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Article

Improving the combustion factor to estimate GHG emissions associated with fire in *Pinus radiata* and *Eucalyptus spp.* plantations in Chile

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Abstract: Forest plantations can substantially contribute to carbon sequestration and greenhouse gases (GHG) mitigation at the country and global scale. Forest fires (specially when combined with droughts) may significantly reduce such carbon sequestration capability. IPCC has global scale estimates for such losses, but they can vary widely depending on crops, climate, topography and management, among others. IPCC defines a factor for biomass loss as a consequence of forest fires, expressed as a fraction of total biomass. This methodology implies using aggregated data and the default emission factor, being only recommended for countries where wildfires are not a key category. In Chile, and over the last decade, there are between 5,000 to 8,000 wildfires annually (average 6,398 for the period 2011-2020), burning an average of 122,328 hectares each year. Countries may progress in the refinement of such factors depending on the availability and reliability of local values. This paper aims at estimating C_f values for the main forest plantation species in Chile: *Pinus radiata*, *Eucalyptus nitens*, and *Eucalyptus globulus*, across different age-classes and forest fire severities. To this aim we assessed the biomass loss after forest fires for a stratified sample of forest plots for the season 2018-2019. We fitted a model to predict the amount of biomass loss during fires, and in this way, predict the emissions associated to wildfires. The model employs very simple predictive variables, age and species, because statistics for burnt areas in plantations are only provided by age-classes and species, without details about productivity or management.

Keywords: wildfires; carbon cycle; forestry carbon emissions

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1. Introduction

Forest plantations can provide a significant contribution to carbon sequestration and greenhouse gas abatement on a national and global scale [1–3]. At the same time, forest fires (specially when combined with droughts) may significantly reduce such carbon sequestration capability [4], in some cases shifting forest from a carbon sink to a carbon source [5]. The Intergovernmental Panel on Climate Change (IPCC) has world scale estimates for such losses, they can vary dramatically depending on crops, climate, terrain, and management, among other factors [6].

Each year wildfires burns an average of 379.5 millions of hectares in the world, [7], mainly grasslands and savannas [8]. This average (2002-2016) shows the relevance and extent, and the potential threat that wildfires poses for urban areas, people and in general terrestrial ecosystems. In South America the estimates varies from 17.8 millions to 29.3

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millions, depending on the algorithm and remote sensing product used for calculations [7]. Worldwide, humans are the main source of ignition on flammable landscapes [8].

In Chile, the historical average (1964-2020) of burned area is 58,890 hectares/year over a total of 4,493 forest fires. However over the last decade, there are between 5,000 to 8,000 wildfires annually (average 6,398 for the period 2011-2020), burning an average of 122,328 hectares each year according to CONAF (Corporación Nacional Forestal) statistics. This large increase in burned area during the last 10 fire-seasons is highly influenced by the mega-fire developed in Central Chile during the 2016/2017 season, affecting 570,197 hectares of which 467,537 hectares were burnt in only 25 days [9**?**]. Fire emissions were so high in 2017 that the historical absorption of the land use, land-use change, and forestry (LULUCF) sector was just 11,710 Kt CO_2 eq, compared to the average of 68,616 Kt CO_2 eq during the previous five years [10,11].

IPCC proposes a generic methodology to assess the quantity of greenhouse emissions from fire in the methodological standards for carbon accounting in forest areas [6,12]. For wildfires, this guide calculate the amount of greenhouse emissions based on: the area burned, the mass of accessible fuel, and the combustion factor (C_f) which has a high level of uncertainty. IPCC sets three levels as Tier 1, Tier 2 and Tier 3 from less to higher certainty in the knowledge of parameters. Countries may progress in the refinement of such factors depending on the availability and reliability of local values. Tier 1 methodology implies using aggregated data and the default emission factor suggested by [6], being only recommended for countries where prescribed burning and wildfire are not a key category. In the case of Chile, and particularly in light of the wildfire events that occurred in 2017, Greenhouse gasses (GHG) emissions from fires meet the criterion of *key categories* as defined by IPCC [13]. Tier 2 follows the same general procedure as Tier 1, but using more refined country-derived factors. Tier 2 coefficients are mostly empirical and only valid within the domain in which they were calibrated. Furthermore, their accuracy is dependent on a thorough understanding of the many strata present [14]. As a consequence, sufficient measurements over the region's variability (i.e. climate, topography, species, age) are required. Finally, Tier 3 approaches are utilized when there is more detailed information available, such as fuel and fire dynamics. Despite the fact that Tier 3 models can produce estimates at fine geographical and temporal resolution, the data required to feed the models is not always available at the country level.

