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Near-Term Climate Change Impacts on Kenyan Tree Cover

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Key Points:

- Following afforestation efforts, Kenyan tree cover is projected to endure into the near-term (2050) under all climate scenarios
- Gains in woody vegetation cover are smaller under all climate scenarios when fire probabilities double
- Attendant declines in herb cover, productivity and aboveground live biomass could impact conservation and sustainability efforts

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract

Afforestation efforts within tropical landscapes are continuing apace to achieve goals related to climate change mitigation, sustainability and conservation. Outcomes from these efforts are likely to be determined by future changes in climate and disturbance regimes. In Kenya, a tropical nation dominated by dryland ecosystems, the government is undertaking an ambitious ecosystem restoration effort via an afforestation program. Using L-Range, an ecosystem model tuned to the conditions extant across Kenya, and the most recent downscaled climate projections we, explored the durability and wider impacts of these efforts. Conditioning the simulations on the achievement of 10% tree cover by 2030, we explored how woody vegetation, herb cover, and ecosystem productivity will respond in the near-term (2050) under multiple Shared Socioeconomic Pathways and scenarios of fire frequency. Our simulations indicate that, under all scenarios, tree cover across Kenya will remain stable or show increasing trends in the near term. This will be accompanied by increases in overall woody vegetation, driven by shrub cover expansion and the contraction of herb cover. These impacts will be particularly pronounced in areas dominated by savannas and deciduous tree cover. Alongside these changes in vegetative cover, simulations indicate declines in net primary productivity and aboveground live biomass. Thus, we find that the persistence of existing and expanded Kenyan tree cover may not be impeded by climate change or disturbance; however, climate change and afforestation can act in concert to undermine achievement of Kenyan goals related to conservation and sustainability.

Plain Language Summary

The East African nation of Kenya is undertaking an ambitious afforestation effort to expand its tree cover to a constitutionally mandated minimum of 10%. The effort is also expected to contribute to Kenya's climate change mitigation and adaptation efforts by enhancing carbon sequestration, biodiversity and the availability of critical ecosystem goods and services. We explored the durability of these efforts by simulating how this enhanced tree cover will fare under future climate-driven changes in temperature and precipitation and disturbances such as fire. We find that under moderate to extreme scenarios of climate change and disturbance, tree cover within existing and newly afforested areas increases or remains stable. However, tree cover persistence is accompanied by declines in herbaceous vegetation and primary productivity indicating implications for biodiversity and pastoral livelihoods. We discuss how afforestation efforts need to be cognizant of these wider impacts. We also discuss the challenges associated with drawing afforestation policy implications from climate change scenario analyses.

1. Introduction

Tropical landscapes today are active venues for large-scale afforestation efforts. For projects leveraging Natural Climate Solutions (NCS), or the trade of carbon credits, enhancing tree cover in the tropics through forest restoration and establishment of plantations remains a key endeavor (Griscom et al., 2017; Koh et al., 2021). Large-scale afforestation commitments have also been made by developing countries in the tropics attempting to achieve their climate mitigation pledges as per their Nationally Determined Contributions (NDCs) and in tandem with their pursuit of development opportunities (Fagan et al., 2020). This emphasis on afforestation in the tropics owes in part to the pre-eminent role played by tropical forests in sequestering carbon (Koch et al., 2021). Additionally, within many tropical landscapes, where communities remain dependent on forest resources, tree cover restoration efforts are underway with the goal of generating co-benefits for people and nature (Zhang & Schwärzel, 2017). Tropical afforestation projects are thus located at the confluence of ambitions related to both climate change mitigation and adaptation. Assuming the presence of enabling governance and investment

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mechanisms, however, the achievement of objectives associated with these projects depends substantially on the ability of tree covered areas to both temper and surmount future climate uncertainties.

Anticipated benefits from afforestation are often tallied assuming that tree cover areas (existing and potential) will persist into a future marked by uncertain climate, disturbance regimes, and socio-economic conditions (Anderegg et al., 2020). With the availability of future climate and corresponding socio-environmental data from climate inter-comparison modeling projects (CMIP; O'Neill et al., 2016), this assumption is receiving closer scrutiny with studies revealing a diversity of probable tree cover futures across the tropics. For example, using a dynamic global vegetation model, Koch and Kaplan (2022) showed that restored tropical forests can retain carbon stocks over the next 80 years, both with and without physiological responses to CO_2 fertilization, and under a range of future climate and disturbance conditions such as fire. In addition, tree cover responses to climate change have been observed to vary by phenology. For example, in Madagascar, warming disproportionately impacts evergreen forests relative to deciduous forests (Brown et al., 2015). Conversely, across Asia and Africa, imperiled tropical dry forests and savannas are experiencing more pronounced threats owing to their exposure to relatively higher rates of warming and drying (Pennington et al., 2018; Siyum, 2020). Notwithstanding the sensitivity of tree cover to climate change, large-scale tropical afforestation can in the near-term precipitate ecosystem-wide changes thereby countervailing or augmenting potential gains in other spheres (Edwards et al., 2021). The wider impacts of tropical afforestation are consequently being examined, and studies have highlighted context-specific impacts on hydrology (Trabucco et al., 2008; Xue et al., 2022), soil properties (Yao et al., 2023), and primary productivity (Nölte et al., 2023). A subtler threat to biodiversity also emerges from biome transitions within tropical dryland habitats resulting from afforestation as well as climate driven expansions in existing woody vegetation (Martens et al., 2021).

