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TABLE OF CONTENTS

1. EXECUTIVE SUMMARY **3**

2. BACKGROUND **4**

3. CARBON DATA **5**

4. NEW PAs AND WILDFIRE LOSSES **7**

- 4.1. Technical approach 7
  - 4.1.1. New PA scenarios 7
  - 4.1.2. Vulnerability of carbon to wildfire 10
  - 4.1.3. 'Business as usual' natural areas loss 12
- 4.2. New PAs and wildfire loss results 14

5. CASE STUDY: RESTORATION OF FIRE-PRONE WESTERN CONIFER FORESTS **19**

- 5.1 Technical approach 20
- 5.2 Fire restoration results 20

6. CASE STUDY: REFORESTATION ACROSS CONUS **21**

- 6.1 Technical approach 22
- 6.2 Reforestation results 23

7. CARBON CONCLUSIONS & CONSIDERATIONS **23**

8. UNCERTAINTIES AND LIMITATIONS **25**

ACKNOWLEDGEMENTS **26**

REFERENCES **27**

1. EXECUTIVE SUMMARY

Leading scientists have called for conserving and restoring 30% of the earth's lands and oceans by 2030, a goal that has now been formalized for the U.S. by the Biden administration. Achieving this level of conservation is likely to enhance critical ecosystem services including carbon storage and sequestration. Indeed, maintaining natural land cover is one of the most important natural climate solutions we have.

We quantified the amount of carbon that could be stored and protected from loss by achieving "30x30", considering multiple scenarios for delineating additional lands for formal protection or conservation (for brevity, referred to as new protected areas or "PAs") that balance the amount of carbon protected with other conservation goals (e.g., conserving at-risk species and ecosystems). Given that carbon in PAs is not invulnerable to loss from disturbance, we accounted for the potential carbon losses due to wildfire in the Western U.S in each of our new PA scenarios. We additionally estimated the potential for each scenario to prevent or forestall the carbon loss associated with future natural areas loss, asking how much loss could be avoided under each new PA scenario. Because passive land protection is crucial but insufficient to optimize carbon benefits, we also explored two restoration pathways: 1) fuel treatments (thinning and prescribed fire) in priority fire-prone forests of the West to reduce potential carbon losses to fire and 2) reforesting priority areas that historically supported tree cover to enhance sequestration.

Key findings:

- Meeting 30x30 goals could lead to two to four times as much carbon protected from loss by 2030 as would be the case if no new PAs were added.
- With no new PAs and the continued conversion of 1.53 million acres of natural area annually, up to 1,200 million metric tons of carbon dioxide equivalent (MmtCO2e) could be lost by 2030. By comparison, the U.S. emits 4,850 MmtCO2e through fossil fuel combustion each year.
- New PA scenarios, after accounting for wildfire losses, may yield carbon storage benefits of between 65,300 and 110,400 MmtCO2e, and safeguard 33-67% of the carbon that would otherwise be lost to natural area conversion.
- With no restoration in the fire prone forests that have been identified by the U.S. Forest Service as targets for restoration, a total of 1,300 MmtCO_2e may be lost.
- Losses of up to 350 MmtCO_2e could be avoided by restoring 10% of fire-prone target areas, and carbon losses of up to 900 MmtCO_2e could be avoided by restoring 30% of target areas.
- Planting trees in 10% of the 114.6-M private acres identified as suitable opportunities for reforestation may sequester 150 MmtCO_2e by 2030 and pursuing a more ambitious 30% reforestation target may sequester 550 MmtCO_2e by 2030.

Table 1. Summary of key findings. All values are in MmtCO_2e

Maximum carbon protected by 2030 - New and existing PAs in CONUS	Maximum carbon protected by 2030 - New and existing PAs in CONUS and Alaska	Maximum carbon saved from loss - Storage (10 yr)	Maximum carbon saved from loss - Sequestration (10 yr)	Carbon losses avoided through wildfire restoration	Sequestration through reforestation on private lands
126,900	136,800	700	110	350-900	150-550

2. BACKGROUND

To mitigate the worst impacts of climate change and to confront the rapid loss of nature and biodiversity, leading scientists have called for conserving or formally protecting 30% of the earth's lands and oceans by 2030, e.g., through the establishment of new reserves, wilderness areas, and conservation easements. Indeed, this target was recently formalized as a national priority: President Biden's Executive Order 14008 *Tackling the Climate Crisis at Home and Abroad* delivers a clear directive to sequester carbon and support biodiversity, in part by conserving "30x30". This mission reflects growing scientific evidence that pursuing conservation at this scale will not only slow biodiversity loss but is essential to mitigating climate change (Strassburg et al. 2010; Soto-Navarro et al. 2020) given the tremendous potential of natural land cover to keep carbon out of the atmosphere through both storage and sequestration (Griscom et al. 2017). While formally protecting landscapes could offer high yields of carbon to address the outlined climate crisis and slow biodiversity loss, President Biden's Executive Order specifically acknowledges the need for *collaborative conservation* which supports the many uses of our nation's lands, and recognizes that a combination of management strategies, from active forest restoration to new land protections, can sequester carbon, support biodiversity, and meet "30x30" goals.

In 2020, the Center for American Progress (CAP) released the results of an analysis estimating the greenhouse gas emissions that could be avoided if the U.S. successfully pursued a 30x30 goal (CAP 2020). This report and the subsequent response demonstrated an appetite for a science-based analysis on the potential climate benefits of achieving 30x30. As the conservation community grapples with what to conserve and the climate community charts the policy course for fighting climate change, a robust analysis of the potential carbon benefits of conservation strategies will contribute to a more precise understanding of how new land conservation actions could be strategically used as a tool for addressing the climate crisis.

While formally protecting or otherwise conserving landscapes with high carbon storage potential will help to mitigate emissions associated with existing rates of natural area loss (e.g., conversion of natural vegetation cover to urban/suburban development or agriculture), protection does not guarantee that carbon is invulnerable to future losses, particularly given increases in high severity wildfire throughout the western United States (Parks and Abatzoglou 2020). Thus, protecting existing carbon stocks *as well as* safeguarding against carbon loss (e.g., through ecological restoration aimed at restoring low-severity, ecologically functional wildfire in fire-prone forest landscapes; Liang et al. 2018, McCauley et al. 2019) will be critical to keeping as much carbon out of the atmosphere as possible. Similarly, carbon sequestration may be augmented through strategic tree planting in historically forested areas that do not currently have robust tree cover (Cook-Patton et al. 2020; Domke et al. 2020), which may enhance habitat conditions as well. These types of ecological restoration strategies represent natural climate solutions that will enhance the carbon benefits associated with the 30x30 framework, as well as yield biodiversity benefits.

The analyses presented here examine two key pathways for maintaining and enhancing the capacity of natural areas to mitigate climate change—(1) via new conservation actions that safeguard natural areas from conversion (e.g., to development or agriculture) and (2) via ecological restoration. Here, we define natural areas as both private and public lands that have largely intact, natural vegetation cover and are subject to little or no human modification (i.e., not developed or used for agricultural purposes). We first quantify the amount of carbon that could be protected from loss by increasing the U.S. protected areas estate to 30% of U.S. land area by 2030, considering multiple prioritization scenarios for achieving this objective that balance the amount of carbon on protected lands with other conservation goals (e.g., conserving at-risk species and ecosystems). We then provide an exploratory analysis of the amount of carbon within these new protections that is potentially vulnerable to wildfire over the next decade (i.e., between the beginning of 2021 and the end of 2030) if no restoration efforts are taken. Given substantial uncertainty around projections of both where wildfires will occur and how much biomass (and thus carbon) may be lost (Littell et al. 2018; Coop et al. 2020), our estimates of carbon losses due to wildfire should be treated as preliminary. Nonetheless, these estimates highlight a key consideration for future conservation actions: the current trajectory of our nation's forests in terms of wildfire-driven loss. Finally, we explore the potential carbon benefits of large-scale restoration through two case studies. We first examine the amount of carbon we could potentially retain through large scale restoration aimed at reducing fire fuels under different restoration targets. Here we focus on federal lands, including the US Forest Service's Collaborative Forest Landscape Restoration Program (CFLRP) and Healthy Forest Restoration Act lands (Schultz et al., 2012), where National Environmental Policy Act (NEPA) documentation specifically points to fuel treatments of forest thinning or prescribed burning as key restoration actions. We then further refine the analysis region to those areas that have been identified as at risk of extreme fire activity. For the second case study, we examine the amount of carbon that could be sequestered over the next several decades (i.e., by 2030 and beyond) through reforestation across the U.S., focusing on areas identified in previous analyses (i.e., Reforestation Hub; Cook-Patton et al. 2020) as key reforestation opportunities.

3. CARBON DATA

To estimate the carbon benefits of new conservation and restoration actions, we relied on global ecosystem carbon datasets derived at a 300-m resolution (Goldstein et al. 2020; Noon et al. *In press*). Specifically, we relied on three datasets:

1. **Total Manageable Carbon (aboveground and belowground carbon storage in "manageable" ecosystems in 2018)**— This dataset estimates contemporary carbon storage in ecosystems where carbon storage may be affected by direct human activities. This manageability criterion therefore excludes rock and ice, tundra, deserts, and xeric shrublands, as well as other aquatic systems. Although carbon storage in these excluded systems may be indirectly affected over time by anthropogenic impacts—including climate change itself—*direct* human actions are unlikely to affect that carbon. For example, rock and ice are unlikely to face the development pressures (and therefore carbon loss) of grasslands near a US urban area; the carbon loss from thawing permafrost in tundra cannot be directly prevented in the same way that creating new forest reserves may halt carbon loss due to intensive harvest. Thus, this manageability criterion ensures that this dataset—and in turn our analyses—reflects only those ecosystems in which humans have direct leverage over carbon storage and sequestration potential. The dataset also excludes heavily human modified areas (urban landscapes and cropland). Aboveground and

belowground biomass values were derived from a global dataset that spans terrestrial ecosystems (Spawn et al. 2020) and supplemented with other estimates for particular coastal systems (e.g., mangrove; Simard et al. 2019). Similarly, soil organic carbon (SOC) values to 30-cm depth for terrestrial systems were derived from the global SoilGrids 2.0 database (Poggio et al. 2021) and supplemented with other estimates (e.g., for mangroves; Sanderman et al. 2018).

