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1. Introduction

Eucalyptus spp. is one of the most planted tree species worldwide and plays a major role in the pulpwood supply chain due to the increasing yields of the new commercial plantations and genetically improved clones (Payn et al., 2015; Turnbull, 1999). Brazil is the second-largest producer of cellulose pulp in the world, owing to the high productivity of the selected tree clones and the short rotation terms of these species under tropical climate conditions (Binkley et al., 2017; Colodette et al., 2014; Gonçalves et al., 2013; Pöyry, 2019). In 2018 alone, the planted forest sector contributed with US$ 22.5 billion to the Brazilian gross domestic product (GDP), representing 6.9% of the industrial GDP (Pöyry, 2019). During the last decade, the eucalypt planted area for pulp and paper production has grown 15% annually, boosted by the increasing local demand for raw material by paper mills (Colodette et al., 2014; IBÁ, 2017). Western Brazil encloses a large fraction of these fast-growing commercial forests, where the newly planted stands increase around 20% every year (70,000 ha yr^{-1}; Souza et al., 2020). This rapid expansion is transforming vast plains of savanna-type vegetation into intensive forest systems (Lapola et al., 2014).

Wildfires are currently the main threat to eucalyptus plantations in Brazil (Booth, 2013; Matthews et al., 2012). Human-induced alterations in the wildlands (i.e., the native vegetation replacement by intensive forests, agricultural lands, and urban development areas), in conjunction with extreme fire-weather projections, may boost wildfire activity across the Brazilian savanna in the near future (Bedia et al., 2015; Jolly et al., 2015; Mistry, 2002; Silva et al., 2019). Burning alters the wood chemistry, causing serious issues for the pulp mills, which have zero-tolerance for charcoal or damaged timber. Charred lumber devalues the paper quality on an industrial scale because the low-density burned particles are exceedingly difficult to wash away during the purification process and, thus, contaminate the bleached pulp (Gomes et al., 1996). Hence, burned stands are not used regardless of the wildfire (Araki, 1999; Dyson, 1999; Gomes et al., 1996). Although the sorting and aggressive debarking can minimize the negative fire effects on the wood quality, burned stands are often replaced with pulpwood purchased in local markets (Watson and Potter, 2004), usually at a higher cost (Siry et al., 2006). In Brazil, eucalypt plantations are affected by around 1,150 fires annually (1998 to 2002; Santos et al., 2014). These events account for 30% of fire ignitions and 16% of the burned area across the monitored extent in Brazil (Santos et al., 2014). Nevertheless, most recent studies focus on the Brazilian Amazon basin (Daldegan et al., 2019; de Oliveira et al., 2019), and little is known about the wildfire incidence in commercial eucalypt plantations (Santos et al., 2014; White et al., 2016a, 2016b).

Long-distance spreading fires account for most economic, social, and environmental impacts (Odion et al., 2004). These events are often driven by extreme weather conditions (Bowman et al., 2017; Rodrigues et al., 2020; Tedim et al., 2018). A better understanding of large wildfire behavior is essential to anticipate the disaster and design preemptive risk mitigation strategies (Ager et al., 2011). Wildfire risk is the expectation of loss to valued resources and assets and integrates wildfire exposure with the potential effects at different burning intensity levels (Finney, 2005). In this context, wildfire simulation has been extensively used in wildfire risk assessments at multiple scales (Bar Massada et al., 2009; Goodrick and Stanturf, 2012; Guedes et al., 2020; Haas et al., 2013; Mistry and Berardi, 2005; Salis et al., 2013). The broadly accepted simulation paradigm accounts for the most hazardous fire weather conditions during the wildfire season plus historically based ignition patterns (Alcasena et al., 2017; Bar Massada et al., 2011; Salis et al., 2015). Ultimately, exposure metrics constitute the baseline to design and implement effective management initiatives to mitigate undesired impacts from wildfires over extensive areas (Calkin et al., 2011). Likewise, the substantial variability that fire exposure may display across regions encourages spatial-explicit valuations of the impacts, which are essential towards effective risk mitigation programs. This quantitative fire risk assessment framework has been widely used in North-American, European, and Australian fire-prone areas (Ager et al., 2011; Alcasena et al., 2016; Bar Massada et al., 2009; Bradstock et al., 2012). However, previous works assessing exposure and risk in other regions, such as the South-American wildlands (Guedes et al., 2020), are scarce. Besides a recent study assessing the economic losses due to wildfires in the timber production sector across the Brazilian Amazon (de Oliveira et al., 2019), the risk assessment quantitative method has not yet been implemented in eucalypt plantations for pulp production. In this work, we assessed wildfire risk to commercial eucalypt plantations at the Mato-Grosso do Sul State of western Brazil. We assumed extreme weather conditions observed during the wildfire season to model burn probabilities across the landscape. The economic loss was then estimated, considering a total loss of stand value given fire burns the eucalypt plantation. Specifically, the objectives in this study were to (i) model wildfire likelihood across the study area and (ii) map stand-level conditional economic losses, to ultimately (iii) assess expected losses in commercial eucalyptus plantations. Our approach not only constituted an advance in exposure assessment for the study region but also integrated annual losses in forest management plans.

2. Materials and methods

2.1. Study area

We conducted this study in the Mato-Grosso do Sul state, a savanna enclave in western Brazil (Fig. 1). The region extends over 79,991 km^2 out of which 8,495 km^2 correspond to eucalypt plantations, roughly

15% of the national eucalypt plantation area (IBÁ, 2017). The relief is mostly flat, with elevation ranging between 253 and 785 m.a.s.l. (meters above the sea level) and the climate is mainly tropical with dry winter (Alvares et al., 2013). The main vegetation types include pastures, grasslands, open woodland, natural riparian forests, agricultural lands, and eucalypt plantations (Table 1). Although the commercial eucalypt forests cover less than 7% of the study area, the large plantation blocks are the dominant vegetation type in the eastern portions of the region. The intensive eucalypt forests are usually planted in dense and clustered plots ($\geq$ 1,600 trees ha^{-1}) to facilitate the management of short rotation (6 to 8 yr) of even-aged stands and reduce the operation costs (Colodette et al., 2014; Gonçalves et al., 2013). Eucalypt clonal plantations of interspecific hybrids of *Eucalyptus grandis* are the most commonly planted species due to their high yields. *Eucalyptus grandis* grows about 40 m^3 ha^{-1} of roundwood per year, ranging from 25 to 60 m^3 ha^{-1} yr^{-1} depending on the managerial technology and the local environmental conditions (Binkley et al., 2017; Gonçalves et al., 2013).