These factors are germane to understanding the extent to which Kenya, a nation in eastern Africa, will accrue benefits from its ongoing and ambitious afforestation and reforestation initiatives. These efforts were originally conceptualized to achieve the constitutionally mandated target of 10% tree cover by 2030. However, having achieved this target, the Kenyan government is now endeavoring to expand its tree cover to 30% by 2032. Kenya's afforestation and reforestation efforts are intended to serve several cross-scale and spatially contextualized goals. This effort constitutes a core component of Kenya's Nationally Determined Contribution (NDC) to climate change mitigation with adaptation co-benefits. Another core goal is to elevate the "shared responsibility towards addressing public concerns with regard to continued deforestation, forest degradation and the need for enhanced protection, conservation and sustainable management of forest resources" (MOEF Kenya, 2019). The afforestation and reforestation program in Kenya is also expected to contribute to the promotion of community climate resilient livelihoods through nature-based solutions, improve landscape and ecosystem governance by strengthening policy, regulatory and institutional frameworks and promote sustainable financing mechanisms and private sector investment for restoration of degraded landscapes and ecosystems (GOK, 2023; MOEF Kenya, 2019). Despite these concerted efforts towards climate change mitigation and adaptation, Kenya is expected to experience adverse changes in temperature and precipitation in the future considering its location in the tropics (Ayugi et al., 2022). Given this context, understanding Kenyan tree cover responses to climate change and its broader ecosystem impacts is vital for Kenyan policy makers engaged in the areas of climate change mitigation, biodiversity conservation and sustainable development.

Through this effort, we explore the durability and broader vegetation interactions of Kenyan tree cover under future climate change scenarios. Recently, challenges associated with quantifying cross-cutting outcomes of afforestation have been made tractable by models that simulate vegetation dynamics (Scheiter et al., 2013). Using first principles, these models simulate vegetation responses to climate, while representing plant competition, disturbance, and biogeochemical cycles with varying degrees of granularity. Prominent examples representing this suite of models include Savanna (Coughenour, 1993), LPJ (Sitch et al., 2003), and aDGVM (Scheiter & Higgins, 2009). We relied on L-Range, a localized version of G-Range—a global rangelands model— to simulate tree cover dynamics across Kenya (Boone, 2024; Boone et al., 2018; Sircely et al., 2019). Natural tree cover across Kenya occurs primarily within patchily distributed evergreen and deciduous forests as well as within the more extensive savanna ecosystem that occurs over the country's vast arid and semi-arid lands (ASALs). Ongoing afforestation efforts include enhancing tree cover across the following ecosystems: forest, freshwater, agro-ecosystem, wetlands, rangelands, and coastal (GoK, 2023; Mengich et al., 2017; MOEF Kenya, 2019). In addition to disturbances such as fire, herbivory is also an important driver of tree cover dynamics, particularly within

Kenyan savanna landscapes that harbor large and diverse populations of wild and domestic herbivores (Holdo et al., 2009; Venter et al., 2018).

L-Range offers several advantages over other models in simulating Kenyan vegetation dynamics, given its attentiveness to the representation of different plant functional groups (herbs, shrubs, and trees), phenology (deciduous/evergreen), herbivory and fire. Current inferences on how Kenyan tree cover will fare under climate change are drawn from global or pan-African studies. The coarse resolution of these studies (Koch & Kaplan, 2022), and the absence of plant functional groups such as shrubs (Martens et al., 2022) make them poorly suited for informing ongoing afforestation activities across Kenya and understanding their wider consequences. Moreover, these models do not accommodate the impacts of grazing on vegetation dynamics, which is vital in the case of Kenya given its vast herbivore-dominated rangelands. With its explicit accommodation of phenology L-Range additionally offers the opportunity to understand how climate change will impact Kenya's evergreen and deciduous tree cover areas.

We used L-Range and downscaled CMIP6 future climate projections for multiple climate scenarios at the finest-available scale to explore how climate change will impact the persistence of 10% (the constitutionally mandated minimum) tree cover across Kenya. Whereas ongoing afforestation efforts across the country have resulted in this goal being surpassed ahead of the 2030 deadline, we use 10% tree cover by 2030 as a baseline against which to measure near-term (2050) climate impacts to limit our inferences to mature tree cover across Kenya. Within this near-term time horizon (2030–2050) we explore changes in tree cover across diverse Kenyan ecosystems and discuss their implications for ongoing afforestation initiatives, biodiversity conservation, carbon sequestration and livelihoods across Kenya. We also engage with the interpretive and practical challenges inherent in leveraging future climate data sets to inform near-term afforestation policies.

2. Materials and Methods

2.1. L-Range Model Description

L-Range simulates plant population dynamics and biogeochemical cycling within a range of Kenyan ecosystems. At monthly time steps it simulates plant regeneration, primary production, decomposition, competitive interactions between herbaceous and woody vegetation, as well as the cycling of nitrogen and carbon, and flow of water through ecosystems. These processes are modeled in a spatially explicit manner with the grid-cell representing the finest scale of inference. Within each grid-cell, vegetation is represented and modeled hierarchically. Parameters governing vegetation dynamics are determined by the type of landscape unit (an area of homogenous vegetation) that the grid-cell belongs to. Three plant functional groups (trees, shrubs, and herbs) are represented as 6 nested populations: (a) Trees, (b) Shrubs under trees, (c) Herbs under trees, (d) Shrubs, (e) Herbs under shrubs, and (f) Herbs. Tree populations are made up of evergreen and deciduous trees, while herbaceous vegetation is composed of annual and perennial plants. Competition among individuals within these populations and responses to disturbances such as fire and herbivory drive biogeochemical and plant vegetation changes at the grid-level. Across all landscape units, herbivory drives a linear decline in biomass with offtake rates remaining constant for the duration of the simulation. Within each grid-cell fire is represented probabilistically, with annual probabilities remaining constant during the simulation in the application used here and fire intensity governed by available fuel-loads. Fertilization with CO_2 drives increases in primary production and concomitant declines in evapotranspiration losses. Detailed model descriptions can be found in Sircely et al. (2019) and Boone et al. (2018). At the end of each timestep (month), L-Range produces gridded outputs representing the relative distribution of plant functional groups, soil nutrients, soil moisture, and plant productivity metrics.

