Early indications of effectiveness in California's forest offset program

By

Jared Richard Stapp

A dissertation submitted in partial satisfaction of the
requirement for the degree of
Doctor of Philosophy
in
Environmental Science, Policy, and Management
in the
Graduate Division
of the
University of California, Berkeley

Committee in charge:
Professor Van Butsic, Chair
Professor Matthew D. Potts
Professor Jeffrey Q. Chambers
Dr. Matthias Baumann

Spring 2022

Early indications of effectiveness in California's forest offset program

by

Jared Richard Stapp

Abstract

Early indications of effectiveness in California's forest offset program

by

Jared Richard Stapp

Doctor of Philosophy in Environmental Science, Policy, and Management

University of California, Berkeley

Professor Van Butsic, Chair

Carbon offsets are widely promoted as a strategy to lower the cost of emission reductions and combat climate change. However, there is limited empirical evidence suggesting that offsets causally reduce emissions by the amount claimed. When sold into a compliance market, offsets will increase net emissions if they do not reflect real reductions beyond the baseline scenario. Here I introduce California's *U.S. Forest Projects Compliance Offset Protocol* and consider the role of additionality in this program.

Chapter 1, "*An overview of forest offsets*," introduces forest offsets as a policy mechanism for combating climate change, focusing in particular on California's *U.S. Forest Projects Compliance Offset Protocol* as one of the largest programs of its kind and Improved Forest Management (IFM) projects as the backbone of California's program. Research completed to date on California's program is reviewed, and challenges associated with measuring the effectiveness of offset programs like the California *U.S. Forest Projects Compliance Offset Protocol* are introduced. Literature reviews of modeling and remote sensing techniques used in past work are provided and approaches seen in later chapters of this dissertation to measure early indications of effectiveness in California's forest offset program are justified.

Chapter 2, "*Assessing participants of California's U.S. Forest Projects Compliance Offset Protocol*," creates an original database of information sufficient to assess IFM project participants in the program to date, including project characteristics, boundaries, and locations. A breakdown of the spatial, demographic, and geographic heterogeneity across projects is provided, and potential barriers to participation in the program based on characteristics of currently enrolled projects are discussed. Results suggest that projects owned by corporate and 'other' interests were most common; the majority of credits in California's program have been allocated to Tribal projects (48.4% of all credits), timber investment management organization (TIMO) and real estate investment trust

(REIT) projects (23.4% of credits) due in part to their larger size, and family landowners are underrepresented in California's offset program relative to private forest owners across the U.S. On average, across ownership classes, projects were stocked at carbon levels of 125% of common practice (the average standing live carbon of forests within the project's Supersection and Assessment Area).

Chapter 3, "*Quantifying historical disturbance rates using remote sensing*," uses remote sensing to create a unique database of harvest history on project and non-project regional lands to more comprehensively understand the IFM projects enrolled in California's forest offset program, where historical forest management-related disturbance serves as an indication that lands were at risk of harvest prior to project commencement. Combining harvest history with the project characteristics and locations introduced in Chapter 2 allows us to probe additionality of these projects. I find that IFM projects have been primarily allocated to forests with relatively low historical disturbance (28% less disturbance than regional averages since 1985). TIMO/REIT-owned forestlands had the largest discrepancy in annual disturbance rate between Supersections (0.43%) and projects (0.17%), followed by corporate-owned forestlands with 0.35% annual rate of disturbance on Supersections and 0.14% annual rate of disturbance on projects. Tribal lands experienced the lowest annual rates of disturbance for both projects and Supersections, with the project rate (0.17%) higher than the Supersection rate (0.1%; $p < 0.001$).

Chapter 4, "*Measuring offset policy effectiveness using quasi-experimental econometric techniques*," I empirically examine the additionality of forest offset projects early in California's offset program by quantifying the impacts of forest offset projects on forest disturbance associated with carbon emissions. While the additionality of forest offset projects is determined by emission reductions over the 100-year project lifespan, optimal management may require early management decisions resulting in disturbance to facilitate improved long-term forest management, I propose that short-term additionality can serve as an early indicator of policy effectiveness. Two novel datasets—project boundary data (Chapter 2) and remotely sensed forest disturbance data (Chapter 3)—provide sufficient temporal and spatial heterogeneity to apply quasi-experimental statistical matching and panel regression techniques to estimate additionality. This analysis suggests limited additionality in enrolled projects, as the creation of forest offset projects did not significantly lower forest disturbance rates 3 and 5 years after project implementation relative to similar non-project lands. These results indicate that California's forest offset protocol may be contributing to an increasingly large carbon debt.

Results suggest that, to date, California's offset program has selected IFM projects that have experienced relatively low disturbance rates over the past 36 years. As such, projects have much higher levels of aboveground carbon stocking than the average stocking within their respective Supersections. If these carbon-rich forests were threatened with harvest, they might be suitable choices for offsetting. These findings, however, suggest that many of the areas offset may have faced little threat of forest harvest in the absence of California's offset program and are therefore non-additional in the short term. Because California's *U.S. Forest Projects Compliance Offset Protocol* is compliance-based, unless the management of offsets changes in the future, the policy may be creating a carbon debt and potentially leading to increased carbon in the atmosphere relative to other carbon reduction policies and initiatives. Altogether, results indicate opportunities to improve California's existing forest offset protocol, particularly in its process of establishing initial carbon baselines. This dissertation concludes with recommendations stemming from this early evaluation of effectiveness in California's forest offset program.

Contents

List of Tables

List of Figures

Acronyms and Definitions

Acronyms

GHG: Greenhouse gas CO2; carbon: Carbon dioxide

CARB: California Air Resources Board

IFM: Improved Forest Management

USFS: US Forest Service

EPA: Environmental Protection Agency

NGO: Non-governmental organization

TIMO: Timber investment management organizations

REIT: Real estate investment trusts

NIPF: Non-industrial private forest landowners

FIA: Forest Inventory and Analysis National Program

SES: Social-ecological systems

CHANS: Coupled human and natural systems

LTS: Landsat Time Series

GEE: Google Earth Engine

GFW: Global Forest Watch

NBR: Normalized Burn Ratio

PDSI: Palmer Drought Severity Index

SMD: Standardized mean difference

SE: Standard error

p = p-value statistic

Definitions

Carbon stocking: The amount of carbon stored in a carbon sink (e.g., the amount of carbon sequestered in one acre of a forest).

Project area: The land located within the boundaries of a forest offset project.

Supersection: Regional delineations based on similar ecosystem types, equivalent to the EPA's Ecoregions Level III designations. Supersections are used by CARB to establish whether a project's baseline carbon stocking is above or below the average in a similar region.

Common practice: The average standing live carbon of forests within the project's Supersection and Assessment Area. Carbon stocking on proposed project areas is compared to the common practice statistic by CARB to calculate credits.

Improved forest management projects: Offset projects that employ conservation-oriented practices to increase the project land's capacity to sequester carbon.

Additional: Changes in land use due to an additional offset project are motivated by the establishment of the project and would not have otherwise existed in a business-as-usual scenario.

Acknowledgments

I feel grateful to have had the opportunity to work closely with so many incredible students, mentors, and faculty at Cal and for their wisdom, support, and encouragement throughout my Ph.D. I am especially grateful to Van Butsic for his guidance, expertise, and patience. Van has always created space for me to pursue research questions that I felt excited to dive into and has always been available to help me explore them. I feel proud to be a part of the Land Use Change Lab and look forward to collaborating throughout my career. Thank you also to Jeff Chambers, who, after taking his remote sensing class in my first year, saw that I shared his excitement for this work, welcomed me into his lab, and encouraged me to explore new methods, get out into the field, and enjoy this work. He has been a great mentor and collaborator to me, and I look forward to getting back outside and continuing our work in the Sierras soon. Thank you to Matthew Potts for helping me throughout my Ph.D. career and being one of the first who encouraged me to pursue a project about forest carbon offsets. Thank you to Matthias Baumann and everyone in the Geography Department at Humboldt University in Berlin. My semester working with Matthias, Christian Levers, and Tobias Kuemmerle was a highlight of my Ph.D., and I look forward to continuing to work with them in the future. Thank you also to Jonas Meckling for giving me so much of your time to help me prepare for my exams and for giving me a foundation in political economy that has greatly influenced this work and how I approach research. I am grateful for my colleagues at UC Berkeley, especially Katherine Siegel, Claudia Herbert, Kyle Hemes, Yanlei Feng, and Diana Moanga.

Thank you to my partner, Sydney Lolli, a gem in my life who has helped me throughout my Ph.D., even while I was writing a dissertation while quarantined at home during a two-year pandemic. Thank you to my little brother, Matthew Stapp, Ken and Melanie Light, and my border collie, Juni.

Chapter 1

Introduction

1.1 An overview of carbon offsets

Mitigating greenhouse gas (GHG) emissions and the risks associated with climate change are among the most pressing challenges society faces today (IPCC, 2021). Central to reaching climate change-related targets is reducing the amount of heat-trapping carbon dioxide (CO2; carbon, hereafter) in the atmosphere (Griscom et al., 2017; Lewis et al., 2019). Since the 1980s, forests and carbon offsets have both been discussed and utilized as tools to aid in mitigating catastrophic climate change: forests can serve as carbon sinks, while carbon offset programs provide a mechanism to ease the expense or complexity of reducing emissions (Brown & Adger 1994; Nature Editorial Board, 2021; Trexler et al., 1989; van der Gaast et al., 2016; Van Kooten & Johnston, 2016).

Emissions trading schemes: Cap-and-trade

While reducing global emissions is paramount, government mandates at the national or state level may significantly burden participating entities. Many economists and political scientists believe that carbon-pricing schemes represent the only realistic path to reaching emissions reduction targets (Stavins, 2011). Cap-and-trade programs gained popularity with the establishment of the Kyoto Protocol as a mechanism to provide economic incentives to reduce emissions, thereby reducing associated costs and facilitating progress toward emission reduction targets (Kossoy & Peszko, 2015; United Nations, 1998). Cap-and-trade systems set limits on the quantity of emissions that entities are permitted to emit over time and establish trading schemes that allow entities to purchase credits to account for a portion of their limit without directly reducing their emissions immediately.

Today, roughly 31 cap-and-trade programs have been planned or implemented worldwide (World Bank, 2020). The EU established the first large emissions trading scheme in 2005, with California following soon after in 2006 (Assembly Bill 32, or AB 32). New Zealand, Quebec, Ontario, and China represent other major global carbon markets. In the EU emissions trading scheme, entities are capped and can subsequently trade leftover allowances to other entities if they reduce emissions to a greater degree than required. While the EU scheme does not award carbon credits for carbon sinks like forests, the majority of existing schemes—including California's—include forest projects as a cost-effective carbon sink and mitigation measure, as forests have absorbed roughly twice as much carbon as they have emitted in the last decade by storing atmospheric carbon in biomass through photosynthesis (Harris et al., 2021; Ristea and Maness, 2009). Therefore, maintaining the carbon stored in Earth's forests is critical to avoiding catastrophic climate change (Goldstein et al., 2020, p. 287).

The role of forests in mitigating climate change

Forest projects are a direct target of climate commitments—as in the Bonn Climate Challenge, the UN Decade of Restoration, and the Trillion Tree Initiative—as well as a tool for entities to sponsor in order to meet their own climate commitments and requirements in large emissions trading schemes like that of California and New Zealand (Manley and Maclaren, 2012), and the pilot scheme in China (Zhang, 2015). Focusing on forest offsets within cap-and-trade systems creates a mutually beneficial situation in which entities can more easily and inexpensively meet their climate commitments while protecting or developing an effective carbon sink, contributing to the maintenance of biodiversity, and potentially reducing poverty by introducing local economic value to ecologically rich areas (Bushnell, 2012).

Forests, globally, serve as carbon sinks and provide potential low-cost options for lowering overall carbon emissions at state, national, and global scales (Amano & Sedjo, 2006; Galik et al., 2013). Slowing the pace of deforestation and forest degradation is argued to be among the most effective strategies for addressing climate change (Agrawal et al., 2014; Bosetti et al., 2011) because forests store significantly more carbon than other land use types, such as agriculture (Palm et al., 1999). In the US, roughly 310 million ha of forests hold roughly 40.9 billion metric tonnes of carbon (FAO and UNEP, 2020). California alone is home to 13.4 million ha of forests, roughly one-third of all land in the state. These forests are increasingly vulnerable to risks associated with climate change and anthropogenic drivers of forest change, raising the concern that these important carbon sinks could become carbon sources (FAO, 2015; Cohen et al., 2016; Poudyal et al., 2016).

Across global carbon pricing initiatives, forest credits comprised 42% of credits issued between 2015 and 2020 (World Bank, 2020). In interviews with experts representing major existing emissions trading schemes, Shrestha et al. (2021) found that forest offsets were perceived as more cost-effective targets for emissions trading schemes than solutions that may require more intensive research and development, such as carbon capture and storage technology, and efficient energy. Based on outputs from climate models, greater adoption of land use activities as a mechanism to meet global emissions reduction targets may reduce the cost of doing so by more than $2 trillion (Bosetti et al., 2011).

Furthermore, forest carbon offset projects are particularly appealing to those purchasing carbon credits, as noted recently by Gifford (2020, p. 294, referencing Wang & Corson 2015a; 2015b): "Buyers of forest carbon credits are drawn to the intangible benefits that come with the look of 'saving forests' or investing in sustainable development. Forests offer what Wang and Corson (2015a, 2015b) and others call 'charismatic carbon,' development interventions that bring offset buyers more 'brand value,' . . . [f]orest conservation makes for good advertising and looks good to shareholders and consumers."

California's *U.S. Forest Projects Compliance Offset Protocol*

Due to the complexity of passing national-level policies, carbon trading schemes and offset programs are increasingly being considered at the sub-federal level, where state governments experience greater jurisdictional authority and institutional support for legislation that can better meet their own goals to address climate change (Houle et al., 2015; Klinsky, 2013). State mandates for companies to reduce their emissions and the growing social pressure for companies to voluntarily commit to becoming carbon neutral have sparked the rapid growth of a carbon offset market in the U.S., wherein businesses and other entities utilize carbon offsets to meet emissions reduction targets. California's cap-and-trade program was established as part of the 2006 Global Warming Solutions Act (AB 32) and approved through 2030 (ARB, 2017).

The California *Compliance Offset Program* began enforcing compliance in 2012 to reach target emissions reduction goals set by the 2006 AB 32 Scoping Plan (CA Legis. Assemb., 2006). In this program, the California Air Resources Board (CARB) calculates and allocates a specific number of offset credits to qualifying projects that reduce or sequester GHG under CARB-approved protocols. Haya (2018; et al., 2020) estimate that for the compliance period between 2021 and 2030, offsets will represent more than 50% of the reductions attributable to California's cap-and-trade program. Offset credits are a "tradable compliance instrument" that represent verified GHG reductions or removal enhancements of one metric ton of [carbon dioxide equivalent] CO2e" and are required to be "real, additional, quantifiable, permanent, verifiable, and enforceable" (ARB, 2015, §95802.14). To comply with mandatory emission reductions, businesses were permitted to purchase these offset credits to substitute a maximum of 8% of their reductions from 2012-to 2020, reducing to 4% from 2021 to 2025 and 6% from 2026 to 2030. As such, offset protocols and related policies influence on what extent these entities need to change their business-as-usual processes to reduce emissions directly (Clapp & Meckling, 2013).

California's *U.S. Forest Offset Compliance Protocol* allows forest offset projects to be established anywhere in the U.S. except for Hawaii and parts of Alaska. It recognizes four major types of forestry offset projects designed to protect or further develop forestland: improved forest management (IFM), land reforestation, avoided conversion, and urban forestry. IFM projects employ conservation-oriented practices to increase the land's capacity to sequester and store carbon, including methods that reduce the risk of tree mortality from fire, pests, and drought and thinning regimens that stimulate healthy stands. Reforestation projects compensate landowners for reforesting land that previously incorporated forest, typically agricultural lands that are no longer viable or profitable. Avoided conversion projects prevent conversion of forest lands that may be more economically valuable if converted to other land use types, such as agriculture or development. Finally, urban forestry projects include large-scale tree planting and stewardship initiatives.

This dissertation focuses on IFM projects, which are the backbone of California's cap-and-trade system: most of the credits (85.5%) allocated by the system have been awarded to U.S. Forest offset projects, nearly all of which (98.6%) were awarded to IFM projects (ARB, 2021). IFM protocols, which support greater sequestration and storage of carbon, can be impactful and cost-effective strategies for reducing atmospheric carbon concentration levels (Fargione et al., 2018; Griscom et al., 2017; Harper et al., 2018; Seddon et al., 2020). To register an IFM offset project, landowners must have their land evaluated to assure that improvements will occur, commit to the agreement for one hundred years, and monitor and report project data throughout its lifetime. The number of offset credits awarded to an individual IFM project is determined by comparing overall carbon stocking on project land to baseline carbon stocking in the Supersection—or region—in which the project is located (the 'common practice statistic,' estimated using data made available by the US Forest Service (USFS) Forest Inventory and Analysis (FIA) National Program).

Forest offsets effectiveness in climate change mitigation strategies

For forest offset projects to be effective in reducing emissions, they need to meet and maintain several criteria: real; verifiable; enforceable; quantifiable; permanent; additional; and exclusive (ARB, 2015, §95802.14; Estrada et al., 2014; Richards and Huebner, 2012).

Real, verifiable, and enforceable. Offset credits must represent a real reduction in emissions, and a third-party verification body must periodically verify credit issuances to ensure real emissions reductions resulting from offset projects. CARB, as the crediting body, has the authority to enforce all criteria.

Quantifiable. Emissions reductions must be measurable and accounted for (e.g., leakage and uncertainty have been accounted for). In addition to being quantifiable, all measurement must be accurate: baseline emissions must not be overestimated, actual emissions must not be underestimated, and projects must not indirectly increase emissions that are not accounted for outside their boundaries. Hahn and Richards (2013) call attention to the difficulty of accounting for and certifying offset credits, and a task force of professional foresters investigating forest carbon offsets concluded that "[o]ffset projects are highly variable and depend on numerous assumptions, most of which are susceptible to bias and 'virtually insurmountable' measurement errors," (Malmsheimer et al., 2011; Oliver, 2013).

Permanent. Emissions reductions from offset projects must not be reversed or compromised by natural or anthropogenic disturbances. The permanence of offset projects may be monitored but not ensured, as natural drivers such as forest fire or disease may compromise or reverse previously offset emissions, resulting in a net larger carbon debt than had the project never existed (as another entity may have purchased these offsets rather than reducing their own emissions).

Additional. Land use changes that involve removal of forests must be motivated by establishing an offset project and must not have otherwise existed in a business-as-usual scenario: "[t]he only activities that count toward the creation of carbon offsets are those that are additional, reducing atmospheric CO2 beyond what would occur in the absence of incentives. Suppose the tree planting activity would have been undertaken in the absence of policy to mitigate climate change. In that case, the carbon benefits (i.e., offset credits) related to the project should not be counted . . . similarly, proponents of forest conservation might lobby for carbon offset credits even though forest conservation might occur in any event for reasons unrelated to climate change mitigation" (Van Kooten & Johnston, 2016, p. 8:6.3).

Exclusive. Emissions reductions must not be claimed by any other entity or claimed more than once: "the selling of multiple environmental services, such as carbon offsets and contracts to protect threatened wildlife habitat, in more than one market is known as double-dipping (Woodward, 2011)," (Van Kooten & Johnston, 2016, p. 8:6.4).

Given the complexity of meeting and verifying these criteria for each forest offset project, concerns have been raised about their effectiveness in successfully reducing emissions (Lang et al., 2019; Nature Editorial Board, 2021, Spash, 2010; Watt, 2021). Interviewed experts—particularly those representing the EU emissions trading scheme, which does not offer forest offsets—have cited several major challenges associated with forest offset implementation, including "leakage [i.e., harvest simply migrating from regulated to unregulated regions, removing reduction advantages from the emissions trading scheme they were intended to benefit (Fell & Maniloff, 2018)], permanence, additionality, and monitoring design features," (Shrestha et al., 2021). According to Van Kooten & Johnston (2016, p. 8:6.3), "[c]arbon offsets are fraught with problems related to uncertainty and corruption, (Helm, 2010; Van Kooten & De Vries, 2013)."

There is inherent subjectivity in forest offset protocols, particularly in assessing additionality and generating baselines (Gillenwater, 2012; Gifford, 2020; Watt, 2021). A study done by Schmitz (2015) interviewed various stakeholders who participated in the development of California's forest offset protocol. She found that various interests were represented at the policymaking table, each of whom "lobbied for design elements favorable to their own market participation, and frequently debated rival preferences when interests conflicted. Yet self-interests were at times subordinated to achieve high technical rigor, production of environmental co-benefits, and broad market participation, and attributes felt necessary for a strong market commodity" (pp. 2-3). Similarly, Gifford 2020 (p. 299; referencing Lovell & MacKenzie, 2011) notes that in this new frontier, "leaders in carbon credit valuation and accreditation stepped up to meet needs created by the creation of carbon markets themselves. In such circumstances, expertise in the field often falls to the organizations who first identified and meet market needs."

Here, we focus on two challenges: additionality and accurate accounting of credits. For IFM projects to be additional, land enrolled in IFM projects should be at risk of disturbance or otherwise not managed optimally for carbon sequestration; after project establishment, harvest risk should be reduced, or the forest managed in a way to sustain or increase carbon stocks: additionality is "fundamental to the very definition of an offset," and to the environmental integrity of the program (Gillenwater, 2012:4; Ramseur, 2009). It enables the separation of forest sequestration activities, all of which produce a public environmental good, into activities eligible for offset credits (i.e., additional) and those that are not" (Ruseva et al., 2017, p. 280).

Failure to develop protocols that ensure this additionality in IFM projects can lead to over-crediting and associated carbon debt (Badgley et al., 2021; Ruseva et al., 2017). Despite legal requirements that projects be additional, there is little empirical evidence that offsets in this program are accurately credited for baselines and additionality (Badgley et al., 2021; Gifford, 2020; Haya, 2019; Ruseva et al., 2017). The process by which California's *U.S. Forest Projects Compliance Offset Protocol* calculates the number of offset credits awarded to projects has come under particular scrutiny when considering accurate crediting and ensured additionality, as the current credit calculation method allows and even incentivizes project applicants to select lands for offsetting that already exhibit higher-than-average carbon stocks to earn more credits (Anderson-Teixeira & Belair, 2022; Badgley et al., 2021). This method of calculating offset credits may contribute to non-additionality as project developers are rewarded with more credits for offsetting lands that have not been recently or ever harvested—and therefore may not be at risk of harvest—in comparison to lands with low carbon stocking that may be at greater risk for harvest.

Confirming and ensuring non-additionality is challenging as business-as-usual scenarios are not directly observable after a project is allocated credits. Theory suggests that this asymmetric information and adverse selection lead to significant instances of non-additionality in California's offset program. From Van Kooten & Johnston (2016, p. 8:6.4), "[c]ontracts to create carbon offsets on forestlands are costly to negotiate and difficult to enforce because of asymmetric information." (Burke, 2016; Joppa & Pfaff, 2009; Millard-Ball, 2013).

In theory, when carbon emissions are offset, the offset project should store or remove carbon from the atmosphere equal to the emissions of the offset purchaser permanently (measured as the duration of the project, often 100 years). Where emission reductions are required by law (i.e., a compliance market), if the amount of carbon removed by an offset is less than the amount that the offset entitles its purchaser to emit, carbon offsetting can lead to higher overall emissions, reduced incentives to develop lower-emissions technologies, and increased warming (Badgley et al., 2021; Van Kooten & Johnston, 2016). Therefore, the effectiveness of offset policies hinges on the offset protocol's ability to measure and ensure equivalence, permanence, and additionality. Ensuring additionality poses the challenge of asymmetric information, as it relies on the assurance of project owners—there are few established methods to verify that an emissions reduction would not have occurred in a business-as-usual scenario without an incentive (Richards & Huebner, 2012). While forest offsets have great potential to contribute to long-term emissions reduction goals, ensuring that offset projects meet and maintain all criteria and verifying the quality and quantity of actual emission reductions through offset projects remains challenging.

1.2 Methods for evaluating policy effectiveness

In the following dissertation, the additionality of forest offset projects is examined at this early stage in California's *U.S. Forest Projects Compliance Offset Protocol* by quantifying the impacts of forest offset projects on the rate forest disturbance associated with carbon emissions. A comprehensive database of characteristics of existing IFM projects was compiled and analyzed, including size, location, ownership class, credits received, baseline carbon stocks, and historical forest disturbance identified with remote sensing techniques to serve as an indication that forestlands were at risk of harvest without the establishment of an offset project. Two major challenges existed in developing methods to explore additionality in California's *U.S. Forest Projects Compliance Offset Protocol*. First, there was no complete project characteristics or information database, as projects are spread across multiple carbon registries, and data must be manually downloaded for each project. Second, additionality relies on assurance from the project applicant rather than utilizing any form of measurement or verification—as such, no history of harvest or other forest disturbance is required to be reported as part of a project application. All eligible project data was downloaded, and boundary data was converted to shapefiles and processed to equal-area conic projection to map projects' spatial and geographic characteristics. In Chapter 2 of this dissertation, this database provides a descriptive overview of IFM projects enrolled in California's offset program.

Van Kooten (2017, p. 87) argues that "when it comes to the creation of carbon offsets, measurement and monitoring issues can be resolved by relying on satellite data… although more effort is required in this regard." In order to better understand the history of offset lands as a predictor of future harvest risk, remote sensing techniques were used to collect a time series of satellite data from the Landsat archive via Google Earth Engine (GEE) and a well-established algorithm for detecting forest disturbance (LandTrendr) was used to map forest disturbances caused by management activity in all projects and respective Supersection (regional) lands between 1985 and 2020 (Kennedy et al., 2010; 2018). With these two unique datasets, I first measure to what extent IFM projects exhibit characteristics commonly associated with lower long-term management-related forest disturbance. As an indicator of policy effectiveness, I then examine whether pre-project disturbance rates on enrolled IFM project lands suggest that enrolled forests were at risk of harvest in the absence of offset credits by using matching and panel regression modeling.

Monitoring forest disturbances using remote sensing

Remote sensing techniques are central to the analyses within this dissertation, as time series of satellite data were utilized to detect and quantify rates of historical forest disturbance on project and regional Supersection lands (Chapter 3). These results were subsequently used to examine the effects of offset project commencement on disturbance rates (Chapter 4). Building on many advancements in the field of remote sensing, the dataset constructed in Chapter 3 distinguishes natural disturbances from harvests by using time series modeling, omitting disturbances such as wildfires, considering spatial and temporal patterns indicative of forest management, and extending the timeframe of commonly used forest change datasets, providing sufficient temporal resolution to understand harvest risk. The methods used here emerged from extensive literature spanning decades that has sought to advance forest change detection methods and attribute their causal mechanisms (Zhu, 2017).

Forest change detection methods

Annually, roughly 30% of all anthropogenic emissions on Earth are absorbed by terrestrial ecosystems, primarily by forests (Anderegg et al., 2020; Canadell & Raupach, 2008; Friedlingstein et al., 2019; Pan et al., 2011; Pugh et al., 2019). The ability of forests to sequester and store carbon makes them critically important carbon sinks for regulating ecological systems and mitigating catastrophic climate change, which makes monitoring them to avoid the emissions that result from deforestation and degradation paramount (Bala et al., 2007; Bonan, 2008; Canadell et al., 2007; Grassi et al., 2017; Griscom et al., 2017; Fargione et al., 2018; Harper et al., 2018; Noon et al., 2022; Van Kooten, 2020). For these reasons, understanding where and why forests change is important, and satellite remote sensing is increasingly the key technology used for improving our understanding of forest change (Frolking et al., 2009; Kennedy et al., 2009; Masek et al., 2015; Negrón-Juárez et al., 2014; Pasquarella et al., 2017; Wulder et al., 2012).

Forest degradation is defined in various ways—typically as a reduction of biomass, biodiversity, or ecosystem productivity—and there are no standard methods for detecting or monitoring degradation (Simula, 2009). For the purpose of this work, forest degradation is defined as harvesting, leading to a decline in structural complexity and standing biomass of managed forests. Past remote sensing studies of forest change have primarily focused on deforestation, i.e., full-canopy removal. However, many land-use practices and climate change lead to smaller-scale or more gradual changes in forest stands, resulting in forest degradation. This can often be the case for forest harvesting activities such as partial thinning. Selecting an appropriate methodology and procedure for detecting forest disturbance is not a clear or standardized process and ultimately depends on characteristics specific to the study area (Lu et al., 2014). Different satellite sensors and techniques offer varied temporal availability, resolution, and spectral range, such that selecting between sensors and techniques requires a tradeoff in one or more of these characteristics as well as associated financial and resource costs. For example, Spot 6/7 and Digital Globe offer fine submeter resolution but are spectrally limited compared to MODIS, Landsat, and Sentinel-2, and will increase the computational, financial, and time cost associated with analysis. Likewise, variable selection is especially important in remote sensing forest degradation analyses and varies based on place-specific variables (Lu et al., 2014). Many forest change detection algorithms require singular inputs selected by the researcher, typically a spectral index calculated using two or more spectral bands. Each spectral index is suited to detect different aspects of environmental landscapes, which introduces further complication as environmental and forested landscapes are not homogenous and exhibit different characteristics. In conducting forest disturbance detection or monitoring, researchers need to select the most appropriate combination of various satellite sensors, techniques, and variables to best suit specific scales and research questions (Zhu et al., 2017).

