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Simulating the effects of prescribed burning on fuel loading and timber production (EcoFL) in managed northern Wisconsin forests

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ABSTRACT

We developed a fuel loading prediction model (EcoFL), which quantified fuel loads at ecosystem level using a classical ecosystem productivity concept and aboveground biomass measurements. EcoFL predicted fuel loading with high precision ($r^2 = 0.94$), but the linear relationship between measured and predicted was slightly off from the 1:1 line (slope = 0.86–1.17). The study showed a possibility of developing landscape level fuel loading model. EcoFL indicated that carbon allocation had to be parameterized accurately to predict fuel loading precisely. Prescribed burning has been widely used to reduce fuel and promote ecosystem functions throughout the United States, but the long-term ecological impacts of prescribed burning are widely unknown. We evaluated the effect of alternative prescribed burning rotations (ROT), magnitude in productivity reduction by prescribed burning (MAG), and duration of productivity reduction (DUR) on fuel loading ($\mathrm{Mg\,ha^{-1}}$) and timber production ($\mathrm{Mg\,ha^{-1}}$) in managed northern hardwood, red pine (*Pinus resinosa*), and jack pine (*P. banksiana*) forests in northern Wisconsin. The results showed that DUR would be the most critical information when deciding ROT in order to preserve timber production and to maintain low fuel loading. The results implied that forest productivity could reduce timber production drastically, if ROT was shorter than DUR and ecosystem productivity was affected cumulatively by prescribed burning. Under a 5-year ROT, the harvested biomass was reduced up to 17.9, 30.4, and 25.5%, respectively, of controls in hardwood, red pine, and jack pine forests. For accurate long-term prediction of prescribed burning, substantial field data are still needed to identify productivity recovery pattern, carbon allocation after burning, and long-term effect of burning on productivity. EcoFL has the potential to be used for evaluating the effect of various disturbances (e.g., thinning, harvesting) on fuel loading, and the output of EcoFL can be used as an input data for fire spread models. The results of this study will be fundamental for forest managers to balance the timber production and fuel reduction using prescribed burning.

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1. Introduction

High fuel accumulation and altered landscape structure, caused by decades of fire suppression and exclusion, have altered fire regimes and increased fire risk (Ryan, 2002; Taylor and Skinner, 2003; Weisberg, 2004). These changes have ultimately increased the importance of fuel reduction, which is an important forest management objective to reduce fire risk and fire damage. Prescribed burning has been accepted widely as a way to reduce fuel loading and to promote ecosystem functions within forest ecosystems throughout the United States (Allen et al., 2002). Moreover, numerous governmental programs (e.g., 2001 Federal Wildland Fire Management Policy, Healthy Forest Restoration Act of 2003) have been developed to direct federal agencies in balancing fire suppression through the use of prescribed burning (Iverson et al., 2004).

Although prescribed burning is an effective tool in controlling fuel loading, there are many uncertainties about the long-term ecological impacts of this management option (Tiedemann et al., 2000; Carter and Foster, 2004; Shang et al., 2004). Raison et al. (1985) reported that even under low-intensity prescribed burning 54–75% of the nitrogen (N), 37–50% of the phosphorus (P), and 43–66% of the potassium (K) were removed from the understory and litter nutrient pools. It is well known that prescribed burning will alter soil chemical and physical properties, including reduction in infiltration rate (DeBano, 2000) and water holding capacity (Boyer and Miller, 1994) and increase in N and P availability (Covington et al., 1991; Wan and Luo, 2001). Wells et al. (1979) found that fuel reduction could influence soil surface susceptibility to the kinetic effects of raindrops, which can potentially break soil aggregates and block soil pores. Other studies also suggested that prescribed fire could negatively affect the productivity in pine forests (Landsberg et al., 1984; Boyer, 1993; Landsberg, 1994; Busse et al., 2000) and oak-savannas (Reich et al., 2001). The decrease in productivity would be a direct result of the fire induced environmental changes; including losses of surface organic matter, soil porosity, and nutrient pools in forest floor (Tiedemann et al., 2000). However, none of these studies included evaluations of the long-term impacts of prescribed burning on forest productivity (Carter and Foster, 2004). Interestingly, there have been few studies focusing on the duration (DUR) and the magnitude (MAG) of decreased productivity related to prescribed burning. Consequently, a limited number of studies have restricted the assessment of interactions between fuel loading, productivity, and prescribed burning. Specifically, there are no known studies evaluating the effects of prescribed burning on forest productivity in northern Wisconsin forests, although prescribed burning started to be applied actively places such as the Chequamegon National Forest (CNF) during the late 1980s to reduce fuel loading and promote rare pine barren/jack pine ecosystems.

Various fire growth models have been generated using vector and cellular automata approaches (Hargrove et al., 2000; Berjak and Hearne, 2002). Vector models estimate the rate of fire spread using analytical solutions (e.g., Huygen's principle) for the propagation of elliptic shape fire perimeters (Karafyllidis and Thanailakis, 1997; Berjak and Hearne, 2002), while cellular automata models predict the rate of fire spread using fixed distances between regularly spaced grid cells to solve for the fires arrival time from one cell to the next (Berjak and Hearne, 2002; Ito, 2005). Some fire growth models have been developed on an assumption of homogeneous fuel loading for both types of modelling approaches (Hargrove et al., 2000; Berjak and Hearne, 2002). However, a fire growth model needs to be spatially explicit and capable of simulating the long-term dynamics of disturbance-prone landscapes to predict the ecological effects of landscape scale fires (Green, 1989; Turner et al., 1889; Hargrove et al., 2000). To achieve this goal, models require adequate characterization of local variability in fuels, which is difficult to estimate because quantity and quality of forest fuels are affected by both biotic and abiotic factors (Hargrove et al., 2000; He et al., 2002). Therefore, the actual quantity and quality of fuels are commonly not available or are unrealistic to obtain for each individual site, so even the fuel treatment decisions of USDA forest service are often based upon data indirectly derived from other biotic and abiotic factors (He et al., 2002). Clearly, developing an easy-to-use, scientifically based, and empirically proven fuel loading prediction model is urgently required.

Computer modelling can be an ideal tool to study the interactions between fuel loading, productivity, and prescribed burning, because it allows testing the interactions under various conditions without disturbing the ecosystem. Additionally, the model results can provide forest managers alternative options of fuel loading and timber production as a result of prescribed burning at the landscape level with statistically acceptable replications, which is often a challenge at broader spatial and temporal scales (Eberhardt and Thomas, 1991; Michner, 1997; Waltz et al., 2003). Simplified and parameter-limited models are especially desirable to landscape level modellings, because landscape level processes incorporate the complex interactions between ecosystems and limit accurate parameterization and simulation (Euskirchen et al., 2002).

The objectives of this study are to evaluate the possibility of predicting fuel loads by fine-tuning and modifying the previously developed simple ecosystem model (Euskirchen et al., 2002; Ryu et al., 2004) and examined the effects of prescribed burning on fuel loading and timber production. We tested the interactions between prescribed burning, fuel loading, and timber production under alternative prescribed burning rotation interval (ROT), magnitude of productivity reduction by burning (MAG), and duration of productivity reduction by burning in northern hardwood, red pine (*Pinus resinosa* Aiton), and jack pine (*P. banksiana* Lambert) forests. We hypothesized that: (1) fuel loading could be accurately predicted with appropriate productivity pattern, carbon allocation, and decay rates and (2) burning interval would be the most important factor determining fuel loading and timber production.