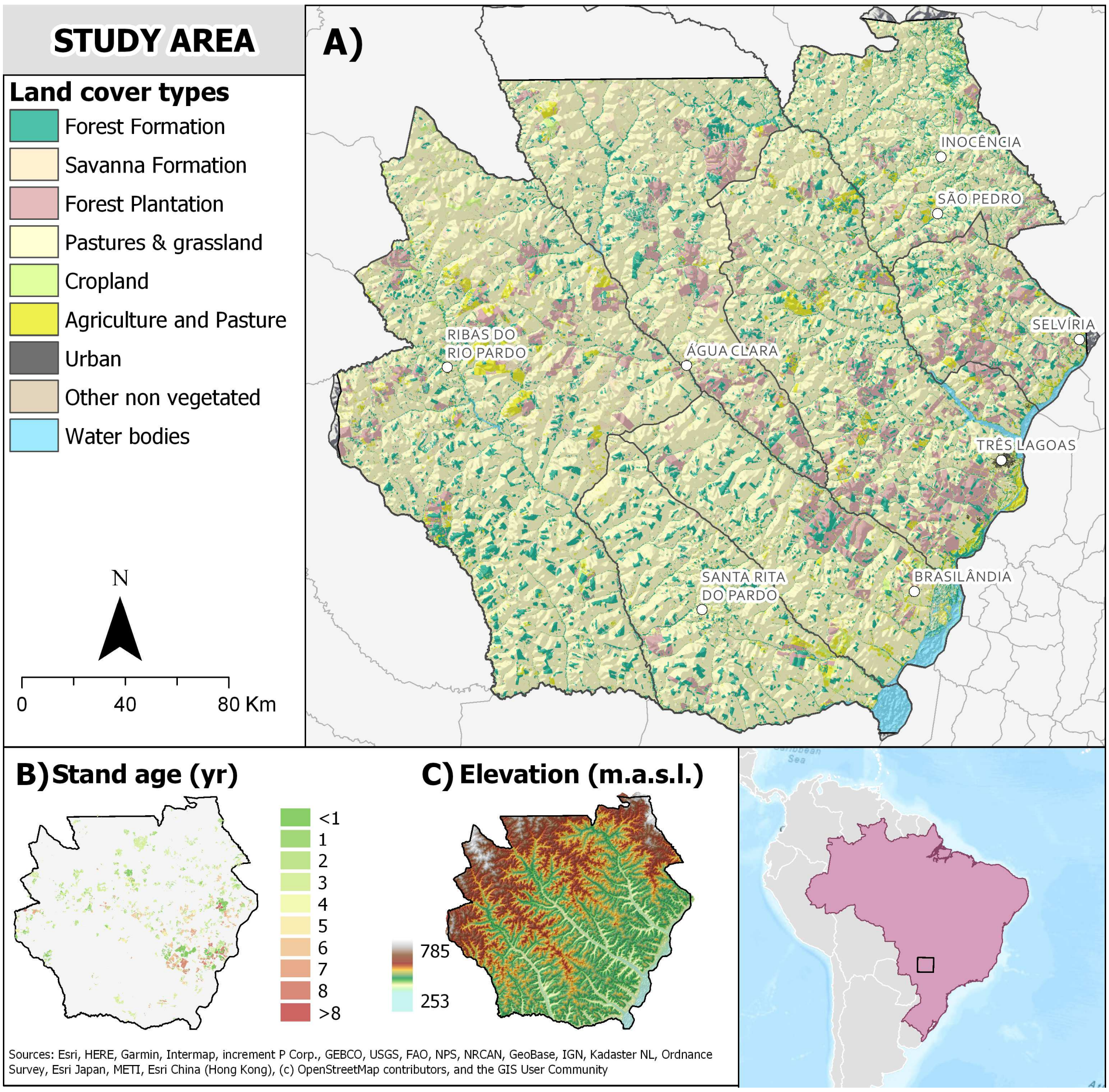


Fig. 1. Land cover (A), eucalypt stand age (B), and topography (C) of the study area in Mato-Grosso do Sul State of Brazil.

The fire season in the study area extends from July to October and concentrates 85% of the annual burned area (3,329 ha; Augusto et al., 2018). Large fires (>100 ha) are common across the commercial plantations. For instance, a single wildfire in 2017 destroyed more than 1,300 hectares of eucalypt plantations, causing an estimated economic loss of 5 million US$, and threatening several communities across the studied extent (Galdiole, 2017). Fire is culturally used to clear and open large areas for agriculture and extensive livestock breeding; thus, humans are responsible for most fire ignitions (Eva and Lambin, 2000; Galizia and Rodrigues, 2019; Jepson, 2005; Mistry, 2002). The region is characterized by low population density (4.8 inh km^{-2}) with a predominance of rural settlements (IBGE, 2012). However, the population in the region has grown 2% per year during the last decade, mainly due to the economic growth associated with the expansion of commercial forest plantations (IBGE, 2012).

2.2. General workflow

The overall procedure was based on the integration of landscape-scale wildfire behavior simulation with the estimated value of eucalypt plantations (Fig. 2). We combined a historically-based fire ignition pattern with landscape data to model large fire spread under extreme weather conditions and assess the annual burn probability. Required wind and fuel moisture content data were derived from 30-years weather records. Then, we combined assembled standard fuel models with custom fuels for eucalypt forests to model fire spread. Stand-level yields were estimated at different successional stages using a forest growth model calibrated for eucalypt plantations in Brazil. Finally, we combined the annual burn probability with stand-level conditional economic losses to assess the wildfire risk.

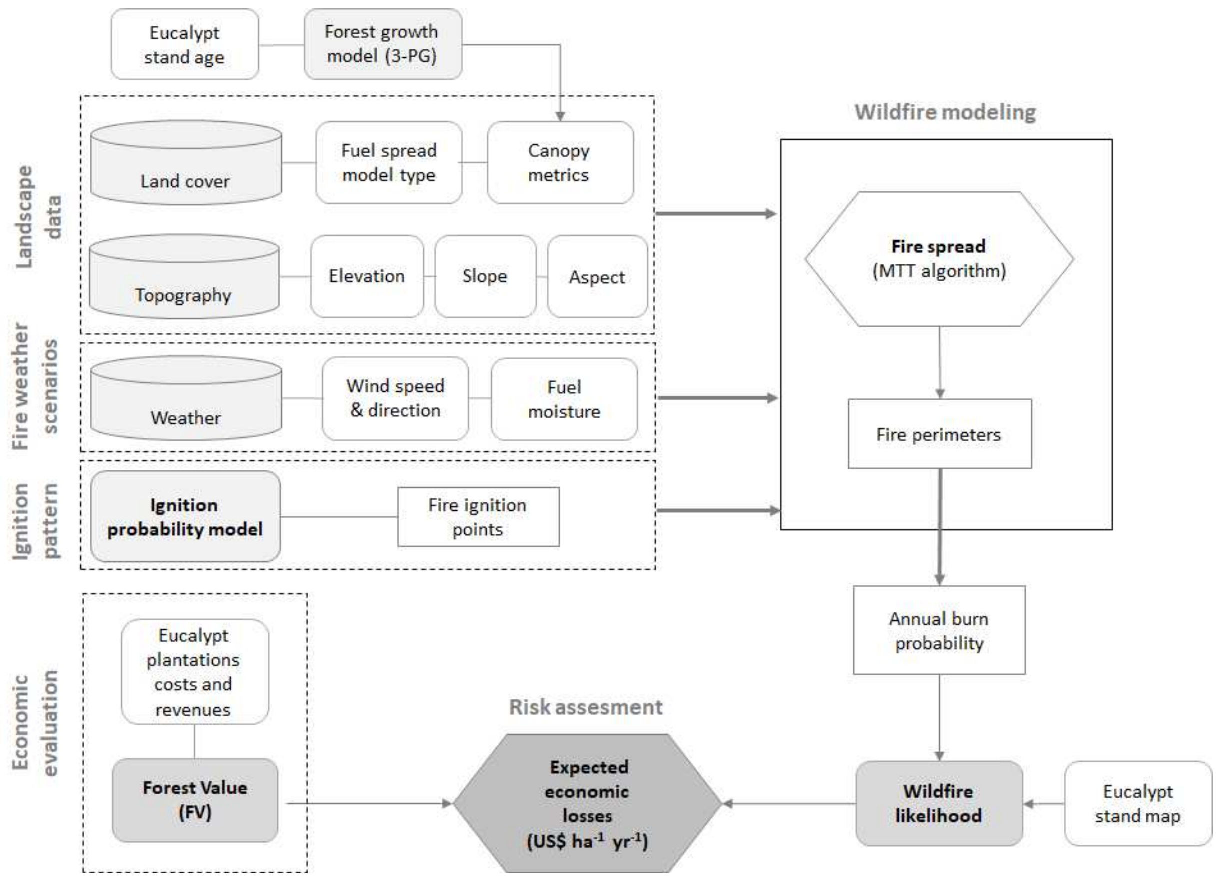


Fig. 2. General workflow for modeling the wildfire risk, including input datasets, MTT algorithm (Finney, 2002), economic evaluation, and expected losses to eucalypt plantations in western Brazil.

2.3. Landscape data

We assembled the required gridded input data for wildfire simulation (i.e., surface fuel models and topography) in a landscape file (LCP) at 100 m resolution (Ager et al., 2011). The surface fuel model grid was built, assigning standard fuel models to the 2014 land cover map (Scott and Burgan, 2005; Souza et al., 2020). Nonetheless, we assigned custom fuel model types to the eucalypt stands based on the structure by growth stage (Fernandes, 2009; Mistry and Berardi, 2005), which is the main wildfire hazard causative factor hazard (Agee and Skinner, 2005; González et al., 2006). We used stand-age interval classes as a consistent reference for the eucalypt forest structure because these equally managed fast-growing plantations are not only regular stands but also coetaneous (Almeida et al., 2004; Binkley et al., 2020). Specifically, we considered 5 classes representing homogeneous forest structures at different growth stages considering the canopy cover (closed or open), canopy height (low or tall), and stand age (Table 1). Note that we used different fuel models to distinguish commercial plantations from non-commercial eucalypt forests (Appendix A). The stand age was retrieved from remote sensing data at 30 m spatial resolution based on annual land cover change maps from 2000 to 2014 (Petersen et al., 2016; Souza et al., 2020). Topographic data including elevation (m.a.s.l.), aspect (azimuth degree) and slope (degrees) were obtained from a 30 m resolution digital elevation model (de Morisson Valeriano and de Fátima Rossetti, 2012). Eucalypt forest canopy metrics (i.e., canopy base height (m), canopy height (m), canopy bulk density (kg m^{-3}) and canopy cover (percent)) were estimated with a forest growth model (3-PG; Landsberg and Waring, 1997), specifically calibrated for *E. grandis* plantations in Brazil (Almeida et al., 2004). The canopy metrics for natural forest and open woodland savanna were retrieved from Mistry (2002) and Mistry and Berardi (2005).

