

**Modeling deforestation and examining trade-offs among carbon stocks and benefits to livelihoods and biodiversity for REDD+ planning in Kenya**



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## ABSTRACT

Reducing deforestation and degradation (REDD+) can lower anthropogenic carbon emissions by 9-11% and is therefore integral to mitigating climate change. REDD+ is a proposed scheme in which developed countries pay developing countries for reduced deforestation. Kenya is one such country participating in REDD+. As such, Kenya must establish a reference emission level (REL) against which it can compare avoided emissions from reduced deforestation. Developing a spatial model of future deforestation will determine the REL for Kenya and provide complementary information on where forests are at risk and drivers of deforestation. REDD+ also offers benefits of poverty alleviation and biodiversity conservation, referred to as “co-benefits.” Since the spatial distributions of carbon and co-benefits may not be congruent, there may be trade-offs among them whereby increasing one decreases others. To assist Kenya in its REDD+ preparations, I build the first spatially explicit deforestation model for the whole of Kenya parametrized with national data. I apply a novel Bayesian inference method which propagates uncertainty in the estimated parameters to the predictions. In addition, I conduct a novel analysis of trade-offs among carbon and co-benefits in three dimensions. I find that predicted forest loss is  $1.68\% \pm 0.06\%$  from 2013 to 2018 (cross-validated AUC = 0.8). There is high deforestation in the Rift Valley and coastal regions attributed to drivers related to accessibility, extraction, and agriculture. Analysis of three-dimensional trade-offs reveals that REDD+ sites could simultaneously include 86% of the maximum possible number of people in poverty and 88% of the maximum possible average proportion of ranges of rare species with the smallest 25% of global ranges with a 10% reduction in carbon. The results presented here may help Kenya spatially target REDD+ interventions and address particular deforestation drivers as well as plan for securing high levels of carbon stocks and co-benefits.

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## LITERATURE REVIEW

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## STATE OF CONSERVATION

Despite conservation efforts since the 1992 adoption of the Convention on Biological Diversity (CBD), biodiversity is in decline (Butchart et al., 2010; Stokstad, 2010). The CBD failed to meet its 2010 goal of significantly slowing biodiversity loss (Stokstad, 2010).

Biodiversity indicators measuring progress toward this goal show that there have been no substantial reductions in the rate of loss, while pressures on biodiversity have increased (Butchart et al., 2010). More species are in trouble; countries are redirecting aid from conservation to fighting climate change; unsustainable consumption of biological resources is increasing; and invasive species continue to spread (Stokstad, 2010). Growing demand for natural resources and modification of the environment are largely responsible for the decline in biodiversity. Since 1800, the growth of human population and intensity of our activities has increased at an exponential rate, placing greater strain on biodiversity (Steffen et al., 2011). Humans appropriate 24% of potential net primary productivity of the biosphere through harvest, land use change, and fire, altering ecosystems and disrupting species on a global scale (Haberl et al., 2007). Croplands and pastures occupy approximately 35% of the ice-free land surface, an amount which rivals global forest cover, leaving less space for biodiversity (Foley et al., 2007; Ramankutty et al., 2008). As a result of these drivers of loss, humans have put many species at the risk of extinction and their threat status continues to deteriorate. Twenty-one percent of extant mammals, 13% of birds, and 41% of amphibians are listed as “threatened” by the International Union for the Conservation of Nature (IUCN) (Hoffmann et al., 2010). From 1980 to 2004, 662 out of 6,246 amphibian species assessed have moved one category closer to extinction on the IUCN Red List Index for measuring extinction risk (Hoffmann et al., 2010). Two hundred and twenty-three out of 9,895 bird species assessed and 156 out of 5,413 mammal species assessed have also deteriorated by at least one category over the periods of 1988 to 2008 and 1996 to 2008,

respectively (Hoffmann et al., 2010). The latest Living Planet Report from the World Wide Fund for Nature (WWF) informs that there has been a 52% decline in the Living Planet Index, which tracks trends in 10,380 closely studied populations of over 3,000 vertebrate species, between 1970 and 2010 (McLellan et al., 2014). On the whole, humans have raised the extinction rate to more than 100 times the background rate, exceeding the planetary boundary for biodiversity loss past which human activities will cause dangerous environmental change (Rockstrom et al., 2009). Between 10 and 690 species are going extinct per week (Monastersky, 2014). Projecting the current rate of extinction of 0.01% to 0.7% of all existing species per year into the future could lead to the loss of more than 75% of species over the next few centuries, qualifying as a mass extinction event (Monastersky, 2014). From the near disappearance of once abundant species such as the Panamanian Golden Frog to the Sumatran Rhino, we may already be in the midst of a “Sixth Extinction” on the same scale as the five preceding mass extinctions in geologic history (Kolbert, 2014).

The loss of biodiversity will likely persist on its current course because protecting habitat for species is expensive when the economic value of alternative land uses such as agriculture or human settlement is high. Protected areas cover about 13% of Earth’s terrestrial surface, although they are typically found at higher elevations, steeper slopes, and greater distances away from roads and cities, which are unsuitable for development and therefore inexpensive to protect (Joppa and Pfaff, 2009). However, there is widespread recognition that species’ habitats provide ecosystem services, ecosystem functions which benefit people, which offer an added incentive for protection beyond just conserving biodiversity (Balmford et al., 2002; Costanza et al., 1997; Daily et al., 2000). Concurrently, there is recognition that biodiversity has economic value in its own right because it increases the efficiency and stability of ecosystem functions as well as the

productivity of ecological communities, thereby contributing to human wellbeing (Cardinale et al., 2012). One such service habitat for species provides is carbon storage, maintaining the stock of carbon in the biosphere and preventing its release into the atmosphere. Forests play an important role in storing carbon. Tropical forests contain 25% of terrestrial carbon and account for 33% of terrestrial net primary productivity (Bonan, 2008). Fertilization by CO<sub>2</sub> from rising anthropogenic carbon emissions is increasing the size of the terrestrial carbon sink, mostly from the uptake of tropical forests (Schimel et al., 2015). Carbon dioxide fertilization may account for up to 60% of the present-day terrestrial carbon sink (Schimel et al., 2015). As atmospheric carbon levels continue to climb, forests will absorb an even greater amount of carbon, but this is contingent on protecting them from deforestation and their response to climate change (Schimel et al., 2015). Destroying forests releases their carbon into the atmosphere, elevating CO<sub>2</sub> concentrations and fueling climate change. Annual carbon emissions from land use and land-use change activities, namely the burning and clearing of forests, account for 9-11% of total anthropogenic emissions from 2000 to 2010 (Smith et al., 2014). Deforestation equates to roughly the same level of carbon emissions from the entire transportation sector, responsible for 14% of global emissions over the same period (Smith et al., 2014). Forests are in turn susceptible to climate change, creating a positive feedback loop whereby increasing deforestation may exacerbate climate change and lead to sustained drought and the eventual dieback of tropical forests (Malhi et al., 2009, 2008). Large-scale deforestation could also directly affect global weather and climate in remote regions through teleconnections with negative implications for agricultural productivity (Lawrence and Vandecar, 2015). Global climate models show that warmer, drier conditions resulting deforestation in the tropics are associated with increased temperature and decreased rainfall at mid-latitudes (Lawrence and Vandecar, 2015). For

example, the complete loss of the Amazon could reduce rainfall throughout the Midwestern, Northwestern, and Southern parts of the United States during the agricultural season (Lawrence and Vandecar, 2015). Complete deforestation of Central Africa could cause declines in rainfall in the Gulf of Mexico, the United States Midwest, Ukraine, and Southern Europe (Lawrence and Vandecar, 2015). Preventing deforestation could mitigate the risks posed by its indirect effects on climate change by lowering carbon emissions and its direct effects on agriculture by preserving local climate conditions in the tropics.

## REDD+ BACKGROUND

The largest proposed program for incentivizing avoided deforestation to maintain carbon stocks and mitigate climate change is the United Nations Framework Convention on Climate Change (UNFCCC) initiative for Reducing Deforestation and Degradation (REDD+). The principle behind REDD+ is that developed countries compensate developing countries for avoided deforestation to lower global emissions (Miles and Kapos, 2008). In 2006, the Stern Review proposed avoided deforestation as a low-cost climate change mitigation option (Stern, 2006). A year later, in 2007, the 13<sup>th</sup> Conference of the Parties (COP) to the UNFCCC adopted the Bali Action Plan, which for the first time included REDD+ in the negotiations (UNFCCC, 2007). The Bali Action Plan expanded the scope of reducing deforestation and degradation to include “the role of conservation, sustainable management of forests and enhancement of forest carbon stocks,” which accounts for the “+” in the acronym (Harvey et al., 2010; UNFCCC, 2007). Outside of the UNFCCC, the United Nations REDD (UN-REDD) program, a collaboration among the Food and Agriculture Organization (FAO), United Nations Environmental Program (UNEP), and the United Nations Development Program (UNDP), as well as the World Bank’s Forest Carbon Partnership Facility (FCPF) were launched in 2008 to

support and finance REDD+ implementation. Since its recognition by the UNFCCC in 2007, UN-REDD and FCPF have been administering funds to countries in preparation for REDD+ while negotiations over the REDD+ mechanism have continued at meetings of the Conference of the Parties. As of yet a global mechanism for transferring funds from developed to developing countries for avoided deforestation and degradation has not been implemented.

Given that REDD+ involves a redistribution of wealth, it could also benefit impoverished people in developing countries in addition to conserving carbon and biodiversity. REDD+ can be viewed as a multi-level payment for ecosystem services (PES) scheme (Angelsen and Wertz-Kanounnikoff, 2008). On the international level, developed, carbon polluting countries pay developing countries with high forest cover, mainly in the tropics, to offset their emissions by avoiding deforestation (Angelsen and Wertz-Kanounnikoff, 2008). On a country level, national governments may pay local governments or land managers for demonstrating emissions reductions in their forests (Angelsen and Wertz-Kanounnikoff, 2008). Locally, REDD+ payments may find their way to people living in and around forests responsible for managing them. Local people who manage forests act as stewards of the ecosystem service of carbon storage. If implemented as a PES scheme, REDD+ would pay them in exchange for increasing carbon storage through avoided deforestation according to the steward-earns principle (Gomez-Baggethun and Ruiz-Perez, 2011). If REDD+ payments are distributed to local forest stewards, they would mostly go to the poor because poor people tend to be located where forests are (Sunderlin et al., 2008). Beyond the potential benefit of payments for carbon storage, local people also benefit more immediately from harvesting forest products such as fuelwood, timber, and charcoal. Forests are an important resource for the 800 million people—more than 10% of the current world population—who inhabit them in the tropics (Chomitz, 2007). The free

products forests offer to impoverished households are sometimes referred to as a “subsidy from nature” (Hecht et al., 1988). These products support millions of people and maintaining the forests that provide them could secure or enhance livelihoods (UNEP-WCMC, 2007).

REDD+ presents a large potential revenue stream for conservationists to tap into to help stem biodiversity loss. REDD+ may also make a significant contribution to local livelihoods. The amount of funds deposited to accounts to implement REDD+ is significant compared to global biodiversity aid. Since 2008, donor countries have deposited a total of US\$ 2.3 billion in multi-lateral climate funds such as UN-REDD and the FCPF (Heinrich Böll Stiftung and ODI, 2014). Over the same period, these multi-lateral funding agencies have approved US\$ 1.07 billion for REDD+ implementation (Heinrich Böll Stiftung and ODI, 2014). The largest contributor is Norway, followed by the United Kingdom, Germany, and the United States (Heinrich Böll Stiftung and ODI, 2014). To quantify global efforts to reduce the rate of biodiversity loss, Butchart et al. (2010) measure trends in biodiversity-related aid from the Organization of Economic Cooperation and Development (OECD), a consortium of 34 donor countries. The OECD requests that donor countries indicate for each development activity they report whether or not it targets environmental objectives (OECD, 2015a). Countries may indicate the purpose of each activity with a general “environment” marker, or with four markers covering the focus areas of the Rio Conventions, including biodiversity, climate change adaptation, climate change mitigation, and desertification (OECD, 2015a). While avoided deforestation may have collateral benefits for biodiversity and livelihoods, countries will likely distinguish this type of activity by marking it for climate change mitigation. The amount of biodiversity-related aid is therefore unlikely to include aid for REDD+ unless activities for avoided deforestation and degradation are designed to maintain or enhance biodiversity (OECD, 2015b). Butchart et al.

(2010) report that the OECD provided US\$ 3.13 billion in biodiversity aid in 2007. The updated figure for 2013 is US\$ 5.8 billion (OECD, 2015c). The OECD similarly requests that countries indicate the objectives of the other types of development activities. Out of the US\$ 135 billion given in aid by the OECD in 2013, 20% falls under the “Education, Health & Population Policies/Reproductive Health” sector, amounting to US\$ 27 billion in aid that goes directly to improving people’s wellbeing and livelihoods (OECD, 2015d). It may not be fair to directly compare REDD+ deposits to biodiversity- and livelihoods-related aid because the former represents a sum since 2008 and the latter the amounts in 2013 alone, although the comparison still demonstrates that REDD+ funding is considerable. REDD+ deposits since 2008 make up over 40% of global biodiversity aid and 9% of livelihoods aid contributed in 2013. REDD+ presents a major funding opportunity for biodiversity conservation and poverty alleviation if it is able to incorporate these objectives into its framework.

Kenya is one of many countries around the world engaging in REDD+ which stands to gain from international payments to protect its forests, conserve its biodiversity, and improve the livelihoods of its people. Kenya is preparing for REDD+ as evidenced by its submission of a Readiness Preparation Proposal (R-PP) to the FCPF (Kenya R-PP, 2010). Kenya’s participation in REDD+ is aligned with its 2005 Forests Act, which requires all forests to be under sustainable forest management, defined as the “conservation and rational utilization of forest resources for the socio-economic development of the country,” regardless of ownership (KFA, 2005). Kenya’s R-PP states that it will design its REDD+ activities to protect and enhance its carbon stocks “in ways that help improve local livelihoods and biodiversity” (Kenya R-PP, 2010). In the forest transition model, which explains the transition from decreasing to increasing forest cover that occurs as countries develop, Kenya is in late transition with most of its forest already lost and its

deforestation rate decreasing (Hosonuma et al., 2012). As such, Kenya has low forest cover and a low deforestation rate. Forests cover 5.6% of Kenya and annual forest loss was between 0.35% and 0.31% from 2005-2010 (FAO, 2010). Despite this there, is still high potential for biodiversity and livelihoods benefits. The Eastern Arc and Coast Forests of southern Kenya and Tanzania are a global hotspot for biodiversity (Myers et al., 2000). The 3,167 km<sup>2</sup> of coastal forests in East Africa, of which 660 km<sup>2</sup> are in southeast Kenya, are an important center of plant and animal endemism (Burgess, 1998). Sub-centers of especially high endemism in Kenya are located along the southeastern coast and Tana River (Burgess, 1998). The Taita Hills in southern Kenya, which form the northern edge of the Eastern Arc Mountains stretching through Tanzania, also have a high concentration of endemic animals and plants (Burgess et al., 2007). Kenya as a whole contains 3,119 animal species, of which 241 are threatened (IUCN, 2015a). Of Kenya's 241 threatened animal species, 30 are mammals, 38 are birds, and 10 are amphibians (IUCN, 2015b). A much higher proportion of Kenya's plant species, 222 out of a total of 723, are threatened (IUCN, 2015c). Poverty is widespread in Kenya. About 53% of rural and 50% of urban Kenyans live below the poverty line of US\$ 0.59 per day in rural areas and US\$ 1.26 per day in urban areas (WRI et al., 2007). The spatial distribution of rural poverty in Kenya is heterogeneous, determined by varying geographical conditions in rural areas, with different levels of influence in each province (Okwi et al., 2007). While reasons for entering and escaping poverty vary across livelihood zones, differentiated by physical and agroecological characteristics that shape people's livelihood activities, national trends show that health problems drive people into poverty and off-farm income gets them out (Kristjanson et al., 2010). Since REDD+ focuses on avoided emissions, before assessing its potential to conserve biodiversity and

improve livelihoods, it is essential to first establish where forest is being lost, what is driving deforestation, and where these drivers occur to predict which forests are at risk.

## DRIVERS OF DEFORESTATION

Avoiding deforestation and the carbon emissions that it releases requires an understanding of where it is likely to occur and what is driving it. Spatial data on observed deforestation and its potential drivers are necessary for building a spatially-explicit model of deforestation to identify which forests are at risk and the causes of forest loss. Following the release of Landsat 7 satellite imagery for free to the public in the late 2000s, for the first time it was possible to classify global forest cover at 30 m resolution and generate wall-to-wall maps of forest change (Hansen et al., 2013). The maps show the percent canopy cover in the base year of 2000 as well as annual forest loss and gain from 2000 to 2012 (Hansen et al., 2013). Prior to the publication of global forest change maps, technicians were required to manually classify remotely sensed images. The availability of high-resolution deforestation maps off the shelf eliminated this step and subsequently made mapping and modeling deforestation more accessible (Margono et al., 2014; Struebig et al., 2015). These maps of global forest change reveal the spatial distribution of deforestation in any given region over time. Knowledge of the drivers that may be responsible for forest loss in the region is needed for acquiring appropriate spatial data to represent drivers of deforestation. Drivers of deforestation are separated into direct and underlying drivers (Kanninen et al., 2007). Direct drivers of deforestation include agricultural expansion, wood extraction, and infrastructure extension whereas underlying drivers include macroeconomic and governance factors as well as cultural, demographic, and technological factors (Kanninen et al., 2007). Underlying factors are more difficult to map because they depend on markets, policies, and social and technological trends which are not inherently spatial,

however their influence is partly reflected in maps of direct drivers. Global patterns in the direct and underlying drivers of tropical deforestation exist with important differences among continents.

Over the past 50 years, the main actors responsible for the majority of tropical deforestation shifted from rural smallholders to large-scale agricultural producers selling to urban and global markets, although this transition did not take place in Africa. From the 1960s to the 1980s, deforestation tended to increase with rural population in the Amazon and Southeast Asia as small-scale farmers with state assistance cleared forested land for agriculture (Rudel et al., 2009). In the subsequent period, an analysis of forest loss from 2000 to 2005 across the tropics revealed that the link between rural population growth and deforestation no longer held (DeFries et al., 2010). More recent deforestation was found to be correlated with urban population growth and the export of agricultural products (DeFries et al., 2010). In an increasingly globalized world, deforestation by wealthy ranchers, farmers, and loggers supplying urban population centers and foreign markets superseded deforestation by small-scale farmers (Rudel et al., 2009). The narrative for Africa, however, was different. While state-sponsored programs to settle people in rainforests did not take place in Africa during the 1960s to the 1980s, increasing rural population over this period was still associated with deforestation as smallholders cleared available land for agriculture (Rudel et al., 2009). Yet, the transition after the 1980s to deforestation mainly by large-scale producers did not occur in Africa and rural people continued to drive deforestation through small-scale agriculture and the extraction of forest products such as wood fuel, timber, and charcoal (Burgess et al., 2002; Fisher, 2010; Rudel et al., 2009). The analysis of forest loss from 2000 to 2005 showed that Africa was an exception to the transition observed in the rest of the tropics (Fisher, 2010). Deforestation in

Africa was weakly correlated with urban growth and not significantly correlated with agricultural exports over this period (DeFries et al., 2010). Further evidence supported the conclusion that rural population continued to drive African deforestation. In the same countries analyzed by DeFries et al. (2010), staple crop production was found to be correlated with deforestation from 2000 to 2005 (Fisher, 2010). The increase in staple crop production was not correlated with yield increases over the same period, implying that higher production was achieved by expanding agricultural land at the expense of forests (Fisher, 2010). Another study of forest loss from 2000 to 2010 provides direct evidence of continued deforestation by smallholders, showing that small-scale agriculture accounted for a higher proportion of deforestation in Africa than in the Americas, but accounted for the same proportion as in Asia (Hosonuma et al., 2012). Within Africa, analysis of forest cover change for Sub-Saharan African countries from 2000 to 2005 reveals that there are regional differences in the rates and drivers of forest loss (Rudel, 2013). In East and West African countries, population growth in the 1990s is positively correlated with deforestation and the proportion of lands that are unsuitable for agriculture is negatively correlated with deforestation (Rudel, 2013). These results demonstrate that East and West African countries with more population growth and suitable land for agriculture experience greater deforestation, affirming the central role of small-scale farmers in forest loss (Rudel, 2013). On the other hand, deforestation is lower in Central African countries where oil and minerals make up a greater proportion of exports (Rudel, 2013). Greater tax revenue on high-value natural resources may have led to rural to urban migration, declines in agriculture, and increased food imports, explaining lower deforestation rates (Rudel, 2013). Together, analyses on global, continental, and country scales show that African deforestation is caused by agricultural expansion and extraction by rural people and that these drivers are more pronounced

in East and West Africa where deforestation is higher. These broad trends offer a starting point for selecting potential drivers to test in regionally specific models of deforestation in Kenya.

Since the prevailing drivers of deforestation in East and West Africa are related to clearing and extraction by rural smallholders, excluding underlying economic drivers from models in these regions may not significantly increase the amount of unexplained variance in forest loss. Spatial data on direct drivers such as population and agriculture may therefore be adequate for explaining the observed distribution of deforestation in Kenya. Fitting a model to spatial data on deforestation and its drivers would test which drivers significantly influence deforestation and show the magnitude of their impact. The model may also be used to predict the future probability of deforestation, producing a map of forests at risk. Spatially explicit models parameterized with spatial data indicating agricultural suitability and population pressure have been used to successfully predict forest loss and show the level of influence of drivers on deforestation in East Africa (Green et al., 2013; Serneels and Lambin, 2001). Previous work has mapped deforestation threat in Kenya on a subnational level, although not yet on a national level using more recent data (Serneels and Lambin, 2001). Developing a national map of future forest loss would establish where deforestation could be avoided in Kenya, and therefore point to areas eligible for REDD+ intervention. Having identified areas eligible for REDD+, it is possible to examine the extent to which different areas contribute to climate change mitigation as well to benefits for biodiversity and livelihoods. Some areas may be more important than others for securing high levels of carbon, biodiversity, and livelihood benefits. Knowing how REDD+ interventions affect multiple objectives in different areas may help Kenya decide on which to prioritize.

## SPATIAL PLANNING FOR MULTIPLE BENEFITS

Up until now, the discussion of REDD+ has only mentioned the ways in which payments for avoided deforestation could benefit biodiversity and livelihoods in addition to mitigating climate change. REDD+ promises to deliver “win-win” solutions whereby protecting forests will simultaneously conserve species and alleviate poverty. These “win-wins,” however, draw attention away from potential trade-offs where gains in one benefit result in losses in another compared to a situation where no action was taken (Hirsch et al., 2011; Muradian et al., 2013). The advantage to a policy narrative of trade-offs over one of “win-wins” is that it acknowledges the possibility of negative outcomes of certain actions (Muradian et al., 2013). A systematic review of the literature on ecosystem services uncovers that trade-offs are three times as common as “win-wins” or synergies (Howe et al., 2014). “Win-wins” are far from guaranteed, but taking insights from the preponderance of cases where trade-offs occurred will ensure that conservation actions are more likely to create “win-win” solutions in the future (Howe et al., 2014). It should therefore be noted that monetizing carbon and prioritizing the protection of forests according to their carbon content alone could potentially lead to declines in biodiversity or damage livelihoods compared to a situation where no REDD+ actions were taken.

REDD+ may deliver multiple benefits of climate change mitigation, biodiversity conservation, and poverty alleviation, although it also poses risks to biodiversity and livelihoods (Hirsch et al., 2011). Biodiversity concerns surrounding REDD+ include displacing deforestation to high biodiversity areas and ignoring the functional importance of biodiversity in maintaining the ecological integrity of forests (Gardner et al., 2012). By focusing protection on forests with high carbon and low biodiversity, REDD+ may displace agricultural expansion to low-carbon, high-biodiversity forests, a phenomenon known as “leakage” (Putz and Redford, 2009). Prioritizing carbon could also overlook the fundamental role biodiversity plays in contributing to

carbon stocks and maintaining their long-term storage. The diversity of plants and soil microbes determines the magnitude, turnover rate, and longevity of carbon stocks in vegetation and soil (Díaz et al., 2009). By enhancing ecosystem resilience, biodiversity supports the permanence of carbon storage (Thompson et al., 2009). With its emphasis on carbon, REDD+ may create perverse incentives to replace resilient forests high in biodiversity with low-diversity monoculture plantations to simultaneously maximize carbon payments and crop yields in the short term (Lindenmayer et al., 2012). REDD+ may additionally adversely affect livelihoods. REDD+ requires a clear definition of land tenure in order to establish the ownership of carbon stocks, incentivize landowners to avoid deforestation, and compensate landowners for their performance (Larson, 2011). REDD+ also requires changes in resource use that may restrict certain activities that supplement livelihoods such as the collection of fuelwood or timber (Larson, 2011). Decisions over who obtains tenure rights and what forest uses are permitted under REDD+ will determine its impact on livelihoods (Larson, 2011). Local livelihoods may suffer if REDD+ undermines tenure rights of forest communities and restricts access to forest resources (Larson, 2011). REDD+ threatens to recentralize forest governance, which could lead central governments to seize land tenure from forest communities and impose excessive restrictions on forest use, believing that they can better manage carbon stocks than these communities (Phelps et al., 2010). Threats to land tenure also exist from powerful and wealthy landholders. Land tenure is often less clear and more contested in forests than in agricultural landscapes (Campbell, 2009). With the possibility of new income from REDD+, elites may assert their tenure rights to capture payments, dispossessing less powerful, poorer landholders and depriving them of REDD+ funds (Campbell, 2009). Dispossession of vulnerable landholders and elite capture of REDD+ payments is more likely where the rule of law is weak and there is

low accountability (Sandbrook et al., 2010). If efforts are not undertaken to strengthen institutions protecting the rights of forest communities, REDD+ may negatively affect their livelihoods by undermining their land tenure (Sandbrook et al., 2010). Restrictions imposed by central government or powerful landowners on land they claim ownership over or restrictions imposed by REDD+ projects on land forest communities own themselves could further damage livelihoods. Much of the income of people living in and around forests comes from collecting fuelwood, food, and other forest products, or from practicing shifting cultivation (Chomitz, 2007). Loss of access to forest resources could hurt livelihoods by taking away a main source of income (Chomitz, 2007). Without addressing issues of leakage, perverse incentives, land tenure, and forest access, REDD+ could harm biodiversity and livelihoods.

Three years after the Bali Action Plan acknowledged avoided deforestation as a strategy for mitigating climate change, in 2010 the 16<sup>th</sup> Conference of Parties adopted a set of draft safeguards attending to the risks REDD+ posed to biodiversity and livelihoods (UNFCCC, 2010). The safeguards pertain to environmental, social, and governance concerns (UNFCCC, 2010). To protect biodiversity from leakage and perverse incentives, they require “actions to reduce displacement of emissions” and that REDD+ “actions are consistent with the conservation of natural forests and biological diversity” (UNFCCC, 2010). To avoid damage to livelihoods from seizure of land tenure and restriction of access to forest resources, they call for “transparent and effective national forest governance” and “full and effective participation of... indigenous people and local communities,” as well as “respect for the knowledge and rights of indigenous peoples and members of local communities” (UNFCCC, 2010). While the Conference of Parties agreed to the principles behind the broad set of safeguards, there is still no consensus on how to implement or monitor them (Visseren-Hamakers et al., 2012). There is debate over whether these

safeguards should be outlined in greater detail (Visseren-Hamakers et al., 2012). The safeguards stress national sovereignty and, as they stand, leave it up to countries to define their own safeguards consistent with national laws and policies (Visseren-Hamakers et al., 2012). Nevertheless, if countries find a way to operationalize these safeguards, adhering to them will mean that incentivizing avoided deforestation will not reduce biodiversity or exacerbate poverty or disenfranchisement. With adequate safeguards, it is only possible for REDD+ to enhance carbon storage, biodiversity conservation, and poverty alleviation through the protection of forests.

Since the spatial distributions among forest benefits do not perfectly align, prioritizing the protection of certain benefits will lower the levels of other benefits. The extent to which prioritizing one benefit lowers another depends on the level of congruence between their distributions. If there is low or negative spatial congruence between two benefits, increasing one benefit will result in a large decrease in the other. In this case, there is a strong trade-off between benefits. If, on the other hand, there is high positive spatial congruence between two benefits, increasing one benefit will result in less of a decrease in the other. In this latter case, there is a weak trade-off between benefits. Conversely, trade-offs can be viewed from the perspective of how much one benefit will increase by decreasing another benefit. For a strong trade-off, decreasing one benefit will result in a large decrease in another. Likewise, for a weak trade-off, decreasing one benefit will result in less of a decrease in the other. From a management point of view, weak trade-offs are favorable because they show that it is possible to protect high levels of multiple benefits at once. The strength of trade-offs therefore describes spatial relationships among the distributions of forest benefits. The term “trade-off” is used here in a different sense than in the literature on REDD+ risks. In the absence of REDD+ safeguards, trade-offs describe

the potential for an increase in one benefit to decrease another compared to a situation where no action was taken. For example, prioritizing carbon storage under REDD+ could result in the displacement of deforestation to low carbon, high biodiversity forests causing a decline in biodiversity that would not have occurred if REDD+ was not implemented. However, assuming that countries adhere to the safeguards to avoid leakage and maintain biodiversity when implementing REDD+, a decline in biodiversity from prioritizing carbon storage would not take place. The assumption that countries adhere to the safeguards makes it only possible for REDD+ to deliver benefits to biodiversity and livelihoods that are additional to a situation where no action was taken. Trade-offs under the assumption of safeguard adherence therefore describe the relative levels of additional benefits attained when benefits have different priority levels. For instance, prioritizing carbon may result in less biodiversity benefits than if both were prioritized equally. Understanding the trade-offs among forest benefits will help decision makers decide on how much to prioritize each of them in order to secure an outcome with acceptable levels of all benefits.

Mapping the distributions of carbon stocks, biodiversity, and potential for poverty alleviation in the case study country of Kenya and examining their spatial congruence will quantify trade-offs among them. Further limiting the extent of the analysis of trade-offs to areas at risk of deforestation using modeled forest loss would restrict its extent to areas eligible for REDD+ because protecting these areas would result in avoided emissions. Carbon stocks are spatially defined as the aboveground live woody vegetation carbon density measured in Mega grams ( $10^6$  grams) of carbon per hectare at 500 m resolution by satellite remote sensing (Baccini et al., 2012). Notably, belowground carbon stocks are absent from this map. A similar map of global carbon stocks includes belowground carbon, although its distribution is identical to that of

aboveground carbon (Saatchi et al., 2011). Including data on belowground carbon derived independently from estimates of aboveground carbon could more accurately capture the distribution of total carbon stocks (FAO et al., 2012). The ranges of all mammal, bird, and amphibian species as well as rare species in these taxa spatially represent biodiversity (IUCN, 2013). Rare species are defined in two ways: those with a global range size less than the median global range size, and those with a global range less than the lower quartile of global range sizes. Data on rare species richness summed across taxa should be interpreted with caution because distributions of rare species richness for individual taxa may diverge from patterns of total rare species richness (Grenyer et al., 2006). Furthermore, total species richness is a simplistic metric for setting conservation priorities that does not account for evolutionary potential and ecosystem services (Kareiva and Marvier, 2003). Spatially targeting high richness areas may also lead to the exclusion and degradation of other areas as well as the preferential protection of less charismatic species that can live in restricted areas rather than species such as primates and large carnivores that require large territories (Kareiva and Marvier, 2003). Census data on the number of people below the poverty line in each of the lowest-level administrative units reveal the distribution of poverty density (CBS, 2001). Poverty density is a proxy for REDD+'s potential impact on livelihoods. It is assumed that REDD+ will have higher benefits for livelihoods when it includes more people below the poverty line because payments will result in a greater proportional increase in the incomes of those who are poor than those who are better off. The protection of forests by REDD+ in areas of high poverty density will also secure access to forest resources for a greater number of people who rely on them to supplement their income. Monetary income, however, is only one metric of poverty, which may be used alongside others representing the multiple dimensions of poverty including health, education, and living standard (Alkire and

Foster, 2011). Incentives for misreporting social data in developing countries exist at multiple levels, calling into question the reliability of the census data on poverty (Sandefur and Glassman, 2015). Countries may misreport data to foreign donors to appeal for more aid or frontline service providers may misreport data to national governments to secure more government funding (Sandefur and Glassman, 2015). Recognizing their limitations, spatial data layers on carbon stocks, biodiversity, and livelihoods allow for trade-offs among them to be tested.

There is an expansive array of literature on spatial planning for biodiversity and ecosystem services that examines the strength of trade-offs among environmental benefits. In the California Central Coast ecoregion, biodiversity is positively correlated with carbon storage, flood control, recreation, and water provision and negatively correlated with forage production and crop pollination (Chan et al., 2006). A conservation network targeting biodiversity alone protects a substantial amount of collateral ecosystem services (Chan et al., 2006). Spatial congruence between the distributions of biodiversity and the majority of the ecosystem services assessed explains how prioritizing one does not decrease the others. Targeting all six ecosystem services, however, achieves higher levels of ecosystem services than the biodiversity only network, although results in 44% less biodiversity (Chan et al., 2006). Biodiversity protection is improved by targeting biodiversity and the four ecosystem services positively associated with it, which results in biodiversity losses of only 7% compared to targeting biodiversity alone (Chan et al., 2006). As before, targeting only ecosystem services positively correlated with biodiversity produces a favorable, weak trade-off because their distributions are congruent. In contrast, targeting additional services negatively correlated with biodiversity produces a strong trade-off as their distributions diverge. Trade-offs between biodiversity and ecosystem services vary widely among ecoregions across the globe (Naidoo et al., 2008). On a global scale, a

conservation network of ecoregions targeting biodiversity protects ecosystem system service levels no greater than a network selected at random (Naidoo et al., 2008). Plotting the global rank of importance of each ecoregion for ecosystem services against its rank of importance for biodiversity reveals where there is potential for favorable trade-offs (Naidoo et al., 2008). Ecoregions in the bottom left and top right of the plot, including the California Central Coast, have equal importance for biodiversity and ecosystem services, and hence have a high potential for protecting the same levels of both (Naidoo et al., 2008). A similar number of ecoregions, however, are found in the top left and bottom right of the plot where the importance for biodiversity and ecosystem services is unequal, indicating strong trade-offs (Naidoo et al., 2008). Trade-offs may also be examined over time under future landscape scenarios. In Oregon's Willamette Basin, biodiversity and ecosystem service levels were quantified for stakeholder-defined scenarios of land-use and land-cover change at ten-year intervals between 1990 and 2050 (Nelson et al., 2009). Scenarios included business-as-usual, increased development, and conservation pathways (Nelson et al., 2009). All three scenarios maintained high levels of ecosystem services and biodiversity, suggesting that favorable, weak trade-offs in the Willamette Basin are robust across scenarios (Nelson et al., 2009). The Willamette Basin may be exceptional in that trade-offs remain weak across scenarios since the stakeholder group in Oregon did not consider major alterations to the landscape given the state's "history of resource protection, social behaviors, and land ownership patterns" (Nelson et al., 2009). Trade-offs may not be as weak across scenarios where greater land-use and land-cover change is considered under business-as-usual and increased development pathways (Nelson et al., 2009). A subset of the literature investigating spatial trade-offs in ecosystem services pertains in particular to the trade-offs between carbon stocks, biodiversity, and poverty, which are relevant to REDD+.