In L-Range, we represented extant conditions across Kenya using gridded data sets representing soil texture, distribution of vegetation classes (herbs, shrubs, and trees), land cover, biomes, and monthly climate (Table 1 and Figure 1). We specified a grid-cell size of 100 km^2 and restricted our simulations to areas dominated by natural vegetation (i.e., urban areas, deserts, bare areas, and water-covered areas were excluded). To represent past and future climatic conditions, we used bias-corrected and downscaled monthly minimum and maximum temperature (tmin and tmax) and total precipitation (pr) projections from 13 Global Circulation Models (GCMs; Supplement), that were part of CMIP6 (Gergel et al., 2023; O'Neill et al., 2016; Table 1). We resampled these data from their native resolution of 50 km to match the resolution of our analysis (10 km). We obtained climate projections for a historic period (1950–2014) as well as for 4 future climate (2015–2100) scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0 and SSP5-8.5). These 4 climate scenarios together encompass a range of possible future climate and

Table 1
Spatial Data Sets Used in L-Range Simulations

Spatial data	Description	Source
Landscape unit classification	Map of potential vegetation across Kenya. 7 biome types occur across Kenya. Savannas dominated in spatial extent	Ramankutty and Foley (1999)
Plant functional group distribution	Distribution of evergreen and deciduous trees, shrubs, and herbs	Tuanmu and Jetz (2014)
Land cover	Distribution of landcover classes. Simulations were limited to four land cover areas (tree cover areas, grass cover areas, shrub cover areas, and agricultural areas with added tree cover)	ESA (2017)
Soil properties	Distribution of 6 soil components (silt, sand, clay, gravel, bulk density, and organic carbon)	Nachtergaele et al. (2009)
Monthly minimum and maximum temperatures (tmin and tmax) and precipitation (pr)	Projections from 13 GCMs for historic and 4 future climate scenarios. (Text S1 and Figure S3–S5 in Supporting Information S1)	
Monthly fire probabilities	Monthly fire incidence capturing fires from natural and anthropogenic sources	Chuvieco et al. (2018)

developmental trajectories. The scenarios facilitate exploration of the societal challenges in achieving climate change mitigation or adaptation. GCM and scenario selection were primarily determined by our goal to assess the impacts of diverse plausible intensities and trajectories of climate change on Kenyan tree cover and additionally constrained by data availability. We considered only those GCMs for which temperature and precipitation data were available across all four scenarios.

2.2. Historic Simulations and Model Evaluation

We conducted a 2000-year spin-up simulation using randomized historical climate data (1950–2014). We first created an ensemble data set for temperature and precipitation for the historic time period. This was done by averaging monthly projections of these variables across the 13 GCMs. The resulting climate data were then randomized (by year) and repeated to create climate inputs for the 2000-year spin-up. At the end of the simulation, we saved individual grid-cell characteristics (vegetation cover, carbon pools, etc.) to an initialization file and used this as starting conditions for subsequent simulations. To evaluate model performance and tune input parameters we ran L-Range simulations using the spin-up output as initial conditions and the historic climate data from each of the 13 GCMs for the period between 1990 and 2014. We compared L-Range simulated estimates of annual net primary productivity (ANPP) for 2001–2014 against a validation data set for the same period (Running & Zhao, 2021). We adjusted L-Range parameters and repeated the historic simulations till we obtained reasonable agreement between simulated and observed estimates (Text S1 and Figure S1 in Supporting Information S1).

2.3. Tree Cover Responses to Climate Change and Disturbance

We created a new spatial layer to emulate tree cover across Kenya in 2030 following anticipated successful afforestation efforts (Text S1 and Figure S2 in Supporting Information S1). This was achieved by adding new tree cover to areas in the proximity of existing patches of tree cover, as well as in agricultural areas proximate to forests, loosely following steps identified by the Kenyan government to achieve 10% tree cover through restoring forests, restoring degraded areas within the ASAL's, and through agroforestry initiatives (MOEF Kenya, 2019). Using this layer and the randomized historic climate data, we conducted another 2000-year spin-up simulation to allow model variables to equilibrate and used the resulting cell characteristics as starting conditions for subsequent simulations. For each of the four 4 future climate scenarios (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) we explored two additional scenarios that explored the impacts of fire—a key source of disturbance within savanna systems and one, that is, expected to intensify due to climate change.

- Historic fire—For each landscape unit, annual fire probability was set to match historic fire probabilities. This was calculated using a remotely sensed data set of fire incidences across Kenya for years 2000–2020 (Chuvieco et al., 2018). Monthly fire probabilities for all cells belonging to a unique landscape unit were averaged to obtain a mean monthly fire probability. Using this mean value, the probability of any cell in the landscape unit experiencing at least one fire event annually was calculated.

