Converting tropical forests to agriculture increases fire risk by fourfold

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Keywords: convection-permitting, fire risk, climate modelling, deforestation, climate extremes, fire weather

Supplementary material for this article is available online

Abstract
Deforestation exacerbates climate change through greenhouse gas emissions, but other climatic alterations linked to the local biophysical changes from deforestation remain poorly understood. Here, we assess the impact of tropical deforestation on fire weather risk—defined as the climate conditions conducive to wildfires—using high-resolution convection-permitting climate simulations. We consider two land cover scenarios for the island of Borneo: land cover in 1980 (forest scenario) and land cover in 2050 (deforestation scenario) to force a convection-permitting climate model, using boundary conditions from ERA-Interim reanalysis for the 2002–2016 period. Our findings revealed significant alterations in post-deforestation fire precursors such as increased temperature, wind speed and potential evapotranspiration and decreased humidity, cloud cover and precipitation. As a result, fire weather events that would occur once a year in the forested scenario, are likely to occur four times a year following deforestation. Likewise, for extreme conditions, such as those occurring on longer time-horizons than 20 years, the magnitude of extreme fire weather is likely to double following deforestation. These increases in extreme fire weather conditions demonstrate the key role of tropical forests in regulating regional climate processes, including reduced fire weather risk.

1. Introduction

Tropical deforestation and its environmental consequences remain a major global concern (Song et al 2018, Hansen et al 2020, Trancoso 2021). Vast areas of tropical forests were converted to agriculture in the Amazon, Congo, and Southeast Asia (SE Asia) over the past decade (FAO 2020) and large areas of remaining tropical forests are at risk of conversion (Meijaard et al 2020). Deforestation increased significantly across SE Asia in the 2000s (Hansen et al 2013, Lewis et al 2015), but decreased over the past decade in some areas (Gaveau et al 2019, FAO 2020), such as Borneo, a hotspot of deforestation in the region. Conversion to oil palm and other plantation crops have contributed to nearly 50% of the recent deforestation (Gaveau et al 2019) and with the continuing demand for vegetable oil, the drivers of deforestation are expected to continue (Meijaard et al 2020).

Forest fires have become more frequent and more intense in SE Asia in recent decades, causing major economic and environmental issues, including air pollution and human health impacts, increased GHG emissions, and a loss in forest ecosystem services (Cochrane 2003, Bowman et al 2017). Deforestation and forest fragmentation, in turn, contribute to increased fire risk, which is further exacerbated by climatic variability frequently associated with
El Niño conditions (the dry phase of ENSO) and anthropogenic climate change. These factors are impacting 'fire weather conditions'—these being the atmospheric component of wildfire risk, by increasing temperature extremes and water vapour deficit (Findell et al 2017, Abatzoglou et al 2019, Park et al 2021, Zhong et al 2021). The interplay between deforestation and fire is evident in Borneo, which experienced extensive deforestation between 1973 and 2015 (Miettinen et al 2016), with many associated vegetation fires (Gaveau et al 2019). Droughts, timber harvesting and forest fragmentation increase the likelihood of forest die-back, flammability and repeated fires (Siegel et al 2001, van Nieuwstadt and Ship 2005, Corlett 2016, Brando et al 2019). Selective tree removal, as commonly practiced in Bornean forests, makes remaining forests more vulnerable to fires due to the opening of the canopy and increased drying within the forest understory (Langner et al 2007, Staal et al 2015). In southern and eastern Borneo, the climate has become hotter and drier with more frequent extremes because of historical deforestation (McAlpine et al 2018).

The assimilation of land cover maps into climate models in one way to assess the impact of land cover changes on regional climate and thus can be used to understand how continuing deforestation could affect the regional climate. However, the spatial resolution of conventional global climate models (100–200 km) or regional models (10–20 km) and the nuances of regional land cover change (<1 km) are poorly matched. Also, the convection parameterization used in these models limit their ability to resolve fine scale climate processes (such as convection) associated with the changes in energy and moisture exchanges between vegetation and atmosphere. Nevertheless, climate models can also be run at very-high spatial resolution (1–4 km), such as those used for weather forecasting, which are called convection-permitting models (CPMs) (Prein et al 2015, Guichard and Couvreux 2017). CPMs represent land-surface characteristics and explicitly resolve small-scale processes in the atmosphere such as the movement of liquid or gas driven by differences in temperature, which is expected to reduce projection uncertainty associated with the convection parameterizations of coarser resolution climate models (RCMs) (Kendon et al 2021). Most studies on the added value of CPMs have focused on extreme climate, especially convective rainfall (Lucas-Picher et al 2021). However, by explicitly representing the landscape, CPMs also offer a great opportunity to tackle how changes in land cover may affect regional climate. Previous assessments of CPM simulations against observations, such as satellite data and flux towers across different land covers have shown CPMs perform better than RCMs distinguishing differences in regional climate over different land covers (Vanden Broucke and Van Lipzig 2017, Ge et al 2021). Yet, to the best of our knowledge, the impact of tropical deforestation on regional climate—that is the changes in the vegetation-atmosphere feedbacks following forest replacement, and the effect on regional atmospheric processes—has not been studied through CPMs. Deforestation is known to increase fire weather risk, but studies quantifying and attributing them are still limited (Findell et al 2017, Zhong et al 2021). Specifically, how the elimination of forest-atmosphere feedbacks and water and energy exchanges following deforestation may affect the precursors of fire weather (e.g. rainfall, evapotranspiration, wind, temperature, humidity) is largely unknown. The use of CPMs, however, offers the opportunity to track both landscape and climate processes simultaneously with a great potential to tease out how deforestation impacts the precursors of fire weather risk.