Table 1. Main vegetation types, coverage, and fuel model assignments for wildfire simulation modeling in the study area. Eucalypt plantations were classified by fuel load, structure, and stand age: open and low (OL), closed and low (CL), closed and tall (CT), open and tall (OT), very open and tall (VT), and non-commercial eucalypt (NC) (Fernandes, 2009; Mistry and Berardi, 2005). Other land-cover classes were classified as the following standard fuel types GR (grass), GS (grass-shrub), SH (shrub), and NB (non-burnable) (Scott and Burgan, 2005). See fuel model parameters in Appendix A. We derived the 97th percentile fuel moisture content from the historic fire-weather index data (Viegas et al., 2001; Wotton, 2009).

Land cover class	Area (ha)	Incidence (%)	Fuel model type	Fuel moisture content (%)				
				1 h (%)	10 h (%)	100 h (%)	Live herbaceous (%)	Live woody (%)
Eucalypt (0-1 yr)	126,413	1.56%	OL	5	6	7	-	124
Eucalypt (1-3 yr)	196,127	2.41%	CL	5	6	7	-	124
Eucalypt (3-8 yr)	147,347	1.81%	CT	5	6	7	-	90
Eucalypt (8-12 yr)	3,680	0.05%	OT	5	6	7	-	90
Eucalypt (> 12 yr)	1,512	0.02%	VT	5	6	7	80	90
Non-commercial eucalypt	63,792	0.79%	NC	5	6	7	-	90
Mosaic agriculture	437,031	5.38%	GR2	4	5	6	60	-
Natural forest	936,871	11.53%	TU3	5	6	7	80	90
Pasture and grassland	4,947,698	60.89%	GR3	4	5	6	60	-
Perennial crop	37,257	0.46%	SH3	4	5	6	-	90
Savanna	540,264	6.65%	GS3	4	5	6	60	90
Urban	5,593	0.08%	NB94	-	-	-	-	-
Open water	680,916	8.38%	NB98	-	-	-	-	-

2.4. Ignition pattern

We used an *ad hoc* fire occurrence model to obtain a fire ignition probability grid (IP) and derive the fire ignition pattern as required for wildfire simulation modeling. The fire occurrence model was calibrated using the Random Forest algorithm, combining historical ignitions with human-related wildfire drivers (e.g., accessibility, proximity to agricultural lands, or human activities, among others) to estimate the ignition probability across the study region (Rodrigues and De la Riva, 2014). The eucalypt forest expansion was also integrated into the fire occurrence model as a critical driver for predicting ignition locations. Model outcomes suggested that fire occurrence was mainly explained by the proximity to agricultural and urban interface areas. See Galizia and Rodrigues (2019) for further details about the methods and model performance. Based on the aforementioned ignition probability grid, we generated a set of spatially-balanced 50,000 ignition points over burnable areas to saturate the landscape with wildfire (Stevens and Olsen, 2004). This fire ignition dataset was then used as input for the wildfire simulation modeling in each fire-weather scenario.

2.4. Fire weather scenarios

We retrieved the weather data from the Copernicus Climate Change Service (C3S; climate.copernicus.edu). We used daily noontime records from 30 years (1987 to 2007) to characterize the weather conditions during the wildfire season (July to October). Specifically, we determined the extreme weather scenarios (97th percentile) in terms of dominant winds and fuel moisture content conditions. The prevailing wind directions (frequency > 8%) in the study area during the wildfire season were 30°, 60º, 90º, and 120º azimuth (n = 4 fire-weather scenarios), with respective probabilities of 24%, 28%, 32%, and 16% (Fig. 3). We derived the wind fields (U and V wind components) from the 31 km resolution ERA-5 raw reanalysis data (ECMWF; Dee et al., 2011). The directional wind U-V components were transformed into wind speed (km h^{-1}) by calculating the module of the vector from the U (zonal velocity, i.e. the component of the horizontal wind towards east) and V (meridional velocity, i.e. the component of the horizontal wind towards north) components.

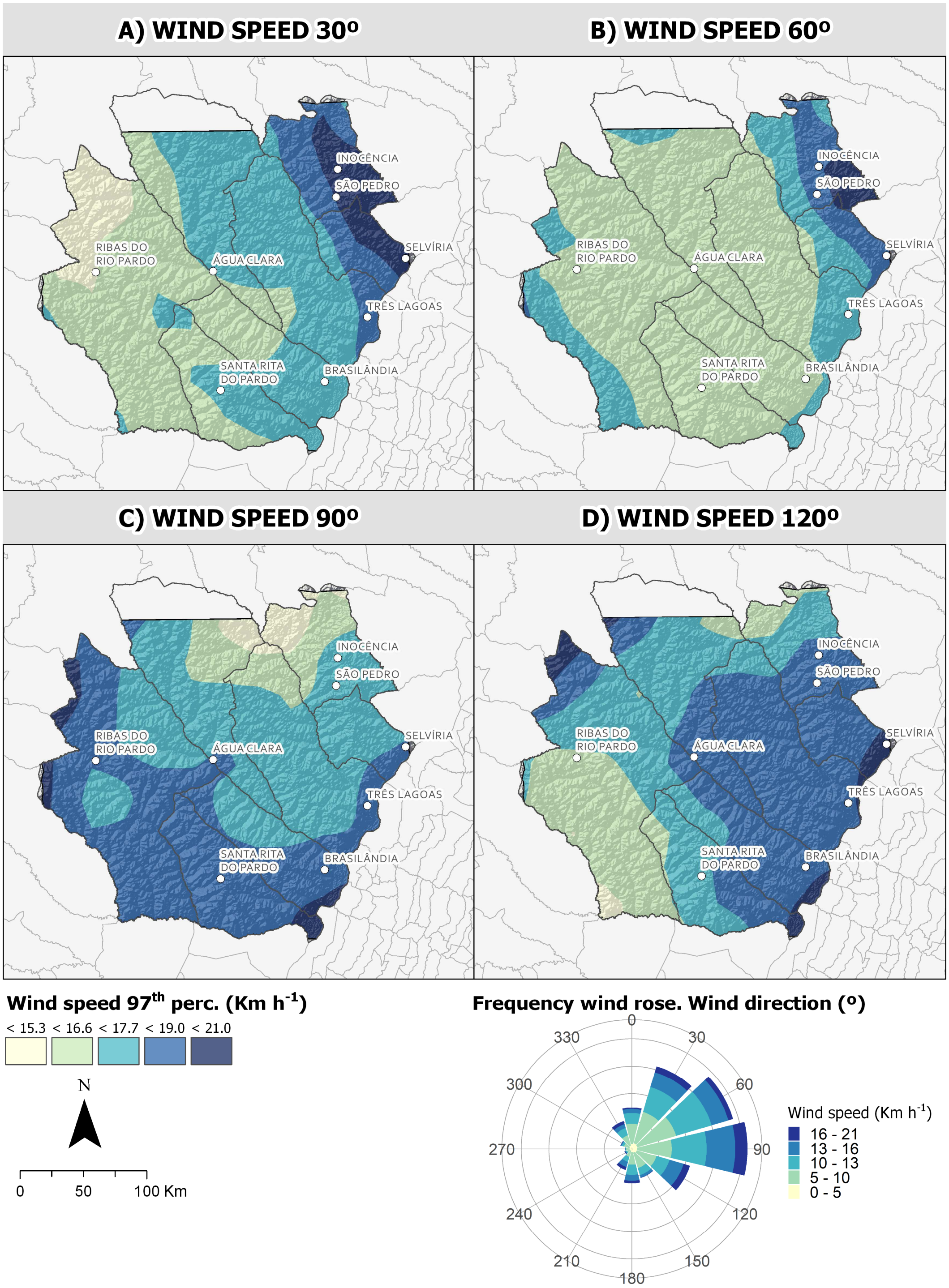
We used the Fine Fuel Moisture Code (FFMC) and Drought Code (DC) Fire Weather Index (FWI; Van Wagner and Forest, 1987) data to derive the fuel moisture content (Table 1). The 97th percentile of FFMC and DC were calculated using the FWI data for the whole temporal span (Vitolo et al., 2019). First, the fine fuel moisture content was estimated as described by Wotton (2009):