Analyses of the trade-offs among carbon stocks, biodiversity, and poverty measure the extent to which REDD+ can deliver additional benefits for biodiversity and livelihoods while protecting carbon stocks. Global analyses demonstrate that it is possible to protect high levels of carbon and biodiversity at once. An assessment of avoided carbon emissions and number of endemic forest vertebrates in each country shows the global trade-off between carbon and biodiversity for a given amount of REDD+ funding (Venter et al., 2009). Allocating REDD+ funding to carbon exclusively would conserve relatively low biodiversity (Venter et al., 2009). However, since the trade-off between carbon and biodiversity is non-linear and weak for high carbon levels, slightly adjusting the allocation of funding could double biodiversity while reducing carbon by only 4-8% (Venter et al., 2009). Similarly, high correlation ( $r = 0.82$ ) among global datasets on carbon storage and terrestrial biodiversity points to a favorable trade-off (Strassburg et al., 2010). Importantly, some regions of high biodiversity are not congruent with high carbon stocks and may be left out of REDD+ (Strassburg et al., 2010). Avoiding leakage is crucial to reducing the increased deforestation pressure in these regions if REDD+ is implemented (Strassburg et al., 2010). Another global study also finds a positive spatial correlation between carbon stocks and endemic species measured for each country, although the strength of this correlation is much lower ( $r = 0.1$ ) (Siikamaki and Newbold, 2012). The correlations between carbon and endemic species for individual taxa vary (Siikamaki and Newbold, 2012). Stronger correlations indicate favorable trade-offs for amphibians ( $r = 0.64$ ) and mammals ( $r = 0.59$ ), but not for birds ( $r = 0.08$ ) (Siikamaki and Newbold, 2012). In contrast to global analyses, country-scale analyses indicate strong trade-offs between carbon and biodiversity. In Indonesia, a weak negative correlation between carbon stocks and biodiversity shows a strong trade-off (Murray et al., 2015). This relationship, however, is highly variable

among islands where there are non-linear relationships between carbon and biodiversity (Murray et al., 2015). Favorable, weak trade-offs may exist on islands where biodiversity increases with carbon stocks, while strong trade-offs may be present on islands where biodiversity decreases with carbon stocks (Murray et al., 2015). Trade-offs between carbon and biodiversity in Indonesia may be explained by the distribution of biodiversity across carbon-dense peat swamp forests and lower-carbon forests on mineral soils (Paoli et al., 2010). Peat swamp forests, which offer the highest emissions reduction potential, have lower total and threatened species richness compared to forests on mineral soils (Paoli et al., 2010). Targeting carbon-dense peat swamp forests in Indonesia under REDD+ will therefore protect less biodiversity (Paoli et al., 2010). As was pointed out at the global level, leakage may displace deforestation to unprotected forests in Indonesia. Prioritizing the protection of peat swamp forests will intensify pressure to establish plantations in biodiversity-rich forests on mineral soils (Paoli et al., 2010). Like biodiversity, poverty has also been found to have a trade-off with avoided emissions at the country-scale in Costa Rica, Thailand, and Indonesia (Ferraro et al., 2015). Protecting areas not only avoids emissions from deforestation, but has also been shown to alleviate poverty (Ferraro et al., 2011). Matching areas by their slope and distance to major city establishes a baseline against which to measure the amount of additional carbon emissions and poverty alleviation resulting from protection (Ferraro et al., 2015). Slopes and distances associated with the most avoided carbon emissions are not always those associated with the most poverty alleviation (Ferraro et al., 2015). For example, as slope increases in Costa Rica and Thailand, poverty alleviation increases, possibly because agriculture is more difficult on steeper slopes, while avoided carbon emissions decrease since unproductive land on steeper slopes is more likely to remain forested in the absence of protection (Ferraro et al., 2015). Protecting areas with slopes and distances to cities

that maximize avoided emissions may do less to alleviate poverty, whereas protecting areas with greater poverty may have little effect on avoided emissions (Ferraro et al., 2015). Analyses of the trade-offs among carbon, biodiversity, and poverty demonstrate that trade-off strength depends on spatial extent and geographic location. Globally, there appears to be a favorable, weak trade-off between carbon and biodiversity, although stronger trade-offs may emerge over smaller extents such as individual countries. Variation over smaller spatial extents makes geographic location an important factor in determining the strength of trade-offs because some areas may have stronger associations among forest benefits than others, as is the case with carbon storage and poverty alleviation. Regardless of the strength of trade-offs among carbon, biodiversity, and poverty, the safeguard avoiding leakage must be upheld or else the protection of forests high in carbon areas may displace deforestation to low-carbon forests with more biodiversity or higher poverty.

Many studies assessing the potential for REDD+ to deliver additional benefits for biodiversity and poverty alleviation examine correlations among spatial data layers representing multiple forest benefits (Ferraro et al., 2015; Murray et al., 2015; Paoli et al., 2010; Siikamaki and Newbold, 2012; Strassburg et al., 2010). Simple correlations, however, may hide more complex spatial relationships (Forest et al., 2007). Some studies such as Venter et al. (2009) hold the amount of funding constant to reduce deforestation by a given amount and adjust the proportion of funding allocated to avoided deforestation and biodiversity. The result is a trade-off which shows the amount of avoided emissions possible while protecting different numbers of species with a fixed budget (Venter et al., 2009). Thomas et al. (2013) employ a related approach to assess the carbon-biodiversity trade-off, except instead of using countries as the unit of analysis as in Venter et al. (2009), they use 50 km grid cells for the New World and 2 km grid

cells for Great Britain. Similarly, the amount of area protected is held constant and weights on carbon stocks and biodiversity are adjusted to uncover the trade-off showing the proportions of biodiversity possible to protect for different proportions of carbon (Thomas et al., 2013).

Correlations may miss sub-regions where high levels of multiple benefits can be protected because they assess the correspondence between carbon and biodiversity data layers for all units in the extent of the analysis. Trade-offs only assess the correspondence between areas with the highest carbon stocks or avoided emissions and biodiversity in a subset of units in the extent of the analysis, revealing possible sub-regions where multiple benefits can be secured. Analyzing trade-offs over smaller extents and units is a step forward in understanding the spatial relationship between carbon and biodiversity because the strength of trade-offs may vary by location and data resolution (Thomas et al., 2013).

Analysis of trade-offs among higher-resolution spatial data for multiple benefits may be refined by limiting the study extent to areas where avoided emissions are economically viable. Venter et al. (2009) correctly consider the differing costs for avoided emissions among countries. The opportunity cost of agriculture is the main cost of avoided deforestation, although there are also implementation and transaction costs (World Bank, 2011). The high economic returns that could be gained from converting forested areas to agricultural land makes protecting forests expensive (Butler et al., 2009; Fisher et al., 2011). Implementation costs to reduce leakage, for example by increasing agricultural yields on existing cropland, may also be considerable (Fisher et al., 2011). Revenues from avoided emissions, calculated by multiplying carbon stocks in high-threat areas by a factor to convert biomass to atmospheric CO<sub>2</sub> emissions and the price of carbon per ton of emissions, offset the costs of REDD+. Subtracting REDD+ costs from avoided emissions revenues show where REDD+ is economically viable. The extent of analysis of high-

resolution trade-offs among multiple forest benefits should therefore firstly be limited to areas at risk of deforestation and secondly be limited to areas where REDD+ is economically viable to focus on trade-offs where REDD+ is likely to be implemented.

Measuring trade-offs among forest benefits on a country scale helps decision makers negotiate on what levels of benefits to protect in order to maximize financial value. People benefit from the services ecosystems provide at multiple scales. The scale of the ecosystem that delivers services does not always match the scale at which humans value those services (de Groot et al., 2002). For instance, forests store carbon locally in the tropics, yet the role of carbon storage in stabilizing global climate is valued internationally. Since the local values of forests from destructive activities such as logging may be high, the international community must pay national governments to make up for the cost of foregone economic opportunities to maintain carbon stocks for climate stabilization (Kremen et al., 2000). Forests also deliver services valued locally which do not preclude their ability to store carbon such as supporting biodiversity and providing forest products including fuelwood and charcoal. Local people may value biodiversity because it regulates ecosystem processes underpinning ecosystem services, directly contributes to ecosystem services, and is a good that has value in and of itself (Mace et al., 2012). In addition to the provision of forest products, forests offer other ecosystem services valued locally which do not prevent forests from storing carbon such as maintaining watershed functions, local climate, soils and biogeochemical processes, and water quality (Stickler et al., 2013). When assessing the optimal level of forest benefits to protect, decision makers may choose to receive less international financing for carbon storage if they could substantially increase the amount of biodiversity and access to forest products to people in poverty. In this case, the financial gain of increasing the provision of local ecosystem services would outweigh the financial losses of

reducing carbon storage. Since estimating the financial value of biodiversity is difficult, countries may want to set thresholds for the amount that they protect and test how picking different thresholds affects the levels of other ecosystem services (Bateman et al., 2013). For example, a study of spatial planning for ecosystem services in the United Kingdom compares the spatial distribution of management scenarios maximizing all ecosystem services to the distribution which maximizes ecosystem services with a constraint of no net loss of wild bird diversity (Bateman et al., 2013). In this way, the opportunity cost of conserving biodiversity could be measured by examining the effect of the constraint on the level of ecosystem services maintained (Bateman et al., 2013).

Measuring trade-offs among forest benefits also helps countries negotiate on what levels to protect based on non-financial values. Trade-offs collapse multiple forms of value down into economic value (Hirsch et al., 2011). For instance, trading off biodiversity against carbon stocks reduces the value of biodiversity to foregone carbon revenues since carbon is widely commoditized and biodiversity does not have a clear value (Phelps et al., 2012). There may be other reasons why decision makers would want to conserve biodiversity such as for its intrinsic value (Phelps et al., 2010). Carbon, biodiversity, and forest products are properties of ecosystems that may have biophysical, socio-cultural, or economic value (de Groot et al., 2010, 2002; Gómez-Baggethun and Barton, 2013). Socio-cultural and economic values are those that people impose on biophysical quantities of ecosystem services (Martín-López et al., 2014). In Doñana National Park in southwest Spain, socio-cultural and economic values measured by surveys of social preferences and various economic valuation techniques, respectively, diverged for different ecosystem services (Martín-López et al., 2014). The socio-cultural value of water quality, climate regulation, ecotourism, environmental education, and satisfaction for conserving

biodiversity is highly recognized in Doñana (Martín-López et al., 2014). Out of these services, only ecotourism has a high economic value (Martín-López et al., 2014). In Kenya, decision makers may value biodiversity because it is part of a national or regional identity. They may also value access to forest products by greater numbers of the people who rely on them to supplement their incomes, indicated by the distribution of poverty density in forested areas. While not a physical property of ecosystems, decision makers may additionally value the distribution of carbon payments to a greater number of people below the poverty line because these payments will increase their incomes by a proportionally greater amount than those who are better off. Measuring trade-offs in biophysical units and units of poverty density allows space for value pluralism. Decision makers with different values may use them to negotiate on what levels of carbon finance, biodiversity conservation, and poverty alleviation they deem acceptable. The trade-offs are invaluable because they give spatial reference to decisions about how much to prioritize certain benefits. Decision makers wishing to prioritize biodiversity and poverty alleviation may encounter resistance from other decision makers who claim that this will lead to significant reductions in carbon stocks and in turn payments for avoided emissions. Trade-offs that show a slight loss in carbon stocks results in disproportionate gains in biodiversity and poverty alleviation would strengthen the argument for prioritizing non-carbon benefits because they would not substantially reduce the amount of carbon protected. Faced with the pressure to maximize profits from avoided emissions, the identification of favorable trade-offs among forest benefits would provide a powerful rationale for demanding that REDD+ deliver greater benefits for biodiversity and livelihoods.

## REFERENCES

- Alkire, S., Foster, J., 2011. Counting and multidimensional poverty measurement. *J. Public Econ.* 95, 476–487. doi:10.1016/j.jpubeco.2010.11.006
- Angelsen, A., Wertz-Kanounnikoff, S., 2008. Chapter 2: What are the key design issues for REDD and the criteria for assessing options?, in: *Moving Ahead with REDD: Issues, Options and Implications*. pp. 11–21. doi:10.1002/tqem.3310060102
- Baccini, A., Goetz, S.J., Walker, W.S., Laporte, N.T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P.S.A., Dubayah, R., Friedl, M.A., Samanta, S., Houghton, R.A., 2012. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nat. Clim. Chang.* doi:10.1038/nclimate1354
- Balmford, A., Bruner, A., Cooper, P., Costanza, R., Farber, S., Green, R.E., Jenkins, M., Jefferiss, P., Jessamy, V., Madden, J., Munro, K., Myers, N., Naeem, S., Paavola, J., Rayment, M., Rosendo, S., Roughgarden, J., Trumper, K., Turner, R.K., 2002. Ecology - Economic reasons for conserving wild nature. *Science* (80- ). 297, 950–953. doi:10.1126/science.1073947
- Bateman, I.J., Harwood, A.R., Mace, G.M., Watson, R.T., Abson, D.J., Andrews, B., Binner, A., Crowe, A., Day, B.H., Dugdale, S., Fezzi, C., Foden, J., Hadley, D., Haines-Young, R., Hulme, M., Kontoleon, A., Lovett, A. a, Munday, P., Pascual, U., Paterson, J., Perino, G., Sen, A., Siriwardena, G., van Soest, D., Termansen, M., 2013. Bringing ecosystem services into economic decision-making: land use in the United Kingdom. *Science* 341, 45–50. doi:10.1126/science.1234379
- Bonan, G.B., 2008. Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. *Science* (80- ). 320, 1444–1449. doi:10.1126/science.1155121
- Burgess, N., 1998. Coastal forests of eastern Africa: status, endemism patterns and their potential causes. *Biol. J. Linn. Soc.* 64, 337–367. doi:10.1006/bijl.1998.0224
- Burgess, N., Doggart, N., Lovett, J.C., 2002. The Uluguru Mountains of eastern Tanzania: the effect of forest loss on biodiversity. *Oryx*. doi:10.1017/S0030605302000212
- Burgess, N.D., Butynski, T.M., Cordeiro, N.J., Doggart, N.H., Fjeldså, J., Howell, K.M., Kilahama, F.B., Loader, S.P., Lovett, J.C., Mbilinyi, B., Menegon, M., Moyer, D.C., Nashanda, E., Perkin, A., Rovero, F., Stanley, W.T., Stuart, S.N., 2007. The biological importance of the Eastern Arc Mountains of Tanzania and Kenya. *Biol. Conserv.* 134, 209–231. doi:10.1016/j.biocon.2006.08.015
- Butchart, S.H.M., Walpole, M., Collen, B., van Strien, A., Scharlemann, J.P.W., Almond, R.E.A., Baillie, J.E.M., Bomhard, B., Brown, C., Bruno, J., Carpenter, K.E., Carr, G.M., Chanson, J., Chenery, A.M., Csirke, J., Davidson, N.C., Dentener, F., Foster, M., Galli, A., Galloway, J.N., Genovesi, P., Gregory, R.D., Hockings, M., Kapos, V., Lamarque, J.-F.,

- Leverington, F., Loh, J., McGeoch, M.A., McRae, L., Minasyan, A., Hernández Morcillo, M., Oldfield, T.E.E., Pauly, D., Quader, S., Revenga, C., Sauer, J.R., Skolnik, B., Spear, D., Stanwell-Smith, D., Stuart, S.N., Symes, A., Tierney, M., Tyrrell, T.D., Vié, J.-C., Watson, R., 2010. Global biodiversity: indicators of recent declines. *Science* 328, 1164–1168. doi:10.1126/science.1187512
- Butler, R.A., Koh, L.P., Ghazoul, J., 2009. REDD in the red: palm oil could undermine carbon payment schemes. *Conserv. Lett.* 2, 67–73. doi:10.1111/j.1755-263X.2009.00047.x
- Campbell, B.M., 2009. Beyond Copenhagen: REDD+, agriculture, adaptation strategies and poverty. *Glob. Environ. Chang.* 19, 397–399. doi:http://dx.doi.org/10.1016/j.gloenvcha.2009.07.010
- Cardinale, B., Duffy, J., Gonzalez, A., 2012. Biodiversity loss and its impact on humanity. *Nature* 486, 59–67. doi:10.1038/nature11148
- CBS, 2001. Central Bureau of Statistics (CBS), Ministry of Finance and Planning. Kenya 1999 Population and Housing Census: Counting our People for Development Volume I. [WWW Document]. URL [http://docs.wri.org/ke\\_poverty1999-cbs\\_location.zip](http://docs.wri.org/ke_poverty1999-cbs_location.zip)
- Chan, K.M.A., Shaw, M.R., Cameron, D.R., Underwood, E.C., Daily, G.C., 2006. Conservation planning for ecosystem services. *Plos Biol.* 4, 2138–2152. doi:10.1371/journal.pbio.0040379
- Chomitz, K.M., 2007. At loggerheads? : agricultural expansion, poverty reduction, and environment in the tropical forests, *Environment*. doi:10.1016/0308-597X(80)90019-6
- Costanza, R., d’Arge, R., de Groot, R., Farber, S., Grasso, M., Hannon, B., Limburg, K., Naeem, S., O’Neill, R. V., Paruelo, J., Raskin, R.G., Sutton, P., van den Belt, M., 1997. The value of the world’s ecosystem services and natural capital. *Nature*. doi:10.1038/387253a0
- Daily, G.C., Söderqvist, T., Aniyar, S., Arrow, K., Dasgupta, P., Ehrlich, P.R., Folke, C., Jansson, A., Jansson, B., Kautsky, N., Lubchenco, J., Mäler, K., Simpson, D., Starrett, D., Tilman, D., Levin, S., Maler, K., Walker, B., 2000. The value of nature and the nature of value. *Science* (80-. ). 289, 395–396. doi:10.1890/154-9295-10.4.171
- De Groot, R.S., Alkemade, R., Braat, L., Hein, L., Willemsen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. *Ecol. Complex.* 7, 260–272. doi:10.1016/j.ecocom.2009.10.006
- De Groot, R.S., Wilson, M.A., Boumans, R.M.J., 2002. A typology for the classification, description and valuation of ecosystem functions, goods and services. *Ecol. Econ.* 41, 393–408. doi:10.1016/s0921-8009(02)00089-7
- DeFries, R.S., Rudel, T., Uriarte, M., Hansen, M., 2010. Deforestation driven by urban population growth and agricultural trade in the twenty-first century. *Nat. Geosci.*

- Díaz, S., Hector, A., Wardle, D.A., 2009. Biodiversity in forest carbon sequestration initiatives: not just a side benefit. *Curr. Opin. Environ. Sustain.* doi:10.1016/j.cosust.2009.08.001
- FAO, 2010. Global Forest Resources Assessment 2010 Country Report Kenya [WWW Document]. URL <http://theredddesk.org/resources/global-forest-resources-assessment-2010-country-report-kenya>
- FAO, IIASA, ISRIC, ISSCAS, JRC, 2012. Harmonized World Soil Database (version 1.2). FAO, Rome, Italy and IIASA, Laxenburg, Austria.
- Ferraro, P.J., Hanauer, M.M., Miteva, D.A., Nelson, J.L., Pattanayak, S.K., Nolte, C., Sims, K.R.E., 2015. Estimating the impacts of conservation on ecosystem services and poverty by integrating modeling and evaluation. *Proc. Natl. Acad. Sci.* 112 , 7420–7425. doi:10.1073/pnas.1406487112
- Ferraro, P.J., Hanauer, M.M., Sims, K.R.E., 2011. Conditions associated with protected area success in conservation and poverty reduction. *Proc. Natl. Acad. Sci. U. S. A.* 108, 13913–13918. doi:10.1073/pnas.1011529108
- Fisher, B., 2010. African exception to drivers of deforestation. *Nat. Geosci.* doi:10.1038/ngeo873
- Fisher, B., Lewis, S.L., Burgess, N.D., Malimbwi, R.E., Munishi, P.K., Swetnam, R.D., Kerry Turner, R., Willcock, S., Balmford, A., 2011. Implementation and opportunity costs of reducing deforestation and forest degradation in Tanzania. *Nat. Clim. Chang.* 1, 161–164.
- Foley, J.A., Monfreda, C., Ramankutty, N., Zaks, D., 2007. Our share of the planetary pie. *Proc. Natl. Acad. Sci. U. S. A.* 104, 12585–12586. doi:10.1073/pnas.0705190104
- Forest, F., Grenyer, R., Rouget, M., Davies, T.J., Cowling, R.M., Faith, D.P., Balmford, A., Manning, J.C., Procheş, S., van der Bank, M., Reeves, G., Hedderson, T.A.J., Savolainen, V., 2007. Preserving the evolutionary potential of floras in biodiversity hotspots. *Nature* 445, 757–760. doi:10.1038/nature05587
- Gardner, T.A., Burgess, N.D., Aguilar-Amuchastegui, N., Barlow, J., Berenguer, E., Clements, T., Danielsen, F., Ferreira, J., Foden, W., Kapos, V., Khan, S.M., Lees, A.C., Parry, L., Roman-Cuesta, R.M., Schmitt, C.B., Strange, N., Theilade, I., Vieira, I.C.G., 2012. A framework for integrating biodiversity concerns into national REDD+ programmes. *Biol. Conserv.* 154, 61–71. doi:10.1016/j.biocon.2011.11.018
- Gómez-Baggethun, E., Barton, D.N., 2013. Classifying and valuing ecosystem services for urban planning. *Ecol. Econ.* 86, 235–245. doi:10.1016/j.ecolecon.2012.08.019
- Gomez-Baggethun, E., Ruiz-Perez, M., 2011. Economic valuation and the commodification of ecosystem services. *Prog. Phys. Geogr.* doi:10.1177/0309133311421708

- Green, J.M.H., Larrosa, C., Burgess, N.D., Balmford, A., Johnston, A., Mbilinyi, B.P., Platts, P.J., Coad, L., 2013. Deforestation in an African biodiversity hotspot: Extent, variation and the effectiveness of protected areas. *Biol. Conserv.* 164, 62–72. doi:10.1016/j.biocon.2013.04.016
- Grenyer, R., Orme, C.D.L., Jackson, S.F., Thomas, G.H., Davies, R.G., Davies, T.J., Jones, K.E., Olson, V.A., Ridgely, R.S., Rasmussen, P.C., Ding, T.-S., Bennett, P.M., Blackburn, T.M., Gaston, K.J., Gittleman, J.L., Owens, I.P.F., 2006. Global distribution and conservation of rare and threatened vertebrates. *Nature* 444, 93–96. doi:10.1038/nature07834
- Haberl, H., Erb, K.H., Krausmann, F., Gaube, V., Bondeau, A., Plutzer, C., Gingrich, S., Lucht, W., Fischer-Kowalski, M., 2007. Quantifying and mapping the human appropriation of net primary production in earth's terrestrial ecosystems. *Proc. Natl. Acad. Sci. U. S. A.* 104, 12942–12947. doi:10.1073/pnas.0704243104
- 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* (80-. ). 342, 850–853. doi:10.1126/science.1244693
- Harvey, C.A., Dickson, B., Kormos, C., 2010. Opportunities for achieving biodiversity conservation through REDD. *Conserv. Lett.* 3, 53–61. doi:10.1111/j.1755-263X.2009.00086.x
- Hecht, S.B., Anderson, A.B., May, P., 1988. The subsidy from nature: shifting cultivation, successional palm forests, and rural development. *Hum. Organ.* 47, 25–35.
- Heinrich Böll Stiftung, ODI, 2014. Focus of funding: REDD [WWW Document]. *Clim. Funds Updat.* URL <http://www.climatefundupdate.org/themes/redd> (accessed 8.19.15).
- Hirsch, P.D., Adams, W.M., Brosius, J.P., Zia, A., Bariola, N., Dammert, J.L., 2011. Acknowledging conservation trade-offs and embracing complexity. *Conserv. Biol.* 25, 259–264. doi:10.1111/j.1523-1739.2010.01608.x
- Hoffmann, M., Hilton-Taylor, C., Angulo, A., Böhm, M., Brooks, T.M., Butchart, S.H.M., Carpenter, K.E., Chanson, J., Collen, B., Cox, N.A., Darwall, W.R.T., Dulvy, N.K., Harrison, L.R., Katariya, V., Pollock, C.M., Quader, S., Richman, N.I., Rodrigues, A.S.L., Tognelli, M.F., Vié, J.-C., Aguiar, J.M., Allen, D.J., Allen, G.R., Amori, G., Ananjeva, N.B., Andreone, F., Andrew, P., Aquino Ortiz, A.L., Baillie, J.E.M., Baldi, R., Bell, B.D., Biju, S.D., Bird, J.P., Black-Decima, P., Blanc, J.J., Bolaños, F., Bolivar-G, W., Burfield, I.J., Burton, J.A., Capper, D.R., Castro, F., Catullo, G., Cavanagh, R.D., Channing, A., Chao, N.L., Chenery, A.M., Chiozza, F., Clausnitzer, V., Collar, N.J., Collett, L.C., Collette, B.B., Cortez Fernandez, C.F., Craig, M.T., Crosby, M.J., Cumberlidge, N., Cuttelod, A., Derocher, A.E., Diesmos, A.C., Donaldson, J.S., Duckworth, J.W., Dutson, G., Dutta, S.K., Emslie, R.H., Farjon, A., Fowler, S., Freyhof, J., Garshelis, D.L., Gerlach, J., Gower, D.J., Grant, T.D., Hammerson, G.A., Harris, R.B., Heaney, L.R., Hedges, S.B.,

Hero, J.-M., Hughes, B., Hussain, S.A., Icochea M, J., Inger, R.F., Ishii, N., Iskandar, D.T., Jenkins, R.K.B., Kaneko, Y., Kottelat, M., Kovacs, K.M., Kuzmin, S.L., La Marca, E., Lamoreux, J.F., Lau, M.W.N., Lavilla, E.O., Leus, K., Lewison, R.L., Lichtenstein, G., Livingstone, S.R., Lukoschek, V., Mallon, D.P., McGowan, P.J.K., McIvor, A., Moehlman, P.D., Molur, S., Muñoz Alonso, A., Musick, J.A., Nowell, K., Nussbaum, R.A., Olech, W., Orlov, N.L., Papenfuss, T.J., Parra-Olea, G., Perrin, W.F., Polidoro, B.A., Pourkazemi, M., Racey, P.A., Ragle, J.S., Ram, M., Rathbun, G., Reynolds, R.P., Rhodin, A.G.J., Richards, S.J., Rodríguez, L.O., Ron, S.R., Rondinini, C., Rylands, A.B., Sadovy de Mitcheson, Y., Sanciangco, J.C., Sanders, K.L., Santos-Barrera, G., Schipper, J., Self-Sullivan, C., Shi, Y., Shoemaker, A., Short, F.T., Sillero-Zubiri, C., Silvano, D.L., Smith, K.G., Smith, A.T., Snoeks, J., Stattersfield, A.J., Symes, A.J., Taber, A.B., Talukdar, B.K., Temple, H.J., Timmins, R., Tobias, J.A., Tsytsulina, K., Tweddle, D., Ubeda, C., Valenti, S. V, van Dijk, P.P., Veiga, L.M., Veloso, A., Wege, D.C., Wilkinson, M., Williamson, E.A., Xie, F., Young, B.E., Akçakaya, H.R., Bennun, L., Blackburn, T.M., Boitani, L., Dublin, H.T., da Fonseca, G.A.B., Gascon, C., Lacher, T.E., Mace, G.M., Mainka, S.A., McNeely, J.A., Mittermeier, R.A., Reid, G.M., Rodriguez, J.P., Rosenberg, A.A., Samways, M.J., Smart, J., Stein, B.A., Stuart, S.N., 2010. The impact of conservation on the status of the world's vertebrates. *Science* 330, 1503–1509. doi:10.1126/science.1194442

Hosonuma, N., Herold, M., De Sy, V., De Fries, R.S., Brockhaus, M., Verchot, L., Angelsen, A., Romijn, E., 2012. An assessment of deforestation and forest degradation drivers in developing countries. *Environ. Res. Lett.* doi:10.1088/1748-9326/7/4/044009

Howe, C., Suich, H., Vira, B., Mace, G.M., 2014. Creating win-wins from trade-offs? Ecosystem services for human well-being: A meta-analysis of ecosystem service trade-offs and synergies in the real world. *Glob. Environ. Chang.* 28, 263–275. doi:http://dx.doi.org/10.1016/j.gloenvcha.2014.07.005

IUCN, 2013. Red List Spatial Data [WWW Document]. URL <http://www.iucnredlist.org/technical-documents/spatial-data>

IUCN, 2015a. Table 6a: Red List Category summary country totals (Animals).

IUCN, 2015b. Table 5: Threatened species in each country (totals by taxonomic group).

IUCN, 2015c. Table 6b: Red List Category summary country totals (Plants).

Joppa, L.N., Pfaff, A., 2009. High and far: Biases in the location of protected areas. *PLoS One* 4. doi:10.1371/journal.pone.0008273

Kanninen, M., Murdiyarso, D., Seymour, F., Angelsen, A., Wunder, S., German, L., 2007. Do trees grow on money?: the implications of deforestation research for policies to promote REDD.

Kareiva, P., Marvier, M., 2003. Conserving biodiversity coldspots. *Am. Sci.* 91, 344–351. doi:10.1511/2003.4.344

- Kenya R-PP, 2010. REDD Readiness Preparation Proposal for Kenya [WWW Document]. URL <http://theredddesk.org/resources/redd-readiness-preparation-proposal-kenya>
- KFA, 2005. Kenya Forests Act [WWW Document]. URL [http://theredddesk.org/sites/default/files/forests\\_act\\_2005\\_kenya\\_1.pdf](http://theredddesk.org/sites/default/files/forests_act_2005_kenya_1.pdf)
- Kolbert, E., 2014. *The Sixth Extinction*. Bloomsbury, London.
- Kremen, C., Niles, J.O., Dalton, M.G., Daily, G.C., Ehrlich, P.R., Fay, J.P., Grewal, D., Guillery, R.P., 2000. Economic incentives for rain forest conservation across scales. *Science* 288, 1828–1832. doi:10.1126/science.288.5472.1828
- Kristjanson, P., Mango, N., Krishna, A., Radeny, M., Johnson, N., 2010. Understanding poverty dynamics in Kenya. *J. Int. Dev.* 22, 978–996. doi:10.1002/jid.1598
- Larson, A.M., 2011. Forest tenure reform in the age of climate change: Lessons for REDD+. *Glob. Environ. Chang.* 21, 540–549. doi:10.1016/j.gloenvcha.2010.11.008
- Lawrence, D., Vandecar, K., 2015. Effects of tropical deforestation on climate and agriculture. *Nat. Clim. Chang.* 5, 27–36.
- Lindenmayer, D.B., Hulvey, K.B., Hobbs, R.J., Colyvan, M., Felton, A., Possingham, H.P., Steffen, W., Wilson, K., Youngentob, K., Gibbons, P., 2012. Avoiding bio-perversity from carbon sequestration solutions. *Conserv. Lett.* 5, 28–36. doi:10.1111/j.1755-263X.2011.00213.x
- Mace, G.M., Norris, K., Fitter, A.H., 2012. Biodiversity and ecosystem services: a multilayered relationship. *Trends Ecol. Evol.* 27, 19–26. doi:10.1016/j.tree.2011.08.006
- Malhi, Y., Aragão, L.E.O.C., Galbraith, D., Huntingford, C., Fisher, R., Zelazowski, P., Sitch, S., McSweeney, C., Meir, P., 2009. Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest. *Proc. Natl. Acad. Sci. U. S. A.* 106, 20610–20615. doi:10.1073/pnas.0804619106
- Malhi, Y., Roberts, J.T., Betts, R.A., Killeen, T.J., Li, W., Nobre, C.A., 2008. Climate change, deforestation, and the fate of the Amazon. *Science* 319, 169–172. doi:10.3832/efor0516-005
- Margono, B.A., Potapov, P. V, Turubanova, S., Stolle, F., Hansen, M.C., 2014. Primary forest cover loss in Indonesia over 2000–2012. *Nat. Clim. Chang.* 1–6. doi:10.1038/NCLIMATE2277
- Martín-López, B., Gómez-Baggethun, E., García-Llorente, M., Montes, C., 2014. Trade-offs across value-domains in ecosystem services assessment. *Ecol. Indic.* 37, 220–228. doi:10.1016/j.ecolind.2013.03.003

- McLellan, R., Iyengar, L., Jeffries, B., Oerlemans, N., 2014. Living Planet Report 2014: species and spaces, people and places. Gland, Switzerland.
- Miles, L., Kapos, V., 2008. Reducing Greenhouse Gas Emissions from Deforestation and Forest Degradation: Global Land-Use Implications. *Science* (80- ). 320, 1454–1455. doi:10.1126/science.1155358
- Monastersky, R., 2014. Biodiversity: Life – a status report [WWW Document]. *Nat. News*. URL <http://www.nature.com/news/biodiversity-life-a-status-report-1.16523>
- Muradian, R., Arsel, M., Pellegrini, L., Adaman, F., Aguilar, B., Agarwal, B., Corbera, E., Ezzine de Blas, D., Farley, J., Froger, G., Garcia-Frapolli, E., Gómez-Baggethun, E., Gowdy, J., Kosoy, N., Le Coq, J.F., Leroy, P., May, P., Méral, P., Mibielli, P., Norgaard, R., Ozkaynak, B., Pascual, U., Pengue, W., Perez, M., Pesche, D., Pirard, R., Ramos-Martin, J., Rival, L., Saenz, F., Van Hecken, G., Vatn, A., Vira, B., Urama, K., 2013. Payments for ecosystem services and the fatal attraction of win-win solutions. *Conserv. Lett.* 6, 274–279. doi:10.1111/j.1755-263X.2012.00309.x
- Murray, J.P., Grenyer, R., Wunder, S., Raes, N., Jones, J.P.G., 2015. Spatial patterns of carbon, biodiversity, deforestation threat, and REDD+ projects in Indonesia. *Conserv. Biol.* n/a–n/a. doi:10.1111/cobi.12500
- Myers, N., Mittermeier, R.A., Mittermeier, C.G., da Fonseca, G.A., Kent, J., 2000. Biodiversity hotspots for conservation priorities. *Nature* 403, 853–858. doi:10.1038/35002501
- Naidoo, R., Balmford, A., Costanza, R., Fisher, B., Green, R.E., Lehner, B., Malcolm, T.R., Ricketts, T.H., 2008. Global mapping of ecosystem services and conservation priorities. *Proc. Natl. Acad. Sci. U. S. A.* 105, 9495–9500. doi:10.1073/pnas.0707823105
- Nelson, E., Mendoza, G., Regetz, J., Polasky, S., Tallis, H., Cameron, D.R., Chan, K.M.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. *Front. Ecol. Environ.* 7, 4–11. doi:10.1890/080023
- OECD, 2015a. OECD Statistics on External Development Finance Targeting Environmental Objectives Including the Rio Conventions [WWW Document]. URL <http://www.oecd.org/dac/stats/rioconventions.htm> (accessed 8.19.15).
- OECD, 2015b. Aid targeting the objectives of the convention on biological diversity [WWW Document]. URL <http://www.oecd.org/dac/stats/46782010.pdf> (accessed 8.19.15).
- OECD, 2015c. Aid activities targeting Global Environmental Objectives [WWW Document]. OECD.Stat. URL <http://stats.oecd.org/Index.aspx?DataSetCode=RIOMARKERS> (accessed 8.19.15).