In this paper, we investigate the impact of continuing the conversion of Borneo’s forest to agriculture on its regional climate using CPMs. The specific objectives are to: (a) assess the key climate drivers of fire weather following deforestation; (b) examine changes in selected climate extreme indices impacting Borneo’s climate; and (c) quantify the changes in fire weather risk induced by deforestation. We developed two land cover scenarios: the forest scenario and the deforestation scenario to force a CPM, using ERA-Interim reanalysis for the 2002–2016 period to assess the impact of deforestation on fire risk.

2. Data and methods

2.1. Study area

Borneo is the world’s second largest tropical island (743 000 km²) after New Guinea and is governed by three countries: Malaysia (Sarawak and Sabah), Indonesia (West, Central, South, East, and North Kalimantan), and the sovereign state of Brunei ‘Negara Brunei Darussalam’. It has an equatorial climate with relatively constant temperatures (25 °C–35 °C) in lowland areas and variable precipitation (Hendon 2003). Precipitation patterns are dominated by monsoonal circulation (Tangang et al 2017) associated with the southeast ‘dry’ monsoon (May–October) and a northwest ‘wet’ monsoon (November–April). Borneo’s highest rainfall is in the West, north-western and central mountain areas, with drier and more seasonal conditions in the eastern and especially south-eastern part of the island. The island’s main natural vegetation is the tall species-rich evergreen rain forest, dominated by canopy trees.

2.2. Land cover scenarios

In order to assess the likely impact of future deforestation on Borneo’s climate, we developed two land cover datasets to use in high-resolution (4 km grid cell size) climate modelling experiments. The two scenarios are representative of land cover in 1980
(forest scenario) and the projected land cover by 2050 (deforestation scenario; figure 1). The forest scenario (figure 2(a)) was derived from the Advanced Very High-Resolution Radiometer satellite data at 1 km spatial resolution (Hansen et al 2000), using a hierarchy of pair-wise class trees where a logic based on vegetation form was applied to find the vegetation classes. The overall agreement per pixel is 65% and the agreement of forest ranged from 81%–92% (Hansen et al 2000). To construct the deforestation scenario, we first derived a 2015 land cover based on MODIS and Sentinel satellites. This product consists of level-1 Ground Range Detected Sentinel-1 images along with MODIS data for palm plantation detection on humid SE Asia which were mosaicked and resampled to 250 m of spatial resolution (Miettinen et al 2016). The reported accuracy is 91.6% for forest, 85.9% for plantations and 76.5% for vegetation mosaic. The large-scale closed canopy oil palm plantation had an accuracy of 93.7%.

The land cover data were reclassified to IGBP classes (Chapman et al 2020), where forests were represented by ‘evergreen broadleaf forest’ (which includes mangroves, peat swamp forest, lowland evergreen forest, lower montane evergreen forest and upper montane evergreen forest). Regrowth vegetation and timber plantations were classified as ‘vegetation mosaic’ and oil palm was included as an additional class as IGBP classification does not account for perennial woody crops. A cellular automata approach was applied to derive progressive deforestation from 2015 to 2050, using historical deforestation rates from 1980 to 2015 over lowland areas (<200 mASL). The approach gradually allocates non-forested gridcells, allowing deforestation to expand over non-deforested cells, driven by connectivity and precluded by topographic and legal territorial constraints. We used the observed forest loss between 1980 and 2015 to predict forest loss to the year 2050. Intact forests that were not protected (Forest Management Zones and Conservation Areas) were replaced by contiguous areas of three oil palm classes (1–5 years, 6–12 years, >12 years) and vegetation mosaic (lands with a mosaic of crop-lands, regrowth forests, shrublands and timber plantations where no one component occupies more than 60% of the landscape). The resulting land cover for 2050 is shown in figure 2(b). Both mapping products were resampled to 4 km to match the Conformal Cubic Atmospheric Model (CCAM) resolution and the vegetation classes were simplified to represent the impacts of the conversion of forest to oil palm plantations and vegetation mosaics. In our experiment, the forest scenario and the climate simulations driven by it are the baseline to assess the impacts of deforestation on climate. The extent of deforestation by 2050 is consistent with projected changes used for the Land Use Model Intercomparison Project—LUMIP (Hurtt et al 2020). Between 1980 and 2050, 422 168 km² of Borneo’s forest was projected to be cleared, which is equivalent to 57.7% of Borneo’s land surface area. It is important to note that the deforestation scenario was designed as a plausible future land cover, consistent with recent past trends, in order to investigate the impact on climate of continuing deforestation. It is not intended to be the most likely scenario.

