Journal
GCB Bioenergy, 15(2)

ISSN
1757-1693

Authors
Di Vittorio, Alan V
Narayan, Kanishka B
Patel, Pralit
et al.

Publication Date
2023-02-01

DOI
10.1111/gcbb.13016

Received: 21 August 2022 | Accepted: 11 October 2022

DOI: 10.1111/gcbb.13016

RESEARCH ARTICLE

GCB-BIOENERGY BIOPRODUCTS FOR A SUSTAINABLE BIOECONOMY Open Access WILEY

Doubling protected land area may be inefficient at preserving the extent of undeveloped land and could cause substantial regional shifts in land use

Alan V. Di Vittorio[1] | **Kanishka B. Narayan**[2] | **Pralit Patel**[2] | **Katherine Calvin**[2] | **Chris R. Vernon**[2]

[1]Lawrence Berkeley National Laboratory, Berkeley, California, USA

[2]Joint Global Change Research Institute, Pacific Northwest National Laboratory, College Park, Maryland, USA

Correspondence
Alan V. Di Vittorio, Lawrence Berkeley National Laboratory, Berkeley, CA, USA.
Email: avdivittorio@lbl.gov

Funding information
U.S. Department of Energy, Grant/Award Number: DE-AC02-05CH11231 and DE-AC05-76RL01830

Abstract

Projection of land use and land-cover change is highly uncertain yet drives critical estimates of carbon emissions, climate change, and food and bioenergy production. We use new, spatially explicit land availability data in conjunction with a model sensitivity analysis to estimate the effects of additional land protection on land use and land cover. The land availability data include protected land and agricultural suitability and is incorporated into the Moirai land data system for initializing the Global Change Analysis Model. Overall, decreasing land availability is relatively inefficient at preserving undeveloped land while having considerable regional land-use impacts. Current amounts of protected area have little effect on land and crop production estimates, but including the spatial distribution of unsuitable (i.e., unavailable) land dramatically shifts bioenergy production from high northern latitudes to the rest of the world, compared with uniform availability. This highlights the importance of spatial heterogeneity in understanding and managing land change. Approximately doubling the current protected area to emulate a 30% protected area target may avoid land conversion by 2050 of less than half the newly protected extent while reducing bioenergy feedstock land by 10.4% and cropland and grazed pasture by over 3%. Regional bioenergy land may be reduced (increased) by up to 46% (36%), cropland reduced by up to 61%, pasture reduced by up to 100%, and harvested forest reduced by up to 35%. Only a few regions show notable gains in some undeveloped land types of up to 36%. Half of the regions can reach the target using only unsuitable land, which would minimize impacts on agriculture but may not meet conservation goals. Rather than focusing on an area target, a more robust approach may be to carefully select newly protected land to meet well-defined conservation goals while minimizing impacts to agriculture.

KEYWORDS

bioenergy, GCAM, land change, land cover, land protection, land suitability, land use, Moirai

1 | INTRODUCTION

Projections of future land change vary considerably across methods, scenarios, initial conditions, assumptions, and goals (Alexander et al., 2017), but the total land area remains relatively constant. Land-use models include stock and flow models (Strapasson et al., 2017), rule-based spatial allocation models (e.g., Ball et al., 2022; Engström et al., 2016; Meiyappan et al., 2014), demand-driven spatial allocation models (e.g., Stehfest et al., 2014; Van Asselen & Verburg, 2013), computable general equilibrium models (e.g., Fujimori et al., 2014; Woltjer & Kuiper, 2014), partial equilibrium models (e.g., Calvin et al., 2019; Dietrich et al., 2019; Havlík et al., 2011; Steinbuks & Hertel, 2016), and disequilibrium models (Breach & Simonovic, 2021). Scenarios are related to research goals, as SSP/RCP scenarios focus on mitigation targets and are used by earth system models (Popp et al., 2017; Riahi et al., 2017), bioenergy scenarios explore various limits and tradeoffs to bioenergy production (Calvin et al., 2014; Humpenöder et al., 2018; Kraxner et al., 2013; Rose et al., 2022; Searle & Malins, 2015; Strapasson et al., 2017), and food security and biodiversity studies consider impacts of changing agricultural productivity and land use in the context of food, fuel, and fiber demands (Delzeit et al., 2017; Henry et al., 2018; Hof et al., 2018; Santangeli et al., 2016; Zabel et al., 2019). One thing that all of these approaches have in common is that initial land type distributions are critical for projecting and understanding land change (Alexander et al., 2017) and its effects on the Earth system (Di Vittorio et al., 2018). Studies indicate that further research is needed to assess the uncertainty and impact of model assumptions on land change projections (Alexander et al., 2017), including assumptions regarding available land for agricultural expansion.