2. Model development and scenario tests

2.1. Model structure and linkages

We developed a phenomenological ecosystem fuel loading model (EcoFL) to evaluate the dynamics of fuel loads interacting with various disturbance types using Stella 7.0 (High Performance System Inc., NH, USA). EcoFL was an improved

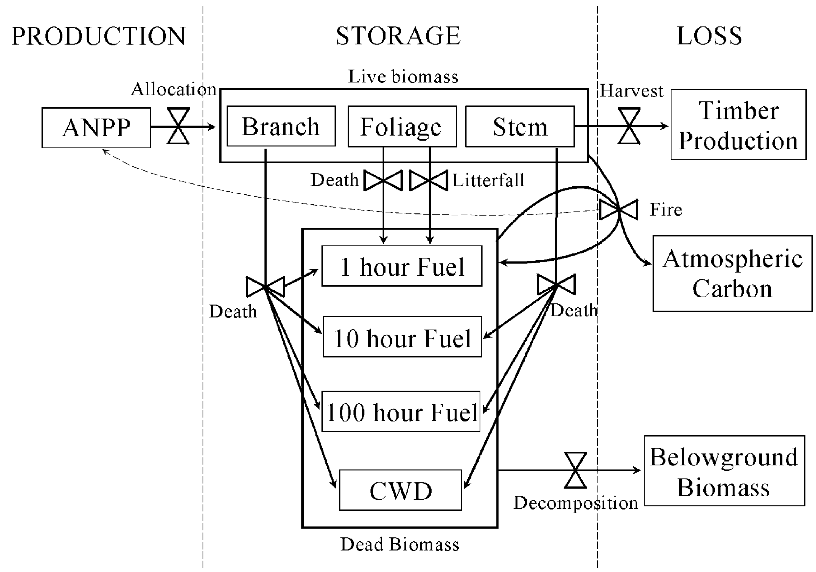

Fig. 1 – The conceptual diagram of carbon flow in a forest ecosystem. Solid line represents carbon flow and dashed line indicates information flow. ANPP represent aboveground net primary production (Mg ha^{-1} year^{-1}). About 1, 10, and 100 h fuels were fuel classification by size; 1 h fuels (Mg ha^{-1}; <0.6 cm in diameter), 10 h fuels (Mg ha^{-1}; >0.6 and <2.5 cm in diameter), and 100 h fuels (Mg ha^{-1}; >2.5 and <7.5 cm in diameter).

version of a previous fuel loading estimation model developed by Ryu et al. (2004). The EcoFL model has three components: PRODUCTION, STORAGE, and LOSS (Fig. 1). PRODUCTION calculates aboveground net primary production (ANPP); STORAGE includes live and dead biomass pools and allocations among these pools (e.g., aboveground biomass, litterfall, and CWD); LOSS estimates decomposition loss and biomass directly removed by disturbances (e.g., decomposition, fire, and harvesting).

ANPP was estimated based on the ecosystem age and the ANPP pattern was described using a simplified model known as LandNEP (Euskirchen et al., 2002). Basically, ANPP pattern changing with age was accomplished using a two-parameter Weibull function (Euskirchen et al., 2002; Ryu et al., 2004). Leaf area index (LAI) was used to estimate the age of maximum ANPP on the assumption that each ecosystem had maximum production, when the canopy closed (Aber, 1979). The magnitude of maximum ANPP of each ecosystem was estimated using the PnET-II model (Aber et al., 1995).

STORAGE was composed of three live biomass pools [e.g., live foliage (LF), live branch (LB), live stem (LS) and four dead fuel loading pools (e.g., 1 h fuels (1 h F), 10 h fuels (10 h F), 100 h fuels (100 h F), and coarse woody debris (CWD; diameter larger than 7.5 cm)]. Fuel loading was determined using a fuel classification system of USDA Forest Service (Brown, 1974; Brown and See, 1981): 1 h fuels (1h F Mg ha^{-1};<0.6 cm in diameter), 10 h fuels (10 h F Mg ha^{-1}; >0.6 and <2.5 cm in diameter), and 100 h fuels (100 h F Mg ha^{-1}; >2.5 and <7.5 cm in diameter). Conversely, each live biomass pool was calculated as a sum of annual growth minus annual death. Annual death represented the transfer of live biomass to dead biomass due to self-thinning, natural tree mortality, and natural senescence. Foliage growth (G_F) followed sigmoid function (Eq. (1)), while branch growth (G_B) followed integrated sigmoid function (Eq. (2)):

$$G_F = a \times (\text{age} - d)^c \times ((\text{age} - d)^c + b^c)^{-1} \quad (1)$$

$$G_B = e \times f^g \times g \times \text{age}^{g-1} \times (\text{age}^g + f^g)^{-2} \quad (2)$$

where a, b, c, and d are constants, representing the maximum growth, half point, growth change rate, and delay factor, respectively. Stem growth (G_S) was calculated as the difference between ANPP and sum of G_F and G_B.

Biomass allocation from live biomass (LF, LB, and LS) to dead biomass (1, 10, and 100 h F, and CWD) was estimated using generic equations. Foliage death (D_F; senescence) was estimated from the same equation of foliage growth (Eq. (1)) while considering foliage retention year (R_{YR}) and mortality (Eq. (3)). Foliage loss by mortality (D_{FM}) was calculated by multiplying the LF with mortality rate (M), where M was calculated by a uniform stochastic function as between zero and a maximum mortality rate, which was estimated from published literatures (Eq. (4)):

$$D_F(\text{age}) = G_F(\text{age} - R_{YR}) \times (\text{LF}/(\text{LF} + D_{FM})) \quad (3)$$

$$M = \text{uniform random} \quad (0, \text{maximum}\, M) \quad (4)$$

D_F was then transferred to the 1 h F.

We developed two generic equations (Eqs. (5) and (6)) to estimate the branch death during seedling stage to self-thinning stage (Eq. (5)), and during and after self-thinning stage (Eq. (6)). Foliage and branch death caused by disturbances (e.g., disease, fire, wind throws) can be added in the calculated of dead biomass, if necessary, but disturbance term was not used in this study because it was beyond the scope of this study:

$$D_B = h \times (\text{age} - k)^j \times ((\text{age} - k)^j + i^j)^{-1} \quad (5)$$

$$D_B = l \times m^n \times n \times (\text{age} - o)^{n-1} \times ((\text{age} - o)^n + m^n)^{-2} \quad (6)$$

where $h(l)$, $i(m)$, $j(n)$, and $k(o)$ are constants representing the maximum death, half point, mortality change, and delay rate, respectively. Dead stem biomass was allocated to 100 h F and CWD according to its diameter at breast height (DBH; cm), which was calculated by multiplying age with mean DBH increase. Dead branch biomass was allocated to the 1, 10, and 100 h F, and CWD in a different proportion upon the assumption that maximum branch diameter is the half of stem DBH.

LOSS was designed for tracking three components: decomposition, fire (combustion), and harvesting. Decomposition is calculated as a single exponential function (Eq. (7)):

$$M_t = M_i \times \exp(-k \times t) \quad (7)$$

where M_t, M_i, k, and t are mass at time t, initial mass, decay rate, and time (year), respectively. Fire has three aspects: fire ignition, fuel consumption by fire, and aboveground biomass consumption by fire. These three aspects were independently estimated to represent the uncertainty of fire ignition and fire removal of forest biomass. Fire ignition was a deterministic function in the study to represent prescribed burning rotation. Fuel consumption by fire was estimated using a uniform stochastic function as a random number between low and maximum fuel consumption rate. Aboveground biomass consumption was calculated using a uniform stochastic function between zero and maximum biomass consumption rate. In the event of a timber harvest, the stem biomass was removed from the ecosystem as harvested timber, while the other aboveground biomass (i.e., branches and foliage) was allocated to dead biomass.

2.2. Study sites

The study landscape is located in the Washburn Ranger District of the CNF in northern Wisconsin, US (46°30′–46°45′N, 91°02′–91°22′W). Within the CNF, the dominant forest types include northern mixed hardwood, red pine, and jack pine (Brosofske et al., 1999; Bresee et al., 2004). The topography is flat to rolling and the elevation range between 232 and 459 m above see level with terraces and outwash landforms. The region is characterized by short, hot summers with between 120–140 growing-degree days and long cold winters.

