species, which was linked to their SOM quality (e.g., higher CN ratio). Our findings underscore that while hydrophobic compounds are a major controller of SWR, soil texture and clay mineral type play a significant role in moderating the occurrence and severity of SWR.

The spatial distribution of predicted SWR was primarily explained by SOC, Sentinel 2 band 3 (SB3_spring), clay content, and coarse sand (Fig. 7). It is uncommon in digital soil mapping to have a few covariates explaining most of the variation of a soil property, and this highlights the importance of these variables in determining the severity and occurrence of SWR. Soil pH is also an important driver of SWR occurrence by affecting the orientation of hydrophobic compounds (Graber et al., 2009a), but a soil pH map is not yet available for Denmark at the spatial resolution of this study.

Partial dependency plots indicate that SWR increases with SOC from 2 to up to 30 %, beyond which no further response is observed (Fig. 8). The relationship between SWR and SOC is consistent with findings from previous local-scale studies (Hermansen et al., 2019; Mao et al., 2019). For SB3_spring, there is no effect on SWR between reflectance values around 500 and 700, followed by a rapid decrease to 900, with lower SWR at higher reflectance values. Sentinel images have been used with success to map different tree species at plot scale (Axelsson et al., 2021) to national scale (Blickensdörfer et al., 2024), and the green band also appear as an important predictor (Persson et al., 2018). Sentinel B3 is sensitive to total chlorophyll, especially in spring, when deciduous trees are more photosynthetically active. Regarding clay content, no effect is noted between 1.5 % and 5 %, but SWR decreases with clay content up to 14 %, beyond which no additional effect is observed. Coarse sand exhibits a contrasting effect. All variables described in the partial dependence plots present peaks, indicating a certain threshold where their effect on SWR becomes visible. This shows that before the peak, other variables may explain the variation in SWR. The intensity of the peak is clearer for the Sentinel image compared with the soil properties. This is because spectral changes from cropland to natural areas and among forest types are more pronounced than gradual spatial changes in soil properties. Although these partial dependency plots show the general trends between SWR and the explanatory variables, they should be interpreted with caution, as our results also indicate that the potential SWR is the result of an interplay between soil and vegetation characteristics. Additionally, it is important to note that the SOC and soil texture values are derived from predicted maps, which limits our ability to discuss these results in greater detail at a local scale.

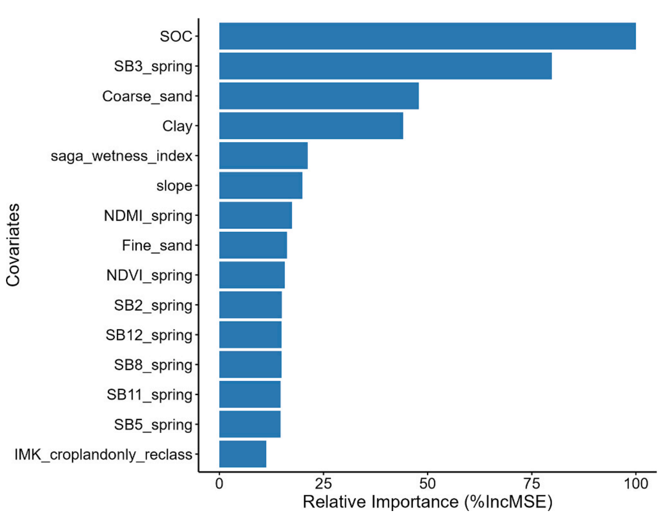

Fig. 7. Relative importance of covariates (% increase of mean square error-MSE) for the prediction of soil water repellency (LST – Liquid Surface Tension) in Denmark. Soil organic carbon (SOC), Sentinel bands (SB2_spring; SB3_spring, SB5_spring, SB8_spring, SB11_spring, SB12_spring, areas without grass in rotation between 2010 and 2021 (IMK_croplandonly_reclass), normalized moisture index (NDMI), normalized vegetation index (NDVI).

4. Conclusions

In this paper, we conducted a national survey of topsoil SWR across all habitats and soil types in Denmark, enabling us to map its spatial distribution and identify the main drivers. While modelling and upscaling SWR does not capture all of its underlying complexities, it provides valuable insights into its spatial variability and key influencing factors at the ecosystem level.

Our study shows that most cropland soils do not have a severe problem, regardless of soil texture, with a gradient of increasing SWR severity from grasslands to forests and heathlands. This SWR gradient supports the hypothesis that SWR is a natural process and indirectly results from the co-evolution between plants and microorganisms in natural habitats, enhancing resilience against environmental stress (Smettem et al., 2021).

The interaction between vegetation and soil texture plays a major role in determining Denmark's spatial distribution of SWR. Soil organic carbon and vegetation spectral data emerged as the two most important variables. These factors are autocorrelated since SOC is primarily produced by vegetation. This highlights the importance of both SOC quantity (SOC content) and quality (represented here by Sentinel band 3). Our findings also reveal clear thresholds for these variables, showing that SWR is positively correlated with SOC and negatively correlated with clay content. However, these trends are derived from partial dependence plots, which only account for the individual effects of each factor. Other factors, such as soil moisture and microorganisms, also play a significant role in the occurrence and severity of SWR.