- OECD, 2015d. Aid at a glance charts [WWW Document]. URL <http://www.oecd.org/dac/stats/aid-at-a-glance.htm> (accessed 8.19.15).
- Okwi, P.O., Ndeng'e, G., Kristjanson, P., Arunga, M., Notenbaert, A., Omolo, A., Henninger, N., Benson, T., Kariuki, P., Owuor, J., 2007. Spatial determinants of poverty in rural Kenya. *Proc. Natl. Acad. Sci. U. S. A.* 104, 16769–16774. doi:10.1073/pnas.0611107104
- Paoli, G.D., Wells, P.L., Meijaard, E., Struebig, M.J., Marshall, A.J., Obidzinski, K., Tan, A., Rafiastanto, A., Yaap, B., Ferry Slik, J., Morel, A., Perumal, B., Wielaard, N., Husson, S., D'Arcy, L., 2010. Biodiversity Conservation in the REDD. *Carbon Balance Manag.* doi:10.1186/1750-0680-5-7
- Phelps, J., Friess, D.A., Webb, E.L., 2012. Win-win REDD+ approaches belie carbon-biodiversity trade-offs. *Biol. Conserv.* 154, 53–60. doi:10.1016/j.biocon.2011.12.031
- Phelps, J., Webb, E.L., Agrawal, A., 2010. Does REDD + Threaten to Recentralize Forest Governance. *Science* (80-. ). 328, 312–313.
- Putz, F.E., Redford, K.H., 2009. Dangers of carbon-based conservation. *Glob. Environ. Chang. Policy Dimens.* 19, 400–401. doi:10.1016/j.gloenvcha.2009.07.005
- Ramankutty, N., Evan, A.T., Monfreda, C., Foley, J.A., 2008. Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochem. Cycles* 22. doi:10.1029/2007GB002952
- Rockstrom, J., Rockstrom, J., Steffen, W., Steffen, W., Noone, K., Noone, K., Persson, A., Persson, A., Chapin, F.S., Chapin, F.S., Lambin, E.F., Lambin, E.F., Lenton, T.M., Lenton, T.M., Scheffer, M., Scheffer, M., Folke, C., Folke, C., Schellnhuber, H.J., Schellnhuber, H.J., Nykvist, B., Nykvist, B., de Wit, C.A., de Wit, C.A., Hughes, T., Hughes, T., van der Leeuw, S., van der Leeuw, S., Rodhe, H., Rodhe, H., Sorlin, S., Sorlin, S., Snyder, P.K., Snyder, P.K., Costanza, R., Costanza, R., Svedin, U., Svedin, U., Falkenmark, M., Falkenmark, M., Karlberg, L., Karlberg, L., Corell, R.W., Corell, R.W., Fabry, V.J., Fabry, V.J., Hansen, J., Hansen, J., Walker, B., Walker, B., Liverman, D., Liverman, D., Richardson, K., Richardson, K., Crutzen, P., Crutzen, P., Foley, J.A., Foley, J.A., 2009. A safe operating space for humanity. *Nature* 461, 472–475. doi:10.1038/461472a
- Rudel, T.K., 2013. The national determinants of deforestation in sub-Saharan Africa. *Philos. Trans. R. Soc. Lond. B. Biol. Sci.* 368, 20120405. doi:10.1098/rstb.2012.0405
- Rudel, T.K., Defries, R., Asner, G.P., Laurance, W.F., 2009. Changing drivers of deforestation and new opportunities for conservation. *Conserv. Biol.* 23, 1396–1405. doi:10.1111/j.1523-1739.2009.01332.x
- Saatchi, S.S., Harris, N.L., Brown, S., Lefsky, M., Mitchard, E.T.A., Salas, W., Zutta, B.R., Buermann, W., Lewis, S.L., Hagen, S., Petrova, S., White, L., Silman, M., Morel, A., 2011.

- Benchmark map of forest carbon stocks in tropical regions across three continents. *Proc. Natl. Acad. Sci. U. S. A.* 108, 9899–9904. doi:10.1073/pnas.1019576108
- Sandbrook, C., Nelson, F., Adams, W.M., Agrawal, A., 2010. Carbon, forests and the REDD paradox. *Oryx* 44, 330–334. doi:10.1017/s0030605310000475
- Sandefur, J., Glassman, A., 2015. The Political Economy of Bad Data: Evidence from African Survey and Administrative Statistics. *J. Dev. Stud.* 51, 116–132. doi:10.1080/00220388.2014.968138
- Schimel, D., Stephens, B.B., Fisher, J.B., 2015. Effect of increasing CO<sub>2</sub> on the terrestrial carbon cycle. *Proc. Natl. Acad. Sci.* 112, 436–441. doi:10.1073/pnas.1407302112
- Serneels, S., Lambin, E.F., 2001. Proximate causes of land-use change in Narok district, Kenya: A spatial statistical model. *Agric. Ecosyst. Environ.* 85, 65–81. doi:10.1016/S0167-8809(01)00188-8
- Siikamaki, J., Newbold, S.C., 2012. Potential Biodiversity Benefits from International Programs to Reduce Carbon Emissions from Deforestation. *Ambio* 41, 78–89. doi:10.1007/s13280-011-0243-4
- Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsidig, E.A., Haberl, H., Harper, R., House, J., Jafari, M., Masera, O., Mbow, C., Ravindranath, N.H., Rice, C.W., Abad, C.R., Romanovskaya, A., Sperling, F., Tubiello, F., 2014. Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, in: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., Stechow, C. von, Zwickel, T., Minx, J.C. (Eds.), . Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Steffen, W., Grinevald, J., Crutzen, P., McNeill, J., 2011. The Anthropocene: conceptual and historical perspectives. *Philos. Trans. A. Math. Phys. Eng. Sci.* 369, 842–867. doi:10.1098/rsta.2010.0327
- Stern, N., 2006. Stern Review: The Economics of Climate Change [WWW Document]. URL [http://webarchive.nationalarchives.gov.uk/20100407011151/http://www.hm-treasury.gov.uk/stern\\_review\\_report.htm](http://webarchive.nationalarchives.gov.uk/20100407011151/http://www.hm-treasury.gov.uk/stern_review_report.htm)
- Stickler, C.M., Nepstad, D.C., Azevedo, A.A., McGrath, D.G., 2013. Defending public interests in private lands: compliance, costs and potential environmental consequences of the Brazilian Forest Code in Mato Grosso. *Philos. Trans. R. Soc. B-Biological Sci.* 368. doi:10.1098/rstb.2012.0160
- Stokstad, E., 2010. Despite progress, biodiversity declines. *Science*. doi:10.1126/science.329.5997.1272

- Strassburg, B.B.N., Kelly, A., Balmford, A., Davies, R.G., Gibbs, H.K., Lovett, A., Miles, L., Orme, C.D.L., Price, J., Turner, R.K., Rodrigues, A.S.L., 2010. Global congruence of carbon storage and biodiversity in terrestrial ecosystems. *Conserv. Lett.* 3, 98–105. doi:10.1111/j.1755-263X.2009.00092.x
- Struebig, M.J., Fischer, M., Gaveau, D.L.A., Meijaard, E., Wich, S.A., Gonner, C., Sykes, R., Wilting, A., Kramer-Schadt, S., 2015. Anticipated climate and land-cover changes reveal refuge areas for Borneo's orang-utans. *Glob. Chang. Biol.* 21, 2891–2904. doi:10.1111/gcb.12814
- Sunderlin, W.D., Dewi, S., Puntodewo, A., Müller, D., Angelsen, A., Epprecht, M., 2008. Why forests are important for global poverty alleviation: A spatial explanation. *Ecol. Soc.* 13. doi:24
- Thomas, C.D., Anderson, B.J., Moilanen, A., Eigenbrod, F., Heinemeyer, A., Quaipe, T., Roy, D.B., Gillings, S., Armsworth, P.R., Gaston, K.J., 2013. Reconciling biodiversity and carbon conservation. *Ecol. Lett.* 16, 39–47. doi:10.1111/ele.12054
- Thompson, I., Mackey, B., McNulty, S., Mosseler, A., 2009. *Forest Resilience, Biodiversity, and Climate Change. A synthesis of the biodiversity/resilience/stability relationship in forest ecosystems*, Technical Series. Montreal, Canada. doi:10.1007/978-3-642-10445-9\_5
- UNEP-WCMC, 2007. *Reducing Emissions from Deforestation: A Key Opportunity for Attaining Multiple Benefits*. Cambridge, U.K.
- UNFCCC, 2007. Decision 1/CP.13. Bali Action Plan. [WWW Document]. Rep. Conf. Parties its Thirteen. Sess. held Bali from 3 to 15 December 2007. Addendum. Part Two Action Tak. by Conf. Parties its Thirteen. Sess. FCCC/CP/2007/6/Add.1. URL <http://unfccc.int/resource/docs/2007/cop13/eng/06a01.pdf>
- UNFCCC, 2010. 1/CP.16. The Cancun Agreements: Outcome of the work of the Ad Hoc Working Group on Long-term Cooperative Action under the Convention [WWW Document]. Rep. Conf. Parties its Sixt. Sess. held Cancun from 29 Novemb. to 10 December 2010. Addendum. Part Two Action Tak. by Conf. Parties its Sixt. Sess. FCCC/CP/2010/7/Add.1. URL <http://unfccc.int/resource/docs/2010/cop16/eng/07a01.pdf>
- Venter, O., Laurance, W.F., Iwamura, T., Wilson, K.A., Fuller, R.A., Possingham, H.P., 2009. Harnessing carbon payments to protect biodiversity. *Science* 326, 1368. doi:10.1126/science.1180289
- Visseren-Hamakers, I.J., McDermott, C., Vijge, M.J., Cashore, B., 2012. Trade-offs, co-benefits and safeguards: current debates on the breadth of REDD+. *Curr. Opin. Environ. Sustain.* 4, 646–653. doi:10.1016/j.cosust.2012.10.005
- World Bank, 2011. *Estimating the opportunity costs of REDD+ A training manual*. Finance 262. doi:10.1016/j.jenvman.2003.12.013

WRI, Department of Resource Surveys and Remote Sensing Kenya, Ministry of Environment and Natural Resources Kenya, Central Bureau of Statistics Kenya, Ministry of Planning and National Development Kenya, International Livestock Research Institute, 2007. Nature's Benefits in Kenya, An Atlas of Ecosystems and Human Well-Being.

## CHAPTER 1

Title: Deforestation modeling for REDD+ planning in Kenya

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## ABSTRACT

Determining emissions from deforestation under a business-as-usual scenario offers a reference against which to measure avoided emissions from reduced deforestation and degradation (REDD+). Reference emission levels (RELs) are important because they indicate the level of avoided emissions possible through reduced deforestation and how much money countries are eligible to receive from REDD+. Methods for calculating RELs are not always spatially explicit. Aggregate measures of historical deforestation or future deforestation predicted by models of development may form the basis of RELs. Spatially explicit models of deforestation, however, provide complementary information with advantages for REDD+ planning. In this study, the first spatially explicit deforestation model is built for the whole of Kenya partly using data collected on the national level. Data on deforestation from 2007-12 and its potential drivers are used to parameterize the model and generate predictions of deforestation in 2013-18. The model has immediate relevance to REDD+ planning in Kenya because it identifies deforestation drivers and hotspots, as well as a national REL. The model also reports uncertainty in the predictions propagated from the estimation of parameters, which has financial implications when establishing the REL. At a price of US\$ 8.60 / tCO<sub>2</sub>e, reducing uncertainty by collecting more, higher-resolution data could increase Kenya's potential REDD+ revenues by US\$ 10.3 million (3.6% of total revenue). The model for Kenya is a case study for how similar models could be used to prioritize regions for REDD+ intervention, develop strategies to address key deforestation drivers, and estimate the value of refining REL estimates.

## INTRODUCTION

Activities that seek to reduce emissions from deforestation and degradation (REDD+) require a reference against which to measure reductions. The reference represents emissions under a business-as-usual scenario (BAU). REDD+ activities produce “additional” emission reductions that contribute to climate change mitigation if they result in lower emissions than the reference (Angelsen 2008). Emissions from deforestation are commonly defined as the product of activities (i.e. area deforested in hectares) and emission factors (i.e. carbon emitted per hectare of forest loss) (Angelsen et al. 2012). It follows that the reduction in emissions is the difference between this product and the reference emissions:

$$\text{Emission reductions} = (\text{activities} * \text{emission factors}) - \text{reference emissions}$$

Reference emissions are also measured as the product of activities and emission factors, although they incorporate activities that would have taken place in the absence of REDD+. Establishing reference emissions is often the first step for both national and project-scale REDD+ initiatives because they are the baseline for determining the effectiveness of interventions to reduce emissions.

The United Nations Framework Convention on Climate Change (UNFCCC) requires countries undertaking REDD+ activities to develop national forest reference emissions levels (RELs) (UNFCCC 2010). The UNFCCC provides guidance on setting RELs, although it does not outline specific instructions on how to do so (UNFCCC 2011). In general, there are two ways of establishing RELs from activity data: they may either be based on historical rates of deforestation from the recent past or on projected BAU deforestation (Gutman and Aguilar-Amuchastegui 2012). Activity data are then multiplied by emission factors to find historical or future emissions. Emission factors vary across different carbon pools; the IPCC offers three tiers for reporting them according to their level of detail and accuracy (IPCC 2003; IPCC 2006;

GOFC-GOLD 2014). In establishing RELs, the activity data and emission factors could be aggregate values reported for the national level relating total deforestation and average carbon stocks. For example, Brazil and Norway agreed to use average deforestation over the past 10 years, updated every 5 years as the REL for the Amazon Fund in Brazil (Angelsen et al. 2012). Similarly, other countries could use national statistics of forest area by year from the Food and Agriculture Organization (FAO) to establish their RELs (FAO 2010). RELs could also be spatial. For instance, deforestation could be tracked by classifying deforestation in images captured by remote sensing over time. Multiplying historical deforestation by a map of carbon stocks would yield historical emissions from deforestation (Harris et al. 2012). The same is true for future BAU activity data. Future deforestation could be made spatially explicit by building more sophisticated models (Huettner et al. 2009). Again, multiplying projected deforestation by maps of carbon stocks would generate future emissions. There is debate over whether to use spatially explicit or non-spatial deforestation for RELs at the national level. Some claim that spatially explicit models are sufficiently accurate at measuring historical deforestation for determining RELs (Olander et al. 2008). Others argue that spatially explicit models may not be accurate enough and call for simpler, coarse-scale baselines (Sloan and Pelletier 2012). Furthermore, countries may lack the forest monitoring capacities to acquire reliable historical activity data on deforestation to generate spatially explicit maps of deforestation or to use as input for models that predict future deforestation (Meridian Institute 2011; Romijn et al. 2012).

Unlike national RELs, project-level RELs are more often spatial. The Verified Carbon Standard, currently the most widespread standard in the voluntary forest carbon market, has four approved methodologies for establishing RELs for avoided unplanned deforestation projects (Angelsen et al. 2012). All four of the methodologies require modeling average deforestation in

the reference region over at least the previous ten years to project future deforestation (Shoch et al. 2011). Two of the four methodologies require spatial modeling of deforestation based on spatial drivers such as digital elevation models and road networks (Shoch et al. 2011). Emissions factors are matched to specific pixels on a map where spatial modeling is included in establishing the REL to calculate baseline emissions.

Even though their use in establishing RELs on a national level is less widely accepted, spatially explicit models of deforestation may offer complementary information for REDD+ planning. They show where forests are at high risk of deforestation, helping countries prioritize where to implement REDD+ activities. Combined with data on the distribution of carbon stocks, maps of deforestation reveal where forested areas with high carbon stocks are under high deforestation pressure. Countries may wish to intervene in these areas first to reduce the most emissions (Harris et al. 2008). Countries may additionally want to prioritize the implementation of REDD+ activities in areas where forests at high risk of deforestation coincide with other forest benefits (Miles and Kapos 2008). Maps of future deforestation go beyond showing where carbon and other forest benefits overlap by showing where these benefits are found in forests that may be lost, eligible for protection under REDD+ (UNEP-WCMC 2008; Venter et al. 2009; Strassburg et al. 2010; Ferraro et al. 2015). Countries may prefer to intervene in at-risk forests that protect biodiversity and minimize harm to local livelihoods. Spatially explicit models also identify immediate drivers of deforestation. Identifying drivers may allow countries to develop interventions to address them (Kissinger et al. 2012).

Spatially explicit models of deforestation that are probabilistic and quantify uncertainty around predictions offer further information for REDD+ planning (Rosa et al. 2013). Countries will likely prioritize areas according to the probability of deforestation and level of certainty.

Where the probability of deforestation is the same, they may prioritize areas with higher certainty. Where the level of certainty is the same, they may prioritize areas with a higher probability of deforestation. In some cases, countries may prioritize areas where the probability of deforestation is lower and the certainty is higher. For example, a risk-averse country may choose to prioritize an area with a moderate probability of deforestation and high certainty over an area with a high deforestation probability and low certainty. The quantification of uncertainty in predictions of forest loss also shows that there is financial value to reducing it similar to the value in reducing the uncertainty in estimates of carbon stocks (Pelletier et al. 2012). National estimates of the uncertainty in the area of predicted forest lost will assist countries in deciding whether it makes financial sense to collect more detailed data to reduce this uncertainty.

Here I build a national-scale, spatially explicit model of deforestation for Kenya to demonstrate how it may be used to facilitate REDD+ planning. Kenya is a UN-REDD partner country and a participant country in the World Bank's Forest Carbon Partnership Facility (FCPF) (UN-REDD Programme 2010). Kenya submitted a Readiness Preparation Proposal (R-PP) to the FCPF and funds were authorized to be disbursed to help it plan for REDD+ (KFS 2010; UN-REDD Programme 2012). Kenya's R-PP does not emphasize spatial modeling of future deforestation in its plans to establish its REL, although there may be benefits to developing such a model in pursuit of other REDD+ objectives (KFS 2010). Kenya may want to prioritize REDD+ activities in areas with a high risk of deforestation and high carbon stocks to optimize emissions reductions. A set of draft REDD+ safeguards adopted by the conference of parties to the UNFCCC at Cancun in 2010 require countries to consider its effects on local people and biodiversity. Kenya's R-PP states that it will design its REDD+ activities with a focus on enhancing local livelihoods and biodiversity (KFS 2010). As such, Kenya may prioritize REDD+

activities in forests under high pressure of deforestation that deliver benefits to livelihoods and biodiversity. Kenya has attempted to identify drivers to aid in selecting strategy options for addressing them in its R-PP and through an independent study (KFS 2010; Kenya Ministry of Forestry and Wildlife 2013). A spatially explicit model of deforestation will help Kenya continue to refine its understanding of drivers. I present an operational model for how deforestation can be mapped with a reasonable level of accuracy, drivers can be identified, and uncertainty can be reported. Other methods and tools for building spatial models of deforestation may be used to a similar effect (Pontius Jr et al. 2001; Verburg et al. 2002). I show that such models provide valuable information for REDD+ planning.

## METHODS

### *Data collection and preprocessing*

Data on observed deforestation were collected from 30 m resolution Landsat imagery. Hansen et al. (2013) report percent canopy closure for all vegetation greater than 5 m tall in 2000. The Kenya Forest Service defines forest as areas with greater than 15% canopy closure and vegetation above 2 m in height (KFS 2010). In line with the KFS forest definition, 2000 forest cover data were masked to > 15% canopy closure. Hansen et al. also offer data on deforestation from 2001-2012. They define deforestation as a change from at least 1% canopy cover to 0% canopy cover. Deforestation taking place within the masked region represents a loss of forest with greater than 15% canopy closure, i.e. a change from > 15% to 0% canopy cover. The deforestation data were then resampled to a 1 km resolution. The deforestation data were further processed by dividing them into two equal, six-year periods from 2001-2006 and 2007-12 (Fig. 1). The data were divided in this way to test how well deforestation in the first period predict deforestation in the second.

Direct drivers of deforestation in Kenya include agricultural expansion, timber harvesting, charcoal production, grazing, and poor governance (Kissinger et al. 2012). Data representing drivers are available from a variety of governmental and non-governmental sources such as the Kenya Bureau of National Statistics (KNBS), Survey of Kenya (SOK), World Resources Institute (WRI), International Livestock Research Institute (ILRI), and others. I made every effort to acquire the most recent data or at least data from near the 2001-12 time window of observed deforestation. I preferred national datasets over global products, e.g. national census data on population levels versus global estimates from satellite imagery of roads, settlements, and lights at night. I included census data on population and poverty at the sublocation level, the lowest administrative level. In many cases, I interpreted the intensity of drivers as the distance to

points, lines, or polygons such as cities, roads, or waterbodies (Fig. 2). I projected feature data into Universal Transverse Mercator coordinates and applied the Euclidean Distance tool in ArcGIS to find the distance from these features in meters. As an equatorial country, longitudinal and angular projection distortion is negligible in Kenya. Finally, all datasets were resampled to a 1 km resolution. I list the drivers, datasets representing drivers, years the datasets cover or their source date, the sources of the datasets, and their source resolutions in Table 1. I provide the source resolutions for raster data or vector data derived from raster data (e.g. location of active fires). I mark the resolution as “Not Applicable” (NA) for vector data that either were not derived from remote sensing (e.g. census data) or may have been derived from remote sensing at an unknown resolution (e.g. distance to rivers). The datasets in Table 1 are continuous except for those denoting protected status, which are categorical (1 = protected, 0 = no protection) (Fig. 2).

Correlation among the predictors, known as “multicollinearity,” may potentially bias the interpretation of model parameters and reduce model accuracy when making predictions beyond the data it was trained on (Dormann et al. 2013). Since I am interested in the association between drivers and deforestation, I sought to remove correlated predictors. I used the R package “usdm” to drop the predictor with the highest Variance Inflation Factor (VIF) from my data frame, recalculate the VIFs, and repeat this process until all VIFs were smaller than a pre-selected threshold (Naimi 2013). I used a stringent threshold of  $VIF > 2$ , recommended when there may be weak associations between predictor and response data (Zuur et al. 2010). After screening the data for collinearity, 16 sets of driver data with  $VIF < 2$  were used as model inputs (Table 2).

### *Model structure*

Data on deforestation consist of observations of whether a cell,  $i$ , was deforested or not from 2007-12. I also have data for each  $i$  on potential drivers of deforestation. My goal is to

relate binary deforestation data to continuous driver data. This is possible using a model that defines the probability of deforestation in cell  $i$ ,  $P_{defor_i}$ , as a function of drivers. One type of model, commonly used to predict the probability of the presence or absence of species, defines  $P_{defor_i}$  as a function of parameters describing Gaussian distributions. That is, the probability of deforestation follows a Gaussian distribution in response to individual drivers and is highest at the optimum level of a given driver. For example,  $P_{defor_i}$  may be highest a short distance away from cities and lower directly adjacent to cities and farther away from cities. The Gaussian distribution returns a value of one for  $P_{defor_i}$  when the driver is at its optimum ( $opt_{Cities}$ ), and otherwise returns a value less than one, depending on how the optimum driver levels compares to the standard deviation ( $\sigma_{Cities}$ ), which specifies the width of the distribution. The standard deviation tells us how sensitive the probability of deforestation is to small changes in the parameter value for the optimum driver level. The smaller the standard deviation, the more quickly the probability of deforestation drops moving away from the optimum value for deforestation. The Gaussian distribution describes a response variable,  $P_{defor_i}$  that must be positive and must return a value between 0 and 1 for driver variables in the range of +/- infinity. The expression below is for the Gaussian response of  $P_{defor_i}$  to a given driver:

$$e^{-\frac{(D-opt)^2}{2\sigma^2}}$$

where  $D$  is the driver value,  $opt$  is the value of the driver for which  $P_{defor_i}$  is highest, and  $\sigma$  is the standard deviation of the probability distribution of  $P_{defor_i}$  over the range of driver values. Together for multiple drivers, the final function for  $P_{defor_i}$  is below. See Table 1 for a full list of drivers initially considered in the model.  $P_{defor_{max}}$  is the maximum probability of deforestation under the optimal conditions for deforestation defined by the optimum values for deforestation for the set of drivers.

$P_{defor_i}(Driver1, Driver2, Driver3\dots) =$

$$P_{defor_{max}} e^{-\frac{(Driver1 - opt_{Driver1})^2}{2\sigma_{Driver1}^2}} e^{-\frac{(Driver2 - opt_{Driver2})^2}{2\sigma_{Driver2}^2}} e^{-\frac{(Driver3 - opt_{Driver3})^2}{2\sigma_{Driver3}^2}} \dots$$

*Bayesian inference*

Bayes' Rule states

$$P(\theta|X) = (P(X|\theta)P(\theta)) / P(X)$$

where  $\theta$  are the model parameters;  $X$  is the observed data;  $P(\theta|X)$ , the target of estimation, is the posterior probability of the parameters given the data;  $P(X|\theta)$  is the likelihood of the data given the parameters;  $P(\theta)$  is the prior probability of the parameters; and  $P(X)$  is the evidence. Markov Chain Monte Carlo (MCMC) sampling can be used to estimate the posterior without having to calculate the evidence since

$$P(\theta|X) \propto P(X|\theta)P(\theta)$$

To carry out parameter estimation, I must therefore define the likelihood function and the prior.

*Likelihood function*

The model is based around  $P_{defor}$ , the probability between 0 and 1 that a cell becomes deforested. The value of 1 represents a deforestation event and 0 represents a cell remaining forested. I assume the underlying distribution deforestation events are drawn from is a Bernoulli distribution, where the value of 1 has probability  $P$  and the value of 0 has probability  $(1 - P)$ . By using the Bernoulli distribution, each deforestation event is treated as independent of others.

I define the likelihood function for the Bernoulli distribution as the product of the probabilities of cells becoming deforested or remaining forested according to the model's parameters ( $\theta$ ) compared to the observed data ( $X$ ). The likelihood function may also be written as  $L(X|\theta)$  since the data remain constant and the parameters vary, although it is shown here as

$L(\theta|X)$  to emphasize that the likelihood is a function of varying parameters  $\theta$ . The probability of deforestation in cell  $i$  is  $Pdefor_i$  if deforestation was observed in that cell ( $obs_i = 1$ ) and  $(1 - Pdefor_i)$  if the cell remained forested ( $obs_i = 0$ ).

$$L(\theta|X) = \prod_{i=1}^n Pdefor_i^{obs_i} (1 - Pdefor_i)^{1-obs_i}$$

Products become sums when computing the log-likelihood.

$$L(\theta|X) = \sum_{i=1}^n obs_i \log(Pdefor_i) + (1 - obs_i) \log(1 - Pdefor_i)$$

### *Prior*

I used flat, uninformative priors for the  $opt$  and  $\sigma$  parameters for the distribution of  $Pdefor_i$  in response to each driver variable. The flat prior assigns a likelihood of 1 to the range of possible values of the parameter. All values outside of this range have a likelihood of 0. In other words, all parameter values that fall within the specified range are equally likely. The reason for using flat priors was that I had no strong prior knowledge about the influence of any of the drivers on the probability of deforestation. A potential advantage to using flat priors is that they eliminate any subjectivity in the fit of the model. A limitation is that they ignore pre-established information regarding the effects of the drivers on deforestation. Using flat priors reduces the estimation of the posterior to the likelihood function.

When  $P(\theta) = 1$ , the posterior is proportional to the likelihood.

$$P(\theta|X) \propto P(X|\theta)$$

The likelihood,  $P(X|\theta)$ , is also expressed as  $L(\theta|X)$ .

$$P(\theta|X) \propto L(\theta|X)$$

### *Parameter estimation*

To parameterize my model, I used “Filzbach,” a freely available C library that can be run from R (<http://research.microsoft.com/en-us/projects/filzbach/>). Filzbach uses the Metropolis Hastings algorithm for MCMC sampling of the posterior distribution. The posterior is the multi-dimensional joint probability distribution of all model parameters over their range of possible values defined by their priors. The algorithm sequentially draws parameter sets from their prior distributions and calculates their likelihood given the observed deforestation data with the likelihood function. According to the algorithm, a change in the model parameters is always accepted if the likelihood is higher and only accepted by chance if the likelihood is lower. In the long run, the number of times the algorithm accepts a set of parameter values is proportional to the probability of those parameter values in the model. For each parameter, Filzbach returns a posterior probability distribution based on the frequencies with which different values of the parameter appear in parameter sets accepted by the algorithm. From a posterior parameter distribution, I can extract a median and credible interval for that parameter.

### *Variable selection*

After the initial screening the driver variables for collinearity, I performed forward stepwise variable selection to identify which to include in the model. Upon parameterizing a model, Filzbach returns the model’s Akaike information criterion (AIC). The AIC is a relative measure of how closely the model predictions fit the observed data. Models with relatively lower AIC have a better fit. AIC penalizes the addition of predictors to the model, allowing for a fair comparison of models with differing numbers of predictors. I started by calculating the AIC of the null model with a single predictor having a constant value across all cells. The predictor in the null model adds no explanatory power because it does not vary with observed deforestation. I

then tested the fit of all models with a single predictor. I substituted each predictor into the model and calculated the model's AIC. The predictor in the model with the lowest AIC was kept and the process was repeated for the second predictor. I continued to add predictors in this manner until the addition of a predictor increased the AIC. At this point, the addition of predictors worsened the fit of the model. Once completed, I was left with a subset of predictors that best predict observed deforestation for use in the final model.

### *Making predictions*

Once the posterior distribution of the parameters has been estimated, the uncertainty in the parameters can be propagated to the predictions of deforestation. To propagate uncertainty, each set of parameters in the Markov chain was substituted into the model. The model was then used to generate predictions of deforestation in each cell in Kenya. Substituting all sets of parameters from the Markov chain into the model and generating predictions produces a series of predictions for each cell. The frequency with which models with given parameter sets from the Markov chain make a certain prediction is proportional to the probability of that prediction. The result of uncertainty propagation is a probability distribution for the probability of deforestation in each cell. Predictions were made for 2007-12 to assess the model's accuracy by comparing them to observed deforestation data from the same period which were not used to fit the model. Predictions were also made for 2013-18 by substituting data on the distance to previous deforestation from 2001-06 with data from 2007-12. Similar to the posterior parameter distributions, I can extract a median and confidence interval from the distributions of the predictions of the probability of deforestation. I plotted the median and size of the credible interval for the distribution of deforestation from 2013-18 in each cell according to its

geographic coordinates to create maps of the median probability of future deforestation and its associated uncertainty.

I also propagated uncertainty in the parameters to predictions of total deforestation from 2013-18 in Kenya, aggregating across cells. As before, I started by substituting each set of parameters in the Markov chain into the model and using the model to make predictions of the probability of deforestation on the cell level. The Markov chain had ~1,500 parameter sets. As explained in the section below on subsampling for variable selection and map generation, I subsampled ~3,000 cells from the ~83,500 cells with > 15% canopy cover in 2000. The resulting matrix of predictions for all parameter sets in the Markov chain had 3,000 rows equal to the number of cells and 1,500 columns equal to the number of parameter sets in the Markov chain. In the first row of the first column, I compared the predicted deforestation probability from the model to a random number drawn from a uniform distribution between zero and one. If the predicted probability was greater than this number, then the cell was considered deforested. If the probability was less, then the cell was left forested. I iterated this procedure over every row in the first column to get a column of 3,000 predictions showing whether cells were deforested or not. I then found the sum of the number of cells that were deforested. For the first column, I repeated the comparison between cell predictions and randomly drawn numbers 20 times, each time finding the sum of deforested cells. Next, I calculated the mean of the 20 sums of the number of deforested cells for the first column. I then moved on to the second column. I continued until I had applied the same process for calculating the mean number of deforested cells to all 1,500 columns in the matrix. I was left with a vector of 1,500 mean sums of deforestation. I divided the sums by the 83,500 forested cells in 2000 to find the proportion of deforestation. For each parameter set in the Markov chain, I now had a mean proportion of

deforestation. The frequency of the mean proportion of deforestation among all parameter sets is proportional to its probability. I plotted the probability distribution of the proportion of deforestation in Kenya and reported its mean and 95% credible interval.