This paper aims at estimating Tier 2 C_f values for the main forest plantation species in Chile: *Pinus radiata*, *Eucalyptus nitens*, and *Eucalyptus globulus*, across different age-classes and forest fire severities. The main goal is to reduce uncertainties in the estimation of greenhouse gas emission associated with forest plantations fires and better understand the role of forest plantations in the national and global carbon cycle.

2. Materials and Methods

2.1. Study area

The study area has a warm-summer Mediterranean climate, and a warm-summer Mediterranean climate with coastal influence (Csb and Csb$_i$, respectively, according to Köppen climate classification [15]). Annual precipitation in the area range from 630 to 1200 mm and a summer precipitation of less than 60 mm. The annual mean temperature is between 12 and 14C, whereas the average summer temperature ranges between 17 and 21C. During the 2019-2020 season we studied 12 wildfire events across three administrative regions in Chile (Maule, Ñuble and Biobío Regions), between latitudes 34S and 38S. These wildfire occurrences impacted 92 stands on 23 different properties totaling around 1,700 hectares in *Pinus radiata* and *Eucalyptus ssp.* forest plantations (Table 1).

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Table 1. Wildfire events sampled during the summer season 2019-2020. Table shows the Farm affected, area affected by fire, specie present and number of sampling plots.

Event Name	Farm	Longitude	Latitude	Event date	pre-fire NBR	post-fire NBR	Burned area [ha]	Planted specie[1]	# of samples
AGUADA DOMKE	Farm_P	-66.18842	-36.05461	27/01/20	24/01/20	30/02/20	26.97	PR	6
CARMEN_HUALQUI	Farm_F	-66.92295	-37.04341	30/12/19	20/12/19	04/01/20	37.84	ESP	4
CARMEN_HUALQUI	Farm_F	-66.92705	-37.04013	30/12/19	20/12/19	04/01/20	43.27	PR	13
CARMEN_HUALQUI	Farm_Q	-66.91797	-37.04141	30/12/19	20/12/19	04/01/20	1.16	ESP	1
CONG SN FRANCI*	Farm_C	-66.89688	-37.02881	02/02/20	29/01/20	08/02/20	10.64	ESP	3
CONG SN FRANCI*	Farm_G	-66.90031	-37.01661	02/02/20	29/01/20	08/02/20	239.29	ESP	44
CONG SN FRANCI*	Farm_G	-66.90092	-37.01560	02/02/20	29/01/20	08/02/20	9.39	PR	5
CONG SN FRANCI*	Farm_Q	-66.90786	-37.02474	02/02/20	29/01/20	08/02/20	3.89	ESP	1
CONG_LEONERA	Farm_M	-65.93062	-35.27152	29/12/19	20/12/19	04/01/20	1.44	PR	1
CONG_LEONERA	Farm_S	-65.93971	-35.27229	29/12/19	20/12/19	04/01/20	0.30	PR	2
EL PERAL MUNOZ	Farm_O	-65.94716	-34.71060	27/01/20	14/01/20	08/02/20	0.25	ESP	1
EL PERAL MUNOZ	Farm_O	-65.94220	-34.70588	27/01/20	14/01/20	08/02/20	6.78	PR	2
LA COLCHA_2	Farm_T	-67.34266	-37.42269	23/12/19	20/12/19	30/12/19	15.07	ESP	5
LA COLCHA_2	Farm_T	-67.34087	-37.41841	23/12/19	20/12/19	30/12/19	12.86	PR	2