2.3. Model parameterization

We used the aboveground biomass data of Radermacher (2004), who developed 55 plots, 490 m^2 within mature stands and 125 m^2 within young stands, to tally DBH in the summers of 2002 and 2003 to estimate the aboveground biomass. In his study, 17, 23, and 15 plots were located in northern mixed hardwood, red pine, and jack pine ecosystems, respectively. Aboveground tree biomass including branch biomass and foliage biomass, was estimated using published biometric equations (TerMikaelian and Korzukhin, 1997). Hemispherical photographs were also taken in 44 plots for estimating leaf area index (LAI) using WinScanopy™2003d software (Regent Instruments Inc., Quebec, Canada). These field data were used to define and parameterize ANPP patterns and carbon allocation, and model predicted aboveground biomass well ($r^2 > 0.90$; Fig. 2).

Foliage samples were taken from the dominant trees to analyze their foliar nitrogen (N) concentration (%) and specific leaf weight (SLW, $g\,m^{-2}$) for eight major species of study area: red maple (*Acer rubrum* L.), sugar maple (*A. saccharum* Marsh.), paper birch (*Betula papyrifera* Marsh.), bigtooth aspen (*Populus grandidentata* Michx.), trembling aspen (*P. tremuloides* Michx.), red oak (*Quercus rubrum* L.), jack pine, and red pine (Table 1). Each of eight species, mature and young trees (except young sugar maple) were selected for foliar N and SLW. Sampled mature trees dominated the closed canopy, 50–60-year-old and 20–25 m tall, while sampled young trees dominated the canopy, 7–15-year-old and 1.5–3.5 m tall. For leaf collection, the crowns of mature trees were divided evenly into three heights and two aspects (south and north), while the crowns of a young tree were divided evenly two heights and two aspects. Consequently, six samples and four samples were taken from each mature tree and young tree, respectively, for SLW and foliar N parameterization (Pan et al., 2004). Mean DBH increase was estimated by DBH measurement and ring counts. Mean DBH increases were 0.5, 0.7, and 0.6 cm for hardwood, red pine, and jack pine, respectively.

The maximum ANPP values for the hardwood, red pine and jack pine ecosystems, 9.5, 8.6, and 7.5 $Mg\,ha^{-1}$, respectively, were calculated using PnET-II simulations. Variables for the growth functions (G_F, G_B, and G_S) were estimated using the field survey data (Table 2). A maximum annual mortality rate of 0.5% was given to the three ecosystem types (Lorimer, 1989) with an exception of 2.2% annual maximum mortality to the jack pine ecosystem after age 40 because jack pine reaches maturity at age 40 and infrequently reaches 150 years old (Martin and Lorimer, 1997; http://www.rook.org/earl/bwca/nature/trees/pinusbank.html). While analyzing field data, we observed that jack pine stand

Table 1 – Mean and standard deviation (S.D.; in parentheses) of specific leaf weight (SLW, $g\,m^{-2}$) and foliage nitrogen content (N, %) eight dominate species in Chequamegon National Forest, Wisconsin in two age class trees: young and mature

Species	Young stand		Mature stand	
	SLW	N	SLW	N
Acer rubrum	71 (16)	1.7 (0.10)	63 (7)	1.7 (0.18)
A. saccharum	N/A	N/A	60 (14)	1.5 (0.10)
Betula papyrifera	72 (10)	2.2 (0.20)	79 (8)	1.8 (0.11)
Populus grandidentata	70 (13)	2.4 (0.18)	68 (7)	2.2 (0.05)
Populus tremuloides	82 (7)	1.9 (0.02)	73 (10)	2.0 (0.07)
Quercus rubrum	77 (7)	2.5 (0.07)	69 (18)	2.1 (0.09)
Pinus banksiana	236 (18)	1.4 (0.05)	192 (20)	1.3 (0.05)
Pinus resinosa	278 (15)	1.1 (0.10)	252 (10)	1.1 (0.05)

Mature trees were 50–60 year-old and 20–25 m tall, while young ones were 7–15 year-old and 1.5–3.5 m tall. N/A indicates data is not available.

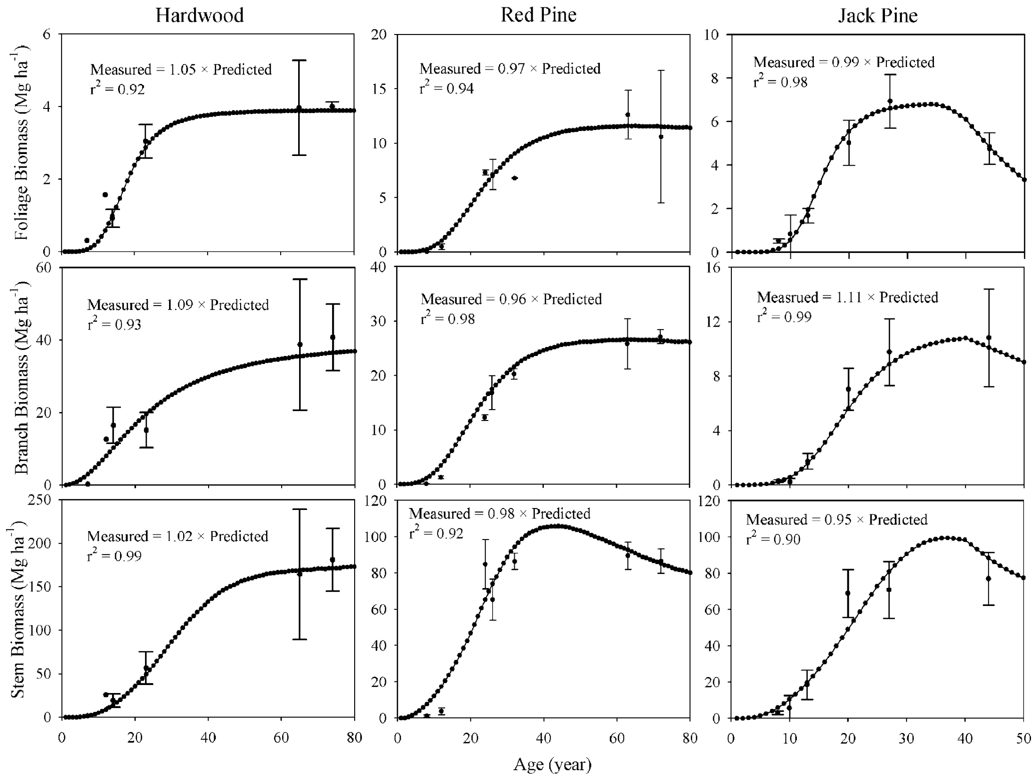

Fig. 2 – Measured and predicted foliage, branch, and stem biomass by age in studied hardwood, red pine, and jack pine forests. Biomass of jack pine ecosystem decreased after age 40 due to high natural mortality.

density decreased abruptly from 796 stems ha^{-1} approximately at age 27–244 stems ha^{-1} at age 44 and was partly replaced by red pine. We estimated the mortality rate as the 244 stems ha^{-1} at age 44 to 24 stems ha^{-1} at age 150 and thus estimated the 2.2% maximum annual mortality rate. Decay rates (k) of 1, 10, and 100 h F, and CWD were estimated using published equations and field data (Meentemeyer, 1978; McLellan et al., 1991; Bolster et al., 1996; Martin and Aber, 1997; Yin, 1999). The estimated k values (year^{-1}) for hardwood 1, 10, and 100 h F and CWD were 0.455, 0.090, 0.064, and 0.051, respectively, and those for red and jack pine were 0.313, 0.038, 0.021, and 0.016, respectively.