Many Landsat Time Series (LTS) methods have been developed to study forest cover dynamics and degradation trends and characterize those changes using various metrics. LTS methods can be broadly stratified by the type of change detected and whether the analysis looks at only past images or images in real-time. The three distinct change types commonly used in LTS algorithms include seasonal or cyclic, gradual, or abrupt (Verbesselt et al., 2012). They are further stratified by whether they are considered 'offline'—meaning they only use historical data to observe time series patterns and detect forest disturbances—or 'online monitoring'—those that operate iteratively using new data as it is made available to continuously detect degradation (Zhu, 2017). Commonly used examples of 'offline' algorithms include DBEST (Detecting Breakpoints and Estimating Segments in Trend, Jamali et al., 2015), BFAST (Breaks for Additive Season and Trend, Verbesselt et al., 2012), and LandTrendr (Landsat-based detection of Trends in Disturbance and Recovery, Kennedy et al., 2010). Commonly used 'online monitoring' methods include CMFDA (Continuous Monitoring of Forest Disturbance Algorithm, Zhu, et al., 2012), CCDC (Continuous Change Detection and Classification, Zhu & Woodcock, 2014; Zhu et al., 2020), and BFAST Monitor (Breaks for Additive Season and Trend Monitor, Verbesselt et al., 2012).

To identify land use change across the longest time period, Landsat is most advantageous primarily because of its extensive archive, as Landsat satellites have been continuously taking images of the planet since the 1970s. Other commonly used moderate-to-high resolution sensors in land use change analyses include MODIS, ASTER, Sentinel-2, and very high resolution (VHR) data such as Rapideye and Spot 6/7. One advantage of Landsat data over VHR is that unlike VHR, there is no cost to access the former. MODIS provides high temporal resolution and acquisition frequency but is much coarser than Landsat and less suited for analysis that might have disturbances occurring at the sub-pixel level.

Analysis at scale: big data and cloud computing

While data-rich time-series analyses like detecting forest disturbance still require massive storage and computational resources, Landsat data is more accessible to researchers than ever before due to developments in cloud-based tooling (see, e.g., Broich et al., 2011; De Vries et al., 2015; Dutrieux et al., 2015; Potapov et al., 2012; Verbesselt et al., 2010; Zhu & Woodcock, 2014; Zhu et al., 2012b; Zhu et al., 2015b; Zhu et al., 2016). Previously, the primary barrier to doing time-series analyses of forest change using extensive satellite imagery collections has been the lack of computational power and ability to store immense amounts of data (Hansen & Loveland, 2012). This analysis differs from many past analyses of forest change in that it was scaled up to the national (U.S.) level with the support of cloud-based tools that host massive amounts of publicly-available satellite datasets and provide the computational power needed to process them in real-time from a browser on a local machine.

Prior to recent years, analyzing such large amounts of satellite data was not feasible for most researchers. In order to do a simple before-after satellite image subtraction in order to look for areas of forest change in 2014, one was required to search for the individual satellite images that were needed for the analysis, submit an order request for them through the USGS data platform, wait several days for the order to be approved and prepared, and then download them individually from the download link provided in response to the order request. Images then needed to be processed, corrected, and potentially converted to surface reflectance by manually accessing the associated metadata .txt file included with the individual images and inputting those data into a pre-built model in ArcMap that would execute the conversion with those inputs. At this point, the actual time series analysis could be carried out on the enormous images processed. A simple projection or subtraction of two full-size Landsat images, for example, could take minutes to hours on university-provided computers, and tasks often timed out or failed after hours of waiting.

GEE, a powerful tool for studying land change, was utilized to conduct the remote sensing analysis that follows in this dissertation. Conducting this type of complex analysis with GEE required communication directly with Google engineers, as few researchers had successfully utilized GEE at this point in its lifetime, and few resources for learning were available. Introduced in 2010, "Google Earth Engine is a cloud-based platform that makes it easy to access high-performance computing resources for processing very large geospatial datasets, without having to suffer the IT pains currently surrounding either. Additionally, and unlike most supercomputing centers, Earth Engine is also designed to help researchers easily disseminate their results to other researchers, policy makers, NGOs, field workers, and even the general public. Once an algorithm has been developed on Earth Engine, users can produce systematic data products or deploy interactive applications backed by Earth Engine's resources, without needing to be an expert in application development, web programming or HTML" (Gorelick et al., 2017, p. 1).

GEE is accessible via a browser-based JavaScript API or using Python. Scripts for running analyses, and geospatial assets (vectors and rasters), can be stored either within the GEE platform or in a Google Cloud Platform storage location. In either case, assets can be called into scripts directly from those locations. GEE has an extensive data catalog that contains petabytes of data, which can also be called directly into scripts within the platform. Computation is executed server-side on Google's servers, such that it is possible to complete massively expensive tasks from virtually any computer connected to the internet. GEE provides the ability to complete entire analyses without moving and storing massive datasets: all parts of analysis occur on the platform until final, tabular results are ready for export. There are many options for exporting data from GEE: it is possible to export to Google Drive accounts, to Google Cloud Platform buckets, or GEE asset folders. All data is technically free to download. Though there are small drawbacks to using the platform—for example, exporting very large datasets or images can take significant time and often times-out due to exceeding provisioned memory—overall, the platform enables researchers worldwide to access tools required for advanced remote sensing analysis without charge. GEE holds the potential to address many of the limitations of past remote sensing techniques, particularly for research at the state, regional, and global spatial scales, which use enormous amounts of data.

Modeling policy effectiveness: Theory and methods

This dissertation explores the effectiveness of forest carbon offsetting in the U.S. as part of a compliance-based emissions reduction scheme, focusing on developing methods and necessary databases to examine additionality. Modeling policy effectiveness is an emerging discipline, and the methodology is continually improving. Recent advancements in modeling policy effectiveness have led, ultimately, to the quasi-experimental econometric modeling used in Chapter 4 of this dissertation to empirically assess the effectiveness of the *U.S. Forest Projects Compliance Offset Protocol*. A difference-in-difference panel model approach is used to estimate the impact of project establishment on forest disturbance rates, incorporating matching, fixed effects, linear probability models, and random effects logit models in order to effectively isolate policy impacts from other factors and control for time-invariant unobservable variables (Bruggeman et al., 2016; Imbens & Wooldridge, 2009; Jones & Lewis, 2015; Jones et al., 2017). The following section reviews the work that has sought to improve how models measure environmental policy effectiveness over the past two decades, leading to quasi-experimental econometric modeling.

Land-use change modeling

Land change science studies the natural and anthropogenic dimensions of land systems on Earth (Rounsevell et al., 2012; Turner et al., 2007). An important tool for land change science is modeling, which can help to understand the processes, causes, and outcomes of observed land-use change patterns or trends (Brown et al., 2014; Meyfroidt, 2016). "This understanding can be represented with degrees of formality varying from informal conceptual models to formal mathematical or computational models. Stochastic aspects of this understanding might be included with otherwise deterministic processes to represent uncertainty and statistical variability in system behavior" (Brown et al., 2014, p. 17). Modeling land-use change is increasingly challenging as factors such as climate change and globalization shift the scale at which natural, social, cultural, and economic processes interact, allowing for the possibility that distant or global-scale drivers may influence local and regional land systems (Verburg et al., 2015; Meyfroidt, 2016; Meyfroidt et al., 2022). Land systems are an example of complex social-ecological systems (SES), which are challenging to model because they are nonlinear, which produces uncertainty; self-organized, which produces emergence; and complex adaptive systems, making modeling policy effectiveness difficult (Rindfuss et al., 2004).

An effective conceptual method for linking observed change with policy changes is to develop counterfactuals, where two comparable units are studied, one which experienced the policy and one that had not. While counterfactuals attempt to compare two units that are as meaningfully similar as possible, such methods as with-versus-without frameworks or comparing a precondition of one place to the treatment can still be prone to issues such as biases: for example, some policies that aim to protect natural resources might succeed based on the site's geography, rather than wholly due to the policy itself. In forest resource conservation and management, several variables are important to incorporate into models designed to assess policy effectiveness in addition to time series of satellite images to control for bias, including landscape and climatic variables such as distance to paved roads, precipitation, and elevation, and socioeconomic variables such as conversion pressure, landowner affluence, dependence on resources, and the ability to access resources. However, these variables are challenging to isolate and control for, often unobserved, and not distributed homogenously across a study site.

Previous models for land-use change have relied primarily on either aggregate landscape-level data or individual decision-making data at the parcel level. Carrión-Flores and Irwin (2004) examine the spatial landscape pattern metrics associated with rural-to-urban sprawl and advanced the literature by modeling the dispersion and fragmentation patterns of development and individual decision-making to explain sprawl at the regional (here, county) scale. A spatial sampling method was used to address issues associated with spatial autocorrelation, which omits spatially dependent observations to construct an independent error structure—methods that are foundational to many future LUC modeling studies.

McConnell et al. (2006) provided an early case study of land-use change models: they examined the effects of market forces and zoning regulations on the density of subdivision development in a Maryland suburb. They argued that restricting their model to a particular location allowed for other factors that affected housing markets to be held constant. Irwin and Bockstael (2007) questioned the validity of the conclusions made by McConnell et al., discussing the challenges of using remotely-sensed datasets for quantifying changes in sprawl; primarily, that changes in land cover in low-density areas are not necessarily indicative of changes in sprawl. For example, there is little impervious cover in comparison to vegetation. This study is important because the Irwin and Bockstael (2007) make the empirically-based argument that land cover and land use are not necessarily correlated. They show that fragmentation, low-density development, and exurban growth are linked, and that previous work employed data that were not sufficient or suitable to detect and explain these relationships.

While early econometric models of land use change were able to control for local variables, their findings were constrained to a small geographic area—in the case of McConnell et al. (2006), a single county. Lubowski et al. (2008) expanded on studies such as McConnell et al. (2006) by examining the effects of markets on land use change decision-making in greater scope and depth, on a national scale. This study was the first to model competition between major land use alternatives. The authors suggested that market-based forces and estimated net returns largely explained historical land use decisions. The developed econometric model was based on assumptions that individuals would choose the alternative that resulted in the highest one-period return. Decisions were based on historical and present-day conditions and did not consider future uncertainties such as risks posed by climate change, despite the authors' mention of the important implications of land use change for global climate change. Unlike the previous studies discussed here, spatial autocorrelation was not perceived as a critical concern and was ultimately left unaddressed because of the computational costs of addressing it at the time.

Early econometric models of competing land use failed to recognize the importance of the support of biodiversity as a model output. Polasky et al. (2005) developed a combined biological and economic model to explore how land-use change affects land suitability for supporting biodiversity and economic returns, concluding that conservation objectives can largely be accomplished without diminishing the economic output of the land, but land use conversions can threaten important habitats needed by certain specifies. Their model was somewhat coarse and did not include major economic activities like recreation, commercial, or residential land uses, nor did it weight species based on whether they were endemic or endangered, but the authors advanced previous work by combining biological and economic models and served as a precursor to future coupled human and natural models.

Coupled natural and human systems modeling

The coupled natural and human systems modeling literature documents the importance of considering social and spatial heterogeneity in assessments of policy effectiveness. In SES, landscape outcomes are an aggregate effect of small-scale, local actions that affect individual behaviors and actions, usually over varied longer time scales. Although simple deterministic models with mild nonlinearities generate important insights, they can still insufficiently isolate the causal effect of the observed behavior or land use and land cover change. Real-world systems exhibit nonlinear dynamics and many interacting elements that comprise them and unobserved variables that are challenging to account for. This complexity brings deep uncertainty that makes policymaking exceedingly difficult in practice, whether the policy targets forest or an epidemic.

Liu et al. (2007) proposed a formal definition of coupled human and natural systems (CHANS): "systems in which human and natural components interact" (p. 639). They developed a general framework for studying CHANS, which they argued requires interdisciplinary thinking and methods, and research designs that incorporate spatial and temporal coupling, focusing beyond traditional boundaries, heterogeneity, and indirect effects. Prior research, they argued, had focused either 1) on human interactions and neglected the environmental context of those interactions; or 2) on pristine environments with few human influences. This dichotomy does not serve present-day challenges, as they occur at the interface of these two schools.

Nelson et al. (2009) advanced CHANS by developing a model specifically designed to measure the trade-offs between ecosystem services and economic activities—the Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model. They compared the findings of economic and ecological models by integrating the two sets of variables and examining their trade-offs and found that economic activities were capable of supporting or enhancing important ecosystem services. Additionally, some observed trade-offs in favor of economic growth could be accounted for if payment for the carbon services scheme were introduced into their model.

In 2015, Byrd et al. set out to explore a more complex system of interactions in CHANS by integrating climate change projections with land use change scenarios to model their combined effects on various ecosystem services in California, like soil, water, and habitat. Mastrangelo and Laterra (2015) advanced CHANS further by integrating theories about resource frontiers (here, agricultural) and "extraregional stakeholders." The authors also argued that a place's environmental and social heterogeneity affect the information that can be inferred from modeling the trade-offs between ecosystem services and production: stakeholder preferences and access to resources influence all else in the model. While Newbold et al. (2015) did not include climate change in their model design, their work serves as an early example of regional analysis at scale: they argued that other studies had focused on large scale—i.e., regional or global—rates of biodiversity loss, but processes largely impact that biodiversity at local scales. They were able to explore rates of biodiversity loss at local levels by developing a model that incorporated a massive amount of data relevant to individual locales encompassing the globe.

Many past studies have previously focused on the importance of variable selection, but equally important is the empirical model chosen to do the analysis (Plantinga, 2021; Siegel et al., 2022). In exploring the effects of open space and associated protection on the value and density of developed landscapes, Lewis (2009) and Lewis et al. (2009) advanced CHANS methodologies by employing a random effects framework to account for unobservable spatial heterogeneity that might influence development decisions. Chakir and Parent (2009) introduced a spatial multinomial probit model for predicting land use change decisions in a region of France, using parcel-level rather than aggregate data; allowing for spatial dependence among parcels and interdependence among land use change alternatives; and addressing unobservable variables with unstructured individual effects and spatially structured components.

In their work aiming to explore the links and feedback between land use and climate change, Mendelsohn and Dinar (2009) suggested that many past studies modeling the effects of land use on climate change had used poor quality datasets and modeling techniques. The authors recommended improving modeling standards, e.g., using computable general equilibrium models for the agricultural sector instead of partial equilibrium, and using dynamic rather than static forest models. Mann et al. (2014) and Lawler et al. (2014), modeling the consequences of land use change on the environment and ecosystem services, also recommended using general equilibrium models to balance market dynamics and account for aggregate market feedback effects land use change.

Causal inference in land use models

While coupled models sought to understand the role of ecosystem and economies in single models, many policymakers are interested in the causal effects of policies. Over the last 20 years, causal inference has grown as a subfield of econometrics, even leading to the Nobel Prize being awarded to Guido Imbens, Joshua Angrist, and David Card in 2021 in recognition of their contributions of natural experiment analysis[1]. The modeling approach used in this dissertation was informed particularly by past studies designed to assess the effectiveness of establishing protected areas (PA) in reducing forest degradation, as many parallels can be drawn between forest offset projects and protected area designations on forestlands (Brandon & Wells, 2009; for recent examples, see Shah et al., 2021; Xin et al., 2021). Both aim to increase the social-environmental co-benefits and ecosystem services that forests provide by improving forest health and reducing the risk of degradation over time. Both require the delineation of a boundary around an area, and the forests within are subjected to some type of change relative to regulations or practices that may have taken place in the absence of project establishment. For PAs designated for conservation purposes, this might mean that development or other specific use cases or forest

[1] https://www.nobelprize.org/prizes/economic-sciences/2021/popular-information/

management practices are restricted or ended altogether. For IFM forest offset projects, management and harvesting practices are altered to reduce potential emissions from harvesting, increase above carbon storage and capacity to sequester carbon, and reduce vulnerability to risks associated with climate change such as wildfire and drought.

Extensive literature has attempted to measure the effects of protected area designation on reducing forest degradation (for a recent review, see Yang et al., 2021). Assessing protected area effectiveness is challenging for many reasons that apply similarly to assessing the effectiveness of offset project establishment, particularly because reducing potential forest degradation, deforestation, conversion, or the emissions that would have been released in any of these scenarios, is not something that can be measured directly (Andam et al., 2008). In other words, one cannot quantify something that never happened. PAs are not designated randomly and are more likely to be established in remote areas with greater land availability and lower acquisition costs, population densities, and conversion pressures (Andam et al., 2008; Baldi et al., 2017; Joppa & Pfaff, 2009). This can bias effectiveness metrics, especially when comparing a protected area to non-protected forest, as PAs established in locations that experience little threat of deforestation are less likely to be effective (Nolte et al., 2013).

These considerations informed the approach to assessing the effectiveness of offset project establishment in this dissertation. Like PAs, forest offset projects are more likely to be established in non-random locations: any privately owned forest in the continental U.S. can be offset, but specific locations and forest owners are more likely to meet the criteria laid out in California's IFM protocol. If a forest parcel is inaccessible by road and far from lumber sawmills, for example, it can be assumed that this parcel is less likely to be harvested for timber than a parcel exhibiting characteristics more conducive to corporate or large-scale forest management. These time-invariant variables such as landscape characteristics and spatial relative distances bias effectiveness metrics if not controlled for. A combination of pre-regression matching of comparable areas and a fixed effects model are suitable to address this limitation of traditional regression techniques.

The complexity and scale of LUC modeling have changed significantly in the past two decades. This dissertation contributes to this evolving literature in three primary ways. First, new computing methods are used to develop a novel dataset used for land use change modeling. Second, these models are applied to a novel and important use case: exploring the impact of forest carbon offset project establishment on real, additional sequestration of carbon and resulting emissions reductions. Last, remotely sensed forest disturbance data is used as an input to a difference-in-difference panel model that incorporates matching, fixed effects linear probability models, and random effects logit models in order to effectively isolate policy impacts from other factors and control for time-invariant unobservable variables (Bruggeman et al., 2016; Imbens & Wooldridge, 2009; Jones & Lewis, 2015; Jones et al., 2017).

Chapter 2

Assessing Participants of California's *U.S. Forest Projects Compliance Offset Protocol*

Abstract

Here, I describe the creation of an original database of information to assess descriptive patterns across 90 IFM projects registered and credited in California's *U.S. Forest Projects Compliance Offset Protocol*. Data collected include GIS (Geographic information system) boundaries and project characteristics such as size, location, landowner type, initial above-ground carbon stocking value, and the Common Practice statistic used to calculate the project's baseline. A breakdown of the spatial, demographic, and geographic heterogeneity across projects is provided, and potential barriers to participation in the program based on characteristics of currently enrolled projects are discussed. I find that IFM project credits have been allocated primarily to forests with high carbon stocks (130% higher baselines than regional averages). Results also suggest that projects owned by corporate and 'other' interests were most common; the majority of credits in California's program have been allocated to Tribal projects (48.4% of all credits) and TIMO/REIT projects (23.4% of credits) due in part to their larger size, and family landowners are underrepresented in California's offset program relative to private forest owners across the U.S. On average, across ownership classes, projects were stocked at carbon levels of 125% relative to the average standing live carbon of forests within the project's Supersection assessment area.

2.1 Introduction

Although forest offsets are a sizable and growing component of climate change mitigation strategies, including that of California's cap-and-trade system, no comprehensive overview of existing California offset project information has been collected and made publicly available. As California's offset protocol represents a substantial amount of land and economic resources, it is important to analyze and evaluate the state of the program as it develops. Analysis of project location and spatial data can provide many insights into the projects that California has and has not enrolled in its protocol thus far: it can help researchers and policymakers better understand the social and environmental context in which projects are currently located; identify patterns such as outliers, hotspots, and drainage; and reveal attributes that may be meaningful in assessing additionality, as in the case of a steeply sloped, untouched project parcel surrounded with forest loss. To conduct any analysis of California's current portfolio of forest offset projects, including remote sensing analysis and econometric models, researchers must manually aggregate spatial data and relevant documentation from each individual project. CARB provides a map of forest offset project locations[2] but does not provide any analysis or synthesis of these projects as part of California's larger *U.S. Forest Projects Compliance Offset Protocol*. Furthermore, CARB does not allow spatial boundaries or location data from their project map to be downloaded.

To better understand the characteristics of existing IFM offset projects in California's *U.S. Forest Projects Compliance Offset Protocol* and comparisons to their respective regional Supersections, I compile and analyze spatial data and relevant information from each credited project in California's protocol. I focus here on measuring to what extent IFM projects exhibit characteristics—such as size, location, ownership class, credits received, and baseline carbon stocks—that are commonly associated with lower long-term management-related disturbance. Data were compiled for 90 projects where CARB credits have been issued in 30 states and 43 Supersections for which spatial project boundaries were obtained

[2] https://webmaps.arb.ca.gov/ARBOCIssuanceMap/

(Table 7). Disparate boundary files for IFM compliance projects were collected, combined, cleaned, and harmonized to create the most complete dataset possible of CARB-credited IFM project boundaries. Prior to this work, no complete California offset project data database, including project characteristics and boundaries, had been publicly available, preventing any large-scale analysis of enrolled projects.

This database of project characteristics was utilized to explore spatial, demographic, and geographic heterogeneity in enrolled IFM projects. As timber patterns and disturbance risks vary by region, heterogeneity was explored across geographies by utilizing Supersections, which are sub-state delineations based on similar ecosystem types and are equivalent to the Environmental Protection Agency's (EPA) Ecoregions[3] Level III designations; the regions range from sub-state at Level IV to large U.S. regions at Level I (Figure 1). CARB uses Supersections to establish whether a project's baseline aboveground carbon stocking is above or below the average in a similar region (ARB, 2015; EPA, 2015).

[3]Omernik & Griffith, 2014; Omernik, 2004 (https://www.epa.gov/eco-research/ecoregions)

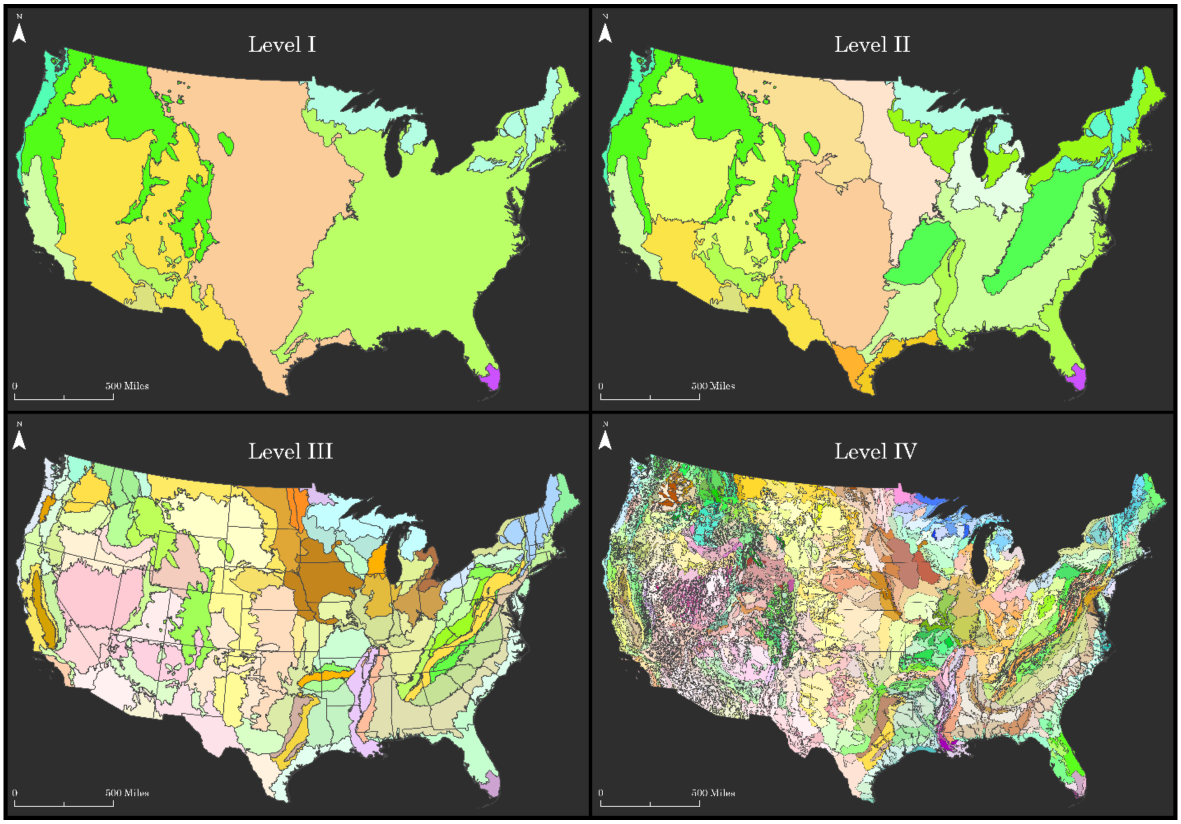

Figure 1. EPA Ecoregion Levels. Level I, made up of 12 regions (top left), and Level II made up of 25 regions (top right), are the coarsest and included to compare against the dataset used for Supersections—Level III, which contains 105 regions (bottom left). Level IV (bottom right) consists of 967 ecoregions, considerably finer scale and more specific to local characteristics than Levels I, II, or III. Vector data was sourced from the EPA's website[4].

[4] https://www.epa.gov/eco-research/ecoregions

Because different landowner types may have divergent management goals (Ruseva et al., 2017), heterogeneity was also explored across landowner types. For example, corporate forest owners typically have predictable forest management goals to maximize profit from timber harvest. In contrast, non-industrial private forest owners (NIPF; Tribal, family, and 'other' owners) may be motivated by alternative goals in addition to or instead of financial gain, such as ecosystem services (Kelly et al., 2017). Here, projects were grouped into five landowner types based on a forest landowner classification stratum developed by the USFS (Sass et al., 2020; Table 1). Ownership classes included corporate timber interests, families, Native American Tribes, timber investment management organizations (TIMO) and real estate investment trusts (REIT), and an aggregate group labeled 'other,' which comprises primarily non-governmental organizations (NGOs) and land trusts (Hewes et al., 2017).

2.2 Methods

The study area included the boundaries for each project and the boundaries of the 43 Supersections in which they are located, the latter of which is used by the California *U.S. Forest Projects Compliance Offset Protocol* to calculate the number of credits awarded to each project by comparing carbon stocking between projects and their respective Supersections. The Supersection shapefile used was obtained from the CARB U.S. Forest Projects website. IFM offset projects were included in our database if they met three criteria: (1) they were compliance projects and not Early Action (where credits were awarded to entities reducing emissions before compliance was required); (2) they were listed on a CARB-designated registry; (3) their boundary GIS data was uploaded or otherwise made available. CARB tasks much of the oversight of projects to three registries: Verified Carbon Standard (now Verra California Offset Project Registry, or VCSOPR), the Climate Action Reserve (CAR), and the American Carbon Registry (ACR). Data on individual projects were collected from each registry, resulting in a unique, complete dataset to enable large-scale analysis of enrolled projects.

When this data was collected, many projects were listed across the three registries that did not satisfy the requirement of boundary file upload and were thus excluded from the analysis. Other issues were encountered, such as some projects not including a valid GIS boundary file with their listing documents, or some projects not being updated from Early Action to Compliance on registry tables. Many of these issues were resolved through direct communication with the registries. An example correspondence from an employee at CAR on April 12, 2017, in response to my request for a list of missing boundary files, exemplifies the challenges described:

> "…some of the projects on this list are duplicates of other projects. For instance, you have listed CAR408 – Big River / Salmon Creek Forests. This project is the same as CAR1100 – Big River / Salmon Creek Forests - ARB. There is a specific reason for this which is generally that CAR408 was originally registered as an "Early Action" project and the project eventually transitioned into the compliance program. We keep all of the previous documents public on our registry. I would suggest filtering the Project Report to only projects that have the "- ARB Compliance" suffix as its project type. This should remove any duplicative projects. The shapefile requirement is only a component of the Compliance program, so no Early Action or Voluntary projects will have their shapefiles publicly available."

