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PeatFire: an agent-based model to simulate fire ignition and spreading in a tropical peatland ecosystem

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Abstract. The increased frequency and spread of tropical peat fires over the last two decades have attracted global attention because they cause significant environmental and health impacts at local to global scales. To understand the relative importance of key factors controlling tropical peatland burning events, we developed PeatFire, an agent-based model simulating the interaction between human-induced ignitions, fire and peat characteristics. The model describes (1) above- and belowground fires, which spread independently but interact with each other; (2) above- and belowground biomass; and (3) the watertable determining peat dryness and susceptibility to fire. We applied PeatFire to a region in South Sumatra that has experienced profound natural rainforest loss due to peat fires. Sensitivity analysis of the model suggests that fire sizes depend mostly on watertable depth, peat-dry-index and number of dry days before ignition. Using pattern-oriented modelling, these factors were parameterised so that the model output matches spatiotemporal fire patterns observed in the study region in 2015. Our results emphasise the risk of a sudden shift from moderate fire occurrence to complete burning and highlight the importance of local context to peatland regulation, which should consider both biophysical and socioeconomic factors and strategies for peatland fire management.

Keywords: agent-based model, burnt area, degraded habitat, Indonesia, peatland, tropical peat fire, watertable depth, wildlife reserve.

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Introduction

Tropical peatlands act as reservoirs of fresh water, which under natural condition can moderate water levels, maintain water flows and buffer against salt water (Wösten *et al.* 2008). They also form some of the richest concentrations of carbon reserves on the planet (Page Siegert *et al.* 2002; Ballhorn *et al.* 2009; Page *et al.* 2011; Hirano *et al.* 2012), and they are recognised as biodiversity hotspots (Morrogh-Bernard *et al.* 2003; Posa 2011; Posa *et al.* 2011). Despite their importance, tropical peatlands remain a neglected ecosystem because of high conversion rates of these ecosystems into man-made ecosystems (Cattau *et al.* 2016).

Peatlands in south-east Asia cover ~25 million ha, comprising ~63% of the global tropical peatland carbon (Wösten *et al.* 2008; Page *et al.* 2009*a*; *b*; Page and Hooijer 2016). Over the past two decades, more than half of Indonesian peatlands have been transformed from a pristine state of perpetual moistness and frequent surface water inundation to a degraded state, which is characterised by a relatively dry and exposed soil profile. Mostly, peatland degradation is caused by the widespread construction of drainage canals and deforestation associated with land-use change (Miettinen *et al.* 2011, 2013; Margono *et al.* 2014; Adrianto *et al.* 2019). This situation has increased emissions from oxidation of exposed peat (Miettinen *et al.* 2017), as well as the frequency of peat fires (Page and Hooijer 2016). It is now widely known that peat fires have severe impacts on emissions to the atmosphere, human health, the economy and biodiversity (Jones 2006; Taylor 2010; Posa 2011; Posa *et al.* 2011; Johnston *et al.* 2012; Marlier *et al.* 2013; Page *et al.* 2013; Hayasaka *et al.* 2014; Crippa *et al.* 2016; Uda *et al.* 2019).

Protecting vulnerable peatland ecosystems from fires in Indonesia is a high priority (Cochrane 2009; Page *et al.* 2013; Page and Hooijer 2016; Goodman and Robinson 2019). Past research demonstrates that extreme burning events in Indonesia are induced by drought conditions associated with El Niño and/or positive Indian Ocean Dipole conditions that disrupt the normal monsoonal rainfall patterns across the maritime continent (Field *et al.* 2015; Spessa *et al.* 2015; Pan *et al.* 2018). Furthermore, deforestation and extensive peat drainage for agriculture and plantation establishment have exacerbated the impact of climatic drivers of peatland fires through non-climatic factors such as increased ignition rates (due to more intensive land use), increased evaporation (due to reduced canopy cover) and lowering of the watertable depth leading to increased desiccation of surface and subsurface peats (Page and Hooijer 2016; Adrianto *et al.* 2019; Baker and Spracklen 2019; Mezbahuddin *et al.* 2019; Nikonovas *et al.* 2019).

Patterns in peat fire occurrence in Indonesia, including the climatic, ecological and socioeconomic factors causing those patterns have been extensively studied (Page *et al.* 2009*a*; Jones 2006; van der Werf *et al.* 2008; Wösten *et al.* 2008; Field *et al.* 2009; Miettinen and Liew 2010; Spessa *et al.* 2010; Marlier *et al.* 2013; Miettinen *et al.* 2013; Page *et al.* 2013; Toriyama *et al.* 2014; Hayasaka *et al.* 2014; Cole *et al.* 2015; Thorburn and Kull 2015; Cattau *et al.* 2016; Yong and Peh 2016; Adrianto *et al.* 2019; Mezbahuddin *et al.* 2019; Nikonovas *et al.* 2019). However, the mechanistic processes linking tropical peat fire and its causal elements and processes are still not well understood. Most studies to date have focused on the broad-scale patterns of fire activity (burnt area) in relation to weather conditions, peat hydrology or land-use classes. For instance, Fanin and van der Werf (2017), Field *et al.* (2015) and Spessa *et al.* (2015) reported a non-linear relationship between rainfall and fire activity. Taufik *et al.* (2017) demonstrated that hydrological drought was highly correlated with burning events. Miettinen *et al.* (2013) highlighted how peatland deforestation, drainage and conversion to agriculture correspond to higher fire frequencies in Jambi province, Indonesia. Adrianto *et al.* (2019) reported similar mechanisms and findings for Riau province, Indonesia. These top–down studies, which are based on statistical modelling, have provided useful insights into the relative importance of different factors driving peat fires and their interactions at regional scales, and can be used for prediction of fires at broad spatiotemporal resolutions. Nonetheless, the management and prediction of peat fires at local scales require quantitative models describing the processes controlling fires and their interactions (Page and Hooijer 2016), which is not possible using a top–down statistical-based approach.

Agent-based models (ABMs) belong to a category of 'bottom–up' simulation models that simulate the actions and interactions of autonomous agents (individual or collective groups) within a defined system (Grimm 1999; Grimm and Railsback 2005). This approach can derive insights and assess emergent system-level behaviours (Abar *et al.* 2017). ABMs have been widely used in different scientific disciplines such as conservation ecology (Imron *et al.* 2011; Heinonen *et al.* 2014), agriculture (Valbuena *et al.* 2010) and climate change mitigation (Purnomo *et al.* 2013; Dislich *et al.* 2018), where the research questions involve the interaction of biophysical condition and human activities.

The problem of peat fires in Indonesia lends itself to an ABM approach because ignitions and fire spread are controlled by both biophysical factors (e.g. peat hydrology and precipitation) and anthropological factors (e.g. human-caused ignitions, land-use and land-cover change). Previous applications of ABMs in Indonesia exist, notably to examine the impact of land-use choices on deforestation (Purnomo *et al.* 2013) and carbon sequestration (Dislich *et al.* 2018); however, an ABM approach focusing on the peat fire problem itself has not yet been developed.

Using a case study of rural peatland area in South Sumatra, this paper describes the PeatFire model, an ABM that captures phenomenologically key biophysical processes and human activities triggering fire occurrences. The paper also presents the results of a series of simulations we performed to assess model behaviour, sensitivity and accuracy through benchmarking against observed fire data in 2015, which was the most severe fire season recorded in the last two decades (Field *et al.* 2016). Finally, we present the results of simulation experiments carried out to assess different scenarios on fire mitigation, which enable us to derive evidence-based recommendations for improved tropical peatland fire management at local scales.

Study area

The Padang Sugihan landscape, situated between 2°41′59″S–3°7′20″S and 104°58′39″E–105°18′18″E in the South Sumatra province of Indonesia (Fig. 1), mainly consists of a protected area, the Padang Sugihan Wildlife Reserve (PSWR), dedicated to Sumatran elephants (*Elephas maximus sumatrae*). The surrounding land uses consist in forest plantations and agricultural areas. Fires occur every year because fire is the cheapest and most effective land-clearing method available to farmers in the region (Cattau *et al.* 2016; Imron *et al.* 2018).

Model description

The following model description conforms with the ODD (Overview, Design concepts, Details) protocol for describing individual- and agent-based models (Grimm *et al.* 2006, 2010).

Purpose

The purpose of the PeatFire model is to understand the role of human-induced fire ignition (considering both the capability of ignition and the number of dry days after a rainy day before the next ignition trial), the spread and interaction of above- and belowground fires, and the watertable dynamics for the fire dynamics in a peat forest. Fire data observed in the PSWR in 2015 serve as benchmark for the suitability of the model to reproduce observed patterns of aboveground fires.

Entities, state variables and scales

Fire ignitions in Indonesian peatlands, like most other tropical ecosystems, are predominately human-caused, with lightning having a negligible role (Field *et al.* 2009). Hence, for our modelling case study, human activities are assumed to be the only source of peat-fire ignitions. Fires occur above and below ground so long as sufficient biomass is available to burn. Above- and belowground fires can spread horizontally separately, but can also ignite mutually (Huang and Rein 2014; Hu *et al.* 2018).

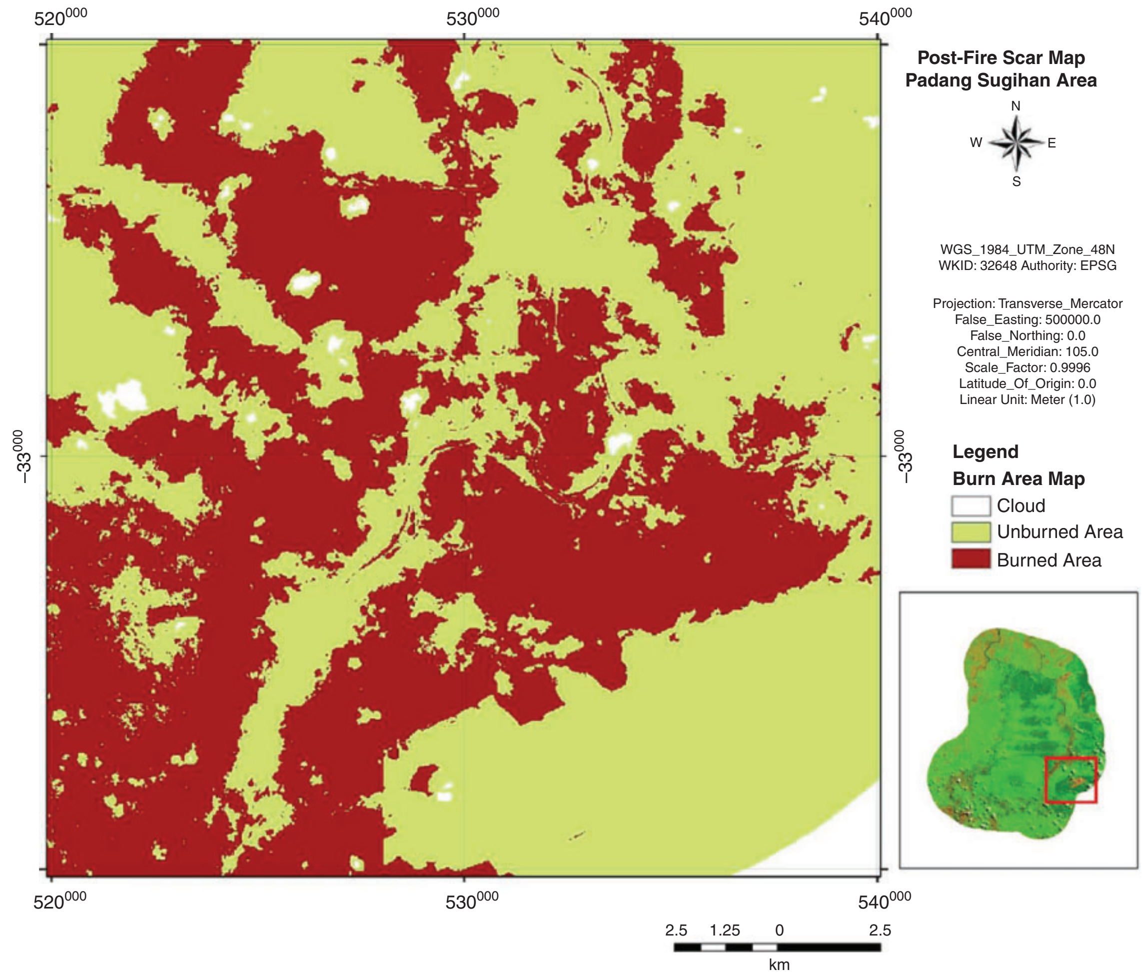

Fig. 1. Map of the study area of Padang Sugihan landscape located in South Sumatra Province, Indonesia. Unburnt patches are shaded green, and burnt patches are shaded red. The map image was taken on 11 November 2015. The colour scheme dark green, green and brown in the inset represents high to low vegetation density.