2. **Vulnerable Carbon (carbon that is vulnerable to being lost in the case of ecosystem conversion).** This dataset represents the magnitude of carbon likely to be lost in a typical conversion event (e.g., deforestation, stand-replacing wildfire, or grassland conversion to agriculture). In developing this layer, Noon et al. (*In press*) assumed all aboveground and belowground biomass would be lost, whereas they assigned each ecosystem a fraction of SOC lost based on published rates and existing meta-analyses.
3. **Irrecoverable Carbon (vulnerable carbon that is not recoverable within 30 years in the case of ecosystem conversion)**. The authors quantified how much carbon could be recovered—and the inverse, could *not* be recovered—within 30 years of a conversion event for a given ecosystem. The 30-year timeframe was used because mid-century (2050) is a target for net-zero emissions and, at the time of the study, was 30 years in the future. Recovery could entail natural regeneration or active restoration. The authors based recovery rates (annual, and 30-year) on average sequestration and accumulation rates for biomass and SOC in each ecosystem during the first 30 years following disturbance (Noon et al. *In press*; Goldstein et al. 2020). For forests, biomass sequestration rates were derived from a global database of empirical measurements (Cook-Patton et al. 2020). For non-forests, biomass sequestration rates were based on published rates in the literature, including a meta-analysis of biomass turnover times (Gill and Jackson 2000). The accumulation of SOC in ecosystems with vulnerable SOC was based on published results from restoration.

In the analyses presented below, we based our estimates of carbon storage on the total manageable carbon layer. We also derived an estimate of the amount of carbon potentially sequestered by 2030 using the following approach: We subtracted irrecoverable carbon from vulnerable carbon for each pixel across the study area, yielding a layer of accumulated carbon that could be recovered over 30 years post-conversion. Dividing this layer by 30 in turn yielded a layer of annual sequestration rates for each pixel. (In essence, this is the reverse of Noon et al.'s [*In press*] methodology: we backed-out of their final data layers to arrive at initial sequestration rates, which the authors agreed was an appropriate approach [A. Goldstein, pers. comm].) We then multiplied these sequestration rates by 10 to derive an estimate of the amount of carbon that could be sequestered over the next decade (i.e., between the beginning of 2021 and the end of 2030).

It is important to note that (1) these sequestration rates are based on coarse, ecosystem-level averages (rather than a quantification of the actual amount of sequestration at a given pixel, Noon et al. [*In press*]) and (2) that these average sequestration rates are most applicable to early successional stages for the ecosystem in question (i.e., the first 30 years following a disturbance; Noon et al. [*In press*). In many systems, sequestration rates decline as the system matures past the early successional stage (Curtis and Gough 2018; Pugh et al. 2021). Inevitably, many of the landscapes we consider in this analysis are beyond that stage such that the averaged sequestration rates we apply are somewhat inflated. For this reason, we present values of carbon storage (i.e., total manageable carbon) and sequestration separately when discussing the results of the new PA scenarios described below.

We elected to use the Noon et al. (*In press*) and Goldstein et al. (2020) datasets given their spatial coverage and the fact that they afforded both storage and sequestration rates, which enabled us to avoid harmonizing disparate storage and sequestration datasets. Still, like all spatially extensive datasets that synthesize diverse source data, these datasets have their limitations and rely on some simplifying assumptions. For example, variability in ecosystem sequestration rates (e.g., by forest stand age, as noted above) is obscured; and carbon loss associated with conversions is imprecise, especially for SOC. There is also uncertainty associated with the pixel-level carbon estimates themselves, given that these estimates were derived from remote sensing products. These limitations and caveats are described in the Supporting Information of Goldstein et al. (2020) and Noon et al. (*In press*). Although these peer-reviewed datasets are among the best available for the purposes of the large-scale analyses conducted here, our estimates of carbon protected by 2030 should be considered approximations.

4. NEW PAs AND WILDFIRE LOSSES

This analysis explores how much carbon could be protected from loss by achieving the goal of conserving 30% of land area in the U.S. by 2030 (e.g., through new reserves, wilderness areas, and conservation easements; here after “new PAs”) while accounting for potential losses of carbon to wildfire in the western U.S. We also examine the additionality of new PAs in terms of their ability to prevent or forestall the carbon impacts of business-as-usual natural areas loss, asking how much natural areas loss could be avoided with new PAs relative to a scenario in which no new PAs are added.

According to the USGS GAP analysis (USGS GAP 2021), 315.8 million acres of land in the U.S. are currently protected (i.e., under GAP 1 or 2 protection status, see below), amounting to 13% of the total area of the U.S. (2.4-billion acres, including all 50 states). Thus, to reach the 30x30 goal, an additional 17% of U.S. land must be protected or conserved, amounting to 414.2 million acres. This acreage target was used in all new PA scenarios described below.

4.1. Technical approach

4.1.1. New PA scenarios

We examined five prioritization scenarios for allocating new PAs across the U.S. These scenarios (described in detail below) either prioritize the maximum amount of carbon that could be stored and sequestered, or balance carbon with other conservation objectives. For each scenario, we selected locations (i.e., pixels in a gridded landscape) with the highest values for a given conservation objective (e.g., carbon, species richness, etc.) until the target acreage of new PAs was achieved. We then summed the amount of carbon expected to be stored in (or sequestered by) these pixels by 2030. As a sixth scenario, we computed the amount of carbon stored or sequestered by randomly allocating the target acreage across all available lands, simulating new PAs that were not based on any consistent conservation strategy. For the six scenarios, we considered both public and private lands in the U.S. to be available for new PAs, as long as they were not already under GAP 1 or 2 protection status, as determined by the Protected Areas Database of the United States (PAD-US version 2.1; USGS 2020). GAP 1 and GAP 2 areas are both permanently protected from conversion and include protected public lands as well as voluntary conservation easements on private lands compiled by the National Conservation Easements Database (National Conservation Easements Database, 2017). GAP 1 areas are managed to remain in a natural state (e.g., with no interference of natural disturbance events), whereas a natural state is primarily promoted in GAP 2 areas, but some management practices are allowed (e.g., prevention or suppression of natural disturbance events such as wildfires; USGS GAP 2021).

As described above, we based carbon values on data layers developed by Noon et al. (*In press*; see also Goldstein et al. 2020), which estimate carbon storage (total manageable carbon) and predicted sequestration at a global scale. For the six scenarios, we calculated the amount of carbon stored or sequestered by 2030 at each pixel and summed pixel-level values for each scenario to estimate the total amount of carbon potentially protected from loss. As noted above, the carbon datasets used here excluded developed areas (including urbanized landscapes and cropland), as well as “unmanageable” ecosystems (e.g., bare rock and ice). Accordingly, these land cover types were also excluded from our set of available lands for new PAs.

For each scenario, we also estimated the amount of carbon in new PAs that could potentially be lost to wildfire in areas of the western United States with a ‘high’ or ‘very high’ Wildfire Hazard Potential (WHP; Dillon et al., 2020). To do so, we calculated the cumulative probability of a fire occurring over the next decade (2021 through 2030) at the subset of scenario locations that are at high or very high risk of extreme fire behavior and therefore high carbon loss. This projection of potential carbon loss was then deducted from the total amount of carbon protected in each scenario (see below for further details).

All six scenarios and wildfire deductions were modeled for the conterminous U.S. (CONUS, i.e., the lower 48 states). We also ran a subset of the scenarios for the conterminous U.S. and Alaska (CONUS + AK). However, due to data limitations in Alaska, we could not run all scenarios for this state, nor could we estimate the amount of carbon at risk from wildfire. For all new PA scenarios, we used the same acreage target (i.e., 414 million acres) for CONUS and CONUS + AK analyses. Finally, for comparison to the above scenarios, we calculated the amount of carbon stored and sequestered within existing PAs (i.e., GAP 1 and 2 status lands) in both CONUS and CONUS + AK.

For all scenarios described below, we calculated the amount of new carbon that would be protected from loss by adding approximately 414 million acres to the total acreage of protected lands in the U.S. This was achieved by thresholding the values of each data layer described below such that only the highest value pixels were retained, calculating the total area of these ”top pixels,” and then iteratively adjusting the threshold value until the cumulative area of top pixels was approximately equal to 414-million acres. We allowed an error in the acreage target of ± 2-million acres (i.e., 0.5%) as, for some data sets, we were unable to determine a threshold value that allowed us to achieve the exact acreage target. We then summed the amount of total carbon storage by 2030 across all locations underlying the top pixels. All data sets described above were reprojected to a spatial resolution of 300 m (i.e., the original resolution of the carbon datasets) to facilitate calculations.