Another correspondence from the same day, from Dr. Kerchner, a proposal developer at ACR, reads:

> "I did make the files public for ACR210, and I re-uploaded them for ACR268 since we had them on hand. I asked the project owners for ACR260, ACR273 and ACR287 to upload the files, but I assume it'll take a couple [of] days and it'll require someone at ACR to make them public. ACR 186 and 187 were early action so not applicable (they have new project numbers under the compliance program). Also ACR209 isn't going forward. I'll need to look into how to deal with the projects that provided the autocad files. We don't have other files from them at this time."

Once project boundary files were collected, all available files were converted to shapefiles and processed to equal-area conic projection. Geometries were checked for validity, and geometrical errors were repaired if present. Three primary metrics were calculated for IFM projects and compared across ownership classes: mean area, mean number of credits awarded, and mean baseline percentage of the common practice statistic (unweighted, weighted by area, and weighted by number of credits). These metrics were stratified across five land ownership types sourced from the USFS: corporate, TIMO/REIT, Tribal, family, and 'other' owners (Table 1).

Table 1. Forest owner types and definitions.

Class	Description
Corporate	Corporate-owned
TIMO/REIT	Timberland investment management organizations/real estate investment trusts
Tribal	Native American Tribal lands
Family	Individuals, families, trusts, estates, and family partnerships
Other	Conservation and natural resource organizations., unincorporated partnerships, and associations

ArcGIS Pro software was used to calculate the area for each project in hectares. The mean area was calculated for all projects overall as well as for projects stratified by each ownership class. All project shapefiles used a projected coordinate system rather than a geographic coordinate system: a projected coordinate system describes how to draw the vector on a two-dimensional surface, while a geographic coordinate system defines where the vector is located on the surface of the Earth. A geographic coordinate system, which uses angular units like degrees, would result in inaccurate area calculations as ArcGIS, like most GIS software, calculates perimeters and areas using a planimetric algorithm. The project areas calculated using this method were slightly different from some of the areas reported in the project reporting documents, as area calculation methodologies varied across projects. The areas calculated here were calculated using a single method and equal-area projection and as such provided more reliable data points for comparison.

Credits for each project were scraped directly from CARB credit issuance tables, posted each month publicly. Credits issued were cross-referenced with credit issuance numbers made available by project registry databases. In the few instances where credit numbers between CARB and project registry databases did not match, due diligence was completed to account for the discrepancy; if no explanation was made available, the greater number of credits was used in our database under the assumption that one table simply had not been updated as recently. Reversals and notes about credits issued for projects were accounted for in our database until analysis began. As with the mean area, mean credits were calculated for all projects overall and for projects stratified by each ownership class. All project listing documents include an initial aboveground carbon stocking estimation and the estimated common practice statistic calculated based on an FIA assessment area database. The baseline percentage of common practice for each project was calculated by dividing the initial aboveground carbon stocking of the project by the generated common practice statistic, then multiplying by 100. Baseline percentages of common practice were calculated for all projects overall and for projects stratified by each ownership class. Mean baseline percentages were additionally weighted by area across ownership classes to account for projects varying drastically by area. Lastly, mean baseline percentages were weighted by credits awarded to account for differences in assessment areas, forest composition, and the associated average carbon stocking attributed to those forest types.

2.3 Results

The credited projects included in this analysis were highly concentrated in the state of California and the Pacific Northwest and the Northeast and throughout Appalachia (Figure 1). While not numerous, projects were located in most eligible parts of the US, including Alaska, except for the Great Plains, Rocky Mountains, and large swaths of the Southwest. The largest projects were found in Northern California, Alaska, and Appalachia. The projects that exhibited, on average, the highest percentage above common practice was located in Appalachia, the Southeast, and the Midwest. Projects were primarily located on forestlands owned by three ownership types: 'other,' comprising primarily NGOs (34.4% of projects), corporate (23.3% of projects), and TIMO/REIT (18.9% of projects) (Table 2). While there were fewer Tribal projects (15.6% of projects), they were substantially larger than projects owned by other ownership classes: on average, they were 46,354 ha, compared to the next largest, TIMO/REIT projects, with an average size of 25,250 ha; corporate projects with an average size of 19,316 ha; and 'other' projects with an average size of 9,760 ha. Projects on family forestlands were less common—only 7.8% of projects—and smaller than other project types, with an average size of 2,352 ha. While projects owned by corporate and 'other' interests were most common, the majority of credits in California's program have been allocated to Tribal projects (48.4% of all credits) and TIMO/REIT projects (23.4% of credits) due in part to their larger size. On average, across ownership classes, projects were stocked at carbon levels of 125% of common practice, the average standing live carbon of forests within the project's Supersection and Assessment Area (Table 2). Family-owned forestlands had the highest average stocking level above common practice at 145%, followed by Tribal forestlands at 135%. TIMO/REIT projects had the lowest aboveground carbon stocking at 119% of common practice. Carbon levels were over 200% of common practice for some individual projects. Kelly & Schmitz (2016) similarly found that average percentages above common practice was high: they ranged from 111% among corporate and TIMO/REIT-owned lands, to 171% on Tribal lands.

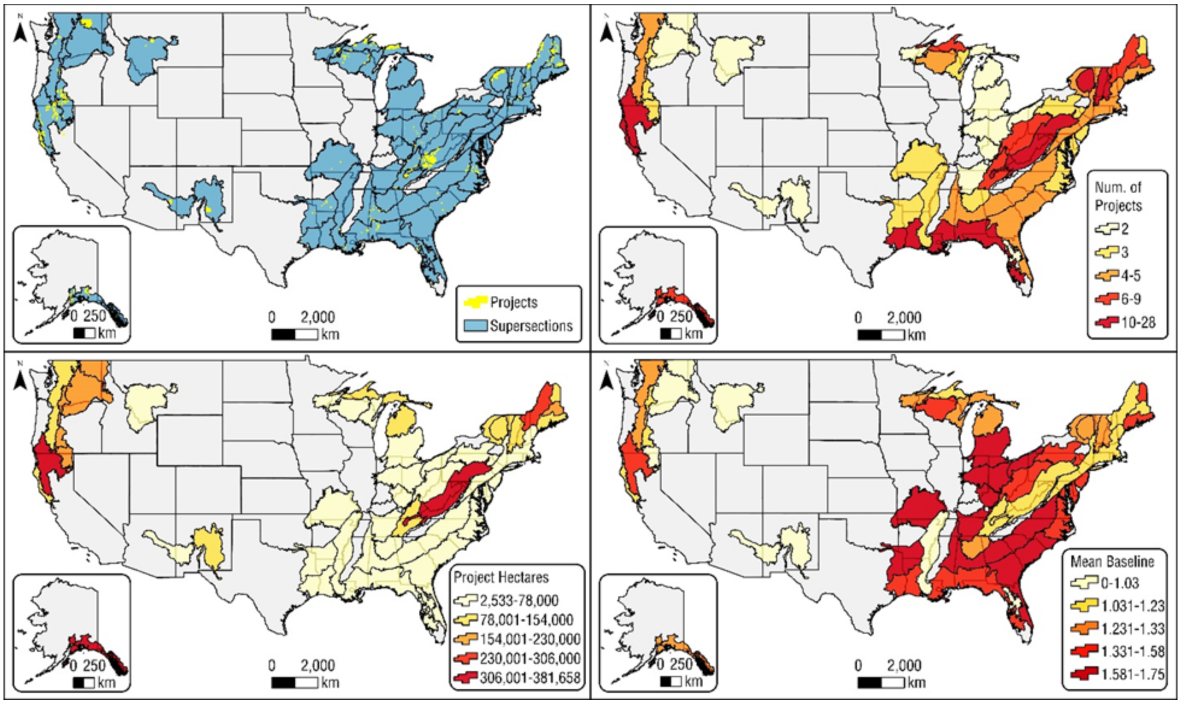

Figure 2. Location of offset projects included in analysis.

Table 2. Size, credits, and baseline percent of common practice by owner type.

Owner Class		All	Corporate	TIMO/REIT	Tribal	Family	Other
Number of projects		90	21	17	14	7	31
Percent of total projects		100%	23.3%	18.9%	15.6%	7.8%	34.4%
Hectares (ha)	Mean	19,872	19,316	25,250	46,354	2,352	9,760
	Min	216	621	433	1,817	622	216
	Max	205,071	166,432	113,651	205,071	5,252	46,786
	Sum	1,808,339	405,634	429,258	648,952	16,466	302,552
	% of total project ha	100%	22.5%	23.8%	36%	0.9%	16.8%
Credits	Mean	1,519,640	677,527	1,881,612	4,728,192	491,906	674,647
	Min	2,616	4,343	43,666	362,722	125,626	2,616
	Max	15,771,683	1,991,514	6,249,083	15,771,683	1,107,495	3,621,175
	Sum	136,767,579	14,228,076	31,987,401	66,194,690	3,443,342	20,914,070
	% of total	100%	10.4%	23.4%	48.4%	2.5%	15.3%
Baseline percent of common practice*	Mean	125%	121%	119%	135%	145%	122%
	Mean weighted by credits	112%	116%	114%	109%	128%	110%
	Mean weighted by ha	99.9%	70.2%	114%	104%	117%	111%
	Min	30%	30%	100%	100%	100%	63%
	Max	259%	259%	163%	209%	256%	242%

2.4 Discussion

The size and number of IFM projects vary by ownership class, particularly concerning Tribal-owned and family-owned projects. Tribal projects are much larger than other types of projects, and family-owned projects are much smaller—the former are nearly 20 times larger than the latter. While families own 61.9% of non-governmental forests in the U.S., only 7.8% of projects are owned by families—instead, most are owned by 'Other' entities like NGOs (34.4%), corporate entities (23.3%), and TIMO/REITs (18.9%) (Figure 2). This discrepancy raises questions about what factors influence participation in California's *U.S. Forest Projects Compliance Offset Protocol*. Regardless of the cause of this discrepancy, the current distribution of forest offset projects and credits is far from representative of forest ownership in the US, particularly for family-owned forests—as such, the potential is currently limited for these forests to be offset.

Participation in California's forest offset protocol is influenced by various institutional and environmental variables that affect the potential economic viability of a new project (Ruseva et al., 2017). It is necessary to understand how eligibility is established to draw meaningful connections between the forest offset projects that are registered, the credits purchased by industries, and the landowners who ultimately experience capital gains. Eligibility, according to CARB, is determined by guidelines set by the *U.S. Forest Projects Compliance Offset Protocol* (ARB, 2015, pp. 11-25). Knox-Hayes (2012) argues that strong coalitions primarily explain California's success in passing ambitious climate change policies. This is evident compared to similar policymaking attempts that have failed, such as the 2008 Lieberman–Warner bill—a suite of climate policies that would have established a national cap-and-trade system in the US. Schmitz and Kelly (2016) suggest that the coalition that had the greatest influence on protocol development consisted primarily of land trusts and forest managers, who pushed for rules to increase their own ability to participate and benefit from the program. As a result of entrenched interests in the policymaking process, participation costs are prohibitively high for small forest landowners and favor large conservation, tribal, and forest industry lands that experience above-average stocking levels and the preexisting ability to comply with program rules (Kelly & Schmitz, 2016).

While family-owned or other relatively small forest parcels in the U.S. may qualify for registration as an offset project, economic and logistic barriers prevent them from proceeding to establish a project. Nonindustrial private forest owners with smaller land parcels often report philosophical alignment with management activity that stores and sequesters carbon, but these landowners report perceiving significant barriers to entry into voluntary offset markets, including high costs, rigorous requirements for reporting, protocol complexity, contract length, and associated withdrawal penalties, and low familiarity with California's carbon market even among landowners within the state (Charnley et al., 2010; Fletcher et al., 2009; Kelly et al., 2017; Miller et al., 2012). A survey conducted by Kelly et al. (2017) of 143 non-participating forest landowners in California showed that 61% would hypothetically be motivated to join the program if it allowed them to receive revenue without harvesting wood products, and 57% would join if they would receive revenue in addition to what they gain for wood products.

Complex project applications with high overhead costs, including required evaluations of proposed projects by third-party carbon registries charging fixed prices regardless of project parcel size, impede participation in carbon sequestration programs among these smaller landowners, foregoing potentially viable avenues to meet emissions reduction targets. As all initial revenue from (IFM) offset project establishment is based on the amount that a project is above common practice at the time of registration, project establishment may be prohibitively expensive for small forest landowners who might currently have unmanaged or poorly managed forests below the average baseline.

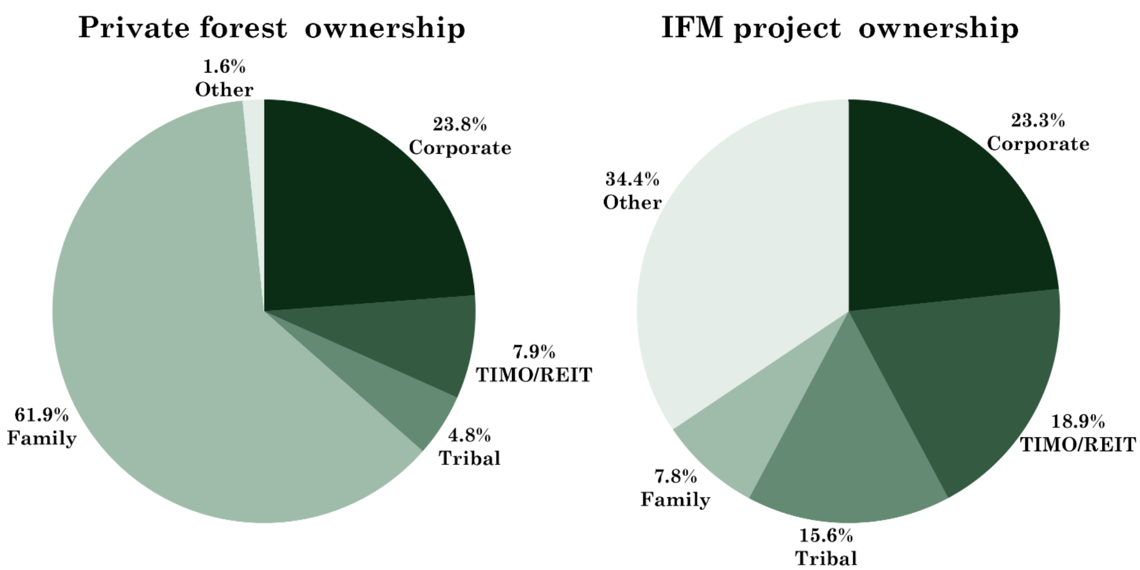

Figure 3. Left: Distribution of private forestland ownership in the U.S. among ownership classes. Right: Percentage of IFM projects in this analysis for each ownership class.

In addition to introducing additional barriers for smaller landowners, the current process for determining credit allocations allows and offers a perverse incentive to offset land that exceeds regional carbon stocking averages to obtain the greatest number of credits. At present, project baselines are calculated by comparing carbon stocking on proposed project land to all land within its Supersection, and projects in California's *U.S. Forest Projects Compliance Offset Protocol* were stocked at carbon levels of 125% of common practice on average. Project applicants are incentivized to offset parcels of forest with high carbon stockings; however, these parcels often have high carbon stockings because it was not possible or profitable to manage them before offsetting them. This general, above-below system of allocating credits also favors large conservation, Tribal, and corporate forestlands that are more likely to experience above-average stocking levels than smaller, family-owned forestlands: these larger lands often benefit from approaching or exceeding compliance with protocol guidelines before project establishment, above-average stocking levels compared to respective regional Supersection lands, and larger issuances of offset credits and economic reward. Kelly and Schmitz (2016) found that "[p]articipation is possible at any stocking level, however only those with higher stocking than regional average . . . earn upfront revenue. According to developers, as few as 5–10% of investigated projects are profitable enough to justify development expenses, and those that are may still be stymied by onerous program constraints, market uncertainty, and opportunity costs (p. 104).

Comparing initial aboveground carbon stocking within projects to that on forests within the project's respective Supersection assessment is argued to be an overly generalized and aggregated region of comparison (Anderson-Teixeira et al., 2022)—particularly because Supersections are equivalent to the EPA's Ecoregions Level III product, and the protocol could just as simply require that comparisons be made using the more specific Level IV Ecoregion dataset (Badgley et al., 2021). "…using any form of geographic aggregation risks a specific type of ecological fallacy known as the modifiable areal unit problem (Gehlke & Biehl, 1934). Simple averaging over underlying variations in climate and its relationship to carbon storage necessarily introduces opportunities for adverse selection," (Badgley et al., 2021, np.). An analysis of offset project records and forest inventory data by Badgley et al. (2021) found that the process of comparing projects against coarse Supersection carbon-stocking averages to award initial credits has led to over-crediting in 29.4% of the credits analyzed, generating $410 million in offset credits that are not representative of legitimate emissions reductions.

Together, these analyses suggest that project baselines would be more accurately determined if initial aboveground carbon stocking on project lands was compared to forest areas with similar characteristics within Supersections rather than all forestlands in the Supersection. Companies like NCX are steadily introducing more robust methods for measuring forest carbon and brokering purchases directly between landowners and companies who wish to offset their emissions to better ensure additionality and reduce the economic barriers for forest landowners to participate in offset programs. A large-scale descriptive analysis of IFM projects can shed light on barriers to participation in California's *U.S. Forest Projects Compliance Offset Protocol* and the perverse incentives to offset forests that may not be at risk of harvest. Forest harvest history for offset projects and their respective Supersections can provide a richer understanding of disturbance risk and the potential incentives necessary to mitigate it.

Chapter 3

Quantifying Historical Disturbance Rates Using Remote Sensing

Abstract

As the California *U.S. Forest Projects Compliance Offset Protocol* does not require harvest history to be shared by projects, a remote sensing analysis of projects and regional Supersections was conducted to better understand the history of offset lands, where historical disturbance may serve as a potential indicator of risk of future disturbance. GEE, a cloud-based geospatial processing platform, was utilized to collect and compile a time series of satellite data from the Landsat archive between 1985 and 2020. LandTrendr, an algorithm designed to detect forest disturbance, was then used to map management-related forest disturbance on projects and Supersections. The total annual disturbed area and disturbance rate over the time series for project areas and Supersections were calculated with this data. Results were further explored across landowner types and at the coarsest EPA Ecoregion level to explore whether ownership type is associated with different baseline disturbance rates. I find that IFM projects have been primarily allocated to forests with low historical disturbance relative to regional averages (28% less disturbance than regional averages since 1985).

3.1 Introduction

IFM projects promote greater storage of carbon and can significantly reduce atmospheric carbon but must meet several criteria to do so, including additionality—that is, they must provide carbon sequestration greater than would be observed in a business-as-usual scenario (Fargione et al., 2018; Griscom et al., 2017; Harper et al., 2018; Seddon et al., 2020). For IFM projects to be additional, land enrolled in IFM projects should be at risk of disturbance or otherwise not managed optimally for carbon sequestration (Richards & Huebner, 2012; Tahvonen & Rautiainen, 2017). After project establishment, harvest risk should be reduced, or the forest managed in a way to sustain or increase carbon stocks.

To understand harvest risk on project lands within this context, it is useful to refer to harvest history as an indicator of future harvest risk, where forest that has experienced disturbance in recent years would have been likely to experience additional future disturbance had an offset project not been established. While harvest history can provide rich information in investigating a project's additionality, only a cursory narrative description of management history from the last 10 years is required in project documentation as part of California's *U.S. Forest Projects Compliance Offset Protocol.* Harvest may occur in rotations that last longer than 10 years—as such, 10 years of management history is not sufficient to accurately characterize patterns of harvest history and predict future harvest risk.

To visualize additional harvest history, researchers' most commonly used dataset is Global Forest Watch (GFW, Hansen et al., 2013). However, this dataset only dates back as far as the year 2000 and may not detect forest change trends associated with partial timber harvesting or in areas with sparse canopy cover. Satellite imagery and the remote sensing techniques utilized in this analysis make it possible to visualize harvest history for the last 36 years. This additional history provides a lengthier, more detailed, more accurate, and more methodologically consistent set of data to identify patterns in harvest history than the 10-year narrative descriptions provided in CARB project documentation. With this bespoke dataset, it is also possible to customize forest change detection methods to detect not only deforestation, as in existing detection methods, but a wider variety of harvesting regimes, including those that do not result in total canopy loss like partial thinning and selected cuts (Kennedy et al., 2010). Altogether, the methods used here for visualizing and detecting harvest history, including 36 years of remotely sensed satellite data and forest disturbance detected with a more specific and relevant algorithm, provide a robust dataset to help identify patterns in harvest history.

Here, remote sensing is utilized to quantify and visualize past forest harvest based on historical, publicly available satellite imagery that spans 36 years. Previously, large-scale analysis of satellite imagery requiring the entirety of an image archive would have been resource-intensive and too computationally expensive to run on a local machine. Advances in the last several years in processing speeds and data storage efficiency, as well as increased access to both by researchers, have made this type of analysis possible on local machines. Using this novel database of remotely sensed satellite data, historical forest disturbance rates were calculated within Supersection and project bounds and compared directly to one another to evaluate disturbance rates on project lands. Results were further explored across landowner types and at the coarsest EPA Ecoregion level (Level I) to explore whether ownership type is associated with different baseline disturbances on project lands.

It is important to note that, despite conducting a validation analysis of the remote sensing results, and parameterizing the analysis to temporally, spectrally, and spatially focus on forest harvesting, it is always possible that non-management related forest disturbances could be present. Some types of non-management related forest disturbances are simpler to control for, but others, such as pests or drought-related declines in forest health (Allen et al., 2010), are more challenging, despite best efforts to do so (Masek et al., 2015).

3.2 Methods

Data preparation

The primary dataset used in this remote sensing analysis was the Landsat archive, though several data sources were utilized (Table 3). All Landsat 4-5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) data available as Surface Reflectance (SR) High-Level Data from the USGS were used for each of the Landsat footprints that overlap the borders of the Supersections, as well as the forest offset projects studied. All SR scenes were Level 1 Terrain corrected (L1T) data provided by the USGS Earth Resources Observation and Science (EROS) Center. Landsat 8 data were processed to SR using the 'L8SR' algorithm, which utilizes Landsat 8-specific characteristics (Sayler, 2020). Landsat 4-7 data were processed to SR using the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) method (Masek et al., 2006, Schmidt et al., 2013; USGS, 2016b). CFmask, a version of the Fmask algorithm (Zhu & Woodcock, 2012a; Zhu et al., 2015) created for implementation in C, was used to mask out bad pixels from each image, including clouds cloud shadows, and bodies of water.

Table 3. Data sources used in remote sensing analysis.

Description	Type	Source(s)
Boundary files for IFM compliance projects	Vector	Verra California Offset Project Registry[5] Climate Action Reserve[6] American Carbon Registry[7]
Supersection shapefiles	Vector	ARB US Forest Projects website Continental US[8] Alaska[9]
Surface Reflectance Tier 1 data and Landsat Archive	Raster	US Geological Survey[10]
Bodies of water	Raster	European Commission's Joint Research Centre Global Surface Water Mapping Layers, v1.2[11]
Burned areas	Vector	MODIS Burned Area Monthly Global 500m[12]
Forest cover	Raster	Global Forest Watch[13]
Roads	Vector	TIGER: US Census Roads[14]

LandTrendr analysis

I created forest disturbance maps indicative of management activities such as clearcutting and selective harvest from 1985 to 2020. The analysis for each project and Supersection was conducted using Google's Earth Engine platform (Google

[5] https://registry.verra.org/
[6] https://thereserve2.apx.com/myModule/rpt/myrpt.asp?r=111
[7] https://acr2.apx.com/myModule/rpt/myrpt.asp?r=111
[8] https://ww3.arb.ca.gov/cc/capandtrade/protocols/usforest/2015/super.section.shapefiles5.4.15.zip
[9] https://ww3.arb.ca.gov/cc/capandtrade/protocols/usforest/2015/ak.se.sc.supersection.shp.5.4.15.zip
[10] https://www.usgs.gov/core-science-systems/nli/landsat/landsat-data-access
[11] https://global-surface-water.appspot.com/download
[12] https://lpdaac.usgs.gov/products/mcd64a1v006/
[13] https://data.globalforestwatch.org/
[14] https://www.census.gov/programs-surveys/geography/guidance/tiger-data-products-guide.html

Developers, 2020) and the LandTrendr algorithm (Gorelick et al., 2017; Kennedy et al., 2010; 2018; Table 4; Figure 3). LandTrendr (Landsat-based detection of trends in disturbance and recovery) has been used in many forest change analyses and was utilized in this work for several reasons. First, LandTrendr is an effective tool for analyzing forest harvest-related disturbances across diverse landscapes (Kennedy et al., 2018). Second, it is optimized to detect and separate abrupt from long-term forest change related to forest management activities like harvesting, e.g., clearcutting, selective harvesting, and thinning, by allowing parameter customization to identify specific types of forest management (Kennedy et al., 2010). Lastly, LandTrendr is effective at large-scale analyses in Google's Earth Engine platform, which provides the computational power to conduct time series at the national scale needed for this analysis (Kennedy et al., 2018).

For each project and Supersection, the Landsat archive—US Geological Survey (USGS) Surface Reflectance Tier 1 data (Masek et al., 2006; Vermote et al., 2016)—was accessed via GEE to create annual composite images for each year between 1984 and 2020 inclusive. Data from 1984 was ultimately omitted from analyses due to the non-uniform availability of imagery. Imagery from all available Landsat sensors was considered in creating the composites, including Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper + (ETM+), and Landsat 8 Operational Land Imager (OLI). The archive was filtered for all images that overlapped the bounds of the project or assessed Supersection. Images were then filtered to those acquired within a peak growing season time range from mid-June to mid-September between 1985 and 2020. A harmonization function was deployed to prepare images in the filtered collection for processing by correcting for discrepancies across images acquired from Landsat 8 and other Landsat sensors (Roy et al., 2016). Clouds, cloud shadows, water, snow/ice, primary and secondary roads, water bodies, and fire activity areas were masked out.

Annual medoid composites were made with the processed and filtered image collection by selecting the images for each year with spectral values most similar to the median spectral values of the series (Kennedy et al., 2018). Areas of forest with less than 30% canopy cover were masked out from the composites with the following process: first, a baseline forest cover image was generated using the GFW Forest cover layer from 2000 as an initial reference point (Hansen et al., 2013). The layer was filtered to include only areas with canopy cover greater than or equal to 30%. A random sample of points was generated within the forested areas, and then the points were then used to sample the Landsat composite image I created for the year 2000. A supervised random forest classification was conducted to classify forest cover areas in the 1985 composite image using the collected training data from 200038. Areas classified in 1985 as non-forest or forest with less than 30% canopy cover were masked out in every subsequent annual image of the time series. These steps were done for each project and Supersection individually. Annual composite images were clipped to project or Supersection extents. The Normalized Burn Ratio (NBR) spectral index (Key & Benson, 2006; Miller & Thode, 2007) was used as the input for LandTrendr, and was computed as follows:

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \quad (1)$$

where NIR is Near Infrared and SWIR is Shortwave Infrared. NBR has been utilized in many studies using LandTrendr to detect forest disturbance (Kennedy et al., 2012; White et al., 2017) and is an exceptionally reliable metric compared to other commonly used indices (Cohen et al., 2017). The LandTrendr algorithm was applied, and the magnitude of change was calculated per pixel. For each pixel time series, if there was more than one disturbance detected, only the greatest magnitude disturbance was ultimately considered. Finally, pixels were clustered into minimum mapping units of 10 pixels using a 10-pixel sieve (Kennedy et al., 2012; Soto-Berelov & Hislop, 2016) to resolve noise (<10 disturbed pixels surrounded by non-disturbance) and small, isolated areas of under-threshold disturbance (<10 non-disturbed pixels surrounded by disturbance).

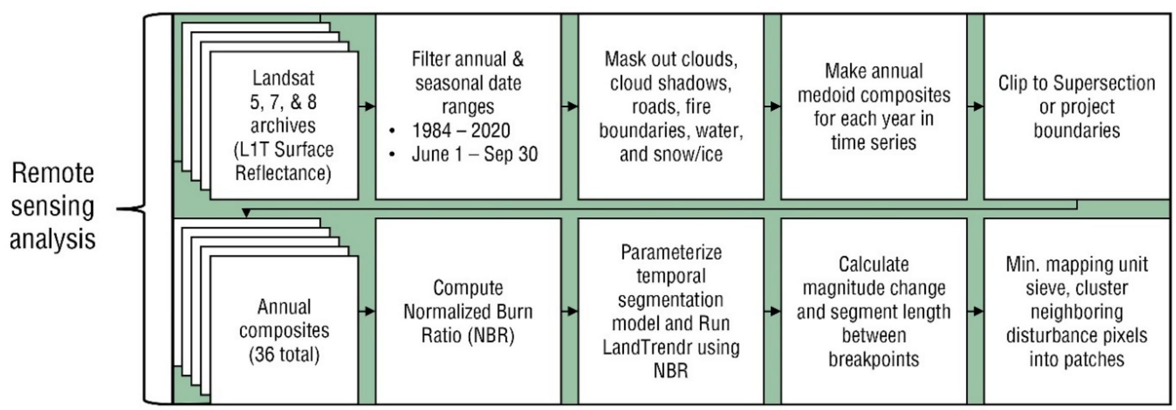

Figure 4. Remote sensing analysis diagram.