Available land for agricultural expansion is not always explicitly defined in land projection studies, and its uncertainty is rarely explored. Available land is often a set parameter, can be based on a variety of metrics, and adjustments sometimes manifest as land protection scenarios. For example, Strapasson et al. (2017) do not limit land availability to estimate land use for food and fuel demand in 2050 under 2, 4, and 6°C mitigation scenarios, and they ensure that food demand is met first. Remaining land is then allocated to bioenergy crops or forest expansion as dictated by the scenario. Delzeit et al. (2017) also do not limit land availability to estimate sufficient food production in 2030 under FAO crop production projections.

The SSP scenarios are applied by several models in various contexts, and while they include three qualitative levels of land-change regulation (Popp et al., 2017), there are no assumptions regarding land availability, which allows various models to apply existing assumptions and develop model-appropriate regulatory policies (Alexander et al., 2017). Baseline land exclusion has been implemented in various ways such as prescribing a percentage (Calvin et al., 2014), defining explicit urban and high-elevation exclusions (Havlík et al., 2011), delineating urban and protected area exclusions (Humpenöder et al., 2018), and in some cases excluding an additional percentage of available land to account for other sources of inaccessibility (Doelman et al., 2018). Further suitability constraints may not be explicitly included (e.g., Calvin et al., 2014), or various biophysical inputs may reduce land availability during model execution (e.g., Doelman et al., 2018; Havlík et al., 2011; Humpenöder et al., 2018). Land regulation scenarios are generally applied via explicit prescription of protection (e.g., Calvin et al., 2014; Doelman et al., 2018), or by applying economic constraints (e.g., Humpenöder et al., 2018). Additional context- and model-specific scenarios are also applied to various models with different land availability assumptions (e.g., Calvin et al., 2014; Havlík et al., 2011, 2012; Kraxner et al., 2013; Popp et al., 2014). Importantly, the results of various land change studies vary in part due to the wide range of model-specific land availability, prior to scenario application. As a result, applying the same scenario to a different model may result in a very different land-use changes due to the differences in baseline land availability in addition to differences in other model assumptions and structures.

This indicates that uncertainty and sensitivity analyses are required to understand the potential implications of land availability in different contexts. However, due to the heterogeneity of approaches described above, existing studies are difficult to compare and model comparison studies are difficult to implement such that they isolate the appropriate factors. Nonetheless, recent research indicates that there is a threshold for land availability below which there are considerable consequences for agricultural expansion and production, bioenergy production, food and bioenergy prices, and other environmental and sustainability indicators (Calvin et al., 2014; Doelman et al., 2018; Dolan et al., 2022; Henry et al., 2018; Humpenöder et al., 2018; Searle & Malins, 2015). This threshold likely varies by approach, which includes both the land availability assumptions and the dynamics of the particular model.

Recent studies have also directly addressed land availability to better characterize some of the uncertainty and variability across modeling approaches. Eitelberg et al. (2015) reviewed studies of potentially available cropland and found that variability depended mainly on the assumptions of which land-cover types were defined as plausible sources and whether or not they were considered protected. For example, Searle and Malins (2015) allow for a 10% expansion of cropland and pasture on forests, grassland, and savanna, then allow 75% of the remaining grassland and shrubland for bioenergy crops to obtain 930 M ha of currently available land. Zabel et al. (2014a) have developed a detailed suitability data set and analyzed it in conjunction with the protected area and land-use/cover data to show how present-day available land for agriculture could range from 460 to 7950 M ha depending on the acceptable level of suitability, protection, and land cover. However, suitability may change asymmetrically across regions in the future. King et al. (2018) use growing degree days to estimate that nearly 1000 M ha of additional boreal land may be suitable by 2100. Hannah et al. (2020) use crop-specific distribution modeling to estimate a range of 1030–2410 M ha of additional agricultural potential globally, based on several climate models and two levels of radiative forcing. They also conclude that a substantial amount of soil carbon could be released due to land conversion to agriculture. Zabel et al. (2014a) estimate a net increase of 480 M ha (excluding protected areas and dense forest), with most of this land having marginal to moderate suitability, and northern regions experiencing most of the gain while some mid-latitude regions experience losses. The findings of these studies warrant further robust analyses on how land availability influences land use projections.