The large number of samples from natural habitats also allowed us to identify that soil texture appears to buffer the effects of hydrophobic compounds in the environment. In natural habitats and agricultural grasslands, SWR generally decreases as clay content exceeds 10 %, with the exception of heathlands. Additionally, the influence of increasing clay content on SWR is less pronounced in coniferous forests than in deciduous forests.

This study represents only part of the complex dynamics of SWR in space. Future research should explore the full spectrum of SWR across different soil moisture content and investigate the physical and biological drivers within natural habitats and their interaction across space and time. The role of SWR on water dynamics is unquestionable, and the maps generated in this study could be used within spatial hydrological models and studies exploring the resistance and resiliency of vegetation to drought events.

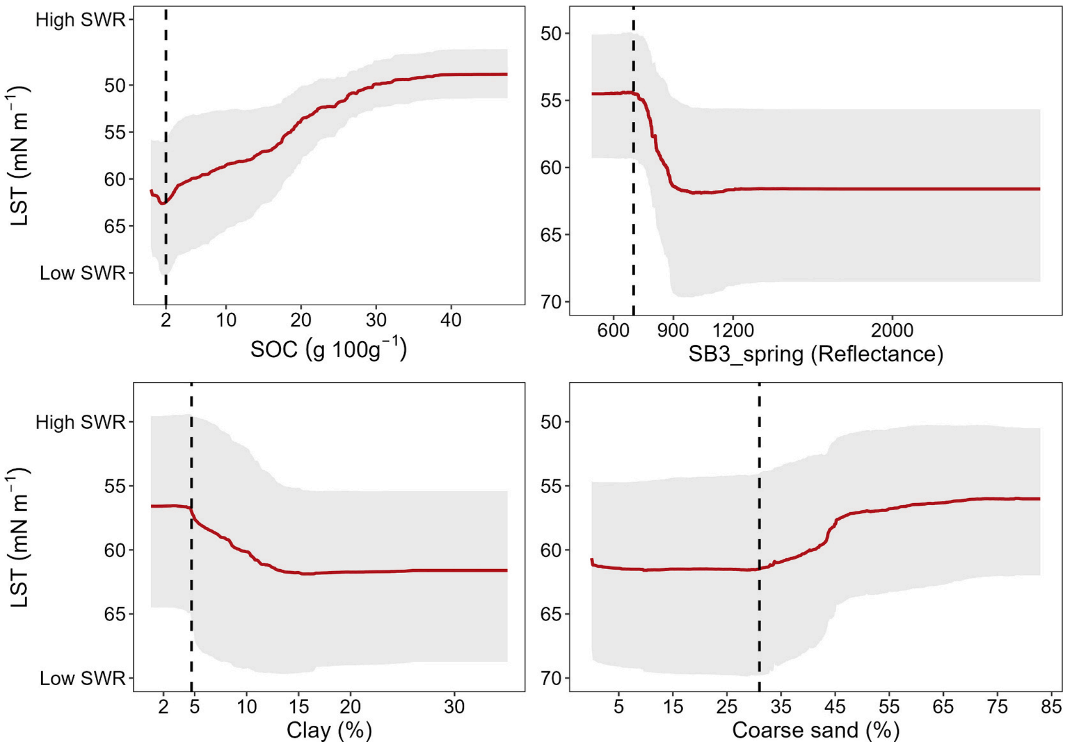

Fig. 8. Partial dependence plots of soil organic carbon (SOC), clay, coarse sand and Sentinel band 3 (SB3_spring) for the prediction of soil water repellency (SWR, LST – Liquid Surface Tension (mN m^{-1})) in Denmark.

CRediT authorship contribution statement

Lucas Carvalho Gomes: Conceptualization, Writing – original draft, Writing – review & editing, Data curation, Visualization. **Peter Lystbæk Weber:** Writing – review & editing, Writing – original draft, Visualization, Data curation, Conceptualization. **Cecilie Hermansen:** Writing – review & editing, Writing – original draft, Visualization, Data curation, Conceptualization. **Anne-Cathrine Storgaard Danielsen:** Writing – review & editing, Data curation. **Sebastian Gutierrez:** Writing – review & editing, Writing – original draft, Conceptualization. **Deividas Mikstas:** Writing – review & editing, Data curation. **Charles Pesch:** Writing – review & editing, Data curation. **Mogens Humlekrog Greve:** Writing – review & editing, Supervision, Resources, Funding acquisition, Conceptualization. **Per Moldrup:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Conceptualization. **David A. Robinson:** Writing – review & editing. **Lis Wollesen de Jonge:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Resources, Project administration, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2025.117280.

Data availability

Data will be made available on request.

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