LA COLCHA_2	Farm_U	-67.33028	-37.40168	23/12/19	20/12/19	30/12/19	4.38	ESP	1
LA COLCHA_2	Farm_U	-67.33057	-37.40412	23/12/19	20/12/19	30/12/19	17.97	PR	4
LOS CAJONES	Farm_N	-65.83813	-35.67986	07/02/20	29/01/20	13/02/20	46.47	PR	11
LOS ENCINOS	Farm_A	-66.94721	-37.01202	30/12/19	20/12/19	04/01/20	12.98	ESP	4
LOS ENCINOS	Farm_B	-66.93243	-37.00070	30/12/19	20/12/19	04/01/20	25.87	ESP	14
LOS ENCINOS	Farm_D	-66.91926	-37.02913	30/12/19	20/12/19	04/01/20	4.72	ESP	2
LOS ENCINOS	Farm_E	-66.95307	-37.02632	30/12/19	20/12/19	04/01/20	76.44	ESP	15
LOS ENCINOS	Farm_F	-66.92089	-37.03543	30/12/19	20/12/19	04/01/20	24.69	ESP	6
LOS ENCINOS	Farm_F	-66.92920	-37.03354	30/12/19	20/12/19	04/01/20	2.60	PR	2
LOS ENCINOS	Farm_G	-66.91431	-37.00769	30/12/19	20/12/19	04/01/20	80.03	ESP	14
LOS ENCINOS	Farm_Q	-66.91479	-37.03589	30/12/19	20/12/19	04/01/20	37.32	ESP	15
LOS ENCINOS	Farm_R	-66.94291	-37.02562	30/12/19	20/12/19	04/01/20	1.15	ESP	2
LOS ENCINOS	Farm_R	-66.93255	-37.02690	30/12/19	20/12/19	04/01/20	138.31	PR	37
MIRADOR STA JUSTINA	Farm_H	-67.00712	-36.91506	24/01/20	14/01/20	29/01/20	5.31	ESP	6
PIDENCO	Farm_V	-66.93248	-38.16559	24/01/20	14/01/20	08/02/20	36.99	PR	5
RESERVA AL BOLDAL_2	Farm_I	-64.98302	-35.00517	27/01/20	14/01/20	08/02/20	89.26	PR	22
RESERVA AL BOLDAL_2	Farm_J	-65.02211	-35.00000	27/01/20	14/01/20	08/02/20	6.23	PR	2
RESERVA AL BOLDAL_2	Farm_K	-64.98454	-34.99500	27/01/20	14/01/20	08/02/20	3.46	PR	6
RESERVA AL BOLDAL_2	Farm_L	-64.99457	-35.00224	27/01/20	14/01/20	08/02/20	14.55	ESP	9
RESERVA AL BOLDAL_2	Farm_L	-65.00494	-34.98986	27/01/20	14/01/20	08/02/20	45.55	PR	18
STA ANA FBB	Farm_W	-66.14083	-36.72628	15/01/20	04/01/20	24/01/20	258.08	PR	27

[1] Planted species are *Pinus radiata* (PR) and *Eucalyptus ssp.*

2.2. Greenhouse gasses emissions associated to forest fires

GHG associated to forest fires (L) can be estimated using equation 2.27 proposed in [6]. This equation relates area burned (A), available fuel (M_B), combustion factor (C_f), and a specific emission factor for every greenhouse gas (G_{ef}) as:

$$L_{\text{fire}} = A \times M_b \times C_f \times G_{ef} \times 10^{-3} \quad (1)$$

There is usually information regarding the burned area (A), which is generally generated from remote sensing products. Available fuel (M_b), biomass in forest plantations, is estimated by knowing planted species and age (sometimes age-classes) and using ad-hoc allometric equations. However, the fraction of fuel that is actually combusted, as indicated by the C_f in this model, is not easily available. Finally, the specific emission factor (G_{ef}) are based on the ones proposed by [16], as suggested by [6].