2.4. Model scenarios

Effects of fire on fuel loads and productivity have three aspects: (1) the frequency of fire (ROT), (2) the magnitude of productivity reduction by fire (MAG), and (3) the duration of the productivity reduction (DUR). We tested four fire rotation (ROT) scenarios: 5, 10, 15, and 20 years fire rotation. Actually, the USDA Forest Service in the CNF applies prescribed burns every 8–10 years. The MAG, DUR, and recovering patterns after fires are rarely known in any forest ecosystem including the CNF. Numerous studies have suggested a negative effect of prescribed burning on productivity if the magnitude of the burn was less than 30.0% (Boyer, 1993; Busse et al., 2000). We tested three levels in the MAG: 10.0, 20.0, and 30.0% of the control condition. In this study, 10.0% MAG was estimated by multiplying 0.9 to the reference ANPP (i.e., ANPP without disturbance). Five levels in DUR were also tested: 1, 2, 3, 4, and 5 years. We assumed that the negative effects of burning on productivity would be reduced linearly. For example, if prescribed burning reduced ANPP 10.0% with 2-year duration at age 50, the ANPPs of age 50 and 51 were calculated by multiplying 0.9 and 0.95 to the reference ANPP of age 50 and 51, respectively. The ANPP reduction was assumed to reduce biomass allocation to foliage, branch, and stem in the same proportion. We included hardwood in the study, although prescribed fire is not generally applied to hardwood forest, because this study is a theoretical study and forest managers occasionally apply fire to hardwood stands in the CNF.

When a fire is applied to the system, fuel consumption by fire was estimated according to fuel type and forest type. To represent the uncertainty of fuel consumption by a fire, fuel consumption rates by fuel and vegetation types were independently estimated using a uniform stochastic function. The pre- and post-burning fuel data was provided by USDA Forest Service, and prescribed burning generally consumed 30–70, 20–90, and 0–60% of 1, 10, and 100 h F, respectively. The fuel consumption was estimated as a random number between minimum and maximum fuel consumption rates by fuel and vegetation types.

Complete factorial designs for the above scenarios were applied in this study to achieve objectives: 4(ROT) × 3(MAG) × 5(DUR) × 3(ecosystem types) = 180 runs. Each scenario (total 180 scenarios) was run 10 times for 400 years, and the mean value for each run was calculated. Mean values were reported for this study, because we wanted to

Table 2 – Model parameters and equations for production, carbon allocation and decomposition and input variables used in this study

Equations	Variables	Vegetation types						
		HW		RP			JP	
Production	λ	10		9			7.5	
$\text{ANPP} = \lambda \times (P - \min(P))$	Min(P)	0.04		0.034			0.0476	
$\times (\max(P) - \min(P))^{-1}$	Max(P)	−0.038		−0.033			−0.0476	
$P = \gamma \times \beta^{-1} \times ((\text{age} - \alpha)/\beta)^{\gamma-1}$	α	11		10			8	
$\times \exp(-((\text{age} - \alpha) \times \beta^{-1})^{\gamma})$	β	22		25			17	
	γ	2		2			2	
Storage (growth)	Age restriction					Age < 33		33 ≤ Age
$G_F = a \times (\text{age} - d)^c$	a	3.9		4.5		1.4		1.4
$\times ((\text{age} - d)^c + b^c)^{-1}$ [Eq. (1)]	b	17		23		14		14
	c	4		3		5		−2
	d	0		0		0		32
$G_B = e \times f^g \times g \times \text{age}^{g-1}$	e	40		31			12	
$\times (\text{age}^g + f^g)^{-2}$ [Eq. (2)]	f	20		23			20	
	g	2		3			4	
Storage (branch death)	Age restriction		Age ≤ 3		3 < Age ≤ 21	Age ≤ 3	3 < Age ≤ 21	50 < Age
$D_B = h \times (\text{age} - k)^j$	h	0.3	0		0.45	0	0.15	1
$\times ((\text{age} - k)^j + i^j)^{-1}$ [Eq. (5)]	i	17			23		14	0
	j	4			3		5	
	k	0			3		3	
	Age restriction			21 < Age			21 < Age ≤ 50	
$D_B = l \times m^n \times n \times (\text{age} - o)^{n-1}$	l			52			120	
$\times ((\text{age} - o)^n + m^n)^{-2}$ [Eq. (6)]	m			25			40	
	n			2.4			6	
	o			21			0	
Decomposition	k for 1 h F	0.455		0.313			0.313	
$= \exp(-k \times \text{time})$ [Eq. (7)]	k for 10 h F	0.090		0.038			0.038	
	k for 100 h F	0.064		0.021			0.021	

G_F and G_B were the generic functions for foliage and branch growth (Mg ha^{-1}), respectively, shown as the allocation from the aboveground net primary production (ANPP; Mg ha^{-1} year^{-1}). D_F and D_B represented the generic functions for foliage and branch death (Mg ha^{-1}), respectively, which were biomass reallocation from live foliage to dead foliage and live branch to dead branch, respectively. There was more than one equation in D_B to represent the self-thinning process and early growth stage. HW, RP, and JP were abbreviations for hardwood, red pine, and jack pine ecosystems, respectively. One hour fuels (1 h F; Mg ha^{-1}), 10 h fuels (10 h F; Mg ha^{-1}), and 100 h fuels (100 h F; Mg ha^{-1}) were fuel classification by fuel size; 1 h F (<0.6 cm in diameter), 10 h F (>0.6 and <2.5 cm in diameter), and 100 h F (>2.5 and <7.5 cm in diameter). The unit of k is year^{-1}.

compare the total fuel loading during simulation. Fuel loading and harvested biomass of each scenario was compared to the control (no prescribed burning): the relative fuel loading (or harvest biomass) (%) = fuel loading (or harvest biomass) from each scenario/fuel loading (or harvest biomass) from control × 100. Analysis of variance (ANOVA) was conducted on mean values of each run (total 1800) to evaluate the effects of various ROT, MAG, and DUR on fuel loading and timber production for each ecosystem type (S-plus, Insightful Corp., Seattle, WA, USA). Harvesting rotations were assumed as 50, 80, and 80 years for jack pine, red pine, and hardwood, respectively (USDA Forest Service, 1986). Harvested stem biomass was estimated and recorded. Post harvesting treatment (i.e., slash removal) is applied commonly in the CNF; 80% of 100 h fuels were removed from the dead fuel pool to represent the post harvesting treatment.

2.5. *Model validation*

The main purpose of the model was to evaluate the interaction between disturbance and productivity on fuel loading in the hardwood, red pine, and jack pine forests in the CNF. Fuel loading on the forest floor was collected and compared with simulated fuel loading estimates under control conditions (i.e., average mortality, no disease, and no fire) for validation. We chose stand ages of 4, 6, 15, 30, 50, and 63-year-old for the hardwood; 12, 17, 30, 32, 50, and 63-year-old for red pine, and 13, 17, 26, and 44-year-old for jack pine. In addition to age class, we did not observe any fire occurrence (e.g., charcoal in the forest floor or scorch on the stem) in those stands. Four 1 m × 1 m plots were installed at each stand for collecting 10 h fuel and three 10 cm × 10 cm subplots were set up for each plot for collecting 1 h fuel. Additionally, fuel loading data was provided by local forest service office, which included age class and cover type information. Forest Service provided five data sets: two hardwood, two red pine, and one jack pine forests. Collected samples were dried (48 h, 65 °C), and the dry weight was compared with the simulated result for a validation.

2.6. Sensitivity analysis

A sensitivity analysis was performed to quantify the relative importance of sensitivity in parameter estimates on predicting fuel loads. The parameters used included maximum ANPP, decay rates (1, 10, and 100 h F), and carbon allocation (Eqs. (1) and (2)). The main purpose of sensitivity analysis in this study was to evaluate the importance of carbon allocation on the fuel loads and timber production. Sensitivity analysis of original model (Ryu et al., 2004) showed that maximum ANPP and decay rate were the parameters impacting the fuel loads the most. For the analysis, 51 values of each parameter were randomly selected with 20% standard deviation using sensitivity analysis routines in Stella. To test the sensitivity of carbon allocation equations, we generated random numbers, which has a mean of 1 with standard deviation of 0.2, to multiply with results of allocation equation. We found no correlation between parameters sets. Each run was conducted for 400 years with 80 years harvesting rotation in hardwood forest. Mean fuel loads were calculated for each run, then ANOVA was conducted to determine the relative contribution of each parameter to model prediction; the type II partial sums of squares for each parameter were interpreted as an indicator showing the relative contribution of a parameter to total variation in fuel loads (Moorehead and Reynolds, 1991). Only the most relevant decay rate was considered for each fuel type in each ANOVA model; 1, 10, and 100 h F decay rates for 1, 10, and 100 h F, respectively.