Furthermore, a major movement to protect 30% of land by 2030 (e.g., Baillie & Zhang, 2018; CBD, 2021) has prompted many governments to pledge additional land conservation goals (COP26, 2021). Currently, about 16% of global land is protected, not including other effective area-based conservation measures (UNEP-WCMC & IUCN, 2022), indicating that the current amount of protected land would need to be nearly doubled to meet the 30% target. Individual governments will determine how to select new lands for protection and also the level of protection, sparking concern over indigenous rights (NGO, 2021) and other impacts on humans (Schleicher et al., 2019). Additionally, agricultural land suitability may play a role in protected land selection as suitability can identify land to either restrict or enable agricultural expansion onto suitable land.

Here we use the Moirai v3.1 land data system (Di Vittorio et al., 2020; Moirai v3.1, 2021) to provide comprehensive, spatially heterogeneous levels of land availability (based on both criteria of land suitability and protection status) to the Global Change Analysis Model (GCAM) and assess the effects on potential land use and bioenergy production. GCAM's default land availability for agricultural expansion is 10% of unmanaged land (Calvin et al., 2019), while Moirai includes agricultural suitability data (Delzeit et al., 2017; Zabel et al., 2014a) and International Union for Conservation of Nature (IUCN) protected area data (IUCN, 2018) to estimate contemporary, spatially explicit levels of land availability. GCAM currently does not distinguish between protected and unsuitable land (both are unavailable), but with Moirai different levels of availability can be selected for GCAM based on these spatially explicit data, rather than using a uniform fraction. We compare different levels of current availability with a series of fixed fractions to assess the effects on land allocation and bioenergy production in the core model. Furthermore, we estimate the impacts on land use of marginal decreases in available land at various starting points and relate these to the contemporary estimates of available land provided by Moirai. Through this relationship, we assess how decreasing land availability from the current state may affect future land use and cover.

2 | MATERIALS AND METHODS

2.1 | Agricultural suitability and protected area updates in Moirai version 3.1

The Moirai land data system (Moirai v3.1, 2021) integrates several data sets to produce initial land data (Di Vittorio et al., 2020) for the GCAM agriculture and land use module. The source data are a mix of raster (Table S1) and tabular (Table S2) data that are combined to generate a consistent set of tabular land data at the intersection of countries and user-specified geographic land units (Figure 1a). The geographic land units used here are 235 water basins as defined for the GCAM water module (Kim et al., 2016). The outputs include circa 2000 harvested area and production for 175 crops, land rent for 12 use sectors, irrigated and rain-fed area for 26 crop classes, water footprint for 18 crop classes and three water types, land-type area from 1800 to 2015 for 19 land types (Table 1) with eight possible land availability classes (Table 2), and soil and vegetation carbon densities for the vegetation land types.

Moirai v3.1 includes new agricultural suitability and protected area data that provide flexibility in assigning the available land area for agricultural use. These data are spatially explicit and enable Moirai to output the fractions of eight mutually exclusive land availability classes for each land type (Tables 1 and 2) within each geographic land unit and country (Figure 1a). There are 16 vegetation land types (undeveloped) and three developed land types (Table 1). The developed land types are also tracked by which vegetation type likely preceded their conversion, and in GCAM the initial cropland and pasture areas are automatically considered suitable and unprotected, regardless of the Moirai availability designation. For 2015, there are only about 260,000 km^2 of unknown land type (0.20% of total land), and all land has a known availability class.