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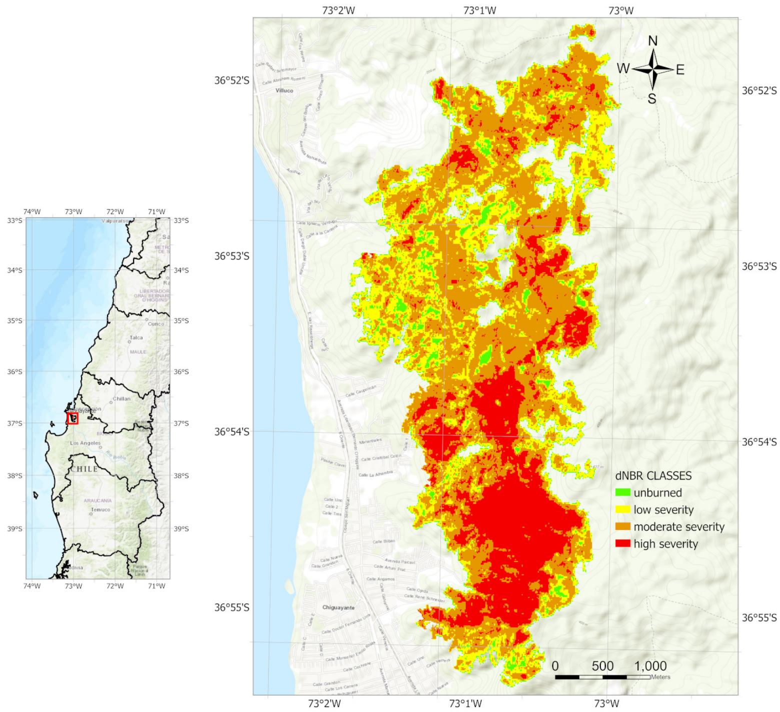

Figure 1. Example of fire severity map as measured with dNBR for the 'MIRADOR STA JUSTINA', that affected more than 5 ha. during 2019. The map shows the area unburn and the areas affected with low, moderate and high severity.

2.3. Fire severity

Fire severity was assessed by estimating the Normalized Burn Ratio (NBR). The NBR is a remote sensing product calculated from the near-infrared and short wave infrared reflectances proposed by [17] and widely used to assess fire severity using remote sensing [18,19]. The difference between pre-fire and post-fire NBR was used to calculate the delta NBR (dNBR), as a measurement of fire severity. For doing this, Sentinel 2 satellite images were selected from dates just before and after the event. Sentinel 2 is a constellation of two satellites (Sentinel 2A and Sentinel 2B), with an spatial resolution of 10 meters on bands 8 (near infrared (NIR), central wavelength 832.8 nm.) and 20 meters on band 11 (short wave infrared (SWIR), central wavelength 1613.7 nm.) [20]. On every pre-fire and post-fire scene, the Normalized Burn Ratio (NBR) was calculated as the normalized difference of NIR and SWIR spectral bands, using the following equation:

$$\mathrm{NBR} = \frac{\mathrm{NIR} - \mathrm{SWIR}}{\mathrm{NIR} + \mathrm{SWIR}} \tag{2}$$

After this, the dNBR was calculated as:

$$\mathrm{dNBR} = \mathrm{NBR}_{\text{pre-fire}} - \mathrm{NBR}_{\text{post-fire}} \tag{3}$$

2.4. Field sampling

To propose a country-derived C_f and its relationship with specie, age and fire severity, several field studies were undertaken throughout the 2019-2020 fire season to assess the amount of biomass and carbon loss on the various biomass components. Field assessments were conducted 2 or 3 weeks after wildfires of varying severity, in *P. radiata* and *Eucalyptus ssp*. forest plantations of varying ages. Damage percentages on various biomass components were correlated with biomass proportions and then related to specie, age, and fire severity to determine the C_f for those conditions.