We decided to include three entities in the PeatFire model: humans (seen rather as household locations from which human activities can be initiated than individual persons), fire, and grid patches of peatland area. Humans have three state variables, namely their location (*loc*), the maximum radius within which patches can be reached and thus potentially be ignited (*dst*), and the actual capability to ignite a patch, described as number of opportunities (*frp*). Fire has two state variables, namely the location and the fire *type*, which specifies whether the fire occurs above ground, below ground, or both above and below ground. The patches are characterised by three state variables: (1) the watertable depth (*wtd*), (2) the aboveground biomass (*bia*), and (3) the belowground biomass (*bib*). Both *bia* and *bib* are considered as relative values bounded between 0 and 100% (see Table 1 for further details).

In addition to the state variables, we defined several global variables (Table 2) that are either assumed to be the same for all agents of an entity (for example, the evapotranspiration rate (*evp*) of patches) or that are basic for some processes (e.g. the wind speed, which defines the speed of the aboveground fire spread).

The PeatFire model comprises 100 × 100 grid cells (patches), each representing 210 × 210 m (= 4.41 ha, which corresponds to the areal extent of the study site). The timestep is 1 day, and a typical simulation run lasts 1 year (365 days).

Process overview and scheduling

At every timestep, the following submodels are executed: *search-and-ignite*, *fire-burning*, *fire-spreading* and *update-watertable* (Fig. 2).

Search-and-ignite

If the sufficient number of dry days after the last rainy day is achieved, a grid cell is randomly selected within the maximum radius around the location of each human. Depending on the fire capability of the household, the dryness index of the patch and the available aboveground biomass, the patch may ignite or not.

Fire-burning

In all ignited patches, the available biomass burns according to the burning rate.

Table 1. List of entities and state variables used in the PeatFire model
μ, mean; σ, standard deviation; λ, number of events

Entities	State variable name	Description	Values and units	Reference
Humans	*frp*	Human capability for ignition. The number of opportunities for a human to ignite a patch	λ: 0–5 times	Assigned (Poisson distributed)
	dst	Maximum distance of a patch they can try to ignite measured from their location	5–25 patches	Assigned (uniformly distributed)
	loc	Location (*x*, *y* position)		Assigned randomly
Fires	*type*	Type of fire	Aboveground, belowground or both	According to the model of Frandsen (1997)
Grid patches	*wtd*	Watertable depth. The value of this state variable represents the state of water level on a patch	μ: 0–1 m, σ: 0.1	Taufik *et al.* (2017); Wösten *et al.* (2008) (Gaussian distributed)
	bia	Aboveground biomass. This state variable represents the amount of available biomass in the aboveground area of a patch	μ: 0–1, σ: 1	Assigned as Gaussian; values are cut between 0 and 1
	bib	Belowground biomass. This state variable represents the amount of available biomass in the belowground area of a patch.	μ: 0–1, σ: 1	Assigned as Gaussian; values are cut between 0 and 1

Table 2. Global parameters used in PeatFire model

Variable name	Description	Values and units	Reference
nof	Number of humans. This parameter initialises the number of humans at the beginning of the model simulation	1–20 persons	Assigned (uniformly distributed)
pdi	Peat-dry-index. This parameter defines the minimum value of watertable depth that categorises the patch into drought condition and thus vulnerable to fire	0–0.5 m	Assigned (uniformly distributed)
evp	Evapotranspiration rate. This defines the rate of water released from a patch to the atmosphere	0.003–0.005 m	Segah *et al.* (2010); Hirano *et al.* (2015) (uniformly distributed)
ddb	Dry-days-before ignition. The minimum number of consecutive dry days after a rainy day preceding a farmer-driven fire ignition	0–14 days	Imron *et al.* (2018) (uniformly distributed)
wsp	Wind speed. Defines the speed of aboveground fire spread to its neighbouring patches	0.1–1	Assigned (uniformly distributed)
bbr	Biomass burning rate. The rate of which an active fire can reduce available biomass on a patch for each time-step	0.1–1	Assigned (uniformly distributed)
psb	The probability of belowground fire spreading. The chance of belowground fire influencing its neighbouring patches is defined in this parameter	0.1–1	Frandsen (1997) (uniformly distributed)

Fire-spreading

At each timestep, all eight neighbouring patches of a burning patch are checked for their vulnerability to fire (defined by the dryness index and the available biomass). Belowground fires spread with the probability *psb* to the eight neighbouring cells and can trigger aboveground fire. Aboveground fires spread not only isometrically according to the wind speed (see Fig. 3*a* for details), but can also jump below ground (NB: this is only described by the states of the fire variable *type* but not as separate fire *layers*; see also Fig. 3*b* for details).

Update-watertable

At the end of every timestep, the watertable depth value for each patch is updated, taking into account the daily amount of precipitation and the evapotranspiration rate.

Design concepts

Basic principles

The vulnerability of peat soil to fire is determined by the variables *watertable depth* (*wtd*) and *biomass* (*bia* and *bib*). These variables represent soil moisture and organic matter content respectively, as existing studies have emphasised (Huang and Rein 2014; Hu *et al.* 2019; Christensen *et al.* 2020). The simulation of watertable dynamics and fire ignition follows the principles introduced by Taufik *et al.* (2017). Thus, the *watertable depth* is influenced by the weather (increasing during dry days and decreasing during rainy days).

We further adapted the detailed physical model of belowground fire smouldering of He *et al.* (2009) and simplified the set of rules governing fire spread both downwards and vertically. Aboveground fire spread simplifies the more

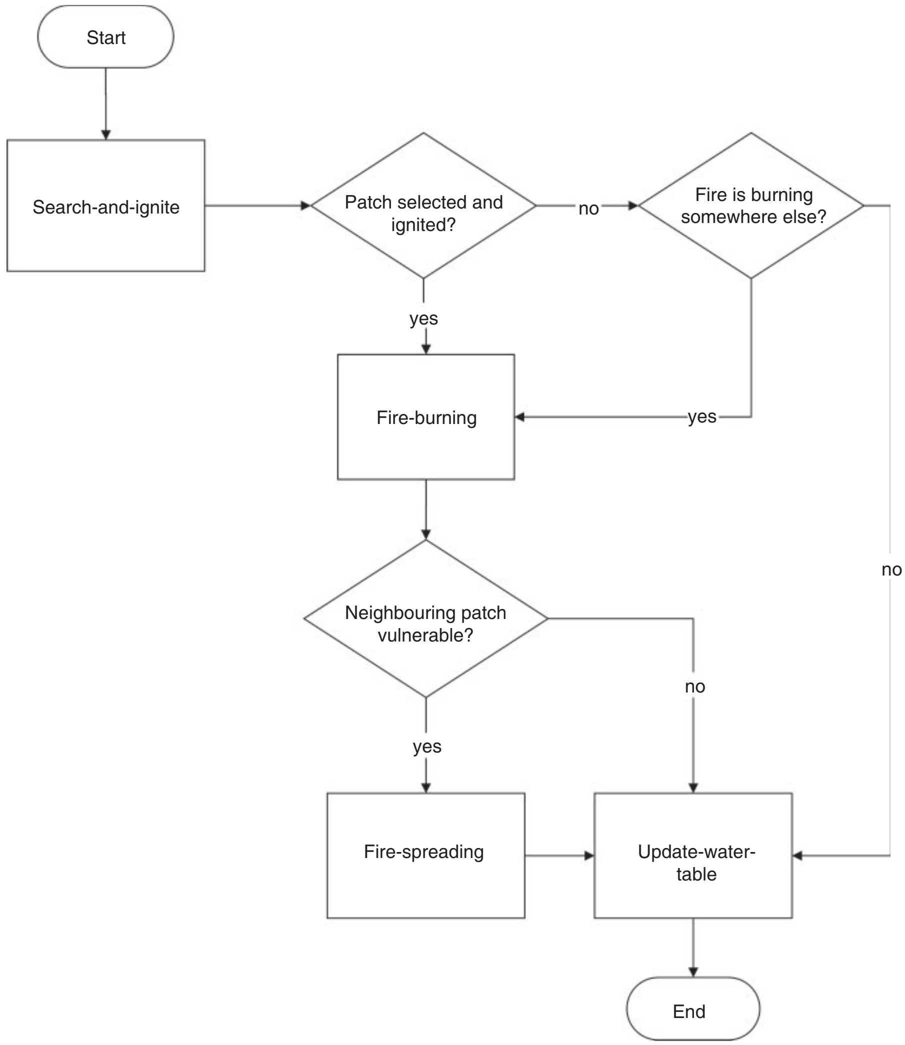

Fig. 2. A summary of processes in the PeatFire model for each time-step. At the beginning of model run, the submodel 'search-and-ignite' is called and may start the ignition of fire. The 'fire-burning' submodel is called after, and represents the biomass burning on each patch. If the neighbouring patch (on the same or the other layer) is vulnerable to fire, the submodel 'fire-spreading' will spread fire to the adjacent patches. Finally, the submodel 'update-watertable' will update the watertable value of each patch according to the current precipitation rate and the evapotranspiration rate.

detailed description of global fire models like the SPITFIRE model (Thonicke *et al.* 2010; Spessa *et al.* 2013; Lehsten *et al.* 2016; Hantson *et al.* 2017), which in turn is based on Rothermel's physical model of fire spread (Rothermel 1972; Rothermel and Rinehart 1983).

Emergence

The spatial pattern of burnt patches is an important emergent property, which arises from the interaction between patch ignition, the dynamics of the peat watertable, and the behaviour of above- and belowground fires.

Interaction

There are no interactions among humans, only between neighbouring cells due to the spread of fire.

Stochasticity

The initial location of *human* activities, *watertable depth*, amount of *belowground biomass*, *ignition* of a patch and fire *spread* have stochastic components.

Initialisation

At model start-up time, values are assigned to state variables and global variables. Owing to the limited available empirical data, we mainly used mathematical distributions (uniform, Poisson, Gaussian) for them. That way, we were able to consider estimated variabilities of these variables. Uniform distributed variables are the *number of humans* (better seen as human activity points – *nof*), which were placed randomly across the simulated landscape and the *maximum distance* within which a human household can reach patches to ignite (*dst*) as well as the global variables including the minimum *dry-days-before* ignition (*ddb*), *biomass burning rate*

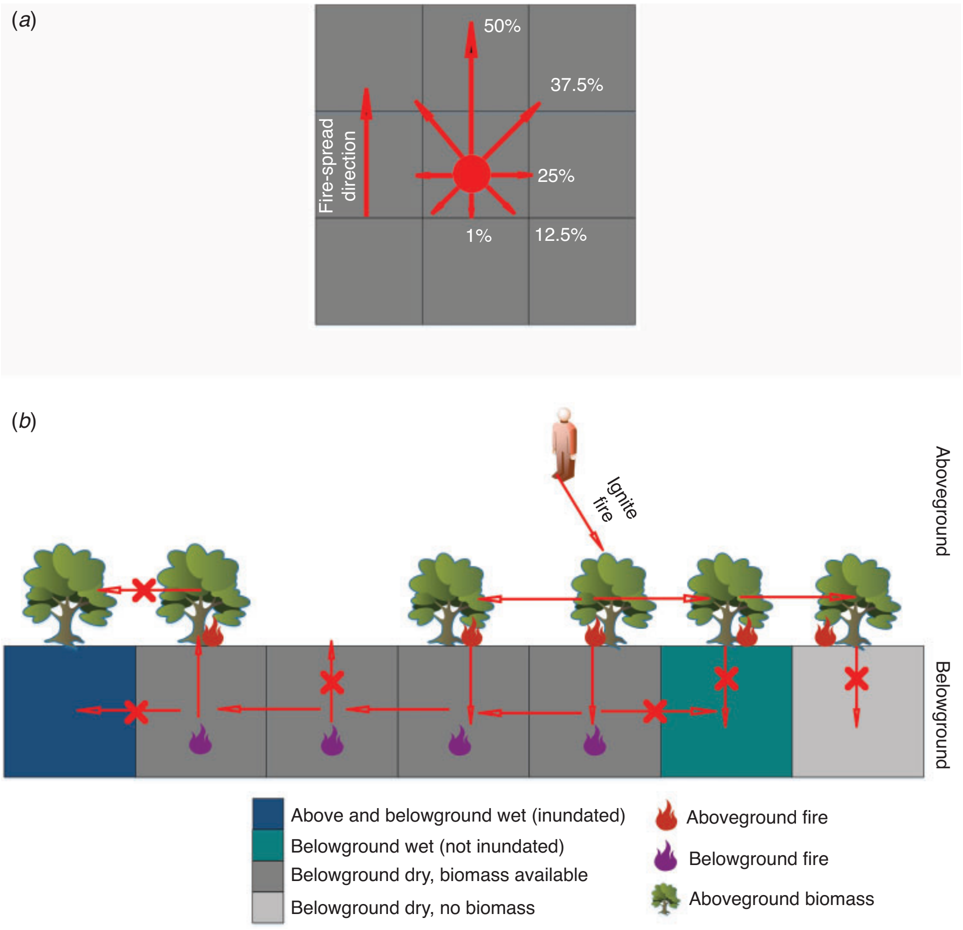

Fig. 3. (*a*) The mechanism of aboveground spreading is based on the wind speed, which is assumed to go in one direction during simulation. (*b*) The process of fire ignition and spreading is based on a patch's susceptibility to fire. Fire starts burning the biomass from the patch surface (aboveground). Aboveground fire can spread to the adjacent patches in the same layer only if aboveground biomass is available and not inundated with water (dark grey, grey or light-blue grid cell). When the belowground layer of the patch is dry and has available biomass (dark grey grid cell), aboveground fire can spread below the surface and start a belowground fire. Belowground fire can spread to the adjacent patches in the belowground layer only if biomass is available and dry (dark grey grid cell) or jump above ground if the cell is vulnerable (dryness and biomass).