Table 4. LandTrendr parameters used in GEE (Modified from GEE, 2020; eMapR[15], 2019; Kennedy et al., 2010).

Parameter	Type	Default	Value	Description
segIndex	Float	N/A	N/A	Index used (Normalized Burn Ratio), multiplied by 1,000
maxSegments	Integer	N/A	6	Max num of segments to be fitted on the time series
spikeThreshold	Float	0.9	0.9	Threshold for dampening spikes (1 = no dampening)
vertexCountOvershoot	Integer	3	3	Initial model can overshoot maxSegments by this amount
preventOneYearRecovery	Boolean	false	true	Prevent segments that represent one-year recoveries
recoveryThreshold	Float	0.25	0.25	If a segment has a recovery rate faster than 1/recoveryThreshold (in yrs.), segment is disallowed
pvalThreshold	Float	0.1	0.05	If fitted model p-value exceeds this threshold, model is discarded, and another is fitted using the Levenberg-Marquardt optimizer
bestModelProportion	Float	1.25	0.75	Takes the model with most vertices that has a p-value that is at most this proportion away from the model with lowest p-value
minObservationsNeeded	Integer	6	6	Min observations needed to perform output fitting
treeloss1	Integer	N/A	175	ΔsegIndex values for 1-year duration dist. ≤ to this threshold will not be included as dist.
treeloss20	Integer	N/A	200	ΔsegIndex values for 20-yr duration dist. ≤ to this threshold will not be included as dist.
preval	Integer	N/A	400	Value to filter NBR values prior to a dist. Because NBR (normalized, -1 to 1) is multiplied by 1,000 in the analysis, 400 refers to pre-change vales > 0.4
mmu	Integer	N/A	10	The min mapping unit: The min number of homogenous neighboring pixels needed to be a dist. patch.
sort	String	N/A	greatest	The type of change to identify if there are more than one change event in a pixel time series. It can be: 'greatest', 'least', 'newest', 'oldest', 'fastest', 'slowest'.
dur	Integer	N/A	34	Option for filtering change events by duration.

[15] https://github.com/eMapR/LT-GEE

Validation of results

The validation of land use change analyses, despite its importance, is challenging, expensive, and oftentimes unvalued (Foody, 2010; Lu et al., 2014; Olofsson et al., 2014; Vogelmann et al., 2016). The most significant challenges for validating such studies reside in the need for validation data collected over time (Foody, 2010; Lu et al., 2014; Olofsson et al., 2013; Vogelmann et al., 2016; see, e.g., Lambert et al., 2013; Rautianinen et al., 2012; Serbin et al., 2013; Steinberg et al., 2006). Validation or 'ground-truthing' data are typically created by researchers by going into the field and assessing the geographic location and specific attributes about that place to be used to classify the rest of the image according to the similar spectral signature. To validate the LandTrendr analysis results, a stratified random sample of 3,114 points was generated based on the area proportions of the disturbed/non-disturbed map to manually confirm or reject each of the three classes within both Supersection and project lands: (1) non-forested areas; (2) forested areas that were not disturbed, and (3) forest areas that were disturbed (Olofsson et al., 2014). I then split this number of validation points in half, sampling half from project land and half from non-project Supersection land. Each point was also assigned a five-year time period from 1985 to 2020. The classification was manually confirmed or rejected using imagery from that five-year period in Google Earth Pro. If imagery was not available, a new random point was assigned with the same parameters (Bruggeman et al., 2016). Each of the three validation classes ultimately had 1,038 total points sampled.

To further validate our results, the total area of pixels that experienced a disturbance in the LandTrendr analysis was compared with the total disturbance areas reported in the GFW dataset, developed by Hansen et al. (2013). Several metrics were calculated and compared because of the temporal and processing differences between our study and GFW data (Figure 4). First, the total forest disturbances detected in the LandTrendr outputs between 1986 and 2020 were calculated at the Supersection level. The same was done for the GFW data for all available data at the time of writing, 2000-2020. Because I masked out certain types of disturbances that could be present in the GFW dataset, such as wildfires, I also applied the same masks to omit them from the GFW data before summarizing it at the Supersection level. A second metric was calculated for the LandTrendr output dataset that summarized disturbances detected within the same period GFW data was available. An important aspect of the LandTrendr model used was a parameter that returned only one disturbance event per observation. For the second GFW summary, any points that had experienced a disturbance before 2000 in the LandTrendr output were masked out, in order to be certain that those areas would not experience a disturbance if only the years 2000-2020 were isolated.

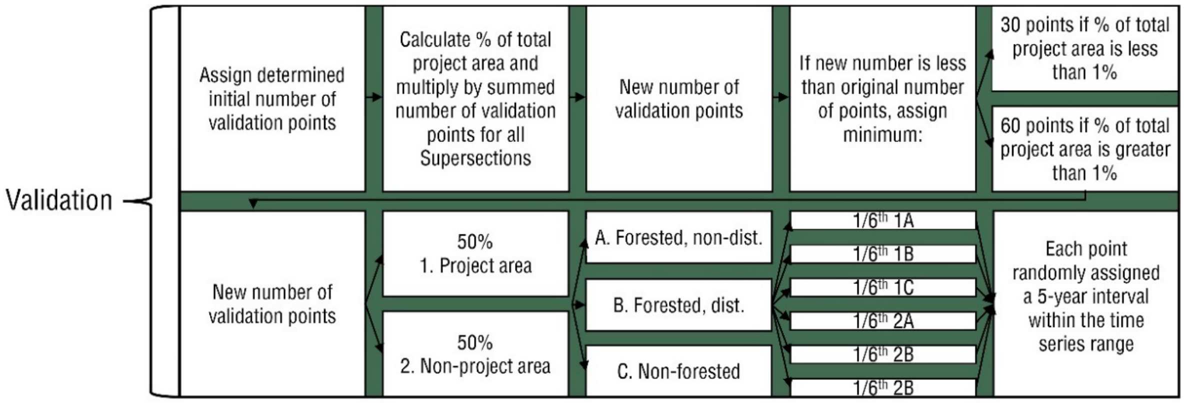

Figure 5. Validation process diagram.

Comparing disturbance rates between projects and Supersections

To explore the difference in forest disturbance rates between projects and Supersections, disturbance rates were calculated for overall project land and overall Supersection land. Disturbance rates were calculated using a random sample of the full dataset. The disturbance rate over time was calculated for 35 time steps, starting with the rate of change from 1985 to 1986 and ending with the rate of change from 2019 to 2020. Disturbance rates were calculated using a sample of the unmatched data due to the enormous quantity of points in the full dataset. Differences were tested for each ownership class and regional aggregation of Supersections—EPA Level 1 Ecoregions (Figure 6; Table 8). Using this randomly sampled dataset, disturbance rate for all projects was then averaged and compared to the average disturbance rate for all Supersections. Pairwise Wilcoxon tests were conducted as a non-parametric alternative to paired t-tests to evaluate significant differences in disturbance rates between projects and Supersections (Hollander et al., 2015).

3.3 Results

LandTrendr analysis validation

Of the 1038 points sampled from each class to validate the LandTrendr analysis, 92% of points classified as non-forest were manually confirmed as non-forest; 89% of points classified as non-disturbed forest were manually confirmed as non-disturbed forest, and 86% of points classified as disturbed forest were manually confirmed as disturbed forest (Table 5). In the second LandTrendr and GFW summaries, Supersections experienced 2,723 km2 and 1,985 km2 of forest disturbance, respectively (Table 6).

Table 5. Results of the validation.

Type	Total Points	Points Confirmed	Percent Confirmed
Non-Forest	1038	950	92%
Forest Non-Disturbed	1038	928	89%
Forest Disturbed	1038	895	86%

Table 6. LandTrendr and GFW summaries and comparison (Haya, 2018). A1: Sum of LandTrendr disturbances between 1986 and 2020 (km2); B1: Sum of GFW disturbances (km2) applying LandTrendr mask 2000-2020; A2: Sum of LandTrendr disturbances that occurred 2000 or later (km2); B2: Sum of GFW disturbances with LandTrendr disturbances that occurred before 2000 masked, as well as other masks used in LandTrendr pre-processing steps (km2).

Supersection	A1	B1	A2	B2	B1 / A2	B2 / A2
Adirondacks & Green Mountains	2,725	1,585	892	491	1.78	0.55
Allegheny & North Cumberland Mountains	9,112	4,077	3,037	1,702	1.34	0.56
Aroostook Hills and Lowlands	1,401	1,409	476	351	2.96	0.74
Atlantic Coastal Plain & Flatwoods	51,213	38,425	15,227	11,592	2.52	0.76
Central Interior Broadleaf Forest Eastern Low	3,247	2,631	1,081	718	2.43	0.66
Central Interior Broadleaf Forest Ozark Highlands	6,929	3,848	2,109	1,230	1.82	0.58
Central Maine & Fundy Coast & Ebayment	3,148	1,546	871	583	1.78	0.67
Central New Mexico	396	215	90	38	2.4	0.42
Columbia Basin	675	826	206	154	4.01	0.75
Eastern Broadleaf Forest Cumberland Plateau	5,001	2,868	1,582	1,014	1.81	0.64
Eastern Cascades	3,746	2,263	967	712	2.34	0.74

Florida Coastal Plains Central Highlands	2,797	2,481	742	532	3.34	0.72
Florida Everglades	625	487	145	87	3.36	0.6
Gulf Coastal Plain	68,222	49,905	21,002	16,411	2.38	0.78
Laurentian Mixed Forest Green Bay Lobe	1,537	1,162	478	338	2.43	0.71
Laurentian Mixed Forest MN & Ontario Lake Plain	4,181	3,723	1,369	1,017	2.72	0.74
Laurentian Mixed Forest NLP EUP	6,907	3,303	2,231	1,447	1.48	0.65
Laurentian Mixed Forest Northern Highlands	1,835	1,770	560	357	3.16	0.64
Laurentian Mixed Forest Southern Superior	2,371	1,286	719	447	1.79	0.62
Laurentian Mixed Forest Western Superior & Lake	1,052	1,056	371	230	2.85	0.62
Lower New England - Northern Appalachia	4,440	2,262	1,467	683	1.54	0.47
Maine - New Brunswick Foothills and Lowlands	3,973	1,566	1,132	704	1.38	0.62
Modoc Plateau	589	456	125	77	3.63	0.62
Montana Rocky Mountains	6,250	3,324	1,572	1,076	2.11	0.68
MS River Delta	3,215	3,007	1,142	885	2.63	0.77
MW Broadleaf Forest Central Till Plains	177	98	48	12	2.05	0.26
MW Broadleaf Forest SC Great Lakes & Lake Whittles	306	263	92	35	2.88	0.38
Northern Allegheny Plateau	1,651	901	533	284	1.69	0.53
Northern Atlantic Coastal Plain	13,465	10,318	4,290	3,198	2.4	0.75
Northern California Coast	3,059	810	638	420	1.27	0.66
Northwest Cascades	20,217	5,813	5,044	3,942	1.15	0.78
Okanogan Highland	8,669	3,589	2,473	1,938	1.45	0.78
SE Middle Mixed Forest Cumberland Plateau & Valley	6,576	6,204	1,993	1,503	3.11	0.75
SE Middle Mixed Forest Piedmont	69,638	45,750	21,067	16,275	2.17	0.77
SE Middle Mixed Forest Western Mid Coastal Plains	33,611	23,238	11,457	9,271	2.03	0.81
Sierra Nevada	4,496	1,568	1,135	628	1.38	0.55
Southeast And South Central Alaska	4,486	1,091	1,458	230	0.75	0.16
Southern Allegheny Plateau	3,680	2,262	1,151	688	1.97	0.6
Southern Cascades	11,033	3,890	2,902	1,934	1.34	0.67
St Lawrence & Mohawk Valley	426	331	137	73	2.42	0.53
Western Allegheny Plateau	497	325	151	68	2.15	0.45
White Mountains	9,586	5,091	2,832	1,938	1.8	0.68
White Mountains - San Francisco Peaks - Mongollon	624	399	110	44	3.63	0.4
Mean	9,018	5,754	2,723	1,985	2.22	0.62

Historical rates of disturbance

Rates of management-related disturbance were relatively low throughout the United States. Overall, about 0.2% of forested pixels in our dataset were disturbed each year, likely due to forest harvest. Annual disturbance rates in projects were statistically lower overall than in Supersections (on average, 0.16% of project land was disturbed each year compared to 0.22% of Supersection land). Overall, average disturbance rates across the 35-year time series were lower for project land than for Supersection land. This pattern of lower disturbance on project land was also observed for almost all individual years of the time series (Figures 5-7). Projects experienced less annual disturbance than Supersections for 31 of the 35 years included in our analysis.

There was, however, heterogeneity within individual projects and their respective Supersections. Not all projects experienced lower rates of disturbance than their Supersections: using pairwise Wilcoxon rank-sum tests to compare each project/Supersection pair, 12% of projects (11 of 90) had significantly higher rates ($p < 0.001$) (Table 7). In 4 of 8 regions, Great Plains ($p < 0.001$), Marine West Coast Forest ($p < 0.001$), North American Desert ($p = 0.032$), and Northwestern Forested Mountains ($p < 0.001$), disturbance rates were statistically higher for all Supersections than all project areas within the region. 71% of projects (64 of 90) had lower annual rates of disturbance than their respective Supersection, 21% of which (19 of 90 projects) had significantly lower annual rates of disturbance than their Supersection ($p < 0.001$).

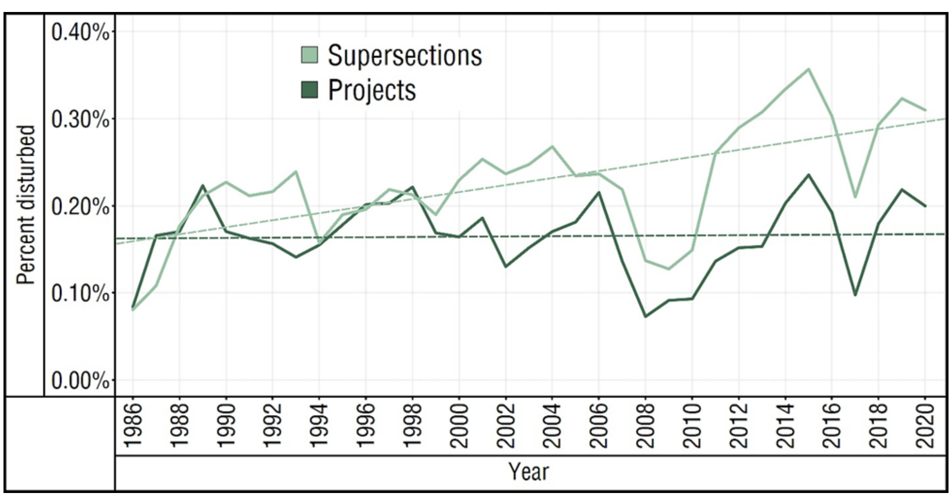

Figure 6. Time series showing the annual percentage of total area disturbed on projects and Supersections. The annual disturbance is reported between 1986 and 2020.

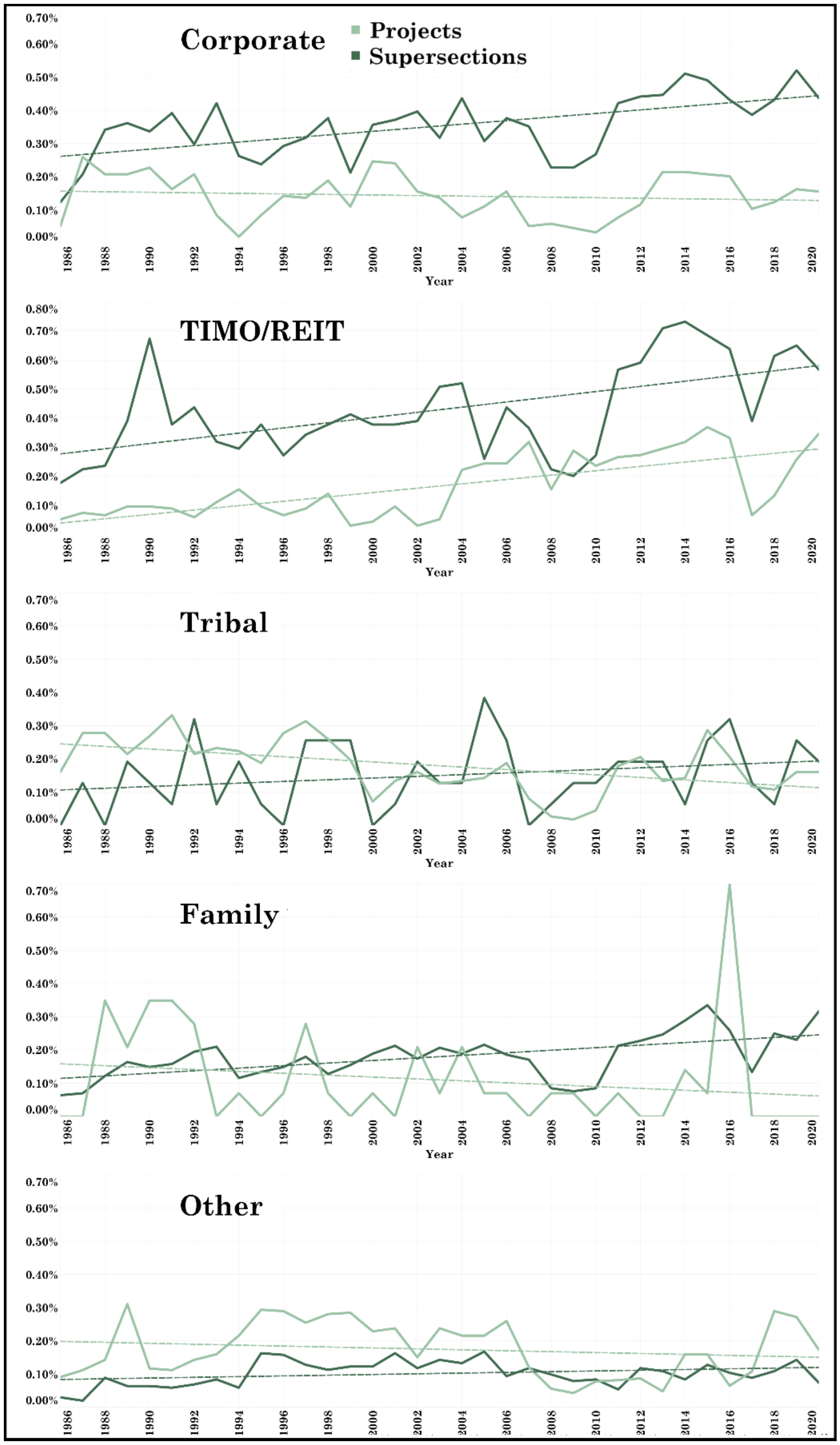

Figure 7. Time series showing the annual percentage of total area disturbed on projects and Supersections. The annual disturbance is reported between 1986 and 2020.

Table 7. Differences between individual projects and the primary Supersections in which they are located for the mean annual percentage of total area disturbed between 1986 and 2020. For instances where projects are located across multiple Supersections, the Supersection with the majority of project area was used to compare disturbance rates. Pairwise Wilcoxon rank-sum tests were used to test for differences in disturbance rates.

Project	ha*	Mean Ann. % Dist.	SD	Supersection	ha*	Mean Ann % Dist.	SD	p
ACR173	5	0.14%	(0.038)	Southern Cascades	505	0.41%	(0.064)	0.067*
ACR182	2	0.27%	(0.052)	Northern California Coast	289	0.41%	(0.064)	0.54
ACR189	3	0.31%	(0.055)	Southern Cascades	505	0.41%	(0.064)	0.66
ACR192	3	0.39%	(0.062)	Atlantic Coastal Plain & Flatwoods	60	0.54%	(0.073)	0.027**
ACR199	109	0.17%	(0.041)	White Mountains	544	0.35%	(0.059)	0.05*
ACR200	1	0%	(0)	Northern California Coast	289	0.41%	(0.064)	0.2
ACR202	68	0.07%	(0.026)	Laurentian Mixed Forest Northern Highlands	69	0.05%	(0.022)	0.0093
ACR210	23	0.01%	(0.011)	Laurentian Mixed Forest Southern Superior	158	0.12%	(0.035)	0.53
ACR211	147	0.03%	(0.018)	White Mountains - San Francisco Peaks - Mongollan	149	0.02%	(0.014)	1
ACR237	20	0.97%	(0.098)	Northern California Coast	289	0.41%	(0.064)	<0.001***
ACR247	64	0.24%	(0.048)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.43
ACR248	85	0.19%	(0.044)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	<0.001***
ACR249	47	0.09%	(0.03)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.19
ACR250	93	0.41%	(0.064)	Northern California Coast	289	0.41%	(0.064)	0.91
ACR251	57	0%	(0)	MS River Delta	59	0.22%	(0.047)	NaN
ACR255	560	0.36%	(0.06)	Okanogan Highland	465	0.55%	(0.074)	0.38
ACR256	82	0.01%	(0.008)	Eastern Broadleaf Forest Cumberland Plateau & Valley	69	0.1%	(0.032)	<0.001***
ACR257	5	0.25%	(0.05)	Gulf Coastal Plain	130	0.59%	(0.077)	0.12
ACR260	44	0.03%	(0.017)	Northwest Cascades	78	1.06%	(0.102)	<0.001***
ACR262	18	0.42%	(0.065)	Northern California Coast	289	0.41%	(0.064)	0.99
ACR267	30	0.03%	(0.016)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.0032**
ACR273	446	0.09%	(0.03)	Eastern Cascades	354	0.51%	(0.071)	0.0017**
ACR274	180	0.37%	(0.061)	Southern Cascades	505	0.41%	(0.064)	0.47
ACR276	35	0.07%	(0.026)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.061*
ACR279	36	0.06%	(0.024)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.029**
ACR280	93	0.06%	(0.025)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.0021**
ACR281	13	0%	(0)	Laurentian Mixed Forest Northern Highlands	69	0.05%	(0.022)	0.28
ACR282	14	0.29%	(0.054)	Northern California Coast	289	0.41%	(0.064)	0.16
ACR284	12	0%	(0)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.0014**
ACR288	1	0.63%	(0.08)	Gulf Coastal Plain	130	0.59%	(0.077)	0.74
ACR289	29	0.68%	(0.082)	Gulf Coastal Plain	130	0.59%	(0.077)	0.022**
ACR290	8	0.31%	(0.056)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.0024**
ACR291	20	0.08%	(0.028)	Northern Allegheny Plateau	71	0.04%	(0.019)	0.43
ACR292	4	0.28%	(0.053)	Northern California Coast	289	0.41%	(0.064)	0.41
ACR293	54	0.01%	(0.012)	Lower New England - Northern Appalachia	54	0.09%	(0.03)	0.62
ACR296	26	0.47%	(0.068)	Southern Cascades	505	0.41%	(0.064)	0.25
ACR297	40	0.42%	(0.065)	SE Middle Mixed Forest Western Mid Coastal Plains	69	0.64%	(0.079)	0.98
ACR298	22	0.56%	(0.074)	Southern Cascades	505	0.41%	(0.064)	0.019**

ACR299	25	0.23%	(0.048)	Laurentian Mixed Forest Western Superior & Lake Plains	51	0.09%	(0.029)	1
ACR300	1	0.95%	(0.097)	Gulf Coastal Plain	130	0.59%	(0.077)	0.26
ACR301	0	2.14%	(0.145)	Gulf Coastal Plain	130	0.59%	(0.077)	0.0064**
ACR307	16	0%	(0)	Gulf Coastal Plain	130	0.59%	(0.077)	<0.001***
ACR324	130	0.09%	(0.03)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
ACR360	580	0.02%	(0.013)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
ACR371	21	0.01%	(0.011)	Lower New England - Northern Appalachia	54	0.09%	(0.03)	0.84
ACR373	23	0.04%	(0.021)	Laurentian Mixed Forest Northern Highlands	69	0.05%	(0.022)	0.27
ACR377	5	0.19%	(0.043)	Southern Cascades	505	0.41%	(0.064)	0.13
ACR378	2	0.24%	(0.049)	Southern Cascades	505	0.41%	(0.064)	0.47
ACR393	8	0%	(0)	Laurentian Mixed Forest Southern Superior	158	0.12%	(0.035)	0.42
ACR396	3	0%	(0)	Atlantic Coastal Plain & Flatwoods	60	0.54%	(0.073)	0.22
ACR406	77	0.03%	(0.018)	Laurentian Mixed Forest Southern Superior	158	0.12%	(0.035)	0.28
ACR412	189	0.01%	(0.011)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
ACR416	40	0.13%	(0.036)	Laurentian Mixed Forest MN & Ontario Lake Plain	40	0.11%	(0.033)	1
ACR420	13	0%	(0)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	0.16
ACR425	12	0.25%	(0.049)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
ACR427	110	0.16%	(0.04)	White Mountains	544	0.35%	(0.059)	0.013**
ACR428	6	0.18%	(0.043)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
ACR437	278	0.14%	(0.037)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.26
ACR439	172	0.02%	(0.014)	Central Interior Broadleaf Forest Eastern Low Plateau	58	0.06%	(0.024)	0.95
ACR456	20	0.15%	(0.039)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
ACR458	116	0.08%	(0.029)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	<0.001***
CAR1006	96	0.38%	(0.062)	Southern Cascades	505	0.41%	(0.064)	0.74
CAR1013	7	0.19%	(0.044)	Northern California Coast	289	0.41%	(0.064)	0.077*
CAR1032	19	0.2%	(0.045)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.052*
CAR1041	17	0.48%	(0.069)	Southern Cascades	505	0.41%	(0.064)	0.26
CAR1046	15	0.44%	(0.066)	Southern Cascades	505	0.41%	(0.064)	0.61
CAR1062	54	0%	(0.007)	Central Interior Broadleaf Forest Ozark Highlands	60	0.09%	(0.031)	0.76
CAR1063	25	0.39%	(0.063)	Maine - New Brunswick Foothills and Lowlands	189	0.42%	(0.065)	0.59
CAR1066	20	0.72%	(0.085)	Southern Cascades	505	0.41%	(0.064)	<0.001***
CAR1067	2	0%	(0)	Southern Cascades	505	0.41%	(0.064)	0.053*
CAR1070	31	0.19%	(0.044)	Southern Cascades	505	0.41%	(0.064)	<0.001***
CAR1086	0	0%	(0)	SE Middle Mixed Forest Western Mid Coastal Plains	69	0.64%	(0.079)	0.59
CAR1088	208	0.21%	(0.046)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.97
CAR1090	19	0.53%	(0.073)	Southern Cascades	505	0.41%	(0.064)	0.061*
CAR1092	18	0.51%	(0.071)	Modoc Plateau	122	0.13%	(0.036)	<0.001***
CAR1094	1	0.29%	(0.053)	Northwest Cascades	78	1.06%	(0.102)	0.98
CAR1095	15	0.14%	(0.038)	Southern Cascades	505	0.41%	(0.064)	0.0025**
CAR1098	10	0.18%	(0.042)	Northern California Coast	289	0.41%	(0.064)	0.018**
CAR1099	6	0.43%	(0.066)	Northern California Coast	289	0.41%	(0.064)	0.92
CAR1100	12	0.69%	(0.083)	Northern California Coast	289	0.41%	(0.064)	0.0046**
CAR1102	2	0.11%	(0.033)	Northern California Coast	289	0.41%	(0.064)	0.14
CAR1103	2	0.14%	(0.037)	Southern Cascades	505	0.41%	(0.064)	0.27
CAR1104	18	0.26%	(0.051)	Southern Cascades	505	0.41%	(0.064)	0.091*
CAR1113	46	0.91%	(0.095)	Southern Cascades	505	0.41%	(0.064)	<0.001***
CAR1115	47	0.01%	(0.007)	Sierra Nevada	78	0.31%	(0.055)	<0.001***
CAR1129	2	0%	(0)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.17
CAR1130	4	0.07%	(0.026)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.54