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Field sampling was done dynamically during the fire season on every fire event that affected and area above 10 ha. The sampling used a fixed density of 4 sampling points per hectare. On every fire event, sampling points were selected using a latin hypercube sampling considering 3 stratification variables: land use, stand age, and fire severity. This sampling strategy provides for a fair characterisation of the strata contained in the data by covering the range of the three grouping variables [21,22]. These three stratum have been categorized as follows: Land use was categorized as *Pinus* or *Eucalyptus* plantations; age was defined as young (0 to 4 years old), medium (5 to 15 years old), and mature (more than 15 years old) plantations for *Pinus* plantations. The age of *Eucalyptus* plantations was divided into three categories: young (0 to 2 years old), medium (3 to 6 years old), and mature plantations (more than 6 years old). Finally, dNBR images were classified as 'unburned' when the dNBR was below 0.1, 'low severity' when the dNBR was between 0.1 and 0.27, 'moderate severity' when the dNBR was between 0.27 and 0.66, and 'high severity' when the dNBR was greater than 0.66.

In the field, trees within a 250-meter radius of the sampling location were measured. The number of trees in each sampling plot was counted, as well as the condition of the forest floor. Furthermore, each tree's height, proportion of damage to bark (considering height of damaged bark but also transverse section of damage), proportion of damage to stem, leaves, branches, and roots were all recorded.

2.5. Above-ground biomass carbon loss

To calculate the combustion factor (C_f), the proportion on damage to each component was weighted considering the proportion of the component to the above-ground biomass, using the following equation:

$$C_f = d_s \times w_s + d_{ba} \times w_{ba} + d_{br} \times w_{br} + d_{lv} \times w_{lv} \tag{4}$$

where d_s, d_{ba}, d_{br}, and d_{lv} are the observed damage to stem, bark, branches and leaves. The weighting coefficients (i.e. w_s, w_{ba}, w_{br}, and w_{lv}) where estimated using allometric equations based on the height of the trees following the procedure presented by Sandoval *et al.* [23].

2.6. A model to predict the combustion factor

The model to estimate C_f for plantations must be compatible with information that can be easily acquired by users and/or supplied publicly by some state agency or other data provider. Nationwide statistics about wildfires are gathered and provided by CONAF (Corporación Nacional Forestal) the forest agency from Chile's Ministry of Agriculture. The information reported include coordinates of the ignition, along with all the administrative information; e.g. region, province, township, and also dates and times for different stages of the wildfire control such as detection, first attack, extinction, etc. Relevant to this model is the information about burned areas and land uses that has been affected by wildfires. The data separates between areas of plantations (*P.radiata*, *Eucalyptus spp.*) and natural vegetation, with 3 age classes (years since planting) for *P.radiata* (1-10, 11-17 and $\geq$ 18) while *Eucalyptus spp* burned areas are aggregated into one total with no details about age. The information provided by CONAF did not include details about fire severity or other information that can be used to separate areas by fire intensity or severity although dNBR was considered as a potential predictive variable for the predictive models.

Individual tree measurements on 176 sampling plots at the designated specie-age-fire severity groups were included in the database used to calibrate the predictive model, however not all combinations were sampled. Aside from C_f, C_f (weighted average), dNBR, age, specie, and plot biomass, the data included information about each plot's geographic and administrative location, such as stand, farm, province, and region, as well as codes to link the plot to a file of digital pictures taken on-site when sampling the burned stands. Other standard plot-level characteristics, such as height, basal area, and number of trees, were not considered as possible predictive variables since the model must be applied to all plantation wildfires across a year, and detailed stand data for all burnt areas is not available. Age or age-class, species (*P. radiata* or *Eucalyptus ssp.*), and dNBR are therefore possible predictive factors for C_f. Pruning was also evaluated as a possible predictive variable using a dummy (0/1) variable to assess the contribution of pruned trees on C_f, but it was not included in the suggested models.