2.3. Experimental design

We used the CABLE Land Model (Community Atmosphere Biosphere Land Exchange version 2.0 CABLE) and the CCAM variable RCMs, both developed by Commonwealth Scientific Research Organisation (CSIRO), to assess the impacts of deforestation on the climate of Borneo (figure 1). CCAM is a global atmospheric model that simulates regional climate over a selected area using a variable resolution grid (MacGregor and Dix 2008, Thatcher and MacGregor 2009). It has been used for regional climate impact assessments (Trancoso et al 2020, Eccles et al 2021). The biosphere atmosphere exchange was described using CABLE (see Kowalczyk et al 2006 for details). CABLE models radiation, heat, water vapour and momentum fluxes across the landscape-atmosphere interface. It captures the interaction among the microclimate, plant physiology and hydrology, enabling vegetation-soil full aerodynamic and radiative interactions (Kowalczyk et al 2006). CABLE’s land surface flux sub-model estimates the coupled transpiration, stomatal conductance, photosynthesis and partitioning of net available energy between latent and sensible heat of sunlit and shaded leaves (Wang and Leuning 1998). In CABLE, functional vegetation characteristics such as leaf area index (LAI), surface roughness, and albedo are represented by a mosaic approach with up to six dominant vegetation types within grid cells. The method estimates a mixed signal of varying functional vegetation characteristics by simulating climate fluxes individually for the six dominant vegetation classes and then linearly combining weights of fractional vegetation at the grid cell basis. In CABLE, IGBP categories are assimilated as plant functional types (PFT), which have specific parametrizations for LAI, roughness and albedo. Three additional PFTs were created for palm oil age classes (1–5 years, 6–12 years, >12 years), which were parametrised as 0.5, 0.7 and 0.9 for fractional cover and 4, 10 and 12 m of height respectively to represent the changes in canopy properties with age (Meijide et al 2017), with roughness set by the canopy height and albedo calculated by radiation balance.

The climate modelling experiments for the forest and deforestation scenarios were run using the stretch grid mode of CCAM with a convection-permitting spatial resolution of 4 km over Borneo. The high-resolution experiments were run using the spectral nudging approach through the scaling selective filter as described by Thatcher and MacGregor (2009). Instead of nudging laterally like RCMs, CCAM uses spectral nudging, which is a large-scale nudging...
Figure 1. Schematic showing the experimental design for assessing how the conversion of Borneo’s forest impacts fire weather risk using convection-permitting climate simulations. The landscape simulation component is shown on top with the derivation of two scenarios—forest scenario (1980) and deforestation scenario (2050). ERA-Interim reanalysis for the 2002–2016 period was nudged to CCAM (middle part), which is forced with the same boundary conditions but distinct land use scenarios as nested simulations to understand the climate impacts of deforestation (bottom part).

following the GCMs, while allowing regional scales to evolve independently. This is specifically designed to allow the regional climate to evolve independently. The boundary conditions for higher resolution downscaling was based on nudging data at six hourly intervals derived from CCAM run at a 20 km spatial resolution over the SE Asian region (see Chapman et al 2020 for details), with boundary conditions from ERA Interim analysis (Dee et al 2011) The variables used were air temperature, wind, and surface pressure. Humidity was not used to allow the hydrological cycle to evolve independently in our CPM. The two parallel climate simulations were performed using CCAM at 4 km spatial resolution for the period 2002–2016 to assess the impact of land cover change on Borneo’s climate. The period 2002–2016 was selected because it is representative of recent El Niño events and has high-quality reanalysis data available.

The key differences between the forest and deforestation scenarios as prescribed in the CCAM-CABLE climate model experiments are shown in figures 2(c) and (d). The oil palm plantations were classified into three age-based classes—juveniles, established and mature—where \( \text{lai} \), vegetation fraction and surface roughness \( \text{zolnd} \) increased with age.

It is important to note that this research does not aim to assess the impact of climate change. The experiment was specifically designed to isolate the influence of land cover on regional climate—that is separate from climate change. By comparing two identical climate simulations nudged to 15 year of historical reanalysis with the same climate change signal in it, we can attribute any emerging difference in regional climate to the land cover change.