(*bbr*), the *probability of belowground fire spreading* (*psb*), *evapotranspiration rate* (*evp*) and *wind speed*. The *human capability* to ignite a patch (= the number of opportunities they have for ignition – *frp*) was described as a Poisson distribution.

Two state variables of patches are described as Gaussian distributed variables, namely *watertable depth* (*wtd*) and the availability of *belowground biomass* (*bib* – restricted to the limits between 0 and 1 to use them as relative values). The global variable peat-dry-index (*pdi*) is also assumed to be normally distributed. Tables 1 and 2 provide further details of the parameters used in PeatFire.

Input data

The aboveground biomass (*bia*) of the patches is estimated based on the vegetation index using NDVI (Normalized Difference Vegetation Index). NDVI serves as a proxy for biomass availability, as has been used in another fire study (Segah *et al.* 2010). The data were imported as a raster map derived from Landsat 8 (https://earthexplorer.usgs.gov/, accessed 23 March 2018) taken from the study site on 26 June 2015. The values were divided into 15 classes and translated into the model input with a range from 0 to 1 as follows:

$$bia = \frac{(\mathrm{NDVI} - 1)}{15} + random - float\left(\frac{1}{15}\right) \qquad (1)$$

Rainfall data to describe daily precipitation were directly taken from 2015 records obtained at the Sultan Baharudin II Airport Palembang of South Sumatra province (https://dataonline.bmkg.go.id, accessed 20 March 2018).

Submodels

Search-and-ignite

Fire ignition of a patch mimics the first step for peat-land conversion to other land-use forms, such as agriculture. We assume that this can occur in every timestep, but only up to a maximum number (human-capability *frp*) per year and household. If the number of required dry days after a rain event is achieved, grid cells are randomly selected within the maximum distance around each human location with $frp > 0$. The human-capability to ignite a fire (*frp*) is decreased after each trial by one.

Fire-burning

In ignited patches, aboveground biomass (*bia*) will burn according to the biomass burning rate *bbr* until the biomass runs out or the patch becomes inundated with water ($wtd < 0$). The same applies for belowground fires, with the difference being that fires stop if the patch becomes wet (*watertable depth* $wtd <$ *peat-dry-index pdi*). A patch that is depleted of aboveground biomass from fire is considered a burnt patch and cannot be ignited again, as the model does not account for biomass regrowth or peat accumulation.

Fire-spreading

When a patch is ignited, a check is made whether the adjacent neighbouring patches are vulnerable to fire. This is the case if dry biomass is available (aboveground, $wtd < 0$; belowground, $wtd > pdi$). Aboveground fire can spread to the neighbouring patches with non-isometric probabilities defined by the wind speed (Fig. 3*a*). Belowground fires spread isometrically to neighbouring cells with probability *psb*. On top, fire can jump over from aboveground to belowground and vice versa with the same probability *psb*.

Update-watertable

At the end of each time-step, the *watertable-depth* value (*wtd*) is actualised based on the daily precipitation and evapotranspiration rate:

$$wrd_{t+1} = wtd_t - precipitation_t + evapotranspiration \qquad (2)$$

The daily $precipitation_t$ is read into the model as an input file containing the amount of rainfall per day during the simulated year. The evapotranspiration rate is a constant global variable applied to all patches containing biomass and does not change during the simulation.

Simulation experiments

To assess PeatFire's behaviour, we analysed the sensitivity of individual parameters and parameter interactions. We then optimised the most important parameters of the model through a process of benchmarking model outputs of burnt area against observed fire patterns using standard techniques from previous ABM studies (Saltelli *et al.* 2006; Imron *et al.* 2012; Jakoby *et al.* 2014).

Global sensitivity analysis

We performed a global sensitivity analysis using Morris screening to consider the entire parameter space (Saltelli *et al.* 2006; Imron *et al.* 2012; Kautz *et al.* 2014) in order to rank the importance of the input parameters on the number of burnt patches. The process generated 120 input sets of parameters and each set of parameters was simulated as part of a 30-member replication ensemble. The three most important parameters were selected.

Local sensitivity analysis

We performed a local sensitivity analysis with the OAT (one-at-a-time) technique (Saltelli *et al.* 2006) to examine the effects of the three selected parameters on the model's behaviour in more detail. In this study, we not only analysed the total number of fires simulated by the model, but also further differentiated these into the number of above- and belowground fires. While varying one parameter in its plausible range, all other parameter values were kept at their median value. Simulation runs were repeated 30 times.

Analysis of parameter interactions

The effects of interactions among the three most influential parameters on the output were examined by a full factorial simulation design using 30 replicates per parameter setting.

Parameter optimisation

We conducted another full factorial experiment in order to identify the best combinations of the input parameter values that reproduce the spatial patterns in observed fire for our case-study region using a pattern-oriented analysis (Wiegand *et al.* 2003; Railsback and Grimm 2011; Grimm and Railsback 2012). The experiment simulated 1815 different parameter combinations, which were each replicated 30 times (54 450 simulation runs). Comparisons between observed and simulated burnt area maps were performed using Cohen's kappa statistic (Cohen 1960), following the procedure described in Lehsten *et al.* (2016), who used the kappa statistic to compare simulated *v.* observed vegetation maps. The simulated results were sorted based on the highest kappa score.

Owing to the unavailability of observations of belowground fires, we could only use the spatial distribution of remotely sensed aboveground fires for model benchmarking. A raster map of burnt and unburnt cells taken at the study site on 11 November 2015 (https://earthexplorer.usgs.gov/, accessed 23 March 2018) served as the benchmark. The image was taken as this date is closest to the reported time of fire events in the study site in this particular year (Martín *et al.* 2006). We used the Normalised Burnt Ratio – Thermal /NBRT1 to identify burnt areas because it is known to have a good ability to separate burnt and unburnt land (Holden *et al.* 2005). We used a quick atmospheric correction (QUAC) to process the Landsat image with *ENVI 5.2*. The accuracy of the burnt–unburnt map used for model benchmarking was assessed following Veraverbeke *et al.* (2010). For this, two high-resolution Sentinel-2 images taken on 25 November 2015 and 5 December 2015 were selected. The assessment showed 83.89% accuracy with 4.05 and 22.83% error of omission and commission respectively. We resized the burnt–unburnt raster map into a 100 $\times$ 100-grid cells matrix in order to compare the observed spatial fire pattern with the simulated ones. For this, we examined the probability distribution of each grid cell to have 0–4 burnt adjacent neighbours (Fig. 4). This analysis was done using a four-neighbourhood window mask provided by the function *focal* in the *R* raster package (Fig. S1).

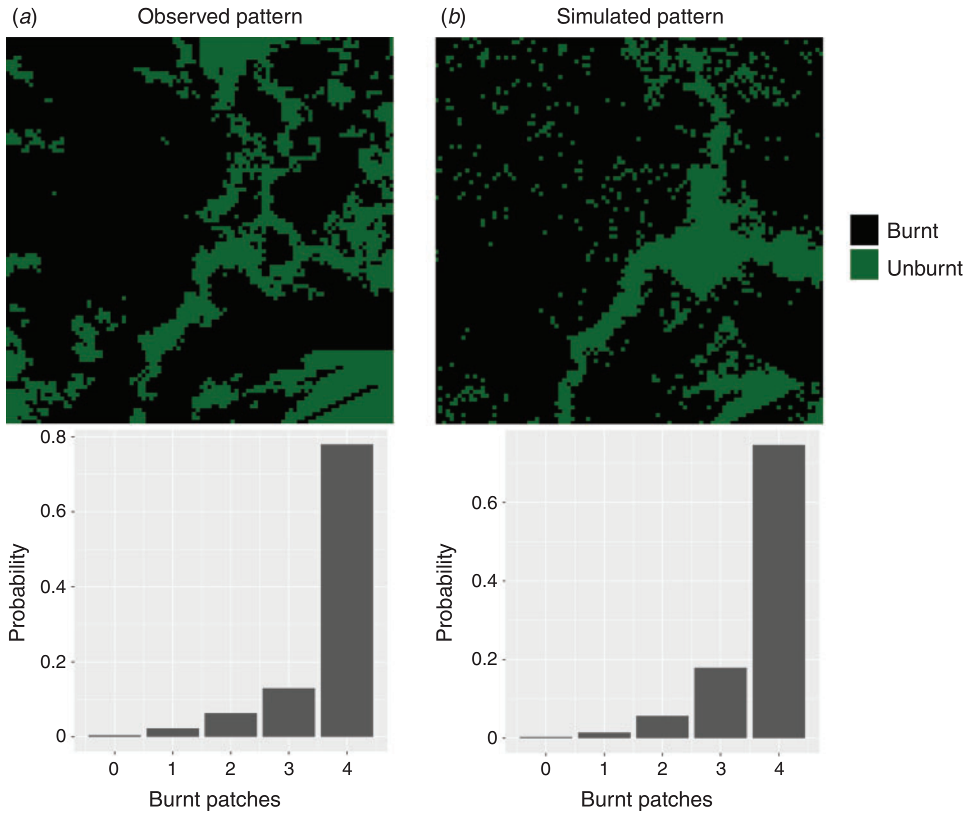

Fig. 4. Raster map of burnt and unburnt patches from (*a*) the study area, and (*b*) the selected model simulation output. The histograms below each map shows probability distribution of a cell in the raster to have 0 to 4 adjacent burnt neighbouring cell.

Model application

The parameter set that produced the closest match between simulated and observed spatial fire patterns was used for model application on the effect of management scenarios influencing watertable depth (*wtd*) on fire dynamics above and below ground. The results are discussed in terms of the potential to improve peat watertable depth management and fire risk mitigation in Indonesia.

All simulation experiments were performed using the open source *R* package *nlrx* (Salecker *et al.* 2019). It provides a comfortable link between the PeatFire model implemented in *NetLogo* (version 6.1.1) and the statistical software environment *R* (version 3.4.4). This allowed us to benefit from the high-performance computing facility available at Technische Universität Dresden (Germany).

Results

Global sensitivity analysis

The results revealed that the number of burnt patches is most sensitive to the parameters watertable depth (*wtd*), peat-dry-index (*pdi*) and dry-days-before (*ddb*) (Fig. 5 and Table 3). The larger the value of μ^* for a specific output parameter, the stronger the effect of changes in the particular input. The larger the value of σ for a specific parameter, the stronger the interaction effect of the input parameters on model output.

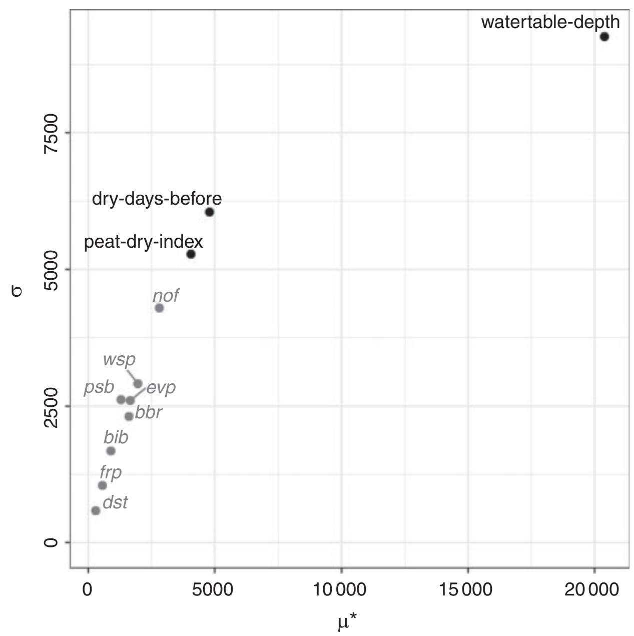

Fig. 5. The projection of μ^* and σ from the sensitivity analysis of the PeatFire model using Morris screening methods for the burnt patches variable. μ^* represents the effect of a parameter on the model output, whereas the value of σ shows the interaction of a parameter on the model output.

Table 3. Values of μ* and σ from Morris parameter screening
μ* corresponds to the effect of the particular parameter and σ corresponds to the strength of the parameter to the output

Parameter name	Burnt patches	
	μ*	σ
Watertable-depth	20 383	9271
Dry-days-before	4782	6059
Peat-dry-index	4049	5282
Number-of-humans	2800	4296
Wind-speed	1941	2915
Evapotranspiration	1646	2605
Biomass-burning-rate	1590	2316
Probability-spread-Below	1283	2620
Biomass-below	877	1684
Human-capability	547	1046
Distance	276	585

Local sensitivity analysis

All three tested parameters have a pronounced effect on the numbers of fire occurrences (Fig. 6). The model exhibits increasing threshold behaviour with respect to variation in parameter *wtd*. This is characterised by a fairly constant low number of fire occurrences for $wtd < 0.2$ m; then an upward shift for $wtd \leq 0.7$ m; which then remains steadily stable for $wtd > 0.7$ m. Gradual change of parameter *pdi* resulted in a sudden increase of belowground fires, but less impact on aboveground fires. Interestingly, fire occurrence showed a slight sudden decrease at different points during gradual increase of the parameter *ddb*.