Because the plots were measured as clusters within stands, and stands are nested within farms, the models will use a mixed-model approach to account for the likely correlation among plots measured within stands and properties, taking also into account random effects for some parameters in the model. Simple linear regression models fitted during the exploration stage show that log transformation (neperian/natural) of the dependent variable (C_f) improves model fit consistently. As a result, the mixed model tested combinations of independent variables and random effects at the stand and farm level for the intercept (β_0) and beta parameters associated with the independent variables. Also, we tested separate models for *P.radiata* and *Eucalyptus spp.* and a single model where a dummy variable was used to account for differences between these 2 species.

The models were evaluated for fit by comparing the Akaike Information Criterion (AIC) [24]; and taking into account the statistical significance and logic of the parameters, as well as the significance of the parameters in the variance-covariance matrix of random errors.

The basic notation of the model is $\ln(C_f) = \beta_0 + \sum \beta_i X_i$, where X might represent age, dNBR, or its log transformation and for the model that use a dummy variable for species. The models were fitted using PROC MIXED in the SAS statistical package v9.4.

3. Results

3.1. Tree and plot data

The data collected on trees was aggregated at the plot level in order to fit a model where C_f represents an area-level estimate of burned biomass more than a tree-level fraction. The potential predictive models for C_f will be used to estimate greenhouse gas emission associated with plantation burned areas, and therefore will use nationwide wildfires statistics, that only reports burned areas by age-classes on plantations. Therefore Table 2 shows simple descriptive statistics for this database.

According to our results, C_f is correlated with age and dNBR, specially for *P. radiata*, and weakly correlated with dNBR, as shown in Figure 2.

Table 2. Descriptive statistics of the database collected during the fire season 2019-2020.

Variable	n	Min	Max	Mean	Median	Var	SD
			Pinus radiata				
Age, y	83	2.0	29.0	12.8	12.0	15.2	3.9
C_f, %	83	9.03	65.36	19.87	18.28	93.96	9.69
dNBR	83	0.10087	0.91576	0.45699	0.43261	0.03396	0.18430
			Eucalyptus spp.				
Age, y	93	1.0	24.0	11.6	11.0	52.2	7.2
C_f, %	93	16.47	100.00	40.09	27.32	732.91	27.07
dNBR	93	0.05459	1.18588	0.43181	0.38381	0.06131	0.24760

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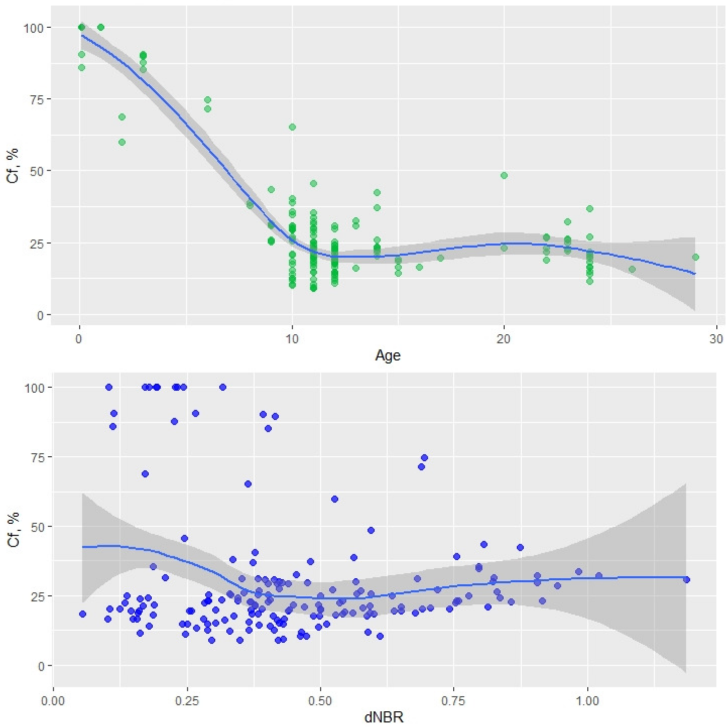

Figure 2. Relationship between the amount of biomass that is actually combusted during a wildfire (C_f) and Age (top) and between C_f and fire severity measured with remote sensing (dNBR) (bottom).