### *Cross validation*

By adding enough predictors and adapting the model structure, any model can accurately predict the data it was trained on, but this comes at the cost of making inaccurate predictions for data the model has not been exposed to (“overfitting.”). To check the accuracy of the model against unknown data, I conduct five-fold cross-validation. In cross-validation, both the predictor and response data are broken up into “training” and “test” data. First, the model is calibrated with the training data. Then, the model is used to make predictions from the test data. Lastly, the predictions from the test data are compared to the actual values to determine how accurately the model predicts data that was not used to calibrate it. In five-fold cross validation, the data are split into five sections or folds. The model is trained on four sections and the accuracy of its predictions is tested on the fifth section. The model is calibrated and its accuracy is assessed five times, each time with a different set of four sections as training data and one section left out as test data.

Values of the response data for cells in a gridded landscape may more likely resemble values in adjacent cells than values in cells farther away (spatial autocorrelation). The term autocorrelation is used because the response data is correlated with itself. If ignored when splitting the data, it is possible that the model will appear to more accurately predict the test data in some sections more than others. Since the influence of response data on itself is not included in the model, predictions may be inaccurate in regions where spatial autocorrelation is high. To avoid the problem of spatial autocorrelation, I randomized the splits among the five sections in

the data. I did so by assigning each grid cell a random number between one and five (Fig. 3). The number of each grid cell indicates which fold it belongs to.

I compared values predicted by the model calibrated with the training data and actual values in the test data with a Receiver Operator Characteristic (ROC) curve. The y-axis of the ROC plot has the number of “hits” or true positives and the x-axis has the number of “misses” or false positives. True positives occur when the model predicts deforestation in a cell and deforestation did in fact occur there. False positives occur when the model predicts deforestation in a cell and it did not occur there. Since the model makes predictions in terms of probabilities, it does not directly predict whether or not deforestation occurs in a cell. The model expresses predictions as the percent chance of deforestation. If the probability is above a certain threshold, the model is said to predict that deforestation occurs in a cell. Each point on the ROC curve is the proportion of true positives to false positives for a given threshold value. A higher proportion of true positives to false positives over a range of thresholds indicates a more accurate model. The area under the ROC curve is a measure of the model’s accuracy. The area under the curve (AUC) ranges from zero to one. A model with  $AUC = 0.5$  generates predictions which are on average no better than random predictions. A model with  $AUC > 0.5$  generates predictions which are better than random. The accuracy of a model increases as the AUC approaches one, in which case model predictions always match the observed data. A model with  $AUC < 0.5$  generates predictions which are worse than random. In this case, the model provides misinformation and it would be better to make random predictions than rely on model predictions. I calculated the AUC of each of the five models in my five-fold cross validation. I report the mean AUC for the five models. ROC curves were plotted and AUC was calculated in the “ROCR” package in R (Sing et al. 2005).

*Subsampling for variable selection and map generation*

Since forward step-wise selection required parameterizing numerous models, I reduced the number of data points in my analysis to expedite MCMC sampling in Filzbach. I kept all points (~1,500) where deforestation was observed from 2007-12 and took a random subsample equal to this number of points (out of ~83,500) where deforestation was not observed over the same period. By subsampling the data, I reduced the number of points I parameterized my model against to ~3,000. To ensure that subsampling did not bias my results, I tested the sensitivity of the model fit to the number of data points the model was parameterized against. I found that the fit of the model parameterized against ~3,000 points (AUC = 0.79) did not vary much from the fit of the model parameterized against all ~85,000 points (AUC = 0.80) (Fig. 4). Finding that subsampling the data on deforestation and its drivers did not substantially affect model fit, I parameterized the final model against an equal number of points where deforestation was observed and where it was not (~3,000). Parameterizing the model against fewer points increased computational speed. I used the inverse distance weighted tool (inverse distance power of 2, 1 km cell size) in the SAGA toolset in QGIS 2.6 to interpolate the probability of deforestation among points. The tool generated continuous surfaces of median deforestation and the 95% credible interval.

## RESULTS

Out of the 22 datasets representing drivers initially considered for inclusion in the model, 16 remained after screening for collinearity ( $VIF > 2$ ) (Table 2). Datasets excluded were often redundant with those indicating similar aspects of drivers. Datasets discarded including distance to motorable roads, distance to permanent rivers, livestock density from 1994-1996, and population growth from 1989-2009 had close analogs that remained under consideration for inclusion in the model. Elevation and poverty density were also excluded, but they lacked direct analogs. Elevation was excluded because of its association with crop intensity and the opportunity cost of land. As elevation increases, crop intensity and opportunity cost decrease because land at higher elevations may be less suitable for agriculture. Poverty density was excluded because of its association with population density. More people are in poverty in the same places where more people are found in general.

Forward stepwise selection identified seven datasets that increased the explanatory power of the model (Table 3). Since Bayesian inference does not test for the significance of the association between deforestation and other datasets, the change in AIC was used instead. As each dataset was added to the model, the decrease in AIC was recorded to measure the dataset's respective explanatory power. A dataset's optimum (opt) divided by its standard deviation (std) indicates its effect size on deforestation. The ratio shows how sensitive the probability of deforestation is to changes in the dataset. A dataset with a low standard deviation relative to its optimum has a higher opt/std ratio and a narrower distribution. When the posterior parameter distributions for this dataset are propagated to the predictions, deforestation probability will decline rapidly with small changes away from the optimum in either the positive or negative direction. The size of the effect of changes in the dataset on deforestation will be large for datasets with a high opt/std ratio and narrow distribution. The sign of the opt/std ratio denotes the

direction of the effect. When the sign is negative, the probability of deforestation decreases as the driver value increases. When the sign is positive, the probability of deforestation increases as the driver value increases from zero up to the value of the optimum and then decreases again past this value. The last column of Table 3 describes the units of measurement for the datasets. For example, the opt/std ratio may show the relative magnitude of change in deforestation probability for a change in meters from the optimum distance for distance to previous deforestation. In contrast, the ratio shows the relative change in deforestation for a change in people/km<sup>2</sup> from the optimum density for population density. Since the opt/std ratio is measured in terms of different units, the effect size of parameters are not directly comparable. Following the previous example, the sensitivity of deforestation to small changes away from the optimum differs for datasets measured on a scale of meters versus people/km<sup>2</sup>.

The change in the AIC and opt/std ratio indicate the strength of the association between a dataset and deforestation as well as the effect size of a change in the dataset's value on deforestation. Datasets identified by forward stepwise selection which represent the driver of agricultural expansion are the most numerous, although they have relatively lower explanatory power. While fewer in number, datasets representing the drivers of accessibility and extraction are more strongly associated with deforestation. Whether a forest is protected or not appears to be unrelated to deforestation. Distance to previous deforestation has an explanatory power that's an order of magnitude higher than that of the other datasets (Table 3). Its effect size is also an order of magnitude greater than that of the other datasets measured in meters. Distance to previous deforestation is strongly associated with deforestation and the probability of deforestation decreases much more rapidly with distance from previous deforestation than it does from the other parameters. The explanatory power of distance to roads is higher than that of

distance to active fires and intermittent rivers, however its effect size is much smaller (Table 3). The explanatory power and effect size of distance to active fires and intermittent rivers are similar, although the effects are in opposite directions. Deforestation probability decreases less rapidly with distance from roads than with distance to fires. The probability of deforestation changes at the same rate with distance from active fires and intermittent rivers, but deforestation decreases with distance from fires and increases with distance from rivers. Population density has the second highest explanatory power and effect size, but its effect size can't be compared to that of other datasets because of differing units (Table 3). Population drives deforestation in a way that runs counter to expectations. Deforestation probability decreases with higher population densities, i.e. deforestation probability is higher in low population density regions rather than high density regions. Slope and opportunity cost have the lowest explanatory power (Table 3). For the same reason as distance to deforestation, their effect sizes can't be compared to those of other datasets. Deforestation probability decreases with steeper slopes and increases with the opportunity cost of land.

The model generated a map of predictions of deforestation from 2013-2018 and a map of the associated 95% interval of uncertainty (Fig. 5). At the national level, hotspots of deforestation ( $\geq 75\%$ ) are in the Rift Valley south of Kisumu and north of Eldoret as well as in the central and southern coast near Mombasa. These areas have relatively low uncertainty (5-10%) south of Kisumu and higher uncertainty (10-15%) north of Eldoret and on the central and southern coast. Additional areas of high uncertainty ( $\geq 15\%$ ) include the border west of Kisumu and Eldoret as well as areas in the Rift Valley south of Kisumu, although these areas have a relatively low probability of deforestation ( $\leq 50\%$ ) excluding the border northwest of Eldoret. The map of the median predictions of deforestation probability for Kenya's water towers shows

that probability is highest ( $\geq 75\%$ ) in the Mau Complex and Cherangani Hills (Fig. 6). The greatest uncertainty ( $\geq 15\%$ ) is in Mt. Elgon, throughout the Cherangani Hills, and southwest of the Mau Complex (Fig. 7). The probability distribution of the total proportion of deforestation in 2013-18 across Kenya has a mean of 1.68% and 95% credible interval of (1.62%, 1.73%) (Fig. 8).

Five-fold cross validation indicates that the model is good at discriminating areas of deforestation from areas of no change (average AUC = 0.8) (Fig. 9). A perfect model that always correctly discriminates deforestation from no change has AUC = 1.0 and a model with no discriminative value has AUC = 0.5. The acceptability of an AUC score depends on the cost of false positives or Type I errors in a particular context. When the cost of false positives is very high, AUC scores must be higher in order to be deemed acceptable. In the case of cancer diagnostics, where a false diagnosis may lead to adverse health effects from treatment, good AUC scores are considered to be between 0.8-0.9 (El Khouli et al. 2009). Given that the threshold for a good AUC score is likely to be higher for predicting cancer than deforestation since the costs of a false positive are greater, AUC = 0.8 should be interpreted as an excellent score in the context of predicting deforestation.

## DISCUSSION

### *Prioritizing areas*

Information from the model may be used for prioritizing where to focus REDD+ efforts. The map of the probability of deforestation shows which areas are under the greatest threat (Fig. 5). The associated uncertainty map shows where these predictions are most certain (Fig. 5). Maps of the deforestation probability and associated uncertainty for the water towers show which areas to prioritize in greater detail (Figs. 6 & 7). Areas with a high probability of deforestation and low uncertainty are the highest priority, namely the forests in the Mau Complex. Areas with a high probability and high uncertainty such as the Cherangani Hills and east side of Mt. Elgon are less of a priority because the probability of deforestation may be higher or lower than the median values predicted. Lower priority areas including the forests in the western Mau Complex have a low probability of deforestation and high uncertainty. These areas may still be relevant to REDD+ since deforestation could be higher than the median predictions on account of greater uncertainty. Areas with the lowest priority such as the east side of Mt. Kenya have a low probability of deforestation and low uncertainty. The distribution of deforestation threat may serve as the initial layer of a spatial analysis of which areas to prioritize. The threat of deforestation establishes which forests are eligible for REDD+ because of the potential for avoided carbon emissions. Economic data may be incorporated to assess where the protection of eligible forests is economically viable. Multiplying the spatial distribution of carbon stocks by a price for carbon emissions reductions yields potential REDD+ revenues. Subtracting the opportunity cost of land, the highest cost of REDD+, as well as transaction and implementation costs from potential carbon revenues would show which areas are profitable for REDD+ (Naidoo and Iwamura 2007; World Bank 2011). Among the sites that are both eligible and profitable for REDD+, countries may prioritize areas that house biodiversity and provide

benefits to livelihoods. Incorporating the distribution of eligible and profitable forests in analyses of the congruence between carbon, biodiversity, and livelihoods may alter priority regions for REDD+ (Venter et al. 2009; Strassburg et al. 2010; Siikamaki and Newbold 2012; Ferraro et al. 2015).

### *Identifying drivers*

As well as prioritizing areas for REDD+, the model may be used to determine which drivers are associated with deforestation, the strength of these associations, whether the effect of drivers on deforestation is positive or negative, and, in cases where the units of drivers are the same, the relative effect size of drivers on deforestation. Two drivers related to accessibility, one related to extraction, and four related to agriculture emerge as drivers associated with deforestation in the model (Table 3).

Drivers in the model related to accessibility include distance to previous deforestation and distance to major roads. Distance to previous deforestation from 2001-06 had an association with deforestation from 2007-12 that was an order of magnitude greater than that of the other drivers (Table 3). The negative effect of distance to previous deforestation means that deforestation increases in areas closer to areas that were previously deforested. The effect size of distance to previous deforestation is more than five times greater than those of the other drivers measured in meters. The result that deforestation is greater nearer to previously deforested sites is unsurprising given evidence from Latin America that deforestation is contagious (Robalino and Pfaff 2012; Rosa et al. 2013). Distance to previous deforestation does not provide clear evidence on what is behind deforestation, although it may indicate that greater accessibility resulting from forest clearing facilitates further deforestation. Distance to major roads is the predictor with the third strongest association with deforestation (Table 3). The negative effect of

distance to major roads means that deforestation increases in areas closer to roads. The effect size of distance to major roads is the lowest out of the effect sizes of the four drivers measured in meters, and is less than a tenth of that of the driver with the next largest effect size. Like previous deforestation, roads may exacerbate other drivers such as extraction and agricultural expansion by opening up access to forests (Ahmed et al. 2013; Ahmed et al. 2014).

The driver in the model related to extraction is 2009 population density. Population density in 2009 is the predictor with the second strongest association with deforestation in the model (Table 3). The negative effect of population density means that deforestation is higher where there are fewer people per unit area, predominantly in rural regions. This finding is inconsistent with trends identified by DeFries et al. (2010) who suggest that, globally, rural people no longer appear to be driving deforestation through extraction and agricultural expansion. Rather, urban and international demand for agricultural products is driving deforestation (DeFries et al. 2010). Yet, in Africa the association between forest loss and urban growth is weak, and its association with agricultural trade is insignificant (DeFries et al. 2010). Expansion of smallholder agriculture and extraction of primary forest products such as fuel, timber, and charcoal for domestic use by rural people continue to be the main drivers of African deforestation (Burgess et al. 2002; Fisher 2010).

The drivers in the model related to agriculture are distance to active fires, distance to intermittent rivers, slope, and opportunity cost. Drivers related to agriculture have a weaker association with deforestation than drivers related to accessibility or extraction (Table 3). The negative effects of distance to active fires and slope mean that deforestation increases in areas closer to fires and areas with shallower slopes. The positive effects of distance to intermittent rivers and opportunity cost mean that deforestation increases in areas farther away from rivers

and areas with a higher opportunity cost. The effect sizes of distance to active fires and intermittent rivers are roughly equal and are less than a fifth of that of distance to previous deforestation, but more than ten times that of distance to major roads. Increased deforestation closer to fires may signify land clearing for agriculture. Deforestation may increase in areas with shallower slopes and a higher opportunity cost for agriculture because they are more suitable for agriculture. Distance to intermittent rivers may also indicate agricultural suitability. Crops may be easier to grow nearer to intermittent rivers because they provide water for irrigation.

Interestingly, I observed that deforestation increases with distance from intermittent rivers rather than decreases as expected. Evidence from the model that distance to active fires, slope, and opportunity cost are related to deforestation in a way that suggests clearing for agriculture agrees with findings that African deforestation is in part the result of agricultural expansion by rural smallholders (Fisher 2010). In Africa, increases in staple crop production are correlated with deforestation, but not with yield increases, indicating that countries achieve higher production as smallholders clear more land (Fisher 2010). The four drivers related to agriculture in the model for Kenya were also associated with deforestation in neighboring Tanzania, although two of these drivers, slope and the opportunity cost of land, had relatively weaker associations than in Kenya (Green et al. 2013). Unlike in this model for Kenya, deforestation in Tanzania was higher closer to rivers. This discrepancy could arise from the fact that the Kenya model only considered the subclass of rivers that were intermittent and not all rivers as in the Tanzania model. Intermittent rivers may not provide dependable water year-round to areas around them, making these areas less suitable for agriculture and in turn less likely to be deforested.

Notably, I did not find that the probability of deforestation was lower in protected areas. Global analyses reveal that protected areas are effective at limiting habitat loss (Scharlemann et

al. 2010; Geldmann et al. 2013). However, there is conflicting evidence on the effectiveness of protected areas in Africa. Eighteen studies of protected areas in individual African countries and throughout Africa show that on average deforestation is 4.7 times lower in protected areas than outside (Geldmann et al. 2013). One of these studies, the only to cover the full extent of tropical forests in Africa showing deforestation both in and outside of protected areas, found that deforestation is 1.34 times higher in protected areas than outside (Scharlemann et al. 2010). Specifically in Kenya, forest cover change both increases and decreases in national parks and forest reserves, although forest cover change in protected areas was not compared to forest change outside of them in this study (Pfeifer et al. 2012).

Identification of proximate drivers of deforestation on a national level could influence the way countries develop and implement REDD+. Countries have multiple strategy options for addressing deforestation. A comprehensive review of REDD+ R-PPs reveals the range of options countries are considering (Kissinger et al. 2012). Countries submit R-PPs to the FCPF as a part of their readiness activities. Within them, they list drivers of deforestation based on an initial assessment and potential options for addressing these drivers. For example, Kenya's R-PP identifies agricultural expansion by smallholders, extraction of primary forest products including timber and charcoal, grazing, and poor governance/institutional failures in the forest sector as direct drivers of deforestation (KFS 2010). The R-PP also lists options to address these drivers such as intensifying agriculture to reduce expansion, promoting agroforestry, afforestation, and reforestation to offset demand for timber and charcoal, improving livestock management to limit the effects of grazing, and strengthening government capacity to improve governance (KFS 2010). Updated information on proximate drivers can help to inform countries which REDD+ interventions to employ to curb deforestation. The drivers identified by the model generally

match the drivers identified in the R-PP, supporting the strategy options recommended to address them. The model shows an association between agricultural expansion and forest loss indicated by active fires, slope, and the opportunity cost of land (Table 3). They also show an association between extraction and forest loss indicated by population density (Table 3). Greater accessibility indicated by distance to previous deforestation and major roads compounds forest loss from agricultural expansion and extraction (Table 3). The lack of association between the protected status of forests and deforestation may point to poor PA governance. The model does not, however, find an association between livestock density and deforestation, suggesting that grazing may not be a strong driver of forest loss. Improving livestock management may not reduce deforestation. Among the drivers associated with deforestation in the model, countries may additionally want to prioritize strategy options that address those with a stronger association (i.e. greater  $\Delta AIC$ ). The model shows that Kenya, for instance, may want to allocate more resources toward policy options that address extraction over agriculture because an indicator of the former has a stronger association with deforestation (Table 3). While the model is able to test the association of direct drivers with deforestation through various indicators, indirect drivers are harder to capture. As such, the model is unable to provide information on which strategy options to choose to address them. Addressing underlying factors such as market forces and government incentives is also crucial to reducing deforestation (Kanninen et al. 2007). Focus on proximate drives should not be to their exclusion.

### *Quantifying uncertainty*

Alongside the map of predicted deforestation, the associated map of uncertainty shows the level of confidence in the model's predictions. As seen in the section on prioritizing areas, quantifying and mapping uncertainty in this way is useful for selecting areas where REDD+

interventions will avoid more deforestation. Quantifying uncertainty in the prediction for aggregate deforestation in Kenya is also useful for assessing the uncertainty in the national reference emission levels for carbon emissions. For example, in Kenya, the difference between the mean and lower and upper bounds of the 95% interval of the predictions for total deforestation is  $\pm 0.06\%$  of forested area (Fig. 8). The total amount of above-ground carbon in Kenya is 546 million tonnes (Baccini et al. 2012). If I assume that the majority of this aboveground carbon is contained in forests with canopy cover greater than 15%, then the amount of uncertainty in the deforestation model equates to  $\pm 3.28 \times 10^5$  tonnes C. As a climate change mitigation mechanism, REDD+ measures avoided deforestation in terms of the CO<sub>2</sub> equivalent (CO<sub>2</sub>e) of avoided emissions. Tonnes C can be converted into tonnes CO<sub>2</sub>e by a conversion factor of 3.67 (IPCC 2001). The resulting uncertainty in the model is  $\pm 1.20$  million tonnes CO<sub>2</sub>e. Another source of uncertainty in the REL is the emission factors. Uncertainty in maps of global carbon stocks contributes to the uncertainty in the emission factors (Mitchard et al. 2013). National and global studies point to the financial value of reducing the uncertainty in carbon stock estimates (Smith et al. in review; Pelletier et al. 2012). Reducing the uncertainty of emission factors may increase the REL, resulting in a greater potential for financial gain from lowering emissions. Likewise, reducing the uncertainty in the deforestation predictions that in part make up the activities, the other component of reference emissions, may also increase the REL and potential financial gain from REDD+. The lower bound of the 95% interval of total deforestation in Kenya represents a conservative estimate of the activity data that may be favored in setting the country's REL. As uncertainty decreases, the 95% interval will shrink such that the lower (and upper) bound will approach the mean. In other words, the conservative estimate of avoided carbon emissions may increase by 1.20 million tonnes CO<sub>2</sub>e. Given that the current spot

price of tradeable European Union Emission Allowances (EUAs) is US\$ 8.60 / tCO<sub>2e</sub>, the potential value of reducing uncertainty in the deforestation model could be as much as US\$ 10.3 million (European Energy Exchange 2015). According to the model, the mean of the expected amount of total deforestation in Kenya is 1.68% (Fig. 8). As with quantifying the value of uncertainty reduction, multiplying the percent of deforestation by tonnes of carbon in Kenya, the CO<sub>2e</sub> conversion factor, and the spot price of carbon quantifies the value of total deforestation. Kenya could be eligible to receive US\$ 290 million through REDD+ for avoided emissions. The potential revenue of uncertainty reduction in the model therefore represents 3.6% of the total revenue Kenya could receive from REDD+.

One strategy for reducing uncertainty in the deforestation predictions is to collect more high quality data on deforestation and its drivers. The uncertainty reported in the predictions derives from the uncertainty in the model parameters. Model parameters describe how various drivers such as distance to deforestation or population influence deforestation. My statistical model was used to infer these parameters from observed data and prior knowledge. Uncertainty in the parameters was then propagated to the predictions. Re-parameterizing the model against more data will likely decrease the uncertainty in the parameters and in turn the predictions. In a spatial context, increasing the quantity of data could simply mean resampling data to a finer spatial grain. This resampling, however, may introduce measurement uncertainty (i.e. error), which reflects the variability in the data for the same measurement. Working at a finer spatial grain may increase the probability that a measured value does not represent its true value. For instance, data on population were originally collected at the sublocation level (an administrative unit equivalent to a county). This data was resampled to a 1 km spatial grain. Resampling it further to 30 m to match the original grain size of the deforestation data may increase uncertainty

because cells with the same population measure may have true values that greatly vary from this measure. Therefore if data are resampled to a finer spatial grain to acquire more data, these data must be of sufficient quality. Otherwise increased measurement error will counteract the reduction in parameter uncertainty from using more data. Collecting more detailed data at finer spatial grain will increase data quality and avoid measurement error. An alternative option to collecting more high quality data would be to consolidate or publish existing data that may be spread across several sources or stored locally. Numerous datasets on drivers for Kenya published online in a single source expedited the modeling process and improved model results (WRI et al. 2007). Countries may find that facilitating access to existing data may achieve uncertainty reduction at a lower price than costly programs to collect new data.

#### *Replicating process*

The modeling process outlined in this study shows how a simple, spatially explicit model of deforestation at the national level can be constructed with reasonable accuracy from available data (Fig. 9). One focus of developing national, spatially explicit models of deforestation has been to establish reference emission levels (Brown et al. 2007). The interpretation of model results for Kenya demonstrates that there are other applications for them, namely prioritizing regions for REDD+ intervention and identifying the proximate drivers of deforestation. Other land use change models such as GEOMOD2 and CLUE-S capable of mapping deforestation at a national scale can provide the same information as the model in this study for REDD+ planning (Pontius Jr et al. 2001; Verburg et al. 2002). The particular model presented here propagates uncertainty in the parameters to the predictions to quantify the level of uncertainty in the activity component of the REL. Employing similar models can show countries the financial value of reducing uncertainty through collecting more high quality data. Input data for deforestation

models may be easier to find for some countries than others. Of the drivers found to be associated with deforestation in Kenya, distance to previous deforestation, distance to active fires, and opportunity costs came from global datasets (Table 3). The rest were from country-specific datasets. National datasets were only used because of their suspected higher quality than global data. It is possible to find global equivalents for the national data included in the model. When modeling deforestation, both the process and input data should be made transparent to allow others to replicate results or rerun the model with higher quality data to reduce uncertainty (Rosa et al. 2014). By providing a template for the design and application of a national, spatially-explicit deforestation model for Kenya, I demonstrate how similar models may be developed to help other countries quantitatively map and measure deforestation and its drivers and move beyond qualitative assessments to improve REDD+ planning.

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## REFERENCES

- Ahmed SE, Ewers RM, Smith MJ (2014) Large scale spatio-temporal patterns of road development in the Amazon rainforest. *Environ Conserv* 41:253–264.
- Ahmed SE, Souza Jr. CM, Riberio J, Ewers RM (2013) Temporal patterns of road network development in the Brazilian Amazon. *Reg Environ Chang* 13:927–937. doi: 10.1007/s10113-012-0397-z
- Angelsen A (ed) (2008) *Moving ahead with REDD: Issues, options and implications*. CIFOR, Bogor, Indonesia
- Angelsen A, Brockhaus M, Sunderlin WD, Verchot LV (eds) (2012) *Analysing REDD+: Challenges and choices*. CIFOR, Bogor, Indonesia
- Baccini A, Goetz SJ, Walker WS, et al (2012) Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nat. Clim. Chang.* 2:182–185.
- Brown S, Hall M, Andrasko K, et al (2007) Baselines for land-use change in the tropics: Application to avoided deforestation projects. *Mitig Adapt Strateg Glob Chang* 12:1001–1026. doi: 10.1007/s11027-006-9062-5
- Burgess N, Doggart N, Lovett JC (2002) The Uluguru Mountains of eastern Tanzania: the effect of forest loss on biodiversity. *Oryx* 36:
- DeFries RS, Rudel T, Uriarte M, Hansen M (2010) Deforestation driven by urban population growth and agricultural trade in the twenty-first century.
- Dormann CF, Elith J, Bacher S, et al (2013) Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. *Ecography (Cop)* 36:27–46. doi: 10.1111/j.1600-0587.2012.07348.x
- El Khouli RH, Macura KJ, Barker PB, et al (2009) Relationship of temporal resolution to diagnostic performance for dynamic contrast enhanced MRI of the breast. *J Magn Reson Imaging* 30:999–1004. doi: 10.1002/jmri.21947
- European Energy Exchange (2015) EU Emission Allowances. Primary Market Auction. <https://www.eex.com/en/market-data/emission-allowances/auction-market/european-emission-allowances-auction#!/2015/07/21>. Accessed 21 Jul 2015
- FAO (2010) *Global forest resources assessment 2010*. Food and Agriculture Organization of the United Nations, Rome
- Ferraro PJ, Hanauer MM, Miteva DA, et al (2015) Estimating the impacts of conservation on ecosystem services and poverty by integrating modeling and evaluation. *Proc Natl Acad Sci* 112 :7420–7425. doi: 10.1073/pnas.1406487112

- Fisher B (2010) African exception to drivers of deforestation. *Nat. Geosci.* 3:375–376.
- Geldmann J, Barnes M, Coad L, et al (2013) Effectiveness of terrestrial protected areas in reducing habitat loss and population declines. *Biol. Conserv.* 161:230–238.
- GOFC-GOLD (2014) A sourcebook of methods and procedures for monitoring and reporting anthropogenic greenhouse gas emissions and removals associated with deforestation, gains and losses of carbon stocks in forests remaining forests, and forestation. GOFC-GOLD Report versio. GOFC-GOLD Land Cover Project Office, Wageningen University, The Netherlands
- Green JMH, Larrosa C, Burgess ND, et al (2013) Deforestation in an African biodiversity hotspot: Extent, variation and the effectiveness of protected areas. *Biol Conserv* 164:62–72. doi: 10.1016/j.biocon.2013.04.016
- Gutman P, Aguilar-Amuchastegui N (2012) Reference levels and payments for REDD+: lessons from the recent Guyana-Norway agreement. World Wildlife Fund USA. [http://assets.panda.org/downloads/rls\\_and\\_payments\\_for\\_redd\\_lessons.pdf](http://assets.panda.org/downloads/rls_and_payments_for_redd_lessons.pdf) .
- Harris NL, Brown S, Hagen SC, et al (2012) Baseline Map of Carbon Emissions from Deforestation in Tropical Regions. *Science* (80-. ). 336:1573–1576.
- Harris NL, Petrova S, Stolle F, Brown S (2008) Identifying optimal areas for REDD intervention: East Kalimantan, Indonesia as a case study. *Environ. Res. Lett.* 3:035006.
- Huettner M, Leemans R, Kok K, Ebeling J (2009) A comparison of baseline methodologies for “Reducing Emissions from Deforestation and Degradation.” *Carbon Balance Manag* 4:4. doi: 10.1186/1750-0680-4-4
- IPCC (2003) Good practice guidance for land use, land-use change and forestry. Institute for Global Environmental Strategies, Hayama, Japan
- IPCC (2006) IPCC guidelines for national greenhouse gas inventories. Institute for Global Environmental Strategies, Hayama, Japan
- IPCC (2001) Working Group III: Mitigation. Appendix IV Units, Conversion Factors, and GDP Deflators. <http://www.ipcc.ch/ipccreports/tar/wg3/index.php?idp=477>.
- Kanninen M, Murdiyarso D, Seymour F, et al (2007) Do trees grow on money?: the implications of deforestation research for policies to promote REDD.
- Kenya Ministry of Forestry and Wildlife (2013) Analysis of drivers and underlying causes of forest cover change in the various forest types of Kenya. [http://www.kenyaforestservice.org/documents/redd/Analysis\\_of\\_Drivers\\_of\\_Deforestation\\_&forest\\_Degradation\\_in\\_Kenya.pdf](http://www.kenyaforestservice.org/documents/redd/Analysis_of_Drivers_of_Deforestation_&forest_Degradation_in_Kenya.pdf).

- KFS (2010) Kenya Forest Service. Revised REDD Readiness Preparation Proposal. Kenya. Submitted to the Forest Carbon Partnership Facility. [http://www.forestcarbonpartnership.org/sites/forestcarbonpartnership.org/files/Documents/PDF/Jun2010/KENYA\\_REDD-RPP-JUNE\\_12th\\_2010.pdf](http://www.forestcarbonpartnership.org/sites/forestcarbonpartnership.org/files/Documents/PDF/Jun2010/KENYA_REDD-RPP-JUNE_12th_2010.pdf).
- Kissinger G, Herold M, Sy V De, et al (2012) Drivers of deforestation and forest degradation: A synthesis report for REDD+ Policymakers.
- Meridian Institute (2011) Modalities for REDD+ reference levels: technical and procedural issues. Prepared for the Government of Norway by Arild Angelsen, Doug Boucher, Sandra Brown, Valérie Merckx, Charlotte Streck, and Daniel Zarin. [www.REDD-OAR.org](http://www.REDD-OAR.org).
- Miles L, Kapos V (2008) Reducing Greenhouse Gas Emissions from Deforestation and Forest Degradation: Global Land-Use Implications. *Science* (80- ) 320:1454–1455. doi: 10.1126/science.1155358
- Mitchard ET, Saatchi SS, Baccini A, et al (2013) Uncertainty in the spatial distribution of tropical forest biomass: a comparison of pan-tropical maps. *Carbon Balance Manag* 8:10. doi: 10.1186/1750-0680-8-10
- Naidoo R, Iwamura T (2007) Global-scale mapping of economic benefits from agricultural lands: Implications for conservation priorities. *Biol Conserv* 140:40–49. doi: 10.1016/j.biocon.2007.07.025
- Naimi B (2013) usdm: Uncertainty analysis for species distribution models. R package version 1.1-12. <http://cran.r-project.org/package=usdm>.
- Olander LP, Gibbs HK, Steininger M, et al (2008) Reference scenarios for deforestation and forest degradation in support of REDD: a review of data and methods. *Environ. Res. Lett.* 3:025011.
- Pelletier J, Kirby KR, Potvin C (2012) Significance of carbon stock uncertainties on emission reductions from deforestation and forest degradation in developing countries. *For Policy Econ* 24:3–11. doi: 10.1016/j.forpol.2010.05.005
- Pfeifer M, Burgess ND, Swetnam RD, et al (2012) Protected areas: Mixed success in conserving East Africa's evergreen forests. *PLoS One*. doi: 10.1371/journal.pone.0039337
- Pontius Jr RG, Cornell JD, Hall CAS (2001) Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agric Ecosyst Environ* 85:191–203. doi: doi:10.1016/S0167-8809(01)00183-9
- Robalino JA, Pfaff A (2012) Contagious development: Neighbor interactions in deforestation. *J Dev Econ* 97:427–436. doi: 10.1016/j.jdeveco.2011.06.003

- Romijn E, Herold M, Kooistra L, et al (2012) Assessing capacities of non-Annex I countries for national forest monitoring in the context of REDD+. *Environ Sci Policy* 19-20:33–48. doi: 10.1016/j.envsci.2012.01.005
- Rosa IMD, Ahmed SE, Ewers RM (2014) The transparency, reliability and utility of tropical rainforest land-use and land-cover change models. *Glob. Chang. Biol.* 20:1707–1722.
- Rosa IMD, Purves D, Souza C, Ewers RM (2013) Predictive Modelling of Contagious Deforestation in the Brazilian Amazon. *PLoS One*. doi: 10.1371/journal.pone.0077231
- Scharlemann JPW, Kapos V, Campbell A, et al (2010) Securing tropical forest carbon: the contribution of protected areas to REDD. *Oryx* 44:352–357.
- Shoch D, Eaton J, Settelmyer S (2011) Project developer’s guidebook to VCS REDD methodologies. Version 1.0/November 2011. Conservation International.
- Siikamaki J, Newbold SC (2012) Potential Biodiversity Benefits from International Programs to Reduce Carbon Emissions from Deforestation. *Ambio* 41:78–89. doi: 10.1007/s13280-011-0243-4
- Sing T, Sander O, Beerenwinkel N, Lengauer T (2005) ROCr: visualizing classifier performance in R. *Bioinformatics*, 21(20), pp. 7881. <http://rocr.bioinf.mpi-sb.mpg.de>.
- Sloan S, Pelletier J (2012) How accurately may we project tropical forest-cover change? A validation of a forward-looking baseline for REDD. *Glob Environ Chang* 22:440–453. doi: 10.1016/j.gloenvcha.2012.02.001
- Smith et al. in review The economic value of uncertainty in terrestrial carbon.
- Strassburg BBN, Kelly A, Balmford A, et al (2010) Global congruence of carbon storage and biodiversity in terrestrial ecosystems. *Conserv. Lett.* 3:98–105.
- UNEP-WCMC (2008) Carbon and biodiversity: a demonstration atlas. UNEP-WCMC, Cambridge, UK
- UNFCCC (2010) Outcome of the work of the Ad Hoc Working Group on long-term Cooperative Action under the Convention. [http://unfccc.int/files/meetings/cop\\_16/application/pdf/cop16\\_lca.pdf](http://unfccc.int/files/meetings/cop_16/application/pdf/cop16_lca.pdf).
- UNFCCC (2011) Draft decision on guidance on systems for providing information on how safeguards are addressed and respected and modalities relating to forest reference emission levels and forest reference levels as referred to in decision 1/CP.16, appendix I. Draft dec. [https://unfccc.int/files/meetings/durban\\_nov\\_2011/decisions/application/pdf/cop17\\_safeguards.pdf](https://unfccc.int/files/meetings/durban_nov_2011/decisions/application/pdf/cop17_safeguards.pdf).