To investigate the behaviour of the sudden shift mechanism in the *ddb* values, we plotted the occurrence of fire and precipitation during simulations for *ddb* values of 5, 10 and 14 days, as shown in Fig. 7. Fewer dry days before ignition led the system to burn all the aboveground biomass early in the year, lowering fire occurrences during the late dry season. Conversely, having more dry days before ignition lowers the chance of fire occurrence early in the year (wet season), thus causing fire to emerge in the dry season (mid to end of year).

Parameter interactions

The analysis of parameter interactions revealed that the watertable depth (*wtd)* has a much smaller interaction effect compared with dry-days-before (*ddb*) and peat-dry-index (*pdi*). The interaction of parameters *ddb* and *pdi* has a pronounced effect both on the total number of fires and the numbers of belowground fires (Fig. 8).

Parameter optimisation

The optimal set of the most influential parameters is $wtd = 0.6$, $pdi = 0.15$ and $ddb = 11$. Fig. 9 shows the spatial pattern of burnt patches from selected simulation results that comprise four different possible states (burnt at the surface only; burnt below ground only; burnt above and below ground; and did not burn). Comparison between burnt area pattern and burnt neighbour probability of observed pattern and selected simulation results are shown in Fig. S2. The three highest-ranked parameter settings produced similar result compared with the observed pattern. Meanwhile, the three middle- and lowest-ranked parameter settings produced different patterns of burnt patches compared with the observed data.

Table 4 shows the kappa scores used to evaluate the accuracy of the model under different parameter settings. The closest match to observed data (highest kappa score 0.338) was obtained with the parameter setting of $wtd = 0.6$, $ddb = 11$ and $pdi = 0.15$ (Table 4).

Model scenario application

We used the optimised PeatFire version to examine the effect of the watertable depth (*wtd*) on the numbers of total fires, aboveground fires and belowground fires (Fig. 10). A clear threshold is seen at $wtd = 0.5$ with a sudden increase in all fire types.

Discussion

We developed an ABM PeatFire that accounts for simplified processes governing fire ignition and fire spreading as known from Indonesian tropical peatland landscapes. To the best of our knowledge, PeatFire is the first ABM developed for tropical peatlands. It thus extends previous regional-scale studies in Indonesia reporting close correlations between burnt area and rainfall (Spessa *et al.* 2015); fire weather (Field *et al.* 2015) and hydrological drought (Taufik *et al.* 2017); and between burnt area and land-use or land-cover change (Stolle and Lambin 2003; Stolle *et al.* 2003; Cattau *et al.* 2016). By explicitly modelling landscape processes (human-induced fire ignition, watertable dynamics and fire spread, both above and below ground), we have shown that PeatFire is suitable to describe fire activity patterns observed in 2015 in our study area. Besides its simplicity, PeatFire supports the assessments of key mechanisms driving fire activities, and this is important for future management of tropical peatlands.

Despite their importance to the terrestrial carbon cycle, belowground fires have received comparatively less research attention than aboveground fires, as the former occur in difficult-to-access locations. Also, they are nearly impossible to observe using optical satellite remote sensing, the prime vehicle by which burnt area is diagnosed globally (Justice *et al.* 2002; Page *et al.* 2002, 2013; Reid *et al.* 2013; Giglio *et al.* 2016). Although most of direct field observations of peat fires have occurred in boreal peatlands and in associated laboratory experiments (Frandsen 1987, 1997; Huang and Rein 2014; Prat-Guitart *et al.* 2015), relatively few studies have directly measured vertical smouldering of peat fires in either boreal or tropical peatlands (Ballhorn *et al.* 2009; Chen *et al.* 2015). Although there is comparatively little data available quantifying the smouldering of organic material both downwards and laterally in peatlands (Frandsen 1987, 1997; Ballhorn *et al.* 2009; He *et al.* 2009), we were able to use the limited information available to construct a belowground fire spreading module within the PeatFire model (Fig. 3*b*). PeatFire can be used to test alternative hypotheses of fire ignition and spread in tropical peatland ecosystems, and importantly, model predictions are amenable to further assessments and improvements through future field and laboratory work.

Our sensitivity analyses and pattern-oriented approach for finding key parameters affecting PeatFire behaviour follow a

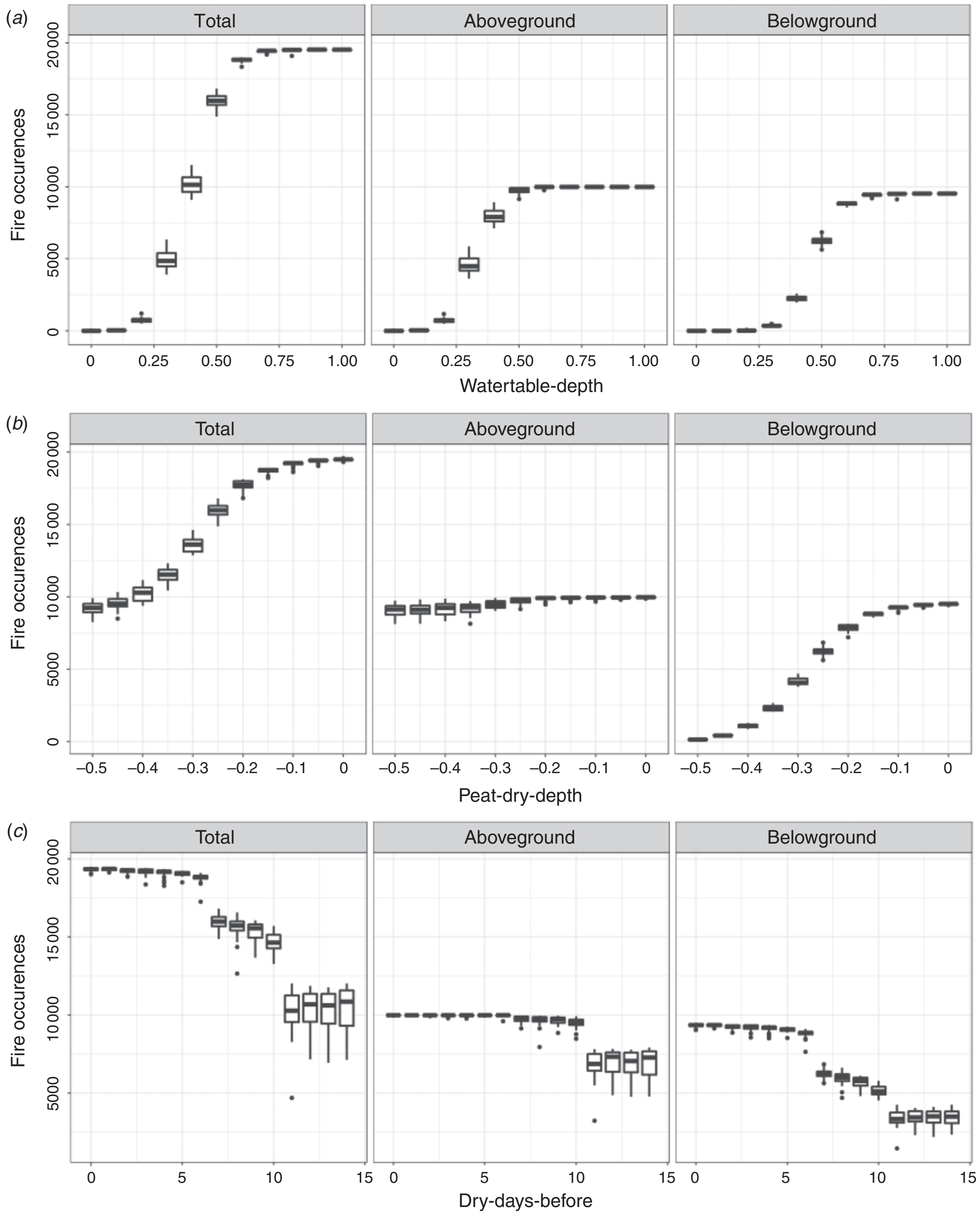

Fig. 6. One-at-a-time (OAT) sensitivity analysis of parameter behaviour in PeatFire model. The total fire occurrences comprise the aboveground + belowground fires during one simulation run. (*a*) Sudden jump of above- and belowground fire occurrences is shown with gradual increase in watertable depth. (*b*) Number of above- and belowground fire drops at certain points when given a gradual increase of the cumulative dry days before ignition. (*c*) The change of peat-dry-index has a more pronounced effect on the belowground fires, with little effect on the aboveground fires.

common procedure for examining the influence of poorly constrained parameters in an ABM (Wang and Grimm 2007; Imron *et al.* 2012; Kautz *et al.* 2014; Carter *et al.* 2015).We found that *wtd* (*watertable-depth*), *pdi* (*peat-dry-index*) and *ddb* (*dry-days-before*) play roles on the emergent dynamics of peat fire patterns (Fig. 5, Fig. 6). The *wtd* and *pdi* parameters are physical factors of peatlands related to watertable condition, which is critical in peatlands (Wösten *et al.* 2008; Kettridge *et al.* 2015; Mezbahuddin *et al.* 2015). The *dry-days-before-ignition* (*ddb*) parameter captures what has been reported as an important

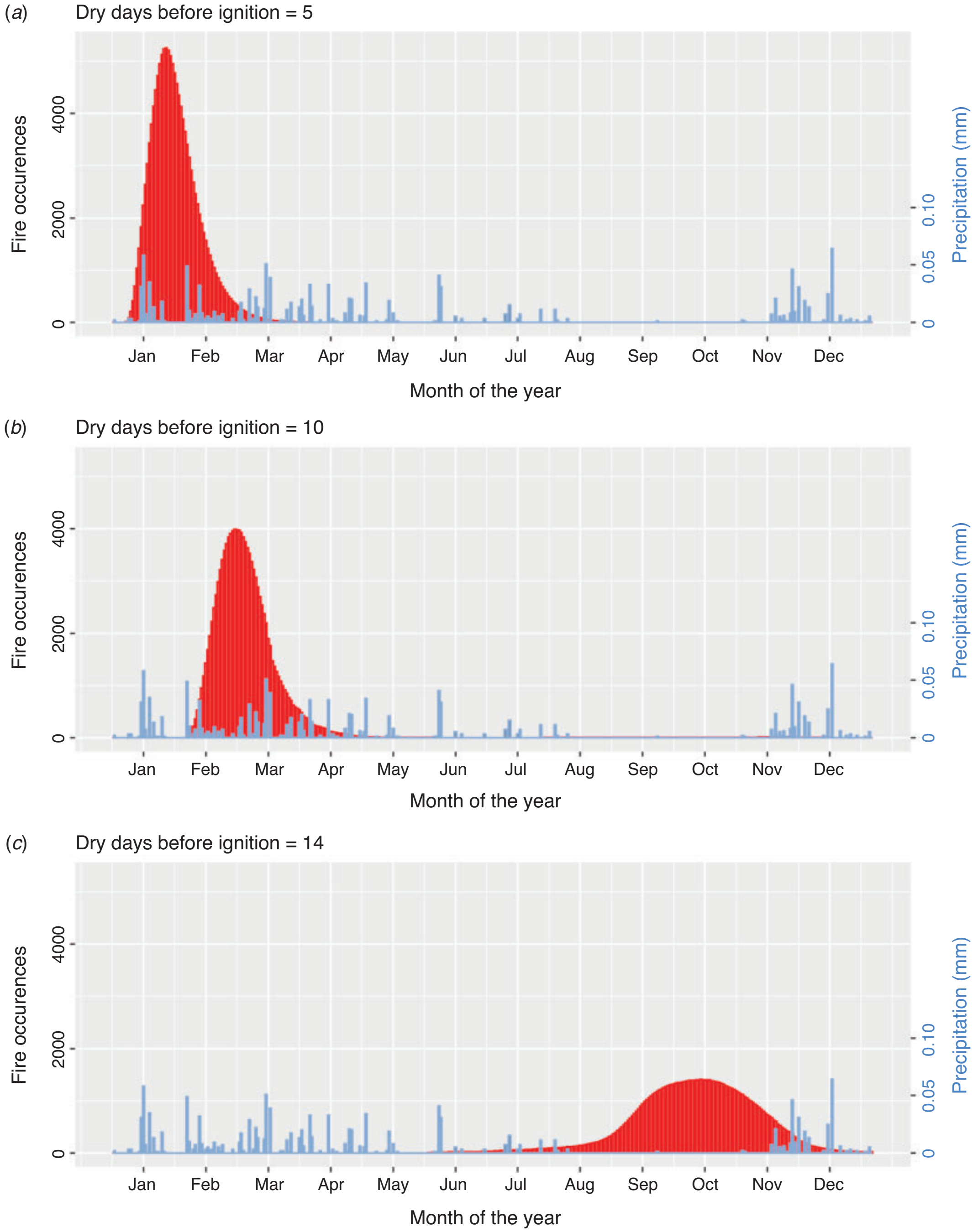

Fig. 7. Different output of simulated daily fire occurrences (red bars) depending on the parameter dry-days-before-ignition (*ddb*) using the same input data for daily precipitation (millimetres; light blue bars). It is shown that with higher waiting time before fire igniting, the fire event shifts further towards the end of year (wet season). The total fire occurrences (averaged from 30 simulations) decreases with the dry days before ignition (plot (*a*) 133 834; plot (*b*) 124 293; plot (*c*) 108 426). NB: the total number does exceed the number of grid cells because fire may repeatedly occur in the same grid cell as long as biomass is still available.