Table 3. Comparison of the quality of the statistical models fitted for the estimation of the combustion factor, its variables and random effects.

Independent Variables	Random effect	AIC
ln(age), binSp	Farm	82.2
ln(age), binSp	Stand	72.8
ln(age), binSp, dNBR	Farm	69.8
ln(age), binSp, dNBR	Stand	44.1

Considering that the models using dNBR are more difficult to use, since it is required to estimate/measure the dNBR for the area before and after the wildfire, it was decided to use the model with stand-level random effects to estimate the value for C_f. Then the model is:

$$\ln C_{f_{ij}} = \beta_0 + \beta_1 \times \ln(\text{age}_{ij}) + \beta_2 \times binSp_{ij} + \beta_{0.j} \tag{5}$$

Where $\ln C_{f_{ij}}$ is the value of the combustion factor for plot i within stand j, age_{ij} is the age (years) of the trees in plot i within stand j, and $binSp_{ij}$ is a dummy variable specifying the specie in stand j. The term $\beta_{0.j}$ is a random deviation from the population-level β_0, representing that each stand has a different intercept. Table 4 shows the value for the parameters β_i.

Table 4. Estimates for model parameters.

Effect	Estimate	Error	df	t-value	Pr > t
Intercept	3.7113	0.0793	44	46.82	> 0.0001
ln(age)	-0.2715	0.0178	129	-15.24	> 0.0001
binSp	0.4043	0.0623	129	6.49	> 0.0001

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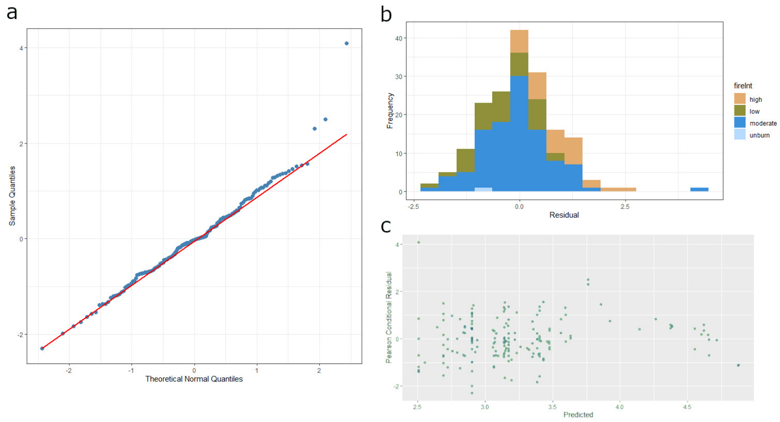

Figure 3. Diagnostic plots for the residuals of the proposed models: Normal Q-Q plot comparing the probability distribution of the residuals with a normal distribution (a), histogram of the distribution of the residuals classified using the fire severity (b), and Person conditional residuals compared with predicted value (c).

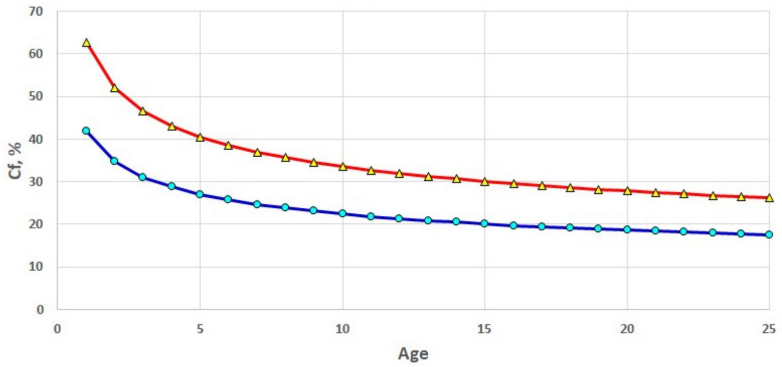

Figure 4. Shape of the combustion factor (C_f) estimated using the proposal model using age, specie and a given stand, for *P. radiata* (red) and *Eucalyptus spp.* (blue).

