Title

Climate change-induced peatland drying in Southeast Asia

Authors

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Abstract

When organic peat soils are sufficiently dry, they become flammable. In Southeast Asian peatlands, widespread deforestation and associated drainage create dry conditions that, when coupled with El Niño-driven drought, result in catastrophic fire events that release large amounts of carbon and deadly smoke to the atmosphere. While the effects of anthropogenic degradation on peat moisture and fire risk have been extensively demonstrated, climate change impacts to peat flammability are poorly understood. These impacts are likely to be mediated primarily through changes in soil moisture. Here, we used neural networks (trained on data from the NASA SMAP satellite) to model soil moisture as a function of climate, degradation, and location. The neural networks were forced with regional climate model projections for 1985-2005 and 2040-2060 climate under RCP8.5 forcing to predict changes in soil moisture. We find that reduced precipitation and increased evaporative demand will lead to median soil moisture decreases about half as strong as those observed during recent El Niño droughts. Such reductions may be expected to accelerate peat emissions. Our results also suggest that soil moisture in degraded areas with less tree cover may be more sensitive to climate change than in other land use types, motivating urgent peatland restoration. Climate change may play an important role in future soil moisture regimes and by extension, future peat fire in Southeast Asian peatlands.

1 Introduction

Peatlands in Insular Southeast Asia contain globally significant carbon stores, estimated at 67 GtC (Page *et al* 2011, Warren *et al* 2017). This carbon is maintained through high water tables that prevent peat oxidation or ignition (Hirano *et al* 2009, Dommain *et al* 2010). However, in the last half a century, degradation has threatened these carbon stores, as only ~6% of peat forests remain in pristine condition (Miettinen *et al* 2016) and widespread drainage has occurred (Dadap *et al* 2021). The resulting drier peat is vulnerable to oxidation (Hooijer *et al* 2012, Jauhiainen *et al* 2012), leading to emissions as large as 155 ± 30 Mt C yr^{-1} in 2015 (Hoyt *et al* 2020), about 70% of annual fossil fuel emissions in Malaysia and Indonesia (Miettinen *et al* 2017).

Climate also affects peatland carbon loss. During drought years, large-scale burning of peatlands (Van Der Werf *et al* 2008, Field *et al* 2016, Taufik *et al* 2017) also leads to globally significant carbon emissions because dry peat is more flammable. For example, fires associated with the 1997 El Niño Southern Oscillation led to an estimated 0.81-2.56 GtC emitted, 13-40% of global mean annual fossil fuel emissions at the time (Page *et al* 2002). Although fire has been a phenomenon in Southeast Asian peatlands for at least 30,000 years (Goldammer *et al* 1989, Anshari *et al* 2001), the frequency and scale of these fires has increased dramatically in recent decades (Page and Hooijer 2016). In the second half of the 20th century, periodic droughts only led to large increases in fire during periods when degradation rates were high (Field *et al* 2009). This evidence suggests that the combined effects of degradation and climate on the soil moisture and groundwater levels in peatlands mediate peat fire (Taufik *et al* 2017, Dadap *et al* 2019). Specifically, degradation can worsen the sensitivity of tropical peatland emissions to meteorological drought (Siegert *et al* 2001), further motivating restoration and conservation efforts (Jaenicke *et al* 2010, Leifeld and Menichetti 2018, Goldstein *et al* 2020).

Given that fire emissions in Southeast Asian peatlands have historically been largest during drought conditions attributable to El Niño Southern Oscillation and the Indian Ocean Dipole (Van Der Werf *et al* 2008), future emissions may also be influenced by long-term trends associated with climate change (Li *et al* 2007). Regional climate simulations have shown that average rainfall will likely decrease in Southeast Asia in future decades (Li *et al* 2007, Tangang *et al* 2020), especially during the dry season (Kang *et al* 2019). Additionally, changes in solar radiation, atmospheric humidity, and temperature may also affect the peat water balance. Understanding how future climate will affect peat vulnerability is necessary to inform management, restoration, and conservations efforts. However, the sensitivity of peatland moisture to climate change is likely highly variable across the region. Several factors influence how different hydroclimatological conditions affect peat moisture including the initial distribution of water table depth, water uptake differences between vegetation types (Hirano *et al* 2015, Manoli *et al* 2018), canal properties including their depth, width, and spatial pattern, (Page *et al* 2009, Dadap *et al* 2021, Cobb *et al* 2020), microtopography, hydraulic properties of the peat and its macropores (Mezbahuddin *et al* 2015, Baird *et al* 2017, Cobb *et al* 2017), and more (Sinclair *et al* 2020). Because the distribution of these factors across the region is poorly understood and highly uncertain, it is not feasible to parameterize physical hydrologic models (or using land surface simulations from existing regional climate models) to understand how climate change affects peat moisture across this region.

Here, we instead used observations and a statistical modeling approach to estimate how climate change will influence peat hydrological conditions in the coming decades. In particular, we considered surface soil moisture, which has previously been shown to be closely related to peat fire risk (Dadap *et al* 2019) and for which observations are widely available across Southeast Asian peatlands using data from the Soil Moisture Active Passive (SMAP) satellite (Entekhabi *et al* 2010, McColl *et al* 2017). In tropical peatlands, surface soil moisture is closely connected to water table depth (Hirano *et al* 2014, Dadap *et al* 2019), the most commonly used metric of peat moisture levels for fire risk studies (e.g., Wösten *et al* 2008, Hooijer *et al* 2012). Using machine learning, we built a statistical model to predict soil moisture variations across the region as a function of several climate factors. The statistical model was then used to analyze the impact of climate change on soil moisture across the region, including its spatial distribution and variation with land use type.

2 Methods

2.1 Approach

This study focused on peatlands in Insular Southeast Asia, an area spanning ~157,000 km^2 on Sumatra, Borneo, and Peninsular Malaysia. All analyses were limited to pixels covered by at least 50% peatlands, as determined from 30 m land cover maps (Miettinen *et al* 2016), and were performed on the 9 km EASE-Grid resolution of the SMAP data (Brodzik *et al* 2012).

Our general approach in this study was to train statistical models (neural networks) to learn relationships between climate, degradation, location, and soil moisture in Southeast Asian peatlands under present climate. The neural networks were then used with projections of future climate to predict future soil moisture. This approach is illustrated in Fig. 1. Such a climate sensitivity approach has been used previously to understand features of hydrologic projections (Short Gianotti *et al* 2020).

The neural networks were trained using remotely sensed soil moisture from SMAP over the 2015-2020 period. Because of the relatively short training period (dictated by the limited observational record), the neural networks' ability to capture interannual variations were explicitly cross-validated to ensure they could predict both spatial and temporal variations of soil moisture. To determine how soil moisture statistics were affected by climate change, the neural networks were then run with a set of regional climate predictions dynamically downscaled from three global climate predictions for a reference (1985-2005) and future time period (2040-2060). To reduce the effect of biases in the global circulation models downscaled by a regional climate model (RCM), all climate inputs were bias-corrected to match the statistics of an observation-driven dataset, here the European Centre for Medium-Range Weather Forecasts ERA5 reanalysis product (Hersbach *et al* 2019).

Here, we directly predict simplified soil moisture statistics to avoid the need for explicit simulation of soil moisture timeseries in the future. These variables were: 1) mean dry season soil moisture ($sm_{dry\ season}$) and 2) percent low soil moisture ($pct_{low\ sm}$), defined here as the percent of time in a given year that the soil moisture is below 0.2 cm^3/cm^3. For mean soil moisture, we focus on the dry season only because that is more closely tied to fire risk. Previous work using both laboratory measurements (Frandsen 1997) and SMAP soil moisture (Dadap *et al* 2019, Figure 3) showed that peat ignition probability (at laboratory scale) and burned area (at remote sensing scales) sharply increase when soil moisture is below a threshold value of about 0.2 cm^3/cm^3. Thus, the $pct_{low\ sm}$ statistic represents the fraction of a given year when the peat is at high fire risk and captures the non-linear response of fire to soil moisture.