'rule of thumb' helping local landholders whether decide to ignite fires or not in Indonesian peatlands (Cattau *et al.* 2016).

Further improvements to PeatFire could be achieved by considering more local climate data. For instance, parameters such as wind speed (*wsp*) were shown to be influential in determining fire spread in PeatFire. Yet in the absence of local wind speed data, the values for these parameters were taken as estimates using an index from 0 to 1, representing low to high wind speed, whereas we used 0–1 m to represent watertable (*wtd*), which determines the critical region for peat fire (Wösten

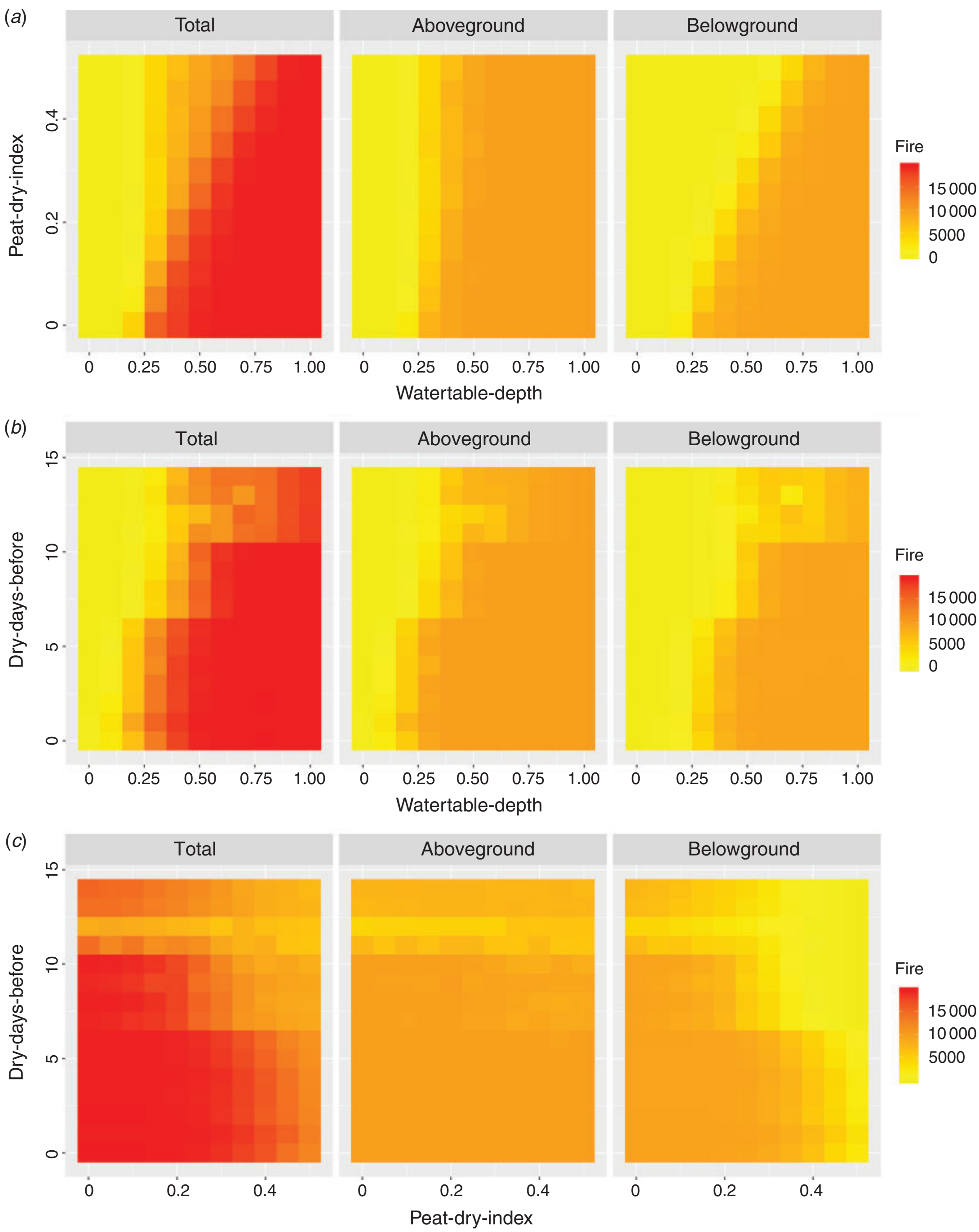

Fig. 8. Heatmaps show the interactions between the three most important parameters of the PeatFire model, namely the watertable-depth (*wtd*), the peat-dry-index (*pdi*) and the dry-days-before (*ddb*). The total number of fires is defined as accumulation of above and belowground fires. Parallel lines indicate interacting effects of the varied parameters on the particular outcome. (*a*) Interaction between parameters *wtd* and *pdi* has a more pronounced effect on belowground rather than aboveground fire. (*b*) Similar behaviour is shown from the interaction of parameters *wtd* and *ddb* to above- and belowground fire occurrences. (*c*) Pronounced effect on belowground fire is shown from the interaction of parameters *pdi* and *ddb*.

et al. 2008; Kettridge *et al.* 2015; Mezbahuddin *et al.* 2015). In addition, biophysical parameters such biomass burning rate (*bbr*) also affected the number of burnt patches, albeit only slightly (Table 3). Future work should try to unpack the effect of these parameters and incorporate the results of field studies into the effect of vegetation, soil moisture and bulk density on fire spread and organic matter combustion, including smouldering combustion (Frandsen 1997; Leach *et al.* 2000; Cochrane 2009; He *et al.* 2009; He and Behrendt 2011). Finally, the incorporation of data on local solar radiation, as previous work has

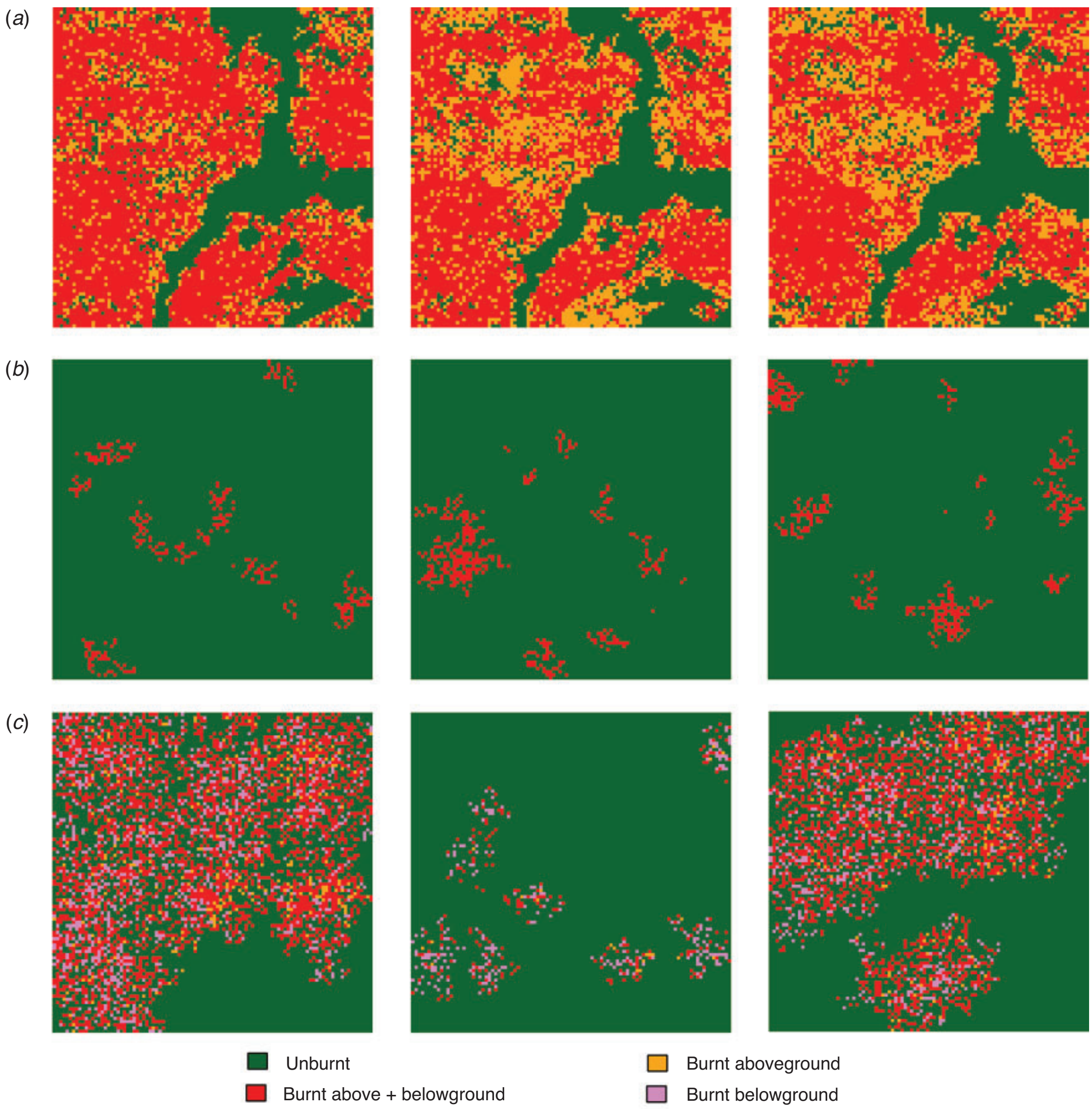

Fig. 9. Spatial pattern from selected model simulation result with the different combinations of parameters watertable-depth, dry-days-before-ignition and peat-dry-index. The spatial pattern is illustrated with a colour scheme showing four possible states of a grid patch in the model (unburnt, burnt aboveground, burnt belowground, and burnt above- + belowground). Simulation results were ranked based on the similarity in the number of burnt patches with the observation and the highest kappa score. The first row (*a*) shows the three highest-ranked patterns obtained from the simulation. The second row (*b*) shows the three middle-ranked patterns, and the third row (*c*) shows the three lowest-ranked spatial patterns.

demonstrated in a more sophisticated peatland hydrological process modelling (Mezbahuddin *et al.* 2015; Valipour 2015), and other physical properties (i.e. water retention, unsaturated conductivity) on humification (Taufik *et al.* 2019) should lead to marked improvements in the simulation of evapotranspiration and watertable depth dynamics in PeatFire.

To improve the representation of both below- and aboveground fires in PeatFire, future work is needed to improve the representation of key hydrological parameters under different vegetation cover categories ranging from pristine to disturbed. Evapotranspiration is a key driver of soil moisture in tropical ecosystems, but comparatively little work has examined hydrological thresholds in tropical peatlands, particularly in relation to changes in vegetation cover (Segah *et al.* 2010; Hirano *et al.* 2012, 2015; Mezbahuddin *et al.* 2014, 2015, 2019). Although PeatFire does not represent disturbed peat swamp forests, our results confirm the importance of watertable, which is also influential in determining soil moisture, and hence aboveground fire occurrence.

Decisions governing fire ignitions in rural settings, such as Indonesian peatlands, involve various considerations by farmers ranging from socioeconomic factors (Cattau *et al.* 2016) and traditional reasons (Ryan *et al.* 2012) to political strategy (Barber and Schweithelm 2000; Yong and Peh 2016). Our modelling results clearly demonstrate the importance of the watertable (*wtd*), and the peat dryness index (*pdi*) contribution to burnt area patterns in the study area along with number of dry days before ignition *(ddb)* (Fig. 5, Fig. 6). This in general reflects current observations and knowledge in Indonesian peatlands (Cochrane 2003; Hooijer *et al.* 2010; Page *et al.* 2011), and thereby improves on past assessments of fire activity drivers based around biophysical factors alone (Wösten *et al.* 2008; Mezbahuddin *et al.* 2014, 2015; Brown *et al.* 2015; Prat-Guitart *et al.* 2015; Hayasaka *et al.* 2016; Taufik *et al.* 2017).