$$1\,h = 147.2 \times \frac{101 - FFMC}{59.5 + FFMC} \qquad (1)$$

where *1h* is the 1-hour fuel size moisture content as a percentage, and the *FFMC* is the fine fuel moisture code index value for desired fire-weather conditions (i.e., 97th percentile FFMC). We assumed 1-h dryer moisture content conditions for herbaceous fuel types rounding the predicted value to the lowest unit. We then estimated the live woody fuel moisture using a model developed for eucalypt forests at similar weather conditions observed in the region under study, as presented in Viegas et al. (2001):

$$LW = 401.1 \times DC^{-0.1793} \qquad (2)$$

where the *LW* is the live woody fuel moisture content as a percentage, and *DC* is the drought code index value for desired fire-weather conditions (i.e., 97th percentile DC).



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186 **Fig. 3.** Wind speed grids (97th percentile) for the dominant wind directions and wind rose (speed and
187 direction) in the study area. Dominant scenarios during wildfire season included (A) 30º, (B) 60º (C), 90º,
188 and (D) 120º directions.

2.5. Wildfire modeling

We simulated wildfire spread using the minimum travel time algorithm (MTT; Finney, 2002) as implemented in FlamMap 6.0 (Finney, 2006). The MTT algorithm has been widely used to model fire spread and behavior over complex terrain landscapes with different vegetation types worldwide (Guedes et al., 2020; Jahdi et al., 2020; Lozano et al., 2017; Palaiologou et al., 2018; Salis et al., 2015). We focused our modeling efforts on large fires because these events account for the bulk of the burned area and losses (Franco et al., 2014; Tedim et al., 2018). We modeled 50,000 fires at 100 m resolution under extreme fire-weather conditions (97^{th} percentile) for each wind direction scenario. We used a different wind speed grid for each scenario instead of considering a constant value for the whole fire modeling domain (Fig. 3). The fire spread duration was set to 9.5 hours, the blow-up event duration providing modeling outputs similar to the observed historical fire size distribution in the study area (Andela et al., 2019). The total number of modeled fires (n= 200,000) burned all pixels at least once and more than twenty times on average. The total burned area from modeled fires was equivalent to more than 35,000 wildfire seasons. We set a 0.25 spot probability to enable showering ember emission and the jump of narrow non-burnable linear barriers (e.g., small rivers and secondary roads) by the heading fires as observed in the study area during extreme events.

Modeled outputs consisted of pixel-level conditional burn probability (BP) grids for each wind direction scenario. The BP value is the ratio between the number of times a pixel burned (i.e., modeled fire perimeter overlay) and the total number of simulated fires per run (Finney, 2005; Salis et al., 2015). In this study, the BP represents the likelihood of a pixel burn given a fire occurs within the study area based on the ignition probability grid. We then estimated the annual burn probability as:

$$aBP_{xy} = \frac{N_{xy}}{n_s} \qquad (3)$$

where the aBP_{xy} is the annual burn probability for the pixel *xy*, *N* is the number times a *xy* pixel burned, and n_s is the total number of modeled wildfire seasons or years (Dillon et al., 2015; Short et al., 2020). Specifically, we obtained *N* from the conditional burn probability outputs assuming a modeled burned area equivalent to 35,000 years and computed the *aBP* grid for each fire-weather scenario. These grids were then assembled into the final aBP map considering the wildfire season frequency for each scenario (i.e. 30°=24%, 90°=28%, 60°= 32%, 120°=16%; Fig. 3).

2.6. Economic evaluation

Wildfire-induced economic losses in the eucalypt plantations were quantified in terms of forest value (FV), accounting for expected changes on the potential financial return of the affected commercial stands. We used the FV to assess the overall stand-level economic value considering: (i) the forest management cash flow, (ii) a predetermined forest cycle timeline, (iii) the land use for a new activity that would start after the harvest and its economic value, and (iv) the occurrence of unexpected events such as wildfires (Prata and Rodriguez, 2014). We assumed a perpetual timber production for eucalypt plantations to assess the expected land value, which can be obtained from the land expectation value (LEV) as (Chang, 1998; Faustmann, 1849):

$$LEV = \frac{NPV \times (1+r)^T}{(1+r)^T - 1} \qquad (4)$$

where LEV is the land expectation value in US\$ ha^{-1}, NPV is the net present value of a plantation (age 0), which is taken to its future value at the end of the cycle at age T (yr), and r is the interest rate as a percentage. Wood revenues were estimated based on the local market price for pulpwood (R7, 2017), which ranged between 11.30 and 12.10 US\$ m^3. Then, the FV was estimated at pixel-level using the model from Prata and Rodriguez (2014) as:

$$FV = \left(\frac{R_T + LEV}{(1+r)^{T-j}}\right) - \left(\sum_{t=j}^{T} \frac{C_t}{(1+r)^t}\right) - LEV \qquad (5)$$

where FV is the forest value in US\$ ha^{-1}, R_T is the total plantation cycle revenue at age T in US\$ ha^{-1}, C_t is the plantation cost management at age t, j is the year of the hazard that interrupts the forest rotation, and r is the interest rate. Management costs include all necessary forest operations over the plantations' cycle (Table 2). Specifically, we considered the implementation of a mechanical treatment at the final stage of the rotation to masticate the surface fuels in the understory. This treatment improves operational conditions in both the quality and productivity of subsequent forest harvesting and logistic operations, thus lowering the total operating (Malinovski et al., 2006; Moreira et al., 2004). We considered an interest rate of 8% per year on the FV calculation, which represented an intermediate value over the last 3 years (BCB, 2019).

Table 2. Eucalypt plantation management costs applied for the pulp and paper industries in the studied region (adapted from Prata and Rodriguez 2014).

Forest management	**Operation**	**Stand age (yr)**	**Cost (US\$ ha^{-1})**
Site establishment	Soil preparation, planting, irrigation, fertilization, and pest control	0 - 1	1483
Stand maintenance	Weed control, pest control, fertilization	1 - 3	441

Stand maintenance	Weed control	3 - 5	38
Stand maintenance	Weed control, pest control	5 - 8	78
Harvest and clearing	Weed control and mechanical mastication	8 - 12	58

2.7. Risk assessment

We quantified wildfire risk in terms of stand-level expected economic losses combining wildfire likelihood (aBP) with the economic value (FV) of the eucalyptus plantations for paper-pulp production (Alcasena et al., 2016; Finney, 2005), as:

$$eL_j = \sum_{i=1}^{I} aBP \times FV_{ji} \qquad (6)$$

where eL_j is the expected economic loss of eucalyptus pulpwood on the stand (US\$ ha^{-1} per yr) at j-th successional stage (i.e., young, intermediate, and mature), *aBP* is the stand-level annual burn probability from Eq. 3, and FV is the forest value at j-th successional stage from Eq. 5. In this case study, there are no benefits from wildfires, and we considered a total loss regardless of the burning i-th fire intensity level. The eucalypt pulpwood in the study area is used to supply local paper mills, and the charred wood is usually discarded to elaborate the pulp. In this work, we assumed the charred wood replacement with pulpwood from general markets.

3. Results

3.1. Wildfire likelihood

The fire spread modeling outputs evidenced complex wildfire likelihood patterns related to ignition probability, fuel type, stand growth stage, and wind speed distribution across the study area (Fig. 4). The mid-eastern zone attained the highest exposure levels (aBP > 0.1), which gradually decreased while moving west (aBP < 0.05). In general, we observed a decline in aBP from the young to the mature eucalypt stands (Fig. 5). Intermediate-age and mature stands (> 4 yr) were less likely to burn (mean aBP ≈ 0.023), while young stands (< 2 yr) showed the highest aBP (mean ≈ 0.034), peaking in newly planted areas (first yr).