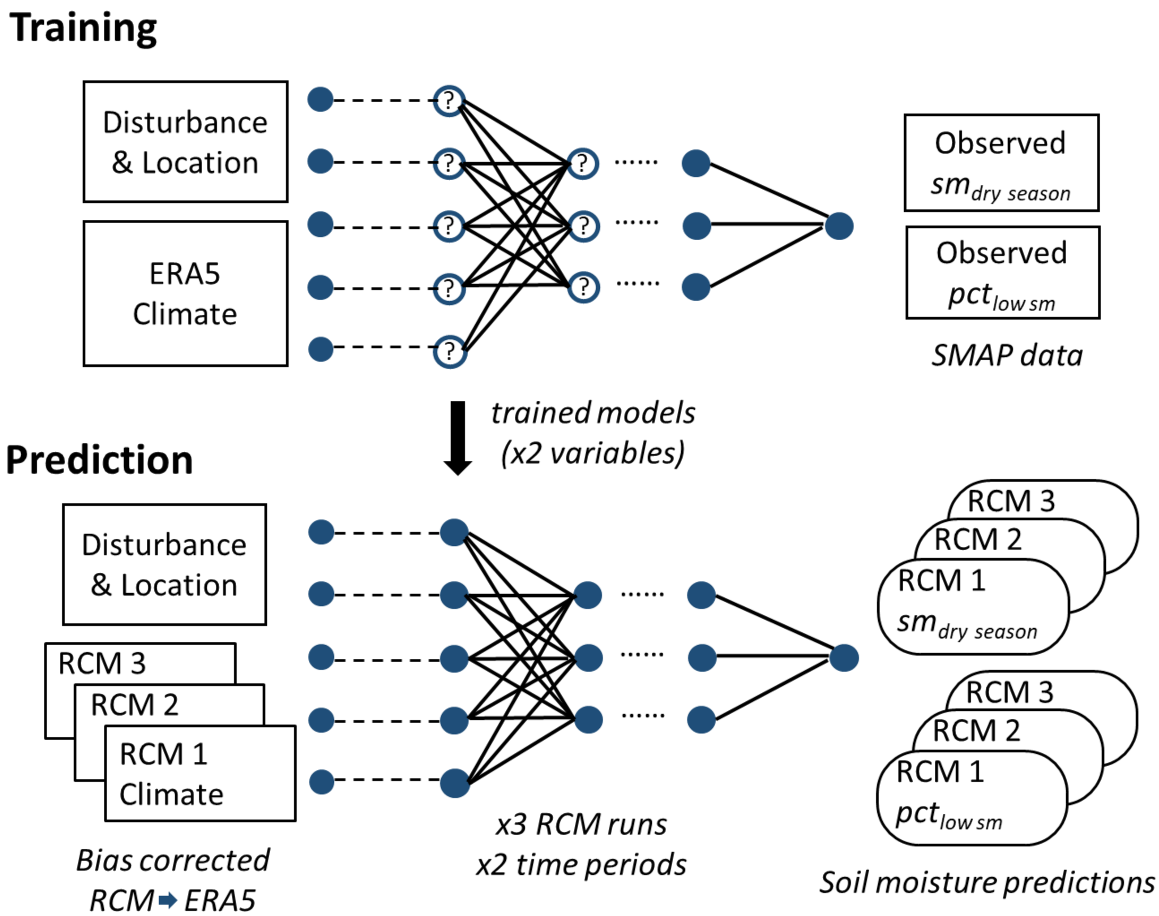

Figure 1. Overview schematic of the soil moisture modeling approach. Squares denote input data while ovals denote neural network predictions. The model is first trained on ERA5 climate and SMAP soil moisture data. Predictions are then calculated for reference (1985-2005) and future (2040-2060) time periods using climate data from a regional climate model forced by three global circulation models. Input climate data are bias-corrected to ERA5 reanalysis data using quantile mapping.

Soil moisture data from SMAP are available every 2-3 days at 9 km resolution during 2015-present. An example SMAP soil moisture timeseries is shown in Supplementary Figure 1. We used soil moisture retrieved from the Multi-Temporal Dual Channel Algorithm (MT-DCA) (Konings *et al* 2016, 2017, Feldman *et al* 2021). Because the MT-DCA retrievals rely on a dielectric mixing model that was developed for mineral soils (Mironov *et al* 2004), an empirical correction was applied to account for the high organic matter content of the peat (Bircher *et al* 2016). Measurements with potentially high error associated with radio frequency interference, urban areas, and precipitation were excluded from the dataset. Microtopography and the presence of organic material on the peat may add error to the soil moisture retrievals, as the presence of litter can affect L-band soil moisture retrievals even in less densely vegetation sites (Kurum *et al* 2012). Thick vegetation can also block remote sensing measurement of soil moisture where present. Furthermore, little in situ validation of SMAP data has been performed in this region. Nevertheless, triple collocation-based (statistical) error analysis of SMAP soil moisture in the region previously showed that retrieval precision is likely on par with the SMAP mission target error of 0.04 cm^3/cm^3 (Dadap *et al* 2019).

2.2 Neural network-based estimation of soil moisture

2.2.1 Input features

Input features were chosen to capture the possible effects of climate, degradation, and location on soil moisture (Supplementary Table 1). Climate variables included precipitation and potential evapotranspiration (PET) to represent water supply and evaporative demand; PET was calculated from radiation and temperature using the Priestly-Taylor method. These were represented in the neural networks with mean dry season PET, mean dry season precipitation, mean annual precipitation and precipitation entropy. Precipitation entropy (calculated as the Shannon entropy of monthly precipitation) was included because it is a descriptor of rainfall seasonality (Feng *et al* 2013), or the degree to which rainfall is distributed between the wet and dry seasons. A smaller entropy value indicates larger seasonal differences in precipitation. Although PET might deviate from actual evapotranspiration, only PET was included here since the RCM and reanalysis data may not capture the differences in water use strategies (and thus, the actual/potential ET ratio) in different land use types.

Because the study area is dominated by coastal areas and topographic complexity, a high resolution simulation is necessary for more accurate prediction of climate variables (Im and Eltahir 2018). Here, we used 25 km regional climate data from the Coordinated Regional Climate Downscaling Experiment - Common Regional Experiment (CORDEX-CORE) as inputs to the neural networks for the reference (1990-2005) and future periods (2030-2070) (Im *et al* 2021, Giorgi *et al* 2021). These data are driven by three global circulation models under Representative Concentration Pathway 8.5 forcing (Meinshausen *et al* 2011), then downscaled using the Regional Climate Model version 4.7.0 (RegCM4.7.0) developed at the Abdus Salam International Centre for Theoretical Physics. This results in three different RCM realizations corresponding to the three GCMs. See Supplementary Text 1 for more information on the climate data.

Peatland degradation features used in the neural network model included the percent of different land use types, tree cover fraction, drainage canal density, fire area, and fire count. These factors are likely to change significantly in the future, but it is difficult to predict how they will change due to shifting economic incentives and regulations (Humpenöder *et al* 2020, Schoneveld *et al* 2019, Suwarno *et al* 2018). We therefore only considered changes in climate variables in this study, but incorporated these additional land use and fire inputs to account for their effect on the soil moisture-climate relationship. Location descriptors including latitude, longitude, region, and distance from the edge of the peat dome were also used as predictors to account for possible spatial autocorrelated factors affecting soil moisture, such as land use history, peat physical properties, and land management practices. See Supplementary Text 1 and Supplementary Table 1 for more information on the input features and neural network structure.

2.2.2 Application of neural networks for future prediction

We compared predictions of $sm_{dry\ season}$ and $pct_{low\ sm}$ between the reference (1985-2005) and future periods (2040-2060). In each case, degradation and location input features were held constant while climate features changed based on bias-corrected RCM predictions. Bias correction of the climate data was necessary because there are biases between the RCM simulations and the pseudo-observational ERA5 data. These differences in distributions would otherwise result in projections of soil moisture incorrectly attributed to changing climate that are instead due to differences between ERA5 and the RCM. We used quantile mapping to correct these biases (Reichle et al., 2004; Miao et al., 2016). Specifically, we matched reference period RCM data to ERA5 data from the same time period, and then applied the same correction to future period RCM data. A separate quantile mapping was applied to each of the three RCM realizations (corresponding to each global circulation model). Both RCM and ERA5 data used for bias-correction were downscaled to 9 km resolution from their original 25 and 30 km grids, respectively, using nearest neighbor resampling.