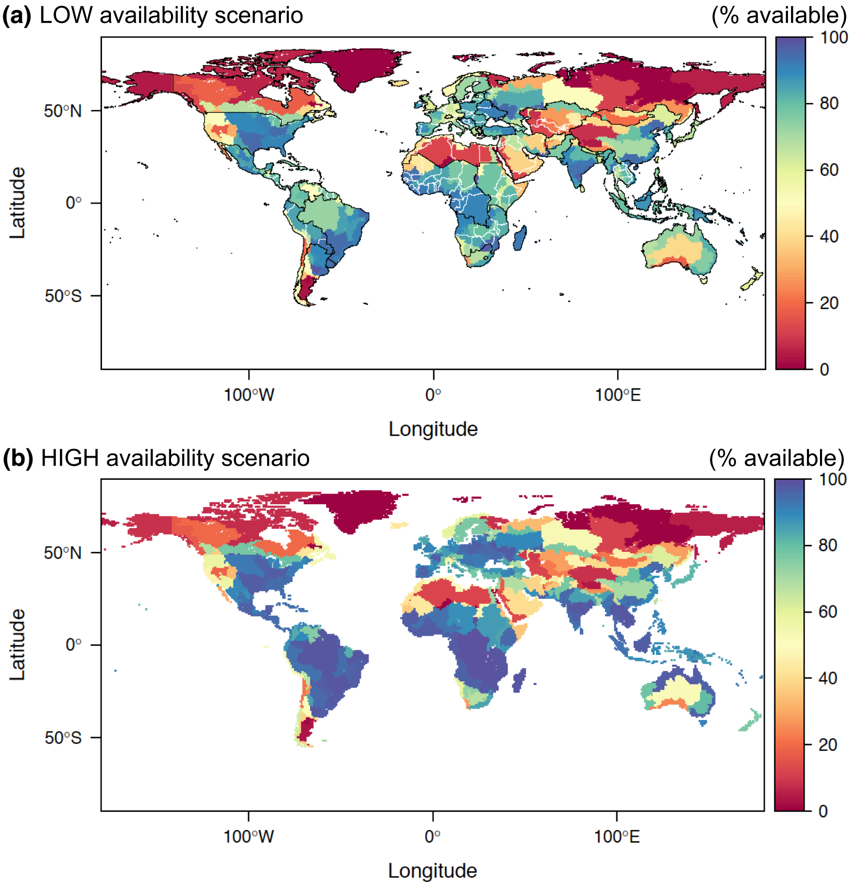

FIGURE 1 Percent of initial convertible land available to agricultural expansion in the (a) LOW and (b) HIGH availability scenarios, by water basin within each Global Change Analysis Model (GCAM) region. The black and white lines in (a) delineate GCAM regions and Moirai countries, respectively. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

TABLE 1 Relationship between Moirai and Global Change Analysis Model (GCAM) land types

Moirai land types	GCAM land types
Unknown	Not included
Tropical evergreen forest/woodland	Forest
Tropical deciduous forest/woodland	
Temperate broadleaf evergreen forest/woodland	
Temperate needleleaf evergreen forest/woodland	
Temperate deciduous forest/woodland	
Boreal evergreen forest/woodland	
Boreal deciduous forest/woodland	
Evergreen/deciduous mixed forest/woodland	
Savanna	Grassland
Grassland/steppe	
Dense shrubland	Shrubland
Open shrubland	
Tundra	Tundra (constant)
Desert	Rock/ice/desert (constant)
Polar desert/rock/ice	
Cropland (developed)	Cropland
Pasture (developed)	Pasture or grassland
Urban land (developed)	Urban land (constant)

Integrating agricultural suitability data with protection status provides a more detailed representation of potential limits to land use expansion and allows some flexibility in assigning available land. Moirai uses a data set representative of circa 2010 (Wade et al., 2020) that combines version 2 of the circa 2010 agricultural suitability data (Delzeit

TABLE 2 Moirai land availability classes and relationship to LOW and HIGH availability scenarios

Land availability classes	LOW scenario available	HIGH scenario available
Unknown (not present)		
Unsuitable and unprotected		
Suitable and unprotected	X	X
Suitable with high level of protection and is intact		X
Suitable with high level of protection that has been deforested		X
Suitable with low level of protection		X
Unsuitable with high level of protection		
Unsuitable with low level of protection		

et al., 2017; Zabel et al., 2014a, 2014b), version 1 of the Global Food Security-Support Analysis Data (GFSAD) 2015 cropland extent (Thenkabail et al., 2021; USGS & NASA, 2017), version 2 of the 2015 cropland, urban, and water area data from the European Space Agency Climate Change Initiative (ESA, 2017), version 1 of 2000–2016 global forest change data (Hansen et al., 2013), and circa 2017 protected area data (IUCN, 2018). Note that suitability data have been binned to either suitable or unsuitable in this data set and do not include the continuous suitability rating. This data set comprises six data layers that are input to Moirai and used to determine how much area of each land type is in each availability class (Table 1). This enables users of the Moirai outputs to combine availability classes in different ways to vary land availability based on both suitability and protection status.

