RESEARCH

A sample article title

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Abstract

NASA's models that simulate nitrogen deposition predict that the rate will increase in the Los Angeles Basin over the next three decades (ORNL DAAC 2006). Due to the fact that this area is a nitrogen limited; these changes will the affect post-fire ecological recuperation in the Los Angeles Basin (Rundel and Parsons 1984; Rundel and Parsons 1980; Mark E. Fenn, Mark A. Poth, Susan L. Schilling, and David B. Grainger 2000). Wildfires radically change the environment and the subsequent recovery of a given ecosystem(CITE?). Following a fire several N parameters change abruptly. However, the long-term effects of a the variability of these parameters on postfire N dynamics remains unknown (Hannan 2017; ADD CITATION). We used the G-NIOM (Generalized Nitrogen Input-Output model) to evaluate future projections of recovery in post-wildfire ecosystem given the variability in climate over the next 30 years.

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Content

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Introduction

Wildfires play an important role in the development of worldwide ecology. The earliest known wildfires burnt during the late Silurian and have had important impacts on the evolutionary trajectory of Earth's ecosystems (Scott and Glasspool 2006; Edwards and Axe 2004). The projected increase in wildfires due to climate variability presents an important opportunity to model the parameters of wildfires in order to better understand their effects (Smithwick, Turner 2005; Hanan 2017). To this end, our group combined our analysis with preexisting data and projections in order to provide a fuller understanding of the lasting impact of wildfires.

Fires present both prolonged and transient consequences for the long and short-term N dynamics through alteration and addition of N-parameters. It is necessary to distinguish the role that fire plays independently from the normal nitrogen cycle in order to measure their effects. Therefore, we considered the N-parameters that were altered after wildfires. As fire consumes above ground biomass, surface litter, and SOM, it results in volatilization and reincorporation of charred necromass and ash into the soil (Knicker 2007;Raison 1979; Smithwick, Turner 2005). After wildfires the N-parameters that are responsible nitrogen flux include nitrogen deposition, nitrogen from rainfall, nitrogen transformations, leaching, soil erosion, plant uptake, microbial immobilization, and spatial heterogeneity(Wan, Hui, Luo 2001; Smithwick, Turner 2005).

The export of N due to volatilization is highly correlated with severity of wildfires and the quantity and quality of the surrounding vegetation. N volatilization initiates at 200C, at temperatures greater than 500C half of N in the organic fraction of the soil is volatilized into the atmosphere as N2 (Knicker 2007). The composition of the ash and charred necromass is strongly influenced by maximum temperatures reached by the fire and the type of fuel that is being burnt.. Light to moderate burning may increase organic matter and N nutrient levels in the upper soil profile presumably as a result of addition and mixing of partially combusted material with the soil (Raison 1979; Kutiel, Navel 1986). We investigated the initial concentrations of nitrogen in the black, white, and grey ash. Precipitation particularly in chaparral ecosystems is a highly variable parameter that changes seasonally (Hannan 2017).

Precipitation as a nitrogen input after wildfires plays an important role in ecological restoration. Current trends suggest that rainfall patterns generally and specifically to the Los Angeles Basin will become more variable in the future which will alter the rate of ecological restoration in chaparral environments after wildfires (Hannan 2017; Sawyer, Hooper, Safford 2014).

Erosion after wildfires increases due to the removal of protective vegetation cover and the alteration of soil's intrinsic chemical and physical properties (Shakespy 2011;Prosser and Williams 1998). The degree of erosion depends on the slope, the severity of the burn, the surrounding vegetation, and the predominant geology (Knicker 2007;Shakespy 2011;Debano and C.E. Conrad 1978). The major pathways for nitrogen loss are driven by rainwater, mass movement, and wind. Due to the limited literature on the later two phenomenon quantifying them remains challenging. However, as a driver rainwater results in two major pathways of nitrogen loss. The first is the loss of debris and the loss of the rainwater itself from a system from runoff water (Debano and C.E. Conrad 1978).