3 Results and Discussion

3.1 Soil moisture models assessment

Cross validation for both soil moisture variables, $sm_{dry\ season}$ and $pct_{low\ sm}$, demonstrated that the neural network models could predict out-of-sample data accurately (Table 1, Supplementary Figure 2). The $sm_{dry\ season}$ model achieved a cross-validation (CV) mean R^2 = 0.83, RMSE = 0.08 cm^3/cm^3, and a bias of 0.001 cm^3/cm^3 on randomly sampled test data. Similarly, the $pct_{low\ sm}$ model achieved a cross-validation mean R^2 = 0.73, RMSE = 16%, and a bias of 0.8% on random test data. When the two networks were cross-validated using a full year's worth of held-out data, R^2 decreased only a slight amount ($\Delta R^2 \approx 0.1$ in both cases), suggesting the networks were able to predict soil moisture behavior on unseen years of data, including simulated future years.

Model	Random CV Train R^2	Random CV Test R^2	Temporal CV Train R^2	Temporal CV Test R^2
$sm_{dry\ season}$	0.95 ± 0.01	0.83 ± 0.02	0.90 ± 0.08	0.73 ± 0.12
$pct_{low\ sm}$	0.92 ± 0.02	0.73 ± 0.03	0.91 ± 0.03	0.64 ± 0.13

Table 1: Cross-validation (“CV”) results +/- standard deviation across folds. Temporal CV was performed by holding out one year of data at a time for the test set, and training on the other years. For example, the data would be trained on 2015-2019 data and evaluated on unseen 2020 data. This was then repeated for all six years of data. Random CV involved random selection of data from all years (across all pixel-times) when performing five-fold cross validation.

3.2 RCM predicts drier future atmospheric conditions

RCM projections show overall drying in the study region, as dry season precipitation is projected to decrease across 89% of the area (Figure 2a), while PET is projected to increase across 98% (Figure 2b). The median change in dry season precipitation is -0.79 mm/day and the median PET change is +0.38 mm/day between the reference (1985-2005) and future (2040-2060) periods (Supplementary Figure 3a). Geographically, there are larger decreases in dry season precipitation in southern Sumatra and larger increases in dry season PET in the southern parts of the study region (Figure 2). Because evapotranspiration (ET) is the dominant water flux out of peatlands (e.g., Hirano *et al* 2015, Cobb and Harvey 2019), increased PET is expected to lead to decreases in soil moisture.

Annual precipitation is projected to decrease by ~0.5 to 2 mm/day in the study region (Figure 2c, Supplementary Figure 3b). Precipitation seasonality, as captured by precipitation entropy, exhibited a mixed change in signal by latitude in Sumatra: generally decreasing south of the equator and increasing north of it (Figure 2d, Supplementary Figure 3b). Decreasing entropy suggests higher seasonality, which may cause drier $sm_{dry\ season}$, as precipitation may be less evenly distributed between the dry and wet seasons. These results are consistent with those of Kang *et al* (2019), who found that Aug-Oct precipitation (corresponding to the dry season across most of the study area) generally decreased while Nov-Jan precipitation generally increased. While our model did not account for possible changes in the timing of the dry season, only relatively minor changes are projected in the timing of the monsoon in this region (Ashfaq *et al* 2020). Overall distributions of climate features shifted under future climate (Supplementary Figure 3), but these shifts generally did not extend far beyond the ranges observed under future climate. This builds confidence that the neural networks trained using present climate-soil moisture relationships can accurately assess the impact of future climate scenarios.

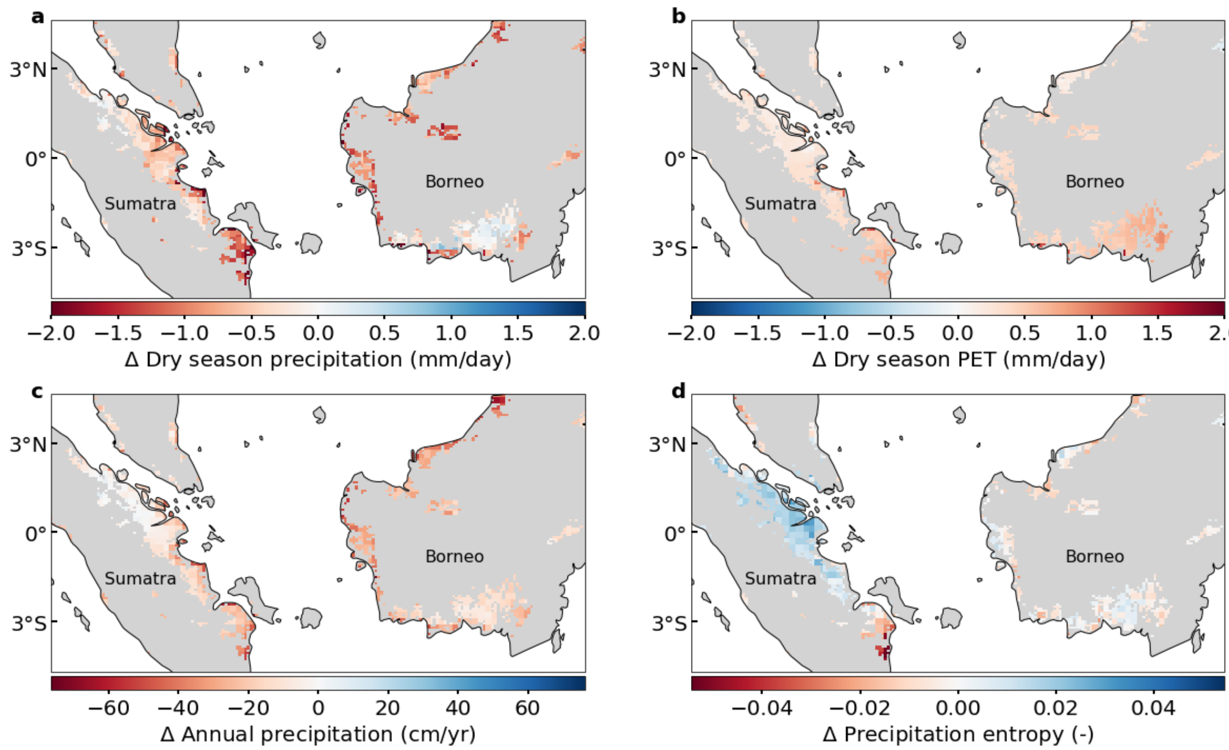

Figure 2. Mean change in climate variables between reference (1985-2005) and future (2040-2060) periods for a) dry season precipitation, b) dry season PET, c) annual precipitation and d) precipitation entropy. Red indicates drier Dry season conditions; note the colorbar is reversed in b). Non-peat areas are shown in gray. These four variables make up the input climate features in the neural networks.

3.3 Climate changes cause substantially drier soils and more prevalent high fire risk regimes

Both soil moisture variables exhibited drier conditions under 2040-2060 climate projections compared to 1985-2005 climate, consistent with the changes in climate forcing. Median $sm_{dry\ season}$ was projected to decrease during the future period by 0.023 cm^3/cm^3 (Figure 3a, c). For context, this decrease is nearly half the magnitude of the 0.056 cm^3/cm^3 decrease in median dry season soil moisture observed by SMAP during the 2015 and 2019 El Niño years relative to non-El Niño years between 2015 and 2020. Recent El Niño years have been associated with a non-linear increase in fire activity (Yin *et al* 2016), suggesting that the magnitude of climate-change induced soil moisture drying, absent other changes, could significantly increase fire risk in the region. However, the impacts of climate change relative to recent El Niño years differ geographically. For example, the predicted soil drying due to climate change is generally greater than impacts observed during recent El Niño droughts north of the equator, while the opposite is true south of the equator in the study region (Figure 4a, b).