Moirai v3.1 also newly incorporates gridded land carbon data for soil and vegetation (above and below ground) to determine carbon densities for each vegetation land type in each geographic land unit within each country. In this study, we use the standard GCAM carbon data as derived from the literature (Houghton, 1999; King et al., 1997) and not the Moirai v3.1 carbon data outputs because of some anomalously high grassland and savanna vegetation carbon densities in some regions. A more recent update (Moirai v3.1.1, 2022) improves the Moirai output carbon data by harmonizing land cover across the source data. In general, the spatially explicit carbon data have slightly lower density values than the original literature values. Using these data would slightly increase the areas of harvested forest and grazed pasture required to meet commodity demands. These increases would have limited effects on our results because these two land types require less than 20% availability in nearly all regions to experience declined allocation.

2.2 | GCAM agriculture and land use module

Global Change Analysis Model is a dynamic-recursive model that includes detailed economic, energy, water, and land systems and is linked to a simplified climate model for exploring climate change mitigation policies (Calvin et al., 2019). As a partial-equilibrium model GCAM solves market prices for all energy, agricultural, and land markets in each 5-year time step such that supply equals demand in all markets. The primary drivers of GCAM are region-specific annual population and initial gross domestic product, with prescribed rates of labor force participation and labor productivity growth. The agriculture and land-use module uses a profit-based land-sharing approach to determine land use/cover, agricultural and forestry production and consumption, land commodity prices, fertilizer use, agricultural water withdrawal and consumption, land carbon dynamics, and agricultural emissions (Wise et al., 2014). In GCAM, increases in demand lead to increases in commodity prices, which may lead to intensification, substitution among crops and land types, and shifts in trade patterns. These effects are simultaneously buffered by competing demands for other land uses, demand reduction at higher prices, and fertilizer and water availability. We use GCAM v5.4 in this study with regional markets and an updated bioenergy scheme (GCAM, 2022). The spatial structure is the intersection of 32 regions and 235 water basins (Figure 1), resulting in 384 distinct and operable land units. Agricultural production is determined within these land units and aggregated to regional markets, which have regional agricultural commodity prices. Primary crop commodities are traded among regions. Historical trade patterns are used to calibrate regional preferences for exports/imports. While these preferences are held constant throughout the simulation period, shifting economics in the model can cause deviations from historical patterns.

The new initialization data provided by Moirai updates the availability of land for agricultural expansion or forest harvest, which affects GCAM land-use dynamics. GCAM v5.4 by default assumes that only 10% of initial convertible land in 2015 (i.e., unmanaged forest, shrubland, and grassland) is available for agricultural expansion. Initial cropland and grazed pasture (referred to as simply 'pasture' in GCAM) are excluded from convertible land. Any areas of unknown land type are completely excluded from GCAM and amount to only 0.2% of GCAM's undeveloped land. Managed (i.e., harvested) forest is also excluded from convertible land. Only 7% of Moirai prescribed pasture is initially grazed in GCAM due to relatively high pasture productivity combined with the estimated animal feed demand that sources fodder crops and some root and fiber crops in addition to grazed pasture. The remaining prescribed pasture area is treated as unmanaged grassland and is designated as the initial area for new grazed pasture to expand into. Tundra, urban land, and barren land (rock, ice, desert) are excluded from convertible land because these land types are constant in GCAM. The new availability data from Moirai allows for different scenarios with available suitable areas ranging from 60% to 67% of initial convertible land. The amount of available land does not change over time in a given scenario, but differences in available land across scenarios can generate differences in land use distribution, crop and forestry production, bioenergy production, and land commodity prices.