In many tropical countries, including Indonesia, land use-cover change and associated changes to human-caused ignitions intensify the impact of interannual variability in climate on fire activity (Langner *et al.* 2007; Aldersley *et al.* 2011; Miettinen *et al.* 2012; Spessa *et al.* 2015; Cattau *et al.* 2016). Existing ABMs of forest fire (Karsai *et al.* 2016; Spies *et al.* 2017) have not implemented the presence of human agents as ignition sources, thereby limiting their usefulness in situations where human ignitions *and* biophysical factors interact to cause fire, as is the case in Indonesian peatlands. The PeatFire model goes beyond this approach, although it addresses ignitions through farmer activities only as local probabilities. A future direction of model development would be to directly address human activities, for example, by considering human settlements and hotspots of activities by means of GIS (geographic information systems) layers. Further improvements in the way PeatFire simulates farmer agent impacts on ignitions should account for local data on the number of households actively using fires and their knowledge and behaviours to manage fire when deciding to convert peatland into agricultural land use.

The PeatFire model does not currently represent interactions between individual or groups of farmers. This omission potentially prevents the model from simulating real-world situations in which farmers may be influenced by other farmers through active communication or simply copying the behaviour of neighbouring farmers or communities when deciding to convert peatland (Hettig *et al.* 2016). The inclusion of a range of possible interactions between farmers on land-use change (Valbuena *et al.* 2010) would improve the simulation of ignitions in the model, and would lead to a richer array of emergent outcomes compared with the case where interactions between actors in an ABM are ignored (Grimm *et al.* 2006).

Table 4. Evaluation score of ranked simulation results (ranked) with regards to the kappa score

No.	Parameter			Kappa	Rank
	wtd	*pdi*	*ddb*		
1	0.6	0.15	11	0.338	Three highest
2	0.6	0.1	13	0.334	
3	0.5	0.45	12	0.332	
1	0.1	0.25	2	0.007	Three middle
2	0.2	0.2	7	0.007	
3	0.1	0.5	3	0.007	
1	0.1	0	0	−0.009	Three lowest
2	0.1	0	1	−0.011	
3	0.2	0	1	−0.012	

Risk of catastrophic shift in peat fire frequency

Under a gradual change in watertable depth, our model showed a sudden shift of fire occurrence, from moderate to severe burning (Fig. 10). Hydrological changes including peat drainage are known to be a trigger for severe burning events (Wösten *et al.* 2008; Miettinen *et al.* 2012). In peat swamp forests, drought and fire lead to peat soil degradation and increase the risk of repeated burning (Page *et al.* 2009*b*). Degraded peatland entails poor quality of soil, which needs a long time to be restored (Könönen *et al.* 2018). Efforts to restore degraded tropical peatland, such as rewetting and canal blocking (Jaenicke *et al.* 2010; Ritzema *et al.* 2014) and revegetation (Blackham *et al.* 2014; Lampela

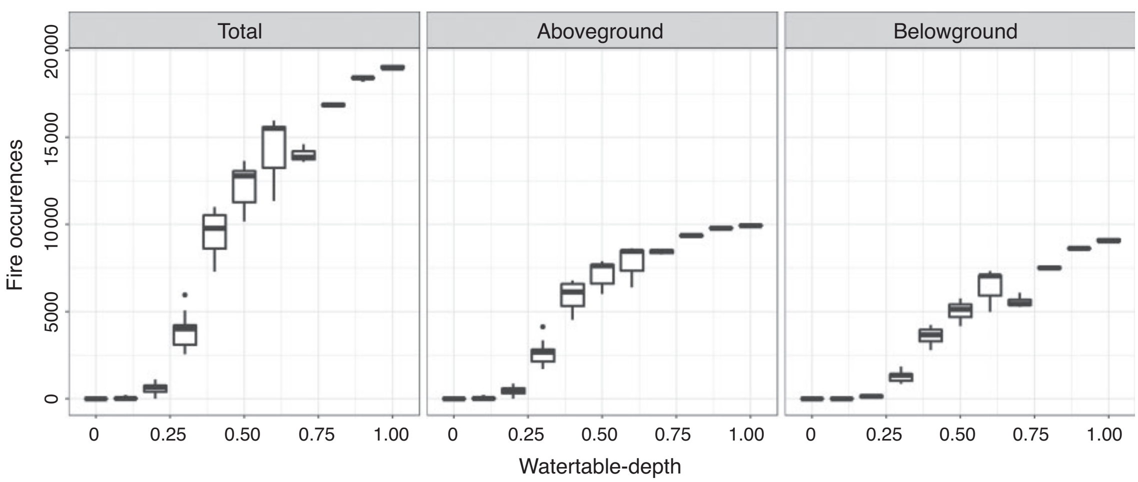

Fig. 10. Box plots showing the effect of varying parameter watertable-depth (*wtd*) on model output (total fire, aboveground fire, belowground fire). The influential parameters *pdi* and *ddb* were set to 0.15 and 11 respectively according to the result of pattern-oriented analysis. Both above- and belowground fire showed a sudden increase when given a gradual change of watertable-depth. This behaviour caused a pronounced sudden shift of the total fire occurrences, from no ignition to a completely severe burning.

et al. 2017) have been carried out. However, the process requires expensive resources (Budiharta *et al.* 2014) with various limitation and barriers (Dohong *et al.* 2018).

Our model represented burn severity by explicitly introducing the effects of above- and belowground fire. Furthermore, by simulating possible sudden shift of fire events, PeatFire has also been able to demonstrate that most burnt patches are damaged both in their above- and belowground layers of peat (Fig. 9). Smouldering fire that spreads vertically underneath peat is a serious threat on tropical peatlands, as it limits the ability of the peat to fully recover after fire (Hu *et al.* 2018). Studies in boreal peatlands have shown that fire could cause peatland to experience a regime shift to mineral soil environment, where a reversal would be hardly possible (Kettridge *et al.* 2015). By showing a potential sudden increase of burning severity, our model reveals the risk of a catastrophic shift (Scheffer *et al.* 2001) if the main drivers of fire cannot be controlled properly. Further development of the model by including modules related to peat restoration would enable the model to simulate different strategies for post-fire recovery.

Implication for peatland management

Despite certain limitations of PeatFire, described above, simulated burnt area patterns generally reflected observed burnt area patterns, supporting the robustness of our findings with respect to peat management. A peat fire study by Ballhorn *et al.* (2009) in Kalimantan reported a burning depth of 30 cm that decreased with repeated burns – key information that we could use for future model improvement. This type of model improvement would increase the utility of PeatFire because the model could then be used to examine peatland management options for peat forest restoration, including canal blocking and rewetting of drained peatlands (Page *et al.* 2009*b*; Jaenicke *et al.* 2010).

Our work demonstrating a strong relationship between the watertable depth (*wtd*) and fire incidence in the model confirms current peatland management practice that applies canal blocking and rewetting to effect peat restoration and protection (Page *et al.* 2009*b*; Ritzema *et al.* 2014; Sekretariat Negara Republik Indonesia 2016). Although precipitation and evapotranspiration have significant effects on fire occurrence, our analyses also demonstrate that initial fire ignition by farmers is the most important driver of fire ignition. Although the importance of both climate and land-use factors in driving fire ignitions and spread in Indonesian peatlands is well known and accepted (Field *et al.* 2009; Miettinen *et al.* 2012, 2013; Page *et al.* 2013; Brown *et al.* 2015; Spessa *et al.* 2015; Page and Hooijer 2016), we have shown here that an ABM, which captures the underlying processes associated with fire ignition and spread at a local scale even approximately can, through emergent model behaviour, reproduce broad-scale patterns in burnt area. The explicit consideration of fire-causing mechanisms in PeatFire underlines its potential usefulness in assessing and developing effective policies for peatland management focused on maintaining natural peat watertable depths and setting limits to land conversion.

Supplementary material

Supplementary material PeatFire model is available to download at https://peatfire-abm.github.io/. Two supplementary figures are available online with this paper.

Conflicts of interest

The authors declare that there is no conflict of interest.

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References

Abar S, Theodoropoulos GK, Lemarinier P, O'Hare GMP (2017) Agent-based modelling and simulation tools: a review of the state-of-art software. *Computer Science Review* **24**, 13–33. doi:10.1016/J.COSREV.2017.03.001

Adrianto HA, Spracklen DV, Arnold SR (2019) Relationship between fire and forest cover loss in Riau Province, Indonesia between 2001 and 2012. *Forests* **10**, 889. doi:10.3390/F10100889

Aldersley A, Murray SJ, Cornell SE (2011) Global and regional analysis of climate and human drivers of wildfire. *The Science of the Total Environment* **409**, 3472–3481. doi:10.1016/J.SCITOTENV.2011.05.032

Baker JCA, Spracklen DV (2019) Climate benefits of intact Amazon forests and the biophysical consequences of disturbance. *Frontiers in Forests and Global Change* **2**, 47. doi:10.3389/FFGC.2019.00047

Ballhorn U, Siegert F, Mason M, Limin S (2009) Derivation of burn scar depths and estimation of carbon emissions with LIDAR in Indonesian peatlands. *Proceedings of the National Academy of Sciences of the United States of America* **106**, 21213–21218. doi:10.1073/PNAS.0906457106

Barber C, Schweithelm J (2000) 'Trial by fire: forest fires and forestry policy in Indonesia's era of crisis and reform.' (World Resources Institute, Washington, DC, USA)

Blackham GV, Webb EL, Corlett RT (2014) Natural regeneration in a degraded tropical peatland, Central Kalimantan, Indonesia: implications for forest restoration. *Forest Ecology and Management* **324**, 8–15. doi:10.1016/J.FORECO.2014.03.041

Brown LE, Holden J, Palmer SM, Johnston K, Sorain JR, Grayson R (2015) Effects of fire on the hydrology, biogeochemistry, and ecology of peatland river systems. *Freshwater Science* **34**, 1406–1425. doi:10.1086/683426

Budiharta S, Meijaard E, Erskine PD, Rondinini C, Pacifici M, Wilson KA (2014) Restoring degraded tropical forests for carbon and biodiversity. *Environmental Research Letters* **9**, 114020. doi:10.1088/1748-9326/9/11/114020

Carter N, Levin S, Barlow A, Grimm V (2015) Modeling tiger population and territory dynamics using an agent-based approach. *Ecological Modelling* **312**, 347–362. doi:10.1016/J.ECOLMODEL.2015.06.008

Cattau ME, Harrison ME, Shinyo I, Tungau S, Uriarte M, DeFries R (2016) Sources of anthropogenic fire ignitions on the peat-swamp landscape in

Kalimantan, Indonesia. *Global Environmental Change* **39**, 205–219. doi:10.1016/J.GLOENVCHA.2016.05.005

Chen H, Rein G, Liu N (2015) Numerical investigation of downward smoldering combustion in an organic soil column. *International Journal of Heat and Mass Transfer* **84**, 253–261. doi:10.1016/J.IJHEATMASSTRANSFER.2015.01.016

Christensen EG, Fernandez-Anez N, Rein G (2020) Influence of soil conditions on the multidimensional spread of smouldering combustion in shallow layers. *Combustion and Flame* **214**, 361–370. doi:10.1016/J.COMBUSTFLAME.2019.11.001

Cochrane MA (2003) Fire science for rainforest. *Nature* **421**, 913–919. doi:10.1038/NATURE01437

Cochrane MA (2009) 'Tropical fire ecology: climate change, land use and ecosystem dynamics.' (Springer-Praxis: Berlin)

Cohen J (1960) A coefficient of agreement for nominal scales. *Educational and Psychological Measurement* **20**, 37–46. doi:10.1177/001316446002000104

Cole LES, Bhagwat SA, Willis KJ (2015) Long-term disturbance dynamics and resilience of tropical peat swamp forests. *Journal of Ecology* **103**, 16–30. doi:10.1111/1365-2745.12329

Crippa P, Castruccio S, Archer-Nicholls S, Lebron GB, Kuwata M, Thota A, Sumin S, Butt E, Wiedinmyer C, Spracklen DV (2016) Population exposure to hazardous air quality due to the 2015 fires in equatorial Asia. *Scientific Reports* **6**, 37074. doi:10.1038/SREP37074

Dislich C, Hettig E, Salecker J, Heinonen J, Lay J, Meyer KM, Wiegand K, Tarigan S (2018) Land-use change in oil palm-dominated tropical landscapes – an agent-based model to explore ecological and socio-economic trade-offs. *PLoS One* **13**, e0190506. doi:10.1371/JOURNAL.PONE.0190506

Dohong A, Abdul Aziz A, Dargusch P (2018) A review of techniques for effective tropical peatland restoration. *Wetlands* **38**, 275–292. doi:10.1007/S13157-018-1017-6

Fanin T, van der Werf GR (2017) Precipitation – fire linkages in Indonesia (1997–2015). *Biogeosciences* **14**, 3995–4008. doi:10.5194/BG-14-3995-2017

Field RD, van der Werf GR, Shen SSP (2009) Human amplification of drought-induced biomass burning in Indonesia since 1960. *Nature Geoscience* **2**, 185–188. doi:10.1038/NGEO443

Field RD, Spessa AC, Aziz NA, Camia A, Cantin A, Carr R, De Groot WJ, Dowdy AJ, Flannigan MD, Manomaiphiboon K, Pappenberger F, Tanpipat V, Wang X (2015) Development of a global fire weather database. *Natural Hazards and Earth System Sciences* **15**, 1407–1423. doi:10.5194/NHESS-15-1407-2015