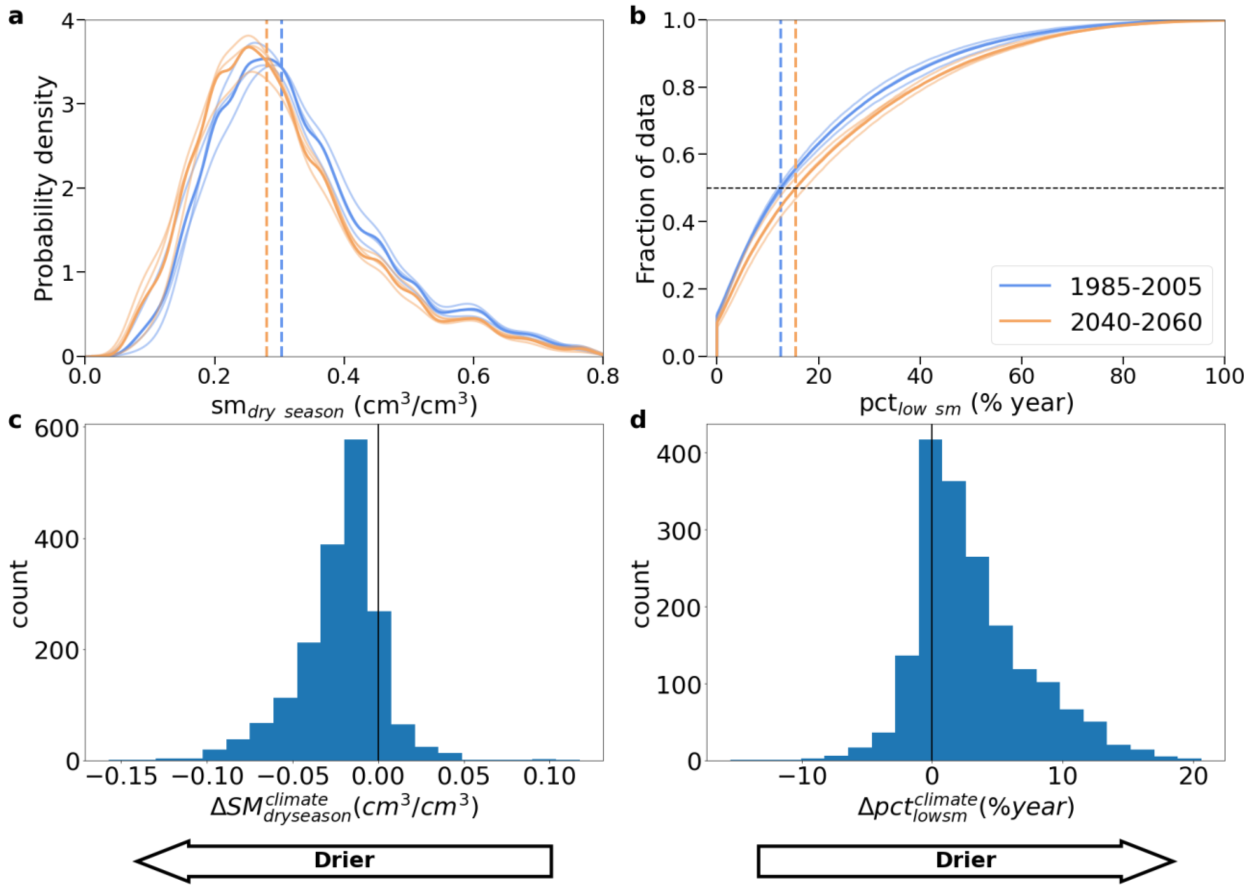

Figure 3. Changes in soil moisture variables between reference (1985-2005) and future (2040-2060) time periods. a) Probability distributions for $sm_{dry\ season}$ smoothed by a kernel density estimator. C) Cumulative distributions for $pct_{low\ sm}$. For a) and b), thin lines denote individual GCM climate projections while the thick line denotes mean distribution across GCMs. c) and d) Histograms showing per-pixel change in $sm_{dry\ season}$ and $pct_{low\ sm}$ due to climate change.

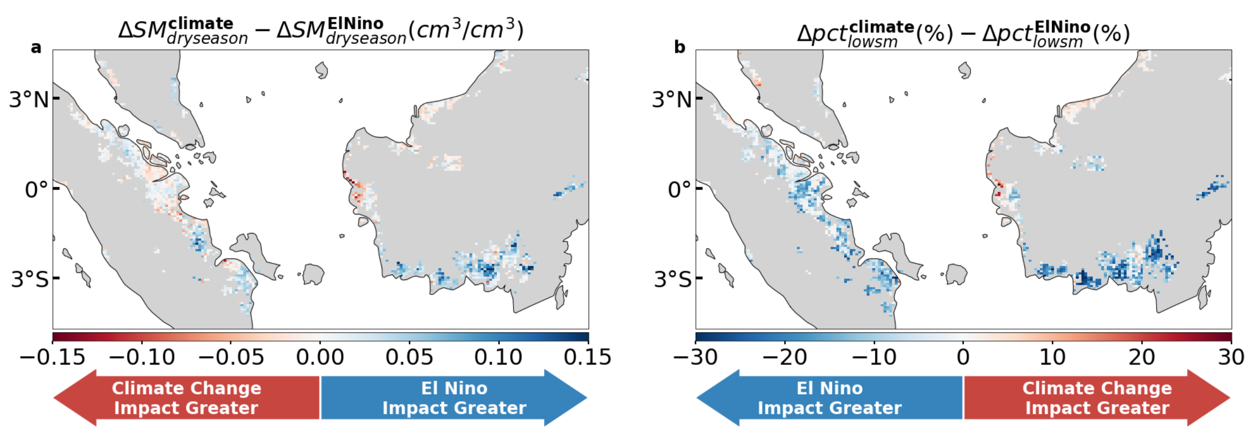

Figure 4. Comparison of future climate impacts with present day El Niño. a) Difference in predicted $\Delta sm_{dry\ season}$ due to climate change vs $\Delta sm_{dry\ season}$ observed during recent El Niño years (2015 & 2019). b) Same as in a) but for $\Delta pct_{low\ sm}$. Non-peat areas are shown in gray.

The pct_{lowsm} variable, a more direct measure of fire risk than $sm_{dry\ season}$, increases over almost the entire region. Our neural network projected a median increase in $pct_{low\ sm}$ of 3% (from 12.5% to 15.5%) (Figure 3b, d), suggesting that extremely dry conditions associated with high fire risk will be more prevalent in the future. To estimate how large the $pct_{low\ sm\ -}$associated impact on burned area might be, we consider a single average burned area associated with dry soil moisture (below 0.2 cm^3/cm^3) and another average burned area for wet soil moisture conditions (as calculated from the curve in Fig. 3a of Dadap *et al* 2019). The increase of the 3% in $pct_{low\ sm}$ would then correspond to a 10% increase in burned area due to future climate change. This calculation, though highly simplified, illustrates the outsized increase in fire risk associated with even small increases in $pct_{low\ sm}$ driven by climate change.

Drought conditions during recent El Niño years have been attributed primarily to precipitation drought (e.g., Field *et al* 2016), but our model suggests that future changes in $sm_{dry\ season}$ are also affected by increased evaporative demand (i.e., increasing PET). This is evident from the higher feature importance of PET compared to precipitation inputs for both neural networks (Supplementary Figure 4). Consistent with this finding, running the model with future (2040-2060) PET but with reference (1985-2005) precipitation resulted in a decrease in median $sm_{dry\ season}$ that was 0.008 cm^3/cm^3, or 36% of the change when precipitation drivers were included. Thus, our results suggest that increased evaporative demand will play a significant role in driving soil moisture changes under climate changes. Land-atmosphere feedbacks may further exacerbate soil drought and atmospheric aridity under future climate (Zhou *et al* 2019).

3.4 Degraded areas exhibit higher sensitivity to future climate change

To better understand where soil moisture changes will occur, we separated model predictions by land use (here determined by the majority land use type in each pixel). During the reference period (1985-2005), pristine forest was predicted to have the wettest median $sm_{dry\ season}$, while open undeveloped was the driest (Figure 4a). Nevertheless, reference period distributions of $sm_{dry\ season}$ were generally found to have little variation across land uses (Figure 4a). This was somewhat surprising, as land use is often used as a proxy for hydrologic disturbance (e.g., Miettinen *et al* 2017, Taufik *et al* 2020). However, our model predictions were mostly consistent with a meta-analysis of in situ soil moisture measurements, which show similar soil moisture magnitudes across land use types and large variation within land uses (Supplementary Figure 5, Supplementary Table 2). Such high variability of soil moisture within land use types is likely due to differences in precipitation regimes, peat physical properties, drainage density, and more.