This study incorporates several bioenergy-related updates that have subsequently been released within GCAM v6 (GCAM6, 2022). Models that estimate bioenergy production, and particularly models similar to GCAM, have been criticized for projecting unreasonably high rates of land conversion (e.g., Turner et al., 2018). Further criticism attributes the correspondingly high estimates of bioenergy production to the models' lack of alternative technologies, innovation, and socio-political barriers (e.g., Koberl, 2019), and to their limited representations of life cycle emissions and externality costs associated with climate effects and more broadly unsustainable environmental effects (e.g., Fuss et al., 2018). GCAM's previous approach to addressing these limitations was to limit bioenergy crop expansion by restricting land availability to 10% of convertible land. However, switching to current, spatially explicit land availability reduced this proxy for keeping bioenergy projections reasonable. For example, in GCAM's core 2.6 W/m^2 target forcing scenario this change in land availability increased peak bioenergy land expansion by 50% and peak bioenergy consumption from 300 EJ/yr to over 400 EJ/yr. While Fuss et al. (2018) report a very large literature range for bioenergy estimates (60–1548 EJ/yr in 2050), they estimate a sustainable production in 2050 that is similar to the 40–110 EJ/yr reported by Searle and Malins (2015). As a result, GCAM's bioenergy scheme has been updated to balance demand with higher land availability such that bioenergy production remains within reasonable estimates of future potential. Rather than reduce discount rates or re-parameterize the profit functions, both of which were difficult to justify at a regional level, we chose to address particular aspects of the bioenergy scheme. With respect to socio-economic factors, consumer fuel preferences have been adjusted to represent transitions, as incomes rise, from traditional (e.g., charcoal) biomass fuels to more modern fuels (e.g., gas, electricity) that may be derived from biomass feedstock (Table S3). Biomass feedstock includes municipal waste, forest and crop residues, and dedicated crops (represented as highly productive grasses), but only bioenergy crop expansion has been assigned an externality cost to account for barriers or sustainability considerations that are not explicitly modeled (Table S4). Additionally, bioenergy crop availability has been reduced to represent a slower-than-anticipated expansion of these crops. For example, annual growth in biofuel production slowed from 10% prior to 2010 to 4% between 2010 and 2016 (Reid et al., 2020). The share of regionally imported bioenergy feedstock has also been reduced to align it with the model's export preferences and to better match current trade. The initial share weight is 0.1, which is comparable with a contemporary estimate of global bio-ethanol trade being less than 10% of total production (e.g., Seabra, 2021). Overall, these modifications help address previous model limitations and do reduce bioenergy crop expansion in GCAM, but the reduction amount depends on the scenario.

2.3 | GCAM land availability scenarios

To evaluate the influence of land availability on land use and bioenergy we compare 11 core model scenarios ranging from zero to 100% land availability at 10% intervals and two core model scenarios that introduce spatially heterogeneous availability to define the global minimum (60%) and global maximum (67%) availability based on the new Moirai data (with 2015 convertible land as the reference; Table 3). GCAM core scenarios are characterized by the SSP2 population estimate and recent data and forecasts for initial GDP, labor productivity growth rates, and labor force participation rates (Calvin et al., 2019). The scenarios used here do not include bioenergy with carbon capture and storage because they are not climate mitigation scenarios. The two spatially explicit scenarios consider only suitable, convertible land as available, with the difference determined by protection status. We directly compare these scenarios to estimate how different levels of land availability affect land-type distribution, crop production and prices, and bioenergy production and consumption.

We use the interval scenarios to estimate the marginal changes in land allocation due to marginal decreases in land availability. We place our LOW and HIGH scenarios in this spectrum based on their respective availabilities to assess how changes from current availability may impact land preservation and agricultural land use. The regional assessment of these effects is more informative than the global as the current spatial distribution of available land (Figure 1; Table S5) influences the results.

TABLE 3 Global land availability scenarios relative to 2015 initial convertible land

Scenario	Available land
10% Intervals—constant value	0%–100% of unmanaged forest, shrubland, and grassland in 10% intervals
LOW—suitable, unprotected land	60% of total unmanaged forest, shrubland, and grassland, corresponding to: 63% of grassland 37% of shrubland 65% of forest
HIGH—all suitable land regardless of protection	67% of total unmanaged forest, shrubland, and grassland, corresponding to: 68% of grassland 44% of shrubland 75% of forest

To assess the potential effects of achieving 30% land protection we start with our contemporary LOW scenario and approximately double GCAM's global protected area. The regional increases vary for each to meet the desired protection target, which is consistent with the current, decentralized approach (COP26, 2021). The additional protected area is defined as the percent of all convertible land and is applied uniformly to all land types to reduce land availability. This analysis is performed by estimating changes in allocation due to changes in availability along the marginal change trajectories determined by the interval scenarios.