3. Results

The predicted fuel loading showed good linear relationship ($r^2 = 0.94$) with the measured fuel loading, but the linear relationship was slightly off from the 1:1 line (slope = 0.86–1.17) (Fig. 3). EcoFL slightly underestimated 1 h fuel (1 h F; slope = 0.86), but the model slightly over-predicted 10 h fuel (10 h F; slope = 1.17) and 100 h fuel (100 h F; slope = 1.04) (Fig. 3).

Sensitivity analysis revealed that maximum ANPP, carbon allocation, and decay rates explained 89.1, 87.7, and 93.1% of variance in 1, 10, and 100 h F, respectively. The impact of parameter estimates on the fuel loads varied by fuel types. One hour fuel was the most sensitive to changes in carbon allocation to foliage (G_F; Eq. (1)), which explained the 44.5% of model variation in 1 h F, and 1 h F decay rate explained the model variation in 1 h F the second most (43.3%). Ten hours fuel was the most sensitive to changes in 10 h F decay rate, which explained 56.6% of model variation in 10 h F. Changes in carbon allocation to tree branches (G_B; Eq. (2)) explained 29.8% of model variation in 10 h F. Hundred hours fuel was the most sensitive to maximum ANPP, which explained 49.2% of model variance in 100 h F, and 100 h F decay rate explained the model variation in 100 h F the second most (36.4%).

3.1. Prescribed burning and fuel loading

The 1, 10, and 100 h F were affected the most by ROT among all factors and interactions in hardwood, red pine, and jack pine forests (Table 3). In multiple regression analysis, ROT had the largest parameter estimates among ROT, MAG, and DUR, which indicated that ROT affected fuel loading the most among three variables (Table 4). Developed multiple regression equations explained more than 86.0% of variation in fuel loading (Table 4). Increases in MAG and DUR reduced the relative fuel loading of 1, 10, and 100 h F up to 9.1, 4.9, and 7.4%, respectively, while the decreases in ROT lowered the relative fuel loading of 1, 10, and 100 h F by 19.5–35.2, 37.1–46.7, and 33.6–40.5%, respectively. Because the effect of ROT on the fuel loading was greater than that of MAG and DUR, relative fuel loading seemed aggregated by ROT (Fig. 4). Fuel loading was reduced more with shorter ROT, higher MAG, and longer DUR (Fig. 4).

Prescribed burning reduced relative fuel loading of 1 h F by 7.7–37.9, 10.9–49.6, and 7.2–39.6% in hardwood, red pine, and jack pine forests, respectively (Fig. 4). Relative fuel loading of 10 h F was decreased by 16.9–66.3, 28.6–72.9, and 36.3–79.0% in

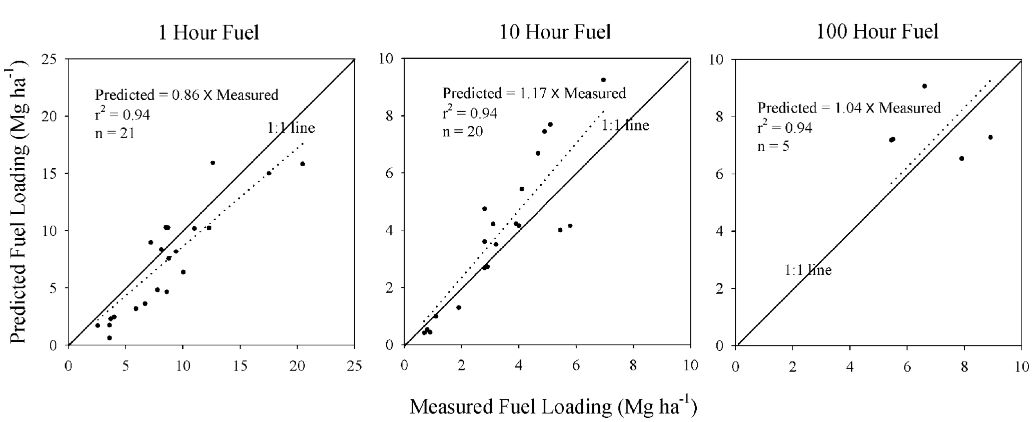

Fig. 3 – The relationship between measured and predicted fuel loading on forest floor in studied hardwood, red pine, and jack pine forests in Northern Wisconsin. About 1, 10, and 100 h fuels were fuel classification by size; 1 h fuels (Mg ha^{-1}; <0.6 cm in diameter), 10 h fuels (Mg ha^{-1}; >0.6 and <2.5 cm in diameter), and 100 h fuels (Mg ha^{-1}; >2.5 and <7.5 cm in diameter).

hardwood, red pine, and jack pine forests, respectively (Fig. 4). Relative fuel loading of 100 h F was reduced by 18.9–60.4, 36.5–78.9, and 37.6–78.5% in hardwood, red pine, and jack pine forests, respectively (Fig. 4). Relative fuel loading of 1 h F was reduced the least by the changes in ROT, MAG, and DUR among three fuel loading types (Fig. 4). The relative fuel loading generally reduced with increases in MAG and DUR, but sometimes it did not decrease consistently with increases in MAG and DUR in 100 h F (Fig. 4).

3.2. *Prescribed burning and harvested biomass*

Harvested biomass was mostly affected by ROT in hardwood, red pine, and jack pine forests (Table 3). In multiple regression analysis, DUR had the largest parameter estimates among ROT, MAG, and DUR, which indicated that ROT affected harvested biomass the most among three variables (Table 4). Developed multiple regression equations explained more than 76.0% of variation in harvested biomass (Table 4).

Relative harvested biomass was reduced by <10.0% under 15 and 20 years ROT under any combination of MAG and DUR. Harvested biomass decreased most with 5 years ROT and 30.0% MAG scenario; the decreased amount was more than twice of that under scenarios with 15 and 20 years ROT (Fig. 4). Harvested biomass was 82.1, 69.6, and 74.5% of the control in hardwood, red pine, and jack pine forests under the shortest ROT (5 years), highest MAG (30.0%), and longest DUR (5 years). We found that harvested biomass decreased abruptly under the shortest ROT and highest MAG (Fig. 4).

4. Discussion

We developed a fuel loading prediction model (EcoFL), which quantified the fuel loads at the ecosystem level using a classical ecosystem productivity concept (Odum, 1969) and aboveground biomass measurements. EcoFL predicted fuel loading with high precision ($r^2 = 0.94$) (Fig. 3). We used ecosystem level

Table 3 – Results of analysis of variance for three ecosystem types in evaluating the effect of prescribed burning rotation (ROT), magnitude of productivity reduction by prescribed fire (MAG), and the duration of productivity reduction (DUR) on fuel loading and harvested biomass