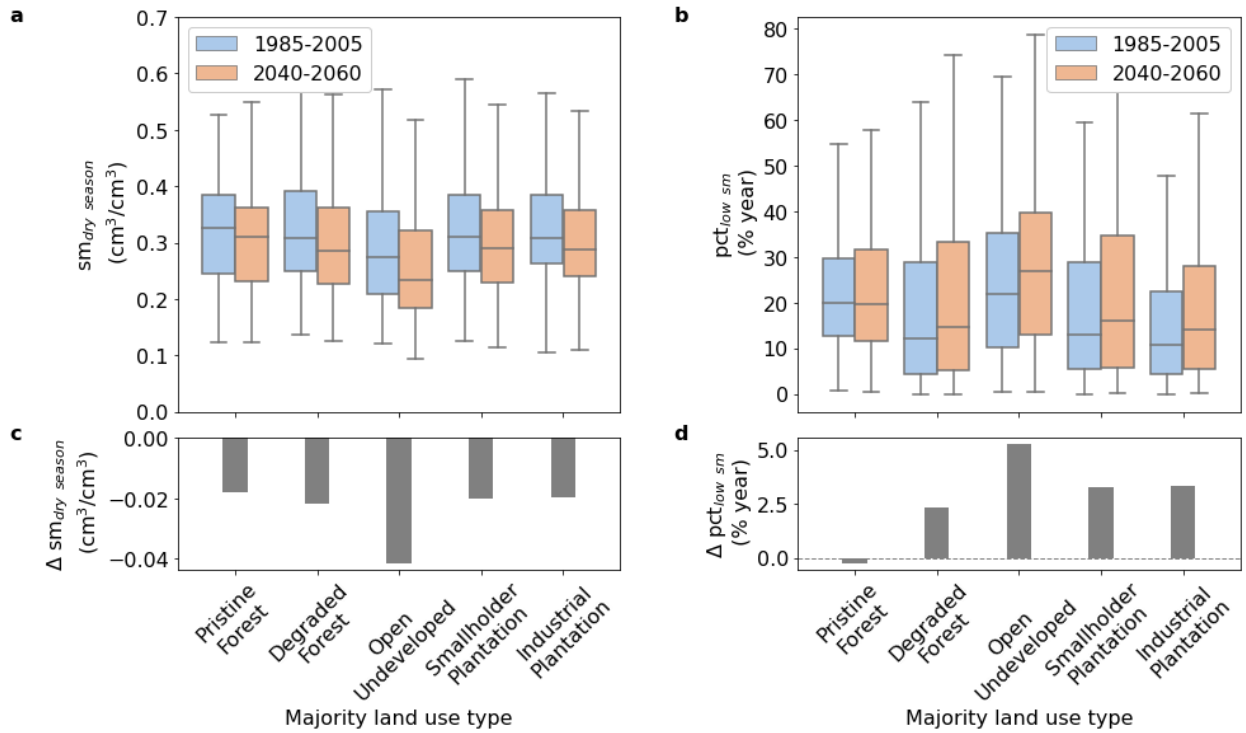

Fig 5. Soil moisture distributions grouped by land use type for a) $sm_{dry\ season}$ and b) $pct_{low\ sm}$ during reference (1985-2005) and future (2040-2060) periods. Box denotes inter-quartile range and median. Change in median c) $sm_{dry\ season}$ and d) $pct_{low\ sm}$ from reference to future periods.

Degraded land use types (including degraded forest, open undeveloped, smallholder plantation, and industrial plantation) exhibit larger magnitudes of drying than pristine forest (Figure 5c, d). In particular, open undeveloped areas are predicted to experience the largest changes, while pristine forests are predicted to experience the smallest changes. Open undeveloped areas generally have the lowest starting soil moistures, suggesting that the driest areas will dry further than wetter areas. The differences in soil moisture changes by land use type could be caused by i) climate changing more in certain land use types and/or ii) certain land use types are inherently more sensitive to changes in climate. However, the former does not appear to be a major factor, because the magnitude of soil moisture changes does not correlate with climate changes when grouped by land use type (Figure 6), except for increases in PET with decreases in $sm_{dry\ season}$. This suggests that land use could affect the sensitivity of soil moisture response to climate change.

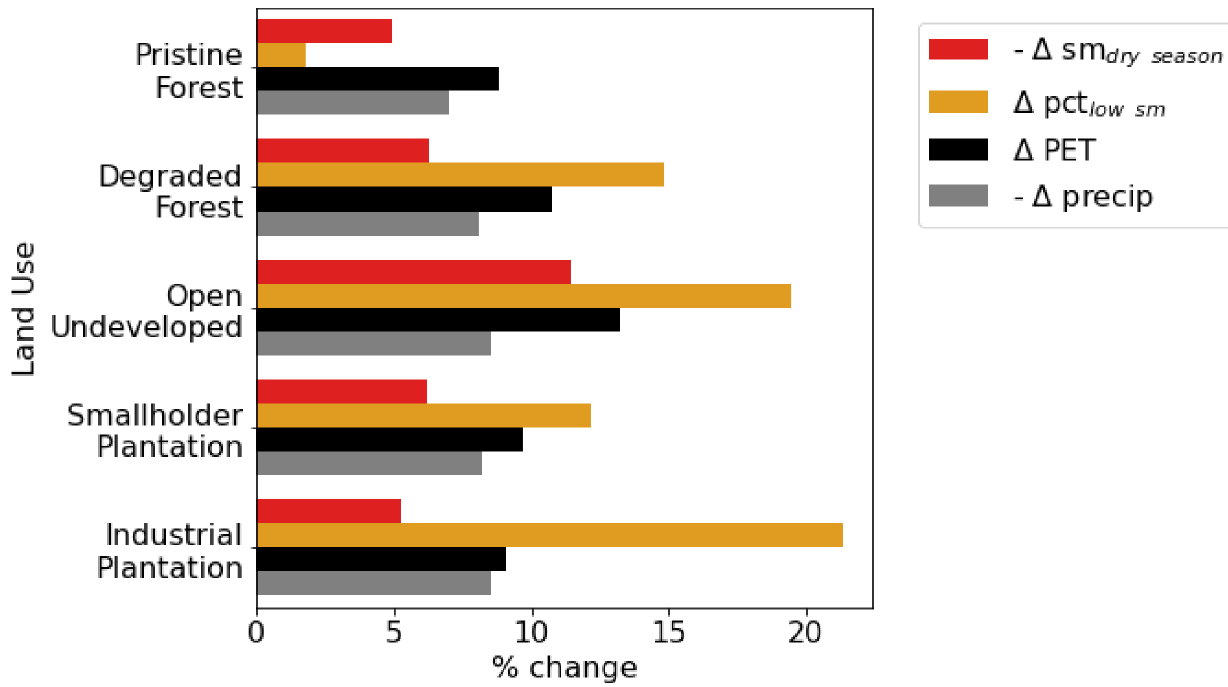

Figure 6. Magnitude of percent change in soil moisture variables ($sm_{dry\ season}$ and $pct_{low\ sm}$) compared to percent change in climate variables (dry season PET and dry season precipitation). Changes in soil moisture do not appear to vary with changes in climate. Note the signs for $sm_{dry\ season}$ and for dry season PET denote negative change.

Our results further suggest that tree cover affects soil moisture sensitivity to climate change. We regressed $\Delta sm_{dry\ season}$ and $\Delta pct_{low\ sm}$ with the input metrics that capture peatland degradation (tree cover, canal density, and fire), and found significant relationships for both variables only with tree cover (Supplementary Figure 6). These relationships suggest that areas with less tree cover are more sensitive to climate changes (i.e., will experience more drying) than areas with more tree cover. This increased sensitivity with less tree cover can be explained by a number of possible mechanisms. First, tree cover reduces the solar radiation reaching the ground surface. In areas with less or shorter vegetation, this effect is minimized, and atmospheric conditions are more likely to determine changes in soil evaporation (Ohkubo *et al* 2021, Fan *et al* 2019). Deforested areas are also more likely to contain degraded soils with increased hydrophobicity (Perdana *et al* 2018, Bechtold *et al* 2018). This in turn could decrease rainfall infiltration, increase soil evaporation, and decrease the capillary connection with the water table and the surface soil, making degraded areas more sensitive to climate changes. Furthermore, reduced hydraulic diversity (Anderegg *et al* 2018), shallower roots, or less stomatal regulation (Manoli *et al* 2018) are characteristic of agricultural areas that have lower tree cover fraction.

It should also be noted that SMAP soil moisture measurement could be affected by differences in peat microtopography by land use type, complicating comparisons of soil moisture between land use types. For example, the duff and litter layers that form the hummock and hollow topography endemic to pristine peatlands are often replaced by a denser, flatter surface when graded or converted to agricultural use (Lim *et al* 2012). These differences could in turn affect the profile of soil moisture measurement relative to the groundwater table. For example, Sakabe *et al* 2018 found high variability in surface soil moisture within pristine forests based on the location of measurement: hummocks averaged 0.06 cm^3/cm^3 while hollows averaged 0.54 cm^3/cm^3, but the drier value would not necessarily imply higher fire risk. Such small-scale spatial variability would be averaged to a single measurement by SMAP, which integrates measurements over 9 km pixels. However, this variability would not exist in land use types where the ground surface is generally flatter. Thus, in situ validation studies are needed to better understand how to interpret differences in SMAP retrievals between land use types and their implications for fire risk and carbon emissions. Nonetheless, comparisons within land use types would not be affected by this potential issue, and the predicted drying trends observed in all land use types underscores the consistent prediction of drying due to climate change.