- ***Prioritize Maximum Carbon.*** This scenario selects the pixels with the greatest total carbon storage in 2030, using the total manageable carbon layer itself as the layer for which high value pixels were identified.
- ***Prioritize Vulnerable Carbon.*** This scenario selects the pixels with the highest values of vulnerable carbon, as described in the *Carbon Data* section above.
- ***Prioritize Most Intact Areas.*** This scenario selects pixels with the highest values of ecological intactness, defined as the degree to which a location remains in a natural (i.e., unmodified) state. Ecological intactness is estimated as 1 - *L*, where *L* is the degree of human modification, ranging from 0 to 1. We drew on existing spatial estimates of human land use intensity previously developed by Conservation Science Partners (CSP 2021, see also Theobald 2013), which incorporated the intensity and extent of multiple human activities, including residential and commercial development, agriculture, energy production and mining, transportation, and forestry (CSP 2019, 2021). Due to differences in dataset availability, estimates of intactness were developed separately for CONUS and Alaska (though both layers share a common 0-1 scale), meaning that the intactness value at a given pixel is relative to other locations within the same geographic extent. For the analysis conducted across the continental U.S. (i.e., CONUS + AK), the CONUS and Alaska intactness layers were combined and pixels were allocated simultaneously across both layers, capturing areas of relatively high intactness across both geographic regions.
- ***Prioritize At Risk Ecoregions.*** This scenario selects the pixels that fall within the most at-risk ecoregions. We identified pixels within at-risk ecoregions based on the Global Deal for Nature analysis of Dinerstein et al (2020). Briefly, these authors categorized the world's terrestrial ecoregions (*n* = 846) based on how much intact habitat remains and the degree of protection within each ecoregion. Our analysis focused on the two most at-risk ecoregion categories: (1) "Imperiled" ecoregions, i.e., those with less than 20% of natural habitat remaining—whether protected or not, and (2) ecoregions that could recover with restoration, i.e., those with 20-50% of natural habitat remaining in protected and unprotected lands. We first selected all pixels within category 1 and then selected sufficient pixels within category 2 to achieve our 414-million acre target, prioritizing pixels in category 2 with the highest values of total manageable carbon.
- ***Prioritize Richness of Imperiled Species.*** This scenario selects the pixels that have the highest richness of imperiled species, based on a data layer developed by NatureServe (2020), which uses habitat suitability models for over 2,200 species in the U.S. that are critically imperiled, imperiled, or listed as endangered or threatened under the Endangered Species Act. These include vertebrates, freshwater invertebrates, pollinators, and vascular plants. High richness values indicate areas where more imperiled species are likely to occur. This data layer is only available for CONUS, and so the imperiled species richness scenario was not analyzed for CONUS + AK
- ***Random Allocation.*** We randomly selected available locations across the focal extent (i.e., CONUS or CONUS + AK) until the target acreage of new PAs was reached and summed the total carbon by 2030 at these random locations. This simulation was run 10 times, and we calculated the mean and standard deviation of carbon values across all iterations. For computational efficiency, we set a minimum block size for random PAs of 24,710 acres (just over 1,000 300-m pixels). However, we tested a range of minimum block sizes, with negligible effects on the

resulting carbon totals. This randomized approach to identifying acres for possible conservation action reflects, in essence, the converse of a strategic, coordinated prioritization approach.

Finally, as noted above, we computed the total carbon that would be stored by 2030 within existing PAs (i.e., the 13% of U.S. lands already protected). This involved a simple summation of the total carbon values of all pixels within existing GAP 1 and 2 protected areas across CONUS and AK. The carbon stored and sequestered in each of the above new PA scenarios is additive to the carbon in these existing PAs.

4.1.2. Vulnerability of carbon to wildfire

In recent decades, western forests have experienced a well-documented increase in 1) the number of wildfires (Dennison et al., 2014, Balch et al. 2017), 2) fire-season length (Westerling 2016; Holden et al. 2018; Goss et al. 2020), 3) total area burned (Abatzoglou and Williams 2016; Mueller et al., 2020), and 4) area burned at high severity (Littell et al., 2009, Singleton et al. 2019; Parks and Abatzoglou 2020). These trends are largely due to anthropogenic factors: the cessation of Indigenous burning and a century of fire suppression, grazing, and logging have effectively removed ecologically functional fire from many ecosystems, resulting in substantial increases in stand density and fuel accumulation (Hessburg et al. 2016; Hagmann et al. 2021). These fuel loads, coupled with increasingly hot, dry conditions, an ever-expanding fire-season, and more human activity in the wildland-urban interface all but guarantee continued increases in fire frequency, fire severity, and annual area burned (Jolly et al. 2015; Westerling 2016; Holden et al. 2018; Parks and Abatzoglou 2020).

These trends have dire implications for the volatility of long-term carbon storage in western forests (Earles et al. 2014; Liang et al. 2016). After all, under these altered disturbance regimes and changing climatic conditions, forest recovery—and the associated carbon sequestration—is not an inevitable conclusion. Instead, ecosystem transformation to persistent, non-forested states following some wildfires will dramatically reduce carbon storage capacity (Davis et al. 2019; Coop et al. 2020). There are certainly carbon emissions associated with combustion during a fire itself, but it is the ongoing post-fire dynamics—failure to regenerate trees, gradual decomposition of dead and downed trees—that render long-term carbon storage capacity most vulnerable (Stenzel et al. 2019). We examined the amount of vulnerable carbon at risk from wildfires, which integrates both short-term emissions and long-term loss of stored carbon, thus capturing the amount of carbon we might expect to lose in stand-replacing wildfire events in the West.

To account for the potential long-term loss of carbon storage capacity across the western U.S., we modeled the cumulative probability of fire occurrence between now and 2030 and used those probabilities to discount carbon storage on the landscape. Given the heterogeneity of drivers for wildfire loss, we constrained this discounting to the western states of CONUS. (i.e., Washington, Oregon, California, Idaho, Montana, South Dakota, Wyoming, Nevada, Utah, Colorado, Arizona, and New Mexico). However, we note that wildfires in the boreal forests of Alaska have significant carbon implications (Walker et al. 2019; Mack et al. 2021); a future analysis examining the trajectory of boreal forest carbon dynamics would be of considerable value.

To generate the cumulative probability of fire unfolding at a given location on the landscape, we applied an existing, nationally consistent dataset that reflects historical fire frequency: the mean fire return interval (FRI; 30-m resolution) from LANDFIRE 2.0.0 (LANDFIRE, 2016). It is critical to note that we are already witnessing dramatic departures from historical fire regimes (Abatzoglou and Williams 2016; Littell et al. 2018), such that mean FRI is a highly conservative approach to estimating fire effects across a landscape and will likely underestimate fire rates into the future. However, applying FRI data is a defensible method for estimating fire likelihood in the near term and over a large spatial domain.

Fire is a highly stochastic process. To estimate the cumulative probability that a fire would occur in a given location over the next decade (2021 through 2030), while accounting for inter-annual variations in wildfire activity, we applied a cumulative hazard function to scale the effects of wildfire by the likelihood that a fire has occurred. The Weibull distribution is frequently used in fire history studies as a model for temporal variation in burn probabilities (Agee 1996) and allows one to simulate how a mean FRI may be realized as fire across any given landscape, accounting for changes in flammability. The “scale” (FRI) and “shape” (temporal change in flammability) parameters of the Weibull distribution can be used to account for how long and how variable fire intervals tend to be, respectively. In our analyses, we set the shape parameter to greater than 1, denoting an increase in flammability in years following growth as fuels dry and die. The scale parameter is determined by the annual burn probability of a given location, or 1/b, where b represents the FRI. The resultant Weibull hazard function allows for the cumulative probability of fire to be estimated at any given timestep (e.g. 5, 10 or 20 years into the future). For the purposes of this analysis, we generated the cumulative probability of fire by year 2030 (i.e., between 2021 and 2030) across the western U.S.

Cumulative burn probabilities reflect the risk of fire at any severity class occurring, but carbon storage capacity is most likely to be indefinitely compromised by high-severity (i.e., >75% tree mortality) fire, from which a forest may not recover. We therefore retained only those pixels—and the associated cumulative probabilities—that fell within the “high” and “very high” categories of the Wildfire Hazard Potential product (WHP; Dillon et al. 2020). Specifically, this dataset maps the relative potential for wildfire that would be difficult for suppression resources to contain and is an integration of modeling outputs (the Large Fire Simulator, FSim), fuels and vegetation data from LANDFIRE, and locations of past fire occurrences (Dillon et al. 2020). Areas categorized as having “high” and “very high” WHP values have fuels that confer a higher probability of extreme fire behavior. Because such behavior is likely to result in high degrees of mortality and greater area burned, we used these classes as a proxy for the sort of fire most likely to lead to ecosystem transformation and an associated decline in biomass. In this way, we conservatively masked our cumulative probabilities of fire occurrence to those pixels where long-term carbon loss is most likely. However, we emphasize that it is all but impossible to predict when or where fire will occur and what the fire effects will be. These analyses are therefore to be interpreted as a coarse approach to quantify anticipated rates of forest ecosystem transformation and associated carbon loss.

We used these masked cumulative probabilities of wildfire to discount carbon storage in 2030 in the western U.S. Specifically, we used them to derive a map of potential vulnerable carbon lost to wildfire. Vulnerable carbon (described above) provides an estimate of the amount of carbon that could be lost in an ecosystem conversion event, such as the transformation of a forest to non-forest following a high severity wildfire. Multiplying the cumulative probabilities of wildfire between now and 2030 by vulnerable carbon allows us to calculate the long-term carbon losses associated with high severity fire while accounting for the chances of such a fire actually taking place at any given location. We note that not *all* vulnerable carbon will be lost immediately in a disturbance event, as vulnerable carbon is not the same as immediate emissions associated with combustion. Nor will all vulnerable carbon have fluxed to the atmosphere within the first few years or even decade following fire—for example, by 2030 in our analyses. Rather, vulnerable carbon represents the amount of carbon we may essentially "commit" to losing through long-term dynamics following high severity fire, including woody material decomposition, limited or delayed regeneration, or the persistence of alternate lower-carbon vegetation conditions (Davis et al. 2019; Stenzel et al. 2019).