The wildfire likelihood was the highest in grasslands and savanna-like land cover types (mean aBP ≈ 0.05), closely followed by agricultural lands (mean aBP ≈ 0.04) and eucalypt plantations (mean aBP ≈

0.03) (Fig. B.1). Fine-scale modeling outcomes revealed substantial differences between ignition (IP) and burn probability (aBP). The northern and southwestern regions (i.e., Água Clara and Ribas do Rio Pardo municipalities) presented both low wildfire likelihood and low fire ignition (IP); hence, they were the least exposed to fire (low aBP). Conversely, the southern and southeastern regions (i.e., Santa Rita do Pardo, Brasilândia, Três Lagoas, and Selvíria municipalities) showed higher IP and aBP. Nonetheless, most of the study area showed strong dissimilarities between IP and aBP. These differences were especially evident in the eastern regions with a great human pressure and a high IP (>0.8) but a low aBP (< 0.03).

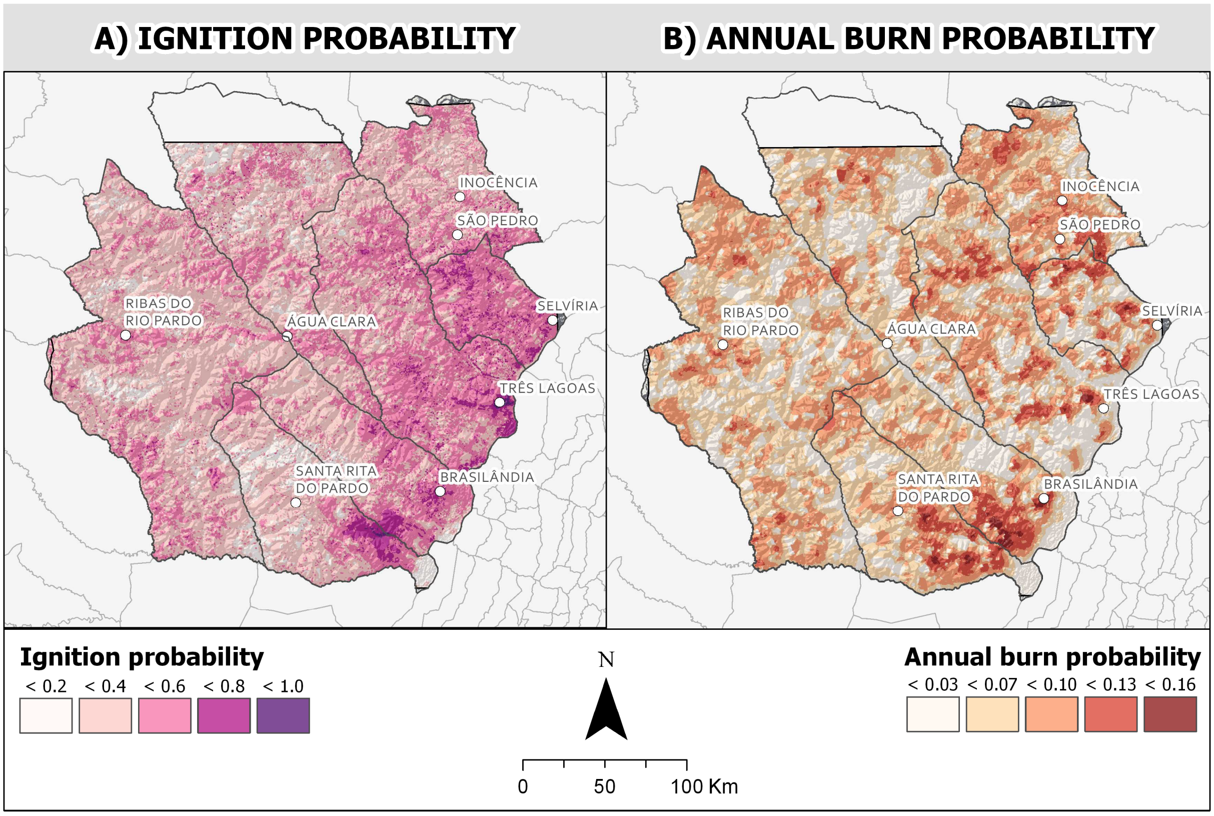

Fig. 4. (A) Wildfire ignition probability (IP; Galizia and Rodrigues, 2019), and (B) annual burn probability (aBP) at 100 m resolution across the study area.

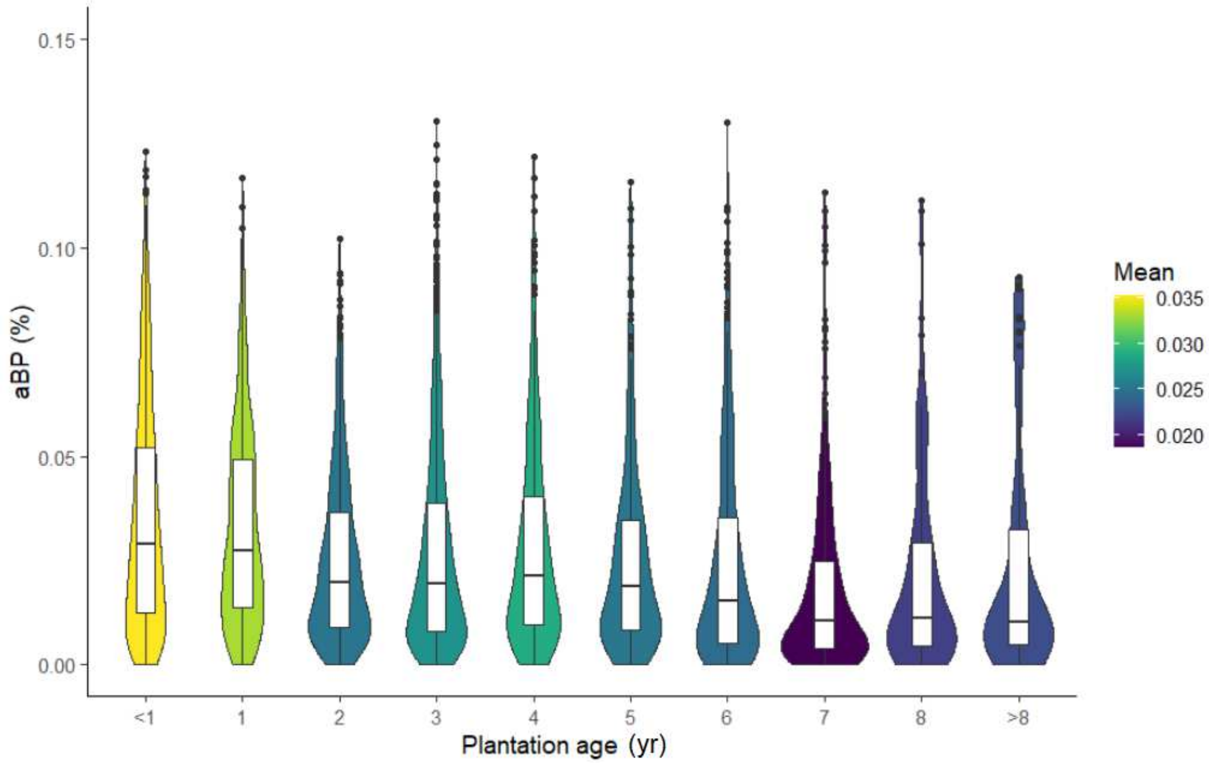

Fig. 5. Violin and boxplot representation of the annual burn probability (aBP) of the eucalypt stands according to the stand age. Boxplot represents the descriptive statistics (e.g. median and interquartile ranges), and the violin plot shows the aBP probability density distribution (Kernel density estimation). The color scale shows the transition of the aBP means over the plantations' age classes.