4 Conclusions

Our model projections suggest that future drier climatic conditions across Southeast Asia will lead to lower mean soil moisture and more frequent periods with dangerously dry peat conditions that would lead to increased fire risk. The median predicted decreases in soil moisture are nearly half the magnitude of those experienced during high-fire drought years associated with El Niño under current climate, portending more prevalent fire risk due to climate change. In contrast to recent droughts, future drier soil conditions also appear to be driven by increased evaporative demand in addition to reduced precipitation. More degraded peatlands with lower tree cover may be especially sensitive to climate change, motivating the importance of restoration in not only reducing current carbon emissions and fire risk, but also towards lessening the impacts from future climate change. Degradation is understood to be a critical determinant of peatland hydrology, but our results suggest that climate change will also play an important role in determining future soil moisture regimes.

5 Data Availability

The code used to train and analyze the model can be obtained from https://github.com/ndadap/future-sm-peatlands.

6 Acknowledgements

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Supplementary Materials for "Climate change-induced peatland drying in Southeast Asia"

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Supplementary Text I: Neural network model information

Input feature information

Predictor features for the neural networks include data on climate, degradation, and location. Descriptions of the climate features are included in Section 2.2.1 of the main text. As noted in that section, degradation features used in the neural network model included percent of different land use types, tree cover fraction, drainage canal density, fire area, and fire count. Land use categories used included pristine forest, degraded forests, open/undeveloped areas, and smallholder and industrial plantations, following categorization by (Miettinen *et al* 2017). Land use data was derived from 2015 maps by (Miettinen *et al* 2016), who visually interpreted Landsat images at 30 m. Analysis was limited to 9x9 km pixels with at least 50% land use of one type. Tree cover fraction data was from the Global Forest Cover Change 2015 dataset (Townshend 2016). Tree cover fraction captures the extent of deforestation, and can affect soil moisture by altering a number of variables such as transpiration, shading, interception, etc. Drainage canal density, a measure of drainage canals length per unit area, was obtained from 2017 maps (Dadap *et al* 2021). Fire area and fire count were from 2012-2015 and calculated from the Visible Infrared Imaging Radiometer Suite (VIIRS) active fire product (Schroeder *et al* 2014). Fire count includes the same spatial areas as the fire area variable, but also accounts for repeated fires. Fires are both a cause and effect of peatland degradation, since they can burn layers of peat and also clear aboveground vegetation. Together, these data constituted the degradation features (Supplementary Table 1).

Location information including latitude, longitude, region, and distance from the edge of the peat boundary were also included as predictors. Use of latitude and longitude in deep learning models is a common practice (e.g., Wang *et al* 2015, Yang *et al* 2018, Shatnawi and Abu Qdais 2019, etc) that enables accounting for possible spatial autocorrelation in unaccounted-for factors affecting soil moisture, such as land use history, peat physical properties, and land management practices (e.g., maintenance of water level, mechanical compaction, etc). The use of region as an input feature serves a similar purpose and refers to four geographic areas: Northwest (Peninsular Malaysia and Sumatra north of the equator), Northeast (northern Borneo), Southwest (southern Sumatra), and Southeast (southern Borneo). Distance from peat edge refers to the distance from the center of a given pixel to the edge of the peatlands defined in Miettinen *et al* (2016). It is a proxy for distance from the nearest river/stream and depth of peat (Hoyt *et al* 2020).

Dry season definition

There are two dominant climate regimes in the study area (Aldrian and Dwi Susanto 2003). Southern Sumatra, Central Kalimantan, and Northwest Borneo experience one dry season from June-October. North Sumatra, Peninsular Malaysia, West Kalimantan, and Northeast Borneo experience two dry seasons in February and June-August. To account for such geographic differences, the dry season was defined independently for each pixel based on the monthly precipitation climatology obtained from 1979-2020 ERA5 reference reanalysis data. Here, the dry season was defined to include any months with monthly average precipitation within the lower third of the annual range, following (Myneni *et al* 2007). Dry season months were not required to be contiguous.

Neural network structure

To train and validate the neural network, a random hyperparameter search was performed to optimize the learning rate, number of layers, number of neurons per layer, and dropout rate of each network. For the $sm_{dry\ season}$ neural network, the learning rate = 0.001, number of layers = 8, and number of neurons per layer = 55. For the $pct_{low\ sm}$ neural network, the learning rate = 0.001, number of layers = 19, number of neurons per layer = 45. The dropout was 0 for both neural networks. The models were then trained for 300 epochs which was sufficient to approach convergence for model accuracy.

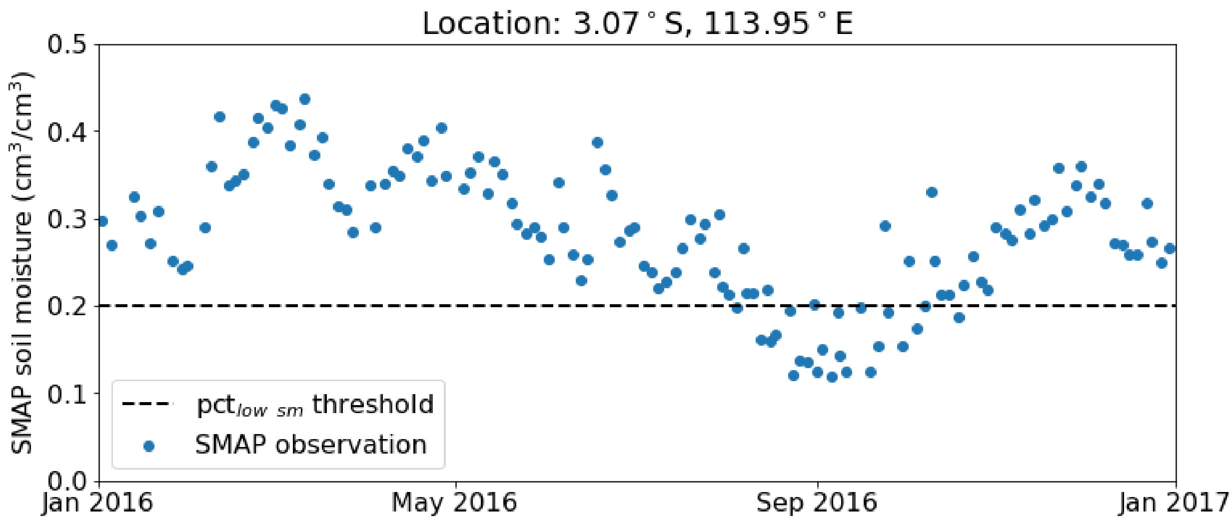
To test the ability of the trained neural network to predict $sm_{dry\ season}$ and $pct_{low\ sm}$ on future years without soil moisture observations, cross-validation was performed by holding out one year of data at a time for the test set, and training on the other years. For example, the data would be trained on 2015-2019 data and evaluated on unseen 2020 data. This was then repeated for all six years of data. To train the models such that data from all years were incorporated into training, we separately performed random five-fold cross validation across all pixel-times. For both variables of interest, the best performing model from the five-fold cross validation was selected.

Climate Data

The downscaled global circulation models used were the Norwegian Earth System Model (NorESM1-M, Bentsen *et al* 2013), the Max Planck Institute for Meteorology Earth System Model-Mixed Resolution (MPI-ESM-ER, Stevens *et al* 2013), and the Met Office Hadley Centre Earth System model (HadGEM2-ES, Jones *et al* 2011), which are representative of low, medium, and high climate sensitivity to greenhouse gas forcing, respectively, and have been shown to perform well in the study domain (Giorgi *et al* 2021). PET was calculated from temperature and net radiation using the Priestley-Taylor method.