Variables	d.f.	Hardwood sum of square	Red pine sum of square	Jack pine sum of square
1 h fuel				
ROT	1	241.8**	843.0**	48.1**
MAG	1	32.4**	80.9**	6.6**
DUR	1	19.2**	47.5**	3.7**
ROT × MAG	1	24.1**	82.4**	5.0**
ROT × DUR	1	9.4**	32.5**	2.3**
MAG × DUR	1	0.8**	9.1**	0.2**
Residuals	603	58.9	199.4	13.0
10 h fuel				
ROT	1	23.0**	91.6**	276.3**
MAG	1	1.3**	8.9**	32.4**
DUR	1	0.8**	5.9**	18.4**
ROT × MAG	1	2.2**	14.2**	53.0**
ROT × DUR	1	0.9**	6.1**	25.9**
MAG × DUR	1	0.6**	3.8**	18.2**
Residuals	603	4.8	27.7	116.8
100 h fuel				
ROT	1	57.9**	195.7**	619.2**
MAG	1	4.7**	26.2**	70.9**
DUR	1	3.1**	15.8**	43.1**
ROT × MAG	1	6.7**	39.7**	131.9**
ROT × DUR	1	3.1**	17.8**	61.5**
MAG × DUR	1	1.4**	10.6**	41.0**
Residuals	603	18.0	97.4	251.2
Harvested biomass				
ROT	1	165610.2**	115412.3**	198527.3**
MAG	1	180458.0**	115354.9**	208403.9**
DUR	1	108284.5**	76191.8**	107900.8**
ROT × MAG	1	35749.6**	25912.4**	43518.2**
ROT × DUR	1	12378.5**	8526.6**	20543.1**
MAG × DUR	1	31424.0**	22270.9**	26498.6**
Residuals	603	60711.9	42287.9	76296.2

One, 10, and 100 h fuels were fuel classification by size; 1 h fuels (Mg ha^{-1}; <0.6 cm in diameter), 10 h fuels (Mg ha^{-1}; >0.6 and <2.5 cm in diameter), and 100 h fuels (Mg ha^{-1}; >2.5 and <7.5 cm in diameter).

** Significant difference at $p = 0.01$.

Table 4 – Results of multiple regression analysis for three ecosystem types in evaluating the relationship of fuel loads and timber production with prescribed burning rotation (ROT), magnitude of productivity reduction by prescribed fire (MAG), and the duration of productivity reduction (DUR) fuel loading and harvested biomass; Fuel loading or timber production = *f*(ROT, MAG, DUR)

Forest types	Variables	Parameter estimates			Intercept	r^2	p
		ROT (year)	MAG (%)	DUR (year)			
Hardwood	1 h[a]	1.455	−0.178	−0.839	71.181	0.885	>0.001
	10 h[a]	2.924	−0.110	−0.483	30.271	0.954	>0.001
	100 h[a]	2.370	−0.127	−0.336	40.182	0.933	>0.001
	Timber	0.382	−0.206	−1.021	98.206	0.779	>0.001
Red pine	1 h[a]	2.028	−0.168	−0.777	55.724	0.910	>0.001
	10 h[a]	2.528	−0.117	−0.606	25.410	0.967	>0.001
	100 h[a]	2.382	−0.124	−0.540	19.421	0.972	>0.001
	Timber	0.658	−0.338	−1.770	97.148	0.765	>0.001
Jack pine	1 h[a]	1.490	−0.180	−0.906	70.357	0.867	>0.001
	10 h[a]	16.89	2.477	−0.105	−0.373	0.972	>0.001
	100 h[a]	2.428	−0.090	−0.443	17.385	0.977	>0.001
	Timber	−0.297	0.561	−1.451	97.389	0.779	>0.001

One, 10, and 100 h fuels were fuel classification by size; 1 h fuels (Mg ha^{-1}; <0.6 cm in diameter), 10 h fuels (Mg ha^{-1}; >0.6 and <2.5 cm in diameter), and 100 h fuels (Mg ha^{-1}; >2.5 and <7.5 cm in diameter). Timber indicates the harvested stem biomass during simulation.

[a] Fuel loading.

aboveground productivity dynamics for developing model. This simple approach allowed reducing parameter needs for estimating ANPP. Reducing the number of parameter was important for this study, because EcoFL was created to show the possibility of developing a parameter-scarce simple model and less parameter was more advantageous to develop a landscape level model (Levin, 1992).

Sensitivity analysis of EcoFL indicated that carbon allocation was as important as productivity and decomposition in fuel loading (Ryu et al., 2004). Additionally, it indicated that carbon allocation had to be parameterized accurately to reduce model error. Carbon allocation routines in EcoFL were parameterized using aboveground biomass, which is relatively easy to measure. These empirical carbon allocation routines will help apply EcoFL to other ecosystems with little effort in parameterization of carbon allocation.

EcoFL fuel loading prediction and field measurements was slightly off from 1:1 line (Fig. 3), and it could be related to an improper model parameter (e.g., decay rate), disturbances history in the sampling plots, and spatial variation of fuel loading. EcoFL has potential to be used for evaluating the effect of various disturbances (e.g., thinning, alternative mortality, post harvest treatment, harvesting age) on fuel loading. Moreover, EcoFL provides the dynamics of fuel loading, which allows estimation of fuel loading by age, forest type, and disturbance history, which will helpful to management. The output of EcoFL can be used as an input data for fire spread prediction models (e.g., FARSITE), and will allow us to evaluate the effect of various landscape structure and/or disturbance history on fire spreading in landscape level.

Although prescribed burning is used extensively in forestry practices, the effects of prescribed burning on the fuel loading or other ecological properties have rarely been quantitatively modelled. Additionally, the economical perspective of prescribed burning has not been thoroughly understood (Hesseln, 2000), and the effect of prescribed burning on timber production is not well understood (Landsberg et al., 1984; Boyer, 1993; Landsberg, 1994; Busse et al., 2000). The developed EcoFL model helped evaluate the possible effect of prescribed burning on the fuel loading and timber production. Moreover, we was able to generate a multiple regression equation (Table 4) evaluating the effect of prescribed burning on the fuel loading and timber production, and it would be useful information for forest managers for quick reference.

Our results showed that the duration (DUR) of productivity reduction by prescribed burning would be the most critical information when deciding the prescribed burning rotation (ROT) in order to preserve timber production and to maintain low fuel loading. After understanding DUR, benefit and cost of prescribed burning can be precisely estimated. We found that harvestable biomass decreased more rapidly when ROT became shorter. For example, harvested biomass reduced up to 17.9, 30.4, and 25.5% for hardwood, red pine, and jack pine forests, respectively, with 5 years ROT (Fig. 4). Our results implied that forest productivity could reduce drastically to decrease large amount of timber production, if ROT was shorter than DUR and ecosystem productivity was affected cumulatively by prescribed burning on the assumption that forest productivity recovered linearly after prescribed burning. Previous studies (Sutherland et al., 1991; Boyer, 1993; Boyer and Miller, 1994; Busse et al., 2000) have reported varying degrees of basal area or biomass reduction due to the implementation of prescribed fire in various regions. We derived a similar conclusion of high variation in the harvested biomass reduction (0.5–30.4%) from our simulation results, which showed the reliability of model results.

The simulation runs also revealed that prescribed burning was an effective tool for reducing fuel loading in hardwood, red pine, and jack pine forests. Our results clearly showed that ROT influenced the amount of fuel reduction most, when the fuel consumption rate was not changed. However, forest managers need to decide ROT by considering the