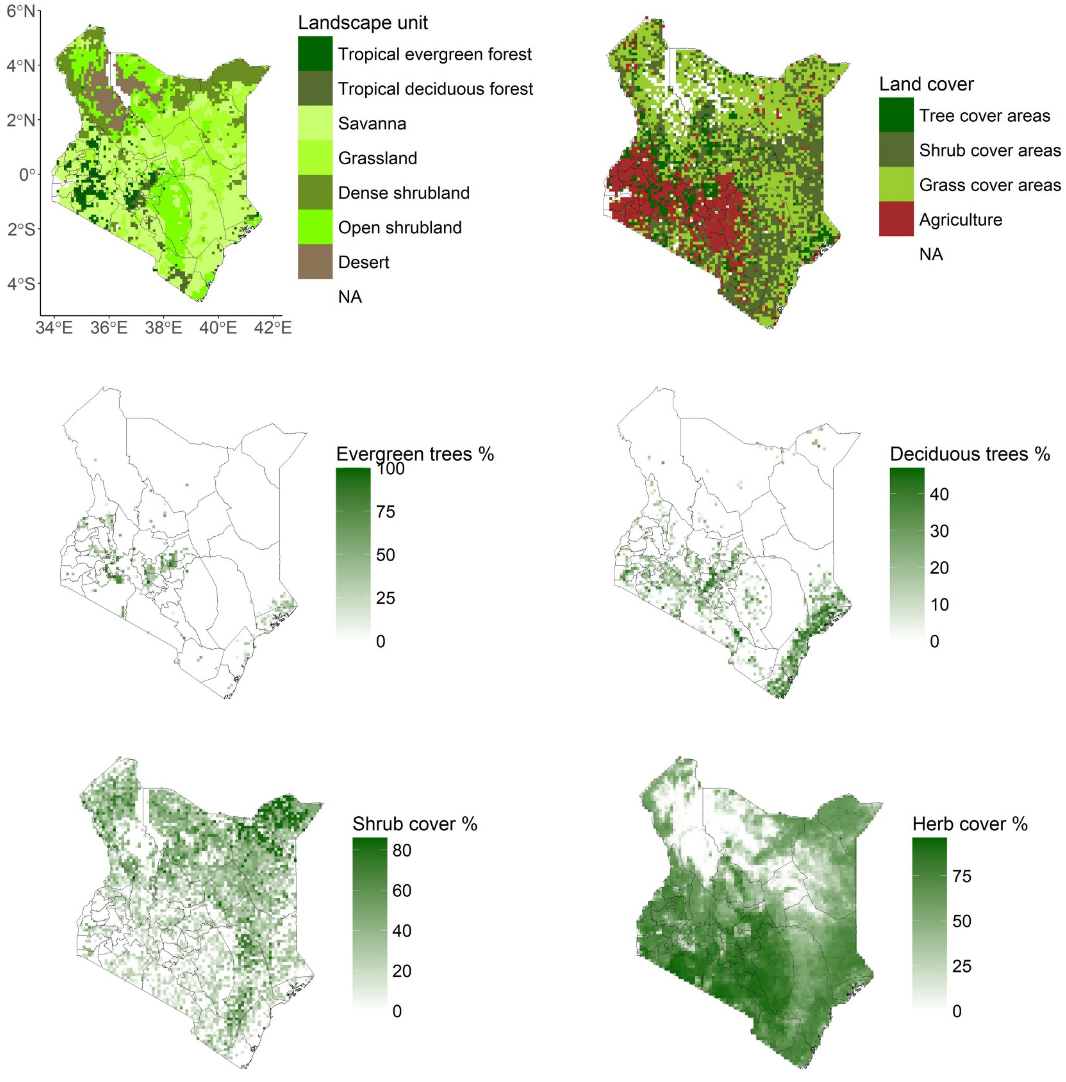

Figure 1. Spatial distribution of landscape units, land cover types and plant functional groups across Kenya. Landscape units represent the potential vegetation expected within a grid cell in the absence of human activity. The land cover classification map shows the distribution of major land cover classes in the year 2015. Herb, shrub, and evergreen and deciduous tree cover is represented for the year 2005.

- Double fire—Forest fire risk is expected to increase under all climate change scenarios and is a key threat to tree cover persistence (Abatzoglou et al., 2025). Whereas fire incidences have declined globally, there has been a two-fold increase in extreme fire events (Cunningham et al., 2024). Between 1990 and 2020, Kenya experienced a four-fold increase in total forest area burned (Rotich et al., 2025). Fire has both anthropogenic and natural origins and social factors can play a significant role in determining fire ignition probabilities (Mukunga et al., 2023). Given that the SSPs project vastly different and in some cases unprecedented (e.g., SSP5) future socioeconomic conditions, fire behavior prediction within these scenarios poses challenges. For example, using a neural networks-based model, Zhang et al. (2024) predicted that under all climate change scenarios, Africa is expected to see a significant increase in burned area by the end of the century with global burned area extents doubling under SSP3-7.0 and SSP5-8.5 scenarios. Conversely, other projections point to a potential decline in future fire probabilities in eastern Africa particularly under low and moderate climate change scenarios (Gallo et al., 2025). To accommodate this uncertainty, we include an extreme disturbance scenario by doubling the annual fire probability such that our eight scenarios together span the full potential range of future climate change and fire-disturbance conditions that can occur over the region.

Table 2
Percent Change in Overall Herb, Shrub and Tree Cover, Mean Monthly Net Primary Productivity (MNP) and Aboveground Live Biomass (ALB) Under Climate Change and Disturbance Scenarios

	Historic fire probability				Double fire probability			
	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5	SSP1-2.6	SSP2-4.5	SSP3-7.0	SSP5-8.5
Herbs	−31.7 (2.6)	−33.3 (2.4)	−33.2 (2)	−32.8 (2.9)	−33.6 (2.95)	−35.1 (2.73)	−35.0 (2.3)	−34.4 (3.4)
Shrubs	17.3 (1.8)	17.1 (3.4)	16.9 (3.1)	15.9 (3.5)	14.9 (1.85)	14.7 (3.75)	14.5 (3.1)	13.3 (3.9)
Trees	10.4 (2.9)	9.63 (4.4)	9.2 (3)	7.23 (5.3)	2.94 (3.35)	2.06 (5.2)	1.57 (3.5)	−0.5 (5.8)
MNP	−3.8 (13.5)	−13.2 (22.6)	−3.14 (30.)	−6.01 (9.44)	−7.48 (13.5)	−17.2 (22.4)	−7.91 (29.9)	−9.11 (9.16)
ALB	−6.7 (6.7)	−7.4 (10.8)	−5.3 (8.2)	−2.7 (13.1)	−18.8 (6.3)	−19.9 (9.71)	−18.1 (7.58)	−15.5 (12.2)

Note. Changes in variables are represented for the year 2050 relative to their values in 2030. Values are means across 13 unique GCM simulations with standard deviations in parentheses.

Given our near-term focus we assumed that primary production increases and evapotranspiration decreases with increasing atmospheric CO_2 concentrations (Wang et al., 2020; Zhu et al., 2016). For each climate scenario, we obtained associated projected annual atmospheric greenhouse gas concentrations, and followed methods described in Boone et al. (2018) to model the effects of atmospheric CO_2 concentration on plant primary production and evapotranspiration. For each climate-disturbance scenario, we repeated L-Range simulations using climate scenario (SSP) and climate model (GCM)-specific temperature and precipitation projections for the period between 2030 and 2050, resulting in a total of 104 simulations. At the end of each simulation, we calculated changes in multiple variables of interest (Table 2) in the year 2050, relative to their baseline values in 2030 (i.e., the start of the simulation and the year in which 10% tree cover was originally intended to be achieved). For each of the 8 climate-disturbance scenarios we summarized estimated changes in variables of interest across the 13 individual GCM-forced runs. Using the R package "sjstats" (Lüdecke & Lüdecke, 2019) we calculated the omega squared (ω^2) statistic, to measure the effect-size contributions of the climate change scenarios (4 SSP-RCP scenarios), the GCMs (13 models; Table S1 in Supporting Information S1), the fire scenarios (Historic/Double), and the two-way interactions between these variables.