The residuals in Figure 3 shows the random distribution around the mean=0 and a reasonable normal distribution as expected.

The model predicts C_f for plantations of *P. radiata* and *Eucalyptus ssp.* in Chile, for any age between plantation and the typical harvest ages for both species (20-25 year for former and 8-12 years for the latter). According to the structure of the models, C_f declines with age for both species, and *P. radiata* losses is anticipated to be greater at the same age. Figure 4 depicts the shape of the models for a given stand of these species.

4. Discussion

Different combinations of independent variables and random effects on the β_i from the models were evaluated, using age, dNBR, their log transformations, and specie represented by a dummy variable ($binSp$) defined as: 1 for *Pinus radiata*; 2 for *Eucalyptus ssp.*. During the exploration stage of model fitting, where different expressions for the independent and dependent variables were tested and we studied approaches to model errors autocorrelation and random effects, the question was raised regarding whether or not is appropriate to fit separate models for P. radiata and Eucalyptus spp. We compare the performance of separate models for each species with the model finally selected, and results indicate that Cf estimates are practically the same for P. radiata at all ages, while for Eucalyptus spp. there is a difference at earlier ages but not for the age considered to be representative of this species (13y). Therefore, we decided to propose a single model to keep it simple.

Random effects were also studied at the stand and farm levels. The best models, according to the results, were those having a random-effect associated with the intercept

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(β_0), either for plots within a certain stand or for plots inside a given farm. Table 3 shows the best fitting models, all of which predict the natural log of C_f.

According to the results (Table 3), there were local effects that needed to be accounted for in order to improve model fitting. The fit of the most basic model, in which age and species were predictors and there was a specific intercept for each farm, which was a cluster of stands, was improved by incorporating a specific intercept at the stand level, and this improvement was statistically significant (p-value=$\leq$ 0.001). When stand-level random effects wew taken into account, the models that add predictor dNBR exhibit the same result, a statistically significant improvement (p-value=$\leq$ 0.001) in model fit.

4.1. C_f values aggregates to age-classes used in Chile.

CONAF provides official information for wildfire areas for all reported fires in Chile. The age of plantations impacted by wildfires is only recorded for *P. radiata*, whereas the areas for *Eucalyptus ssp.* are only reported as a cumulative amount. *P. radiata*'s age classes are (in years) 0-10, 11-17, and $\geq$ 18. The models predictions and proposed revised values for Cf utilize the mean age of these age-classes for *P. radiata* and 13y for *Eucalyptus ssp.* (average age of samples). The proposed values, rounded to the nearest integer, are presented in Table 5.

Table 5. C_f values aggregates to age-classes used in Chile.

Specie	Age-class	Age	C_f	CI[1] lower bound	CI[1] upper bound	C_f range age-class
P. radiata	1–10	5	0.41	0.35	0.45	0.63–0.33
P. radiata	11–17	14	0.31	0.26	0.34	0.33–0.29
P. radiata	$>$ 18	22	0.27	0.24	0.30	–
Eucalyptus ssp.	1–20	13	0.21	0.18	0.23	0.42–0.18

[1] CI: confidence interval.

5. Conclusions

The model uses very simple predictive variables, age and species, because statistics in Chile for burnt areas in plantations are only provided by age-classes and species. Details about forest management, tree density, productivity, and fire intensity are not registered on the statistics, all of which can be used to make better estimates of biomass and then C_f.

Some of these variables may be aggregated to reports in burnt areas in the future, but there is no indication of change in the disaggregation for *Eucalyptus spp.* plantations areas, which can be used to have separate values in C_f for young and older plantations, or addition of dNBR or dNBR-classes in the set of variables reported for each wildfire, to use the better model (AIC=44.1).

The AIC for the best non-mixed, simple regression model was 116.5, and the models presented in this report show the importance of stand factors in the estimation of C_f values, with only adding a factor for nesting in the statistical model improving the model's fit significantly when compared to non-random effects models or the farm-level nesting factor.

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