Transformations of nitrogen post fire also can contribute to its short and long term dynamics. In particular, after fires n-fixation is stimulated after wildfires(Raison 1979;Smithwick, Turner 2005) which provides an import input for post-wildfire ecosystems. The N parameter that this study is most concerned with is N deposition. Our study is located in the Los Angeles Basin. The area's urbanization and heavy reliance on automobiles has resulted in increases in the rate of N-deposition (ORNL DAAC 2006). This increased input over time will affect the N-input output space in the Los Angeles basin for both undisturbed and post-wildfire soils.

The effects of climate patterns on postfire N dynamics are poorly understood. Although an abundance of literature exists regarding impact of N-parameters on post-fire ecosystems, long-term projections are undetermined. In order to understand the influence of N-parameters on the wildfire recuperation it is necessary to develop quantitative understanding of their rates and their how they interact.

Generalized modeling techniques provide insight into a gamut of possible post-fire scenarios. Given the complexity of the processes which take place after fires discrepant accounts are reported (Wan, Hui, Luo 2001). The challenge of modeling is to provide generalized parameters that can accommodate these discrepancies while simultaneously maintaining the robustness of the results. The model that we propose is able to build from the fundamental ecological processes which govern

N-regulation while also synthesizing new projections of climatic variability in order to project the recovery into the future.

G-NIOM Model

G-NIOM is an input-output model that has been created in order to simulate large scale nitrogen regeneration after wildfires by using generalized N-parameters. Unlike previous models that utilized constant rates of Nitrogen Deposition (Hannan 2016) our model projects into the future with a varying rate of N-deposition.The assimilation of N parameters of differing rates gives rise to a system of first-order linear differential equation that measures N-flux. The first differential equation measures the rate inside of the fire perimeter whereas the second differential equation measures the rate outside of the fire perimeter.

Let N(t) be the amount of nitrogen at a given location. Let M be the flux of a given N-parameter inside of the fire perimeter and let $M^{'}$ be the flux of a given N-parameter outside of the fire perimeter. An outflux will carry a negative sign while an influx will carry a positive sign.

$$\begin{cases} \frac{dN}{dt}_{insidefireperimeter} = \sum_{i=1}^{j} M_i \\ \frac{dN}{dt}_{outsidefireperimeter} = \sum_{i=1}^{j} M_i^{'} \end{cases}$$

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Sub-sub-sub heading for section Text for this sub-sub-sub-heading . . . In this section we examine the growth rate of the mean of Z_0, Z_1 and Z_2. In addition, we examine a common modeling assumption and note the importance of considering the tails of the extinction time T_x in studies of escape dynamics. We will first consider the expected resistant population at vT_x for some $v > 0$, (and temporarily assume $\alpha = 0$)

$$E\big[Z_1(vT_x)\big] = E\left[\mu T_x \int_0^{v\wedge 1} Z_0(uT_x)\exp\big(\lambda_1 T_x(v-u)\big)\,du\right].$$

If we assume that sensitive cells follow a deterministic decay $Z_0(t) = xe^{\lambda_0 t}$ and approximate their extinction time as $T_x \approx -\frac{1}{\lambda_0}\log x$, then we can heuristically estimate the expected value as

$$\begin{aligned} E\big[Z_1(vT_x)\big] &= \frac{\mu}{r}\log x \int_0^{v\wedge 1} x^{1-u} x^{(\lambda_1/r)(v-u)}\,du \\ &= \frac{\mu}{r} x^{1-\lambda_1/\lambda_0 v}\log x \int_0^{v\wedge 1} x^{-u(1+\lambda_1/r)}\,du \\ &= \frac{\mu}{\lambda_1-\lambda_0} x^{1+\lambda_1/rv}\left(1-\exp\left[-(v\wedge 1)\left(1+\frac{\lambda_1}{r}\right)\log x\right]\right). \quad (1) \end{aligned}$$

Thus we observe that this expected value is finite for all $v > 0$ (also see [1, 2, 3, 4, 5]).

Competing interests
The authors declare that they have no competing interests.

Author's contributions
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Figures

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Tables

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