Feature importance

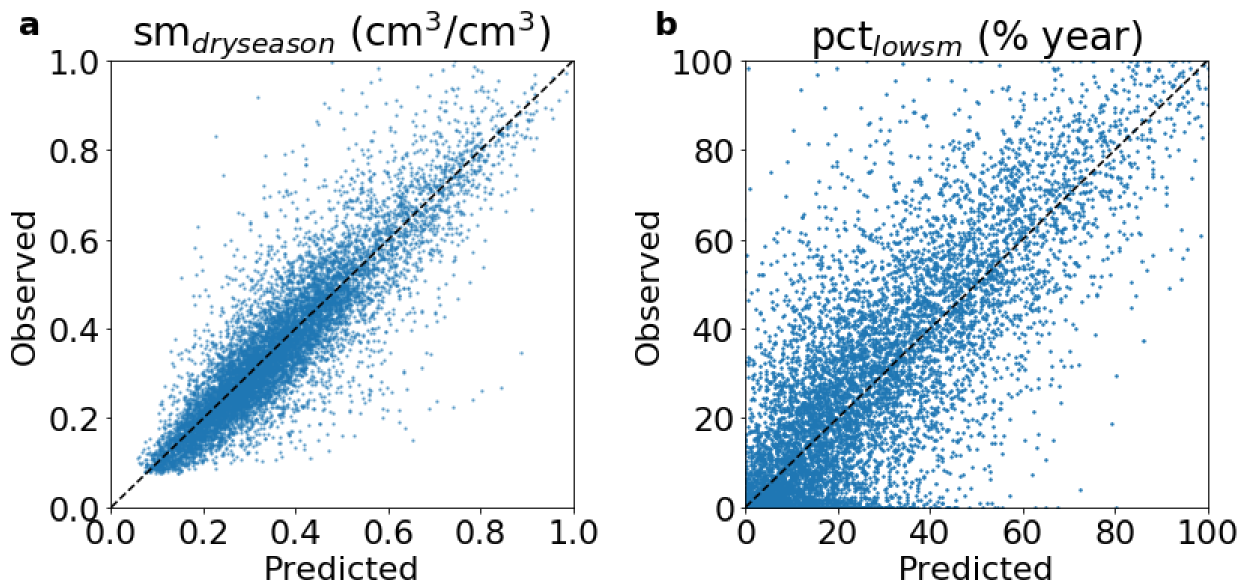
Feature importance was calculated by randomly shuffling one feature at a time and calculating the change in root-mean-squared-error (RMSE) of the neural network's predictions. Larger increases in root mean squared error when shuffling a given feature implies higher importance of that feature.



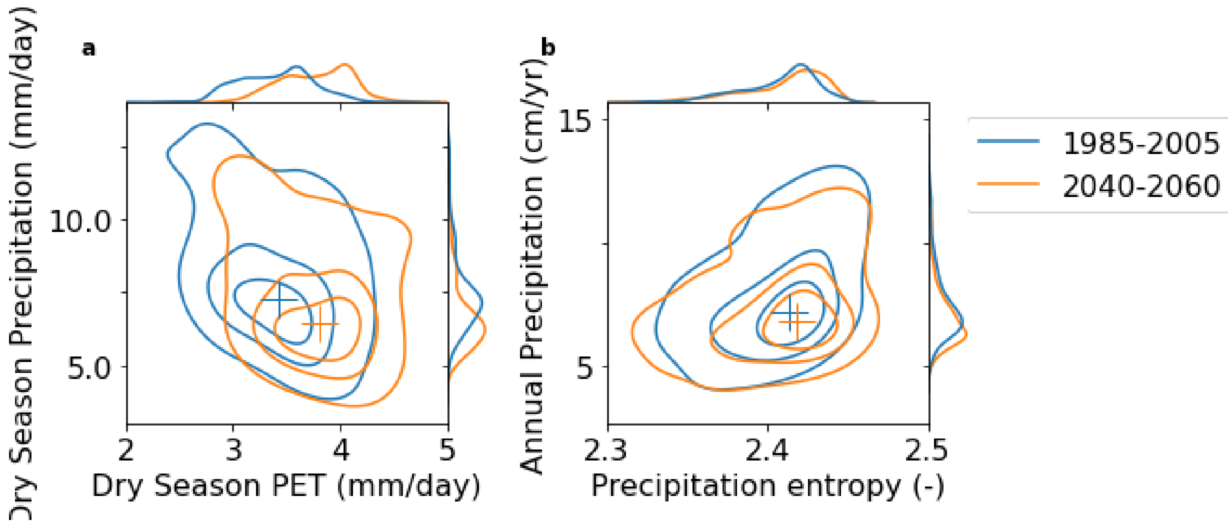
Supplementary Figure 1. Example SMAP soil moisture time series from Central Kalimantan. Low soil moisture threshold of 0.2 cm^3/cm^3 is shown as dashed line.

Variable	Category	Source	Native resolution
Annual precipitation	Climate	ERA5, RCM	25 km, 30 km
Dry season precipitation	Climate	ERA5, RCM	25 km, 30 km
Dry season PET	Climate	ERA5, RCM	25 km, 30 km
Precipitation entropy	Climate	ERA5, RCM	25 km, 30 km
Tree cover fraction	Degradation	Global Forest Cover Change 2015 (GFCC30TCv003)	30 m
Drainage canal density	Degradation	Dadap et al 2021	5 m
Fire area	Degradation	VIIRS Active Fire	375 m
Fire count	Degradation	VIIRS Active Fire	375 m
Land use type	Degradation	Miettinen et al 2016	30 m
Distance from peat edge	Location	Calculated from peatland map, Miettinen et al 2016	N/A
Latitude	Location	EASE Grid 2.0	N/A
Longitude	Location	EASE Grid 2.0	N/A
Region	Location	Determined from Lat/Lon	N/A

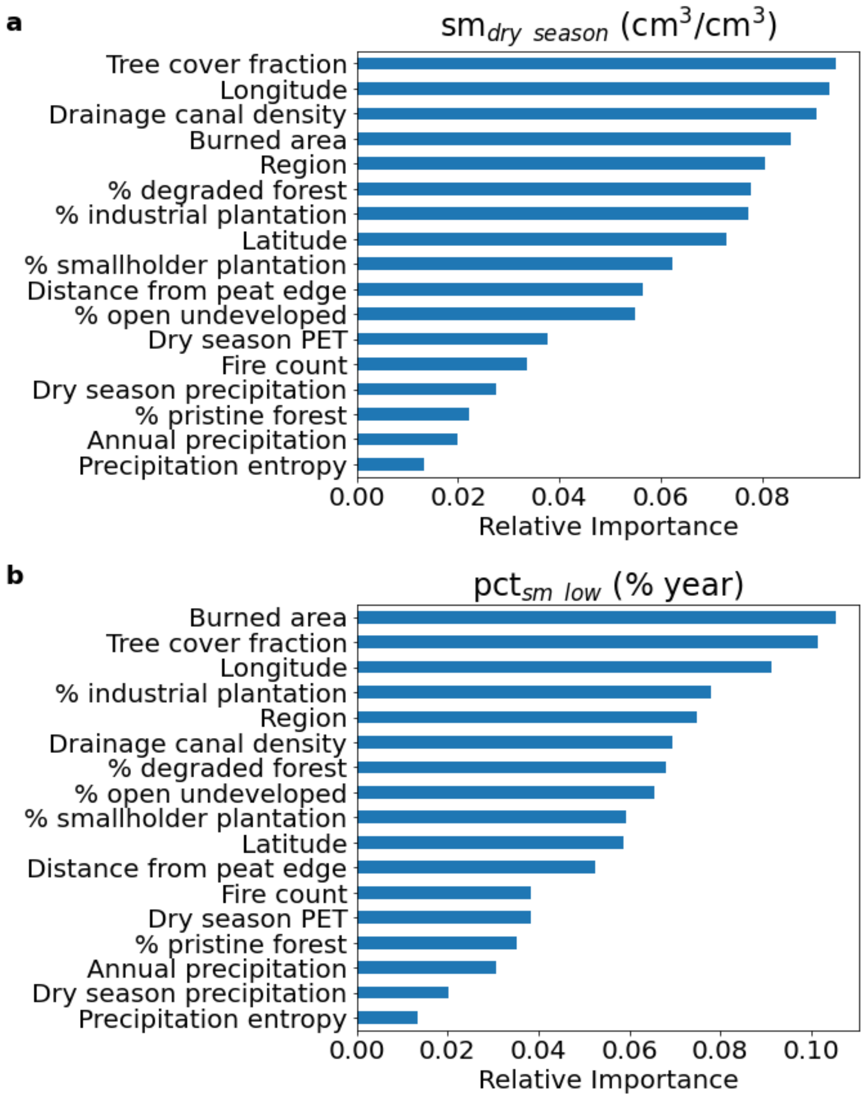
Supplementary Table 1. Predictor features