2.4. Data analysis

The analysis focussed on the drivers of fire weather conditions resulting from the replacement of tropical forest with oil palm plantations and vegetation mosaic of regrowth and timber plantations. We used data from the CCAM experiments to derive seasonal averages over the length of experiments (2002–2016) for annual and dry season (May–October). We also analysed changes in climate extreme indices during the 2015 El Niño event, where the Oceanic Niño
Table 1. Summary of key variables derived from the climate modelling experiments used in this study.

| Variable name                  | Definition                                                                 | Time-scale |
|--------------------------------|---------------------------------------------------------------------------|------------|
| **Mean climate**               |                                                                           |            |
| Surface temperature (tsu)      | Surface temperature is the temperature at or near a surface.              | Seasonal   |
| Relative humidity (rhscrn)     | The amount of water vapour present in air expressed as a percentage of the amount needed for saturation at the same temperature. | Seasonal   |
| 10 m wind speed (u10)          | Wind speed ten meters above the vegetation.                                | Seasonal   |
| Low cloud cover (lcc)          | Portion of sky covered by clouds whose base heights are below 2 km altitude. | Seasonal   |
| **Climate extreme indices**    |                                                                           |            |
| Warm spell duration (wsd)      | Annual count of days with at least four consecutive days when daily maximum temperature >90th percentile | Annual     |
| Wet days (wd)                  | Annual count of days with daily precipitation ≥1 mm                        | Annual     |
| Heavy precipitation days (hpd) | Annual count of days with daily precipitation ≥10 mm                       | Annual     |
| **Water Balance**              |                                                                           |            |
| Precipitation (P)              | The water released from clouds in the form of rain, freezing rain, sleet, snow, or hail. | Annual     |
| Potential evapotranspiration (PET) | The amount of evaporation that would occur if a sufficient water source were available. | Annual     |
| Climatic water balance (WB)    | Difference between atmospheric supply (P) and demand (PET), related to water deficit. | Monthly    |
| Aridity index (AI)             | Measures the degree of aridity by the ratio of atmospheric demand (PET) to atmospheric supply (P) | Annual     |
| **Fire weather**               |                                                                           |            |
| McArthur Forest Fire Danger Index (FFDI) | Measures the degree of danger of fire associated to atmospheric conditions | 6-hourly and daily |

Index—a 3 month running mean of sea surface temperature (SSTs) anomalies in the Niño 3.4 region (5°N–5°S, 120°–170°W)—had the strongest positive anomalies during the length of the experiment.

First, we focused on the changes in near surface weather conditions associated with increasing fire risk, including screen level temperature and relative humidity, 10 m wind speed and low cloud cover (lcc). In addition, daily data was used to derive selected extreme climate indices (Zhang et al 2011) for warm spell duration, wet days and heavy precipitation days (table 1). We also assessed the water balance-related components to constrain changes in drought conditions, such as precipitation (P), potential evapotranspiration (PET), climatic water balance (P—PET) and aridity index (PET/P) (Trancoso et al 2016). Two fire weather indices used globally were selected as potentially relevant for this study—the McArthur Forest Fire Danger Index (FFDI) (Dowdy et al 2019) and the Fire Weather Index (FWI) (Van Wagner 1974).

To select one of these indices we assessed daily time-series from both the FFDI and FWI calculated from ERA-5 reanalysis and made available by Copernicus climate services. We extracted daily time-series for the study area—Kalimantan Tengah in Indonesian Borneo for the 2002–2016 period. Figure S1 shows that the indices are rather similar and have a linear relationship and correlation coefficient of 0.91. A more comprehensive assessment of the indices (Dowdy et al 2010) indicated that: (a) FWI is more sensitive to wind speed and rainfall and less sensitive to temperature and relative humidity than FFDI; (b) FWI and FFDI are similar regarding sensitivity to wind speed, relative humidity and temperature; and (c) the formulation of the FWI includes many complexities such as conditional discontinuities and its mathematical implementation is not as easy as for the FFDI. As the increase in extreme fire weather risk has also been linked to changing atmospheric humidity and temperature (Jain et al 2022), we concluded that the FFDI is more suitable for this application.
Thus, the McArthur FFDI was selected to measure the atmospheric risk of forest fire (Dowdy et al. 2019). The risk of wildfire on the ground has two levels of controls operating at the land surface and atmospheric levels. The FFDI does not account for the landscape controls such as vegetation characteristics, fuel availability and potential sources of fire ignition. Rather, it aims to assess solely the atmospheric component of wildfire risk—that is the fire weather conditions.

When comparing the differences between our nested simulations, variables like tsu, rhscrn, P and PET are more likely to reflect local impacts of deforestation on water and energy exchanges, whereas u10 and lcc are associated with changes in atmospheric circulation processes as a result of deforestation.

The McArthur FFDI was calculated following Dowdy et al. (2019) as shown in equation (1).

$$\text{FFDI} = 2e^{(0.0338 T + 0.0234 W - 0.0345 RH + 0.987 \ln(DF) - 0.45)}$$  

(1)

The daily maximum temperature at a 2 m height (T), mid-afternoon screen level relative humidity (RH) and mid-afternoon 10 m wind speed (W) were derived from the CCAM simulations. In addition, the drought factor (DF) representing fuel availability was based on a soil moisture deficit. The soil moisture deficit is represented by the Keetch Byram Drought Index calculated from daily rainfall and screen level maximum temperature at a height of 2 m. For a detailed description of the drought factor as well as assessment of the performance of different drought factors (see Holgate et al. (2017)).

