Structure and Function in Degraded Forests in the Amazon from Multi-source Remote Sensing

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Thesis submitted in fulfilment of the requirements for the degree of

Doctor of Philosophy

under the supervision of Distinguished Professor Alfredo Huete

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Certificate of Original Authorship

I, Ekena Rangel Pinagé, declare that this thesis is submitted in fulfilment of the requirements for the award of the degree of Doctor of Philosophy, in the Faculty of Science at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise reference or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by an Australian Government Research Training Program.

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Abstract

Tropical forests provide critical ecosystem services for global climate and biodiversity, and sustain the livelihoods of millions of people. Yet, they have become hotspots of land-use change. The Southern border of the Brazilian Amazon has been a focus of land development with large swaths of tropical forests converted to agriculture. Degradation of forests by selective logging and fires has accompanied the advance of the frontier and has resulted in significant impacts on Amazonian ecosystems. While the agricultural use in the region is well quantified, forest degradation is more challenging to study. Given that changes in tree cover and structure have large impacts on forest function, there is an urgent need to quantify these properties for degraded forests.

The overarching goal of this thesis is to investigate the functional and structural linkages in degraded forests in the Amazon and assess whether forest structure mediates forest responses to disturbance. To achieve this goal, I (1) compared phenological patterns of intact and degraded forests using time-series of spectral indices; (2) examined the relationship between forest structure and photosynthesis across a gradient of forest degradation, by integrating structural variables and solar-induced fluorescence (SIF) data; and finally, (3) investigated the influence of forest structure on evapotranspiration and land surface temperature. These broad thesis objectives were accomplished using multi-source remote sensing (MODIS, Landsat and TROPOMI SIF satellite data combined with airborne and orbital lidar observations) and statistical methods.

My results showed that fires had a stronger effect than selective logging on ecosystem functioning (e.g., stronger phenological shifts and alterations in evapotranspiration and land surface temperature) and caused more dramatic changes in forest structure (e.g., lower forest canopy and leaf area index, more abundant understory). I also found that shifts in ecosystem functioning related to forest degradation were exacerbated by the dry season in the study region. Finally, I found that the most heavily disturbed forests presented strong structure-function relationships that do not hold in the least disturbed forests, suggesting that forest structure acts as a mediator of forest recovery.

My findings help to elucidate the effects of human-induced disturbances in ecosystem fluxes and can inform public policy related to forest management and land use planning. Besides, my results provide inputs regarding the role of phenology and forest structure in degraded forests for ecosystem demography models. The importance of this research is underscored by the recent surge in deforestation in the Brazilian Amazon and associated forest fires.