For each new PA scenario and the scenario considering only existing PAs, we evaluated overlap with wildfire-driven loss (see above). We then summed the amount of carbon potentially lost to wildfire across all these locations. This value provides an estimate of the amount of carbon that, even if protected under a 30x30 design, could nonetheless be lost to wildfire.

4.1.3. 'Business as usual' natural areas loss

The ongoing loss of natural areas to, for example, urban and suburban development, conversion to agriculture, and other forms of anthropogenic landscape modification, will impact the ability of landscapes to store and sequester carbon in plant biomass and soils (Sanderman et al. 2017; Fargione et al. 2018; Sleeter et al. 2018). Across the U.S., more than 24-million acres of natural areas were lost to development and other factors between 2001 and 2017 (CSP 2019). To quantify the potential for each of the above new PA scenarios to prevent or forestall the carbon impacts of further natural areas loss, we first estimated the total amount of carbon storage and annual sequestration expected to be lost by 2030 under current rates of natural areas loss and with no new PAs added. In short, these values estimate the amount of carbon lost by 2030 given 'business-as-usual' rates of natural areas loss. We then determined how much of that storage and sequestration loss could be avoided under each of the new PA scenarios. This analysis was conducted for CONUS only, given the lack of data on natural areas loss in AK.

Between 2001 and 2017, natural area loss across CONUS occurred at a rate of 1.53-million acres per year (CSP 2019). Assuming this rate remains constant into the future, we considered the amount of natural area lost over the next decade (2021 through 2030) with no new protections to be 15.3-million acres. For comparison, this is equivalent in area to nearly 80 New York Cities or seven Yellowstone National Parks. We simulated the carbon impacts of this natural areas loss by first randomly allocating 15.3-million acres (± 0.5-million acres) across all undeveloped and unprotected (i.e., not GAP 1 or 2) lands in CONUS using a minimum block size of approximately 200 acres. We used PAD-US as above to exclude protected lands from consideration and used the 2016 National Land Cover Database (Yang et al., 2018) to identify natural areas, excluding all development categories (open space and low, medium, and high intensity development), as well as open water, perennial ice and snow, barren lands, pasture/hay, and cultivated crops; all other land cover types were considered "natural." We then estimated the amount of carbon storage lost by 2030 as the sum of vulnerable carbon (i.e., the amount of carbon expected to be lost in an ecosystem conversion event) across the randomly allocated 15.3-million acres. This value represented the potential cumulative carbon storage lost over the next decade. Below we also provide an estimate of vulnerable carbon lost in the year 2030 alone, based on a 1-yr loss of 1.53 million acres of natural area. We estimated the amount of lost sequestration due to natural areas loss over the next decade by assuming that 1.53 million acres of natural area was lost each year between 2021 and 2030. Acres lost in 2021 were assumed to forgo ten year's worth of potential sequestration by the end of 2030 (i.e., sequestration that would have happened if those acres had remained in natural vegetation), while acres lost in 2022 were assumed to forgo nine year's worth of potential sequestration, and so on. We summed the carbon sequestration loss that would occur in each year (based on estimates of annual sequestration rates described in the *Carbon Data* section above) to arrive at a total carbon sequestration loss estimate for the decade ending in 2030. We also provide an estimate of the amount of potential sequestration lost in the year 2030 alone by summing our estimate of annual sequestration rate across all pixels comprising the randomly allocated 15.3-million acres. We again note that our estimates of lost sequestration are necessarily coarse, being based on the average sequestration rates for a given ecosystem post-disturbance, as determined through a literature review (see above), and that these estimates are most applicable to ecosystems in early successional stages (i.e., immediately following a disturbance) whereas sequestration rates in mature ecosystems may be substantially lower. The sequestration values presented below therefore provide an approximation of the carbon that may otherwise have been sequestered had the vegetation on the 15.3-million acres of natural lands not been lost, but should be used with caution for the reasons just stated.

Having established potential carbon losses associated with ongoing natural area loss, we next estimated the potential for each of our six new PA scenarios to mitigate those losses. For each new PA scenario, we determined the overlap between the spatial footprint of that scenario (i.e., the 414-million acres that would be protected/conserved under the scenario) and the footprint of projected natural areas loss by 2030 (i.e., the 15.3-million acres lost to conversion). Areas that overlapped between these two datasets were considered "avoided loss", i.e., natural areas that were protected and thus not subject to conversion. We calculated the amount of carbon storage (vulnerable carbon) and sequestration on these "avoided loss" pixels as the amount of carbon loss avoided by 2030 under the new PA scenario. It is worth reiterating that we calculated the overlap between cumulative (10-year) footprints of natural areas loss and new PAs, which assumes that a constant proportion of natural areas loss is offset by new PAs throughout the decade between 2021 and 2030 and that natural areas loss prevented by the establishment of new PAs is not simply diverted elsewhere. We also calculated the amount of loss avoided in the year 2030 alone, assuming 1.53 million acres of natural areas loss in that year and assuming that the cumulative footprint of new PAs was in place.

To account for uncertainty in where future natural areas loss will occur, we ran the above simulation ten times, randomly reallocating natural areas loss, calculating the amount of carbon lost, and calculating the amount of loss avoided under each new PA scenario. We considered ten simulations to be sufficient in capturing the variation in carbon outcomes, with the coefficient of variation for all carbon estimates being less ≤ 1%. For one of our new PA scenarios (*random allocation*, which also involved multiple model runs), we randomly chose a single iteration of new PAs and overlapped this map with each of the iterations of future natural areas loss.

For all new PA, wildfire, and natural areas loss analyses, we conducted analyses in Google Earth Engine (GEE) and Python (v3.8.2) using the GEE Python API (v0.1.246). Given the large spatial scale considered in these analyses (all of CONUS and/or Alaska) and given the uncertainty inherent in the carbon datasets (see above), we rounded carbon values to the nearest 100 million metric tons (Mmt) to represent a realistic level of precision. (The exception is our estimates of single-year sequestration losses in the natural areas loss analysis, which were consistently less than 100 million metric tons and were therefore rounded to the nearest metric ton.)

4.2. New PAs and wildfire loss results

Our scenarios suggest that, depending on the underlying strategy by which new PAs are targeted, meeting the 30x30 goal could lead to two to four times as much carbon protected from loss by 2030 as would be the case if no new PAs were added. In CONUS, our maximum carbon scenario would yield up to 34,600 million metric tons of carbon (MmtC) stored and sequestered in PAs (or approximately 126,900 million metric tons of CO_2 equivalent; $MmtCO_2e$) by 2030. We estimate that adding these new PAs will save 204 MmtC (716 $MmtCO_2e$) of carbon storage and sequestration that would otherwise be lost to natural areas conversion.

We found that existing PAs store approximately 7,900 MmtC (29,000 $MmtCO_2e$). When considering sequestration rates, existing PAs could sequester up to 1,000 MmtC (3,700 $MmtCO_2e$) by 2030, though see caveats noted above regarding substantially lower sequestration rates in mature ecosystems. Approximately 200 MmtC (700 $MmtCO_2e$) of vulnerable carbon within existing PAs are at risk from wildfires between now and 2030.

As noted above, all new PA scenarios were run separately for CONUS and CONUS + AK. Table 2 presents the amount of carbon stored and/or sequestered under each of the six scenarios in CONUS, as well as the amount of vulnerable carbon within the footprint of these new and existing PAs that is at risk from wildfires. Note that Table 2 represents estimates of the maximum amount of carbon either protected or vulnerable under each scenario. For instance, prioritizing intactness in CONUS could lead to the protection of *up to* 17,800 MmtC (65,300 $MmtCO_2e$) of carbon storage (or 20,700 MmtC [75,900 $MmtCO_2e$] if considering storage and potential sequestration), notwithstanding uncertainties inherent to calculating carbon outcomes of hypothetical situations at large spatial scales (see Section 8 *Uncertainties and Limitations*). Figure 1 provides a visual comparison across all scenarios for CONUS, highlighting the maximum additional carbon that would be stored in each scenario beyond that stored within existing PAs. It is important to note that each of these values represents an idealized scenario in which all new PAs between now and 2030 are directed at the specific locations across the country that have the highest value for a given conservation objective, regardless of the actual feasibility of protecting those areas.

The maximum carbon scenario yields, by design, the largest amount of carbon stored and sequestered by 2030 in CONUS. Under this scenario, new PAs on the 17% of U.S. lands still required to reach the 30x30 goal would store up to 23,600 MmtC (86,500 $MmtCO_2e$) and could potentially sequester up to an additional 3,500 MmtC (12,800 $MmtCO_2e$). When added to the amount of carbon within existing PAs, this maximum carbon scenario could store up to 31,500 MmtC (115,500 $MmtCO_2e$) and could protect up to 36,000 MmtC (132,000 $MmtCO_2e$) if potential maximum sequestration is considered. However, without restoration, we estimate that wildfires in the western U.S. threaten up to 1,400 Mmt of vulnerable carbon (5,100 $MmtCO_2e$) within existing PAs and the new PAs added under this scenario. Discounting this at-risk carbon from the total carbon storage yields a net storage of 30,100 MmtC (110,400 $MmtCO_2e$), or 34,600 MmtC (126,900 $MmtCO_2e$) when sequestration is considered.