We assessed the changes in the return period of FFDI focussing on values exceeding the 99.7th percentile (i.e. 1/365) of the daily gridded time-series, which is equivalent to 1:1 year return period. The daily data from the forest scenario for the full length of the experiment (2002–2016) was used to determine the 1:1 year FFDI thresholds at grid cell basis. The thresholds obtained for the forest scenario were used to calculate the equivalent FFDI return period for the deforestation scenario.

To assess the impact of deforestation on the frequency of extreme events, the data was fitted to the generalized extreme value (GEV) distribution (Coles 2001, van Oldenborgh et al. 2021). To this end, we sampled the annual maxima using focal spatial statistics and estimated the extreme FFDI for both scenarios at 1:5, 1:10, 1:20, 1:50 and 1:100 years return periods. The GEV distribution is shown in equation (2).

$$P(x) = \exp \left( -\left(1 + \frac{x - \mu}{\sigma} \right)^{-1/\xi} \right)^{-1}$$  

(2)

where x is the FFDI; and $\mu$, $\sigma$ and $\xi$ are the GEV fitting parameters for location, scale and shape respectively.

To assess the continuous impacts of deforestation on fire weather conditions at a regional scale, we constrained the analysis to the lowland regions of the Indonesian province of Kalimantan Tengah (figure 2). We extracted a timeseries of daily FFDI for grid cells with a reduction in $lai > 2$ to 2050 to ensure they had a substantial change in vegetation properties from the forest to deforestation scenarios. We also assessed the impact on higher recurrence intervals of FFDI specifically in tropical forest, oil palm and vegetation mosaic. This approach ensured a clearer deforestation signal with reduced noise from mixing Borneo’s climate regions and land covers.

The statistical significance of changes in climate variables between the forest and deforestation scenarios was evaluated across the entire island of Borneo as well as in deforested areas using the two-tailed t-test modified to account for serial correlation in climate data (Zwiers and Storch 1995).

3. Results

3.1. Impacts of deforestation on fire weather precursors

In the forest scenario, representative of 1980’s land cover, Borneo’s tropical forest covered 636 773 km$^2$ (86.8% of the island). This is an estimate limited by the coarse resolution satellite imagery, which does not capture small-scale deforestation (e.g. <100 ha), logging and forest degradation. However, it holds great value for high-resolution climate modelling (figure 2(a)). By 2050, we project an estimated remaining forest cover of 239 707 km$^2$, meaning only 32.7% of Borneo’s surface is projected to sustain tropical forests by 2050 (figure 2(b)), should similar historical deforestation trends be maintained. The deforested areas were converted to oil palm plantations and vegetation mosaics, occupying 126 296 km$^2$ (17.2%) and 367 930 km$^2$ (50.1%) of Borneo respectively. Between 1980 to 2015, 37.1% of Borneo’s primary forest cover had already been cleared, the deforestation scenario projects a further 20.6% decline in primary forest cover by 2050. The deforestation rate projected for 2016–2050 was 46% lower than the observed deforestation rate for the period 1980–2015. This was driven by a reduction in the availability of suitable areas for agriculture. The replacement of the rough, variable height forest canopy with blocks of uniform-aged oil palm and timber plantations decreased the $lai$ (figure 2(c)) and surface roughness (z0ld; figure 2(d)).

The conversion of forest to oil palm plantations and vegetation mosaic resulted in warmer and drier near surface-atmospheric conditions, shifting the distributions of atmospheric precursors of wildfires. We selected four climate metrics associated with convection processes and fire risk to show how they shift following the conversion of forest to palm oil plantations. Figure 3 assesses these changes over...
Figure 2. Land cover scenarios used to assess the impacts of tropical deforestation on Borneo’s climate: (A) land use in 1980—forest scenario, (B) land use in 2050—deforestation scenario, change in (C) leaf area index (lai) and (D) surface roughness (zolnd).

highly deforested areas across Kalimantan Tengah (see figure 2(b)) using joint distributions—i.e. the combined probability of two atmospheric precursors of wildfire at the same location and time. The joint distribution of seasonal anomalies in temperature (tsu) and cloud cover (lcc) shows substantial changes from the forest to the deforestation scenario. In the simulation with the forest scenario, both tsu and lcc had narrow distributions centred around the long-term climatological averages. In the simulations for the deforestation scenario, the anomalies show a broader distribution with a reduction in lcc and increases in seasonal tsu of up to 2 °C. In the deforestation scenario, more than 80% of the joint distribution is outside of the forest scenario range for the periods June–August (jja) and September–November (son) (figures 3(a) and (b)). It is important to note that for all the climate metrics assessed the mean estimated changes following deforestation is greater than one standard deviation of the forest scenario, which is the baseline (refer to annotations in figure 3). This suggests that the estimated changes are greater than the uncertainty. In addition, the differences between forest and deforestation scenarios are statistically significant following the paired t-test for both tsu and lcc in jja (tsu: $t = -219.1$, $df = 31,394$, $p < 0.001$; lcc: $t = 328.6$, $df = 31,394$, $p < 0.001$) and son (tsu: $t = -200.1$, $df = 31,394$, $p < 0.001$; lcc: $t = 340.7$, $df = 31,394$, $p < 0.001$). The values reported with the figures here and henceforth indicate the paired t-test ($t$), degrees of freedom or number of grid cells ($df$) and statistical significance ($p$). Near surface wind speed (u10) and relative humidity (rh) are amongst the key meteorological drivers impacting fire weather. Figures 3(C) and (d) show the joint distribution of u10 and rh anomalies for jja and son seasons for both
scenarios. There is a separation of the joint distributions with little overlap for jja and total separation for son. The differences between forest and deforestation scenarios are statistically significant following the paired t-test for both u10 and rh in jja (u10: $t = -392.9$, $df = 31394$, $p < 0.001$; rh: $t = 303.6$, $df = 31394$, $p < 0.001$) and son (u10: $t = -392.9$, $df = 31394$, $p < 0.001$; rh: $t = 360.5$, $df = 31394$, $p < 0.001$). This represents a significant shift in the near surface climate regime towards hotter and drier conditions with increasing u10 as a consequence of deforestation. Such changes were more pronounced over the deforested regions in the deforestation scenario, with reduced lcc by up to 10% and increased u10 by up to 0.6 m s$^{-1}$ (figures S1 and S2).