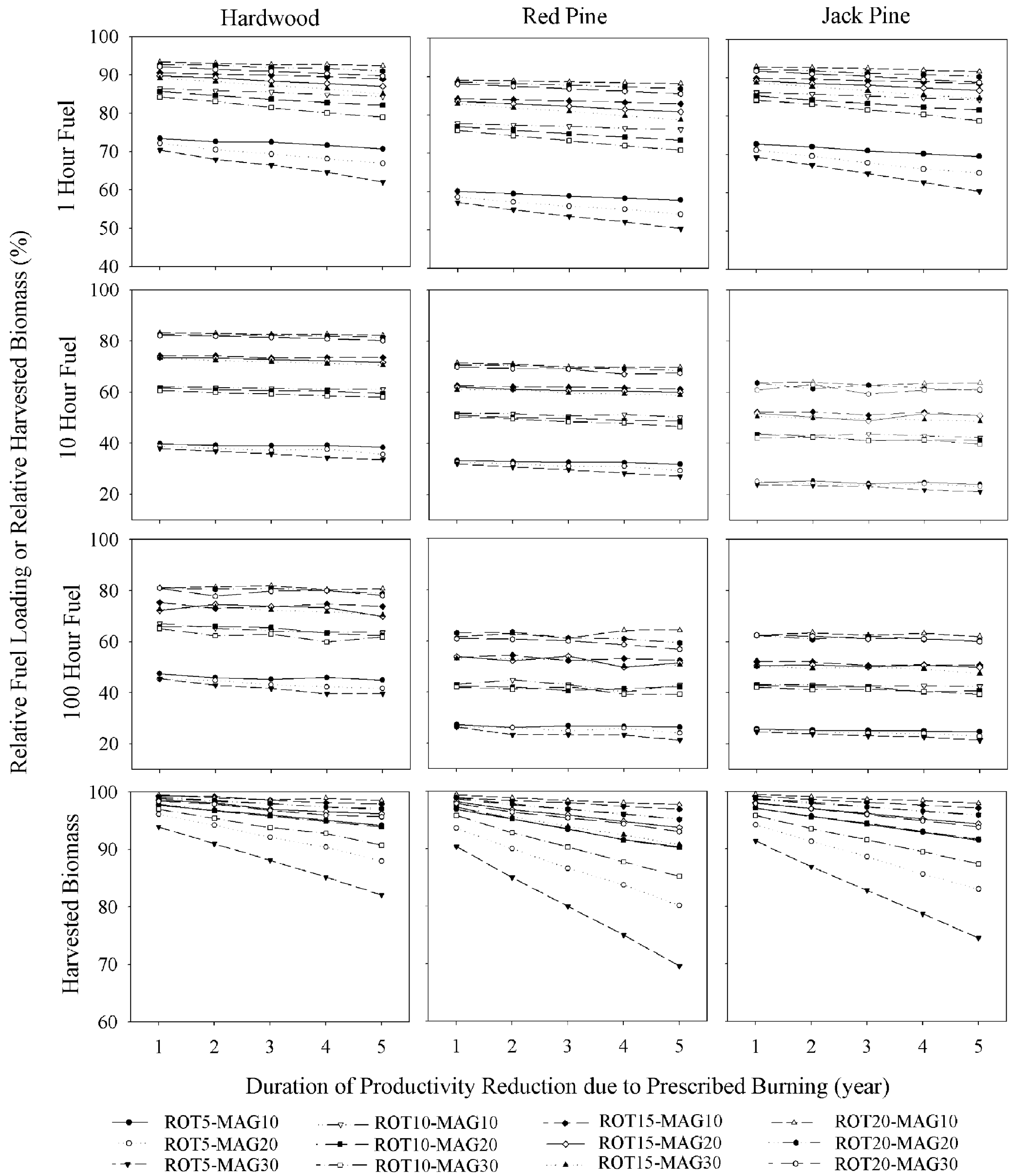

Fig. 4 – Relative fuel loading and harvested biomass (scenario/control × 100). The effects of prescribed burning on fuel loading and harvested biomass were tested under various prescribed burning rotation (ROT), magnitude of productivity reduction (MAG), and duration of productivity reduction (DUR) scenarios. ROT5, ROT10, ROT15, and ROT20 indicate 5, 10, 15, and 20 years of burning rotation. MAG10, MAG20, and MAG30 indicate 10, 20, and 30% productivity reduction after burning. Five DUR scenarios were also tested. Productivity reduction was assumed to be recovered to the control condition in a linear pattern; productivity recovery rate = MAG/DUR.

target fuel loading, as well as the ecological and economical perspectives (e.g., nitrogen cycling, and timber production). Specifically, long-term ecological impacts (e.g., biogeochemical cycling, fragmentation, and biodiversity) of prescribed burning need to be understood thoroughly before applying prescribed burning to large spatial scale (Amiro et al., 2001). Overall, the amount of fuel reduction was greater in pine than hardwood forests, suggesting that prescribed burning was more effective for fuel management in pine than hardwood forests (Fig. 4). Prescribed burning decreased 1 h F the least among three fuel types (Fig. 4), because 1 h F had a fast turnover rate due to high decomposition and high fuel input.

Carbon allocation patterns potentially vary after prescribed burning, and these changes in carbon allocation can potentially affect timber production. For example, if productivity reduced after prescribed burning and assimilated carbon were allocated to the crown first, stem growth would be even slower. Clearly, substantial field data is still needed to identify the productivity recovery pattern and duration, carbon allocation after burning, and long-term burning and productivity relationship for accurately predicting the effect of prescribed burning on timber production.

5. Conclusion and research needs

The goal of this study was to develop a simple, limited parameter, and ecosystem model. The resulting EcoFL model successfully predicts the aboveground carbon pools and fuel loading in three major forest types in northern Wisconsin. The sensitivity analysis showed the importance of carbon allocation in EcoFL model, and it will be important to parameterize carbon allocation routine properly to apply the model to other ecosystems. The simulation runs indicated that information on the magnitude and duration of productivity reduction by prescribed burning would be critical in order to preserve timber production with maintaining low fuel loading under frequent prescribed burns and to develop sustainable, economic, and efficient prescribed burning plan. Our results revealed that prescribed burning can be an effective tool for reducing fuel loading in hardwood, red pine, and jack pine forests, and it was more effective in pine forests than hardwood forests. Prescribed burning frequency decided the amount of fuel reduction when the fuel consumption rate by fire was not changed. The EcoFL will be a good academic tool for evaluating the interactions between disturbances and carbon pools in forest ecosystem. The results of this study will be a fundamental tool for forest managers when trying to balance timber production and fuel reduction when using prescribed burning. Further studies are needed to collect empirical data to assess the productivity recovery pattern, carbon allocation after burning, and long-term burning and productivity relationship for precise evaluation on the interaction of prescribed fire and forest productivity.

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REFERENCES

Aber, J., 1979. Foliage-height profiles and succession in northern hardwood forests. Ecology 60, 18–23.

Aber, J.D., Ollinger, S.V., Federer, C.A., Reich, P.B., Goulden, M.L., Kicklighter, D.W., Melillo, J.M., Lathrop, R.G., 1995. Predicting the effects of climate change on water yield and forest production in the northeastern United States. Clim. Res. 5, 207–222.

Allen, C.D., Savage, M., Falk, D.A., Suckling, K.F., Swetnam, T.W., Schulke, T., Stacey, P.B., Morgan, P., Hoffman, M., Klingel, J.T., 2002. Ecological restoration of southwestern ponderosa pine ecosystems: a broad perspective. Ecol. Appl. 12, 1418–1433.

Amiro, B.D., Stocks, B.J., Alexander, M.E., Flannigan, M.D., Wotton, B.M., 2001. Fire, climate change, carbon and fuel management in the Canadian boreal forest. Int. J. Wildland Fire 10, 405–413.

Berjak, S.G., Hearne, J.W., 2002. An improved cellular automaton model for simulating fire in a spatially heterogeneous Savanna system. Ecol. Model. 148, 133–151.

Bolster, K.L., Martin, M.E., Aber, J.D., 1996. Determination of carbon fraction and nitrogen concentration in tree foliage by near infrared reflectance: a comparison of statistical methods. Can. J. For. Res. 26, 590–600.

Boyer, W.D., 1993. Eighteen years of seasonal burning in longleaf pine: effects on overstory growth. Proceedings of the 12th Conference on Fire and Forest Meteorology, Jekyll Islands, GA. Soc. Am. For., 602–610.

Boyer, W.D., Miller, J.H., 1994. Effects of burning and brush treatments on nutrient and soil physical properties in young longleaf pine stands. For. Ecol. Manage. 70, 311–318.

Bresee, M., Le Moine, J., Mather, S., Brosofske, K.D., Chen, J., Crow, T.R., Rademacher, J., 2001. Disturbance and landscape dynamics in the Chequamegon National Forest Wisconsin, USA, from 1972 to 2001. Lands. Ecol. 19, 291–309.

Brosofske, K.D., Chen, J., Crow, T.R., Saunders, S.C., 1999. Vegetation responses to landscape structure at multiple scales across a Northern Wisconsin, USA, pine barrens landscape. Plant Ecol. 143, 203–218.