To understand the implications of tree cover futures for Kenya, we first summarized these variables across all the grid-cells that were part of the simulation ("All" in Figure 4). To assess whether ongoing afforestation efforts will result in persistent tree cover in 2050, we summarized tree cover changes within grid-cells where trees were added to emulate the successful afforestation scenario for 2030 ("New" in Figure 4). Finally, to understand the ecosystem-wide impacts of afforestation, we summarized variables within grid-cells representing tropical evergreen forest, tropical deciduous forest and savanna ecosystems ("Evergreen," "Deciduous," and "Savanna" in Figure 4). For the tropical evergreen and deciduous forests ecosystems, we limit our inference to those grid-cells with at least 30% tree cover.

3. Results

3.1. Past and Future Temperature and Precipitation Trends

Across all climate scenarios, temperature and precipitation are characterized by steady increasing trends in the future, relative to the historic time period (1950–2014). Mean annual precipitation in the period between 2030 and 2050 is approximately 10% higher under the most extreme climate change scenario (SSP5-8.5). Comparing scenarios, in the same period, mean annual precipitation is slightly lower under SPP2-4.5 and SSP3-7.0. Annual mean minimum and maximum temperatures are almost 2°C higher in 2050 relative to 1950. Like precipitation, mean temperatures in the 2030–2050 period are highest under SSP5-8.5 and lowest under SSP1-2.6. For both temperature and precipitation, considerable variability exists in projections from the 13 GCMs (Figures S3 and S5 in Supporting Information S1). Taken together, SSP5-8.5 represents a future scenario with the warmest and wettest conditions, whereas SSP1-2.6 is characterized by lower temperature increases, with these differences becoming more apparent closer to 2050.

Future changes in temperature and precipitation are spatially heterogeneous (Figure 2). Compared to historic conditions and relative to deciduous and evergreen areas, savanna areas experience larger increases in temperature and precipitation under all scenarios (Figure 3). Within savannas, future changes in precipitation are also

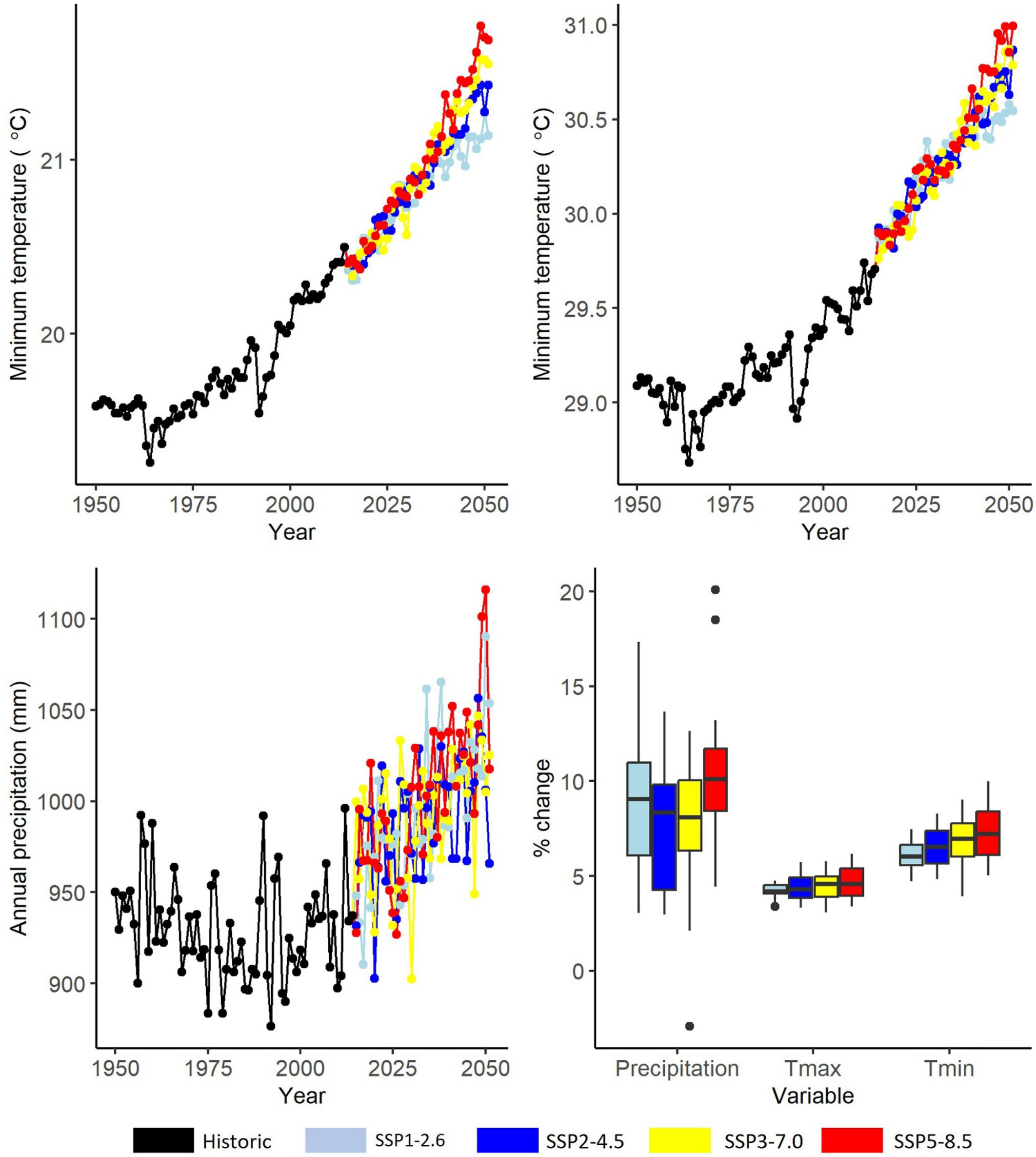

Figure 2. Historic (black line) and future annual temperature and precipitation projections based on an ensemble of 13 GCMs. Boxplots show % change in precipitation and temperature in the future time period (2015–2050) relative to historic time period (1950–2014). In the boxplot black dots represent outliers and horizontal black lines within boxes represent median responses.

highly spatially variable with increases ranging from 5% to 25% over historical conditions. Precipitation increases are lowest under SSP3-7.0. Deciduous areas are projected to experience more variable and lower mean annual temperatures in the future.