CAR1134	30	0.15%	(0.038)	Atlantic Coastal Plain & Flatwoods	60	0.54%	(0.073)	0.84
CAR1139	19	0.11%	(0.033)	Northern California Coast	289	0.41%	(0.064)	<0.001***
CAR1140	8	0.22%	(0.047)	Northern California Coast	289	0.41%	(0.064)	0.084*
CAR1141	1	0%	(0)	Northern California Coast	289	0.41%	(0.064)	0.17
CAR1147	11	0.02%	(0.015)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.069*
CAR1159	3	0.1%	(0.031)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.8
CAR1161	5	0.1%	(0.032)	Maine - New Brunswick Foothills and Lowlands	189	0.42%	(0.065)	0.024**
CAR1162	1	0%	(0)	Maine - New Brunswick Foothills and Lowlands	189	0.42%	(0.065)	0.24
CAR1173	11	0.02%	(0.015)	Eastern Broadleaf Forest Cumberland Plateau & Valley	69	0.1%	(0.032)	0.15
CAR1175	170	0.3%	(0.055)	Maine - New Brunswick Foothills and Lowlands	189	0.42%	(0.065)	<0.001***
CAR1176	83	0.64%	(0.08)	Gulf Coastal Plain	130	0.59%	(0.077)	0.012**
CAR1180	6	0.04%	(0.021)	Northern California Coast	289	0.41%	(0.064)	0.0057**
CAR1183	254	0.23%	(0.048)	Central New Mexico	72	0.3%	(0.055)	1
CAR1185	44	0.07%	(0.026)	Southern Allegheny Plateau	64	0.05%	(0.023)	0.69
CAR1186	2	0.23%	(0.048)	Southern Allegheny Plateau	64	0.05%	(0.023)	0.056*
CAR1187	6	0.84%	(0.091)	Northern California Coast	289	0.41%	(0.064)	0.0026**
CAR1191	9	0.14%	(0.037)	Northern California Coast	289	0.41%	(0.064)	0.0089**
CAR1195	14	0.02%	(0.013)	Florida Everglades	31	0.06%	(0.024)	1
CAR1196	9	0.06%	(0.024)	Atlantic Coastal Plain & Flatwoods	60	0.54%	(0.073)	0.21
CAR1199	75	0.41%	(0.064)	SE Middle Mixed Forest Piedmont	64	0.54%	(0.073)	<0.001***
CAR1200	25	0.47%	(0.069)	Northern Atlantic Coastal Plain	59	0.37%	(0.061)	0.46
CAR1201	1	0.95%	(0.097)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.001**
CAR1202	103	0.27%	(0.051)	Aroostook Hills and Lowlands	191	0.22%	(0.047)	0.87
CAR1203	218	0.38%	(0.062)	Aroostook Hills and Lowlands	191	0.22%	(0.047)	<0.001***
CAR1204	157	0.26%	(0.051)	White Mountains	544	0.35%	(0.059)	0.051*
CAR1205	59	0.03%	(0.018)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	<0.001***
CAR1206	24	0.06%	(0.025)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.11
CAR1207	16	1.14%	(0.106)	SE Middle Mixed Forest Piedmont	64	0.54%	(0.073)	<0.001***
CAR1208	152	0.1%	(0.032)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	0.22
CAR1209	56	0.02%	(0.014)	Laurentian Mixed Forest Northern Highlands	69	0.05%	(0.022)	0.74
CAR1211	23	0.4%	(0.063)	SE Middle Mixed Forest Piedmont	64	0.54%	(0.073)	0.015**
CAR1212	6	0.79%	(0.088)	Gulf Coastal Plain	130	0.59%	(0.077)	0.059*
CAR1213	147	0.2%	(0.044)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.49
CAR1215	73	0.21%	(0.046)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	<0.001***
CAR1216	5	0.11%	(0.033)	Laurentian Mixed Forest Southern Superior	158	0.12%	(0.035)	0.02**
CAR1217	21	0.53%	(0.073)	Maine - New Brunswick Foothills and Lowlands	189	0.42%	(0.065)	0.2
CAR1293	27	0%	(0)	Southeast And South Central Alaska	1,145	0.01%	(0.01)	0.046**
CAR1297	40	0.09%	(0.03)	Montana Rocky Mountains	63	0.23%	(0.048)	1
CAR1313	91	0.37%	(0.061)	Northern California Coast	289	0.41%	(0.064)	0.22
CAR973	239	0.2%	(0.045)	Laurentian Mixed Forest NLP EUP	180	0.13%	(0.036)	0.013**
CAR993	15	0.25%	(0.05)	Southern Cascades	505	0.41%	(0.064)	0.081*
VCSOPR10	30	0%	(0)	Central Interior Broadleaf Forest Ozark Highlands	60	0.09%	(0.031)	0.55
VCSOPR11	50	0.24%	(0.049)	Allegheny & North Cumberland Mountains	926	0.09%	(0.03)	<0.001***
VCSOPR12	21	0.3%	(0.055)	White Mountains	544	0.35%	(0.059)	0.14
VCSOPR13	2	0.16%	(0.04)	Atlantic Coastal Plain & Flatwoods	60	0.54%	(0.073)	0.88
VCSOPR14	6	0%	(0)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.026**
VCSOPR15	55	0.12%	(0.034)	Northern Allegheny Plateau	71	0.04%	(0.019)	0.83
VCSOPR16	20	0.07%	(0.026)	Adirondacks & Green Mountains	393	0.08%	(0.027)	0.0058**
VCSOPR5	16	0.75%	(0.087)	Northwest Cascades	78	1.06%	(0.102)	<0.001***

Note: SD = standard deviation; p = p-value statistic (* p <0.1; ** p <0.05; *** p <0.01); *ha = total size of sampled area.

Comparing mean annual disturbance rates by ownership class for all Supersections and all projects in the analysis, disturbance rates were significantly higher in Supersections than projects ($p < 0.001$) on TIMO/REIT, corporate, and family-owned forestlands. TIMO/REIT-owned forestlands had the largest discrepancy in annual disturbance rate between Supersections (0.43%) and projects (0.17%). There was also a large difference in annual disturbance rates for corporate-owned forestlands between Supersections (0.35%) and projects (0.14%). Tribal lands experienced the lowest annual rates of disturbance for both projects and Supersections, with the project rate (0.17%) higher than the Supersection rate (0.1%; $p < 0.001$). No significant difference was found between 'other' projects and their respective Supersections. In 4 of 8 regions, Great Plains ($p < 0.001$), Marine West Coast Forest ($p < 0.001$), North American Desert ($p = 0.032$), and Northwestern Forested Mountains ($p < 0.001$), disturbance rates were statistically higher for all Supersections than all project areas within the region (Figure 6; Table 8).

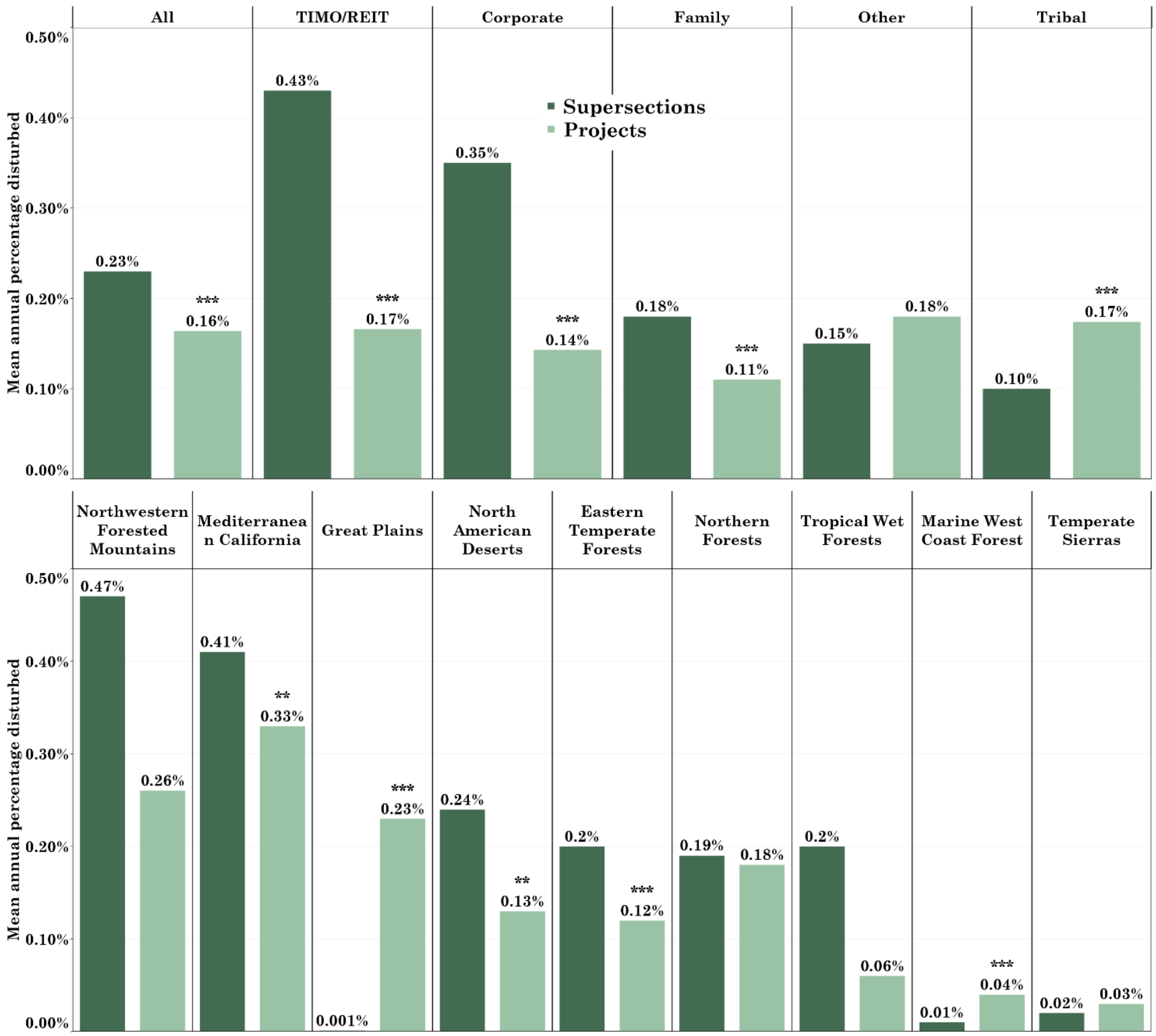

Figure 8. Mean annual percentage of total area disturbed between 1986 and 2020. For each ownership class (top) or region (bottom), p-value statistics result from Wilcoxon rank sum tests between projects and Supersection pairs (* p < 0.1; ** p < 0.05; *** p < 0.01).

Table 8. Differences between Supersections, all projects, and credited projects (the projects used for the primary analysis) for the mean annual percentage of total area disturbed between 1986 and 2020. For each ownership class or region, p-values for projects compare project disturbance rate to Supersection disturbance rate.

Ownership Class / Region	Area type	Sample (ha)	Mean Annual % Dist.	SD	p
All	Projects	7,497	0.196%***	0.044	<0.001
	Credited Projects	5,814	0.164%***	0.041	<0.001
	Supersections	7,497	0.227%	0.048	
Owner: Corporate	Projects	2,224	0.228%***	(0.048)	<0.001
	Credited Projects	1,382	0.143%***	(0.038)	<0.001
	Supersections	1,814	0.353%	(0.059)	
Owner: TIMO/REIT	Projects	1,687	0.214%***	(0.046)	<0.001
	Credited Projects	1,219	0.166%***	(0.041)	<0.001
	Supersections	762	0.428%	(0.065)	
Owner: Tribal	Projects	2,290	0.161%***	(0.04)	<0.001
	Credited Projects	2,081	0.174%***	(0.042)	<0.001
	Supersections	1,824	0.102%	(0.032)	
Owner: Family	Projects	222	0.237%***	(0.049)	<0.001
	Credited Projects	129	0.11%***	(0.033)	<0.001
	Supersections	2,956	0.18%	(0.042)	
Owner: Other	Projects	1,074	0.17%	(0.041)	0.29
	Credited Projects	1,004	0.179%	(0.042)	0.12
	Supersections	141	0.15%	(0.039)	
Region: Eastern Temperate Forests	Projects	2,498	0.195%	(0.044)	0.35
	Credited Projects	1,615	0.12%***	(0.035)	<0.001
	Supersections	2,492	0.201%	(0.045)	
Region: Great Plains	Projects	254	0.23%***	(0.048)	<0.001
	Credited Projects	254	0.23%***	(0.048)	<0.001
	Supersections	198	0.001%	(0.004)	
Region: Marine West Coast Forest	Projects	1,093	0.037%***	(0.019)	<0.001
	Credited Projects	884	0.04%***	(0.02)	<0.001
	Supersections	1,145	0.011%	(0.01)	
Region: Mediterranean California	Projects	293	0.419%	(0.065)	0.75
	Credited Projects	188	0.328%**	(0.057)	0.0047
	Supersections	289	0.41%	(0.064)	
Region: North American Deserts	Projects	37	0.131%**	(0.036)	0.032
	Credited Projects	37	0.131%**	(0.036)	0.032
	Supersections	40	0.238%	(0.049)	
Region: Northern Forests	Projects	1,453	0.176%	(0.042)	0.1
	Credited Projects	1,268	0.178%	(0.042)	0.2
	Supersections	1,488	0.189%	(0.043)	
Region: Northwestern Forested Mountains	Projects	1,708	0.292%***	(0.054)	<0.001
	Credited Projects	1,422	0.261%***	(0.051)	<0.001
	Supersections	1,665	0.467%	(0.068)	
Region: Temperate Sierras	Projects	147	0.032%	(0.018)	0.18
	Credited Projects	147	0.032%	(0.018)	0.18
	Supersections	149	0.019%	(0.014)	
Region: Tropical Wet Forests	Projects	14	0.018%	(0.013)	0.24
	Credited Projects	31	0.059%	(0.024)	-
	Supersections	2,498	0.195%	(0.044)	

Note: SD = standard deviation; p = p-value statistic calculated from Pairwise Wilcoxon rank-sum tests conducted between either all observations across projects and Supersections or credited projects and Supersections for the respective owner class or region. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

3.4 Discussion

Discrepancies in harvesting patterns

Management decisions on private lands depend on several factors: landowners' skills and expertise, the qualities of their land, and how they can manage their land to provide maximum economic and other (e.g., social, environmental) returns (Ruben et al., 2008). Public policies can influence private management decisions by introducing novel incentives as offset programs. Kelly et al. (2017) studied the discrepancies between who owns private forests in the U.S. and who participates in the U.S. Forest Offsets protocol. They found that NIPF landowners were unlikely to offset their forests due to the time and money required to complete the project development process. Other NIPF landowners were unaware that the option was available to them. "Though most landowners indicated they would not likely join the market, we asked what would motivate them to participate—in other words, why they might feel compelled to join. Overall, landowners were most motivated by the opportunity to receive revenue from their forests, followed by improving forest health and reducing greenhouse gases," (Kelly et al., 2017, p. 889). Van Kooten (2018) found that forest carbon offset projects and forestry-related jobs that could be supported in tandem to offset projects can result in direct income from credits, jobs, healthier forests capable of storing more carbon, and other non-market social-environmental benefits.

There is not much data available about forest management trends on Tribal forestlands in the U.S. According to the USFS (2014), only 8% of individual and family forest landowners in the U.S. actively manage their forests for timber. However, a 2020 congressional amendment to the *Tribal Forest Protection Act of 2004* reports that Native American forestland totals 15,990,000 acres, with 5,700,000 acres used for commercial forestry and 8,700,000 acres of woodland (USC, 2020) lands are not harvested. This means that a little over one-third of Tribal forests are actively managed for timber. Harvesting or offsetting Tribal forestlands might also be lower because the 2020 amendment to the *Tribal Forest Protection Act of 2004* 1) recognizes the monetary value of Tribal forests and 2) allows the Federal Government to collect 10% of all revenue made with Tribal forests.

TIMO/REIT groups own roughly 20% of all private forestlands in the U.S. Gifford (2020, citing Kay, 2017) describes them as “financial investors who used the disintegration of the pulp and paper industry as a chance to acquire large forestland holdings . . . The primary goal of a TIMO is financial: to achieve profitability via diversification of large investment portfolios. “Most conservation TIMOs are structured as private equity firms, with 10–15-year ownership horizons. Once this period has lapsed, the land will be sold to another buyer” . . . This timing structure sets up TIMO forests as strong contenders for carbon offset schemes. Once a TIMO has aggressively harvested forest products, other timberland investors are not interested in taking over the land, as it would require 40– 50 years to regenerate timber value. Therefore, TIMOs have two potential buyers for their land: developers or conservation organizations” (pp. 294-95). This could explain the results reported for TIMO/REIT rates of disturbance, where Supersections were found to have experienced more than twice as much disturbance as projects. It seems likely that a TIMO/REIT, could, for example, aggressively harvest on acquired forestlands and then aggregate the areas that were not economically viable to harvest and register them as an offset project. In this way, the return on investment for forestlands is maximized: acquired forests that are suitable for harvesting are done so aggressively, the areas that are not are turned into a profitable offset project, and the depleted areas that were harvested can be sold to developers or conservation organizations.

Limitations of results

The results presented here provide insight into whether or not projects have experienced a forest disturbance history indicative of forest harvesting over the past 36 years. While this information is useful in assessing the potential future risk of harvesting and, therefore, the utility of offsetting the land, it is limited.

First, the harvesting rates are compared directly to all Supersection assessment area forests. For some projects, the detected disturbance rate was zero or close to zero, indicating little or no risk of harvesting based on historical patterns regardless of comparison to regional rates. However, the disturbance rates for all other projects and the associated potential risk of harvesting are interpreted relative to the disturbance rates in each project's respective Supersection assessment area. This direct comparison approach does not effectively isolate policy impacts from other factors or properly control time-invariant unobservable variables (Bruggeman et al., 2016; Imbens & Wooldridge, 2009; Jones & Lewis, 2015; Jones et al., 2017). A more robust method for comparing disturbance rates would be to compare offset project forestlands to forest areas within the Supersection that are statistically comparable based on landscape, climatic, spatial, and economic characteristics and then incorporate those variables into a statistical model to better assess the causal mechanisms behind disturbance rates. The difference between projects and Supersections that we are most interested in isolating is project establishment. Understanding the effect of project establishment would result in a more robust and informative interpretation of past forest disturbance rates.

Second, LandTrendr, as all forest change detection methods, has limitations (Kennedy et al., 2010; Masek et al., 2015; Zhu et al., 2017). The spectral-temporal segmentation results will vary based on the model parameters that are input, the spectral index used, and whether or not they are well suited for the characteristics of the analysis location (Hislop et al., 2019). Although the validation results were quite positive, this study could have been improved by collecting ground-truthing data rather than relying on very high resolution data. Ideally, ground-truthing data would have been collected on the ground over multiple time periods to use in the validation of these results (Foody, 2010; Lu et al., 2014; Olofsson et al., 2013; Vogelmann et al., 2016; see, e.g., Lambert et al., 2013; Rautianinen et al., 2012; Serbin et al., 2013; Steinberg et al., 2006). The ability to collect validation data (or training samples) on the ground in order to improve remote sensing analyses, however, becomes prohibitively costly, time consuming, and logistically challenging as the scope of the study is scaled-up. Finally, despite conducting a validation analysis, and parameterizing the model to focus on forest harvesting temporally, spectrally, and spatially, it is always possible that non-management related forest disturbances could be present in these results, such as pests or drought-related declines in forest health.

Chapter 4

Measuring Offset Policy Effectiveness Using Quasi-Experimental Econometric Techniques

Abstract

While credits have been allocated primarily to forests with low historical disturbance rates, it is not possible to make conclusions about causality without controlling for factors impacting project establishment. To establish causality, forest disturbance was observed before and after project establishment, and quasi-experimental econometric techniques were used to investigate whether forest disturbance is reduced relative to comparable lands after projects are established—that is, whether projects show clear signs of additionality. To estimate the effect of project commencement on forest disturbance, a difference-in-difference panel regression was conducted. To isolate the effect of other confounding factors, like landscape, climatic and geographical characteristics, matching was applied to points on projects and Supersections (regional lands). The points resulting from the matching analysis were used as input for panel regression models. This analysis in Chapter 4 suggests limited additionality, as the establishment of forest offset projects did not significantly lower forest disturbance rates 3 and 5 years after project implementation relative to similar, regional non-project lands.

4.1 Introduction

To explore additionality in enrolled IFM projects, I focused on two main questions: (1) Do pre-project disturbance rates on IFM projects suggest that enrolled forests were at a lower risk of harvest than non-enrolled forests even in the absence of credits? In Chapter 3, I find that IFM projects have been primarily allocated to forests with low historical disturbance relative to regional averages. (2) After projects are established, is forest disturbance reduced relative to comparable lands—that is, do projects show clear signs of additionality? To estimate the effect of project commencement on forest disturbance, a difference-in-difference panel regression was conducted. To isolate the effect of other confounding factors, like landscape, climatic and geographical characteristics, matching was applied to points on projects and Supersections. The points resulting from the matching analysis were used as input for the panel regression models. The methods that are used in this analysis to assess the effectiveness of IFM forest offset projects are borrowed and adapted from econometric analyses and have increasingly been used as quasi-experimental approaches for addressing ecological and environmental policy research questions such as assessing the effectiveness of protected area establishment on reducing forest degradation (Chapter 1).

For these reasons, assessments of offset projects and associated forest change should adhere to the same safeguards that would be optimally designed into models that assess protected area effectiveness. Offset project locations should not be assumed to be random, and the forests within should not be compared to all other forests within the Supersection assessment area as the current *U.S. Forest Projects Compliance Offset Protocol* calls for. These two factors have the potential to introduce bias into the analysis. It is possible, for example, that an IFM offset project location is selected where it is not economically viable for a landowner to harvest timber due to landscape characteristics, accessibility, or distance to mills.

4.2 Methods

Matching

Matching (Rosenbaum & Rubin, 1983) was used to create a dataset that consists of comparable control and treatment observations to minimize selection bias due to the nonrandom locations and characteristics of projects (Andam et al., 2008; Blackman et al., 2015; Brandt et al., 2015; Ferraro, 2009; Ferraro et al., 2013;

Ferraro and Hanauer 2014; Ho et al., 2007; Pfaff et al., 2015; Shah & Baylis, 2015; Shah et al., 2021; Sims, 2010; Yang et al., 2021). Matching was done between project and non-project points within Supersections, then all data for each Supersections was combined. The points resulting from the matching analysis were used as input for the panel regression models. To match points between project land and non-project Supersection land, I calculated and compiled several variables known to be spatial determinants of forest harvesting (Table 9), including slope, aspect, elevation, distance to roads, distance to mills, and landcover type (Pokharel et al., 2019). The TIGER US Census Roads dataset was used to calculate the distance to roads, and the US Wood-Using Mill Locations dataset to calculate the distance to mills. A nearest-neighbor matching method and a logistic regression method were used to measure distance with the MatchIt package in R (Ho et al., 2007). A 0.2 caliper value and a random matching order were used (Ho et al., 2007).

Table 9. Data sources used in matching analysis.

Description	Type	Source
Forest cover	Raster	Chapter 2
Terrain (slope, aspect, and elevation)	Raster	ALOS DSM: Global 30m[16]
Palmer Drought Severity Index (PDSI)	Raster	GRIDMET Drought: CONUS[17]
Min & Max temperature	Raster	TerraClimate[18]
US Wood-Using Mill Locations	Vector	US Forest Service[19]
Roads	Vector	TIGER: US Census Roads[20]

The matching procedure was done using the full dataset and produced 5,997,312 data points split equally between project and non-project Supersection points. I matched points individually within Supersections and then combined Supersection data to create the panel used in the difference-in-differences model.

---

[16] Tadano et al., 2014; 2016; Takaku et al., 2014; 2016;
[17] Abatzoglou, 2013
[18] Abatzoglou et al., 2018
[19] https://www.srs.fs.usda.gov/econ/data/mills/
[20] US Census Bureau; https://www.census.gov/programs-surveys/geography/guidance/tiger-data-products-guide.html

The balance between matched and non-matched observations was interrogated by comparing the standardized mean difference (SMD) between matched and unmatched data. The matched dataset was used in a difference-in-differences regression framework, and results were modeled for (1) three years before and after project designation and (2) five years before and after project designation. Standard errors (SE) were clustered at the Supersection level. Two models were specified: a fixed effects linear probability model and a random effects logit model (Tables 11-15).

Panel models

The panel models used here required a complete time series for each observation, generated in Chapter 3. First, the matched project and Supersection data were converted from long to wide format. Forests generally do not recover quickly enough to experience competing large-scale harvest events, so it is typical in forest change time series analysis to extract only the greatest disturbance for each pixel. As such, the LandTrendr segmentation and disturbance detection analysis in Chapter 3 was parameterized to extract the greatest magnitude disturbance for each pixel and omit all other detected disturbance events. Points were then expanded to record every other year of the time series (n = 34) as not having experienced a disturbance. For example: if a pixel had a disturbance detection year value of 2015, the greatest magnitude disturbance was detected in 2015; all other detected disturbance events, if any, were omitted; and the years 1986-2014 and 2016-2018 were recorded as not having experienced a disturbance. The model was estimated:

$$\mathrm{Disturbance}_{it} = \mathrm{constant} + \mathrm{Project}_{i} + \mathrm{After}_{it} + \mathrm{Project}_{it} * \mathrm{After}_{it} + \mathrm{Slope}_{i} + \mathrm{Elevation}_{i} + \mathrm{Distroads}_{i} + \mathrm{Distmill}_{i} + \mathrm{MaxTemp}_{it} + \mathrm{Mintemp}_{it} + \mathrm{Drought}_{it} + \mathrm{Landcover}_{it} + p_i + e_{it}$$

Where Disturbance is equal to one if a human-caused disturbance is observed at point i in year t and equal to zero otherwise. $\mathrm{Project}_i$ identifies if a point is part of a project (1) or not (0). After_{it} indicates if a time period is before (0) or after (1) project commencement. The interaction term $\mathrm{Project}_{it} * \mathrm{After}_{it}$ identifies observations that are both projects and in time periods after the project has commenced versus observations that are either not projects or projects before commencement. The other variables refer to static and time-varying co-variants that impact forest harvest. The error term can be segregated into a unit-specific error term p_i and an observation-specific error term e_it.

Two models were used to estimate this formula. First, a fixed effects linear probability model with SEs clustered at the Supersection level was used. In this model, all time-invariant variables in the regression equation fall out of the estimator. Second, a random effects logit model with SEs clustered at the Supersection level was used. Each model has its own advantages: the random effects model more accurately reflects the dependent variable's binomial nature, while the linear probability model allows for the inclusion of fixed effects. The impact of project commencement was estimated at three years and five years pre- and post-commencement to isolate policy effects on additionality—i.e., whether forest disturbance rates decreased. Both logit and linear probability models were conducted in Stata using the xtlogit and xtreg commands.

4.3 Results

Matching

The SMD statistics between matched and unmatched points were calculated for numeric variables in the matching model at the Supersection level, and the standard mean difference was reduced overall, which is a positive indicator of matching quality (Stuart, 2010; Figure 10). For each variable used in the matching model, the SMD for project and Supersection points is reported, and the p-value (p) resulting from Pairwise Wilcoxon rank-sum tests indicates whether a significant difference was found between project and Supersection (Table 10). After completing the matching process, the annual disturbance rates resulting from the analysis in Chapter 3 were recalculated with the matched dataset and compared to results from the full dataset. Less difference between annual disturbance rates was observed between projects and Supersections in the matched dataset, suggesting statistically comparable control and treatment observations, i.e., high-quality matches (Figure 8).

Table 10. Improved balance between unmatched and matched points.

	Unmatched				Matched			
	Supersection	**Project**	**SMD**	**p**	**Supersection**	**Project**	**SMD**	**p**
Elevation (mean)	572.7 (514.94)	698.3 (623.76)	0.22	**<0.001*** **	638.5 (520.49)	624.6 (508.53)	0.027	**<0.001*** **
Slope (mean)	8.5 (7.84)	9 (8.21)	0.066	**<0.001*** **	9.5 (8.31)	9.1 (7.92)	0.047	**<0.001*** **
Aspect (mean)	183.2 (100.64)	182.9 (100.24)	0.003	0.087	182.8 (101.39)	180.9 (99.73)	0.018	**<0.001*** **
Dist. to road (mean)	8.7 (17.22)	7.4 (10.41)	0.088	**<0.001*** **	8.6 (13.87)	8.3 (13.76)	0.025	**<0.001*** **
Dist. to mill (mean)	403.3 (744.61)	340 (629.62)	0.092	**<0.001*** **	505 (819.71)	507.6 (832.7)	0.003	**<0.001*** **
Num. of points	340,449	376,431			83,296	83,296		

Note: *Values in parentheses = standard deviations* SMD = standard mean deviation; p = p-value statistic (* p <0.1; ** p <0.05; *** p <0.