Brown, J.K., 1974. Handbook for Inventorying Downed Woody Material. USDA Forest Service, GTR INT-16.

Brown, J.K., See, T.S., 1981. Downed Dead Woody Fuel and Biomass in the Northern Rocky Mountains. USDA Forest Service, GTR INT-117.

Busse, M.D., Simon, S.A., Riegel, G.M., 2000. Tree-growth and understory responses to low-severity prescribed burning in thinned *Pinus ponderosa* forest of contral Oregon. For. Sci. 46, 258–268.

Carter, M.C., Foster, C.D., 2004. Prescribed burning and productivity in southern pine forests: a review. For. Ecol. Manage. 191, 93–109.

Covington, W.W., DeBano, L.F., Huntsberger, T.G., 1991. Soil N changes associated with slash pile burning in pinyon-juniper woodlands. For. Sci. 37, 347–355.

DeBano, L.F., 2000. The role of fire and soil heating on water repellence in wildland environments: a review. J. Hydrol. 231/232, 195–206.

Eberhardt, L.L., Thomas, J.M., 1991. Designing environmental field studies. Ecol. Monogr. 6, 53–73.

Euskirchen, E.S., Chen, J.Q., Li, H.B., Gustafson, E.J., Crow, T.R., 2002. Modeling landscape net ecosystem productivity (LandNEP) under alternative management regimes. Ecol. Model. 154, 75–91.

Green, D.G., 1989. Simulated effects of fire, dispersal, and spatial pattern on competition within forest mosaics. Vegetatio 82, 139–153.

Hargrove, W.W., Gardner, R.H., Turner, M.G., Romme, W.H., Despain, D.G., 2000. Simulating fire patterns in heterogeneous landscapes. Ecol. Model. 135, 243–263.

He, H.S., Shang, B.Z., Crow, T.R., Gustafson, E.J., Shifley, S.R., 2002. Simulating forest fuel and fire risk dynamics across landscapes-LANDIS fuel module design. Ecol. Model. 180, 135–151.

Hesseln, H., 2000. The economics of prescribed burning: a research review. For. Sci. 46, 322–334.

Ito, A., 2005. Modelling of carbon cycle and fire regime in an east Siberian larch forest. Ecol. Model. 187, 121–139.

Iverson, L.R., Yaussy, D.A., Rebbeck, J., Hutchison, T.F., Long, R.P., Prasad, A.M., 2004. A comparison of thermocouples and temperature paints to monitor spatial and temporal characteristics of landscape-scale prescribed fires. Int. J. Wildland Fire 13, 311–322.

Karafyllidis, I., Thanailakis, A., 1997. A model for predicting forest fire spreading using cellular automata. Ecol. Model. 99, 87–97.
Landsberg, J.D., 1994. A review of prescribed fire and tree growth response in the genus *Pinus*. Proceedings 13th Conference on Fire and Forest Meteorology. Soc. Am. For., 326.
Landsberg, J.D., Cochran, P.H., Finck, M.M., Martin, R.E., 1984. Foliar Nitrogen Content and Tree Growth After Prescribed Fire in Ponderosa Pine. USDA Forest Service Research Note, PNW-RN-412, pp. 15.
Levin, S.A., 1992. The problem of pattern and scale in ecology. Ecology 73, 1943–1967.
Lorimer, C.G., 1989. Relative effects of small and large disturbances on temperate hardwood forest structure. Ecology 70, 565–567.
Martin, J., Lorimer, C., 1997. How to Manage Jack Pine. UW-Madison Department of Forest Ecology and Management, Forestry Fact.
Martin, M.E., Aber, J.D., 1997. High spectral resolution remote sensing of forest canopy lignin, nitrogen, and ecosystem processes. Ecol. Appl. 7, 431–443.
McLellan, T.M., Aber, J.D., Martin, M.E., Melillo, J.M., Nadelhoffer, K.J., 1991. Determination of nitrogen, lignin, and cellulose content of decomposing leaf material by near-infrared reflectance spectroscopy. Can. J. For. Res. 21, 1684–1688.
Meentemeyer, V., 1978. Macroclimate and lignin control of litter decomposition rates. Ecology 59, 465–472.
Michner, W.K., 1997. Quantitatively evaluating restoration "experiments"; research design, statistical analysis, and data management considerations. Restor. Ecol. 5, 324.
Moorehead, D.L., Reynolds, J.F., 1991. A general model of litter decomposition in the northern Chihuahuan Desert. Ecol. Model. 56, 197–219.
Odum, E.P., 1969. The strategy of ecosystem development. Science 164, 262–270.
Radermacher, J.A. 2004. Forest structure and carbon allocation within and between two Northern-Mixed Hardwood Edges. Master of Science Thesis, The University of Toledo.
Pan, Y.D., Horn, J., Jenkins, J., Birdsey, R., 2004. Importance of foliar nitrogen concentration to predict forest productivity in the Mid-Atlantic region. For. Sci. 50, 279–289.
Raison, R.J., Khanna, P.K., Woods, P.V., 1985. Transfer of elements to the atmosphere during low-intensity prescribed fires in three Australian subalpine eucalypt forests. Can. J. For. Res. 15, 657–664.
Reich, P.B., Peterson, D.W., Wedin, D.A., Wrage, K., 2001. Fire and vegetation effects on productivity and nitrogen cycling across a forest-grassland continuum. Ecology 82, 1703–1719.
Ryan, K.C., 2002. Dynamic interactions between forest structure and fire behavior in boreal ecosystems. Silva. Fenn. 36, 13–39.
Ryu, S., Chen, J., Crow, T.R., Saunders, S.C., 2004. Available fuel dynamics in nine contrasting forest ecosystems in North America. Environ. Manage. 33, S87–S107.
Shang, B.Z., He, H.S., Crow, T.R., Shifley, S.R., 2004. Fuel load reduction and fire risk in central hardwood forests of the United States: a spatial simulation study. Ecol. Model. 180, 89–102.
Sutherland, E.K., Covington, W.W., Andariese, S., 1991. A model of ponderosa pine growth—response to prescribed burning. For. Ecol. Manage. 44, 161–173.
Taylor, A.H., Skinner, C.N., 2003. Spatial patterns and controls on historical fire regimes and forest structure in the Klamath Mountains. Ecol. Appl. 13, 704–719.
TerMikaelian, M.T., Korzukhin, M.D., 1997. Biomass equations for sixty-five North American tree species. For. Ecol. Manage. 97, 1–24.
Tiedemann, A.R., Klemmedson, J.O., Bull, E.L., 2000. Solution of forest health problems with prescribed fire: are forest productivity and wildlife at risk? For. Ecol. Manage. 127, 1–18.
Turner, M.G., Gardner, R.H., Dale, V.H., O'Neill, R.V., 1889. Predicting the spread of disturbance across heterogeneous landscapes. Oikos 55, 121–129.
USDA Forest Service, 1986. Chequamegon Forest Plan. Washburn Ranger District, Chequamegon National Forest, Washburn, WI.
Waltz, A.E.M., Fule, P.Z., Covington, W.W., Moore, M.M., 2003. Diversity in ponderosa pine forest structure following ecological restoration treatments. For. Sci. 49, 885–900.
Wan, S.H.D., Luo, Y., 2001. Fire effects on N pools and dynamics in terrestrial ecosystems: a meta-analysis. Ecol. Appl. 11, 1349–1365.
Weisberg, P.J., 2004. Importance of non-stand-replacing fire for development of forest structure in the Pacific Northwest, USA. For. Sci. 50, 245–258.
Wells, C.G., Campbell, R.E., DeBano, L.F., Lewis, C.E., Fredricksen, R.L., Franklin, E.C., Froelich, R.C., Dunn, P.H., 1979. Effects of Fire on Soil. Forest Service, GTR WO-7.
Yin, X.W., 1999. The decay of forest woody debris: numerical modeling and implications based on some 300 data cases from North America. Oecologia 121, 81–98.