3.2. Changes in Tree Cover

All scenarios of climate change and disturbance are characterized by stable or increasing overall tree cover across Kenya by 2050, relative to the 2030 baseline (Figure 4 "All"). Across all scenarios, the largest changes in tree cover outcomes occur when more intense fire disturbance regimes prevail. When controlling for climate change scenario (SSP-RCP), effect sizes associated with fire scenarios (ω^2) was 0.42. Similarly, when controlling for choice of global circulation models (GCM), ω^2 associated with fire scenarios was 0.43. The SSP-RCP scenarios and associated GCM contributed minimally to explaining variation in total tree cover outcomes in 2050 (Tables S2 and S3 in Supporting Information S1).

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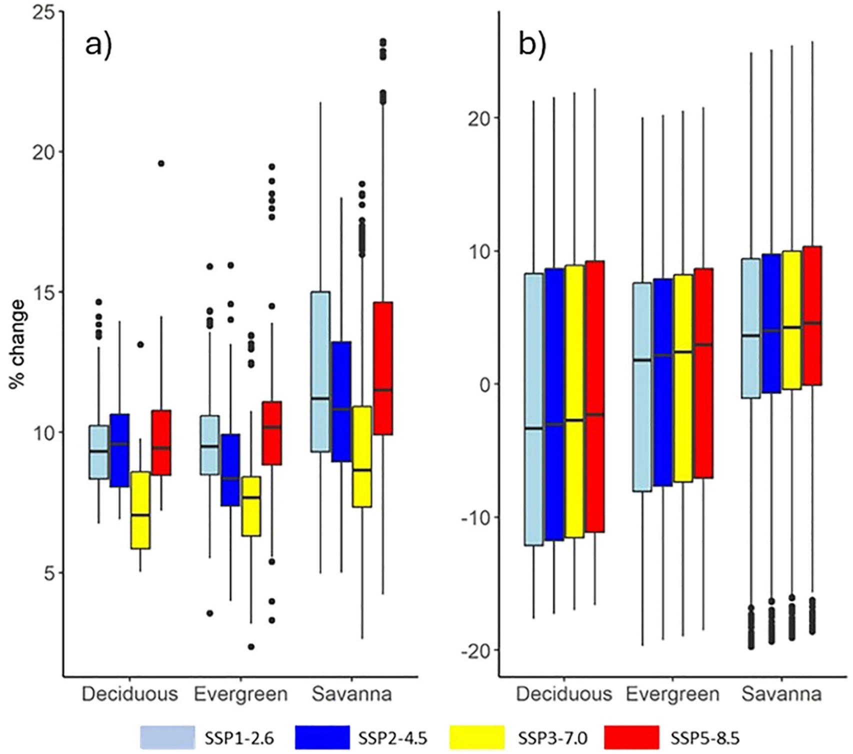

Figure 3. Percent change in annual precipitation (a) and mean monthly temperature (b) in the future (2015–2050) relative to the historic period (1950–2014) within deciduous, evergreen, and savanna areas. Black dots represent outliers. Horizontal black lines within boxes represent the median response.

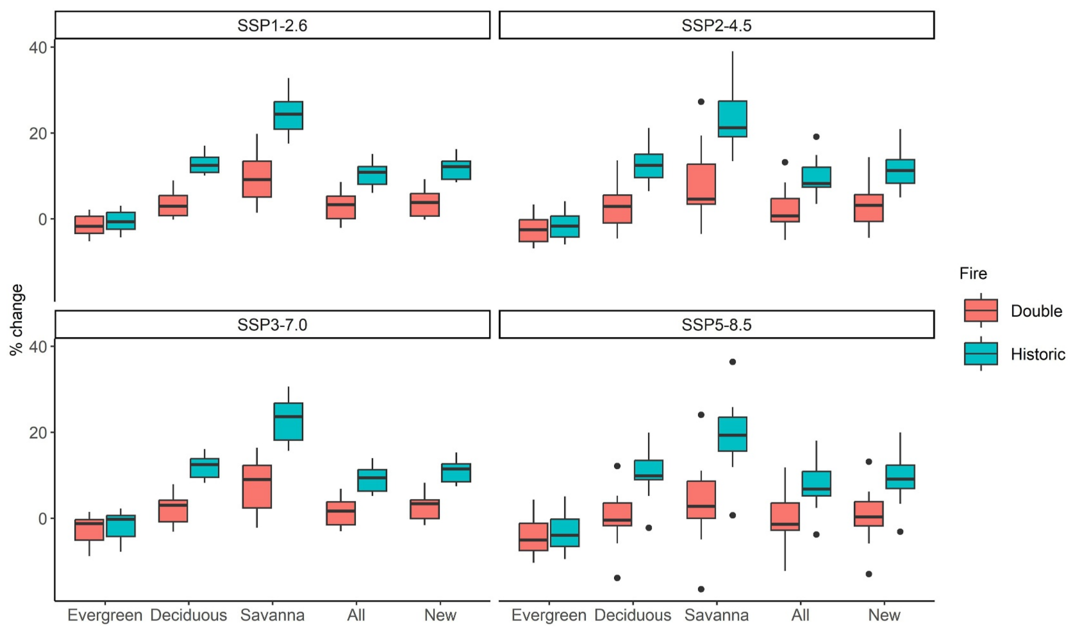

Figure 4. Percent change in tree cover in 2050 relative to baseline conditions (2030) under historic (Historic) and enhanced (Double) fire regimes. Black dots represent outliers and horizontal black lines within boxes represent the median response across 13 GCM runs.

Deciduous areas experience increases in tree cover under all climate scenarios when historic fire frequencies prevail. On the contrary, tree cover within evergreen areas shows a slight decline in all scenarios except SSP1-2.6. Savanna areas experience the largest gains in tree cover in all scenarios. Across newly planted areas (Figure 4 "New") tree cover remains above baseline conditions (cover in 2030) under all scenarios. When fire probability is doubled, overall tree cover remains stable, except under SSP5-8.5 where a slight decline is apparent. Overall tree cover at the end of 2050 is however lower than in scenarios where historic fire conditions prevail. These differences are driven largely by tree cover dynamics within deciduous and savanna areas where doubling fire frequencies results in smaller tree cover gains relative to the corresponding historic fire scenario.