UN-REDD Programme (2010) Eight New Countries Join the UN-REDD Programme.  
[http://www.un-redd.org/Newsletter6\\_Eight\\_New\\_Observer\\_Countries/tabid/3277/language/en-US/Default.aspx](http://www.un-redd.org/Newsletter6_Eight_New_Observer_Countries/tabid/3277/language/en-US/Default.aspx).

UN-REDD Programme (2012) Kenya Advances its REDD+ Readiness Roadmap.  
[http://www.un-redd.org/Newsletter31/Kenya\\_Readiness\\_Roadmap/tabid/102679/Default.aspx](http://www.un-redd.org/Newsletter31/Kenya_Readiness_Roadmap/tabid/102679/Default.aspx).

Venter O, Laurance WF, Iwamura T, et al (2009) Harnessing carbon payments to protect biodiversity. *Science* 326:1368. doi: 10.1126/science.1180289

Verburg PH, Soepboer W, Veldkamp A, et al (2002) Modeling the spatial dynamics of regional land use: The CLUE-S model. *Environ Manage* 30:391–405. doi: 10.1007/s00267-002-2630-x

World Bank (2011) Estimating the opportunity costs of REDD+ A training manual. *Finance* 262. doi: 10.1016/j.jenvman.2003.12.013

WRI, Department of Resource Surveys and Remote Sensing Kenya, Ministry of Environment and Natural Resources Kenya, et al (2007) Nature's Benefits in Kenya, An Atlas of Ecosystems and Human Well-Being.

Zuur AF, Ieno EN, Elphick CS (2010) A protocol for data exploration to avoid common statistical problems. *Methods Ecol Evol* 1:3–14. doi: 10.1111/j.2041-210X.2009.00001.x

## FIGURES

Fig. 1. Forest cover above 5 m in height with greater than 15% canopy cover appears in green. Deforestation (the reduction of canopy cover from > 15% to ~0%) from 2001-06 appears in orange and from 2007-12 appears in red. Forest cover and deforestation data are from Hansen et al. (2013).

Fig. 2. Examples of preprocessed driver layers. The top and middle panels show the distance from major cities and roads, respectively, with cooler colors representing farther distances. The bottom panel shows protected areas in green and unprotected areas in beige.

Fig. 3. Depiction of the spatial randomization of five folds used in cross validation.

Fig. 4. Area under the curve (AUC) for random subsamples of 3K, 9K, 16K, 31K, and 60K points out of 85K points.

Fig. 5. Median predictions of the probability of deforestation and 95% uncertainty interval of the predictions. The model predicts a probability distribution for the percent chance of deforestation for each grid cell. The median is the most likely prediction or highest point in the distribution. The model predicts a probability distribution for the percent chance of deforestation for each grid cell. The interval represents a range of predictions that are less likely than the median, but more likely than the extreme predictions that account for 5% of the total probability.

Fig. 6. Median predictions of the probability of deforestation in Kenya's five, main high-elevation forested watersheds ("water towers"). The hatching represents >65% canopy cover

according to a 2010 forest cover map by KFS. The black cells represent deforestation from 2007-2012 from Hansen et al. (2012).

Fig. 7. 95% uncertainty interval of predictions of the probability of deforestation in Kenya's water towers. The hatching represents >65% canopy cover according to a 2010 forest cover map by KFS.

Fig. 8. Probability distribution of the proportion of total deforestation in Kenya. Deforestation estimates for individual cells in Fig. 5 were aggregated to determine the proportion of cells deforested across the whole of Kenya. Mean = 1.68%. Lower and upper bound of 95% interval = (1.62%, 1.73%). Potential uncertainty reduction (i.e. difference between median and lower bound of 95% uncertainty interval) = 0.06%.

Fig. 9. Average ROC curve and AUC for five-fold cross validation.

Fig. 1.

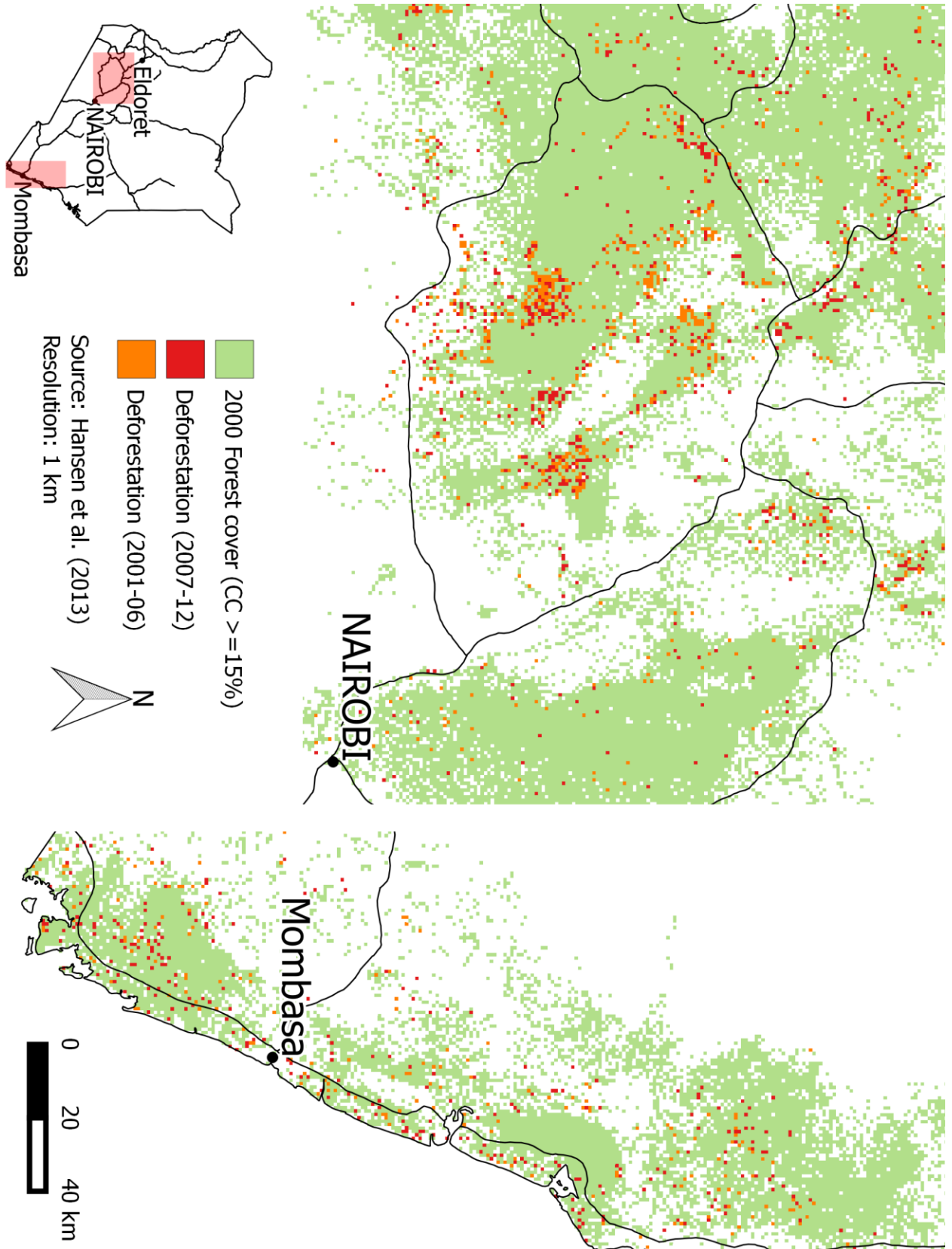


Fig. 2.

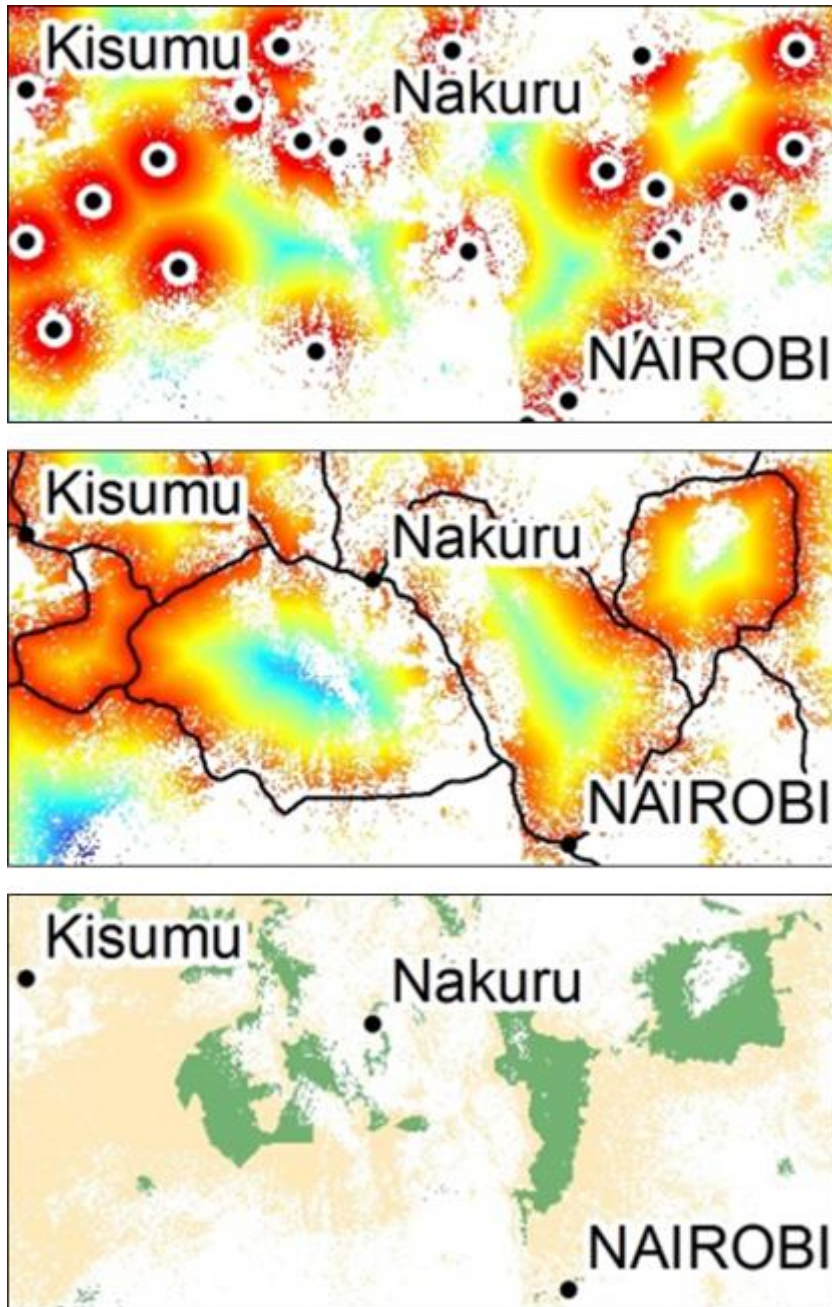
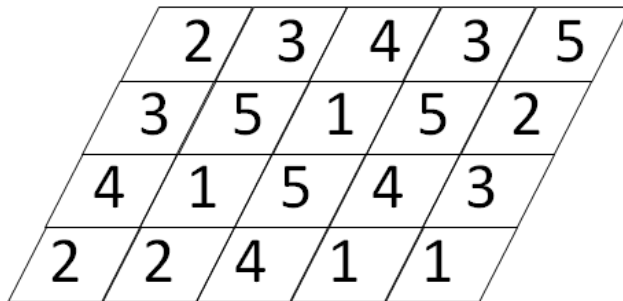


Fig. 3.



A 4x5 grid of numbers, tilted to the right. The numbers are arranged as follows:

2	3	4	3	5
3	5	1	5	2
4	1	5	4	3
2	2	4	1	1

Fig. 4.

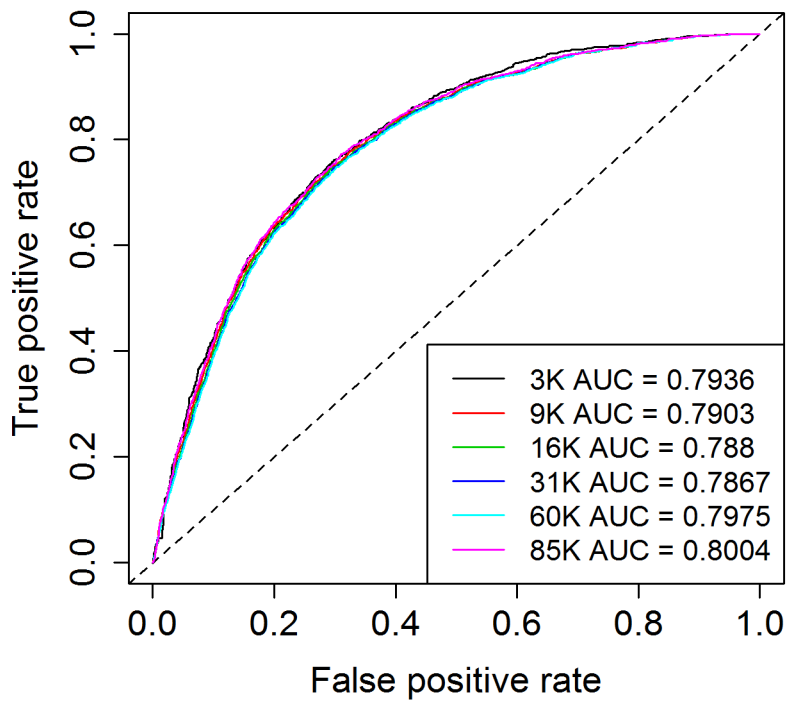


Fig. 5.

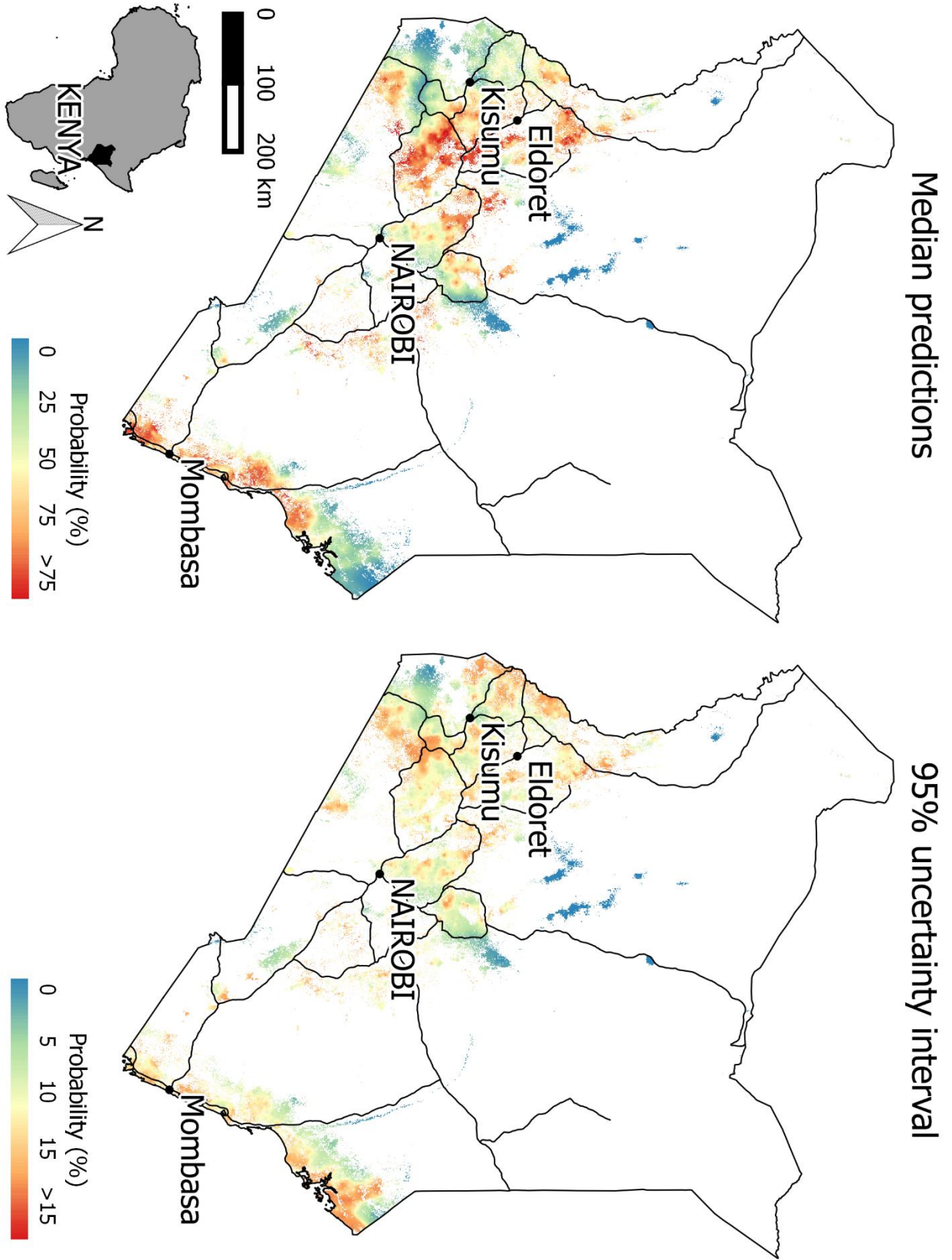


Fig. 6.

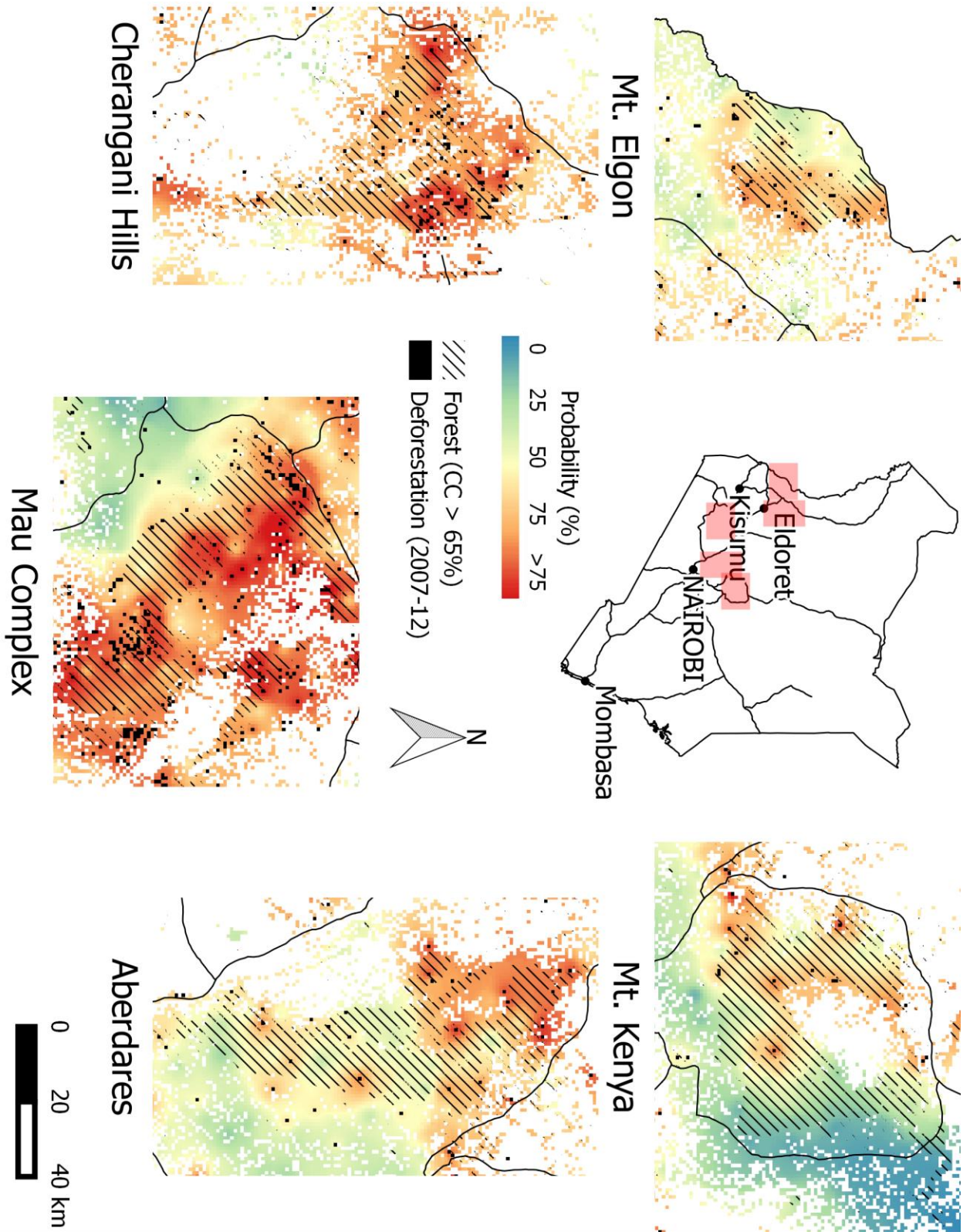


Fig. 7.

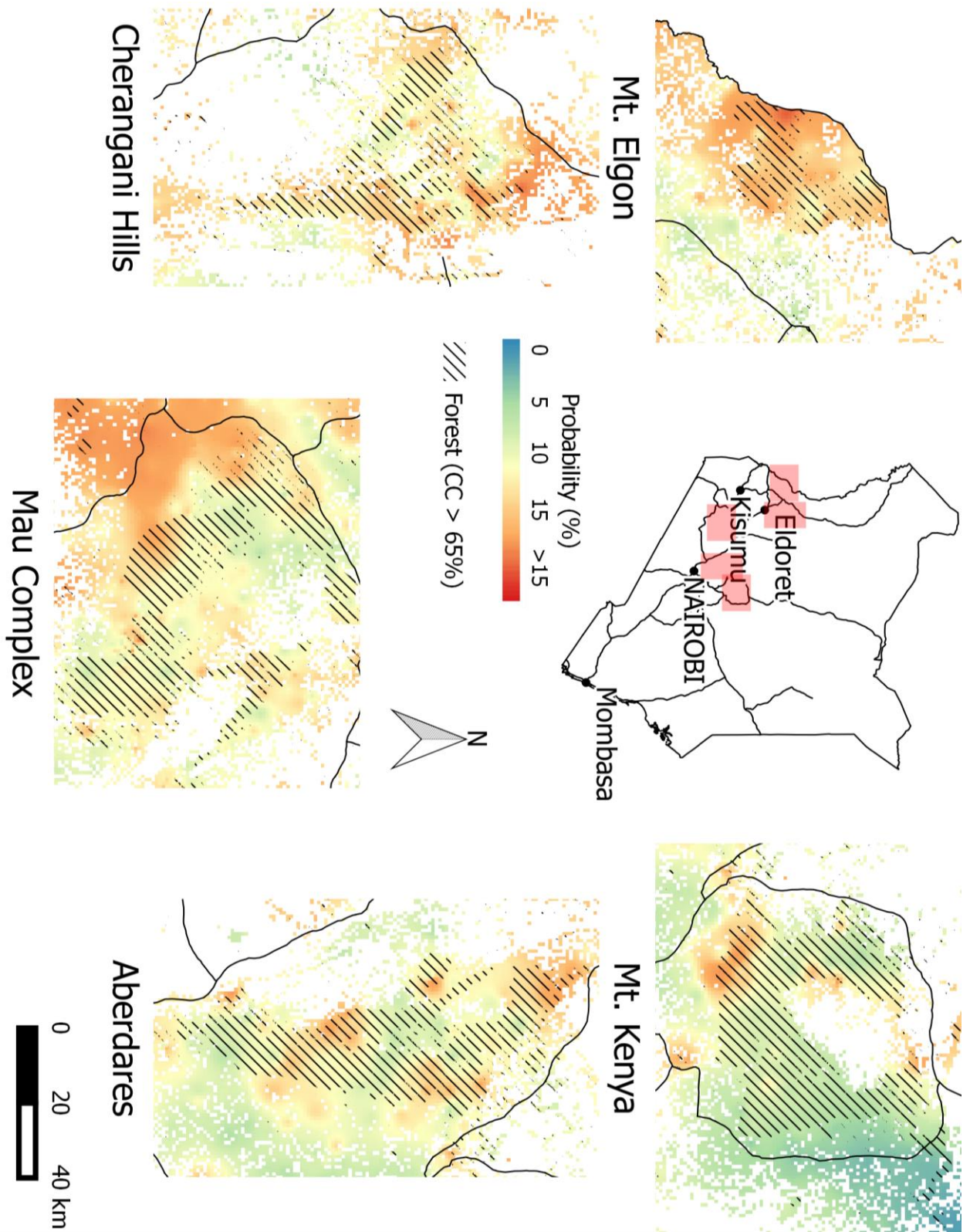


Fig. 8.

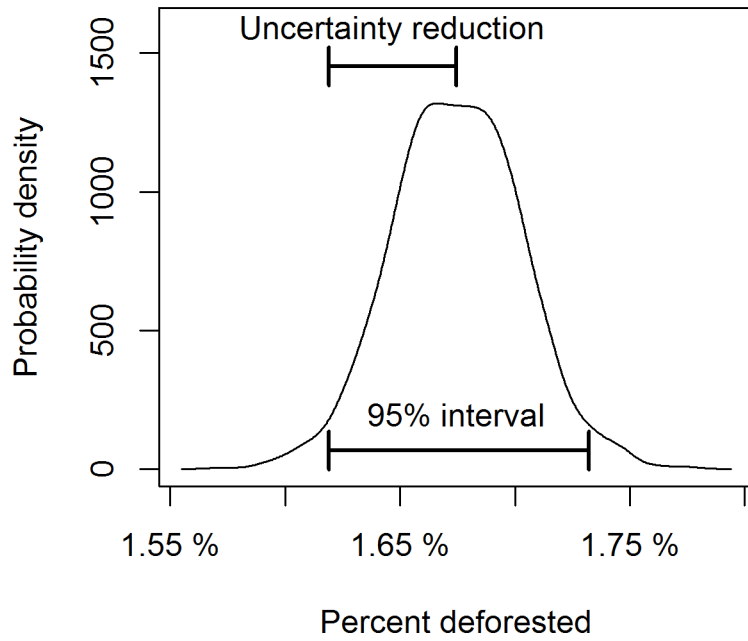
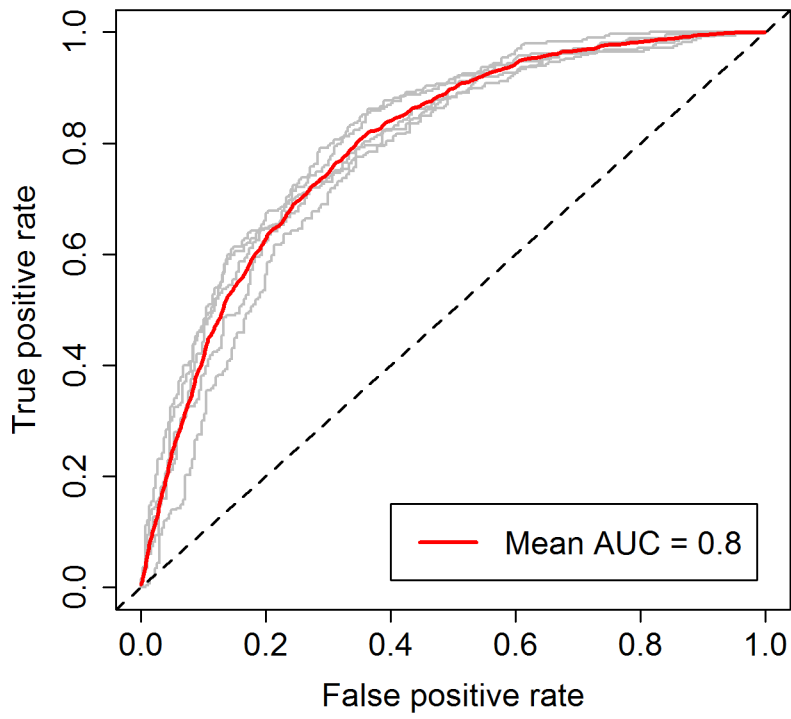


Fig. 9.



## TABLES

Table 1. Driver datasets initially considered in the model.

Table 2. Driver datasets remaining after screening for multicollinearity.

Table 3. Model driver explanatory power (AIC change), relative effect size (opt/std), and units.

Dividing a dataset's optimum by its standard deviation reveals the direction and relative size of its effect. Effect size is how much the probability of deforestation changes with a given change in the level of a proxy dataset for a driver in the model. The explanatory power is how well the model fits the proxy data for drivers and data for deforestation. A driver may have high explanatory power, but a low effect size. In this case, the predictions are accurate, but a large change in the driver level results in a small change in the predicted deforestation probability.

Conversely, a driver with low explanatory power and a large effect size has less accurate predictions, however a small change in the level of the driver results in a large change in predicted deforestation probability. Drivers with high explanatory power and a large effect size are the most influential in the model.

Table 4. Model parameter estimates.

Table 1.

Driver	Dataset	Year(s)	Source	Res.
Accessibility	Distance to major roads	1996	SoK, JICA, ILRI	NA
	Distance to motorable roads	2011	RCMRD, SoK	NA
	Distance to tracks/footpaths	2011	RCMRD, SoK	NA
Agriculture	Distance to previous deforestation	2001-2006	Hansen et al. 2013	30 m
	Crop intensity	2000	FAO	30 m
	Elevation	2000	NIMA	90 m
	Livestock density	1994-1996	ILRI	5 km
	Livestock density	2005	FAO	5 km
	Opportunity cost	2007	Naidoo & Iwamura	10 km
	Distance to active fires	2007-2012	NASA FIRMS	1 km
	Distance to intermittent rivers	1997	NIMA	NA
	Distance to permanent rivers	1997	NIMA	NA
	Distance to waterbodies	2000	FAO	30 m
	Slope	2000	NIMA	90 m
Extraction	Distance to major towns	2000	SoK, ILRI	NA
	Population density	2009	Bright et al.	1 km
	Population density	2009	KNBS	NA
	Population density	1999	CBS	NA
	Population growth	1989-2009	CBS, KNBS	NA
	Population growth	1999-2009	CBS, KNBS	NA
	Poverty density	1999	CBS	NA
Protection	Protected areas	2014	WDPA	NA

Table 2.

Dataset	Year(s)	Source	VIF
Distance to major roads	1996	SoK, JICA, ILRI	1.44
Distance to tracks/footpaths	2011	RCMRD, SoK	1.29
Distance to previous deforestation	2001-2006	Hansen et al. 2013	1.17
Crop intensity	2000	FAO	1.52
Distance to active fires	2007-2012	NASA FIRMS	1.3
Distance to intermittent rivers	1997	NIMA	1.54
Distance to waterbodies	2000	FAO	1.28
Livestock density	2005	FAO	1.3
Opportunity cost	2007	Naidoo & Iwamura	1.16
Slope	2000	NIMA	1.1
Distance to major towns	2000	SoK, ILRI	1.75
Population density	2009	Bright et al.	1.11
Population density	2009	KNBS	1.87
Population density	1999	CBS	1.89
Population growth	1999-2009	CBS, KNBS	1.12
Protected areas	2014	WDPA	1.07

Table 3.

Driver	Dataset	$\Delta$ AIC	opt/std	Units
Accessibility	Distance to previous deforestation	691.3	-2.71	meters
Extraction	Population density 2009 (KNBS)	66.1	-1.71	people/km <sup>2</sup>
Accessibility	Distance to major roads	50.7	-0.03	meters
Agriculture	Distance to active fires	17.6	-0.46	meters
Agriculture	Distance to intermittent rivers	12.1	0.50	meters
Agriculture	Slope	10.1	-0.21	degrees
Agriculture	Opportunity cost	5.2	0.58	\$US/km <sup>2</sup>

Table 4.