We estimated that, with no new PAs and a constant rate of natural areas loss of 1.53 million acres per year over the next decade, up to 300 Mmt of vulnerable carbon (1,200 $MmtCO_2e$) and 50 Mmt of potential sequestration (200 $MmtCO_2e$) could be lost by 2030. In the year 2030 alone, up to 30 Mmt of vulnerable carbon (120 $MmtCO_2e$) and 8 MmtC of sequestration (30 $MmtCO_2e$) could be lost. Table 3 presents the amount of vulnerable carbon and sequestration loss that could potentially be avoided under each of the new PA scenarios, assuming that a constant proportion of natural areas loss is offset by new PAs throughout the decade between 2021 and 2030. The greatest avoided loss would occur under both the maximum carbon and vulnerable carbon scenarios. The maximum carbon scenario would avoid the loss of up to 200 Mmt of vulnerable carbon (700 $MmtCO_2e$) and 20 MmtC of sequestration (70 $MmtCO_2e$), over the next decade thus avoiding 67% of the vulnerable carbon loss and 50% of the sequestration loss that would otherwise occur with no new PAs.

Table 2. Values of carbon stored and potentially sequestered, as well as vulnerable carbon potentially at risk from wildfires in the conterminous U.S. (CONUS) under each of the new PA scenarios. All values are given in MmtC ($MmtCO_2e$). For each scenario, values represent the maximum amount of carbon stored, sequestered, or threatened by fire under that scenario. The random allocation scenario was run multiple times (see *Technical Approach* above) and values represent the mean ± standard deviation of all simulations.

Scenario	C Stored in New PAs	C Sequestered in New PAs	All C Stored[a]	All C Sequestered[b]	Total C[c]	Vulnerable C at Risk from Fire[d]	Net C Stored[e]	Net C Total[f]
Maximum carbon	23,600 (86,500)	3,500 (12,800)	31,500 (115,500)	4,500 (16,500)	36,000 (132,000)	1,400 (5,100)	30,100 (110,400)	34,600 (126,900)
Vulnerable carbon	22,300 (81,800)	3,600 (13,200)	30,200 (110,700)	4,600 (16,900)	34,800 (127,600)	1,300 (4,800)	28,900 (106,000)	33,500 (122,800)
Intactness	11,000 (40,300)	1,900 (7,000)	18,900 (69,300)	2,900 (10,600)	21,800 (79,900)	1,100 (4,000)	17,800 (65,300)	20,700 (75,900)
At risk ecoregions	16,900 (62,000)	3,100 (11,400)	24,800 (90,900)	4,100 (15,000)	28,900 (106,000)	800 (2,900)	24,000 (88,000)	28,100 (103,000)
Imperiled species richness	18,000 (66,000)	3,100 (11,400)	25,900 (95,000)	4,100 (15,000)	30,000 (110,000)	500 (1,800)	25,400 (93,100)	29,500 (108,200)
Random allocation	12,800 ± 52 (46,900 ± 191)	2,300 ± 10 (8,400 ± 37)	20,700 (75,900)	3,300 (12,100)	24,000 (88,000)	700 (2,600)	20,000 (73,300)	23,300 (85,400)

[a]Carbon stored in new PAs plus carbon stored in existing PAs (7,900 MmtC, see text)
[b]Carbon sequestered in new PAs plus carbon sequestered in existing PAs (1,000 MmtC, see text)
[c]All C stored plus All C sequestered
[d]Includes C at risk from wildfire in both new PAs (amount depends on scenario) and existing PAs (200 MmtC, see text)
[e]All C stored minus vulnerable C at risk from fire
[f]Total C minus vulnerable C at risk from fire

Table 3. The total amount of carbon loss associated with natural areas loss over the next decade that could be avoided under each new protection scenario. Also shown are the mean values of avoided loss as a percentage of the total projected vulnerable carbon and sequestration loss if no new protections are added. Note that values of avoided loss are means from ten simulations (see *Technical Approach* above), with very little variation between simulations (coefficient of varion ≤ 1% for each scenario).

Scenario	**Avoided loss of vulnerable carbon**				**Avoided loss of sequestration**			
	1 Year (2030)		10 Year		1 Year (2030)		10 Year	
	Amount - MmtC (MmtCO2e)	% Total loss avoided[a]	Amount - MmtC (MmtCO2e)	% Total loss avoided[b]	Amount - MmtC (MmtCO2e)	% Total loss avoided[c]	Amount - MmtC (MmtCO2e)	% Total loss avoided[d]
Maximum carbon	20 (70)	67%	200 (700)	67%	4 (15)	50%	20 (70)	40%
Vulnerable carbon	20 (70)	67%	200 (700)	67%	4 (15)	50%	30 (110)	60%
Intactness	10 (40)	33%	100 (400)	33%	3 (11)	38%	10 (40)	20%
At risk ecoregions	10 (40)	33%	100 (400)	33%	3 (11)	38%	20 (70)	40%
Imperiled species richness	10 (40)	33%	100 (400)	33%	3 (11)	38%	20 (70)	40%
Random allocation	10 (40)	33%	100 (400)	33%	3 (11)	38%	20 (70)	40%

[a]As a percentage of vulnerable carbon lost in the year 2030 with no new PAs: 30 Mmtc (120 MmtCO_2e)

[b]As a percentage of vulnerable carbon lost between 2021 and 2030 with no new PAs: 300 Mmtc (1,200 MmtCO_2e)

[c]As a percentage of sequestration lost in the year 2030 with no new PAs: 8 Mmtc (30 MmtCO_2e)

[d]As a percentage of sequestration lost between 2021 and 2030 with no new PAs: 50 Mmtc (200 MmtCO_2e)

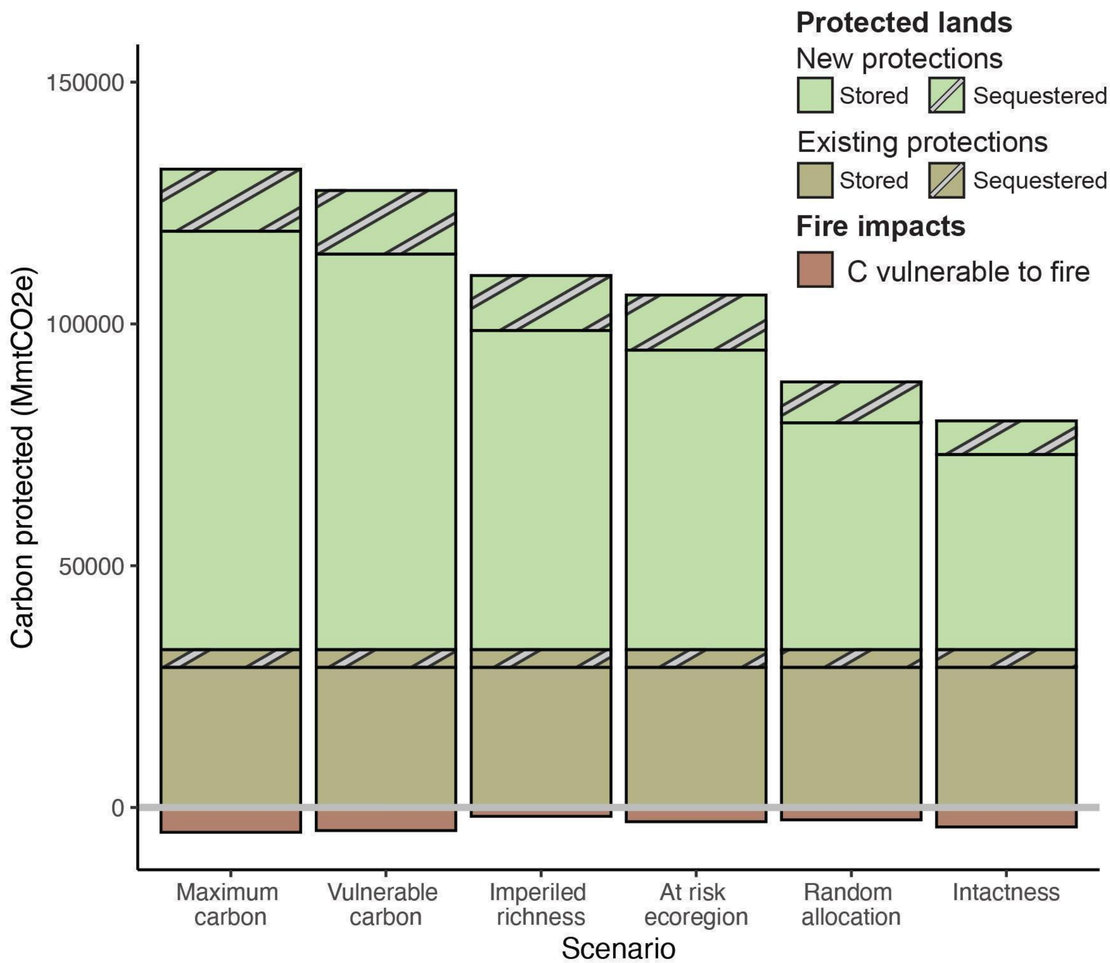

Figure 1. Maximum amount (in $MmtCO_2e$) of carbon protected by 2030 in CONUS under each new PA scenario (light green), shown as additional to the amount of carbon within existing PAs (dark green). Amounts of carbon stored (solid bars) and potentially sequestered (striped boxes) are shown separately for both new and existing PAs. The amount of vulnerable carbon at risk from wildfires across existing and new PAs (brown) is shown as negative values below the zero line (grey horizontal line).

Allocating new PAs across both CONUS and Alaska (CONUS + AK) yields comparable but slightly higher values of carbon stored and sequestered for most scenarios (Table 4, Figure 2). These subtle increases may in part be attributed to the contributions of the approximately 20-million acres of temperate rainforests of Southeast Alaska, which store tremendous quantities of carbon (Yatskov et al. 2019). The single exception is the at-risk ecosystems scenario in which the amount of carbon protected is the same when considering CONUS or CONUS + AK because all of ecosystem types at highest risk are found in CONUS. (The necessary datasets to run the imperiled species richness scenario and to calculate the amount of vulnerable carbon at risk from wildfire were not available for Alaska.) As with the CONUS-only results, the largest value of carbon potentially protected by 2030 is given by the maximum carbon scenario, which, when added to the amount of carbon by 2030 within existing PAs, yields total storage of up to 33,100 MmtC (121,400 $MmtCO_2e$). When sequestration is considered, the maximum carbon scenario could protect up to 37,300 MmtC (136,800 $MmtCO_2e$).