Field RD, Werf GR, Van Der , Fanin T, Fetzer EJ, Fuller R, Jethva H, Levy R (2016) Indonesian fire activity and smoke pollution in 2015 show persistent non-linear sensitivity to El Niño-induced drought. *Proceedings of the National Academy of Sciences* **113**, 9204–9209. doi:10.1073/PNAS.1524888113

Frandsen WH (1987) The influence of moisture and mineral soil on the combustion limits of smoldering forest duff. *Canadian Journal of Forest Research* **17**, 1540–1544. doi:10.1139/X87-236

Frandsen WH (1997) Ignition probability of organic soils. *Canadian Journal of Forest Research* **27**, 1471–1477. doi:10.1139/X97-106

Giglio L, Schroeder W, Justice CO (2016) The Collection 6 MODIS active fire detection algorithm and fire products. *Remote Sensing of Environment* **178**, 31–41. doi:10.1016/J.RSE.2016.02.054

Goodman J, Robinson O (2019) Forest fires: are they worse than in previous years? *BBC News*. Available at https://www.bbc.com/news/world-49515462 [verified 21 October 2020]

Grimm V (1999) Ten years of individual-based modelling in ecology: what have we learned and what could we learn in the future? *Ecological Modelling* **115**, 129–148. doi:10.1016/S0304-3800(98)00188-4

Grimm V, Railsback S (2005) 'Individual-based modeling and ecology.' (Princeton University Press: Princeton, NJ, USA)

Grimm V, Railsback SF (2012) Pattern-oriented modelling: a 'multi-scope' for predictive systems ecology. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* **367**, 298–310. doi:10.1098/RSTB.2011.0180

Grimm V, Berger U, Bastiansen F, Eliassen S, Ginot V, Giske J, Goss-Custard J, Grand T, Heinz SK, Huse G, Huth A, Jepsen JU, Jørgensen C, Mooij WM, Müller B, Pe'er G, Piou C, Railsback SF, Robbins AM, Robbins MM, Rossmanith E, Rüger N, Strand E, Souissi S, Stillman RA, Vabø R, Visser U, DeAngelis DL (2006) A standard protocol for describing individual-based and agent-based models. *Ecological Modelling* **198**, 115–126. doi:10.1016/J.ECOLMODEL.2006.04.023

Grimm V, Berger U, DeAngelis DL, Polhill JG, Giske J, Railsback SF (2010) The ODD protocol: a review and first update. *Ecological Modelling* **221**, 2760–2768. doi:10.1016/J.ECOLMODEL.2010.08.019

Hantson S, Knorr W, Schurgers G, Pugh TAM, Arneth A (2017) Global isoprene and monoterpene emissions under changing climate, vegetation, CO_2 and land use. *Atmospheric Environment* **155**, 35–45. doi:10.1016/J.ATMOSENV.2017.02.010

Hayasaka H, Noguchi I, Putra EI, Yulianti N, Vadrevu K (2014) Peat-fire-related air pollution in Central Kalimantan, Indonesia. *Environmental Pollution* **195**, 257–266. doi:10.1016/J.ENVPOL.2014.06.031

Hayasaka H, Takahashi H, Limin SH, Yulianti N, Usup A (2016) Peat fire occurrence. In 'Tropical peatland ecosystems'. (Eds M Osaki, N Tsuji) pp. 377–395. (Springer: Tokyo, Japan) DOI:10.1007/978-4-431-55681-7_25

He F, Behrendt F (2011) Experimental investigation of natural smoldering of char granules in a packed bed. *Fire Safety Journal* **46**, 406–413. doi:10.1016/J.FIRESAF.2011.06.007

He F, Zobel N, Zha W, Behrendt F (2009) Effects of physical properties on one-dimensional downward smoldering of char: numerical analysis. *Biomass and Bioenergy* **33**, 1019–1029. doi:10.1016/J.BIOMBIOE.2009.02.008

Heinonen JPM, Palmer SCF, Redpath SM, Travis JMJ (2014) Modelling hen harrier dynamics to inform human–wildlife conflict resolution: a spatially realistic, individual-based approach. *PLoS One* **9**, e112492. doi:10.1371/JOURNAL.PONE.0112492

Hettig E, Lay J, Sipangule K (2016) Drivers of households' land-use decisions: a critical review of microlevel studies in tropical regions. *Land* **5**, 32. doi:10.3390/LAND5040032

Hirano T, Segah H, Kusin K, Limin S, Takahashi H, Osaki M (2012) Effects of disturbances on the carbon balance of tropical peat swamp forests. *Global Change Biology* **18**, 3410–3422. doi:10.1111/J.1365-2486.2012.02793.X

Hirano T, Kusin K, Limin S, Osaki M (2015) Evapotranspiration of tropical peat swamp forests. *Global Change Biology* **21**, 1914–1927. doi:10.1111/GCB.12653

Holden ZA, Smith AMS, Morgan P, Rollins MG, Gessler PE (2005) Evaluation of novel thermally enhanced spectral indices for mapping fire perimeters and comparisons with fire atlas data. *International Journal of Remote Sensing* **26**, 4801–4808. doi:10.1080/01431160500239008

Hooijer A, Page S, Canadell JG, Silvius M, Kwadijk J, Wösten H, Jauhiainen J (2010) Current and future CO_2 emissions from drained peatlands in south-east Asia. *Biogeosciences* **7**, 1505–1514. doi:10.5194/BG-7-1505-2010

Hu Y, Fernandez-Anez N, Smith TEL, Rein G (2018) Review of emissions from smouldering peat fires and their contribution to regional haze episodes. *International Journal of Wildland Fire* **27**, 293–312. doi:10.1071/WF17084

Hu Y, Christensen EG, Amin HMF, Smith TEL, Rein G (2019) Experimental study of moisture content effects on the transient gas and particle emissions from peat fires. *Combustion and Flame* **209**, 408–417. doi:10.1016/J.COMBUSTFLAME.2019.07.046

Huang X, Rein G (2014) Smouldering combustion of peat in wildfires: inverse modelling of the drying and the thermal and oxidative

decomposition kinetics. *Combustion and Flame* **161**, 1633–1644. doi:10.1016/J.COMBUSTFLAME.2013.12.013
Imron MA, Herzog S, Berger U (2011) The influence of agroforestry and other land-use types on the persistence of a Sumatran tiger (*Panthera tigris sumatrae*) population: an individual-based model approach. *Environmental Management* **48**, 276–288. doi:10.1007/S00267-010-9577-0
Imron MA, Gergs A, Berger U (2012) Structure and sensitivity analysis of individual-based predator–prey models. *Reliability Engineering & System Safety* **107**, 71–81. doi:10.1016/J.RESS.2011.07.005
Imron MA, Widyastuti K, Satria RA, Prayoga W, Pradopo ST, Suryatmojo H, Sopha BM, Berger U (2018) Beyond climatic variation: human disturbances alter the effectiveness of a protected area to reduce fires in tropical peatlands of Sumatra, Indonesia. *bioRxiv* . doi:10.1101/351817
Jaenicke J, Wösten H, Budiman A, Siegert F (2010) Planning hydrological restoration of peatlands in Indonesia to mitigate carbon dioxide emissions. *Mitigation and Adaptation Strategies for Global Change* **15**, 223–239. doi:10.1007/S11027-010-9214-5
Jakoby O, Grimm V, Frank K (2014) Pattern-oriented parameterization of general models for ecological application: towards realistic evaluations of management approaches. *Ecological Modelling* **275**, 78–88. doi:10.1016/J.ECOLMODEL.2013.12.009
Johnston FH, Henderson SB, Chen Y, Randerson JT, Marlier M, DeFries RS, Kinney P, Bowman DMJS, Brauer M (2012) Estimated global mortality attributable to smoke from landscape fires. *Environmental Health Perspectives* **120**, 695–701. doi:10.1289/EHP.1104422
Jones DS (2006) ASEAN and transboundary haze pollution in south-east Asia. *Asia Europe Journal* **4**, 431–446. doi:10.1007/S10308-006-0067-1
Justice CO, Giglio L, Korontzi S, Owens J, Morisette JT, Roy D, Descloitres J, Alleaume S, Petitcolin F, Kaufman Y (2002) The MODIS fire products. *Remote Sensing of Environment* **83**, 244–262. doi:10.1016/S0034-4257(02)00076-7
Karsai I, Roland B, Kampis G (2016) The effect of fire on an abstract forest ecosystem: an agent-based study. *Ecological Complexity* **28**, 12–23. doi:10.1016/J.ECOCOM.2016.09.001
Kautz M, Schopf R, Imron MA (2014) Individual traits as drivers of spatial dispersal and infestation patterns in a host–bark beetle system. *Ecological Modelling* **273**, 264–276. doi:10.1016/J.ECOLMODEL.2013.11.022
Kettridge N, Turetsky MR, Sherwood JH, Thompson DK, Miller CA, Benscoter BW, Flannigan MD, Wotton BM, Waddington JM (2015) Moderate drop in water table increases peatland vulnerability to post-fire regime shift. *Scientific Reports* **5**, 8063. doi:10.1038/SREP08063
Könönen M, Jauhiainen J, Vasander H, Straková P, Laiho R, Heinonsalo J, Kusin K, Limin S (2018) Deforested and drained tropical peatland sites show poorer peat substrate quality and lower microbial biomass and activity than unmanaged swamp forest. *Soil Biology & Biochemistry* **123**, 229–241. doi:10.1016/J.SOILBIO.2018.04.028
Lampela M, Jauhiainen J, Sarkkola S, Vasander H (2017) Promising native tree species for reforestation of degraded tropical peatlands. *Forest Ecology and Management* **394**, 52–63. doi:10.1016/J.FORECO.2016.12.004
Langner A, Miettinen J, Siegert F (2007) Land cover change 2002–2005 in Borneo and the role of fire derived from MODIS imagery. *Global Change Biology* **13**, 2329–2340. doi:10.1111/J.1365-2486.2007.01442.X
Leach SV, Rein G, Ellzey JL, Ezekoye OA, Torero JL (2000) Kinetic and fuel property effects on forward smoldering combustion. *Combustion and Flame* **120**, 346–358. doi:10.1016/S0010-2180(99)00089-9
Lehsten V, de Groot W, Sallaba F (2016) Fuel fragmentation and fire size distributions in managed and unmanaged boreal forests in the province of Saskatchewan, Canada. *Forest Ecology and Management* **376**, 148–157. doi:10.1016/J.FORECO.2016.06.014
Margono BA, Potapov PV, Turubanova S, Stolle F, Hansen MC (2014) Primary forest cover loss in Indonesia over 2000–2012. *Nature Climate Change* **4**, 730–735. doi:10.1038/NCLIMATE2277
Marlier ME, Defries RS, Voulgarakis A, Kinney PL, Randerson JT, Shindell DT, Chen Y, Faluvegi G (2013) El Niño and health risks from landscape fire emissions in south-east Asia. *Nature Climate Change* **3**, 131–136. doi:10.1038/NCLIMATE1658
Martín MP, Gómez I, Chuvieco E (2006) Burnt Area Index (BAIM) for burned area discrimination at regional scale using MODIS data. *Forest Ecology and Management* **234**, S221. doi:10.1016/J.FORECO.2006.08.248
Mezbahuddin M, Grant RF, Hirano T (2014) Modelling effects of seasonal variation in water table depth on net ecosystem CO_2 exchange of a tropical peatland. *Biogeosciences* **11**, 577–599. doi:10.5194/BG-11-577-2014
Mezbahuddin M, Grant RF, Hirano T (2015) How hydrology determines seasonal and interannual variations in water table depth, surface energy exchange and water stress in a tropical peatland: modelling vs. measurements. *Journal of Geophysical Research. Biogeosciences* **120**, 2132–2157. doi:10.1002/2015JG003005
Mezbahuddin S, Nikonovas T, Spessa A, Grant R (2019) Modelling large-scale seasonal variations in water table depth over tropical peatlands in Riau, Sumatra. Poster presentation in 'European Geophysical Union General Assembly', (Earth and Space Science Open Archive). doi:10.1002/ESSOAR.10501280.1
Miettinen J, Liew SC (2010) Status of peatland degradation and development in Sumatra and Kalimantan. *Ambio* **39**, 394–401. doi:10.1007/S13280-010-0051-2
Miettinen J, Shi C, Liew SC (2011) Deforestation rates in insular south-east Asia between 2000 and 2010. *Global Change Biology* **17**, 2261–2270. doi:10.1111/J.1365-2486.2011.02398.X
Miettinen J, Hooijer A, Wang J, Shi C, Liew SC (2012) Peatland degradation and conversion sequences and interrelations in Sumatra. *Regional Environmental Change* **12**, 729–737. doi:10.1007/S10113-012-0290-9
Miettinen J, Wang J, Hooijer A, Liew S (2013) Peatland conversion and degradation processes in insular south-east Asia: a case study in Jambi, Indonesia. *Land Degradation & Development* **24**, 334–341. doi:10.1002/LDR.1130
Miettinen J, Hooijer A, Vernimmen R, Liew SC, Page SE (2017) From carbon sink to carbon source: extensive peat oxidation in insular south-east Asia since 1990. *Environmental Research Letters* **12**, 2. doi:10.1088/1748-9326/AA5B6F
Morrogh-Bernard H, Husson S, Page SE, Rieley JO (2003) Population status of the Bornean orang-utan (*Pongo pygmaeus*) in the Sebangau peat swamp forest, Central Kalimantan, Indonesia. *Biological Conservation* **110**, 141–152. doi:10.1016/S0006-3207(02)00186-6
Nikonovas T, Spessa A, Mezbahuddin S (2019) Forecasting fire activity in Indonesia as a function of fire weather and land cover change. Geophysical Research Abstracts. European Geosciences Union General Assembly. **21**, 8082. Available at https://ui.adsabs.harvard.edu/abs/2019EGUGA..21.8082N/abstract [verified 26 October 2020]
Page S, Hooijer A (2016) In the line of fire: the peatlands of south-east Asia. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences* **371**. doi:10.1098/RSTB.2015.0176
Page S, Siegert F, Rieley JO, Boehm H-DV, Jaya A, Limin SH (2002) The amount of carbon released from peat and forest fires in Indonesia during 1997. *Nature* **420**, 61–65. doi:10.1038/NATURE01131
Page S, Langner A, Tansey K, Siegert F, Limin S, Rieley J (2009*a*) Chapter 9: Tropical peatland fires in Southeast Asia. 'Tropical Fire Ecology' (Editor: MA Cochrane) pp. 263–287. (Springer Berlin Heidelberg). doi:10.1007/978-3-540-77381-8_9
Page S, Hosciło A, Wösten H, Jauhiainen J, Silvius M, Rieley J, Ritzema H, Tansey K, Graham L, Vasander H, Limin S (2009*b*) Restoration ecology of lowland tropical peatlands in south-east Asia: current knowledge and future research directions. *Ecosystems* **12**, 888–905. doi:10.1007/S10021-008-9216-2