Parameter	Driver	lb95	mean	ub95
prob		127.8867	277.4883	406.4299
opt	Distance to previous deforestation	-137814	-127013	-112312
	Population density 2009 (KNBS)	-6861.73	-5835.28	-4906.34
	Distance to major roads	-36557.2	-2148.25	16406.42
	Distance to active fires	-18764.4	-13570.5	-6078.05
	Distance to intermittent rivers	54792.53	66437.41	76884.54
	Slope	-22.9396	-11.1105	1.994241
	Opportunity cost	443.3266	878.421	1853.786
std ( $\sigma$ )	Distance to previous deforestation	45719.1	46821.73	48808.62
	Population density 2009 (KNBS)	3084.413	3418.237	4057.296
	Distance to major roads	62461.87	84884.87	123258.9
	Distance to active fires	23562.41	29705.83	35949.88
	Distance to intermittent rivers	112506	131981.8	154507
	Slope	34.72096	52.48457	74.2519
	Opportunity cost	1005.619	1511.096	2543.003

## CHAPTER 2

Title: Protecting carbon stocks benefits livelihoods and biodiversity in Kenya

### Highlights:

- Reducing deforestation (REDD+) protects carbon stocks and could provide benefits to livelihoods and biodiversity (i.e. “co-benefits”).
- Distributions of carbon and co-benefits are not congruent, resulting in trade-offs.
- I analyze trade-offs among carbon and co-benefits in two and three dimensions in Kenya.
- Fixed area could represent > 86% of the maximum number of impoverished people and average proportion of rare species ranges while maintaining 90% of maximum carbon.
- Favorable trade-offs suggest that REDD+ could be designed with a focus on co-benefits without large sacrifices in carbon stocks.

Keywords: REDD+, co-benefits, poverty, biodiversity, trade-offs, Kenya

Word count: 7,850 (excluding highlights, abstract, and references)

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## ABSTRACT

Reducing deforestation and degradation (REDD+) is integral to the strategy for cutting global carbon emissions. However, it poses risks to forest communities and biodiversity. Assuming that social, environmental, and governance safeguards adequately mitigate these risks, REDD+ provides the opportunity to direct climate change mitigation funds toward additional benefits, referred to as “co-benefits,” including poverty alleviation and biodiversity conservation. If implemented as a payment for ecosystem services scheme, REDD+ would distribute payments to local stewards of forest resources. Just as avoided deforestation in REDD+ sites protects the biodiversity in those sites, it also may supplement the incomes of the people who live there. Depending on the extent to which forest benefits overlap, there may be trade-offs among them. This study quantifies trade-offs in Kenya, a country planning for REDD+, by examining the change in the proportions of carbon and co-benefits protected in a fixed area under different relative weightings between them. Results show that by using poverty and biodiversity distribution information in Kenya, fixed area could represent 90% of the maximum possible number of people below the poverty line, or 84% and 95% of the maximum possible average proportion of ranges of rare species with the smallest 50% and 25% of global ranges in REDD+ sites with only a 10% reduction in carbon. A novel analysis of trade-offs in three dimensions reveals that REDD+ sites could simultaneously include 86% of the maximum possible number of people in poverty and 88% of the maximum possible average proportion of ranges of rare species with the smallest 25% of global ranges with a 10% reduction in carbon (Fig. 16). These proportions represent a significant strategic gain over a carbon-only strategy. Stakeholders with different values for carbon and co-benefits may use these trade-offs to decide on their optimal levels.

## INTRODUCTION

### *REDD+ background*

Burning and clearing forests makes a significant contribution to anthropogenic greenhouse gas emissions, accounting for 9-11% of total emissions in 2000-10 (Smith et al. 2014). Emissions from deforestation and degradation are so great that they approximately equal those from the transportation sector, responsible for 14% of annual emissions over the same period (Smith et al. 2014). The United Nations Framework Committee on Climate Change (UNFCCC) has identified avoided deforestation as a cost-effective and cheap mitigation option (Stern 2006). A diverse set of actors including intergovernmental organizations, national governments, conservation and development non-governmental organizations, and indigenous groups have invested considerable time and effort in planning a program for Reducing Emissions from Deforestation and Degradation (REDD). The principle behind REDD is that developing countries sell credits equal to the amount of carbon stored in forests through avoided deforestation to developed countries required to offset their emissions (Miles and Kapos 2008). A popular way proposed to implement REDD is through national or sub-national payments for reductions in deforestation and degradation (Bond et al. 2009). REDD payments follow the “steward earns principle” whereby compensation is provided to landowners who maintain forests that would otherwise be deforested (Gomez-Baggethun and Ruiz-Perez 2011). The activities for emissions reductions eligible for REDD incentives have since expanded to include enhancing carbon storage through forest restoration, rehabilitation, and afforestation/reforestation in what became known as REDD+ (Campbell 2009).

*Risks to biodiversity and livelihoods*

Because REDD+ offers payments for forest conservation, it is often portrayed as a “win-win” strategy, delivering benefits in addition to climate mitigation such as poverty alleviation and biodiversity conservation. Proponents of REDD+ should exercise caution when using the language of “win-wins” since it could gloss over risks (Hirsch et al. 2011; Muradian et al. 2013). Central governments are increasingly allowing local people to manage forest resources (Agrawal et al. 2008). REDD+ threatens to reverse this trend by recentralizing forest governance (Phelps et al. 2010). Recentralized governance could result in elites taking away property rights from smallholders and reducing forest-related benefits for the poor (Sandbrook et al. 2010). An analysis of 80 forest commons in 10 countries across Asia, Africa, and Latin America shows that without secure tenure, local communities will maintain lower carbon storage in forest commons and extract at greater rates whereas when tenure is secure, they will conserve biomass and defer extraction (Chhatre and Agrawal 2009). REDD+ also poses risks to biodiversity. Land owners may replace primary forest with monoculture plantations that support fewer species to maximize carbon payments and crops (Lindenmayer et al. 2012). REDD+ incentives for carbon storage could also lead to the destruction of biodiversity by displacing agricultural expansion to low-carbon and high-biodiversity forests (Putz and Redford 2009). Failure of REDD+ to address these social and environmental risks could dispossess local people of their land as well as cause greater deforestation and biodiversity loss.

*REDD+ safeguards and co-benefits*

In response to the discussion of risks, a set of safeguards were drafted as a part of the 2010 Cancun Agreement at the 16<sup>th</sup> Conference of the Parties to the UNFCCC. To avoid seizure of land tenure from smallholders by large landowners, and damage to the livelihoods of local

people, the safeguards call for “transparent and effective national forest governance” and “respect for the knowledge and rights of indigenous peoples and members of local communities” (Visseren-Hamakers et al. 2012). To protect biodiversity, they require that “actions are consistent with the conservation of natural forests and biological diversity” (Visseren-Hamakers et al. 2012). The safeguards seek to mitigate against risks that could harm local people or biodiversity. If these safeguards are adhered to, REDD+ would direct funds toward conserving natural forests and biodiversity and improving the livelihoods of local forest stewards that would otherwise not be available. In other words, if implemented in line with the safeguards, REDD+ would only serve to improve the livelihoods of local people or increase biodiversity. There may however be trade-offs between the extent to which REDD+ could provide climate mitigation services and additional co-benefits because the spatial distribution of carbon stocks may not align with the distribution of co-benefits. A trade-off occurs when the increase in one benefit results in the reduction of another. Analyses have already been conducted to identify the potential trade-offs between carbon and biodiversity co-benefits (Venter et al. 2009; Strassburg et al. 2010; Siikamaki and Newbold 2012; Thomas et al. 2013), but fewer for trade-offs between carbon and poverty alleviation (Ferraro et al. 2015), and none for trade-offs between carbon and both biodiversity and poverty alleviation.

### *REDD+ in Kenya*

Since individual countries will decide how REDD+ is implemented at a national scale, analyses of trade-offs between carbon and additional co-benefits are likely to be conducted for individual countries. One such country is Kenya, which has begun undertaking readiness activities to prepare for REDD+ as evidenced by its submission of a Readiness Preparation Proposal (R-PP) to the World Bank’s Forest Carbon Partnership Facility (Kenya R-PP 2010).

Kenya's participation in REDD+ is in accordance with its 2005 Forests Act, which requires all forests to be under sustainable forest management, including "conservation and rational utilization of forest resources for the socio-economic development of the country," regardless of ownership (KFA 2005). Kenya's R-PP states that activities will be designed with a focus on co-benefits such as improving biodiversity and livelihoods of forest dependent people (Kenya R-PP 2010). Kenya is a country with low forest cover and a low deforestation rate. Forests cover 5.6% of Kenya and annual loss of this forest stock was between 0.35% and 0.31% from 2005-2010 (FAO 2010). Despite this, there is high potential for REDD+ to deliver co-benefits in Kenya. About 53% of rural and 50% of urban Kenyans live below the poverty line (WRI et al. 2007). The Eastern Arc and Coast Forests of southern Kenya and Tanzania are a global hotspot of biodiversity (Burgess 1998; Myers et al. 2000; Burgess et al. 2007).

## METHODS

### *Data*

Gridded spatial data were gathered for carbon, biodiversity, and livelihoods for input into the analysis on the trade-offs between carbon and co-benefits. Aboveground forest carbon data measured in Megatons were derived from 30 m resolution satellite observations resampled to 10 km (Fig. 1) (Baccini et al. 2012). To quantify the potential of REDD+ to contribute to local livelihoods, census data from 1999 on poverty density at the sublocation level, the lowest administrative level (i.e. highest resolution), were used under the assumption that carbon payments delivered to people locally would benefit areas with the highest poverty density most (CBS 2001). REDD+ payments would make up a greater proportion of the income of people in poverty than the income of people who are wealthier and would therefore have higher proportional benefits for the poor. Delivering REDD+ payments to areas with the highest poverty density would provide these benefits to a greater number of people in poverty, maximizing their potential to elevate livelihoods. Poverty density is defined as the number of people per square km living below the poverty line of US\$ 0.59/day in rural areas and US\$ 1.26/day in urban areas (WRI et al. 2007). Kenya's sublocations in 1999 had a mean size of 240 km<sup>2</sup> with a standard deviation of 610 km<sup>2</sup> and a range between 0.5 km<sup>2</sup> and 10,715 km<sup>2</sup>. A shapefile with poverty data mapped on the sublocation level was converted to a raster with 10 km resolution (Fig. 2). Areas in the eastern and central parts of the country are missing because no data on poverty were collected here. These areas were excluded from subsequent analyses. Since the most recent poverty data available at the sublocation available are more than 15 years old, the correlation between poverty density in 1999 and 2006 at a higher administrative level, the district level, was examined. A strong correlation between years would indicate that while there may have been an increase in the number of people below the poverty line with population growth, the district-level

distribution of poverty has not changed significantly. In turn, no change in district-level poverty distribution may imply low change in sub-location poverty from 1994-2006 and possibly beyond. Biodiversity data from 2013 were acquired in the form of shapefiles describing the global ranges of bird, mammal, and amphibian species from BirdLife International and the International Union for the Conservation of Nature (IUCN 2013). Species with ranges intersecting the area of Kenya were used in the analysis including those of 679 birds (544 passiformes and 135 non-passeriformes), 356 mammals, and 98 amphibians. The shapefiles of species ranges were converted to rasters with values 1 and 0 denoting presence/absence and resampled to a 10 km resolution and clipped to the extent of Kenya. The areas of all global species ranges were calculated from the original shapefiles to identify globally rare species. To establish rarity, the size of a global species range was only compared to the global range sizes of other species in its taxon. Rare species were defined in two ways: those with a global range size less than the median global range size (smallest 50% of global ranges), and those with a global range less than the lower quartile of global range sizes (smallest 25% of global ranges). Species richness raster maps were calculated by summation for all species (Fig. 3), submedian species (Fig.4) and lower quartile species (Fig.5). Correlations between aboveground carbon, the richness of the three classes of species, and poverty density were examined to explore spatial relationships in the data.

### *Trade-offs*

Trade-offs between carbon and co-benefits were examined with Zonation, a spatial conservation planning tool (Moilanen et al. 2012). Zonation takes in multiple sets of gridded data on the distributions of environmental features like species or ecosystem services. The tool successively discards cells in the landscape which minimize the loss in the overall proportion of

these features protected. The Core-Area Zonation cell removal rule was used in the analysis, which makes it harder to discard a cell if it contains more features with smaller ranges than cells containing features with larger ranges. The tool ranks cells in terms of their priority for conservation. Cells removed first have a lower priority than cells removed last. Zonation also records the decline in the overall proportion of features protected during cell removal. The two main outputs from Zonation are a map of the relative priority of each grid cell for conserving the greatest proportion of input features and the shape of the decline in the proportion of features protected with proportion of area lost. Rather than studying the decline in features with area lost, Zonation was run several times with the same input data to record the variation in the proportion of features protected in a fixed proportion of total area of 0.3 or 30%. The area constraint chosen is consistent with that of Thomas et al. (2013) who studied the trade-offs between carbon and biodiversity by means of a similar method. Choosing the same constraint allows for comparison of the results presented here to the results reported by Thomas et al. The sensitivity of the trade-offs to the area constraint was also tested for both a greater proportion (50%) and lesser proportion (10%) of the total area included in the analysis. The difference between each run with the same input data and area constraint was that some features were weighed more heavily to increase their priority. Users are able to adjust feature weights in the cell removal rule such that more heavily weighted cells will be removed later and take on a higher priority. In the comparison of carbon and poverty density, weights were assigned to carbon ranging from 0.000244 ( $2^{-12}$ ), which strongly prioritizes poverty, to 8 ( $2^3$ ), which strongly prioritizes carbon. The same results could be found by assigning the weights to poverty because they are relative. Repeatedly running Zonation with different relative weightings and extracting the proportion of carbon and poverty protected in 30% of the landscape shows the trade-off between them.

Increasing the relative weight of poverty or carbon will increase the proportion protected of one at the expense of another. Bookending the interval of weights are runs of Zonation where either carbon or poverty had a weight of zero, effectively removing one or the other from the analysis. When carbon has a weight of zero, the proportion protected of poverty is the maximum proportion of total poverty that can be included in 30% of the cells in the landscape. Similarly, when poverty has a weight of zero, the proportion protected of carbon is the maximum proportion of total carbon that can be included in 30% of cells. A plot of the trade-off between carbon and poverty shows the relative weights on the x-axis and the proportions of carbon protected and poverty protected (i.e. people below the poverty line included in priority regions) on the y-axis. To express the trade-off between carbon and poverty in terms of carbon instead of poverty, the weights listed on the x-axis of the trade-off plot are the inverse of the weights assigned to carbon. For example, a weight of  $2^{-12}$  on carbon relative to a weight of  $2^1$  on poverty is shown as a weight of  $2^1$  on carbon relative to a weight of  $2^{12}$  on poverty. A dashed line delimits the weights on poverty above which carbon is lower than 90% of its maximum possible value. Adjacent to the trade-off plot, the proportion of people included in priority regions is plotted against the proportion of carbon protected. Through the east of Kenya and in parts of the center, no data were collected on poverty density in 1999. The extent of the data on aboveground carbon was clipped to the area of the poverty data to assess the spatial trade-offs between them where data on poverty were available. The method for exploring trade-offs between carbon and biodiversity differed from the one used to explore the trade-off between carbon and poverty in that the distribution of each species was an input to the analysis. The range maps of individual species that make up the aggregate maps of species richness in Figs. 3-5 were included as layers in Zonation. In total, 1133 species ranges were included in the trade-off of carbon with all

species, 187 with rare species with the smallest 50% of global ranges, and 51 with rare species with the smallest 25% global of ranges. The weights assigned to carbon in these trade-offs varied in proportion to the number of species (N) such that the weights on carbon were 8N, 4N, 2N, 1N, ... , 0.001953N, 0.000977N, 0.000488N, 0.000244N. Again, because the weights are relative, the inverse of the weights on carbon was taken to express the trade-offs in terms of the weights on biodiversity. The biodiversity value at a given weighting was found by averaging the proportions remaining of all the individual species distributions. In addition to tracing the change in the average proportion of species protected over the range of weights, histograms were plotted for certain weights to show the spread of the proportions remaining across individual species ranges. When biodiversity has a higher weight, more species will have a greater proportion of their ranges protected than when biodiversity has a lower weight. The same technique for examining trade-offs in two dimensions can be extended to three. The trade-offs among carbon, poverty, and rare species with the smallest 25% of global ranges were tested by first limiting the extent of carbon and rare species ranges to that of the areas where poverty data were available. Then, holding the weight of carbon constant, varying weights were assigned to poverty and the distributions of rare species. The weights assigned to the individual layers of species ranges varied between 0.125 ( $2^{-3}$ ) and 4,096 ( $2^{12}$ ). The same set of weights were assigned to poverty except, given that there are 51 species with the smallest 25% of global ranges, the weights on poverty were multiplied by 51 to ensure that they varied in proportion with the combined weights on rare species. For each weight between 0.125 and 4,096 assigned to rare species relative to carbon, a range of weights between 6.375 ( $0.125 \times 51$ ) and 208,896 ( $4,096 \times 51$ ) were assigned to poverty relative to carbon. The proportions protected for the three features were recorded for the 256 combinations of weights (16 weights on rare species \* 16 weights on

poverty). As before, the proportion protected of rare species with the smallest 25% of global ranges represents the average of the proportions remaining of the ranges for individual species. In this way, three 16 x 16 grids were created for the proportions protected of carbon, poverty, and rare species under all possible combinations of weights on poverty and biodiversity relative to carbon. The three grids were converted into surfaces and plotted in three dimensions in “rgl,” a 3D visualization package in R (Adler and Murdoch 2015). On the z-axis of the three-dimensional plot is the proportion of features protected. The x- and y-axes show the weights of poverty and rare species with the smallest 25% of global ranges, respectively. Each surface depicts carbon, poverty, or rare species. A lattice is plotted alongside the feature surfaces, above which the proportion of carbon protected is greater than 90% of the maximum carbon possible to protect. Once the trade-offs among carbon, poverty, and biodiversity were plotted in two and three dimensions, they were used to find the level of co-benefits that could be protected with a 10% loss in maximum carbon. An interval of weights was identified for each trade-off over which carbon appeared to drop by 10% from its maximum. Through trial and error, weights over successively smaller intervals were applied to carbon or co-benefits until the proportion of carbon remaining was approximately 90% of its maximum. The proportions of the other features at these weights were then recorded. On the two-dimensional graphs, crosses mark the proportions of carbon and the co-benefit protected with a 10% reduction in carbon.

## RESULTS

Correlations between carbon and poverty, rare species with the smallest 50% and 25% of global ranges, and all species were significant but with low explanatory power ( $R^2 < 0.1$ ) (Figs. 6-9). Yet, weak correlations between carbon and co-benefits do not indicate the relative spatial distribution of high priority cells in each layer. A more detailed study of the trade-offs between carbon and co-benefits under varying weights in Zonation reveals the extent of spatial co-occurrence among high priority cells in these data layers. Where there is greater overlap among high priority cells across layers, trade-offs will be more moderate and there will be a greater opportunity for achieving multiple objectives. The trade-offs here demonstrate that there is high potential for REDD+ to contribute to livelihoods and conserve rare species without large losses in carbon. Conserving a greater proportion of the ranges of all species by prioritizing biodiversity, however, requires larger sacrifices in carbon storage.

The shapes of the curves in Figs. 11-15 show the extent of the trade-offs between carbon and co-benefits. Two parameters influence the potential for REDD+ to simultaneously protect carbon and deliver co-benefits: the difference between the maximum and minimum amount of carbon and co-benefits possible to protect and the slopes of the curves. The asymptotes of the curves show the maximum and minimum amount of carbon and co-benefits conserved in the 30% of Kenya protected. The curves asymptote when changing the relative weighting no longer influences the proportion of carbon or co-benefits protected. At this point, there are no greater gains possible by prioritizing one forest benefit more than the other. The left side of the graph represents a “carbon only” solution that maximizes carbon storage and the right side represents a “co-benefit only” solution that maximizes the co-benefit. The slopes of the curves indicate how sensitive co-benefits and carbon are to the relative weighting between the two. A curve with a

shallow slope shows a low sensitivity to the relative weighting between a co-benefit and carbon. Conversely, a curve with a steep slope shows a high sensitivity.

REDD+ has the potential to protect carbon and deliver significantly greater co-benefits when their relationship meets two conditions. The first is when the y-axis range between the maximum and minimum proportions of the co-benefit is roughly equal to or greater than the proportional range of carbon. The second is when the slope or sensitivity of the co-benefit curve to the relative weighting is roughly equal to or greater than the slope of the carbon curve. The relationship between carbon and the number of people below the poverty line as well as carbon and the average proportion of rare species ranges meet both these conditions (Figs. 11-12 & 14). It is possible to include 90% of the maximum possible number of people below the poverty line in REDD+ sites with a 10% reduction in carbon compared to the carbon only solution (Table 1). Similarly, it is possible to conserve 84% of the maximum average proportion of ranges of rare species with the smallest 50% of global ranges with a 10% reduction in maximum carbon (Table 2). Reducing the range size criterion for rarity to the smallest 25% of global ranges makes it possible to conserve 95% of the maximum average proportion of ranges of rare species with a 10% reduction in maximum carbon (Table 4). In contrast, the relationship between carbon and species richness fails to meet both conditions for REDD+ to be able to conserve a significantly greater proportion of the average ranges of all species (Fig. 13). The slopes of the two curves are similar, although the range of the average proportion of all species ranges protected is only 0.17 (Table 3). It is possible to conserve 85% of the maximum average proportion of all species ranges with a 10% reduction in maximum carbon, yet this only represents a 20% increase in the average proportion of all species ranges compared to the carbon only solution (Table 3).

A 10% in reduction in maximum carbon maintains a high overall average proportion of the ranges of rare species as well as more than 80% of the individual ranges of a high number of rare species. Maximizing rare species with the smallest 50% of global ranges protects more than 80% of the individual ranges of 96 species while a 10% reduction in maximum carbon protects more than 80% of the individual ranges of 60 species (Fig. 12). A solution that accepts a 10% reduction in maximum carbon protects more than 80% of the ranges of even more rare species when they are defined as having the smallest 25% of global ranges sizes. A 10% reduction in carbon protects more than 80% of the ranges of 42 rare species with the smallest 25% of global ranges compared to 45 rare species when the average proportion of the ranges of rare species is maximized (Fig. 14). Reducing carbon by 10%, however, only protects more than 80% of the ranges of 142 of all species compared to 250 when maximizing the average proportion of the ranges of all species (Fig. 13).

A sensitivity analysis of the trade-offs to the area constraint pointed to the strong influence of the proportion of the landscape over which trade-offs were assessed on the ranges and slopes of trade-offs between carbon and heterogeneously distributed data. Across co-benefits, decreasing the area constraint from 30% to 10% exaggerated the trade-offs by increasing their slopes and ranges (Fig. 15). Conversely, increasing the area constraint to 50% moderated the trade-offs by decreasing their slopes and ranges (Fig. 15). The magnitude of exaggeration and moderation depends on the spatial heterogeneity of the co-benefit data. The trade-offs of carbon with poverty as well as rare species with the smallest 25% of global ranges are more sensitive to the area constraint because data on these co-benefits are more heterogeneously distributed (Figs. 2 & 5). Meanwhile, the trade-offs of carbon with rare species

with the smallest 50% of global ranges and total species richness are less sensitive because they are more homogenously distributed (Figs. 3-4).

Considering the trade-offs among carbon, poverty, and rare species with the smallest 25% of global ranges at the same time in three dimensions shows that it is possible to protect high levels of both co-benefits while maintaining more than 90% of maximum carbon (Fig. 16). A 10% reduction in maximum carbon at the same time includes 86% of the maximum number of people below the poverty line and protects 88% of the maximum average proportion of ranges of rare species with the smallest 25% of global ranges (Fig. 16). A map of the areas making up 30% of Kenya (shown in shades of red) that achieve these targets is depicted in Fig. 17.

## DISCUSSION

### *Data distributions and co-benefits opportunities*

The high potential for co-benefits relates to the spatial distribution of carbon and co-benefits. When they are more heterogeneously distributed across the landscape, there is a greater range over which the proportion protected varies. Poverty is the most heterogeneous with a range of 0.52 (Table 1). Rare species with the smallest 25% and 50% of global ranges are less so with ranges of 0.43 and 0.33, respectively (Tables 2 & 4). Carbon has a range of 0.33 over the whole of Kenya (Tables 2-4) and a range of 0.26 when limited to the extent of areas in Kenya where poverty data is available (Table 1). Total species richness is the least heterogeneous with a range of 0.17 (Table 3). The different spatial patterns explain why there are larger proportional gains in the average proportion of ranges of rare species than all species for the same amount of carbon loss. Since rare species have range sizes smaller than the global median, the number of species whose ranges cover a certain region is highly variable across different regions. A strategy that prioritizes carbon is prone to excluding regions occupied by greater numbers of rare species because these regions are less likely to correspond with areas of high carbon. Given that most of the species in the data have large range sizes since a majority of them are birds, the distribution of total species richness is more homogenous than the distributions of rare species. Areas with higher carbon are more likely to contain regions occupied by a similar number of species as areas with lower carbon. Therefore weighing carbon more heavily will not result in dramatic differences in the average proportion of the ranges of all species protected. The potential for REDD+ to contribute to livelihoods is even greater than its potential to conserve rare species because poverty has higher spatial heterogeneity. Prioritizing areas with higher poverty density will include a much greater proportion of people in REDD+ sites who may benefit most from carbon payments.

*Biodiversity trade-offs*

Results show that in Kenya it is possible to protect 84% of the maximum average proportion of ranges of rare species with the smallest 50% of global ranges, 85% of the average proportion of ranges of all species, and 95% of the average proportion of ranges of rare species with the smallest 25% of global ranges with a 10% reduction in carbon. These results are consistent with results showing that a combined carbon-biodiversity strategy could simultaneously protect 90% of carbon stocks and > 90% of biodiversity in the New World and Great Britain (Thomas et al. 2013). The key difference is that weighing biodiversity more heavily in Kenya only has the potential to increase the average proportion of the ranges of all species protected by 0.17 compared to 0.33 and 0.43 for rare species with the smallest 50% and 25% of global ranges, respectively, on account of their more heterogeneous distributions with respect to high carbon values (Tables 3, 2, & 4). In general, the conditions that result in a favorable trade-off whereby a slight reduction in carbon amounts to a much larger gain in co-benefits apply across scales. A large spread in the values of the co-benefits and the heterogeneous distribution of high and low co-benefit values across high carbon values that generate favorable trade-offs for Kenya will also generate them globally. Like rare species in Kenya, high and low values of total species richness are likely heterogeneously distributed with respect to high values of carbon at a global scale. This fact may explain why a global analysis of carbon and biodiversity found that biodiversity could be doubled by reducing carbon outcomes by only 4 to 8% (Venter et al. 2009).

Simple correlations between carbon and co-benefits do not always provide sufficient information for assessing the trade-offs between areas with the highest values for carbon and biodiversity. For example, the global distribution of endemic species only explains 1% of the variation in the global carbon distribution, suggesting a conflict between carbon and biodiversity

because areas high in carbon generally have low levels of endemic species (Siikamaki and Newbold 2012). As in Kenya, it may be the case at the global scale that there is a weak overall correlation between carbon and endemic species, however there is a favorable trade-off in areas with the highest carbon and endemic species values. Areas with the highest carbon values may contain highly variable levels of endemic species, although a subset of these high carbon areas such as 30% may contain relatively high values of endemic species. If these conditions hold, then a substantial gain in endemic species is possible with only a low loss in carbon in the 30% of cells protected. When, on the other hand, carbon and co-benefits are strongly correlated, prioritizing cells with slightly less carbon is less likely to yield much higher levels of co-benefits. The global distribution of species richness explains 82% of the variation in the global distribution of carbon, indicating that species richness is high in areas of high carbon (Strassburg et al. 2010). The high correlation presents limited opportunity for conserving higher levels of species richness by protecting areas with slightly less carbon because prioritizing cells with lower carbon will also lower species richness by the same amount given that the two are tightly coupled.

### *Valuing trade-offs*

Several pitfalls exist in using the trade-offs framework. One of them is that the framework collapses multiple incommensurable forms of value down into economic value to find the most cost-effective solution (Hirsch et al. 2011). Value is the worth or importance of something, and ecosystems have different types of value. Carbon and biodiversity are properties of ecosystems that may have biophysical, socio-cultural, or economic value (de Groot et al. 2002; Gomez-Baggethun et al. 2010; Gómez-Baggethun and Barton 2013). Biophysical value measures the level of an ecosystem property, process, or function using various ecological

indicators. Socio-cultural and economic values are the values people place on the material aspects of ecosystems measured with surveys or money.

In the context of REDD+, as currently designed, carbon storage is the only ecosystem function that has economic value because it provides the service of climate change mitigation. Biodiversity also has economic value as a regulator of ecosystem processes, a contributor to final ecosystem services, and a final good in and of itself (Mace et al. 2012). As of yet though, REDD+ does not offer financial incentives for protecting biodiversity that is additional to the level of biodiversity found in a carbon-only solution. The optimal solution for earning the most from REDD+ is to maximize carbon. However, national decision makers may have different priorities based on the scale over which services are delivered and their non-economic values.

The scale of the physical ecosystem that delivers services does not always match the scale at which humans value those services (de Groot et al. 2002). Economic benefits of forests and biodiversity accrue across different scales. Forests provide a global service of climate mitigation while the biodiversity they house provides more local services such as ecotourism or pollination. Decision makers may decide to opt for less money from protecting carbon because the biodiversity conserved in the less carbon-rich forests that they do protect could generate services worth more than the foregone income from carbon. The trade-offs in Figures 11-14 could help national decision makers decide on the optimal level of carbon to protect to receive international payments and biodiversity to protect to deliver local ecosystem services.

Decision makers may also be motivated by non-economic values to protect additional biodiversity and compensate people that are particularly economically disadvantaged. Biodiversity may have socio-cultural value because, for example, it is part of national or regional identity. Decision makers may therefore choose to protect more biodiversity not because it will

produce greater economic returns, but because it is socio-culturally important. The same goes for the co-benefit of improving livelihoods. Livelihood co-benefits are not material aspects of ecosystems like biodiversity, although decision makers may still value them. Decision makers may therefore choose to conserve forests with less carbon in areas with greater poverty to assist the people that live there.

Though no valuation was done, the trade-offs shown in this study for the multiple environmental and social benefits derived from forests allow space for value pluralism. The economic value and socio-cultural importance of ecosystem services have been shown to diverge for different services (Martín-López et al. 2014). For example, in the Doñana social-ecological system in southwestern Spain, water quality, climate regulation, environmental education, and satisfaction for conserving biodiversity were highly recognized as socio-cultural preferences, although they had a low monetary value (Martín-López et al. 2014). Expressing trade-offs in terms of economic value may hide alternative trade-offs in socio-cultural value. Leaving the trade-offs in biophysical units or units of poverty density enables decision makers to apply different sets of values to them. Decision makers may express the relative strength of their values through their choice of weights for forest benefits and observe how they change the level of carbon and co-benefits protected. For example, one decision maker may see forests for their economic value and wish to maximize carbon to receive higher payments. Yet competing values of other stakeholders may lead the decision maker to compromise on economic values to accommodate the socio-cultural value of biodiversity and the value of poverty alleviation. The trade-off curves in Figures 11-14 show the level of economic returns forfeited from carbon storage in such a negotiation. The decision maker who values money may still find that a 10% reduction in carbon payments is an acceptable loss in return for carbon payments reaching 90%

of the nation's poor or for protecting 84% of the average proportion of ranges of rare species with the smallest 50% of global ranges. Extending the analysis of trade-offs into three dimensions shows that it may be possible to satisfy at once all three sets of stakeholders who each value one of the forest benefits more highly than the others. A 10% reduction in carbon payments simultaneously ensures that they will reach 86% of people in poverty and protect 88% of the average proportion of ranges of rare species with the smallest 25% of ranges.

### *Limitations to poverty alleviation*

The finding that with a 10% sacrifice in carbon it is possible for REDD+ to benefit 90% of Kenya's poor in the trade-off between carbon and poverty as well as 86% of the poor in the trade-off among carbon, poverty, and biodiversity rests on the assumption that carbon payments will in fact reach those occupying forests who are in greatest need and that the risks posed by REDD+ will not negatively affect them. In order not to harm and to potentially improve the livelihoods of people living in and around forests, the implementation of REDD+ must adhere to the safeguards guaranteeing effective governance and respecting the rights of indigenous and local people. Trusting that REDD+ will meet these safeguards is widely debated. REDD+ may have no effect on, benefit, or harm local people (Larson 2011). Transaction costs and rights to land tenure may work in favor of large landholders such as the state, concession holders, or private companies (Campbell 2009). Higher transaction costs for numerous smallholders and less secure land tenure may exclude them from receiving payments for avoided deforestation. If so, large, wealthy landowners would disproportionately benefit from REDD+ and the program would have limited effect on the livelihoods of local people. REDD+ may also hurt local livelihoods by providing financial incentives for large landowners to reassert their tenure (Campbell 2009). Faced with the prospects of greater returns from managing forested land for

carbon storage, large landowners may withdraw from formal or informal agreements with local people who harvest forest products or farm the land such as sharecroppers. The conflict over land tenure may therefore restrict access to forest goods and dispossess smallholders of land for agriculture. The potential for payments for ecosystem services like carbon storage to harm local livelihoods is why it is important for REDD+ policies to be sensitive to institutional contexts such as conflicts over property rights and social relations regarding forest access to forest resources (Corbera et al. 2007). Designing REDD+ with this context in mind is critical to ensure it reduces poverty and delivers equitable outcomes. Meeting the safeguards are a necessary, but not a sufficient condition for improving livelihoods. In order to alleviate poverty, REDD+ must at minimum compensate local people for the cost of foregone opportunities of harvesting forest goods or clearing forest for agriculture (Wunder 2008). It remains to be seen whether beneficiaries of carbon storage in the developed world would provide enough compensation to local ecosystem services providers to exceed opportunity costs and improve livelihoods (Campbell 2009). Even if carbon payments break even with opportunity costs, REDD+, if suitably designed, may still enhance livelihoods by offering non-monetary benefits such as securing land tenure, strengthening local identity, and empowering communities to manage forests sustainably (Larson 2011).

## CONCLUSION

The spatial distributions of carbon and co-benefits are configured in Kenya such that REDD+ could contribute greater benefits to livelihoods and the conservation of rare species while protecting high levels of carbon. The differing spatial heterogeneity of rare species and species richness explains why carbon-biodiversity trade-offs in this study concur with or vary from those in similar analyses. Showing how biophysical units and units of poverty density trade off against one another allows decision makers with different sets of values to negotiate on the optimal level of carbon and co-benefits to conserve. There are limitations to the assumption that countries implementing REDD+ will adhere to safeguards and distribute payments fairly and locally. Assuming they do, incorporating information about the distribution of people below the poverty line could help REDD+ deliver payments to those most in need. The analysis presented here holds promise for compromise. While maintaining 90% of maximum carbon stocks, it is possible to include 86% of the maximum number of people below the poverty line and 88% of the maximum average proportion of the ranges of rare species with the smallest 25% of global ranges in REDD+ priority regions in Kenya.