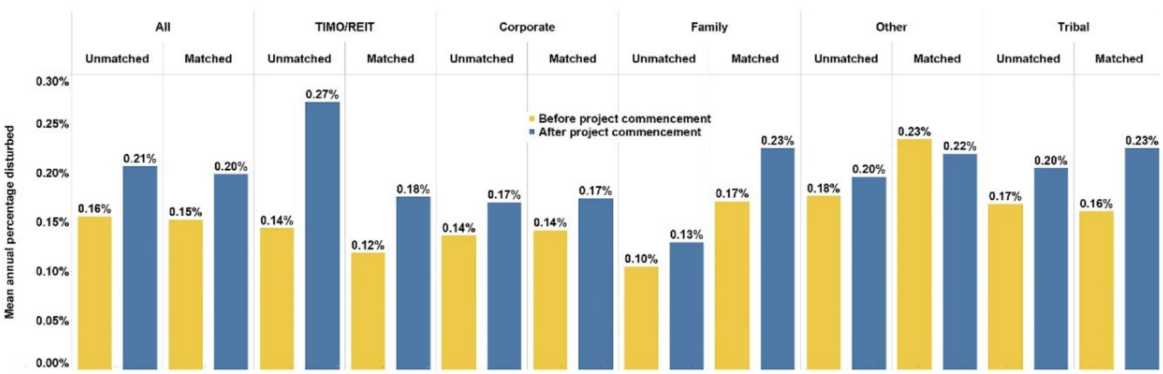

Figure 9. Mean annual percentage of total area disturbed between 1986-2020. For each ownership class rates for unmatched and matched data are compared before and after project commencement.

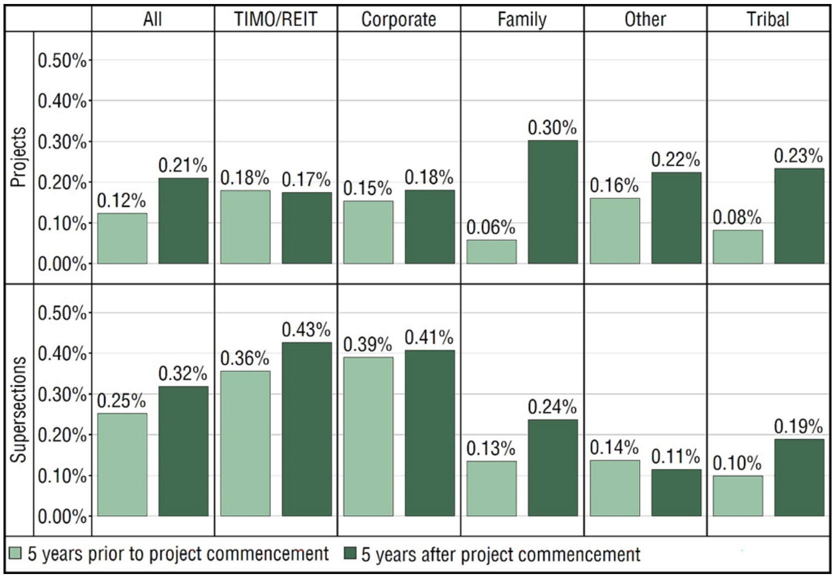

Figure 10. Mean annual percentage of total area disturbed five years before and after project commencement. For each ownership class, rates for matched data are compared between all projects and all Supersections five years before and after project commencement.

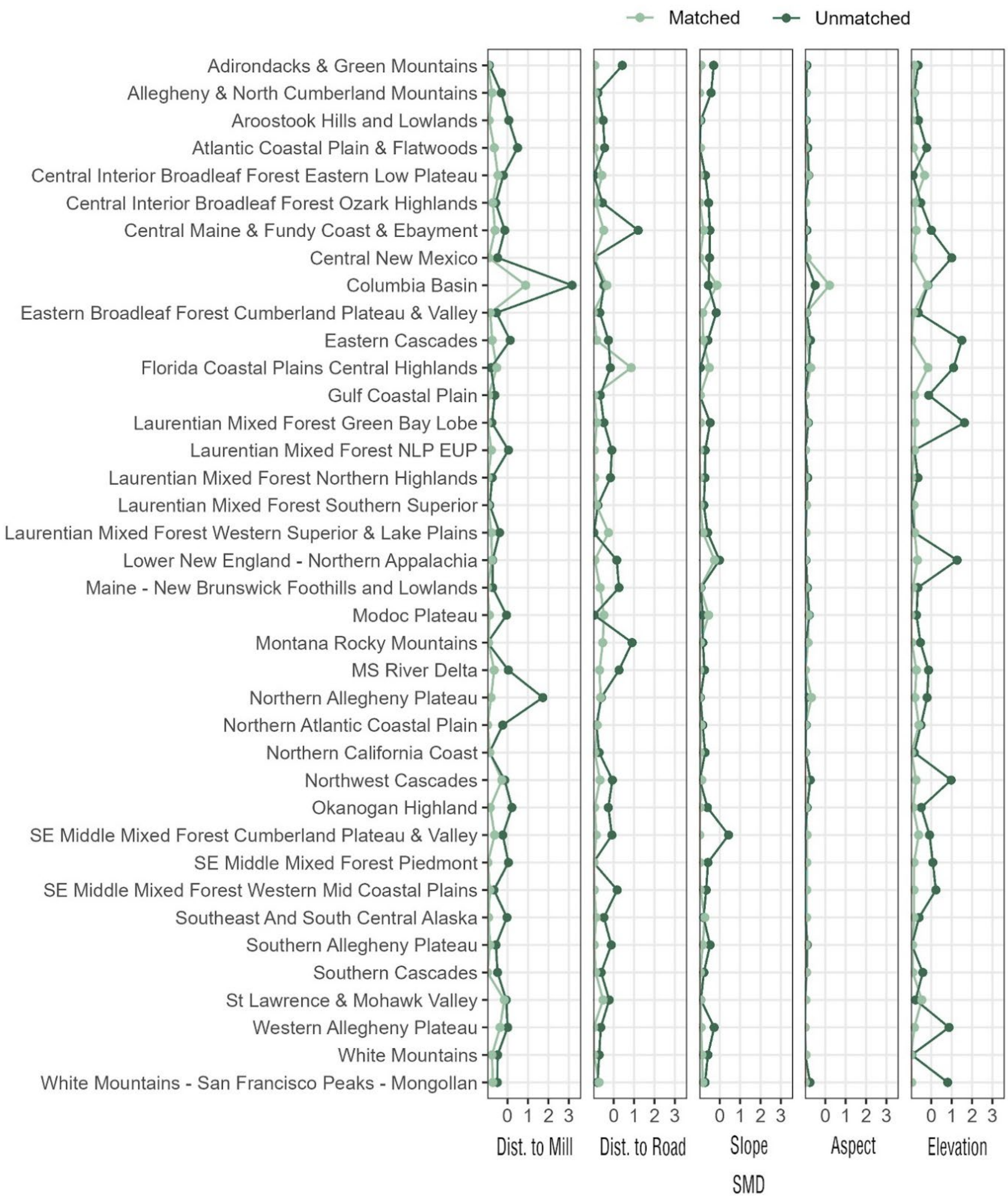

Figure 11. Comparing improvement between unmatched and matched points.

Panel models

The logit and linear probability models suggest limited additionality in California's forest carbon offset program at this early stage. Project establishment is associated with increased forest harvest for 'other' projects, and when data is pooled across land ownership types ('all'), project establishment has no significant impact for either timeframe (Table 11). Indeed, the only ownership class with a significantly negative impact on project establishment is the TIMO/REIT class, and the effect, while significant, is small and only statistically significantly observable in the five-year post-project commencement timeframe. TIMO/REIT-owned land demonstrated an increasingly significant impact of project commencement on disturbance over time. As an ownership group, the models show that TIMO-REIT projects appear to exhibit the most additionality at this stage.

When data is pooled across land ownership types ('all'), there is no statistical impact of project establishment in either the fixed or random effects models, three and five years after project commencement (Tables 12-15). Fixed effects and random effects models showed different results for three years and five years before and after project commencement regarding ownership classes. In the fixed effects models, 'other' projects showed increased disturbance three years after project commencement, while TIMO/REIT-owned projects were the only ownership class to show decreased disturbance five years after project commencement. In the random effects models, family-owned projects showed increased disturbance three years after project commencement, while 'other' projects were the only ownership class to show increased disturbance five years after project commencement. While both the fixed and random effects models are useful to consider, I ultimately focus on reporting the results of the fixed effects model for pre- and post-commencement coefficients because time-invariant variables can be controlled for within fixed effects models, while the underlying assumption of random effects models is that there are no relevant omitted variables that have relationships with the dependent variable. Due to the complexity of this type of analysis (see Chapter 1), fixed effects models were the more robust choice because they account for bias produced by time-invariant and unobservable variables.

Random effects models are included here as the model output shows the relationship between time-invariant variables that drop out of the fixed effects models—like slope, elevation, and aspect—and the dependent variable, whether or not project disturbance decreased after project establishment. In the random effects three-year model (Table 12), PDSI was positive for corporate projects and negative for TIMO/REIT, Tribal, and family-owned projects. Max temp was positive for all projects, as well as corporate-owned projects specifically and negative for Tribal projects. Min temp was positive for corporate projects. In the random effects five-year model (Table 13), PDSI was negative for TIMO/REIT and family-owned projects. Max temp was not significant for any projects, and min temp was negative for TIMO/REIT-owned projects. For the fixed effects three-years model (Table 14), PDSI was negative for all projects and TIMO/REIT (the latter consistent with the random effects three-year model). Max temp was positive for Tribal projects (in opposition to its negative impact on Tribal projects in the random effects model). Min temp was negative for all, corporate, and Tribal-owned projects, but positive for 'other' projects. For the fixed effects five year model (Table 15), neither PDSI nor max temp had a significant effect. Min temp was negative for corporate-owned projects.

Table 11. Coefficients for the impact of projects on forest harvests from fixed effects linear probability model on the matched dataset. Coefficients can be interpreted as the percentage point change in the likelihood of forest harvest after establishing the offset project. Models are run for periods of three and five years before and after project establishment. Full regression coefficients are available in Tables 12-15 (Note: Standard error displayed in parentheses. p = p-value statistic for |z| (* p <0.1; ** p <0.05; *** p <0.01).

	All	Corporate	TIMO/REIT	Tribal	Family	Other
Three Year Impact	0.00038 (-0.00056)	0.000636 (-0.00098)	-0.00115* (-0.00062)	0.000461 (-0.00075)	0.00398 (-0.00286)	**0.00118**** (-0.00055)
Five Year Impact	0.000278 (-0.00054)	0.000251 (-0.00064)	**-0.00101**** (-0.00038)	0.000932 (-0.00093)	0.00156 (-0.0005)	0.000772 (-0.0005)

Table 12. Random effects model coefficients for three years before and after project commencement. Coefficients resulted from difference-in-difference analysis for three years before and after project commencement, stratified by owner type. Six-year dummy variables and twelve landcover dummy variables are not displayed.

Variable	All	Corporate	TIMO/REIT	Tribal	Family	Other
After project commenc.	0.0000155 (-0.000402)	0.000464 (-0.000377)	**-0.000976*** (-0.0005)	**-0.00214***** (-0.000261)	-0.0000444 (-0.00065)	0.000801 (-0.000718)
Type: project	-0.000615* (-0.000318)	**-0.000881***** (-0.000273)	**-0.00137***** (-0.000445)	-0.0000302 (-0.000175)	-0.000843* (-0.000445)	-0.0000904 (-0.000595)
After project commenc. x type: project	0.000152 (-0.000422)	0.000266 (-0.00036)	-0.000841 (-0.000585)	0.00025 (-0.000234)	**0.00137**** (-0.000566)	0.00051 (-0.000778)
Elevation	-0.000000597 (-0.000000379)	0.000000126 (-0.000000343)	0.00000116 (-0.00000113)	-0.000000212 (-0.000000312)	-0.000000273 (-0.000000626)	-0.00000107 (-0.00000115)
Slope	-0.0000134	0.0000108	**-0.000124*****	-0.00001	-0.0000148	-0.0000663*

	(-0.0000153)	(-0.0000129)	(-0.0000283)	(-0.00000865)	(-0.0000211)	(-0.0000365)
Aspect	0.0000011	0.00000165*	0.00000215	-0.000000885	-0.00000111	-0.00000127
	(-0.00000104)	(-0.00000088)	(-0.00000142)	(-0.000000597)	(-0.00000127)	(-0.0000019)
Distance to road	0	**0.000586*** **	0.000406**	-0.0000628	**0.00102*** **	**0.00143*** **
	(0)	(-0.000134)	(-0.000199)	(-0.0000652)	(-0.000251)	(-0.000271)
Distance to mill	**-0.000514** **	-0.0000787	**-0.00069** **	**-0.00169*** **	**0.00101*** **	-0.000351
	(-0.000216)	(-0.000165)	(-0.000306)	(-0.000217)	(-0.000285)	(-0.000345)
PDSI	-0.00000054	**0.00000176*** **	**-0.00000221*** **	**-0.00000164*** **	**-0.00000203** **	-0.000000501
	(-0.000000466)	(-0.000000437)	(-0.000000841)	(-0.000000298)	(-0.000000792)	(-0.000000843)
Max temp	**0.0000277*** **	**0.0000271*** **	0.0000212	**-0.0000237*** **	0.0000106*	0.00000912
	(-0.00000627)	(-0.00000594)	(-0.0000171)	(-0.00000416)	(-0.0000064)	(-0.0000146)
Min temp	-0.00000693	**0.0000563*** **	-0.00000235	-0.000000512	-0.00000789	-0.0000194
	(-0.00000967)	(-0.00000998)	(-0.0000286)	(-0.00000595)	(-0.0000152)	(-0.0000213)
Constant	0	-0.00404	-0.000932	**0.0156*** **	0	0
	(0)	(-0.00986)	(-0.0105)	(-0.00249)	(0)	(0)
Obs.	229044	447732	164625	393662	96203	44231
Num. IDs	33284	64211	24026	58157	13761	6434

Note: Standard errors in parentheses; PDSI = Palmer Drought Severity Index; * p <0.1; ** p <0.05; *** p <0.01.

Table 13. Random effects model coefficients for five years before and after project commencement. Coefficients resulted from difference-in-difference analysis for five years before and after project commencement, stratified by owner type. Ten-year dummy variables and twelve landcover dummy variables are not displayed.

Variable	All	Corporate	TIMO/REIT	Tribal	Family	Other
After project commenc.	-0.260	-0.0896	0.0291	**-1.056*** **	-1.208	0.154
	(0.220)	(0.161)	(0.136)	(0.357)	(1.163)	(0.333)
Type: project	-0.570*	-0.583	**-0.632** **	-0.111	-1.098	0.343
	(0.291)	(0.481)	(0.249)	(0.0940)	(1.045)	(0.716)
After project commenc. x type: project	0.359	0.200	-0.320*	0.366*	2.135*	**1.062*** **
	(0.256)	(0.462)	(0.189)	(0.214)	(1.166)	(0.271)
Elevation	-0.000292	-0.000214	0.000690	0.000132	2.16e-05	-0.000622
	(0.000244)	(0.000396)	(0.000774)	(0.000502)	(0.000296)	(0.00151)
Slope	0.00413	0.00288	-0.0358	-0.00595	-0.00324	-0.0642
	(0.0100)	(0.0112)	(0.0239)	(0.00646)	(0.0256)	(0.0474)
Aspect	5.39e-05	0.000130	0.000558	-0.000439	-0.000811	-0.00125
	(0.000495)	(0.000509)	(0.000551)	(0.000388)	(0.00130)	(0.00110)
Distance to road	0.0155**	0.00134	-0.00499	0.00816	0.0693	**0.0765*** **
	(0.00651)	(0.0142)	(0.00707)	(0.0391)	(0.0735)	(0.0150)
Distance to mill	-0.272*	-0.119	**0.419*** **	**-1.708*** **	**0.601*** **	-0.323*
	(0.144)	(0.177)	(0.124)	(0.661)	(0.206)	(0.180)
PDSI	-8.42e-05	0.000574*	**-0.000920** **	-0.000302	-0.000449**	0.000311
	(0.000325)	(0.000330)	(0.000399)	(0.000431)	(0.000223)	(0.000682)
Max temp	0.00929	0.00298	0.00893	0.00840	0.00406	-0.00789
	(0.00659)	(0.00468)	(0.0138)	(0.0298)	(0.00330)	(0.0113)

Min temp	-0.0143	0.00862	**-0.0327****	-0.0438	-0.00213	0.000403
	(0.0109)	(0.00710)	(0.0166)	(0.0535)	(0.0139)	(0.0381)
Constant	**-10.32*****	**-11.29*****	-5.358	-4.063	**-12.41****	-6.274
	(2.014)	(2.474)	(4.603)	(6.216)	(5.033)	(12.41)
Obs.	229,298	256,964	115,031	308,214	42,419	31,460
Num. IDs	32,933	36,957	17,008	44,083	6,217	4,887

Note: Standard errors in parentheses; PDSI = Palmer Drought Severity Index; * p <0.1; ** p <0.05; *** p <0.01.

Table 14. Fixed effects model coefficients for three years before and after project commencement. Coefficients resulted from difference-in-difference analysis for five years before and after project commencement, stratified by owner type. Six year dummy variables are not displayed.

Variable	All	Corporate	TIMO/REIT	Tribal	Family	Other
After project commenc.	-0.000773 (0.000675)	-0.00169 (0.00111)	7.34e-05 (0.000638)	-0.000906 (0.000511)	-0.00348 (0.00327)	0.000476 (0.00147)
After project commenc. x type: project	0.000380 (0.000564)	0.000636 (0.000982)	-0.00115* (0.000623)	0.000461 (0.000750)	0.00398 (0.00286)	**0.00118**** (0.000554)
PDSI	**-1.17e-06***** (3.63e-07)	8.39e-08 (4.91e-07)	**-3.08e-06***** (1.00e-06)	-1.02e-06* (5.20e-07)	-2.02e-06 (1.35e-06)	7.25e-07 (1.44e-06)
Max temp	6.47e-05 (5.46e-05)	6.95e-05 (4.28e-05)	-7.91e-05 (8.38e-05)	0.000132** (4.99e-05)	-4.36e-05 (0.000135)	-4.77e-05 (4.28e-05)
Min temp	**-0.000108**** (4.72e-05)	**-0.000106***** (3.03e-05)	4.73e-05 (0.000101)	**-0.000168***** (5.09e-05)	-0.000112 (7.27e-05)	6.90e-05** (2.77e-05)
Constant	-0.00434 (0.00898)	-0.00660 (0.00917)	0.0137 (0.00914)	-0.0154* (0.00742)	0.0242 (0.0397)	0.00512 (0.00751)
Obs.	382,805	257,997	119,928	308,865	45,187	35,409
R-squared	0.001	0.001	0.001	0.001	0.004	0.001
Num. IDs	54,987	37,106	17,318	44,176	6,473	5,157

Note: Standard errors in parentheses; PDSI = Palmer Drought Severity Index; * p <0.1; ** p <0.05; *** p <0.01.

Table 15. Fixed effects model coefficients for five years before and after project commencement. Coefficients resulted from difference-in-difference analysis for five years before and after project commencement, stratified by owner type. Ten-year dummy variables are not displayed.

Variable	All	Corporate	TIMO/REIT	Tribal	Family	Other
After project commenc.	-0.000172 (0.000599)	-0.000981* (0.000525)	0.000256 (0.000538)	-0.00115 (0.000691)	-0.00174 (0.00250)	-6.24e-05 (0.000783)
After project commenc. x type: project	0.000278 (0.000543)	0.000251 (0.000643)	**-0.00101**** (0.000376)	0.000932 (0.000928)	0.00156 (0.00165)	0.000772 (0.000501)

PDSI	-9.06e-07*	-2.76e-07	-8.35e-07	-1.43e-06	8.32e-08	-4.42e-08
	(5.05e-07)	(2.36e-07)	(6.62e-07)	(8.66e-07)	(4.83e-07)	(9.82e-07)
Max temp	1.64e-05	1.59e-05	-3.53e-05	1.70e-05	0.000114	4.87e-05
	(2.01e-05)	(2.45e-05)	(5.05e-05)	(1.36e-05)	(5.15e-05)	(6.18e-05)
Min temp	-4.35e-05	**-3.88e-05****	1.67e-05	-5.69e-05*	-0.000124*	-2.07e-05
	(2.64e-05)	(1.80e-05)	(5.03e-05)	(3.11e-05)	(4.01e-05)	(6.37e-05)
Constant	0.00183	0.00746	0.00839	0.00153	-0.0167	-0.00940
	(0.00296)	(0.00452)	(0.00715)	(0.00267)	(0.0127)	(0.00905)
Obs.	569,336	390,643	184,632	441,336	70,625	54,045
R-squared	0.000	0.000	0.001	0.001	0.002	0.000
Num. IDs	54,987	37,106	17,318	44,176	6,473	5,157

Note: Standard errors in parentheses; PDSI = Palmer Drought Severity Index; * p <0.1; ** p <0.05; *** p <0.01.

4.4 Discussion & Conclusion

The incentive structure of California’s *U.S. Forest Projects Compliance Offset Protocol* is reflected in results from the analyses in this dissertation, wherein California’s protocol issues credits by comparing a project's baseline against common practice statistics. Highly stocked forests are issued large credits, and developers are paid immediately for existing carbon stocks. Setting baselines in this way rewards landowners for past decisions not to harvest. However, these may be the very landowners and locations that are also unlikely to harvest in the future. In this way, California's program fails to properly incentivize additionality and potentially suffers from strong adverse selection—presenting “significant design challenges to decision-makers adopting offset programs and offset standards as part of emissions trading programs” (Bento et al., 2015a, 2015b; Bushnell, 2011; Gillenwater, 2012; Gren et al., 2016; Montero, 2000; Ruseva et al., 2017, p. 278). This is reflected in results from these analyses, where we cannot statistically document decreases in forest harvest patterns three and five years after project establishment for the program by any landowner type except TIMO/REIT.

Limitations of this work

While these results suggest limited additionality, and I believe our findings are explained by the incentives provided by California's policy, I stress that this is an early assessment of a program that requires forests to maintain carbon stocks for 100 years. While differences in forest harvest patterns three and five years after project establishment were not detected, disturbance rates were low—

particularly in project areas—and the difference in disturbance rates may widen as forest harvest occurs outside of project areas over time. Optimal carbon management over the project period may require early management actions that result in forest disturbance but lead to greater carbon throughout the project. There is a chance that the positive coefficients for forest disturbance for 'other' forestlands identify early management that may lead to longer-term sequestration. Further research at the individual project forest management plans level will help clarify if this is the case.

As this program is in its infancy, many registered and even credited IFM offset projects were omitted from this analysis, primarily due to a lack of available data. In addition, the program's early participants are likely to have skewed toward larger landowners with the interest and capital available to participate. The full demographic of potential participants has not yet participated in this program, particularly concerning family landowners who own the majority of privately-owned forestland in the U.S. but comprise fewer than 10% of offset projects. The profile of offset projects and landowners may evolve moving forward, especially with potential policy revisions and outreach to smaller landowners. Further research to understand differences in landowner motivations, management approaches, and forest types can contribute to a greater understanding of why project establishment was affected by disturbance on TIMO/REIT project lands but not on other types of land.

Furthermore, this analysis does not cover the reversal risk of offsets and the associated difficulties of measuring this risk, particularly in natural disturbances like wildfires. CARB requires a portion of each project's credits to be relinquished into a central pool that acts as an insurance buffer against potential reversals to account for reversal risk. However, CARB may not be assigning accurate risk probabilities to offset lands and therefore not adequately ensuring against potential threats. Two examples of this include Tribal project owners, who are not required to contribute any credits to buffer the risk of harvest on Tribal lands; and California project owners, who are only required to contribute 2% of credits (if landowners have completed any fire reduction work to reduce risk of wildfire for the project area) or 4% of credits (with no fire reduction work to reduce risk of wildfire) despite a likely more significant risk of wildfire. Finally, the matching methods used in Chapter 4 highlight the importance of comparing historical disturbance rates of forest disturbance to statistically comparable forestlands within the Supersection assessment area. The *U.S. Forest Projects Compliance Offset Protocol* instructs project developers to generate a common practice statistic to quantify how much (%) above or below the project's initial above-ground carbon stocking is compared to all forests in the Supersection assessment area. Future studies could reassess the common practice statistic using matched points generated using the methods described in Chapter 4, likely improving the initial percentage above common practice statistic for new projects.

Significance and policy recommendations

At this early stage in California's program, I suggest strengthening protocols to assure additionality. CARB should reconsider assessing baselines and business-as-usual carbon stocking scenarios relative to regional data. Data on past forest harvest, both inside and outside of project areas, can be used to provide compelling and credible insight into the historical risks of forest harvesting–whether that risk is minimal or severe. The data used throughout this dissertation is publicly available at sufficiently high resolution for all areas covered by the *U.S. Forest Projects Compliance Offset Protocol*. All tools needed to conduct these analyses—QGIS (in place of ArcGIS Pro or ArcMap), R, GDAL, & GEE—are free for any researcher to use without limits. Future availability of spatial data assessments of carbon stocking at fine resolutions and long temporal scales will hopefully simplify the scope and effort required in conducting future research.

Van Kooten et al. (2021) reinforce two key insights that have emerged in doing this work. First, it is important to scrutinize climate policies as soon as data availability and robust methods allow. Since the Kyoto Protocol of the United Nations' Framework Convention on Climate Change, we have increasingly seen the emergence of voluntary and state-mandated initiatives designed to reduce GHG emissions, from individuals to states to nations. Forestry-based climate change solutions can require a substantial investment of time to realize projects' full potential benefits, which underscores the timeliness of analyses such as this. "… if there is an urgent need to address climate change, investments in forest restoration could come too late to make a difference … one can conclude that a forestry strategy needs to be implemented immediately or not at all" (Van Kooten et al., 2021, p. 4). It is particularly important to promptly evaluate and improve upon California's *U.S. Forest Projects Compliance Offset Protocol*, as California has developed ambitious climate change policies and programs over the last two decades that stand to influence younger programs as they emerge in years to come.

Second, it is fundamentally important to consider the benefits and utility of forest offset programs against risks, including the possibility that investing in forest offsets may embolden companies or other entities to delay reducing point-source emissions longer than they would have in a compliance market without the opportunity to purchase credits (Van Kooten et al., 2021). Offsets serve a purpose and can contribute to the success of an emissions trading scheme such as California's cap-and-trade program. However, to maximize GHG reductions with the short-term goal of mitigating catastrophic climate change, there is no substitution—no matter how it is measured or modeled—for actual, verifiable, point source emissions reductions.

In this dissertation, I have focused on California's *U.S. Forest Projects Compliance Offset Protocol* under the state's cap-and-trade system—the first such program in the United States and one of the world's largest (Kelly & Schmitz, 2016). As of May 2022, 237 million offset credits had been issued (CARB, 2022). Outcomes of decisions made in California's program are likely to influence the development of offset programs elsewhere, and as such, the *U.S. Forest Projects Compliance Offset Protocol* must serve the overall goal it was designed to aid in achieving. Current incentives encourage the offsetting of carbon-rich forests but do not sufficiently address additionality. I suggest that strong reforms are needed for California's offset program to continue to be a world-leading standard.

Bibliography

Abatzoglou, J. T., Dobrowski, S. Z., Parks, S. A., & Hegewisch, K. C. (2018). TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958-2015. *Scientific Data*, *5*, 1–12. https://doi.org/10.1038/sdata.2017.191

Abatzoglou, J. T. (2013). Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, *33*(1), 121–131. https://doi.org/10.1002/joc.3413

Agrawal, A., Wollenberg, E., & Persha, L. (2014). Governing agriculture-forest landscapes to achieve climate change mitigation. *Global Environmental Change*, *29*(2014), 270–280. https://doi.org/10.1016/j.gloenvcha.2014.10.001

Allen, C. D., Macalady, A. K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., Kitzberger, T., Rigling, A., Breshears, D. D., Hogg, E. H. (Ted., Gonzalez, P., Fensham, R., Zhang, Z., Castro, J., Demidova, N., Lim, J. H., Allard, G., Running, S. W., Semerci, A., & Cobb, N. (2010). A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. Forest Ecology and Management, 259(4), 660–684. https://doi.org/10.1016/j.foreco.2009.09.001

Amano, M., & Sedjo, R. A. (2006). *Forest Sequestration – Performance in Selected Countries in the Kyoto Period and the Potential Role of Sequestration in Post-Kyoto Agreements*. *May*, 65.