3 | RESULTS

3.1 | Land allocation

Globally, decreasing the amount of available land decreases land use extent and increases the area of unmanaged forest, shrubland, and grassland (Figure 2). In terms of land allocation, food crops contract the most across the full availability range, with pasture and bioenergy feedstock (biomass) crops also losing considerable area. Grassland gains the most area, with unmanaged forest also gaining considerably while shrubland experiences smaller gains. Managed forest requires relatively low availability to experience a decrease, likely because wood demand is less elastic than other commodities. Grassland has the greatest range across availability because a portion of it is easily converted to pasture when available. Caloric demand is met in GCAM (Edmonds et al., 2017), which constrains the minimum amount of agricultural land, and in conjunction with the relative ease of converting some grassland to pasture helps explain the increase in pasture under zero percent availability that compensates for the loss in cropland. The LOW and HIGH scenarios have similar dynamics because they differ by a relatively small amount in availability (the area of suitable, protected land: 6,199,000 km^2, or only 7% of convertible land) compared with their prescribed availabilities of 60% and 67%. Nonetheless, the HIGH scenario has slightly more agricultural land and slightly less shrubland, unmanaged forest, and grassland.

Regional land allocation patterns mostly match the global dynamics, with a few exceptions (Figure S1). In China and South Korea post-2060, global demand and relatively static trade parameters drive a reversion of the global pattern such that increases in land use and decreases in undeveloped land occur during this period even at low levels of land availability. In some regions, grassland is slightly higher for the HIGH scenario than for the LOW scenario, likely because allowing protected land to be used for agriculture allows more conversion of forest or shrubland, thus relieving pressure to convert grassland. These regions include Australia/New Zealand, Central America/Caribbean, Columbia, Europe-non-EU, Mexico, Northern South America, Southern South America, and the United States. There is also a dramatic deviation from the global pattern in the regional patterns of land allocated to biomass for bioenergy in the LOW and HIGH scenarios. Russia and Canada have relatively low allocations for bioenergy feedstock while most other regions have more bioenergy feedstock area than the 100% uniform availability case. This is due to unsuitable land being unavailable in the spatially explicit scenarios, which dramatically reduces availability in northern high latitudes (Figure 1). Northern South America and Japan show differences in bioenergy feedstock area between the LOW and HIGH scenarios, demonstrating that protected forest (and also shrubland in Japan) clearly reduces bioenergy crop expansion in these regions.

The land availability threshold at which land allocation in 2050 changes by at least 10% from its path under full availability varies by specific land type and region, but generally follows a global pattern (Figure 3). Cropland allocation begins to decrease between 80% and 90% land availability. Pasture and managed forest allocation start to decrease when land availability drops to 30%–40%. Bioenergy feedstock allocation begins to decrease