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## REFERENCES

- Adler D, Murdoch D (2015) rgl: 3D Visualization Using OpenGL. R package version 0.95.1247. <http://cran.r-project.org/package=rgl>.
- Agrawal A, Chhatre A, Hardin R (2008) Changing governance of the world's forests. *Science* 320:1460–1462. doi: 10.1126/science.1155369
- Baccini A, Goetz SJ, Walker WS, et al (2012) Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nat. Clim. Chang.* 2:182–185.
- Bond I, Grieg-Gran M, Wertz-Kanounnikoff S, et al (2009) Incentives to sustain forest ecosystem services: a review and lessons for REDD. *IIED Nat Resour Issues* x + 47 pp. doi: 10.1080/02255189.2011.596037
- Burgess N (1998) Coastal forests of eastern Africa: status, endemism patterns and their potential causes. *Biol J Linn Soc* 64:337–367. doi: 10.1006/bijl.1998.0224
- Burgess ND, Butynski TM, Cordeiro NJ, et al (2007) The biological importance of the Eastern Arc Mountains of Tanzania and Kenya. *Biol Conserv* 134:209–231. doi: 10.1016/j.biocon.2006.08.015
- Campbell BM (2009) Beyond Copenhagen: REDD+, agriculture, adaptation strategies and poverty. *Glob Environ Chang* 19:397–399. doi: <http://dx.doi.org/10.1016/j.gloenvcha.2009.07.010>
- CBS (2001) Central Bureau of Statistics (CBS), Ministry of Finance and Planning. Kenya 1999 Population and Housing Census: Counting our People for Development Volume I. [http://docs.wri.org/ke\\_poverty1999-cbs\\_location.zip](http://docs.wri.org/ke_poverty1999-cbs_location.zip).
- Chhatre A, Agrawal A (2009) Trade-offs and synergies between carbon storage and livelihood benefits from forest commons. *Proc Natl Acad Sci U S A* 106:17667–17670. doi: 10.1073/pnas.0905308106
- Corbera E, Kosoy N, Martínez Tuna M (2007) Equity implications of marketing ecosystem services in protected areas and rural communities: Case studies from Meso-America. *Glob Environ Chang* 17:365–380. doi: 10.1016/j.gloenvcha.2006.12.005
- De Groot RS, Wilson MA, Boumans RMJ (2002) A typology for the classification, description and valuation of ecosystem functions, goods and services. *Ecol Econ* 41:393–408. doi: 10.1016/s0921-8009(02)00089-7
- FAO (2010) Global Forest Resources Assessment 2010 Country Report Kenya. <http://theredddesk.org/resources/global-forest-resources-assessment-2010-country-report-kenya>.

- Ferraro PJ, Hanauer MM, Miteva DA, et al (2015) Estimating the impacts of conservation on ecosystem services and poverty by integrating modeling and evaluation. *Proc Natl Acad Sci* 112 :7420–7425. doi: 10.1073/pnas.1406487112
- Gómez-Baggethun E, Barton DN (2013) Classifying and valuing ecosystem services for urban planning. *Ecol Econ* 86:235–245. doi: 10.1016/j.ecolecon.2012.08.019
- Gomez-Baggethun E, de Groot R, Lomas PL, Montes C (2010) The history of ecosystem services in economic theory and practice: From early notions to markets and payment schemes. *Ecol Econ* 69:1209–1218. doi: 10.1016/j.ecolecon.2009.11.007
- Gomez-Baggethun E, Ruiz-Perez M (2011) Economic valuation and the commodification of ecosystem services. *Prog. Phys. Geogr.* 35:613–628.
- Hirsch PD, Adams WM, Brosius JP, et al (2011) Acknowledging conservation trade-offs and embracing complexity. *Conserv Biol* 25:259–264. doi: 10.1111/j.1523-1739.2010.01608.x
- IUCN (2013) Red List Spatial Data. <http://www.iucnredlist.org/technical-documents/spatial-data>.
- Kenya R-PP (2010) REDD Readiness Preparation Proposal for Kenya. <http://theredddesk.org/resources/redd-readiness-preparation-proposal-kenya>.
- KFA (2005) Kenya Forests Act. [http://theredddesk.org/sites/default/files/forests\\_act\\_2005\\_kenya\\_1.pdf](http://theredddesk.org/sites/default/files/forests_act_2005_kenya_1.pdf).
- Larson AM (2011) Forest tenure reform in the age of climate change: Lessons for REDD+. *Glob Environ Chang* 21:540–549. doi: 10.1016/j.gloenvcha.2010.11.008
- Lindenmayer DB, Hulvey KB, Hobbs RJ, et al (2012) Avoiding bio-perversity from carbon sequestration solutions. *Conserv Lett* 5:28–36. doi: 10.1111/j.1755-263X.2011.00213.x
- Mace GM, Norris K, Fitter AH (2012) Biodiversity and ecosystem services: a multilayered relationship. *Trends Ecol Evol* 27:19–26. doi: 10.1016/j.tree.2011.08.006
- Martín-López B, Gómez-Baggethun E, García-Llorente M, Montes C (2014) Trade-offs across value-domains in ecosystem services assessment. *Ecol Indic* 37:220–228. doi: 10.1016/j.ecolind.2013.03.003
- Miles L, Kapos V (2008) Reducing Greenhouse Gas Emissions from Deforestation and Forest Degradation: Global Land-Use Implications. *Science* (80- ) 320:1454–1455. doi: 10.1126/science.1155358
- Moilanen A, Meller L, Leppänen J, et al (2012) Zonation Version 3.1 User manual. [http://www.helsinki.fi/bioscience/consplan/software/Zonation/ZONATION\\_v3.1\\_Manual\\_120416.pdf](http://www.helsinki.fi/bioscience/consplan/software/Zonation/ZONATION_v3.1_Manual_120416.pdf).

- Muradian R, Arsel M, Pellegrini L, et al (2013) Payments for ecosystem services and the fatal attraction of win-win solutions. *Conserv Lett* 6:274–279. doi: 10.1111/j.1755-263X.2012.00309.x
- Myers N, Mittermeier RA, Mittermeier CG, et al (2000) Biodiversity hotspots for conservation priorities. *Nature* 403:853–858. doi: 10.1038/35002501
- Phelps J, Webb EL, Agrawal A (2010) Does REDD + Threaten to Recentralize Forest Governance. *Science* (80- ) 328:312–313.
- Putz FE, Redford KH (2009) Dangers of carbon-based conservation. *Glob Environ Chang Policy Dimens* 19:400–401. doi: 10.1016/j.gloenvcha.2009.07.005
- Sandbrook C, Nelson F, Adams WM, Agrawal A (2010) Carbon, forests and the REDD paradox. *Oryx* 44:330–334. doi: 10.1017/s0030605310000475
- Siikamaki J, Newbold SC (2012) Potential Biodiversity Benefits from International Programs to Reduce Carbon Emissions from Deforestation. *Ambio* 41:78–89. doi: 10.1007/s13280-011-0243-4
- Smith P, Bustamante M, Ahammad H, et al (2014) Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. In: Edenhofer O, Pichs-Madruga R, Sokona Y, et al. (eds). Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA,
- Stern N (2006) Stern Review: The Economics of Climate Change. [http://webarchive.nationalarchives.gov.uk/20100407011151/http://www.hm-treasury.gov.uk/stern\\_review\\_report.htm](http://webarchive.nationalarchives.gov.uk/20100407011151/http://www.hm-treasury.gov.uk/stern_review_report.htm).
- Strassburg BBN, Kelly A, Balmford A, et al (2010) Global congruence of carbon storage and biodiversity in terrestrial ecosystems. *Conserv. Lett.* 3:98–105.
- Thomas CD, Anderson BJ, Moilanen A, et al (2013) Reconciling biodiversity and carbon conservation. *Ecol Lett* 16:39–47. doi: 10.1111/ele.12054
- Venter O, Laurance WF, Iwamura T, et al (2009) Harnessing carbon payments to protect biodiversity. *Science* 326:1368. doi: 10.1126/science.1180289
- Visseren-Hamakers IJ, McDermott C, Vijge MJ, Cashore B (2012) Trade-offs, co-benefits and safeguards: current debates on the breadth of REDD+. *Curr Opin Environ Sustain* 4:646–653. doi: 10.1016/j.cosust.2012.10.005
- WRI, Department of Resource Surveys and Remote Sensing Kenya, Ministry of Environment and Natural Resources Kenya, et al (2007) Nature’s Benefits in Kenya, An Atlas of Ecosystems and Human Well-Being.

Wunder S (2008) Payments for environmental services and the poor: concepts and preliminary evidence. *Environ Dev Econ*. doi: 10.1017/S1355770X08004282

## FIGURES

Fig. 1. Distribution of aboveground carbon in Kenya at 10 km resolution.

Fig. 2. Distribution of poverty density in Kenya at 10 km resolution.

Fig. 3. Distribution of the 187 rare species in Kenya with the smallest 50% of global ranges at 10 km resolution.

Fig. 4. Distribution of all 1133 species in Kenya at 10 km resolution.

Fig. 5. Distribution of the 51 rare species in Kenya with the smallest 25% of global ranges at 10 km resolution.

Fig. 6. Correlation between aboveground carbon and people below the poverty line. The correlation is significant at  $p < 0.05$  (Poverty =  $0.248 * \text{Carbon} + 21.7$ ,  $t\text{-value} = 7.93$ ,  $df = 3730$ ).

Fig. 7. Correlation between aboveground carbon and rare species with the smallest 50% of global ranges. The correlation is significant at  $p < 0.05$  (Species =  $0.110 * \text{Carbon} + 11.4$ ,  $t\text{-value} = 26.3$ ,  $df = 5835$ ).

Fig. 8. Correlation between aboveground carbon and species richness. The correlation is significant at  $p < 0.05$  (Species =  $1.09 * \text{Carbon} + 376$ ,  $t\text{-value} = 25.3$ ,  $df = 5835$ ).

Fig. 9. Correlation between aboveground carbon and species richness with the smallest 25% of global ranges. The correlation is significant at  $p < 0.05$  (Species =  $0.002 * \text{Carbon} + 0.250$ , t-value = 12.1, df = 5835).

Fig. 10. Relationship between Kenya District level poverty data from 1999 and 2006. The correlation is significant at  $p < 0.05$  (Poverty\_06 =  $0.907 * \text{Poverty}_{99} + 41750$ , t-value = 11.8, df = 63).

Fig. 11. Trade-off between carbon and number of people below the poverty line. The left side shows the proportion of carbon and people when carbon is weighed more heavily and the right when poverty is weighed more heavily. A 10% reduction (dashed line) in maximum carbon includes 90% of the maximum number of people below the poverty line.

Fig. 12. Trade-off between carbon and rare species with the smallest 50% of global ranges. The left side shows the proportion of carbon and the average proportion of rare species ranges when carbon is weighed more heavily and the right when rare species are weighed more heavily. A 10% reduction (dashed line) in maximum carbon maintains 84% of the maximum average proportion of ranges of rare species with the smallest 50% of global ranges.

Fig. 13. Trade-off between carbon and species richness. The left side shows the proportion of carbon and average proportion of all species ranges when carbon is weighed more heavily and the right when species richness is weighed more heavily. A 10% reduction (dashed line) in

maximum carbon maintains 85% of the maximum average proportion of the ranges of all species.

Fig. 14. Trade-off between carbon and rare species with the smallest 25% of global ranges. The left side shows the proportion of carbon and average proportion of rare species ranges when carbon is weighed more heavily and the right when rare species are weighed more heavily. A 10% reduction (dashed line) in maximum carbon maintains 94% of the maximum average proportion of ranges of rare species with the smallest 25% of global ranges.

Fig. 15. Trade-offs between carbon and poverty (a), rare species with the smallest 50% of global ranges (b), species richness (c), and rare species with the smallest 25% of global ranges (d) with 10%, 30%, and 50% of the total area of Kenya protected.

Fig. 16. Trade-offs between carbon, poverty, and rare species with the smallest 25% of global ranges. A 10% reduction (horizontal lattice) in maximum carbon includes 86% of the maximum number of people below the poverty line and maintains 88% of the maximum average proportion of ranges of rare species with the smallest 25% global of ranges. An interactive version of this figure is available at <https://dl.dropboxusercontent.com/u/60111098/index.html>.

Fig. 17. Optimal Zonation output that allows for the simultaneous inclusion of 90% of maximum carbon, 86% of maximum poverty, and 88% of the maximum average proportion of the ranges of rare species with the smallest 25% of global ranges in 30% of Kenya. The 30% of cells with the highest rank (shown in shades of red) are those that achieve these targets. In this Zonation run,

carbon has a weight of 51, poverty a weight of 58.6, and lower quartile species a collective weight of 58.65.

Fig. 1.

## Aboveground C

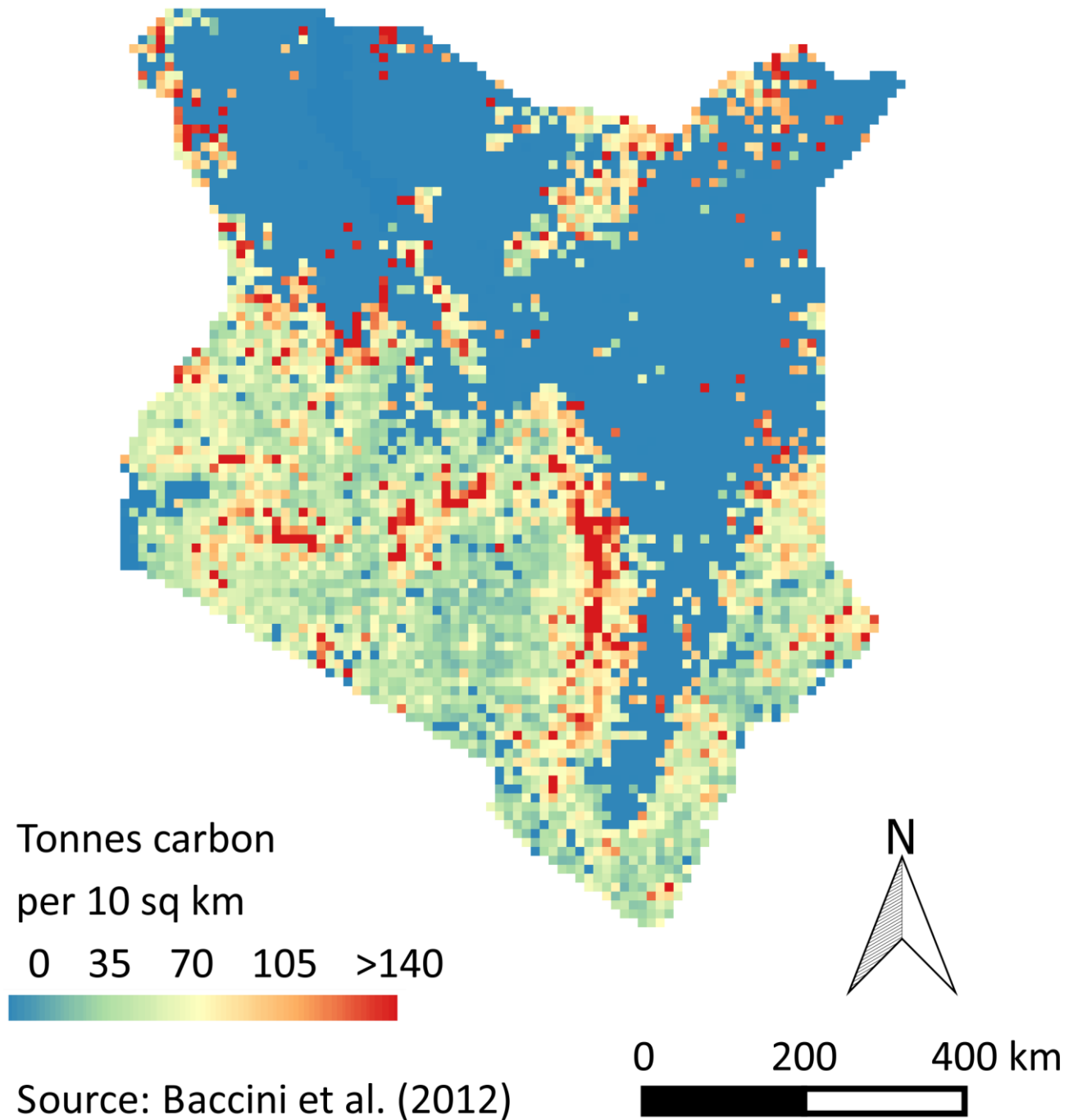


Fig. 2.

## Poverty density

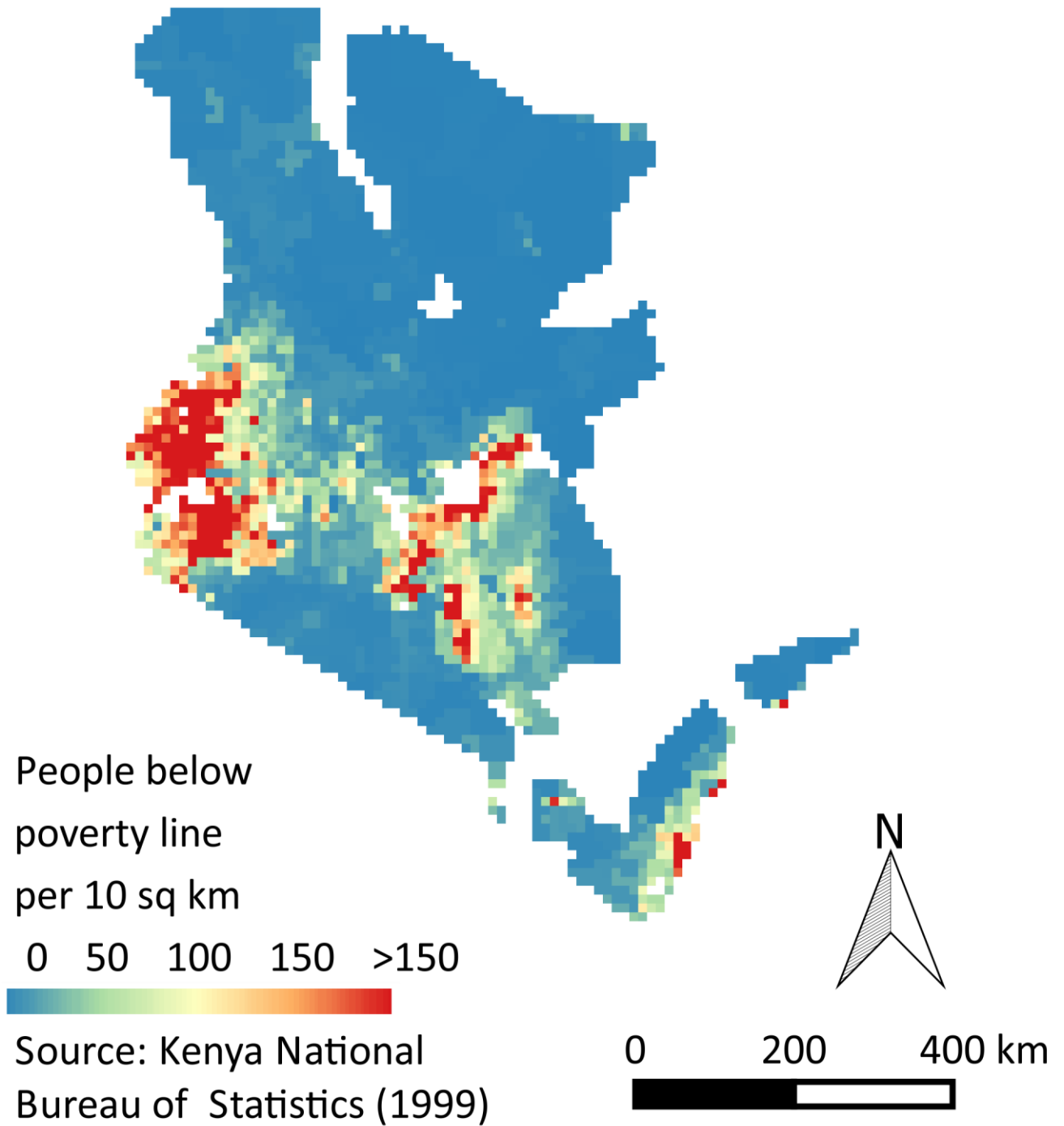


Fig. 3.

### Rare species (smallest 50% ranges)

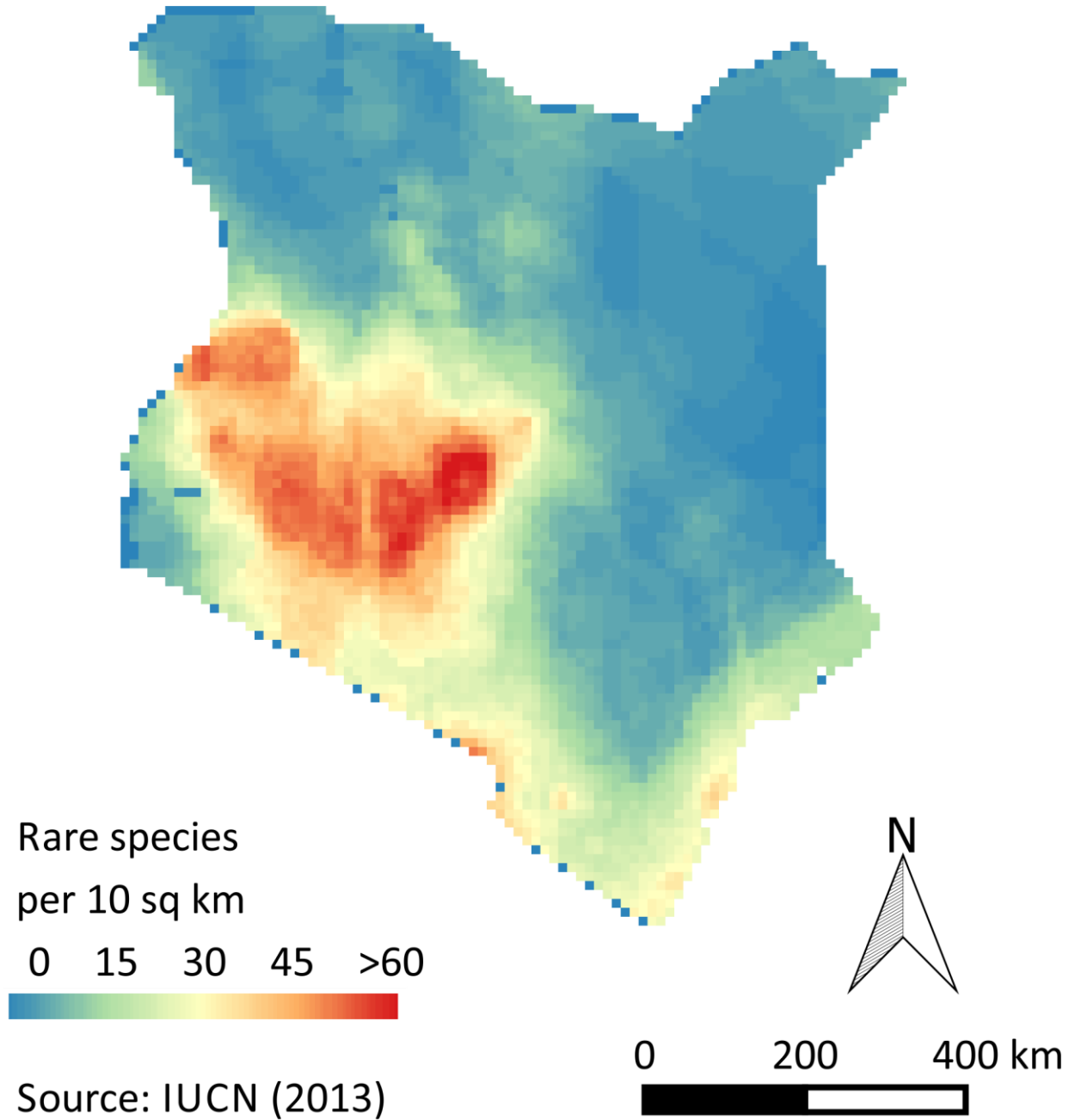


Fig. 4.

## Species richness

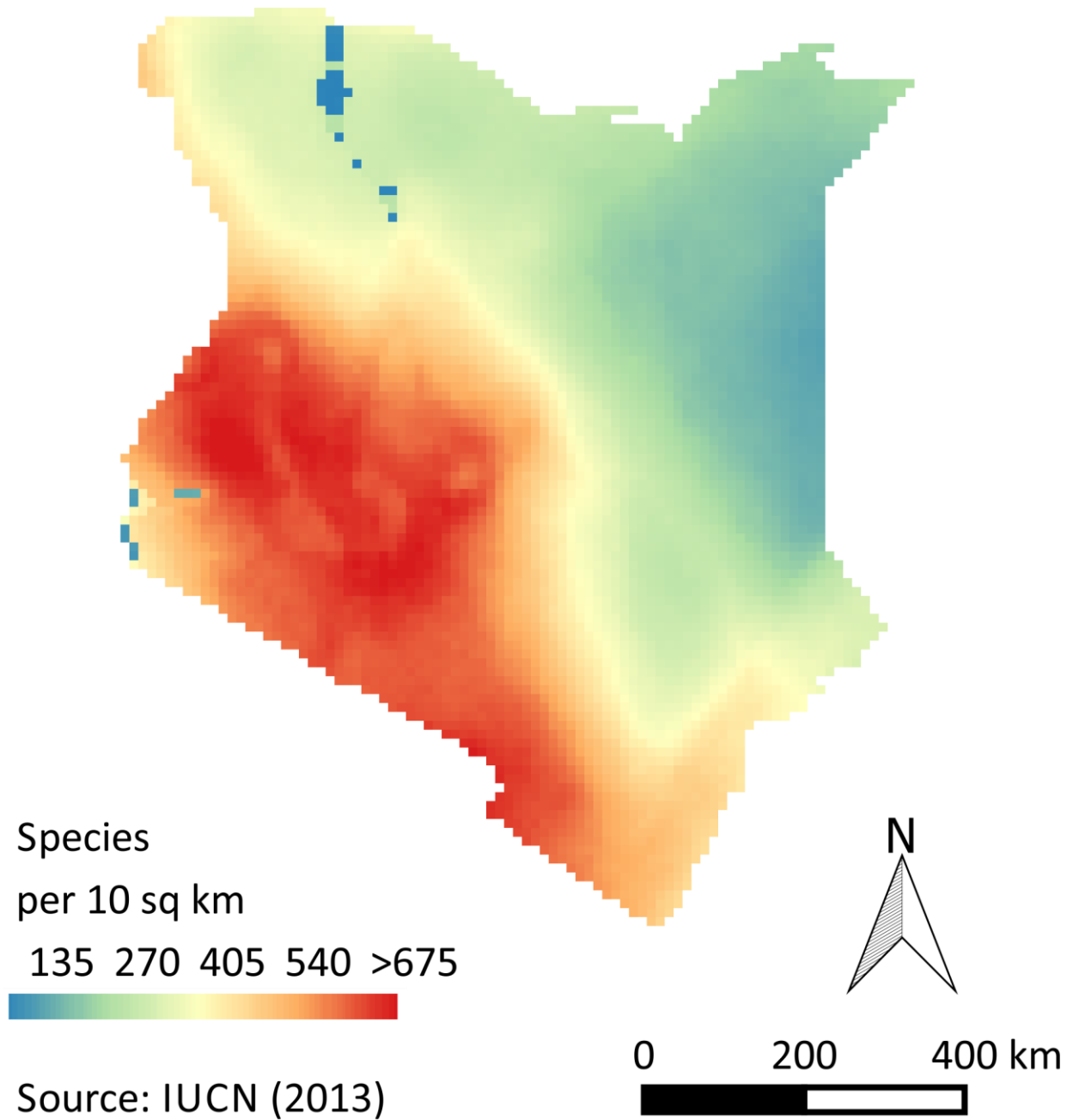


Fig. 5.

### Rare species (smallest 25% ranges)

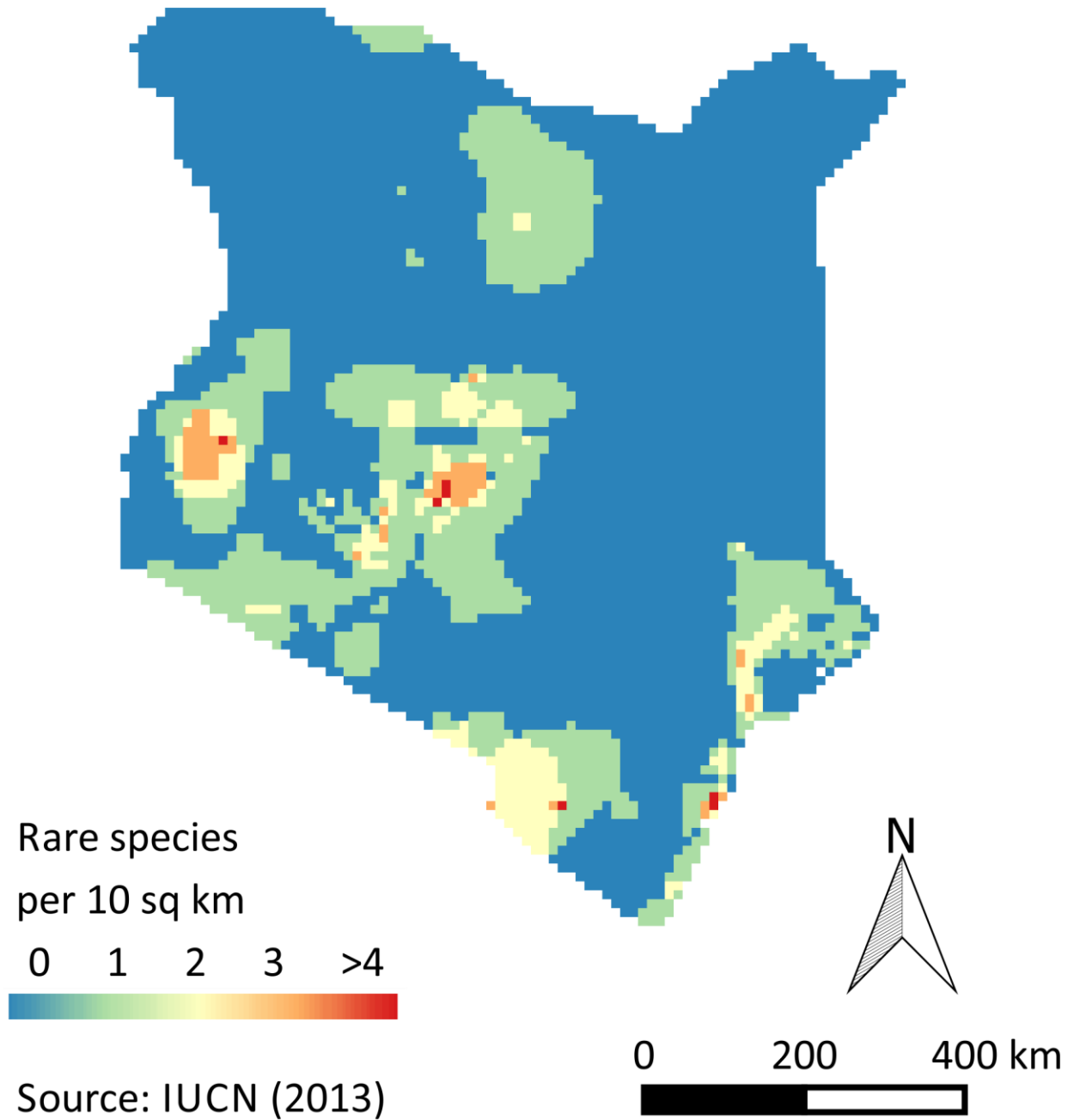


Fig. 6.

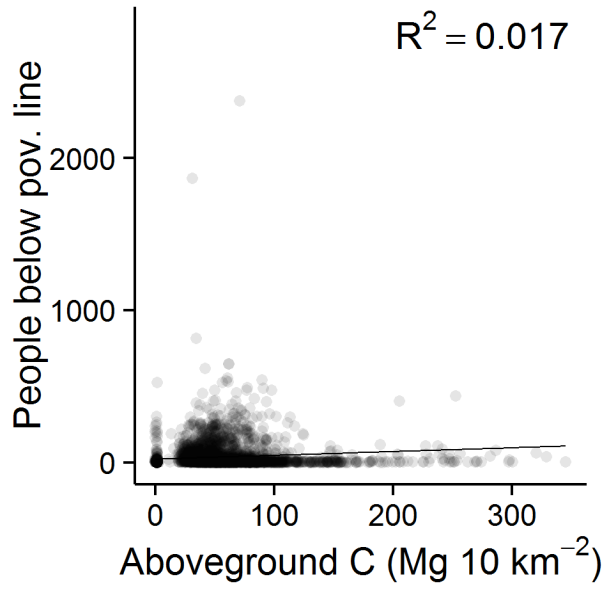


Fig. 7.

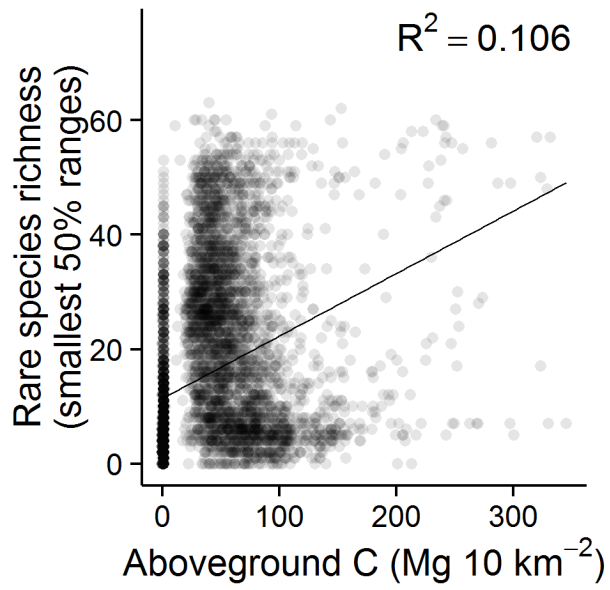


Fig. 8.