Andam, K. S., Ferraro, P. J., Pfaff, A., Sanchez-Azofeifa, G. A., & Robalino, J. A. (2008). Measuring the effectiveness of protected area networks in reducing deforestation. *Proceedings of the National Academy of Sciences*, *105*(42), 16089–16094. https://doi.org/10.1073/pnas.0800437105

Anderegg, W. R. L., Trugman, A. T., Badgley, G., Anderson, C. M., Bartuska, A., Ciais, P., Cullenward, D., Field, C. B., Freeman, J., Goetz, S. J., Hicke, J. A., Huntzinger, D., Jackson, R. B., Nickerson, J., Pacala, S., & Randerson, J. T. (2020). Climate-driven risks to the climate mitigation potential of forests. *Science*, *368*(6497). https://doi.org/10.1126/science.aaz7005

Anderson-Teixeira, K. J., & Belair, E. P. (2022). Effective forest-based climate change mitigation requires our best science. *Global Change Biology*, *28*(4), 1200–1203. https://doi.org/10.1111/gcb.16008

Badgley, G., Freeman, J., Hamman, J. J., Haya, B., Trugman, A. T., Anderegg, W. R. L., & Cullenward, D. (2021). Systematic over-crediting in California's forest carbon offsets program. *Global Change Biology*, 2021.04.28.441870. https://doi.org/10.1111/gcb.15943

Bala, G., Caldeira, K., Wickett, M., Phillips, T. J., Lobell, D. B., Delire, C., & Mirin, A. (2007). Combined climate and carbon-cycle effects of large-scale deforestation. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(16), 6550–6555. https://doi.org/10.1073/pnas.0608998104

Baldi, G., Texeira, M., Martin, O. A., Grau, H. R., & Jobbágy, E. G. (2017). Opportunities drive the global distribution of protected areas. *PeerJ*, *2017*(2). https://doi.org/10.7717/peerj.2989

Bento, A. M., Kanbur, R., & Leard, B. (2015). Designing efficient markets for carbon offsets with distributional constraints. *Journal of Environmental Economics and Management*, *70*, 51–71. https://doi.org/10.1016/j.jeem.2014.10.003

Bento, A., Ho, B., & Ramirez-Basora, M. (2015). Optimal monitoring and offset prices in voluntary emissions markets. *Resource and Energy Economics*, *41*, 202–223. https://doi.org/10.1016/j.reseneeco.2015.05.002

Blackman, A., Pfaff, A., & Robalino, J. (2015). Paper park performance: Mexico's natural protected areas in the 1990s. *Global Environmental Change*, *31*, 50–61. https://doi.org/10.1016/j.gloenvcha.2014.12.004

Bonan, G. B. (2008). Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. *Science*, *320*(5882), 1444–1449. https://doi.org/10.1126/science.1155121

Bosetti, V., Lubowski, R., Golub, A., & Markandya, A. (2011). Linking reduced deforestation and a global carbon market: Implications for clean energy technology and policy flexibility. *Environment and Development Economics*, *16*(4), 479–505. https://doi.org/10.1017/S1355770X10000549

Brandon, K., & Wells, M. (2009). Lessons for REDD+ from protected areas and integrated conservation and development projects. In A. Angelsen, M. Brockhaus, M. Kanninen, E. Sills, W. D. Sunderlin, & S. Wertz-Kanounnikoff (Eds.), *Realising REDD+: National strategy and policy options* (pp. 225–236). Center for International Forestry Research (CIFOR). https://books.google.co.in/books?hl=en&lr=&id=vNavVSPOtioC&oi=fnd&pg=PA225&dq=brandon+and+wells+2009&ots=C5y3XX5l33&sig=53EFokxP03MmJFrJdYIYl6CoikE

Brandt, J. S., Butsic, V., Schwab, B., Kuemmerle, T., & Radeloff, V. C. (2015). The relative effectiveness of protected areas, a logging ban, and sacred areas for old-growth forest protection in southwest China. *Biological Conservation*, *181*, 1–8. https://doi.org/10.1016/j.biocon.2014.09.043

Broich, M., Hansen, M. C., Potapov, P., Adusei, B., Lindquist, E., & Stehman, S. V. (2011). Time-series analysis of multi-resolution optical imagery for quantifying forest cover loss in Sumatra and Kalimantan, Indonesia. *International Journal of Applied Earth Observation and Geoinformation*, *13*(2), 277–291. https://doi.org/10.1016/j.jag.2010.11.004

Brown, D. G., Band, L., Green, K., Irwin, E., Jain, A., Pontius, R., Seto, K., Turner, B. L., & Verburg, P. (2014). *Advancing Land Change Modeling*. National Academies Press. https://doi.org/10.17226/18385

Brown, K., & Neil Adger, W. (1994). Economic and political feasibility of international carbon offsets. *Forest Ecology and Management*, *68*(2–3), 217–229. https://doi.org/10.1016/0378-1127(94)90047-7

Bruggeman, D., Meyfroidt, P., & Lambin, E. F. (2016). Forest cover changes in Bhutan: Revisiting the forest transition. *Applied Geography*, *67*, 49–66. https://doi.org/10.1016/j.apgeog.2015.11.019

Burke, P. J. (2016). Undermined by adverse selection: Australia's direct action abatement subsidies. *Economic Papers*, *35*(3), 216–229. https://doi.org/10.1111/1759-3441.12138

Bushnell, J. B. (2011). Adverse Selection and Emissions Offsets. *EI @ Haas WP 222*, *September*. https://ei.haas.berkeley.edu/research/papers/WP222.pdf

Bushnell, J. B. (2012). The Economics of Carbon Offsets. *The Design and Implementation of U.S. Climate Policy*, *2012*, 197–209.

Byrd, K. B., Flint, L. E., Alvarez, P., Casey, C. F., Sleeter, B. M., Soulard, C. E., Flint, A. L., & Sohl, T. L. (2015). Integrated climate and land use change scenarios for California rangeland ecosystem services: wildlife habitat, soil carbon, and water supply. *Landscape Ecology*, *30*(4), 729–750. https://doi.org/10.1007/s10980-015-0159-7

AB-32 Air pollution: greenhouse gases: California Global Warming Solutions Act of 2006., (2006) (testimony of CA Legis. Assemb.).

California Air Resources Board. (2017). *California's 2017 Climate Change Scoping Plan*.

Compliance Offset Protocol US Forest Projects, Pub. L. No. 95802.14 (2015).

California Air Resources Board. (2022). *ARB Offset Credit Issuance Table*. https://ww2.arb.ca.gov/our-work/programs/compliance-offset-program/arb-offset-credit-issuance

California Air Resources Board. (2021). *ARB Offset Credit Issuance Table*. https://ww3.arb.ca.gov/cc/capandtrade/offsets/issuance/arboc_issuance.xlsx

Canadell, J. G., & Raupach, M. R. (2008). Managing Forests for Climate Change Mitigation. *Science*, *320*(5882), 1456–1457. https://doi.org/10.1126/science.1155458

Canadell, J. G., Le Quéré, C., Raupach, M. R., Field, C. B., Buitenhuis, E. T., Ciais, P., Conway, T. J., Gillett, N. P., Houghton, R. A., & Marland, G. (2007). Contributions to accelerating atmospheric CO2 growth from economic activity, carbon intensity, and efficiency of natural sinks. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(47), 18866–18870. https://doi.org/10.1073/pnas.0702737104

Carrión-Flores, C., & Irwin, E. G. (2004). Determinants of residential land-use conversion and sprawl at the rural-urban fringe. *American Journal of Agricultural Economics*, *86*(4), 889–904. https://doi.org/10.1111/j.0002-9092.2004.00641.x

Chakir, R., & Parent, O. (2009). Determinants of land use changes: A spatial multinomial probit approach. *Papers in Regional Science*, *88*(2), 327–344. https://doi.org/10.1111/j.1435-5957.2009.00239.x

Charnley, S., Diaz, D., & Gosnell, H. (2010). Mitigating Climate Change Through Small-Scale Forestry in the USA: Opportunities and Challenges. *Small-Scale Forestry*, *9*, 445–462.

Clapp, J., & Meckling, J. (2013). Business as a Global Actor. *The Handbook of Global Climate and Environment Policy*, 286–303. https://doi.org/10.1002/9781118326213.ch17

Cohen, W. B., Yang, Z., Healey, S. P., Kennedy, R. E., & Gorelick, N. (2017). A LandTrendr Multispectral Ensemble for Forest Disturbance Detection. *Remote Sensing of Environment*, *205*(July), 11–13. https://doi.org/10.1016/j.rse.2017.11.015

Cohen, W. B., Yang, Z., Stehman, S. V., Schroeder, T. A., Bell, D. M., Masek, J. G., Huang, C., & Meigs, G. W. (2016). Forest disturbance across the conterminous United States from 1985-2012: The emerging dominance of forest decline. *Forest Ecology and Management*, *360*, 242–252. https://doi.org/10.1016/j.foreco.2015.10.042

DeVries, B., Verbesselt, J., Kooistra, L., & Herold, M. (2015). Robust monitoring of small-scale forest disturbances in a tropical montane forest using Landsat time series. *Remote Sensing of Environment*, *161*, 107–121. https://doi.org/10.1016/j.rse.2015.02.012

Dutrieux, L. P. L. P., Verbesselt, J., Kooistra, L., & Herold, M. (2015). Monitoring forest cover loss using multiple data streams, a case study of a tropical dry forest in Bolivia. *ISPRS Journal of Photogrammetry and Remote Sensing*, *107*, 112–125. https://doi.org/10.1016/j.isprsjprs.2015.03.015

Estrada, M., Lee, D., Murray, B., Sullivan, R., Penman, J., & Streck, C. (2014). *Land Use in a Future Climate Agreement*. http://merid.org/land-use-in-ADP/

FAO. (2015). Global Forest Resources Assessment 2015. In *FAO Forestry*. https://doi.org/10.1002/2014GB005021

FAO and UNEP. (2020). *The State of the World's Forests 2020. Forests, biodiversity and people.* https://doi.org/10.4060/ca8642en

Fargione, J. E., Bassett, S., Boucher, T., Bridgham, S. D., Conant, R. T., Cook-Patton, S. C., Ellis, P. W., Falcucci, A., Fourqurean, J. W., Gopalakrishna, T., Gu, H., Henderson, B., Hurteau, M. D., Kroeger, K. D., Kroeger, T., Lark, T. J., Leavitt, S. M., Lomax, G., McDonald, R. I., … Griscom, B. W. (2018). Natural climate solutions for the United States. *Science Advances*, *4*(11), 1–15. https://doi.org/10.1126/sciadv.aat1869

Fell, H., & Maniloff, P. (2018). Leakage in regional environmental policy: The case of the regional greenhouse gas initiative. *Journal of Environmental Economics and Management*, *87*, 1–23. https://doi.org/https://doi.org/10.1016/j.jeem.2017.10.007

Ferraro, P. J., & Hanauer, M. M. (2014). Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(11), 4332–4337. https://doi.org/10.1073/pnas.1307712111

Fletcher, L. S., Kittredge Jr., D., & Stevens, T. (2009). Forest Landowners' Willingness to Sell Carbon Credits: A Pilot Study. *Northern Journal of Applied Forestry*, *26*(1), 35–37. https://doi.org/10.1093/njaf/26.1.35

Foody, G. M. (2010). Assessing the accuracy of land cover change with imperfect ground reference data. *Remote Sensing of Environment*, *114*(10), 2271–2285. https://doi.org/10.1016/j.rse.2010.05.003

Friedlingstein, P., Jones, M. W., O'Sullivan, M., Andrew, R. M., Hauck, J., Peters, G. P., Peters, W., Pongratz, J., Sitch, S., Le Quéré, C., Bakker, D. C. E., Canadell, J. G., Ciais, P., & Jackson, R. S. (2019). Research Collection: Global carbon budget 2019. *Optimal Parameter Tuning of Feedback Controllers with Application to Biomolecular Antithetic Integral Control*, *10*(3), 12–19. https://doi.org/10.3929/ethz-a-010025751

Frolking, S., Palace, M. W., Clark, D. B., Chambers, J. Q., Shugart, H. H., & Hurtt, G. C. (2009). Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. *Journal of Geophysical Research: Biogeosciences*, *114*(3). https://doi.org/10.1029/2008JG000911

Galik, C. S., Murray, B. C., & Mercer, D. E. (2013). Where is the carbon? carbon sequestration potential from private forestland in the southern United States. *Journal of Forestry*, *111*(1), 17–25. https://doi.org/10.5849/jof.12-055

Gehlke, C. E., & Biehl, K. (1934). Certain Effects of Grouping Upon the Size of the Correlation Coefficient in Census Tract Material. *Journal of the American Statistical Association*, *29*(185), 169–170. https://www-jstor-org.libproxy.berkeley.edu/stable/2277827?sid=primo&seq=1

Gifford, L. (2020). "You can't value what you can't measure": a critical look at forest carbon accounting. *Climatic Change*, *161*(2), 291–306. https://doi.org/10.1007/s10584-020-02653-1

Gillenwater, M. (2012). What is Additionality? Part 1: a long standing problem. *GHG Management Institute, Discussion Paper n. 1 / Vers. 03*, *001*.

Goldstein, A., Turner, W. R., Spawn, S. A., Anderson-Teixeira, K. J., Cook-Patton, S., Fargione, J., Gibbs, H. K., Griscom, B., Hewson, J. H., Howard, J. F., Ledezma, J. C., Page, S., Koh, L. P., Rockström, J., Sanderman, J., & Hole, D. G. (2020). Protecting irrecoverable carbon in Earth's ecosystems. *Nature Climate Change*, *10*(4), 287–295. https://doi.org/10.1038/s41558-020-0738-8

Google Developers. (2020). *ee.Algorithms.TemporalSegmentation.LandTrendr*. Google Earth Engine (GEE).

Gorelick, N., Hancher, M., Dixon, M., Ilyushchenko, S., Thau, D., & Moore, R. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, *202*, 18–27. https://doi.org/10.1016/j.rse.2017.06.031

Grassi, G., House, J., Dentener, F., Federici, S., Den Elzen, M., & Penman, J. (2017). The key role of forests in meeting climate targets requires science for credible mitigation. *Nature Climate Change*, *7*(3), 220–226. https://doi.org/10.1038/nclimate3227

Gren, I.-M. M., Aklilu, A. Z., & Zeleke, A. A. (2016). Policy design for forest carbon sequestration: A review of the literature. *Forest Policy and Economics*, *70*, 128–136. https://doi.org/10.1016/j.forpol.2016.06.008

Griscom, B. W., Adams, J., Ellis, P. W., Houghton, R. A., Lomax, G., Miteva, D. A., Schlesinger, W. H., Shoch, D., Siikamäki, J. V., Smith, P., Woodbury, P., Zganjar, C., Blackman, A., Campari, J., Conant, R. T., Delgado, C., Elias, P., Gopalakrishna, T., Hamsik, M. R., … Fargione, J. (2017). Natural climate solutions. *Proceedings of the National Academy of Sciences*, *114*(44), 11645–11650. https://doi.org/10.1073/pnas.1710465114

Hahn, R., & Richards, K. (2013). Understanding the effectiveness of environmental offset policies. *Journal of Regulatory Economics*, *44*(1), 103–119. https://doi.org/10.1007/s11149-013-9211-1

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

Hansen, M. C., & Loveland, T. R. (2012). A review of large area monitoring of land cover change using Landsat data. *Remote Sensing of Environment*, *122*, 66–74. https://doi.org/10.1016/j.rse.2011.08.024

Harper, A. B., Powell, T., Cox, P. M., House, J., Huntingford, C., Lenton, T. M., Sitch, S., Burke, E., Chadburn, S. E., Collins, W. J., Comyn-Platt, E., Daioglou, V., Doelman, J. C., Hayman, G., Robertson, E., van Vuuren, D., Wiltshire, A., Webber, C. P., Bastos, A., … Shu, S. (2018). Land-use emissions play a critical role in land-based mitigation for Paris climate targets. *Nature Communications*, *9*(1). https://doi.org/10.1038/s41467-018-05340-z

Harris, N. L., Gibbs, D. A., Baccini, A., Birdsey, R. A., de Bruin, S., Farina, M., Fatoyinbo, L., Hansen, M. C., Herold, M., Houghton, R. A., Potapov, P. V., Suarez, D. R., Roman-Cuesta, R. M., Saatchi, S. S., Slay, C. M., Turubanova, S. A., & Tyukavina, A. (2021). Global maps of twenty-first century forest carbon fluxes. *Nature Climate Change*, *11*(3), 234–240. https://doi.org/10.1038/s41558-020-00976-6

Haya, B. (2018). *The Size of California's Carbon Offset Program*. http://bhaya.berkeley.edu/docs/FACTSHEET-the-size-of-CAs-offset-program-Haya.pdf

Haya, B. (2019). *The California Air Resources Board's U.S. Forest Offset Protocol Underestimates Leakage* (Goldman School of Public Policy Working Paper, University of California, Berkeley). https://gspp.berkeley.edu/assets/uploads/research/pdf/Policy_Brief-US_Forest_Projects-Leakage-Haya_4.pdf

Haya, B., Cullenward, D., Strong, A. L., Grubert, E., Heilmayr, R., Sivas, D. A., & Wara, M. (2020). Managing uncertainty in carbon offsets: insights from California's standardized approach. *Climate Policy*, *20*(9), 1112–1126. https://doi.org/10.1080/14693062.2020.1781035

Helm, D. (2010). Government failure, rent-seeking, and capture: The design of climate change policy. *Oxford Review of Economic Policy*, *26*(2), 182–196. https://doi.org/10.1093/oxrep/grq006

Hewes, J. H., Butler, B. J., & Liknes, G. C. (2017). Forest ownership in the conterminous United States circa 2014: distribution of seven ownership types - geospatial dataset. *Fort Collins, CO: Forest Service Research Data Archive*.

Hislop, S., Jones, S., Soto-Berelov, M., Skidmore, A., Haywood, A., & Nguyen, T. H. (2019). A fusion approach to forest disturbance mapping using time series ensemble techniques. *Remote Sensing of Environment*, *221*(November 2018), 188–197. https://doi.org/10.1016/j.rse.2018.11.025

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political Analysis*, *15*(3), 199–236. https://doi.org/10.1093/pan/mpl013

Hollander, M., Wolfe, D. A., & Chicken, E. (2015). Nonparametric statistical methods. In *Nonparametric Statistical Methods*. https://doi.org/10.1002/9781119196037

Houle, D., Lachapelle, E., & Purdon, M. (2015). Comparative Politics of Sub-Federal Cap-and-Trade: Implementing the Western Climate Initiative. *Global Environmental Politics*, *15*(3), 49–73. https://doi.org/10.1162/GLEP_a_00311

Ihlen, V. (2019). *Landsat 8 Data Users Handbook* (Version 5.0; LSDS-1574). https://d9-wret.s3.us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/atoms/files/LSDS-1574_L8_Data_Users_Handbook-v5.0.pdf

Imbens, G. W., & Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, *47*(1), 5–86. https://doi.org/10.1257/jel.47.1.5

IPCC. (2021). IPCC, 2021: Summary for Policymakers. In V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R. Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zhou (Eds.), *Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change: Vol. In Press*. Cambridge University Press. https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SPM.pdf

Irwin, E. G., & Bockstael, N. E. (2007). The evolution of urban sprawl: Evidence of spatial heterogeneity and increasing land fragmentation. *Proceedings of the National Academy of Sciences*, *104*(52), 20672–20677. https://doi.org/10.1073/pnas.0705527105

Jamali, S., Jönsson, P., Eklundh, L., Ardö, J., & Seaquist, J. (2015). Detecting changes in vegetation trends using time series segmentation. *Remote Sensing of Environment*, *156*, 182–195. https://doi.org/10.1016/j.rse.2014.09.010

Jones, K. W., Holland, M. B., Naughton-Treves, L., Morales, M., Suarez, L., & Keenan, K. (2017). Forest conservation incentives and deforestation in the Ecuadorian Amazon. *Environmental Conservation*, *44*(1), 56–65. https://doi.org/10.1017/S0376892916000308

Jones, K. W., & Lewis, D. J. (2015). Estimating the counterfactual impact of conservation programs on land cover outcomes: The role of matching and panel regression techniques. *PLoS ONE*, *10*(10), 1–22. https://doi.org/10.1371/journal.pone.0141380

Joppa, L. N., & Pfaff, A. (2009). High and far: Biases in the location of protected areas. *PLoS ONE*, *4*(12), e8273. https://doi.org/10.1371/journal.pone.0008273

Kay, K. (2017). Rural Rentierism and the Financial Enclosure of Maine's Open Lands Tradition. *Annals of the American Association of Geographers*, *107*(6), 1407–1423. https://doi.org/10.1080/24694452.2017.1328305

Kelly, E. C., Gold, G. J., & Di Tommaso, J. (2017). The Willingness of Non-Industrial Private Forest Owners to Enter California's Carbon Offset Market. *Environmental Management*, *60*(5), 882–895. https://doi.org/10.1007/s00267-017-0918-0

Kelly, E. C., & Schmitz, M. B. (2016). Forest offsets and the California compliance market: Bringing an abstract ecosystem good to market. *Geoforum*, *75*, 99–109. https://doi.org/10.1016/j.geoforum.2016.06.021

Kennedy, R. E., Townsend, P. A., Gross, J. E., Cohen, W. B., Bolstad, P., Wang, Y. Q., & Adams, P. (2009). Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects. *Remote Sensing of Environment*, *113*(7), 1382–1396. https://doi.org/10.1016/j.rse.2008.07.018

Kennedy, R. E., Yang, Z., & Cohen, W. B. (2010). Detecting trends in forest disturbance and recovery using yearly Landsat time series: 1. LandTrendr - Temporal segmentation algorithms. *Remote Sensing of Environment*, *114*(12), 2897–2910. https://doi.org/10.1016/j.rse.2010.07.008

Kennedy, R. E., Yang, Z., Cohen, W. B., Pfaff, E., Braaten, J., & Nelson, P. (2012). Spatial and temporal patterns of forest disturbance and regrowth within the area of the Northwest Forest Plan. *Remote Sensing of Environment*, *122*, 117–133. https://doi.org/10.1016/j.rse.2011.09.024

Kennedy, R. E., Yang, Z., Gorelick, N., Braaten, J., Cavalcante, L., Cohen, W. B., & Healey, S. (2018). Implementation of the LandTrendr algorithm on Google Earth Engine. *Remote Sensing*, *10*(5), 1–10. https://doi.org/10.3390/rs10050691

Key, C. H., & Benson, N. C. (2006). Landscape assessment: ground measure of severity, the composite burn index; and remote sensing of severity, the normalized burn ratio. In D. C. Lutes (Ed.), *FIREMON: Fire effects monitoring and inventory system. Gen. Tech. Rpt. RMRS-GTR-164-CD: LAI-15*. USDA Forest Service, Rocky Mountain Research Station. file:///C:/Users/jcronan.000/Documents/UW/JFSP_ASF/ASF_Info_Library Key&Benson_2006_CBI.FIREMON-2367368725/Key&Benson_2006_CBI.FIREMON.pdf

Klinsky, S. (2013). Bottom-up policy lessons emerging from the Western Climate Initiative's development challenges. *Climate Policy*, *13*(2), 143–169. https://doi.org/10.1080/14693062.2012.712457

Knox-Hayes, J. (2012). Negotiating climate legislation: Policy path dependence and coalition stabilization. *Regulation and Governance*, *6*(4), 545–567. https://doi.org/10.1111/j.1748-5991.2012.01138.x

Lambert, J., Drenou, C., Denux, J. P., Balent, G., & Cheret, V. (2013). Monitoring forest decline through remote sensing time series analysis. *GIScience & Remote Sensing*, *50*(March 2015), 437–457. https://doi.org/10.1080/15481603.2013.820070

Lang, S., Blum, M., & Leipold, S. (2019). What future for the voluntary carbon offset market after Paris? An explorative study based on the Discursive Agency Approach. *Climate Policy*, *19*(4), 414–426. https://doi.org/10.1080/14693062.2018.1556152

Lawler, J. J., Lewis, D. J., Nelson, E., Plantinga, A. J., Polasky, S., Withey, J. C., Helmers, D. P., Martinuzzi, S., Pennington, D., & Radeloff, V. C. (2014). Projected land-use change impacts on ecosystem services in the United States. *Proceedings of the National Academy of Sciences*, *111*(20), 7492–7497. https://doi.org/10.1073/pnas.1405557111

Lewis, D. J. (2009). Open space issues at the rural-urban fringe: Discussion. *American Journal of Agricultural Economics*, *91*(5), 1326–1327. https://doi.org/10.1111/j.1467-8276.2009.01305.x

Lewis, D. J., Provencher, B., & Butsic, V. (2009). The dynamic effects of open-space conservation policies on residential development density. *Journal of Environmental Economics and Management*, *57*(3), 239–252. https://doi.org/10.1016/j.jeem.2008.11.001

Lewis, S. L., Wheeler, C. E., Mitchard, E. T. A., & Koch, A. (2019). Restoring natural forests is the best way to remove atmospheric carbon. *Nature*, *568*(7750), 25–28. https://doi.org/10.1038/d41586-019-01026-8

Liu, J., Dietz, T., Carpenter, S. R., Folke, C., Alberti, M., Redman, C. L., Schneider, S. H., Ostrom, E., Pell, A. N., Lubchenco, J., Taylor, W. W., Ouyang, Z., Deadman, P., Kratz, T., & Provencher, W. (2007). Coupled human and natural systems. *Ambio*, *36*(8), 639–649. https://doi.org/doi: 10.1579/0044-7447(2007)36%5B639:chans%5D2.0.co;2

Lovell, H., & Mackenzie, D. (2011). Accounting for Carbon: The Role of Accounting Professional Organisations in Governing Climate Change. *Antipode*, *43*, 704–730. https://doi.org/10.1111/j.1467-8330.2011.00883.x

Lu, D., Li, G., & Moran, E. (2014). Current situation and needs of change detection techniques. *International Journal of Image and Data Fusion*, *5*(1), 13–38. https://doi.org/10.1080/19479832.2013.868372

Lubowski, R. N., Plantinga, A. J., & Stavins, R. N. (2008). What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions. *Land Economics*, *84*(4), 529–550. http://www.jstor.org/stable/27647846

Malmsheimer, R. W., Bowyer, J. L., Fried, J. ' S., Gee, E., Izlar, R. L., Miner, R. A., Munn, I. A., Oneil, E., & Stewart, W. C. (2011). Managing forests because carbon matters: Integrating energy, products, and land management policy. *Journal of Forestry*, *S1*, S7–S50.