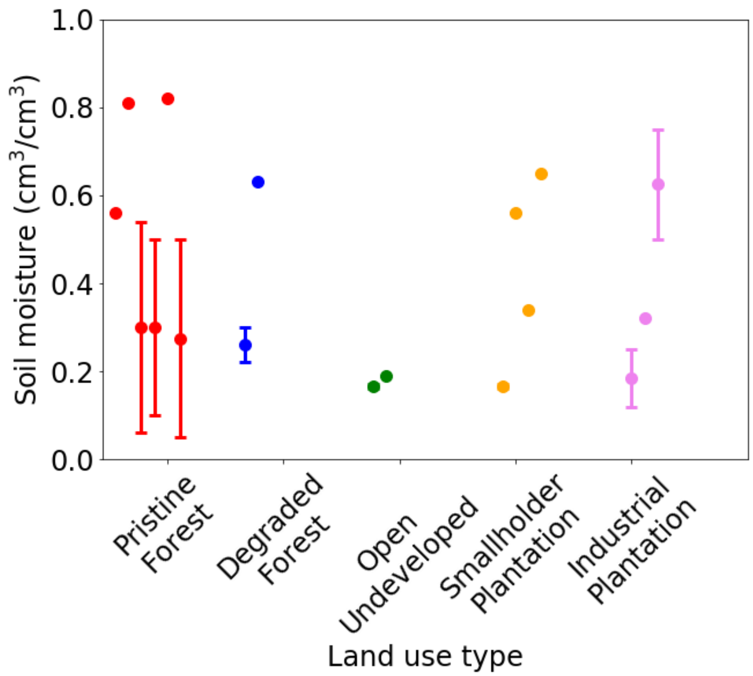
Supplementary Figure 2. Scatterplot showing model performance for a) $sm_{dry\ season}$ and b) pct_{lowsm}. These were computed using hold-one-year-out cross-validation.



Supplementary Figure 3. Change in distributions of input climate features. Contours depict probability density and cross denotes median. a) Dry season precipitation and PET. b) Annual precipitation and precipitation entropy. Higher precipitation entropy implies lower seasonality.



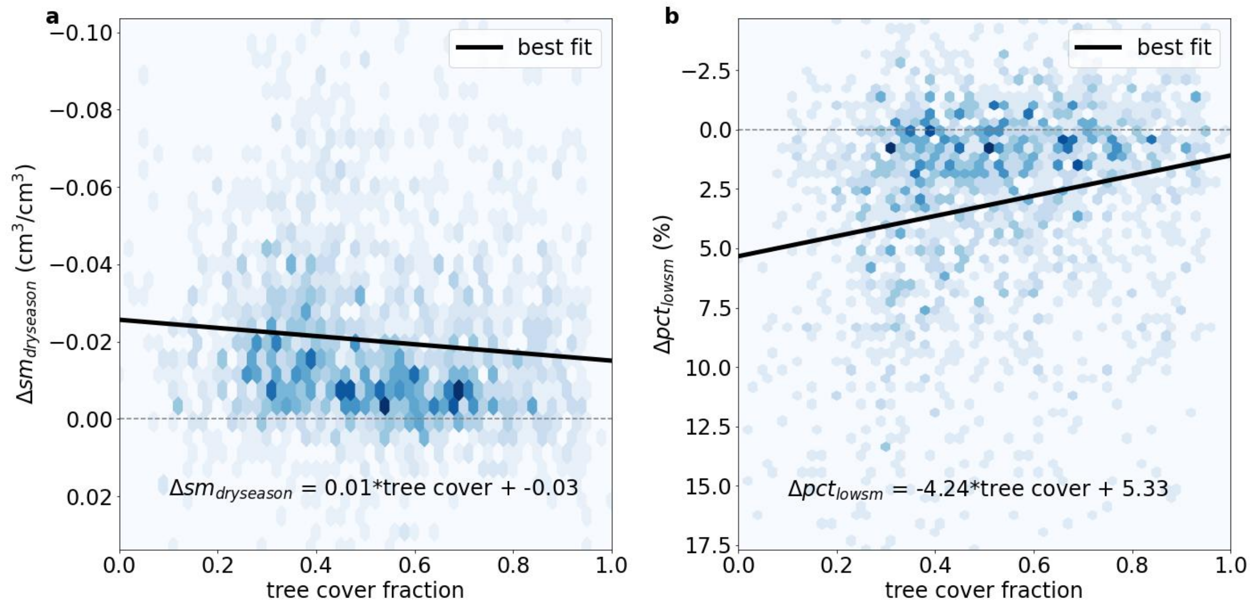
Supplementary Figure 4. Feature importance for a) $sm_{\text{dry season}}$ and b) $pct_{\text{low sm}}$. These were calculated by comparing the relative increases in cross-validation error when randomly shuffling a given predictor feature. Higher resulting error corresponds to higher importance. Values are normalized to sum to one.



Supplementary Figure 5: In situ surface soil measurements from literature (Supplementary Table 2). Where applicable, range of values is denoted by whiskers.

Supplementary Table 2. In situ soil moisture (SM) measurements from literature, during the dry season.

Paper	Land Use	Low SM	High SM	Mean SM	Where	Time Avg	Depth (cm)	Setting
Hirano *et al* 2007	Degraded Forest	0.22	0.3	0.25	Block C, ex-Mega Rice Project area	Monthly	0-20	Tree vegetation, lots of leaf litter, drainage canal present
Jauhiainen *et al* 2014	Open Undeveloped	0.16	0.17	0.165	ex-Mega Rice Project area	Yes	0-10	Clear felled, large drainage canals, surface compacted
Jauhiainen *et al* 2014	Smallholder Plantation	0.16	0.17	0.165	ex-Mega Rice Project area	Yes	0-10	Usually drained to 30-50 cm, raised, fallow, surface compacted
Hergoualc'h *et al* 2017	Smallholder Plantation			0.56	Central Kalimantan	Yes	0-10	Oil palm
Hergoualc'h *et al* 2017	Pristine Forest			0.56	Tanjung Puting, Central Kalimantan	Yes	0-10	National park
Matysek *et al* 2018	Industrial Plantation	0.12	0.25	0.2	South Selangor	Monthly	5-8	
Könönen *et al* 2018	Pristine Forest			0.81	Sabangau, Central Kalimantan	Yes	0-5	Selective logging and small ditches prior to 1997
Könönen *et al* 2018	Degraded Forest			0.63	Sabangau, Central Kalimantan	Yes	0-5	Reforested drained site 3-4 m deep canal
Könönen *et al* 2018	Open Undeveloped			0.19	Sabangau, Central Kalimantan	Yes	0-5	Drained site 3-4 m deep canal
Könönen *et al* 2018	Smallholder Plantation			0.34	Sabangau, Central Kalimantan	Yes	0-5	
Sakabe *et al* 2018	Pristine Forest	0.06	0.54	0.31	Palangkaraya, Central Kalimantan	Yes	0-20	Hummock is low number, hollow is high number. Hollow covers 65-80 % of area
Wong *et al* 2018	Pristine Forest	0.1	0.5	0.4	Maludam National Park, Sarawak	Monthly	0-30	
Manning *et al* 2019	Industrial Plantation			0.32	Sarawak	Yes	0-10	Highly variable values depending on location (0.14-0.64 cm^3/cm^3)
Marwanto *et al* 2019	Industrial Plantation	0.5	0.75	0.61	Riau	No	0-10	
Swails *et al* 2019	Smallholder Plantation			0.65	Tanjung Puting, Central Kalimantan		0-5	
Swails *et al* 2019	Pristine Forest			0.82	Tanjung Puting, Central Kalimantan		0-5	
Tang *et al* 2020	Pristine Forest	0.05	0.5	0.33	Maludam National Park, Sarawak	Yes	0-30	SM probes averaged over flat and hummock terrain



Supplementary Figure 6: Relationship between change in a) dry season soil moisture ($sm_{dry\ season}$) and b) percent low soil moisture ($pct_{low\ sm}$) with tree cover fraction. Equations show best fit linear regression line with $p<<0.01$ for the regression slope for both variables. Background shows binned density of the two variables. Data is clipped on the y-axis to show the 2^{nd}-98^{th} percentile range of the soil moisture variables.

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