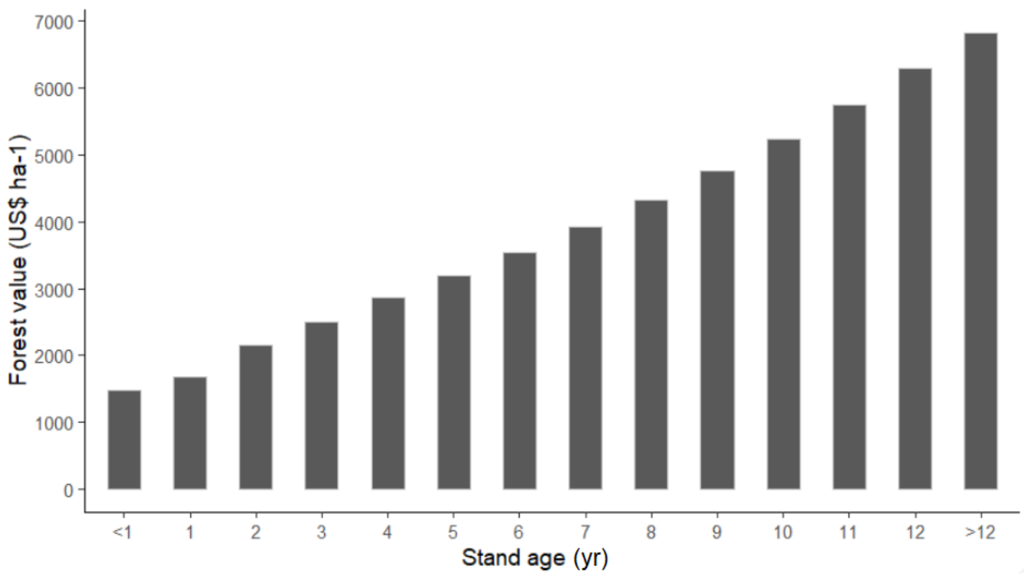

Fig. 6. Changes in eucalypt plantation's forest value (FV in US\$ ha^{-1}) over one cycle. FV was quantified by means of potential economic return (Eq. 5).

3.2. Economic evaluation

The economic evaluation of eucalypt stands showed a linear increase during the plantation cycle, with an FV ranging from 1,485 US\$ ha^{-1} in year 1 to 7,982 US\$ ha^{-1}. The FV presented an average annual growth of 614 US\$ ha^{-1}. In other timber products, the market value per volume is substantially higher for larger logs, but this is not the case in the paper pulp industry. As expected, the highest economic value (mean = 5,524; std. dev. = 943 US\$ ha^{-1}) was found in the mature stage stands (> 8 yr), due to the higher wood volume and greater resources spent during the plantation cycle (Fig. 6). The plantation's FV spatial distribution showed that the most valuable stands concentrate in the center-eastern zone of the study area (i.e., Brasilândia, Três Lagoas, and Selvíria municipalities), closer to the urban areas (forest industries) and, consequently, to the local market (Fig. 7). On the other hand, low-value eucalypt stands were spread around the mature plantations, representing the most recent eucalypt's expansion in the study area.

3.3. Risk assessment

The total annual loss from wildfires in the eucalypt plantations was equivalent to 19,961,115 US\$ yr^{-1}, approximately 1.75% of total FV. The spatial pattern of expected economic losses (eEL) broadly matches burn probability distribution across the study area (Fig. 7). Even though pixel-level eEL was highly variable throughout the study area, the highest expected loss was found in the mature stands (> 8 yr) on the mid-eastern and southeastern zones, also with the highest aBP values of the study area. The areas with a high aBP and a low eEL (e.g., the central part of the study area), were mainly occupied by young plantations with a low FV (< 1,800 US\$ ha^{-1}). These young plantations were dominant in the outer edge of eucalypt plantation clusters of the study area. Not surprisingly, we observed an overall increase in the eEL from young to mature eucalypt stands (Fig. 8) as with the conditional losses (i.e., FV). Mean values for expected economic losses between stand age classes ranged between 45 and 95 US\$ ha^{-1} per yr. Stand-level wildfire risk profiles within the different age classes (Fig. 8) presented a much wider dispersion than in the wildfire likelihood estimates (Fig. 7).

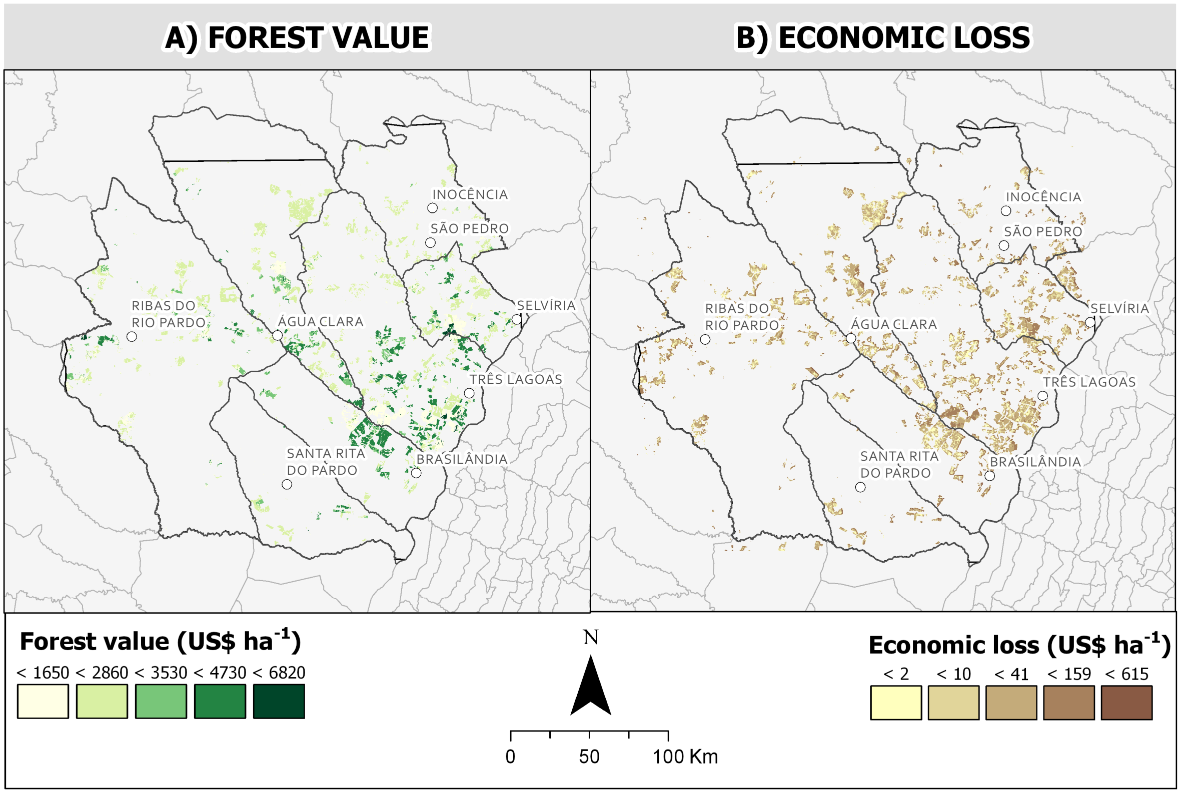

Fig. 7. (A) Expected economic loss (eEL) from wildfires across the eucalypt plantations stands and (B) eucalypt plantations economic value (FV) across the study area.