3.3. Changes in Overall Vegetation Characteristics and Ecosystem Productivity

All scenarios of climate change and disturbance are characterized by marked declines in herb cover and increases in shrub and tree cover (Table 2). Relative to 2030 baseline values, herb cover declines by 31%–35%. The declines are driven largely by herb cover losses within deciduous and savanna areas, with larger losses occurring under more intense climate change scenarios (Figure S6 in Supporting Information S1). Regardless of the climate change scenario, herb cover losses within these areas are higher when fire probabilities double. Overall shrub cover increases in all scenarios. Changes in shrub cover are spatially heterogeneous with increases in cover occurring within deciduous and savanna areas and declines occurring within evergreen areas (Figure S7 in Supporting Information S1). In deciduous areas, shrub cover increases range between 31% and 40%, whereas within savanna areas the increase ranges between 16% and 28%. Within evergreen areas, shrub cover declines under all scenarios and the loss in cover relative to the 2030 baseline ranges between −12% and −22%. Unlike deciduous and savanna areas, within evergreen areas the most pronounced losses occur under the more extreme climate (SSP5-8.5) and disturbance scenario (double fires).

All climate change and disturbance scenarios are characterized by declines in mean monthly net primary productivity (MNP) with the largest declines occurring under SSP2-4.5, followed by SSP5-8.5 in combination with higher fire probabilities (Table 2). Declines in MNP within savanna areas primarily contribute to the overall reduction in primary production (Figure S8 in Supporting Information S1). Within savanna areas MNP declines range between −5% and −24%. In these areas the largest declines occur under a high fire probability SSP2-4.5 scenario. In this scenario, deciduous areas also experience a decline in MNP (−4.5%), whereas across the remaining scenarios these areas experience gains in primary production. Evergreen areas also experience gains in MNP ranging from 1.2% to 11.6% across all scenarios.

Aboveground live biomass (ALB) declines under all climate scenarios with more pronounced declines occurring under scenarios of higher fire probability (Table 2). These trends are primarily driven by ALB declines in savanna areas (Figure S9 in Supporting Information S1). Under the high fire probability scenarios, ALB declines range between −12% and −18%. Similar trends unfold within evergreen areas as well, where ALB declines occur only in the high fire scenario. On the contrary, within deciduous areas, all scenarios are characterized by increases in ALB, however these increases are smaller when fire probabilities are doubled.

4. Discussion

Kenyan tree cover, both existing and planned, is characterized by stable or increasing trends till 2050 under a range of climate conditions, disturbance regimes, and with CO_2 fertilization. This finding is consistent with several recent simulation-based pan-tropical and pan-continental studies which confirm the persistence of tropical tree cover areas under climate change (Koch & Kaplan, 2022; Martens et al., 2022). Unlike these studies, our work focuses on tree cover change in the near-term, and our findings additionally suggest that mid-century tree cover changes in Kenya do not differ substantially among climate change scenarios. This may in part be driven by the fact that changes in temperature, precipitation, and CO_2 concentrations in the 2030–2050 period do not differ substantially between the four scenarios. Distinct changes in these variables begin to appear post 2050, when mitigation efforts associated with the SSP1-2.6 and SSP2-4.5 scenarios begin to manifest (Riahi et al., 2017).

4.1. Implications for Kenyan Sustainability Goals

Kenya's afforestation policy outlines broad goals and guidelines, however, specific interventions and strategies related to tree cover expansion across the nation are governed by local contexts (MOEF, Kenya, 2019). Given that the goal of 10% tree cover has already been achieved, results from our simulations serve primarily to illuminate

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the range of plausible future outcomes associated with tree cover enhancements within Kenya's diverse ecosystems. We discuss these outcomes and associated tradeoffs within the context of ongoing afforestation actions (aimed at achieving 30% tree cover) and efforts to sustain biodiversity and local livelihoods.

4.1.1. Ongoing Afforestation Efforts

Under all climate scenarios, we find that increasing fire probabilities lead to smaller gains in tree cover, relative to the 2030 baseline, suggesting that in the near-term fire and not climate is likely to have a larger determining impact on tree cover persistence in Kenya (Holdo et al., 2009). Because wildfires often have anthropogenic origins (Rotich et al., 2025) this finding suggests that reducing fire risks is the most substantive management action that can be undertaken to ensure tree cover persistence Within savanna areas, however, fire suppression has a complicated legacy underpinned by a mischaracterization of savannas as "wastelands" and traditional burning practices as "bad land management," consequently warranting deeper community-engagement in the management of tree cover and fires (Croker et al., 2023). Tree cover increases are most pronounced in savanna areas followed by tropical deciduous forests, while cover remains stable or declines slightly within evergreen forest areas. These responses may be driven, in part, by the differences in the severity of temperature and precipitation changes within these ecosystems (Figure 3). For example, compared to savanna and deciduous forest ecosystems, in evergreen forested areas, temperature increases in the future are not accompanied by large increases in precipitation potentially leading to overall drier conditions (Bowman et al., 2014; Tao et al., 2022). The stable to declining trends in tree cover within evergreen forest areas suggests that, in the near term, achieving biodiversity and carbon sequestration related goals within areas with evergreen forests can benefit from a greater understanding of tree species sensitivity to climate change (Feeley et al., 2023). Our spin-up simulations and subsequent model tuning ensured that tree cover is made up of deciduous and evergreen individuals adapted to different ecosystems across Kenya. In practice, tree cover persistence and broader biodiversity outcomes would depend on the judicious selection of tree species (Wu et al., 2021).

4.1.2. Biodiversity Conservation

Under all scenarios, tree cover extents increase substantially within savanna areas. While this may suggest that savanna areas may serve as optimal venues for focusing afforestation efforts to achieve targets related to carbon sequestration, trends in other ecosystems variables unveil the potential tradeoffs and pitfalls associated with this strategy. Tree cover expansion in savannas is accompanied by large declines in herbaceous vegetation, net primary productivity and aboveground live biomass. This suggests, and is corroborated by other studies, that afforestation driven gains within savannas come at the cost of reducing overall habitats for herbivores and ecosystem-wide declines in carbon sequestration potential (Boone et al., 2018; Godde et al., 2020; Martens et al., 2022). Some of these unintended consequences will be exacerbated by the suppression of fire, which while promoting carbon sequestration, may cause further woody encroachments within savannas (Stevens et al., 2017). In addition, herbivory by large-bodied browsers plays a limiting role on woody cover expansion (trees and shrubs) within deciduous and savanna systems, further complicating the calculus of reconciling afforestation and biodiversity conservation goals (Bond, 2008). Positioning ongoing afforestation activities within these systems as efforts at ecosystem restoration would require additional concerted efforts toward restoring grass cover and herbivore communities (Parr et al., 2024).