Table 4. Values of carbon stored and potentially sequestered in the conterminous United States and Alaska (CONUS + AK) under each of the new PA scenarios. All values are given in MmtC (and $MmtCO_2e$). For each scenario, values represent the maximum amount of carbon stored or sequestered under that scenario. The random allocation scenario was run multiple times (see *Technical Approach* above) and values represent the mean ± standard deviation of each simulation.

Scenario	C Stored in New PAs	C Sequestered in New PAs	All C Stored[a]	All C Sequestered[b]	Total C[c]
Maximum carbon	25,200 (92,400)	3,200 (11,700)	33,100 (121,400)	4,200 (15,400)	37,300 (136,800)
Vulnerable carbon	23,400 (85,800)	3,600 (13,200)	31,300 (114,800)	4,600 (16,900)	35,900 (131,600)
Intactness	12,700 (46,600)	1,600 (5,900)	20,600 (75,500)	2,600 (9,500)	23,200 (85,100)
At risk ecoregions	16,900 (62,000)	3,100 (11,400)	24,800 (90,900)	4,100 (15,000)	28,900 (106,000)
Random allocation	13,400 ± 42 (49,100 ± 154)	2,200 ± 7 (8,100 ± 26)	21,300 (78,100)	3,200 (11,700)	24,500 (89,800)

[a]Carbon stored in new PAs plus carbon stored in existing PAs (7,900 MmtC, see text)
[b]Carbon sequestered in new PAs plus carbon sequestered in existing PAs (1,000 MmtC, see text)
[c]All C stored plus All C sequestered

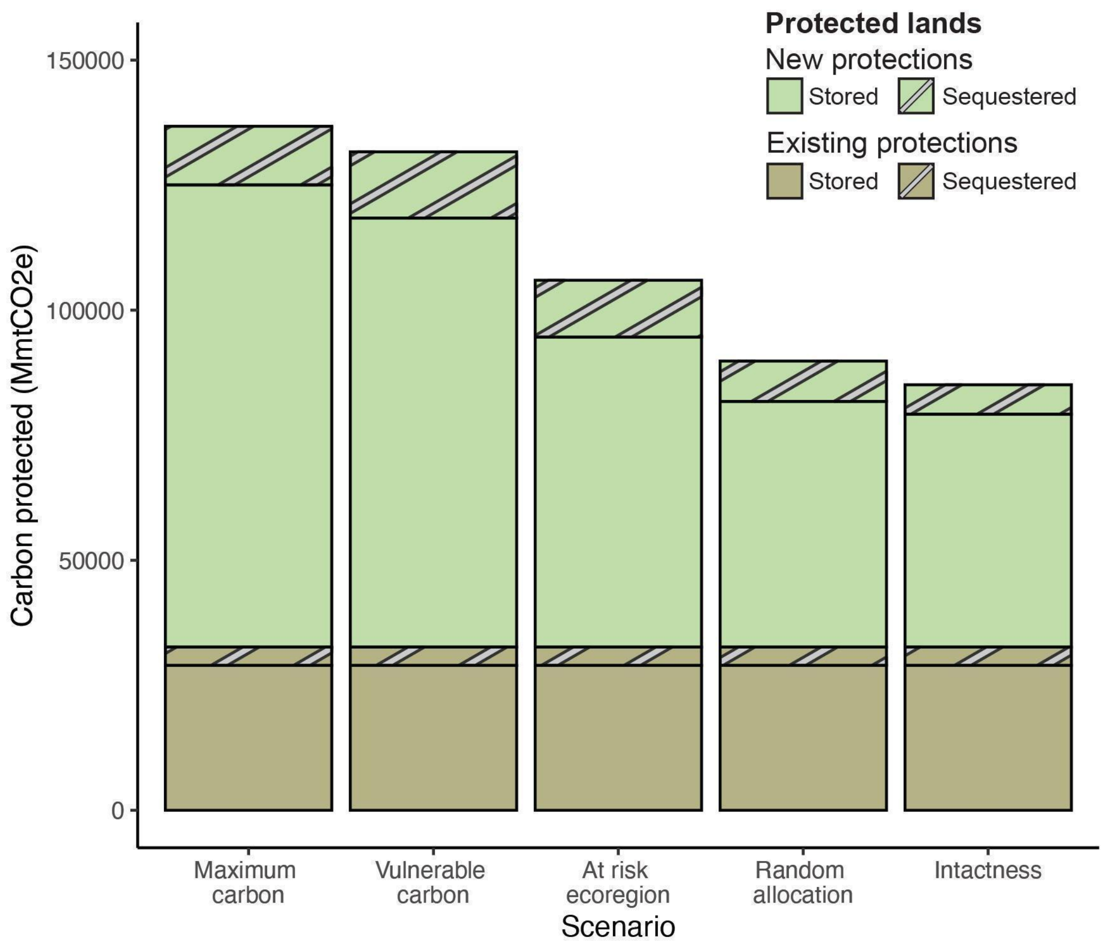

Figure 2. Maximum amount (in $MmtCO_2e$) of carbon protected by 2030 in CONUS + AK under each new PA scenario (light green), shown as additional to the amount of carbon within existing PAs (dark green). Amounts of carbon stored (solid bars) and potentially sequestered (striped boxes) are shown separately for both new and existing PAs.

5. CASE STUDY: RESTORATION OF FIRE-PRONE WESTERN CONIFER FORESTS

There is wide agreement that restoration treatments in fire-prone forests—largely mechanical thinning of small trees, the reintroduction of low-severity surface fire, or both—are necessary to mitigate current wildfire trends (McCauley et al. 2019, Foster et al. 2020). Such restoration treatments reduce fuel loads, improve forest health, and can reduce the severity of future wildfire (Lydersen et al. 2017; Prichard et al. 2020). While restoration treatments themselves often have an initial carbon cost (Chiono et al. 2017; Goodwin et al. 2020), such treatments act to maintain forest cover in the long-term through reduced wildfire severity resulting in additional, more secure carbon storage (Hurteau et al. 2016; Liang et al. 2018). As an attempt to decelerate current rates of high-severity wildfire, the U.S. Forest Service (USFS) and partners have identified ~65-82 million acres of forest as in need of restoration treatments (U.S. Forest Service, 2012). In response to this challenge, programs such as the CFLRP, have emerged to pursue restoration in high-priority, multi-ownership landscapes ranging from 130,000 to 2.4 million acres

(Schultz et al. 2012). We focused on these high-priority landscapes in the following case study to explore how much carbon loss may be avoided with successful restoration.

5.1 Technical approach

Current USFS geodetic shapefiles document ~50 million acres of western forests with fuel treatment plans (U.S. Forest Service 2017, 2021). To estimate the potential carbon benefits of restoration, we simulated the amount of carbon loss that could be avoided if 10% or 30% of these total restoration priority areas were restored by 2030 to reduce high-severity fire risk and therefore the loss of carbon. Specifically, we used priority areas identified by the Forest Service CFLRP (Forest Service 2021) and the Healthy Forests Restoration Act (Forest Service 2017) where fuel treatments and thinnings were specified as the treatment actions (insecticide treatments were removed). We further refined this footprint to areas deemed at "high" or "very high" risk of extreme fire behavior per the WHP dataset (described above) and hereafter refer to these areas as the "restoration target". Within the restoration target, we randomly selected pixels amounting to either 10% (approximately 5 million acres) or 30% (approximately 15 million acres) of the total restoration target area and summed the potential carbon lost to wildfire (i.e., vulnerable carbon x cumulative burn probability, see *Vulnerability of carbon to wildfire* above) across those pixels. This sum represents the carbon loss that could be avoided by conducting restoration on those randomly selected pixels. For context, the 10% restoration target would constitute approximately two larger CFLRP projects such as the Four Forest Restoration Initiative (4FRI) in Arizona, and 30% would encompass all of the first 10 CFLRP projects delineated at the start of the program in 2010, plus an additional ~5 million acres of projects that have since been identified. We conducted the random selections 10 times for each percentage target, with restoration modeled to occur in blocks with a minimum size of approximately 200 acres. (As with the random allocation PA scenario described above, varying the minimum block size had negligible effects on our results.) Values presented below represent mean carbon loss avoided across all simulations for a given percentage target. For comparison, we also calculated the amount of carbon that could potentially be lost across the restoration target area if *no* restoration were conducted by taking the product of vulnerable carbon and cumulative burn probability at each location and summing these values across all pixels in the restoration target area. Note that this analysis of avoided carbon loss is not tied to the footprint of any of our new PA scenarios above; rather, it is restricted to the restoration target areas, which are independent of (but may happen to coincide with) new PAs. Thus, the carbon loss avoided in this restoration scenario is *additional* to that protected through the establishment of new PAs. Given that this analysis was restricted to a smaller spatial extent than the new PA scenarios above, it yielded smaller absolute carbon values. Accordingly, we rounded values in this analysis to the nearest 50 million metric tons (and in the case of 2030 values, to 1 million metric tons) to represent a reasonable level of precision.