### 3.2. Impacts of deforestation on water balance and aridity

Fire weather conditions conducive to wildfires rely on the exchanges of water and energy between vegetation and the atmosphere. We next assess how the water balance components as well as the aridity index changed between the forest and deforestation scenarios.

The water balance analysis during the 2002–2016 simulations shows a simultaneous decrease in precipitation (P) (figure 4(a); P: $t = -22.9$, $df = 74447$, $p < 0.001$) with local reductions of up to 0.37 mm d$^{-1}$ and increased potential evaporation (PET) (figure 4(b); PET: $t = 107.7$, $df = 74447$, $p < 0.001$) with regional increases of up
Figure 4. Projected changes in water availability due to deforestation in Borneo. Long-term average (2002–2016) change in annual: (A) precipitation (P), (B) potential evapotranspiration (PET), (C) climatic water balance (P-PET) and (D) aridity index (PET/P). Time-series of (E) climatic water balance and (F) cumulative climatic water balance. Dashed blue and red lines on (E) show long-term averages for 1980 (P-PET = 23.6 mm) and 2050 (P-PET = 15.40 mm) respectively.

The combined effect of these P and PET is expressed through the climatic water balance WB, which increased up to 0.5 mm d\(^{-1}\) (figure 4(c); WB: \(t = -83.1\), \(df = 74,447\), \(p < 0.001\)). There was a widespread reduction in WB within deforested areas, especially in the lowland regions of southern Borneo where most deforestation is projected. Similarly, an increase in the Aridity Index by up to 0.15 occurring during the 2002–2016 period also indicates drying (figure 4(d); AI: \(t = 98.4\), \(df = 74,447\), \(p < 0.001\)). The regions within Kalimantan Tengah (figure 2(c)) with changes in \(lai > 2 \text{ m}^2 \text{ m}^{-2}\) experienced a decrease in water availability with an average reduction of 8.2 mm/month (figure 4(e)). When accumulated for the period 2002–2016, there was a

to 0.38 mm d\(^{-1}\) in highly deforested areas. The combined effect of these P and PET is expressed through the climatic water balance WB, which increased up to 0.5 mm d\(^{-1}\) (figure 4(c); WB: \(t = -83.1\), \(df = 74,447\), \(p < 0.001\)). There was a widespread reduction in WB within deforested areas, especially in the lowland regions of southern Borneo where most deforestation is projected. Similarly, an increase in the Aridity Index by up to 0.15 occurring during the 2002–2016 period also indicates drying (figure 4(d); AI: \(t = 98.4\), \(df = 74,447\), \(p < 0.001\)). The regions within Kalimantan Tengah (figure 2(c)) with changes in \(lai > 2 \text{ m}^2 \text{ m}^{-2}\) experienced a decrease in water availability with an average reduction of 8.2 mm/month (figure 4(e)). When accumulated for the period 2002–2016, there was a
substantial reduction in the water budget of more than 1200 mm between the forest and deforestation scenarios (figure 4(f)).

3.3. Impacts of deforestation and El Niño on climate extreme indices
The shift in near surface climate regime towards hotter and drier conditions also affects climate extremes. We next test if the conversion of forest to deforestation affects a selection of climate extreme indices and if the magnitude of the impact is increased during the 2015 El Niño event, which had the strongest positive SSTs anomalies in the Niño 3.4 region during the length of the experiment.