Manley, B., & Maclaren, P. (2012). Potential impact of carbon trading on forest management in New Zealand. *Forest Policy and Economics*, *24*, 35–40. https://doi.org/https://doi.org/10.1016/j.forpol.2010.01.001

Mann, M. L., Berck, P., Moritz, M. A., Batllori, E., Baldwin, J. G., Gately, C. K., & Cameron, D. R. (2014). Modeling residential development in California from 2000 to 2050: Integrating wildfire risk, wildland and agricultural encroachment. *Land Use Policy*, *41*(June 2009), 438–452. https://doi.org/10.1016/j.landusepol.2014.06.020

Masek, J. G., Hayes, D. J., Joseph Hughes, M., Healey, S. P., & Turner, D. P. (2015). The role of remote sensing in process-scaling studies of managed forest ecosystems. *Forest Ecology and Management*, *355*, 109–123. https://doi.org/10.1016/j.foreco.2015.05.032

Masek, J. G., Vermote, E. F., Saleous, N. E., Wolfe, R., Hall, F. G., Huemmrich, K. F., Gao, F., Kutler, J., & Lim, T. K. (2006). A landsat surface reflectance dataset for North America, 1990-2000. *IEEE Geoscience and Remote Sensing Letters*, *3*(1), 68–72. https://doi.org/10.1109/LGRS.2005.857030

Mastrangelo, M. E., & Laterra, P. (2015). *From biophysical to social-ecological trade-offs : Integrating biodiversity conservation and agricultural production in ... From biophysical to social-ecological trade-offs : integrating biodiversity conservation and agricultural production in the Argenti*. *20*(February). https://doi.org/10.5751/ES-07186-200120

McConnell, V., Walls, M., & Kopits, E. (2006). Zoning, TDRs and the density of development. *Journal of Urban Economics*, *59*(3), 440–457. https://doi.org/10.1016/j.jue.2005.12.005

Mendelsohn, R., & Dinar, A. (2009). Land Use and Climate Change Interactions. *Annual Review of Resource Economics*, *1*(1), 309–332. https://doi.org/10.1146/annurev.resource.050708.144246

Meyfroidt, P. (2016). Approaches and terminology for causal analysis in land systems science. *Journal of Land Use Science*, *11*(5), 501–522. https://doi.org/10.1080/1747423X.2015.1117530

Meyfroidt, P., de Bremond, A., Ryan, C. M., Archer, E., Aspinall, R., Chhabra, A., Camara, G., Corbera, E., DeFries, R., Díaz, S., Dong, J., Ellis, E. C., Erb, K. H., Fisher, J. A., Garrett, R. D., Golubiewski, N. E., Grau, H. R., Grove, J. M., Haberl, H., … zu Ermgassen, E. K. H. J. (2022). Ten facts about land systems for sustainability. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(7), 1–12. https://doi.org/10.1073/pnas.2109217118

Millard-Ball, A. (2013). The trouble with voluntary emissions trading: Uncertainty and adverse selection in sectoral crediting programs. *Journal of Environmental Economics and Management*, *65*(1), 40–55. https://doi.org/10.1016/j.jeem.2012.05.007

Miller, J. D., & Thode, A. E. (2007). Quantifying burn severity in a heterogeneous landscape with a relative version of the delta Normalized Burn Ratio (dNBR). *Remote Sensing of Environment*, *109*(1), 66–80. https://doi.org/10.1016/j.rse.2006.12.006

Miller, K. A., Snyder, S. A., & Kilgore, M. A. (2012). An assessment of forest landowner interest in selling forest carbon credits in the Lake States, USA. *Forest Policy and Economics*, *25*, 113–122. https://doi.org/10.1016/j.forpol.2012.09.009

Montero, J. P. (2000). Optimal design of a phase-in emissions trading program. *Journal of Public Economics*, *75*(2), 273–291. https://doi.org/10.1016/S0047-2727(99)00050-X

Nature. (2021). Net-zero carbon pledges must be meaningful to avert climate disaster. *Nature*, *592*(7852), 8–8. https://doi.org/10.1038/d41586-021-00864-9

Negrón-Juárez, R. I., Chambers, J. Q., Hurtt, G. C., Annane, B., Cocke, S., Powell, M., Stott, M., Goosem, S., Metcalfe, D. J., & Saatchi, S. S. (2014). Remote sensing assessment of forest disturbance across complex mountainous terrain: The pattern and severity of impacts of tropical cyclone Yasi on Australian rainforests. *Remote Sensing*, *6*(6), 5633–5649. https://doi.org/10.3390/rs6065633

Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D. R., Chan, K. M. A. A., Daily, G. C., Goldstein, J., Kareiva, P. M., Lonsdorf, E., Naidoo, R., Ricketts, T. H., & Shaw, M. R. (2009). Modeling multiple ecosystem services, biodiversity conservation, commodity production, and tradeoffs at landscape scales. *Frontiers in Ecology and the Environment*, *7*(1), 4–11. https://doi.org/10.1890/080023

Newbold, T., Hudson, L. N., Hill, S. L. L. L., Contu, S., Lysenko, I., Senior, R. A., Börger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., De Palma, A., Díaz, S., Echeverria-Londoño, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K. K., Alhusseini, T., … Purvis, A. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. https://doi.org/10.1038/nature14324

Nolte, C., Agrawal, A., Silvius, K. M., & Britaldo, S. S. F. (2013). Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(13), 4956–4961. https://doi.org/10.1073/pnas.1214786110

Noon, M. L., Goldstein, A., Ledezma, J. C., Roehrdanz, P. R., Cook-Patton, S. C., Spawn-Lee, S. A., Wright, T. M., Gonzalez-Roglich, M., Hole, D. G., Rockström, J., & Turner, W. R. (2022). Mapping the irrecoverable carbon in Earth's ecosystems. *Nature Sustainability*, *5*(1), 37–46. https://doi.org/10.1038/s41893-021-00803-6

Oliver, M. (2013). Do carbon offsets work? The role of forest management in greenhouse gas mitigation. In *Science Findings* (Vol. 155). http://www.fs.fed.us/pnw/publications/subscription.

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Omernik, J. M. (2004). Perspectives on the nature and definition of ecological regions. *Environmental Management*, *34 Suppl 1*, 27–39. https://doi.org/10.1007/s00267-003-5197-2

Omernik, J. M., & Griffith, G. E. (2014). Ecoregions of the Conterminous United States: Evolution of a Hierarchical Spatial Framework. *Environmental Management*, *54*(6), 1249–1266. https://doi.org/10.1007/s00267-014-0364-1

Palm, C. a, Woomer, P. L., of Nairobi, U., Alegre, J., Arevalo, L., Castilla, C., Cordeiro, D. G., Feigl, B., Hairiah, K., University, B., Kotto-Same, J., Mendes, A., Moukam, A., Murdiyarso, D., Njomgang, R., Parton, W. J., Ricse, A., Rodrigues, V., Sitompul, S. M., & van Noordwijk, M. (1999). Carbon Sequestration and Trace Gas Emissions in Slash-and-Burn and Alternative Land Uses in the Humid Tropics Asb Climate Change Working Group. *ASB Climate Change Working Group Final Report, Phase II*, 39.

Pan, Y., Birdsey, R. A., Fang, J., Houghton, R., Kauppi, P. E., Kurz, W. A., Phillips, O. L., Shvidenko, A., Lewis, S. L., Canadell, J. G., Ciais, P., Jackson, R. B., Pacala, S. W., McGuire, A. D., Piao, S., Rautiainen, A., Sitch, S., & Hayes, D. (2011). A large and persistent carbon sink in the world's forests. *Science*, *333*(6045), 988–993. https://doi.org/10.1126/science.1201609

Pasquarella, V. J., Bradley, B. A., & Woodcock, C. E. (2017). Near-real-time monitoring of insect defoliation using Landsat time series. *Forests*, *8*(8). https://doi.org/10.3390/f8080275

Pfaff, A., Robalino, J., Sandoval, C., & Herrera, D. (2015). Protected area types, strategies and impacts in Brazil's Amazon: Public protected area strategies do not yield a consistent ranking of protected area types by impact. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *370*(1681). https://doi.org/10.1098/rstb.2014.0273

Plantinga, A. J. (2021). Recent advances in empirical land-use modeling. *Annual Review of Resource Economics*, *13*, 1–15. https://doi.org/10.1146/annurev-resource-100620-045839

Pokharel, R., Grala, R. K., Grebner, D. L., & Cooke, W. H. (2019). Mill Willingness to Use Logging Residues to Produce Electricity: A Spatial Logistic Regression Approach. *Forest Science*, *65*(3), 277–288. https://doi.org/10.1093/forsci/fxy061

Polasky, S., Nelson, E., Lonsdorf, E., Fackler, P., & Starfield, A. (2005). Conserving Species in a Working Landscape : Land Use with Biological and Economic Objectives Published by : Ecological Society of America CONSERVING SPECIES IN A WORKING LANDSCAPE : LAND USE WITH BIOLOGICAL AND ECONOMIC OBJECTIVES. *Ecological Applications*, *15*(4), 1387–1401. https://doi.org/10.1890/03-5423

Potapov, P. V., Turubanova, S. A., Hansen, M. C., Adusei, B., Broich, M., Altstatt, A., Mane, L., & Justice, C. O. (2012). Quantifying forest cover loss in Democratic Republic of the Congo, 2000-2010, with Landsat ETM+ data. *Remote Sensing of Environment*, *122*, 106–116. https://doi.org/10.1016/j.rse.2011.08.027

Poudyal, N. C., Elkins, D., Nibbelink, N., Cordell, H. K., & Gyawali, B. (2016). An exploratory spatial analysis of projected hotspots of population growth, natural land loss, and climate change in the conterminous United States. *Land Use Policy*, *51*, 325–334. https://doi.org/10.1016/j.landusepol.2015.11.021

Pugh, T. A. M., Lindeskog, M., Smith, B., Poulter, B., Arneth, A., Haverd, V., & Calle, L. (2019). Role of forest regrowth in global carbon sink dynamics. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(10), 4382–4387. https://doi.org/10.1073/pnas.1810512116

Ramseur, J. L. (2009). *CRS Report for Congress Voluntary Carbon Offsets: Overview and Assessment*. www.crs.gov

Rautiainen, M., Heiskanen, J., & Korhonen, L. (2012). Seasonal changes in canopy leaf area index and moDis vegetation products for a boreal forest site in central Finland. *Boreal Environment Research*, *17*, 72–84. www.metla.fi/metinfo/fenologia/index-

Richards, K. R., & Huebner, G. E. (2012). Evaluating protocols and standards for forest carbon-offset programs, Part A: Additionality, baselines and permanence. *Carbon Management*, *3*(4), 393–410. https://doi.org/10.4155/cmt.12.38

Rindfuss, R. R., Walsh, S. J., Turner, B. L., Fox, J., & Mishra, V. (2004). Developing a science of land change: Challenges and methodological issues. *Proceedings of the National Academy of Sciences of the United States of America*, *101*(39), 13976–13981. https://doi.org/10.1073/pnas.0401545101

Ristea, C., & Maness, T. C. (2009). Opportunities, challenges and markets for forest carbon offset projects. *Forestry Chronicle*, *85*(5), 715–718. www.greenhousegas.nsw.gov.au

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1017/CBO9780511810725.016

Rounsevell, M. D. A., Pedroli, B., Erb, K. H., Gramberger, M., Busck, A. G., Haberl, H., Kristensen, S., Kuemmerle, T., Lavorel, S., Lindner, M., Lotze-Campen, H., Metzger, M. J., Murray-Rust, D., Popp, A., Pérez-Soba, M., Reenberg, A., Vadineanu, A., Verburg, P. H., & Wolfslehner, B. (2012). Challenges for land system science. *Land Use Policy*, *29*(4), 899–910. https://doi.org/10.1016/j.landusepol.2012.01.007

Roy, D. P., Kovalskyy, V., Zhang, H. K., Vermote, E. F., Yan, L., Kumar, S. S., & Egorov, A. (2016). Characterization of Landsat-7 to Landsat-8 reflective wavelength and normalized difference vegetation index continuity. *Remote Sensing of Environment*, *185*, 57–70. https://doi.org/10.1016/j.rse.2015.12.024

Ruben, N. L., Andrew, J. P., & Robert, N. S. (2008). What Drives Land-Use Change in the United States? A National Analysis of Landowner Decisions. *Land Economics*, *84*(4), 529. https://doi.org/10.3368/le.84.4.529

Ruseva, T., Marland, E., Szymanski, C., Hoyle, J., Marland, G., & Kowalczyk, T. (2017). Additionality and permanence standards in California's Forest Offset Protocol: A review of project and program level implications. *Journal of Environmental Management*, *198*, 277–288. https://doi.org/10.1016/j.jenvman.2017.04.082

Sass, E. S., Butler, B. J., & Markowski-Lindsay, M. (2020). *Estimated distribution of forest ownership across the conterminous United States - geospatial database*. https://doi.org/10.2737/NRS-RMAP-11

Sayler, K. (2020). *Landsat 8 Collection 1 (C1) Land Surface Reflectance Code (LaSRC) Product Guide* (Version 3.0; LSDS-1368). https://d9-wret.s3.us-west-2.amazonaws.com/assets/palladium/production/s3fs-public/atoms/files/LSDS-1368_L8_C1-LandSurfaceReflectanceCode-LASRC_ProductGuide-v3.pdf

Schmidt, G., Jenkerson, C., Masek, J., Vermote, E., & Gao, F. (2013). Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) Algorithm Description. *U.S. Geological Survey*, *1057*. http://www.usgs.gov/pubprod

Schmitz, M. (2015). *Environmental Governance: Neoliberalism and the development of a Forest Protocol at the Forefront of Cap-and-Trade*.

Schmitz, M. B., & Kelly, E. C. (2016). Ecosystem Service Commodification: Lessons from California. *Global Environmental Politics*, *14*(2), 90–110. https://doi.org/10.1162/GLEP_a_00374

Seddon, N., Daniels, E., Davis, R., Chausson, A., Harris, R., Hou-Jones, X., Huq, S., Kapos, V., Mace, G. M., Rizvi, A. R., Reid, H., Roe, D., Turner, B., & Wicander, S. (2020). Global recognition of the importance of nature-based solutions to the impacts of climate change. *Global Sustainability*, *3*. https://doi.org/10.1017/sus.2020.8

Serbin, S. P., Ahl, D. E., & Gower, S. T. (2013). Spatial and temporal validation of the MODIS LAI and FPAR products across a boreal forest wildfire chronosequence. *Remote Sensing of Environment*, *133*, 71–84. https://doi.org/10.1016/j.rse.2013.01.022

Shah, P., & Baylis, K. (2015). Evaluating heterogeneous conservation effects of forest protection in Indonesia. *PLoS ONE*, *10*(6), 1–21. https://doi.org/10.1371/journal.pone.0124872

Shah, P., Baylis, K., Busch, J., & Engelmann, J. (2021). What determines the effectiveness of national protected area networks? *Environmental Research Letters*, *16*(7). https://doi.org/10.1088/1748-9326/ac05ed

Shrestha, A., Eshpeter, S., Li, N., Li, J., Nile, J. O., & Wang, G. (2021). Inclusion of forestry offsets in emission trading schemes: insights from global experts. *Journal of Forestry Research*, *33*(1), 279–287. https://doi.org/10.1007/s11676-021-01329-5

Siegel, K., Perez, A. F., Kinnebrew, E., Mills-Novoa1, M., Ochoa, J., & Shoffner, E. (2022). Integration of qualitative and quantitative methods for land-use-change modeling in a deforestation frontier. *Conservation Biology*, 1–42. https://doi.org/10.1111/cobi.13924

Sims, K. R. E. (2010). Conservation and development: Evidence from Thai protected areas. *Journal of Environmental Economics and Management*, *60*(2), 94–114. https://doi.org/10.1016/j.jeem.2010.05.003

Simula, M. (2009). Towards defining forest degradation: comparative analysis of existing definitions. In *Forest Resources Assessment Programme working Paper* (No. 154). http://www.ardot.fi/Documents_2/Degradationdefintions.pdf

Soto-Berelov, M., & Hislop, S. (2016). Approaches used for pixel based time series analysis of Landsat data Literature Review A Monitoring and Forecasting Framework for the Sustainable Management of SE Australian Forests at the Large Area Scale. In *Project* (Vol. 4104). https://www.crcsi.com.au/assets/Program-4/Agriculture/4.104-LandFor/Project4-104-LandFor-LitRevTimeSeriesV1-1.pdf

Spash, C. L. (2010). The brave new world of carbon trading. *New Political Economy*, *15*(2), 169–195. https://doi.org/10.1080/13563460903556049

Stavins, R. N. (2011). *AB 32 and Climate Change: The National Context of State Policies for a Global Commons Problem* (Harvard Project on Climate Agreements, Belfer Center, Issue February). http://belfercenter.ksg.harvard.edu/publication/20703/ab_32_and_climate_change.html

Steinberg, D. C., Goetz, S. J., & Hyer, E. J. (2006). Validation of MODIS FPAR products in boreal forests of alaska. *IEEE Transactions on Geoscience and Remote Sensing*, *44*(7), 1818–1828. https://doi.org/10.1109/TGRS.2005.862266

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*(1), 1–21. https://doi.org/10.1214/09-STS313

Tahvonen, O., & Rautiainen, A. (2017). Economics of forest carbon storage and the additionality principle. *Resource and Energy Economics*, *50*, 124–134. https://doi.org/10.1016/j.reseneeco.2017.07.001

Tadono, T., Ishida, H., Oda, F., Naito, S., Minakawa, K., & Iwamoto, H. (2014). Precise Global DEM Generation by ALOS PRISM. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *II–4*(May), 71–76. https://doi.org/10.5194/isprsannals-ii-4-71-2014

Takaku, J., Tadono, T., & Tsutsui, K. (2014). Generation of high resolution global DSM from ALOS PRISM. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *40*(4), 243–248. https://doi.org/10.5194/isprsarchives-XL-4-243-2014

Takaku, J., Tadono, T., Tsutsui, K., & Ichikawa, M. (2016). Validation of "Aw3D" Global Dsm Generated From Alos Prism. *ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences*, *III–4*(July), 25–31. https://doi.org/10.5194/isprsannals-iii-4-25-2016

Tadono, T., Nagai, H., Ishida, H., Oda, F., Naito, S., Minakawa, K., & Iwamoto, H. (2016). Generation of the 30 M-MESH global digital surface model by alos prism. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *41*(July), 157–162. https://doi.org/10.5194/isprsarchives-XLI-B4-157-2016

Trexler, M. C., Faeth, P. E., & Kramer, J. M. (1989). *Forestry as a response to global warming: an analysis of the Guatemala Agroforestry and Carbon Sequestration Project.*

Turner, B. L., Lambin, E. F., & Reenberg, A. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences*, *104*(52), 20666–20671. https://doi.org/10.1073/pnas.0704119104

United Nations. (1998). *Kyoto Protocol to the United Nations Framework Convention on Climate Change.*

United States Forest Service (USFS). (2018). *Toward Shared Stewardship Across Landscapes: An Outcome-Based Investment Strategy* (Issue August). https://www.fs.fed.us/sites/default/files/toward-shared-stewardship.pdf

US Environmental Protection Agency (EPA). (2015, November 25). *Ecoregions of North America*.

Tribal Forest Protection Act of 2004, Act to Authorize the Secretary of Agriculture and the Secretary of the Interior to Enter into an Agreement or Contract with Indian Tribes Meeting Certain Criteria to Carry Out Projects to Protect Indian Forest Land (2004).

van der Gaast, W., Sikkema, R., & Vohrer, M. (2016). The contribution of forest carbon credit projects to addressing the climate change challenge. *Climate Policy*, *3062*(December), 1–7. https://doi.org/10.1080/14693062.2016.1242056

van Kooten, G. C. (2018). The Economic Challenge of Mitigating Climate Change through Forestry Activities. *Ecological Economics*, *146*, 35–43. https://doi.org/10.1016/j.ecolecon.2017.10.002

van Kooten, C. G., & Johnston, C. M. T. (2016). The Economics of Forest Carbon Offsets. *Annual Review of Resource Economics*, *8*(1), 8:6.1-6.20. https://doi.org/10.1146/annurev-resource-100815-095548

van Kooten, G. C. (2018). The Economic Challenge of Mitigating Climate Change through Forestry Activities. *Ecological Economics*, *146*, 35–43. https://doi.org/10.1016/j.ecolecon.2017.10.002

Verbesselt, J., Hyndman, R., Newnham, G., & Culvenor, D. (2010). Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment*, *114*(1), 106–115. https://doi.org/10.1016/j.rse.2009.08.014

Verbesselt, J., Zeileis, A., & Herold, M. (2012). Near real-time disturbance detection using satellite image time series. *Remote Sensing of Environment*, *123*, 98–108. https://doi.org/10.1016/j.rse.2012.02.022

Verburg, P. H., Crossman, N., Ellis, E. C., Heinimann, A., Hostert, P., Mertz, O., Nagendra, H., Sikor, T., Erb, K. H., Golubiewski, N., Grau, R., Grove, M., Konaté, S., Meyfroidt, P., Parker, D. C., Chowdhury, R. R., Shibata, H., Thomson, A., & Zhen, L. (2015). Land system science and sustainable development of the earth system: A global land project perspective. *Anthropocene*, *12*, 29–41. https://doi.org/10.1016/j.ancene.2015.09.004

Vermote, E., Justice, C., Claverie, M., & Franch, B. (2016). Preliminary analysis of the performance of the Landsat 8/OLI land surface reflectance product. *Remote Sensing of Environment*, *185*. https://doi.org/10.1016/j.rse.2016.04.008

Vogelmann, J. E., Gallant, A. L., Shi, H., & Zhu, Z. (2016). Perspectives on monitoring gradual change across the continuity of Landsat sensors using time-series data. *Remote Sensing of Environment*, *185*, 258–270. https://doi.org/10.1016/j.rse.2016.02.060

Wang, Y., & Corson, C. (2015). The making of a 'charismatic' carbon credit: clean cookstoves and 'uncooperative' women in western Kenya. *Environment and Planning A: Economy and Space*, *47*(10), 2064–2079. https://doi.org/10.1068/a130233p

Watt, R. (2021). The fantasy of carbon offsetting. *Environmental Politics*, *00*(00), 1–20. https://doi.org/10.1080/09644016.2021.1877063

Wendland, K. J., Baumann, M., Lewis, D. J., Sieber, A., & Radeloff, V. C. (2015). Protected area effectiveness in European Russia: A postmatching panel data analysis. *Land Economics*, *91*(1), 149–168. https://doi.org/10.3368/le.91.1.149

Wendland, K. J., Baumann, M., Lewis, D. J., Sieber, A., & Radeloff, V. C. (2015). Protected area effectiveness in European Russia: A postmatching panel data analysis. *Land Economics*, *91*(1), 149–168. https://doi.org/10.3368/le.91.1.149

White, J. C., Wulder, M. A., Hermosilla, T., Coops, N. C., & Hobart, G. W. (2017). A nationwide annual characterization of 25 years of forest disturbance and recovery for Canada using Landsat time series. *Remote Sensing of Environment*, *194*, 303–321. https://doi.org/10.1016/j.rse.2017.03.035

Woodward, R. T. (2011). Double-dipping in environmental markets. *Journal of Environmental Economics and Management*, *61*(2), 153–169. https://doi.org/10.1016/j.jeem.2010.07.004

World Bank Group. (2019). World Bank Report: State and Trends of Carbon Pricing 2019. In *State and Trends of Carbon Pricing* (Issue June). https://openknowledge.worldbank.org/handle/10986/31755

World Bank Group. (2015). World Bank Report: State and Trends of Carbon Pricing 2015. In *State and Trends of Carbon Pricing October 2015*. The World Bank; Ecofys. https://doi.org/10.1596/978-1-4648-0725-1

Wulder, M. A., Masek, J. G., Cohen, W. B., Loveland, T. R., & Woodcock, C. E. (2012). Opening the archive: How free data has enabled the science and monitoring promise of Landsat. *Remote Sensing of Environment*, *122*, 2–10. https://doi.org/10.1016/j.rse.2012.01.010

Xin, Y., Sun, L., & Hansen, M. C. (2021). Biophysical and socioeconomic drivers of oil palm expansion in Indonesia. *Environmental Research Letters*, *16*(3). https://doi.org/10.1088/1748-9326/abce83

Yang, H., Viña, A., Winkler, J. A., Chung, M. G., Huang, Q., Dou, Y., McShea, W. J., Songer, M., Zhang, J., & Liu, J. (2021). A global assessment of the impact of individual protected areas on preventing forest loss. *Science of the Total Environment*, *777*. https://doi.org/10.1016/j.scitotenv.2021.145995

Zhang, Z. (2015). Carbon emissions trading in China: the evolution from pilots to a nationwide scheme. *Climate Policy*, *15*(sup1), S104–S126. https://doi.org/10.1080/14693062.2015.1096231

Zhu, Z. (2017). Change detection using landsat time series: A review of frequencies, preprocessing, algorithms, and applications. *ISPRS Journal of Photogrammetry and Remote Sensing*, *130*, 370–384. https://doi.org/10.1016/j.isprsjprs.2017.06.013

Zhu, Z., Fu, Y., Woodcock, C. E., Olofsson, P., Vogelmann, J. E., Holden, C., Wang, M., Dai, S., & Yu, Y. (2016). Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). *Remote Sensing of Environment*, *185*, 243–257. https://doi.org/10.1016/j.rse.2016.03.036

Zhu, Z., Wang, S., & Woodcock, C. E. (2015). Improvement and expansion of the Fmask algorithm: Cloud, cloud shadow, and snow detection for Landsats 4-7, 8, and Sentinel 2 images. *Remote Sensing of Environment*, *159*, 269–277. https://doi.org/10.1016/j.rse.2014.12.014

Zhu, Z., & Woodcock, C. E. (2012). Object-based cloud and cloud shadow detection in Landsat imagery. *Remote Sensing of Environment*, *118*, 83–94. https://doi.org/10.1016/j.rse.2011.10.028

Zhu, Z., & Woodcock, C. E. (2014). Automated cloud, cloud shadow, and snow detection in multitemporal Landsat data: An algorithm designed specifically for monitoring land cover change. *Remote Sensing of Environment*, *152*, 217–234. https://doi.org/10.1016/j.rse.2014.06.012

Zhu, Z., & Woodcock, C. E. (2014). Continuous change detection and classification of land cover using all available Landsat data. *Remote Sensing of Environment*, *144*, 152–171. https://doi.org/10.1016/j.rse.2014.01.011

Zhu, Z., Woodcock, C. E., & Olofsson, P. (2012). Continuous monitoring of forest disturbance using all available Landsat imagery. *Remote Sensing of Environment*, *122*, 75–91. https://doi.org/10.1016/j.rse.2011.10.030

Zhu, Z., Zhang, J., Yang, Z., Aljaddani, A. H., Cohen, W. B., Qiu, S., & Zhou, C. (2020). Continuous monitoring of land disturbance based on Landsat time series. *Remote Sensing of Environment*, *238*. https://doi.org/10.1016/j.rse.2019.03.009

Annex

Variable	Description
ID	Project ID
ARB_ID	ARB ID
Status	Project status (as recorded by the registry for which the project belongs)
Acres	Project acres (as recorded in the project's listing document or provided by the registry)
Credits	Total credits received (as recorded by the registry for which the project belongs)
Credited	Whether or not the project has received credits (1 = Yes, 0 = No)
Active	Whether or not the project is a presently active project (1 = Yes, 0 = No)
Project_Commencement_Date	Project commencement date (as recorded in the project's listing document or provided by the registry)
Name	Project name (as recorded in the project's listing document or provided by the registry)
Location	Project location (as recorded in the project's listing document or provided by the registry)
State	State that the project is located within
Developer_Owner_Operator_Designee	Four fields combined into one and separated by underscores: 1) Project developer; 2) Project owner; 3) Project operator; 4) Project designee.
Individual	Entity or person determined to be spearheading the project--sometimes the same as owner, developer, operator, or designee. Determined by Jared Stapp and colleagues in conversation, and by consulting the project's documents and/or media or other online sources about the project.
Individual_Type	Project developer class, as determined by Jared Stapp and colleagues in conversation, and relevant literature. This is an initial ownership class designation based off of *Individual* and used to then determine *Class*.
Class	Ownership class
Verifier	Project verifier (as recorded in the project's listing document)
initial_above_ground_standing_live_tree_carbon_stocks_per_acre_c02e	Initial above-ground standing live tree carbon stocks per acre within the project area (MT CO2e/acre). (as recorded in the project's listing document)
adjusted_initial_above_ground_standing_live_tree_carbon_stocks_per_acre_c02e2	Adjusted above-ground standing live tree carbon stocks per acre within the project area (MT CO2e/acre) (as recorded in the project's listing document).
Project_Baseline_Used	= *adjusted_initial_above_ground_standing_live_tree_carbon_stocks_per_acre_c02e2* unless no adjusted value is given, in which case, *initial_above_ground_standing_live_tree_carbon_stocks_per_acre_c02e* is used.
common_practice__above_ground_carbon_stocks_tonnes_per_acre_c02e	The calculated common practice, which is, "for the purposes of this protocol, the average carbon stocks (metric tons) of the above-ground portion of standing live tree from within the forest project's assessment area, derived from FIA plots on all private lands within the defined assessment area" (s. 1.2(17) of the *Compliance Offset Protocol U.S. Forest Projects*, p. 3).
baseline_percent_of_common_practice	= (*common_practice__above_ground_carbon_stocks_tonnes_per_acre_c02e)* / (*Project_Baseline_Used) (For true percentage value, multiply by 100).*
above_or_below_cp	= "above" if *baseline_percent_of_common_practice* is > 1; = "below" if *baseline_percent_of_common_practice* is < 1.

Primary_Supersection	Primary Supersection that the project resides within. The project might be located partially in multiple Supersections, or solely in the *Primary_Supersection.* If the project is located within multiple Supersections, the *Primary_Supersection* is the Supersection with the largest portion of the project's acreage.
Primary_Supersection_Acres	Number of project acres within the *Primary_Supersection.*
Secondary_Supersection	If the project is located within two or more Supersections, the *Secondary_Supersection* is the Supersection with the second largest portion of the project's acreage.
Secondary_Supersection_Acres	Number of project acres within the *Seondary_Supersection.*
Third_Supersection	If the project is located within three or more Supersections, the *Third_Supersection* is the Supersection with the third largest portion of the project's acreage.
Third_Supersection_Acres	Number of project acres within the *Third_Supersection.*
Fourth_Supersection	If the project is located within four or more Supersections (uncommon), the *Fourth_Supersection* is the Supersection with the fourth largest portion of the project's acreage.
fourth_Supersection_Acres	Number of project acres within the *Fourth_Supersection.*
Acres_Dist_1986 Through Acres_Dist_2018	Acres disturbed in the given year within the project boundaries. Calculated from the LandTrendr output disturbance raster layer. Pixels with their greatest magnitude disturbance for the time series for the given year are summed and acreage is calculated by multiplying the sum by the spatial resolution of the raster layer and then converting square meters to acres by dividing the value by 4047.
Percent_of_Total_Area_All_Acres_1986 Through Percent_of_Total_Area_All_Acres_2018	The percentage of total project area disturbed for the given year.
Mean_Percent_of_Total_Area_All_Acres	The mean value for all years' *Percent_of_Total_Area_All_Acres*
Notes	Optional. Notes about the project, either recorded by the author or taken from the registry "Notes" field of the registry table entry for the project
Description	Optional. Description about the project, either recorded by the author or taken from the registry "Description" field of the registry table entry for the project

Annex Table 1. Metadata for project database.