5.2 Fire restoration results

Currently, fire restoration target areas set by the United States Forest Service that meet criteria for extreme fire behavior (see *Technical Approach* above) store more than 800 Mmt of carbon (2,900 MmtCO$_2$e). Over the coming decade (2021-2030) with *no* restoration, we predict that these target areas could lose a total of 350 Mmt of carbon (1,300 MmtCO$_2$e). By simulating wildfire restoration randomly across selected subsets of the restoration target areas, we found that losses of up to 100 MmtC (350 $MmtCO_2e$) of carbon could be avoided by restoring 10% of the restoration target area over the coming decade, and carbon losses of up to 250 MmtC (900 $MmtCO_2e$) could be avoided by restoring 30% of the target area. In other words, restoring 30% of forests in need of fuel treatments could retain more than 90% of the carbon in these target areas, whereas failure to pursue restoration could result in a long-term loss of approximately 50% of current carbon stores (Fig. 3). Without proactive restoration, approximately 30 MmtC (110 $MmtCO_2e$) may be lost to fire in the year 2030 alone, whereas achieving restoration targets of 10% or 30% could prevent losses of approximately 3 MmtC (10 $MmtCO_2e$) or 8 MmtC (30 $MmtCO_2e$), respectively, in 2030 alone. (Note that potential prevented losses change from year to year, given the non-linear increases in cumulative probability of burning over time. Accordingly, avoided losses for 2030 cannot be applied to prior years nor to subsequent years.)

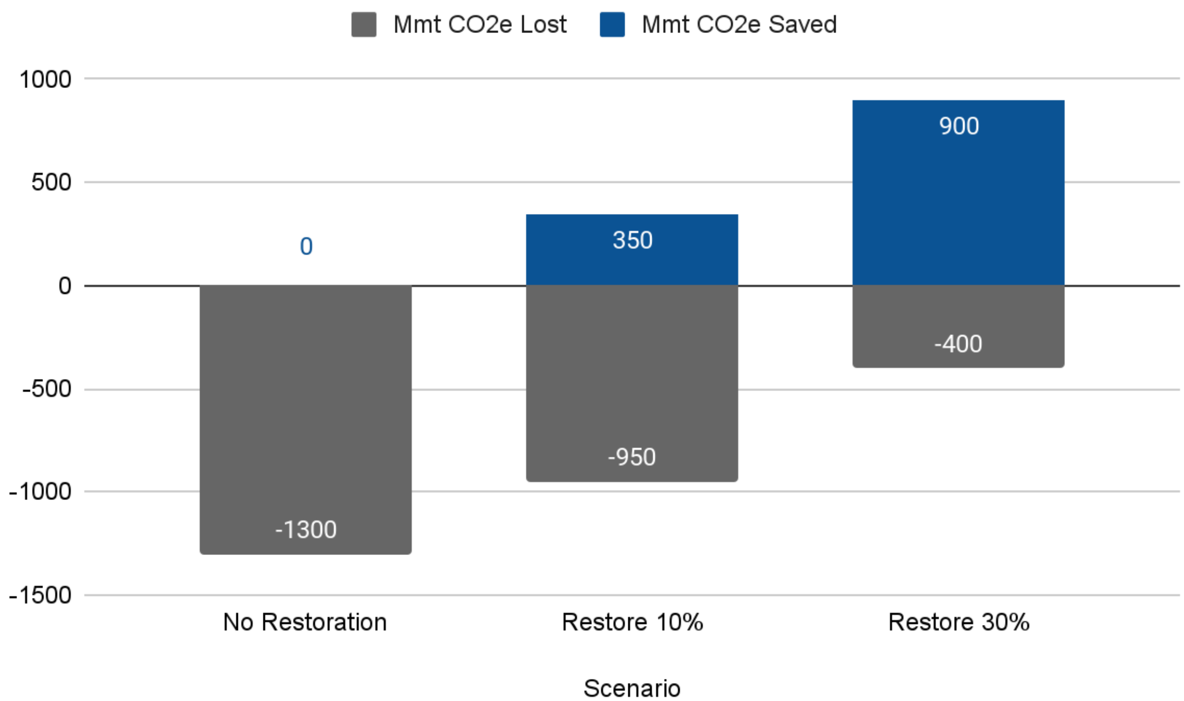

Figure 3. Long-term carbon implications of forest restoration for the western U.S. Gray bars show potential loss of current vulnerable carbon storage under no restoration, a 10% restoration target, and a 30% restoration target. Blue bars show initial carbon that would be retained in these target areas under the same restoration actions.

6. CASE STUDY: REFORESTATION ACROSS CONUS

Tremendous reforestation opportunities exist in areas that were once forested, particularly on private lands (Fargione et al. 2018; Cook-Patton et al. 2020). Restoring tree cover in these once-treed areas may not only yield carbon benefits, but may also safeguard habitat and ecological functions that in turn support important ecosystem services and climate adaptation capacity (Pramova et al. 2012). In this case study, we explored the potential carbon sequestration associated with a decade of reforestation on private lands across CONUS, following targets established by other groups working in this arena (e.g., The Nature Conservancy and American Forests). Carbon sequestration associated with reforestation is independent of the carbon storage and sequestration calculated in the new PA scenarios above. As such, carbon gains associated with this reforestation case study are *additional* to the carbon storage reported above. This underscores the point that passive land protection alone may not optimize carbon benefits. Rather, land protection combined with strategies like restoration in western fire-prone forests and reforestation in understocked areas may minimize carbon loss and maximize carbon gain, respectively (Fargione et al. 2018).

6.1 Technical approach

We leveraged a model of reforestation opportunities and associated carbon sequestration that were generated by The Nature Conservancy. This Reforestation Hub (www.reforestationhub.org) identifies areas of opportunity across CONUS. Detailed methods are described by Cook-Patton et al. (2020). Briefly, they identified areas that historically had ≥ 25% tree cover, but that currently lack forest cover. They also excluded from consideration several land cover types (e.g., including productive croplands, wetlands, developed areas, and roadways), accounted for natural openings in some forest systems, and removed some areas anticipated to naturally regrow (e.g., following disturbance). The remaining lands include non-stocked forest patches, shrublands, pastureland in forest ecosystems, marginal croplands, urban open spaces, floodplains, and river corridors, among several others. To estimate carbon sequestration associated with these lands, they applied forest growth curve values (for the first decade of growth) developed by the US Forest Service, which are specific to forest types and regions (Smith et al. 2006). The final Reforestation Hub thus reflects a range of data inputs--each with their own uncertainties--and inherently relies on some simplifying assumptions. For example, carbon sequestration rates are highly site-dependent, even within the same forest type. Nevertheless, the Reforestation Hub represents the most comprehensive spatial product available.

We analyzed the carbon sequestration potential of reforestation across CONUS, which Reforestation Hub identifies as having 132.9-M acres prime for reforestation. Private land constitutes most of this acreage, and we therefore focused this analysis on private lands (114.6-M acres). We explored reforestation targets of 10% of area by 2030 and 30% of area by 2030, which are consistent with targets set forth by American Forests (50% of available area by 2040; American Forests 2021).

We used Reforestation Hub’s tabular county-level summaries (of acreage and sequestration rates) to estimate total potential carbon sequestration associated with reforesting these 114.6 M private acres over the next decade (2021 through 2030). Specifically, we assumed 1/10th of the area within each county would be planted each year in the coming decade (i.e., an equal area in each of the 10 years). Thus, trees planted in the first year would grow (and sequester carbon) for ten years, trees planted in the second year would grow (and sequester carbon) for nine years, and so on. We iteratively summed the carbon sequestration that would occur in each year in each county for 10 years to arrive at a total carbon sequestration estimate in 2030. Because this initial reforestation investment would continue to sequester carbon into the future, we also estimated total carbon sequestration associated with this decade of planting in 2040 and 2050. It is important to note, however, that we applied carbon sequestration rates associated with the first decade of tree growth to these 2040 and 2050 estimates (two and three decades after planting). Depending on the forest type, sequestration rates often begin to taper in the second and third decades of growth, and so these 2040 and 2050 values likely overestimate sequestration. We rounded all carbon values to 50 million metric tons to represent a reasonable level of precision

6.2 Reforestation results

We estimate that meeting a 10% reforestation target across CONUS may sequester 150 MmtCO_2e by 2030, or nearly 50 MmtCO_2e in 2030 alone. That same reforestation investment would sequester 550 MmtCO2e by 2040 and 750 Mmt CO2e by 2050. Pursuing a more ambitious 30% reforestation target across CONUS may sequester 550 MmtCO_2e by 2030 (nearly 100 MmtCO_2e in 2030 alone), 1,450 MmtCO2e by 2040, and 2,400 MmtCO2e by 2050. (Per the methods above, results for 2040 and 2050 should be interpreted with care, given uncertainty in the estimates.)

7. CARBON CONCLUSIONS & CONSIDERATIONS

With no new PAs, and considering potential losses from wildfire in the western states of CONUS, existing PAs will store approximately 28,300 MmtCO_2e by 2030 and could sequester up to 3,700 MmtCO_2e (though again we note that sequestration estimates assume an early successional stage and actual net sequestration by 2030 may be closer to zero for many mature ecosystems). Similarly, with no new PAs, and assuming that the loss of natural areas in CONUS continues apace at approximately 1.53 million acres per year, we would expect to lose up to 1,200 MmtCO_2e of carbon storage by 2030 through conversion of natural areas to development and agriculture (which could lead to a loss of up to 31 MmtCO_2e of potential sequestration in 2030). All the new PA scenarios described above would lead to substantial increases in the amount of carbon storage protected in CONUS after accounting for wildfire losses, yielding total protections of between 65,300 and 110,400 MmtCO_2e, depending on the scenario (and potentially sequestering an additional 10,600 to 16,500 MmtCO_2e, under the assumption of high sequestration rates associated with newly regenerating ecosystems). These new PAs would safeguard 33-67% of the vulnerable carbon that would otherwise be lost to natural areas conversion. As noted above, we were unable to consider wildfire and natural areas loss in Alaska due to data limitations (despite wildfire in particular being a substantial concern in Alaska; Walker et al. 2019, Whitman et al. 2019). However, without considering potential losses from wildfire, adding new PAs across both CONUS and Alaska to existing PAs could protect between 75,500 and 121,400 MmtCO_2e of carbon storage (and potentially sequester an additional 9,500 to 15,400 MmtCO_2e). As an illustration, consider that total U.S. emissions exceed 6,550 MmtCO_2e annually (not including land-use change and forestry), with over 4,850 MmtCO_2e attributable to fossil fuel combustion alone (EPA 2021). Of course, emissions values (fluxes) cannot be directly compared to protected carbon amounts (pools), but the difference in orders of magnitude underscores the invaluable role that protected natural areas must play.