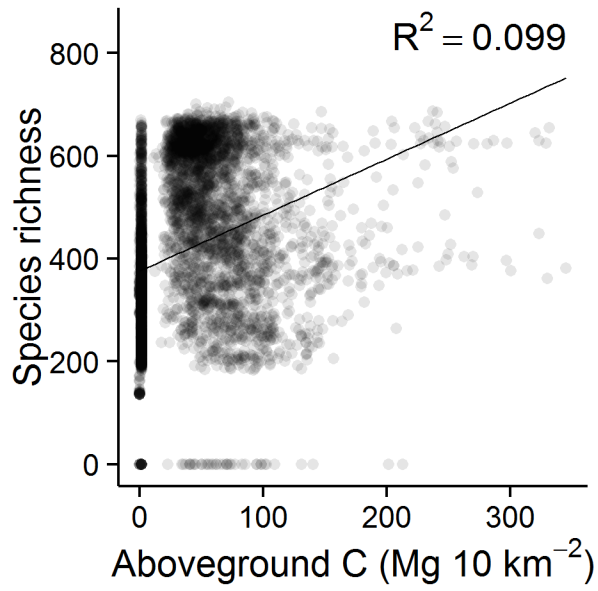


Fig. 9.

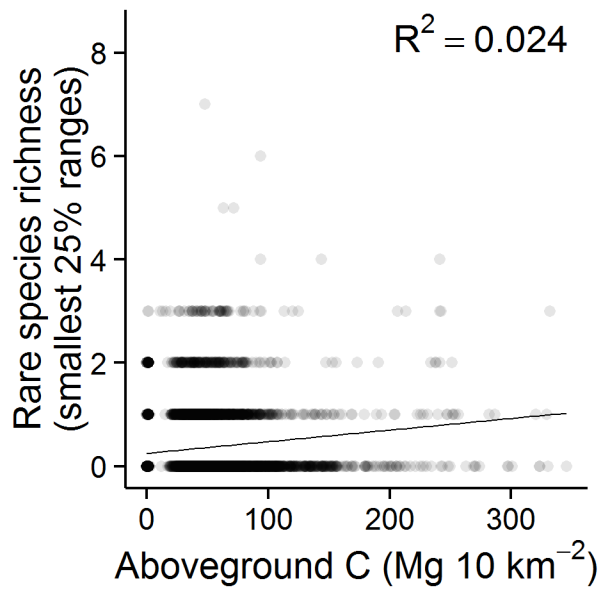


Fig. 10.

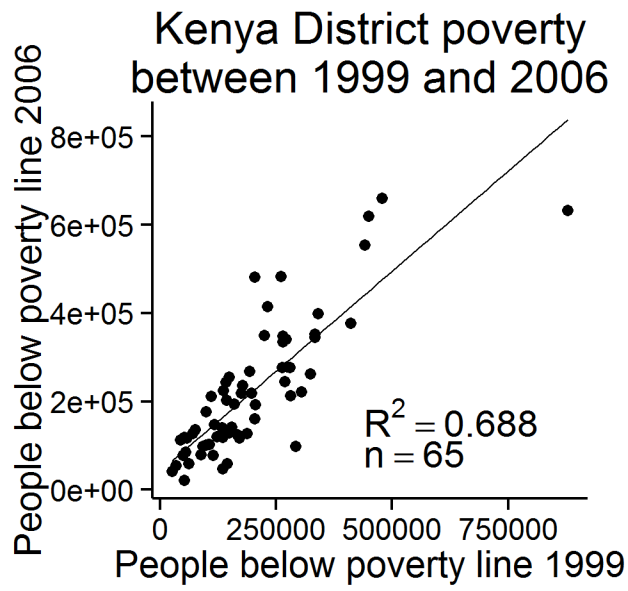


Fig. 11.

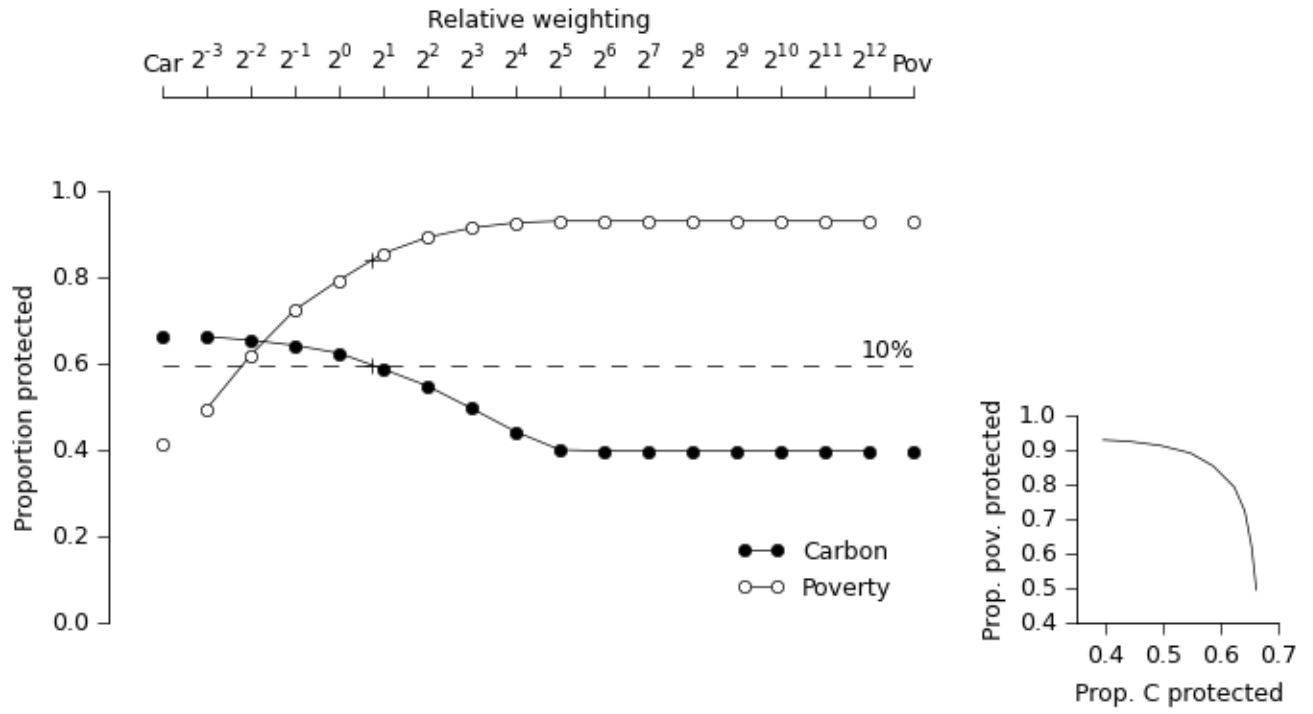


Fig. 12.

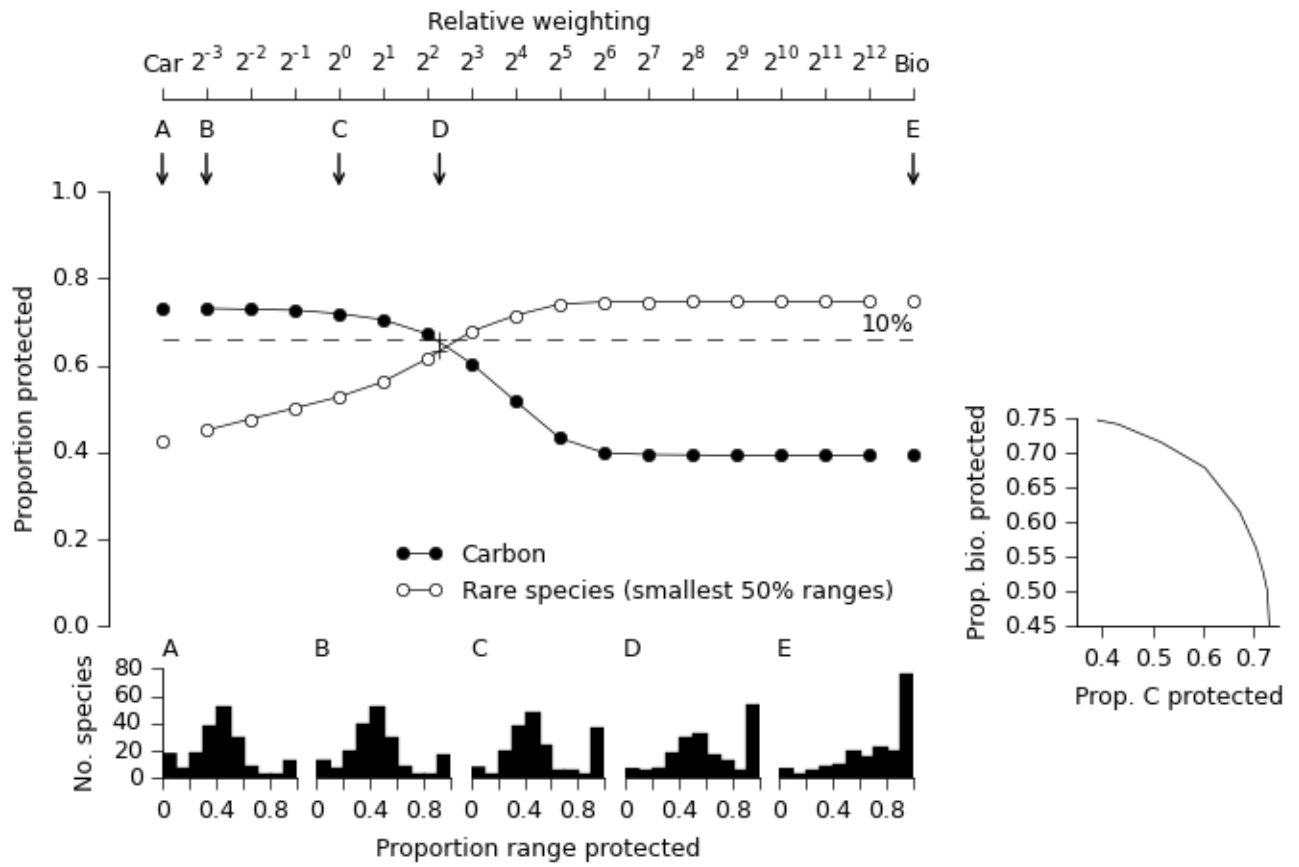


Fig. 13.

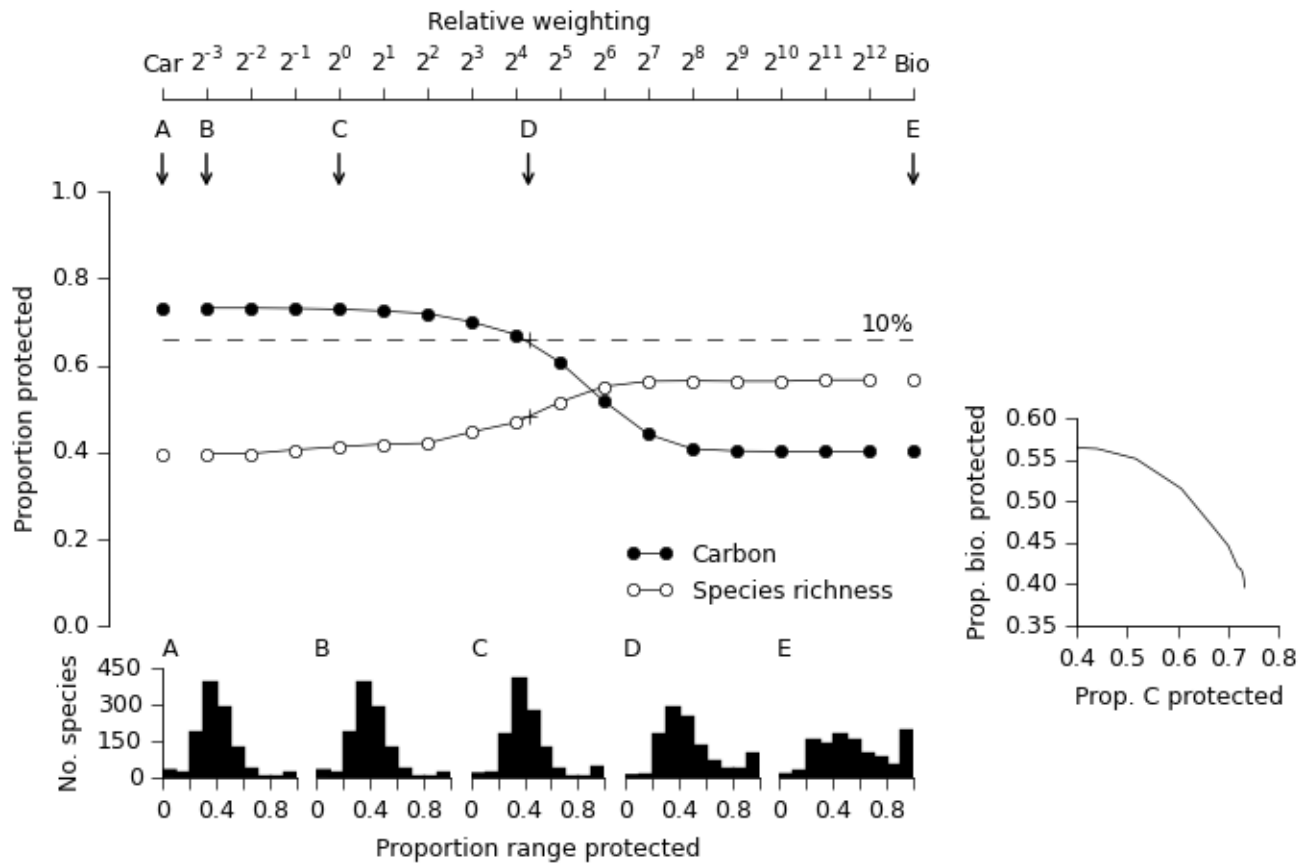


Fig. 14.

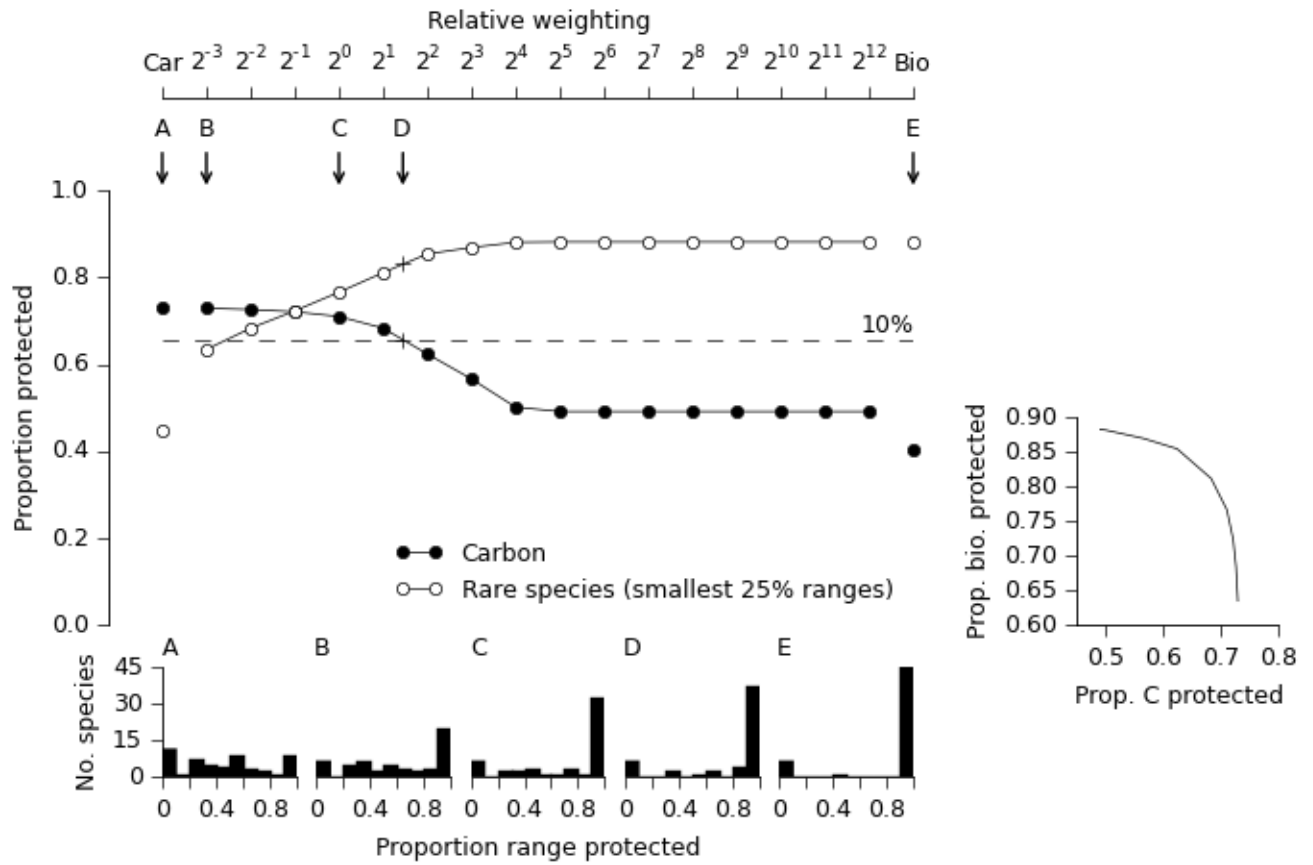


Fig. 15.

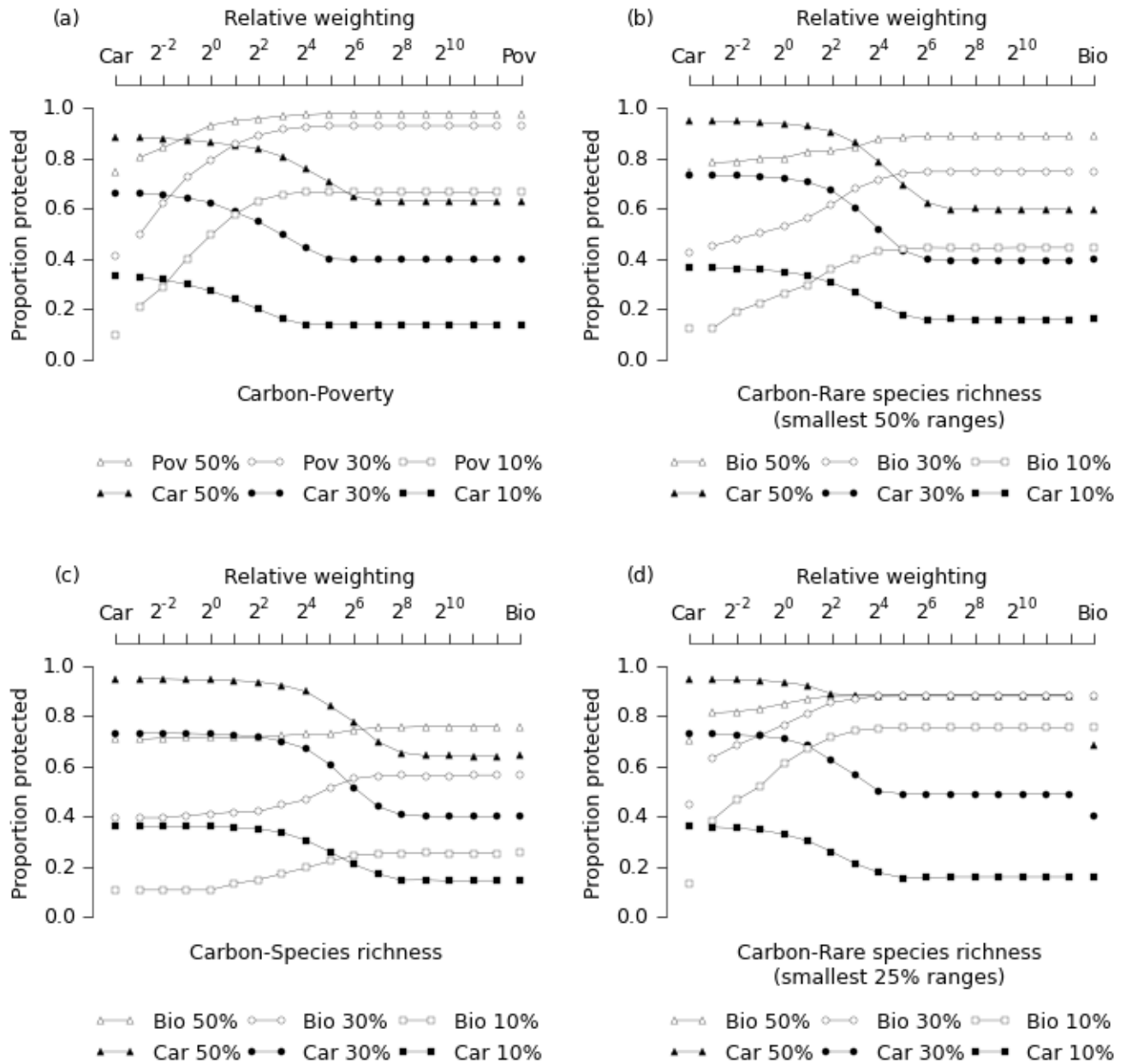


Fig. 16.

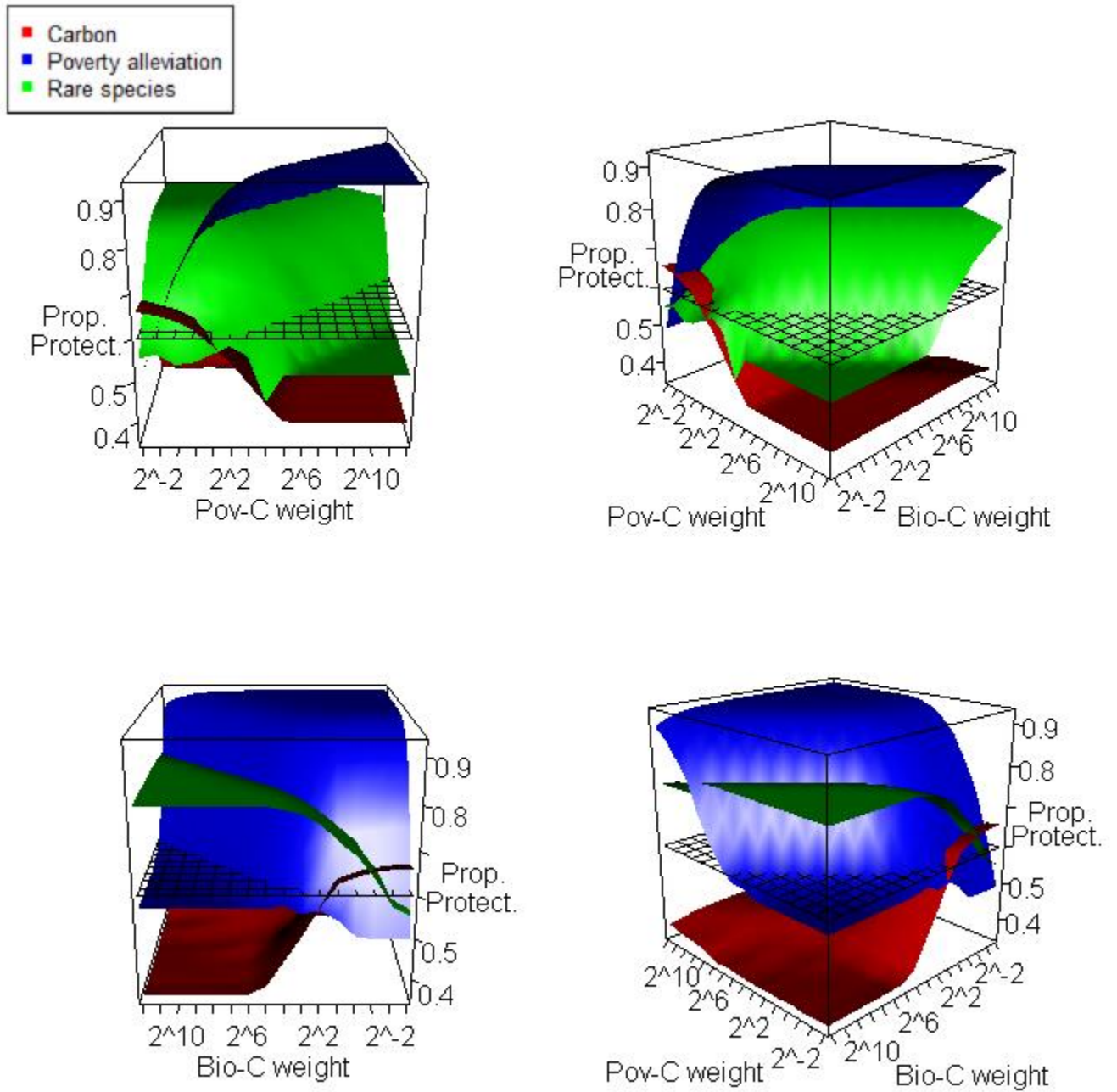
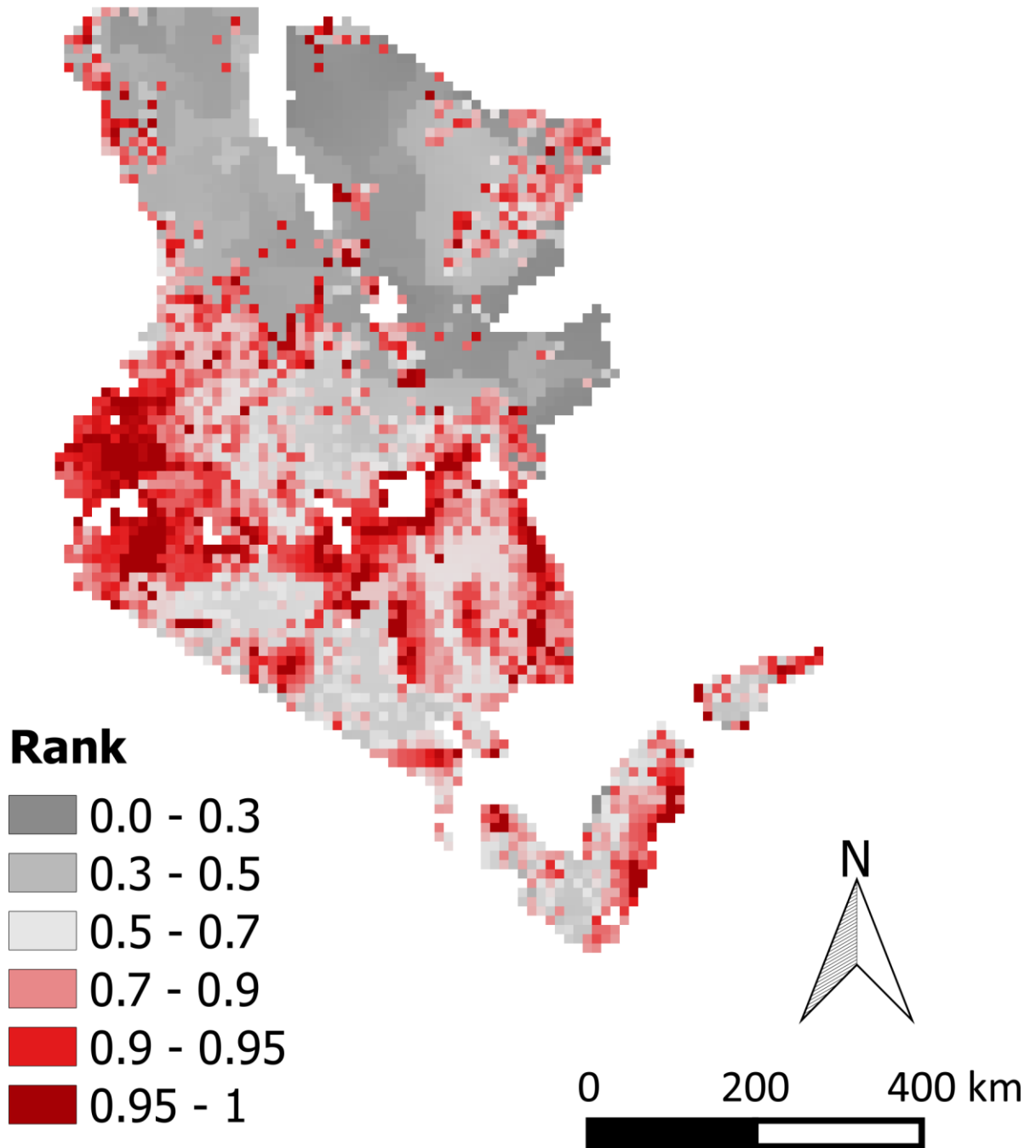


Fig. 17.

Optimal Zonation output  
(90% C, 86% poverty, 88% lower quartile species)



## TABLES

Table 1: Proportion of carbon and people below the poverty line represented under varying relative weightings between poverty and carbon.

Table 2: Proportion of carbon and rare species with the smallest 50% of global ranges represented under varying relative weightings between rare species and carbon.

Table 3: Proportion of carbon and species richness represented under varying relative weightings between species richness and carbon.

Table 4: Proportion of carbon and rare species with the smallest 25% of global ranges represented under varying relative weightings between rare species and carbon.

Table 1.

Weight	Carbon	Poverty	% C lost	% Pov represented
Car only	0.66	0.41	0%	44%
$2^{-3}$	0.66	0.49	0%	53%
$2^{-2}$	0.65	0.62	2%	67%
$2^{-1}$	0.64	0.72	3%	78%
$2^0$	0.62	0.79	6%	85%
$2^{0.735}$	0.59	0.84	10%	90%
$2^1$	0.59	0.85	12%	92%
$2^2$	0.55	0.89	17%	96%
$2^3$	0.49	0.91	25%	98%
$2^4$	0.44	0.93	33%	100%
$2^5$	0.40	0.93	40%	100%
$2^6$	0.40	0.93	40%	100%
$2^7$	0.40	0.93	40%	100%
$2^8$	0.40	0.93	40%	100%
$2^9$	0.40	0.93	40%	100%
$2^{10}$	0.40	0.93	40%	100%
$2^{11}$	0.40	0.93	40%	100%
$2^{12}$	0.40	0.93	40%	100%
Pov only	0.40	0.93	40%	100%

Table 2.

Weight	Carbon	Rare species (50%)	% C lost	% Rare (50%) conserved
Car only	0.73	0.42	0%	57%
2 <sup>-3</sup>	0.73	0.45	0%	60%
2 <sup>-2</sup>	0.73	0.48	0%	64%
2 <sup>-1</sup>	0.73	0.50	1%	67%
2 <sup>0</sup>	0.72	0.53	2%	70%
2 <sup>1</sup>	0.71	0.56	4%	75%
2 <sup>2</sup>	0.67	0.62	8%	82%
2 <sup>2.28</sup>	0.66	0.63	10%	84%
2 <sup>3</sup>	0.60	0.68	17%	91%
2 <sup>4</sup>	0.52	0.72	29%	96%
2 <sup>5</sup>	0.43	0.74	41%	99%
2 <sup>6</sup>	0.40	0.75	46%	100%
2 <sup>7</sup>	0.39	0.75	46%	100%
2 <sup>8</sup>	0.39	0.75	46%	100%
2 <sup>9</sup>	0.39	0.75	46%	100%
2 <sup>10</sup>	0.39	0.75	46%	100%
2 <sup>11</sup>	0.39	0.75	46%	100%
2 <sup>12</sup>	0.39	0.75	46%	100%
Bio only	0.40	0.75	46%	100%

Table 3.

Weight	Carbon	Species richness	% C lost	% Species conserved
Car only	0.73	0.40	0%	70%
2 <sup>-3</sup>	0.73	0.40	0%	70%
2 <sup>-2</sup>	0.73	0.40	0%	70%
2 <sup>-1</sup>	0.73	0.41	0%	72%
2 <sup>0</sup>	0.73	0.41	0%	73%
2 <sup>1</sup>	0.73	0.42	1%	74%
2 <sup>2</sup>	0.72	0.42	2%	74%
2 <sup>3</sup>	0.70	0.45	4%	79%
2 <sup>4</sup>	0.67	0.47	8%	83%
2 <sup>4.29</sup>	0.66	0.48	10%	85%
2 <sup>5</sup>	0.61	0.52	17%	91%
2 <sup>6</sup>	0.52	0.55	29%	97%
2 <sup>7</sup>	0.44	0.56	40%	100%
2 <sup>8</sup>	0.41	0.56	44%	100%
2 <sup>9</sup>	0.40	0.56	45%	100%
2 <sup>10</sup>	0.40	0.56	45%	100%
2 <sup>11</sup>	0.40	0.57	45%	100%
2 <sup>12</sup>	0.40	0.57	45%	100%
Bio only	0.40	0.57	45%	100%

Table 4.

Weight	Carbon	Rare species (25%)	% C lost	% Rare (25%) conserved
Car only	0.73	0.45	0%	51%
2 <sup>-3</sup>	0.73	0.63	0%	72%
2 <sup>-2</sup>	0.73	0.68	1%	77%
2 <sup>-1</sup>	0.72	0.72	1%	82%
2 <sup>0</sup>	0.71	0.77	3%	87%
2 <sup>1</sup>	0.68	0.81	7%	92%
2 <sup>1.45</sup>	0.66	0.83	10%	95%
2 <sup>2</sup>	0.62	0.85	15%	97%
2 <sup>3</sup>	0.57	0.87	23%	98%
2 <sup>4</sup>	0.50	0.88	32%	100%
2 <sup>5</sup>	0.49	0.88	33%	100%
2 <sup>6</sup>	0.49	0.88	33%	100%
2 <sup>7</sup>	0.49	0.88	33%	100%
2 <sup>8</sup>	0.49	0.88	33%	100%
2 <sup>9</sup>	0.49	0.88	33%	100%
2 <sup>10</sup>	0.49	0.88	33%	100%
2 <sup>11</sup>	0.49	0.88	33%	100%
2 <sup>12</sup>	0.49	0.88	33%	100%
Bio only	0.40	0.88	45%	100%