Page S, Rieley JO, Banks CJ (2011) Global and regional importance of the tropical peatland carbon pool. *Global Change Biology* **17**, 798–818. doi:10.1111/J.1365-2486.2010.02279.X

Page S, Rieley J, Hoscilo A, Spessa A, Weber U (2013) Current fire regimes, impacts and the likely changes – IV: Tropical south-east Asia. In 'Vegetation fires and global change – Challenges for concerted international action'. A White Paper directed to the United Nations and International Organizations. (Ed JG Goldammer) pp. 88–99. (Kessel Publishing House: Remagen-Oberwinter, Germany).

Pan M, Yang Y, Fisher CK, Lin P, Turmon M, Hobbs J, Emery CM, Reager JTI, David CH, Wood EF (2018) Enhancing discharge interpolation for SWOT. In 'American Geophysical Union Fall Meeting Abstracts' pp OS53C-1342.

Posa MRC (2011) Peat swamp forest avifauna of Central Kalimantan, Indonesia: effects of habitat loss and degradation. *Biological Conservation* **144**, 2548–2556. doi:10.1016/J.BIOCON.2011.07.015

Posa MRC, Wijedasa LS, Corlett RT (2011) Biodiversity and conservation of tropical peat swamp forests. *Bioscience* **61**, 49–57. doi:10.1525/BIO.2011.61.1.10

Prat-Guitart N, Rein G, Hadden RM, Belcher CM, Yearsley JM (2015) Effects of spatial heterogeneity in moisture content on the horizontal spread of peat fires. *The Science of the Total Environment* **572**, 1422–1430. doi: 10.1016/J.SCITOTENV.2016.02.145

Purnomo H, Suyamto D, Irawati RH (2013) Harnessing the climate commons: an agent-based modelling approach to making reducing emission from deforestation and degradation (REDD)+work. *Mitigation and Adaptation Strategies for Global Change* **18**, 471–489. doi:10.1007/S11027-012-9370-X

Railsback SF, Grimm V (2011) 'Agent-based and individual-based modeling.' (Princeton University Press: Princeton, NJ)

Reid JS, Hyer EJ, Johnson RS, Holben BN, Yokelson RJ, Zhang J, Campbell JR, Christopher SA, Di Girolamo L, Giglio L, Holz RE, Kearney C, Miettinen J, Reid EA, Turk FJ, Wang J, Xian P, Zhao G, Balasubramanian R, Chew BN, Janjai S, Lagrosas N, Lestari P, Lin NH, Mahmud M, Nguyen AX, Norris B, Oanh NTK, Oo M, Salinas SV, Welton EJ, Liew SC (2013) Observing and understanding the south-east Asian aerosol system by remote sensing: an initial review and analysis for the Seven Southeast Asian Studies (7SEAS) program. *Atmospheric Research* **122**, 403–468. doi:10.1016/J.ATMOSRES.2012.06.005

Ritzema H, Limin S, Kusin K, Jauhiainen J, Wösten H (2014) Canal blocking strategies for hydrological restoration of degraded tropical peatlands in Central Kalimantan, Indonesia. *Catena* **114**, 11–20. doi:10.1016/J.CATENA.2013.10.009

Rothermel RC (1972) A mathematical model for predicting fire spread in wildland fuels. USDA Forest Service, Intermountain Forest and Range Experiment Station, Research Paper INT-RP-115. (Ogden, UT, USA)

Rothermel RC, Rinehart GC (1983) Field procedures for verification and adjustment of fire behavior predictions. USDA Forest Service, Intermountain Forest and Range Experiment Station, General Technical Report INT-142. (Ogden, UT, USA). doi:10.2737/INT-GTR-142

Ryan KC, Jones TA, Koerner CL, Lee KM (2012) Wildland fire in ecosystems: effects of fire on cultural resources and archaeology. USDA Forest Service, Rocky Mountain Research Station, General Technical Report RMRS-GTR-42-Vol. 3. (Fort Collins, CO, USA). doi:10.2737/RMRS-GTR-42

Salecker J, Sciaini M, Meyer KM, Wiegand K (2019) The NLRX R package: a next-generation framework for reproducible *NetLogo* model analyses. *Methods in Ecology and Evolution* **10**, 1854–1863. doi:10.1111/2041-210X.13286

Saltelli A, Ratto M, Tarantola S, Campolongo F (2006) Sensitivity analysis practices: strategies for model-based inference. *Reliability Engineering & System Safety* **91**, 1109–1125. doi:10.1016/J.RESS.2005.11.014

Scheffer M, Carpenter S, Foley JA, Folke C, Walker B (2001) Catastrophic shifts in ecosystems. *Nature* **413**, 591–596. doi:10.1038/35098000

Segah H, Tani H, Hirano T (2010) Detection of fire impact and vegetation recovery over tropical peat swamp forest by satellite data and ground-based NDVI instrument. *International Journal of Remote Sensing* **31**, 5297–5314. doi:10.1080/01431160903302981

Sekretariat Negara Republik Indonesia (2016) 'Peraturan Pemerintah RI No. 57 Tahun 2016 tentang Perubahan PP No. 71 tahun 2014 tentang Perlindungan dan Pengelolaan Ekosistem Gambut.' Available at https://peraturan.bpk.go.id/Home/Details/5778/pp-no-57-tahun-2016 [verified 26 October 2020].

Spessa A, Weber U (2010) Fire in the vegetation and peatlands of Borneo, 1997–2007: patterns, drivers and emissions from biomass burning. Geophysical Research Abstracts. European Geosciences Union General Assembly. **12**, 7149. Available at https://ui.adsabs.harvard.edu/#abs/2010EGUGA..12.7149S/abstract [verified 21 October 2020]

Spessa A, van der Werf G, Thonicke K, Dans JG, Lehsten V, Fisher R, Forrest M (2013) Modeling vegetation fires and fire emissions. In 'Vegetation fires and global change – Challenges for concerted international action'. A White Paper directed to the United Nations and International Organizations. (Ed JG Goldammer) pp. 180–207. (Kessel Publishing House: Remagen-Oberwinter, Germany)

Spessa A, Field R, Pappenberger F, Langner A, Englhart S, Weber U, Stockdale T, Siegert F, Kaiser JW, Moore J (2015) Seasonal forecasting of fire over Kalimantan, Indonesia. *Natural Hazards and Earth System Sciences* **15**, 429–442. doi:10.5194/NHESS-15-429-2015

Spies TA, White E, Ager A, Kline Jeffrey D, Bolte JP, Platt EK, Olsen KA, Pabst RJ, Barros AMG, Bailey JD, Charnley Susanand Koch J, Steen-Adams MM, Singleton Peter H, Sulzman J, Schwartz C, Csuti B (2017) Using an agent-based model to examine forest management outcomes in a fire-prone landscape in Oregon, USA. *Ecology and Society* **22**, 25. doi:10.5751/ES-08841-220125

Stolle F, Lambin EF (2003) Interprovincial and interannual differences in the causes of land-use fires in Sumatra, Indonesia. *Environmental Conservation* **30**, 375–387. doi:10.1017/S0376892903000390

Stolle F, Chomitz KM, Lambin EF, Tomich TP (2003) Land use and vegetation fires in Jambi Province, Sumatra, Indonesia. *Forest Ecology and Management* **179**, 277–292. doi:10.1016/S0378-1127(02)00547-9

Taufik M, Torfs PJJF, Uijlenhoet R, Jones PD, Murdiyarso D, Van Lanen HAJ (2017) Amplification of wildfire area burnt by hydrological drought in the humid tropics. *Nature Climate Change* **7**, 428–431. doi:10.1038/NCLIMATE3280

Taufik M, Veldhuizen AA, Wösten JHM, van Lanen HAJ (2019) Exploration of the importance of physical properties of Indonesian peatlands to assess critical groundwater table depths, associated drought and fire hazard. *Geoderma* **347**, 160–169. doi:10.1016/J.GEODERMA.2019.04.001

Taylor D (2010) Biomass burning, humans and climate change in south-east Asia. *Biodiversity and Conservation* **19**, 1025–1042. doi:10.1007/S10531-009-9756-6

Thonicke K, Spessa A, Prentice IC, Harrison SP, Dong L, Carmona-Moreno C (2010) The influence of vegetation, fire spread and fire behaviour on biomass burning and trace gas emissions: results from a process-based model. *Biogeosciences* **7**, 1991–2011. doi:10.5194/BG-7-1991-2010

Thorburn CC, Kull CA (2015) Peatlands and plantations in Sumatra, Indonesia: complex realities for resource governance, rural development and climate change mitigation. *Asia Pacific Viewpoint* **56**, 153–168. doi:10.1111/APV.12045

Toriyama J, Takahashi T, Nishimura S, Sato T, Monda Y, Saito H, Awaya Y, Limin SH, Susanto AR, Darma F, Krisyoyo , Kiyono Y (2014) Estimation of fuel mass and its loss during a forest fire in peat swamp forests of Central Kalimantan, Indonesia. *Forest Ecology and Management* **314**, 1–8. doi:10.1016/J.FORECO.2013.11.034

Uda SK, Hein L, Atmoko D (2019) Assessing the health impacts of peatland fires: a case study for Central Kalimantan, Indonesia. *Environmental Science and Pollution Research* **26**, 31315–31327. doi:10.1007/S11356-019-06264-X

Valbuena D, Verburg PH, Bregt AK, Ligtenberg A (2010) An agent-based approach to model land-use change at a regional scale. *Landscape Ecology* **25**, 185–199. doi:10.1007/S10980-009-9380-6

Valipour M (2015) Importance of solar radiation, temperature, relative humidity, and wind speed for calculation of reference evapotranspiration. *Archives of Agronomy and Soil Science* **61**, 239–255. doi:10.1080/03650340.2014.925107

van der Werf GR, Randerson JT, Giglio L, Gobron N, Dolman AJ (2008) Climate controls on the variability of fires in the tropics and subtropics. *Global Biogeochemical Cycles* **22**, GB3028. doi:10.1029/2007GB003122

Veraverbeke S, Verstraeten WW, Lhermitte S, Goossens R (2010) Evaluating Landsat Thematic Mapper spectral indices for estimating burn severity of the 2007 Peloponnese wildfires in Greece. *International Journal of Wildland Fire* **19**, 558. doi:10.1071/WF09069

Wang M, Grimm V (2007) Home range dynamics and population regulation: an individual-based model of the common shrew *Sorex araneus*. *Ecological Modelling* **205**, 397–409. doi:10.1016/J.ECOLMODEL.2007.03.003

Wiegand T, Jeltsch F, Hanski I, Grimm V (2003) Using pattern-oriented modeling for revealing hidden information: a key for reconciling ecological theory and application. *Oikos* **100**, 209–222. doi:10.1034/J.1600-0706.2003.12027.X

Wösten JHM, Clymans E, Page SE, Rieley JO, Limin SH (2008) Peat–water interrelationships in a tropical peatland ecosystem in south-east Asia. *Catena* **73**, 212–224. doi:10.1016/J.CATENA.2007.07.010

Yong DL, Peh KS-H (2016) South-east Asia's forest fires: blazing the policy trail. *Oryx* **50**, 213. doi:10.1017/S0030605316000211