Importantly, our analyses also highlight potential strategies for balancing the dual conservation goals of mitigating climate change and stemming biodiversity loss (Soto-Navarro et al. 2020). While the maximum carbon scenario always yielded the highest carbon protections (by design), the scenario focused on conserving areas with highest imperiled species richness also yielded substantial carbon benefits. In CONUS, the imperiled species richness scenario would protect 82% of the carbon storage protected under the maximum carbon scenario. Interestingly, the intactness scenario, focused on conserving the least modified landscapes, resulted in the lowest carbon storage in CONUS, protecting only 60% of the carbon storage protected under the maximum carbon scenario. This pattern may be attributed to the fact that human land uses and natural resource extraction (e.g., forestry, agriculture) rely upon or are best suited to areas with high degrees of biomass (and therefore carbon) whereas landscapes with lower biomass (e.g., arid sage-steppe) may be poorly suited to human uses and are therefore left intact.

The uncertainties associated with estimating carbon losses and gains are challenging to overcome, as we emphasize in our methods and below. Still, we have confidence in our estimates, based on conclusions drawn by other studies that examine potential long-term carbon losses due to wildfire and avoided losses attributable to restoration (e.g., Hurteau et al. 2016; James et al. 2018; Liang et al. 2018; McCauley et al. 2019). We note that it is challenging, if not impossible, to precisely compare our results with metrics reported elsewhere, given unique study domains, timeframes, treatments, and response variables (e.g., carbon pools). Moreover, we expressly focus on existing restoration priorities—both with regards to fuels treatments and reforestation—and new PAs in areas where actions are likely to yield the greatest benefits, rather than focusing on, for example, case studies in specific geographies. Accordingly, our results may indicate more substantial avoided carbon losses and greater carbon gains than other analyses that present geography-specific case studies or shorter timeframes. We emphasize again that the choices and assumptions underpinning our analyses, as well as the inherent uncertainties in the datasets we use, mean our estimates should be considered approximations. Nevertheless, the potential carbon benefits and potential carbon losses, even if uncertain, compel us to act swiftly—to curtail greenhouse gas emissions and to leverage natural climate solutions to the greatest extent possible.

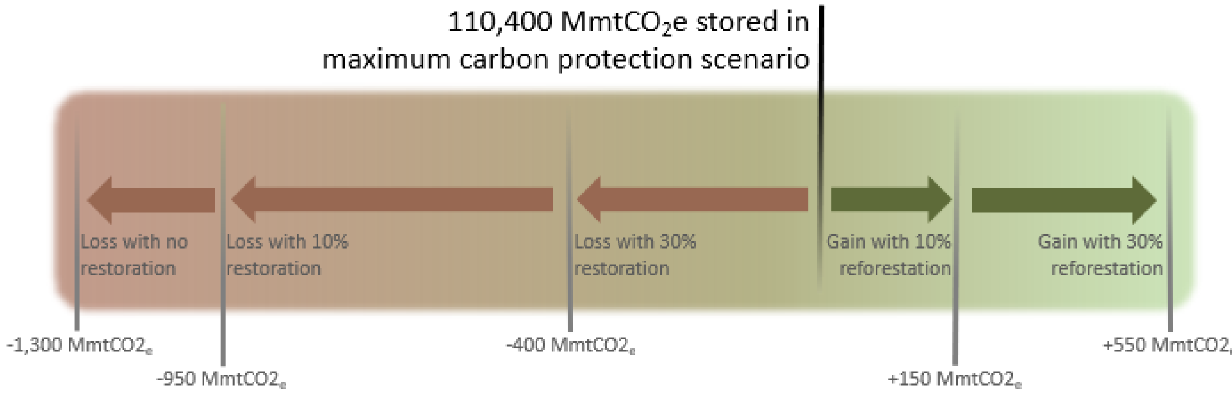

Figure 4. Potential carbon storage associated with the maximum carbon new PA scenario, including potential wildfire losses, with additional potential gains if 10% or 30% of reforestation targets were achieved by 2030 (illustrated with green arrows and positive values) and with additional potential losses if no western conifer forest restoration were to occur or if 10% and 30% of restoration targets were achieved by 2030 (illustrated with orange arrows and negative values). Intervals between numbers are approximately to scale.

8. UNCERTAINTIES AND LIMITATIONS

While ambitious, the scenarios and case studies we examined are underpinned by data and decision rules that reflect the most rigorous, up-to-date information available. Nevertheless, it is important to acknowledge inherent limitations to our approach as well as uncertainties in the results. First, the carbon datasets that underpin our analyses have high degrees of variability and inherent error, which may be propagated and compounded with each layer of analysis. We briefly discuss these sources of uncertainty in the *Technical Approach* sections above, and the authors of the datasets document and elaborate upon them in their respective manuscripts (e.g., Goldstein et al. 2020, Noon et al *In press*; see also Spawn et al. 2020). These datasets are likely the largest source of uncertainty in our final results (S. Spawn, pers. comm.).

Second, the new PA scenarios are based on the deterministic selection of pixels from large-scale spatial datasets, which are then overlaid upon a separate carbon dataset. Such overlays are bound to have subtle spatial mismatches, but we have confidence that the broad scale of our analyses renders these mismatches negligible in our final calculations. More practically, our pixel selection with multiple datasets across hundreds of millions of acres gives a range of optimized carbon protection possibilities, but allocations of new PAs across such a vast area would assuredly unfold in a variety of different ways. For example, for practical and legal reasons, some areas may simply be unavailable for protections; elsewhere, protection and conservation opportunities may arise that do not inherently optimize carbon or conservation priorities. In addition, new PAs would not be delineated at the scale of individual pixels (e.g., at a 300-m resolution) and instead would be aggregated over much larger areas.

More conceptually, the *America the Beautiful* report (Haaland et al. 2021), following President Biden's 30x30 declaration, emphasizes the key contributions of local actions and prioritizations in guiding on-the-ground expansion of our collective protected area estate, which our nation-wide analysis does not accommodate. Even more importantly, the benefits associated with conservation actions ought to be equitably distributed and acknowledge the needs and priorities of all communities, particularly those that have been disproportionately underrepresented in (or harmed by) conservation efforts. *America the Beautiful* expressly acknowledges this: "*Science can provide information about the places that are most rich in wildlife, that store the most carbon, or that are most rare or imperiled, but data alone should not be the sole guide or measure of success for how the nation protects, conserves, or restores its lands and waters.*" Accordingly, our final results should be interpreted as possible carbon protection outcomes that reflect discrete conservation prioritizations (e.g., maximum carbon or at-risk species) and do not integrate the full range of important environmental and social considerations.

Importantly, protecting an area does not guarantee carbon therein will remain. It may be lost due to anthropogenic causes, disturbances amplified by climate change, or declines and mortality in vegetation due to heat stress and drought. The act of protection itself may have contingencies that keep more or less carbon out of the atmosphere over all. For example, protections may spur other conservation investments nearby, thereby protecting even more carbon. Alternatively, protections may result in activities elsewhere that release an amount of carbon comparable to that which is newly protected (e.g., "leakage," or the shifting of forest harvesting activities when harvesting in one location is reduced). While our analyses addressed one major contingency affecting the amount of carbon ultimately protected at a particular location, the risk of loss due to wildfire in western states, substantial additional research will be required to develop a comprehensive picture of the factors affecting long-term carbon storage. Both of our restoration case studies—regarding western wildfire and reforestation—are predicated on sufficient resources and budget being available. For example, the U.S. Forest Service has determined that 65-82-million acres of forest are in need of restoration (U.S. Forest Service, 2012), which will require a monumental acceleration of recent rates that hover around 4-million acres annually (U.S. Forest Service, 2015). Meanwhile, the nation's tree nursery sector will have to double in scale to meet targets (American Forests, 2021; Fargione et al. 2021). These prerequisites, contingencies, and uncertainties—especially in the face of emerging threats and novel future conditions--underscore the importance of interpreting our results as high-level possibilities for carbon protection.

Finally, we reiterate that our estimates of carbon potentially at risk from wildfire are preliminary and meant to provide an approximation of how much carbon can actually be protected across the U.S. without major increases in restoring fire-prone landscapes. Projecting where future wildfires will occur and how much carbon will be lost in a particular fire is an active area of research and subject to substantial uncertainty (Littell et al. 2018; Coop et al. 2020). While our estimates of wildfire burn probability draw on peer-reviewed methodologies (VCS Methodology for Improved Forest Management for Fire Resilient Forests, available upon request), it was not within the scope of this project to develop a model that fully accounts for all factors affecting the likelihood and intensity of wildfire across the U.S. We were also limited by data availability and have thus restricted our analysis of wildfire impacts to western states in CONUS despite, e.g., the potentially substantial impacts of wildfire on carbon storage in Alaska (Walker et al. 2019; Mack et al. 2021). We strongly encourage additional research linking predictions of future wildfire impacts with the benefits of natural climate solutions stemming in new PAs.

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