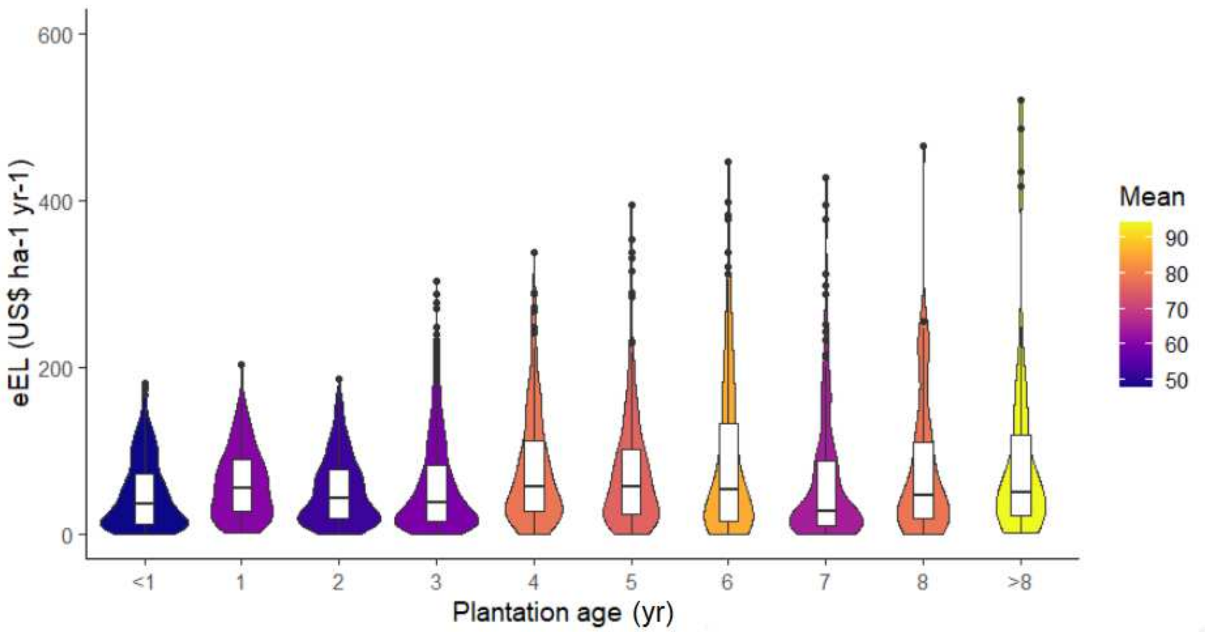

Fig. 8. Expected economic loss (eEL) by plantation age. Boxplot represents the descriptive statistics, and the violin plot shows the eEL probability density distribution (Kernel density estimation). The color scale shows the transition of the eEL means over the plantations' age classes

5. Discussion

In this work, we extended the current understanding of eucalypt plantations' wildfire risk assessing the expected economic losses (US\$ ha^{-1} yr^{-1}) in a fire-prone region of Brazil. We leveraged wildfire simulation modeling and a novel forest valuation approach to conduct a spatially explicit and economically detailed risk assessment in a vast landscape. Our study considered the 'worst case' fire-weather conditions (97th percentile) to model fire spread and neglected early suppression effects. Although it might lead to overestimating the large fires' contribution to the burned areas compared to the historical fire size distributions, we considered a widely accepted opportunistic suppression scenario where firefighting is only effective under mild weather conditions (Martell, 2006; Reed and McKelvey, 2002).

Despite the large variability observed in forest value (FV) due to the existing differences in stand age, the wildfire likelihood (aBP) was the most crucial factor modulating the economic loss across the region. We found the highest exposure levels in the central-eastern and southeastern regions, closely mirroring the observed distribution of young (< 2 yr) versus intermediate-age to mature (> 4 yr) eucalypt stands. Young eucalypt stands presented the highest aBP among eucalypt forest types (Fig. 5), despite their low fine fuel load in the 1-h dead class (Table A.1). The spatial arrangement of newly planted stands may explain this outcome, which are very often placed in clusters surrounding and enclosing preexisting (thus older) stands. Given that most fires start along human-related interfaces (e.g., agricultural lands, urban development, and main roads; Galizia and Rodrigues, 2019), wildfires will likely burn first the youngest stands located on the edge of the plantation clusters. In addition, recent studies also found that extreme weather conditions plus fuel rearrangement are the most relevant factors explaining wildfire occurrence and intensity in wildfires burning eucalypt woodlands (Cawson et al., 2020).

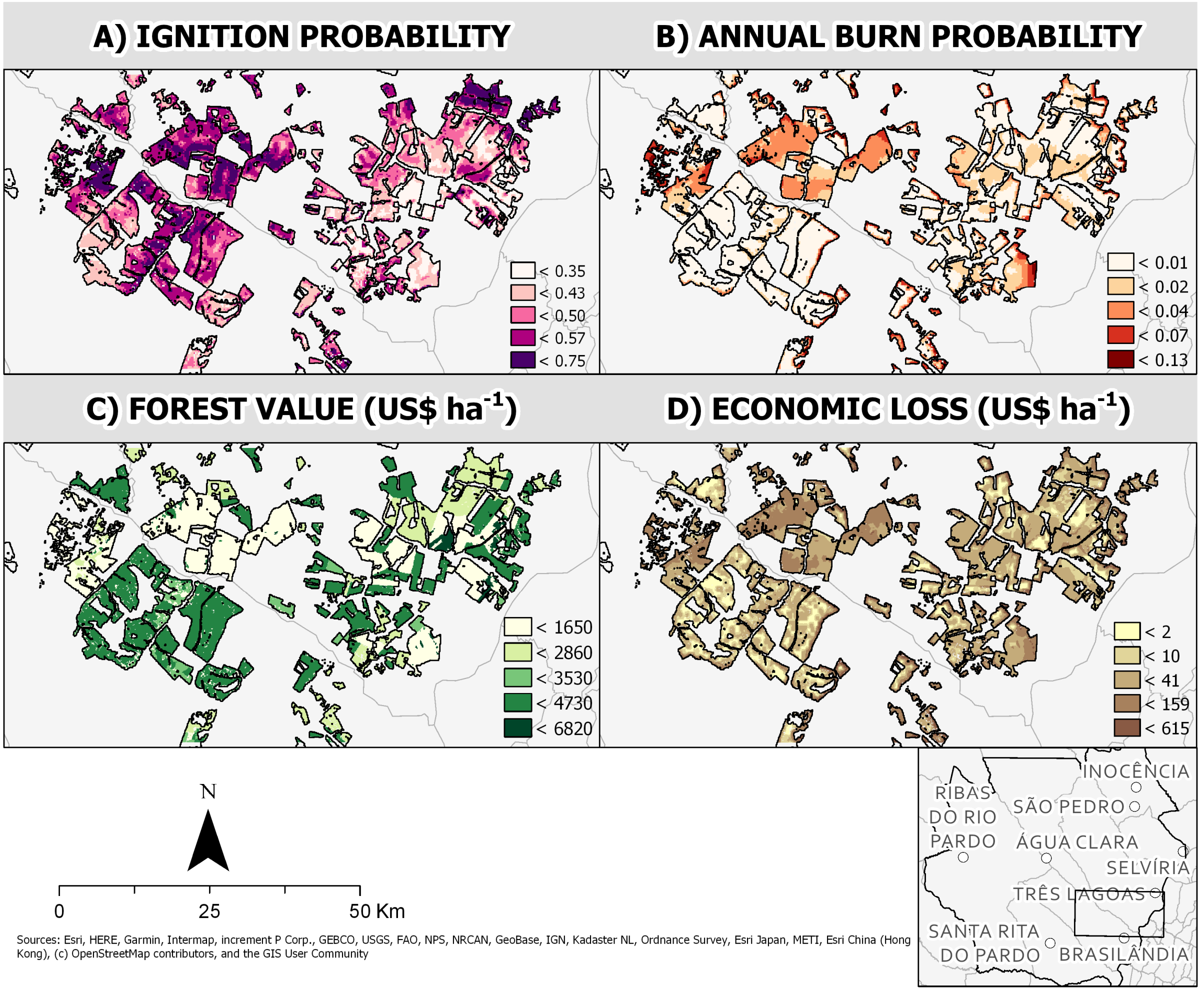

Fig. 9. Inset view of IP (A), aBP (B), FV (C), and eEL (D) in a eucalypt plantation cluster located in the southeast of the study area.

We estimated a total expected annual loss disregarding the economic value of charred wood. Assessing the potential revenue from charred wood was exceedingly complex for the purpose of this study. Moreover, changes in the overall economic assessment would lead to non-significant differences since charred wood is discarded to elaborate the pulp. We believe that low economic loss is related mostly to the eucalypt age distribution in stands across the study area. Young stands hold the lowest FV and are the most widespread (48% of the total plantation area). In general, mature stands with the highest in FV located in low burn probability zones, but the exceptions showed the largest economic losses (> 400.00 US\$ ha^{-1} yr^{-1}). We demonstrated that the aBP was the main causative factor explaining the economic losses across eucalypt plantations (Fig. 9). Managed mature stands may restrict large fire spread and reduce aBP due to higher moisture content and a high canopy structure (i.e. less likely to crown fire) (Fernandes et al., 2019; Silva et al., 2009). Guedes (2020) also found that commercial eucalypt plantations imposed slight fire protection (lower BP) to natural forests in southeast Brazil. These plantations are frequently managed intensively and present firebreaks, patrolling fire brigades during the wildfire season, and wildfire detection towers to allow a rapid initial attack. On a broader scale, Fernandes (2019) concluded that the expansion of eucalypt plantations had no effect on the increment of the burned area observed in Portugal in the last three decades. Although future impacts on the fire regime should not be excluded, fire incidence was lower in eucalypt stands than in the remaining forest types.