4.1.3. Livelihoods

In our simulations, to create our 2030 baseline scenario map, trees were added to agricultural lands proximate to existing forests to emulate widespread adoption of agroforestry as envisaged by the Kenyan government. While tree cover expansion within these areas is not limited by climate or disturbance, they may be limited by the availability of land. *In L-Range processes within grid-cells are not spatially explicit and vegetation growth represents the biophysical potential while assuming unconstrained land availability. This, however, is seldom true, particularly in areas experiencing agricultural expansion* (Doelman et al., 2020). *Consequently, these results may be interpreted to mean that newly afforested areas have the potential to retain tree cover in the near term under a range of climate and disturbance scenarios in the absence of competing land use demands.* While new areas of tree cover show overall persistence up to 2050, there are also areas, such as within the agriculture dominated Kenyan highlands, where losses in cover occur. This vulnerability underscores the need for agroforestry initiatives within agricultural landscapes to include safeguards and incentives to protect community

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livelihoods and food security (Fleischman et al., 2020). For pastoral communities, afforestation within rangelands coupled with woody encroachment and loss of herbaceous cover poses livelihood threats even as restored tree cover will enhance access to firewood (Boone et al., 2018; Martens et al., 2022).

4.2. Implications for Tropical Afforestation Efforts

These findings have implications for afforestation activities beyond Kenya. Afforestation is increasingly being proposed and adopted as a measure to mitigate climate change and biodiversity declines globally. Initiatives such as the United Nations Strategic Plan for Forests 2030, and the Bonn Challenge are notable examples of global afforestation commitments (Seymour, 2020). Similarly, agroforestry is being increasingly promoted globally as a strategy to attain UN Sustainable Development Goals (Ickowitz et al., 2022). To this end multiple independent studies and national governments have identified areas with afforestation potential, which often include large swaths of grassland and savanna areas that are mischaracterized as wastelands in need of restoration (Veldman et al., 2015). With our findings we join other studies in cautioning that afforestation efforts within savannas should not be undertaken without deeper consideration of their potential impacts on native biodiversity and community livelihoods (Kumar et al., 2020; Nerlekar et al., 2024; Temperton et al., 2019).

4.3. Future Time Horizon

We use 2050 as a time horizon to assess the outcome of ongoing afforestation efforts for three reasons. First, it enables the exploration of changes under all the available climate scenarios while avoiding the larger uncertainties associated with climate projections in the latter half of this century (Riahi et al., 2017). By deliberately exploring the nearer-term to the year 2050, our analysis is intended to provide more meaningful information for policy and to stimulate more adaptive policy making. Second, focusing on 2050 circumvents the issue of our simulations not accounting for land cover-climate feedbacks (Mahmood et al., 2014). Successful afforestation within Kenya and potentially other tropical nations will result in carbon capture that can have local and global climate implications within the study timeline. This is not accounted for in our models and remains a source of uncertainty. Similarly, Integrated Assessment Models (IAMs) include large assumptions about land use, and it is unclear how these would interact with our simulation setting (Popp et al., 2017). For example, are we planting trees in places where the IAMs already assume tree cover? Third, it allows us to explore tree cover sensitivities within a narrow range of climate and CO_2 extremes, which helps ensure the plausibility of our results.

4.4. Climate Change Scenarios and Afforestation Policy

The four climate change scenarios together represent vastly different worlds underpinned by distinct global developmental trajectories. In conjunction with the two disturbance scenarios, we simulate tree cover outcomes under plausible future conditions ranging from the optimistic (SSP1-Historic fire) to the extremely pessimistic (SSP5-Double fire). Our explorations, however, do not accommodate the global or regional socio-economic-political currents that are part of each SSP storyline that profoundly influence climate trajectories, disturbance trends, afforestation policy and resource use. For example, using a stakeholder-driven approach, Talebian et al. (2021) explored potential future trans-boundary impacts by developing a set of Kenya-specific scenarios that extend the four SSPs that we consider here. Their extended SSP1 scenario is characterized by a future where there is extensive trans-boundary cooperation on resource use and high levels of data-driven policy decision-making. Under the extended SSP5 scenario, climate change adaptation, sustainable development and environmental policy are not priorities for Kenya or any other nation in the region. This aspect of the SSP-based climate projections necessitates the introduction of caveats in interpreting our findings in a policy-relevant manner. In as much as our results suggest that tree cover is characterized by increasing trends in all future scenarios, these trends are path-dependent and not mutually comparable. This endeavor is also complicated by the dynamic nature of ongoing afforestation policy as exemplified by the fact that during this work, the Kenyan government updated its afforestation targets from 10% by 2030 to 30% by 2032 (MOEF Kenya). Consequently, we interpret our findings as providing insights that widen definitions of success and failure with regards to achieving goals and outcomes related to afforestation in Kenya. If other enabling conditions exist, climate change does not hinder the achievement of Kenyan afforestation goals. However, this success may be inimical to achieving goals in spheres such as biodiversity conservation and climate change mitigation.

Inclusion in Global Research Statement

The central aim of this work was to produce actionable insights while reconciling end-user needs and data and modeling limitations. To enable this, this research was co-designed in direct collaboration with partners located in Kenya (see co-authors). Likewise, the work was shared with end-users in Kenya during a workshop in 2023, and user feedback improved our understanding of the scientific results presented here.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

All data used in the analysis are available via the Dryad Digital Repository accessible at https://doi.org/10.5061/dryad.sj3tx96j0 (Warrier et al., 2026b). The version of L-Range adapted for Kenya is available via Zenodo accessible at https://doi.org/10.5281/zenodo.19055160 (Warrier et al., 2026a).

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