Our selected climate extreme indices show an increase in the warm spell duration during the dry season of up to 7 d on average for the duration of the simulations (2002–2016) (figure 5(a); \( t = 200.8, df = 1116.719, p < 0.001 \)) and up to 16 d during the 2015 El Niño event (figure 5(b); \( t = 69.24, df = 74.447, p < 0.001 \)). Likewise, the average number of wet days during the dry season declined by as much as 7 d in highly deforested locations over the simulation period (figure 5(c); \( t = -115.8, df = 1116.719, p < 0.001 \)) and by 14 d in the 2015 El Niño event (figure 5(d); \( t = -69.56, df = 74.447, p < 0.001 \)). The heavy precipitation days are reduced during the dry season with up to 8 d yr\(^{-1} \) for the full length of the simulations (figure 5(e); \( t = -74.0, df = 1116.719, p < 0.001 \)) and up to 13 d yr\(^{-1} \) during the 2015 El Niño event (figure 5(f); \( t = 64.86, df = 74.447, p < 0.001 \)). Hence, our results show that the conversion of forest to deforestation has increased the incidence of extreme heat and heavy precipitation events throughout the experiment, and this impact was intensified during the 2015 El Niño. It is worth noting that during the 2009–2010 El Niño event, the magnitude of the changes of these events was still greater than for the 2015 El Niño event, despite the weaker signal on sea tsu anomalies (figure S4). There-}

3.4. Impacts of deforestation on fire weather risk
To assess the cumulative impact of deforestation on fire weather risk, we calculated the FFDI using data from forest and deforestation scenarios. The FFDI measures the atmospheric risk of fire, combining variables such as rainfall, evaporation, wind speed, temperature and humidity. Figure 6(a) shows the temporal variability of FFDI from 2002 to 2016 for the forest and deforestation simulations. The data shows the FFDI area average for the Kalimantan Tengah region, for gridcells with a reduction in \( \text{lai} > 2 \). The key difference between the two scenarios is the increasing frequency of high FFDI values for the deforestation scenario compared to the forest scenario. For instance, the most prominent fire weather conditions estimated for the forest scenario throughout the 15 years period, would be equalled or exceeded four times in the deforestation scenario over the same period. This means a change in the return period of the FFDI obtained for the forest scenario from 1:15 to 1:3.75 years after converting forest to oil palm plantations and vegetation mosaics. These changes in FFDI values are most prominent during the dry season with an average increase in daily values of 45% for \( jia \) and 40% for \( son \) for those regions experiencing a reduction in \( \text{lai} > 2 \) in Kalimantan Tengah (figure 6(b)). To illustrate spatial changes in the frequency distribution of FFDI values between the two scenarios, we computed the equivalent FFDI return period for the deforestation scenario based on the 1:1 year threshold obtained from the forest scenario. Figure 6(c) shows the spatial pattern of FFDI return period for the deforestation scenario equivalent to 1:1 year return period in the forest scenario. The frequency of fire weather risk increased by more than fourfold across 18.6% of Borneo, especially over lowlands converted to oil palm plantations and vegetation mosaics, where the most prominent yearly fire weather conditions occur at least every three months. This means that the atmospheric conditions conducive to wildfires that occur once a year in the forest scenario, become more frequently after the replacement of forest to plantations and vegetation mosaics, occurring four times a year across highly deforested regions, such as Kalimantan Tengah. When exploring higher return periods by fitting a GEV statistical distribution, the increasing fire weather risk is maintained for the areas converted to oil palm and vegetation mosaic (figure 6(d)). While areas with tropical forest had little to no changes in the extreme FFDI (i.e. median change of 3.2%–3.6% for return periods of 5–100 years), the areas converted to vegetation mosaic experienced substantial changes in extreme FFDI (i.e. median change of 79.6%–109.5% for return periods of 5–100 years). Interestingly, oil palm plantations had a more progressive increase in the changes in extreme FFDI when compared to the other land uses, with median changes of 33.9%–89.1% for return periods of 5–100 years.

4. Discussion
We used a high-resolution convection-permitting climate model (CCAM) forced by ERA-Interim reanalysis to quantify the impact of converting tropical forests to agriculture on fire weather risk across Borneo’s ecosystems. Our results show that the key drivers of extreme fire weather—including precipitation, potential evapotranspiration, temperature, and relative humidity—are altered at the landscape scale by deforestation, which in turn affects regional atmospheric processes such as wind speed and cloud cover.
Hence, once in a year fire weather conditions in largely intact forest cover, are projected to occur every three months following deforestation. Borneo has been a hotspot of deforestation associated with the conversion to oil palm plantations and has seen an increase in fire frequency in recent decades (Gaveau...
et al 2019) with these fires associated with land conversion and El Niño droughts (Sloan et al 2017). This is consistent with our main findings in which deforestation increases fire weather risk, especially during El Niño conditions. We provide further evidence on the detrimental impact of deforestation on fire weather risk by quantifying the changes in fire weather precursors and its recurrence, assuming deforestation trends are maintained from 1980 to 2050.

Tropical rainforests play a critical role in regulating regional climate by maintaining the optimal range of temperature and moisture. Extensive areas of intact forest ensure the optimal range is maintained by the evaporative cooling in the canopy (Bonan 2008). The clearing of tropical forest cover disrupts the climate regulation function of forests permitting hotter and more extreme temperatures (Thirumalai et al 2017). This effect is especially pronounced during hot and dry conditions such as those occurring in Borneo during El Niño events (Taufik et al 2017). Our results are consistent with these findings. We show increases in the duration of longer warm spells, and decreased frequency of wet days and heavy precipitation days after deforestation. Fewer rain days matters as reduced rainfall increases water deficit and fuel flammability, thus increasing fire risk (Field et al 2016). Sustained declines in precipitation over longer periods reduce water availability, and hence increase fire risk.