Based on our aBP outcomes, it would be feasible to design prevention plans to minimize future wildfire impacts by means of fuel load reduction, forest management, or alternative solutions like prescribed burning around productive areas. Fuel reduction programs, including mechanical treatments along plantation edges (especially around young stands) plus slash mastication after harvesting on the high burn probability areas may help reduce the exposure level. Likewise, controlled burnings around plantations´ interfaces will contribute to modifying fuel structure and decrease fuel loads (Ager et al., 2011). Wildfire exposure reduction should also include breaking the fuel continuity (horizontally and vertically), as well as increasing the diversity of age-classes among the eucalypt stands (Soares, 2014). Other measures, including ignition prevention, rapid response on fire source hot-spots (Fig. 4A), would likely present a solution for reducing fire transmission to eucalypt plantations.

Forest cooperatives, such as REFLORE (regional cooperative in Mato Grosso do Sul), may play an important role in fire risk mitigation. This type of organization reflects the collective interests of the associated forest producers and may facilitate the early detection of wildfires, the firefighting resources sharing and the integration of risk management plans beyond the boundaries of properties. Furthermore, Brazil's government must develop an effective strategy to mitigate wildfire risk in the fire-prone regions, considering, educational programs about the correct fire usage and environmental protection policies. Environmental agencies should effectively control fire usages following the federal legislation (such as the 2012 Brazilian Forest Code), which prohibits the use of fire in natural vegetation, without prior authorization. National wildfire prevention programs like PREVFOGO (Brazilian fire prevention program) should be reinforced to be able to hire and train firefighters to effectively control the fire spread at risk periods. Public-private partnerships may be an alternative to collect resources for wildfire prevention and environmental law enforcement in high-value zones at risk.

Eucalypt plantations are steadily progressing through the study region and future projections suggest the planted area will keep expanding, driven by the increasing demand for bioproducts (d'Annunzio et al., 2015; Payn et al., 2015). Changes in the plantation management due to enhancing the industrial process (e.g., shortening of plantations cycle), plant diseases, or climate changes may foster more extreme fire behavior in the near future (Elli et al., 2020; Lozano et al., 2017; Urbieta et al., 2015). Studies like ours may help in preparing for such eventualities. Considering both aBP and FV as spatial-temporal factors that drive the economic losses across the plantations, our risk assessment framework would allow extrapolations of potential economic losses. By addressing different stand stages, for instance, it would be possible to predict the future economic losses of a specific stands. Likewise, more hazardous weather conditions can be simulated. Even though we already accounted for the most extreme fire weather conditions, those were still retrieved from historical weather data. Hence, new weather scenarios based on unprecedented situations may require further investigation (Bedia et al., 2015; Jolly et al., 2015; Raftery et al., 2017; Silva et al., 2019).

Nevertheless, modeling efforts are still required to achieve more precise assessments. The wildfire spread model accuracy could be improved with the refinement of spatial precision of canopy-related features. For example, canopy metrics (such as height or bulk density) can be derived from LiDAR data (Marino et al., 2016; Moran et al., 2020) which were unavailable in the study area. Furthermore, specific fuel spread models (e.g. eucalypt plantations, tropical savanna) and the initial fuel moisture estimation (e.g. custom models) must be calibrated in the region (Cruz et al., 2018; White et al., 2016a). The development and integration of species-specific mortality models in future studies would allow assessing fire effects based on fire intensity levels and provide a valuable information to improve the accuracy of wildfire risk assessments in eucalypt plantations (Catry et al., 2010).. In addition, the refinement of the economic evaluation of each pulp and paper industry, including stand-specific management and logistics costs may improve the economic figures and, for instance, support the decision-making process of each company individually.

4. Conclusions

This work presents the first attempt to quantify potential economic losses from wildfires in eucalypt plantations in a fire-prone region of Brazil. Our modeling framework provides clear guidance for fire risk management, providing valuable information for outlining critical areas for wildfire mitigation and risk management planning at the landscape scale. In addition, future scenarios, including climate change and land cover changes, may be simulated within this framework in order to assess changes in risk patterns across the study area.

Our findings suggest that local forest managers should account for 1.75% of expected annual losses in terms of raw material provision volume equivalent to 19,961,115.00 US$ yr^{-1}. Eucalypt plantations' economic losses showed high variability across the study areas, with intermediate age to mature stands (> 4 yr) more likely to experience economic loss. Special attention should be given on the young eucalypt plantation stands, due to its potential risk to burn and mature stands, due to its potential economic losses. Forest managers may also benefit from the spatial-explicit risk assessment implemented here to refine forest management plans.

Fuel reduction programs on the high burn probability areas plus ignition prevention and rapid response on fire source hot-spots would reduce risk to eucalypt plantations. Protective measures to mitigate the risk should include breaking the fuel continuity (horizontally and vertically), as well as increasing the diversity of vegetation cover (fuel type), among the eucalyptus´ stands. Fire preventive measures should be integrated into pasture and grasslands, due to its high potential of fire transmissions and its important role as a booster of fire ignitions across the studied landscape. Forest cooperatives may enable the integration of risk management plans beyond the boundaries of properties. In addition, the development of policies such as ignition mitigation programs directed toward farmers, and followed by effective inspection and application of penalties in cases of inappropriate fire usages could mitigate the risk.

Future studies using high-quality datasets and specific fuel spread models would refine the modeling and provide further insights on wildfire risk management across the South American tropical savanna.

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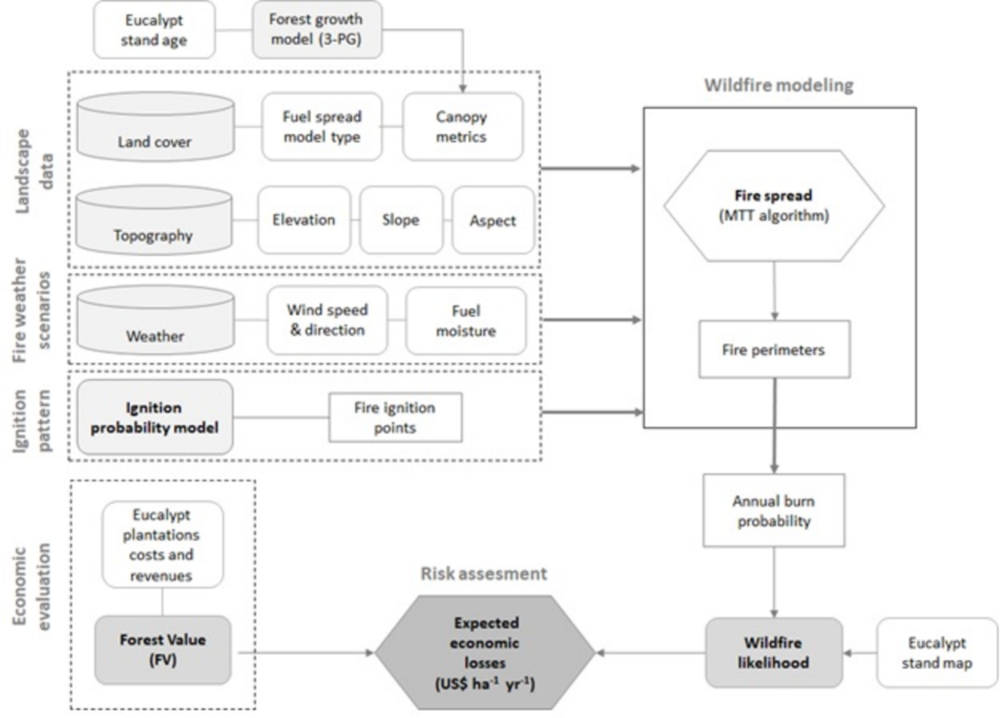

Eucalypt stand age
Forest growth model (3-PG)
Landscape data
Land cover
Fuel spread model type
Canopy metrics
Topography
Elevation
Slope
Aspect
Fire weather scenarios
Weather
Wind speed & direction
Fuel moisture
Ignition pattern
Ignition probability model
Fire ignition points
Wildfire modeling
Fire spread (MTT algorithm)
Fire perimeters
Annual burn probability
Economic evaluation
Eucalypt plantations costs and revenues
Forest Value (FV)
Risk assesment
Expected economic losses (US$ ha-1 yr-1)
Wildfire likelihood
Eucalypt stand map