Deforestation and forest fragmentation result in remnant forest being more vulnerable to fires due to the opening of the canopy, increased extent of edge habitats, and hotter and drier conditions (Cochrane and Laurance 2002, Langner et al 2007, Staal et al 2015). The higher humidity and surface roughness of forested environments also contribute to the maintenance of key regional atmospheric processes (Baker and Spracklen 2019). In our experiment, deforestation reduced the cloud cover by up to 10% and increased surface wind speed by up to 0.6 m s$^{-1}$. The effect of clearing the forest was amplified in the dry season and during El Niño events, where the duration of warm spells increased by up to 7 d/year and the number of wet days decreased by up to 7 d/year over southern Borneo on average. These changes are amplified 2-3-fold during El Niño events. Likewise, the atmospheric water balance was substantially altered over deforested areas with decreased precipitation and increased potential evapotranspiration. In summary, the results suggest that deforestation alters the climate.
Figure 7. Schematic representation of main findings of the impacts of deforestation (conversion of forest to agriculture) on fire weather conditions at local and regional scales with amplification of impacts via atmospheric teleconnections associated with El Niño.

atmospheric conditions conducive with wildfires at both the local and regional scales (figure 7). This is consistent with what Zhong et al (2021) found for the United States, where fire weather conditions and fire risk were intensified following replacement of native vegetation with anthropogenic land cover. Similarly, recent assessments in the Amazon indicate that the alterations in forest microclimate resulting from deforestation—mostly exchanges in moisture and energy (Baker and Spracklen 2019), contribute to increasing probability of fire occurrence (Fonseca et al 2019).

The impacts of deforestation on fire weather are exacerbated by droughts (Rogers et al 2020). Also, the edge effects associated with oil palm plantations extends over 300 m into the forests (Nunes et al 2021), increasing fire risk across the forest’s edges. Consequently, the compounding effects of deforestation, droughts and fires can bring tropical forests closer to a tipping point beyond which run-away cycles of deforestation-induced fires result in further deforestation (Zemp et al 2017, Lovejoy and Nobre 2018, Lenton et al 2019, Staal et al 2020). Our models, despite their innovative scale and ability to better resolve key atmospheric processes, remain simplifications and uncertainties around the simulation of rainfall and moist convection remain a recognised challenge for climate models (Stevens and Bony 2013, Marotzke et al 2017). CPMs such as applied here, however, emerged as enhanced alternatives to tackle these challenges across specific regions and offer a new avenue to unravel the climate impacts of changing landscapes.

5. Conclusion

We assessed the impact of deforestation on Borneo’s fire weather conditions using a landscape-climate modelling approach with a convection-permitting climate model. Deforestation increased fire weather risk, especially in southern and eastern Borneo (e.g. Indonesian Province of Kalimantan Tengah), where most of the forest clearing occurred. These impacts arose at both the local and regional scales by altering the water and energy exchanges and modifying the local climate (i.e. reduced precipitation, increased potential evapotranspiration, increased temperature, and reduced relative humidity), which in turn, affects regional climatic circulation processes resulting in reduced cloud cover and increased wind speed. We show that the higher FFDI following the El Niño conditions exacerbated these changes, further increasing fire risk. Viewed in their entirety, our findings indicate that fire weather conditions that would otherwise occur once a year, may occur every three months following deforestation. This represents a fourfold increase in fire weather risk attributed to deforestation. In addition, under more extreme conditions, such as those occurring on longer time-horizons (e.g. return periods \( \geq 20 \) years), the event magnitude may become twice as great following deforestation. The results clearly demonstrate the important role
of tropical forests in regulating microclimate and regional climate processes, including fire weather. Therefore, further deforestation and land conversion for agriculture in Borneo are likely to increase wild- 
fires, in conjunction with climate change.

Data availability statement
Data will be made available at the Terrestrial Ecosystem Research Network portal.

The data that support the findings of this study are available upon reasonable request from the authors.

Acknowledgments
This research was funded by the Australian Research Council Discovery Project Grant No. DP160102107. It was supported by computational resources provided by the Australian Government through National Computational Infrastructure under the National Computational Merit Allocation Scheme. We thank Sarah Chapman for providing comments to improve readability. We acknowledge UQ-Research Computing Centre and QCIF for accessing the clusters and QRISCloud data storage infrastructure as well as the Queensland Government to perform the analysis using high performance computation.

Author contributions
R T, J S and C A M conceived the original idea and drafted the paper. All other authors (A S, M T, N T, K K W, E M and D S) have provided input to the paper and participated in various ways in the data collection and processing.

Conflict of interest
The authors declare no competing interest.

Computer code
Computer code is available upon request.

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