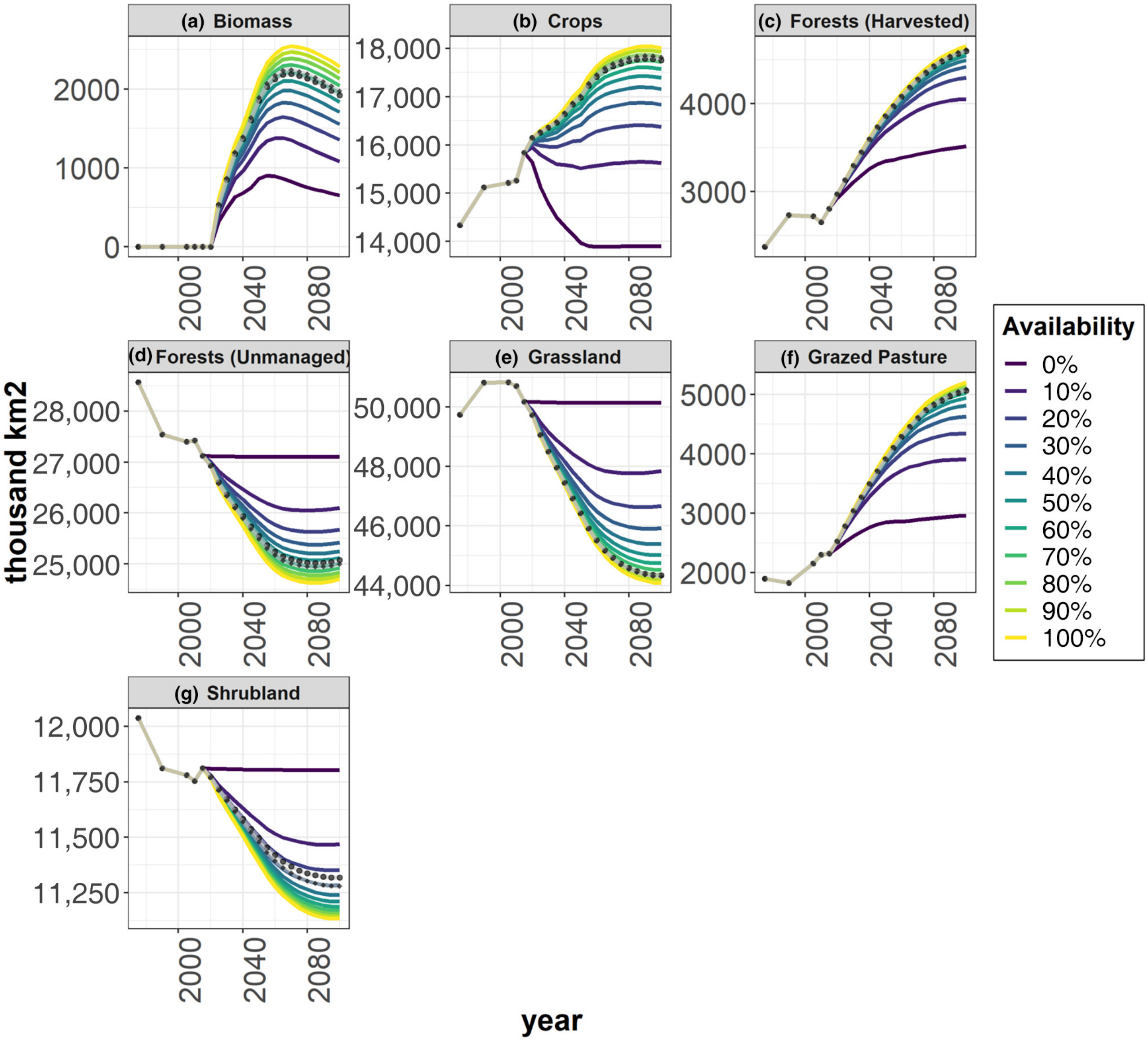

FIGURE 2 Global land allocation by land type (panels (a–g)) under different availability constraints. Dots represent the LOW availability scenario and diamonds represent the HIGH availability scenario.

between 70% and 80% availability. Conversely, unmanaged land types lose less area than under full availability as land availability decreases. Forest area begins to show less loss at 70%–80% availability, while grassland and shrubland begin to have reduced loss between 60% and 70% availability. Cropland (including bioenergy crops) is more impacted than undeveloped land types because the need to meet demands shifts agriculture to more productive areas and areas with more available land as overall land availability decreases. Pasture and harvested forest require greater losses in land availability than their source land types (grassland and forest, respectively) because (1) their initial areas are less than or equal to 1% of their source types, so their relative changes are much greater than those of their source types, which means that pasture and harvested forest require larger decreases in land availability to reduce their changes by the same fraction and (2) overall demand is essentially the same across the cases, and these types produce commodities with relatively low elasticity and so they maintain their allocation under greater availability loss to meet demand. This variability poses challenges for making practical tradeoffs between land use and ecological conservation. For example, cropland allocation declines by 10% with 10%–20% of land becoming unavailable, but to reduce grassland loss by 10% at least 30%–40% of unmanaged land must become unavailable for agricultural expansion.

The application of spatially explicit estimates of contemporary land availability poses a further challenge in that it influences land allocation in a different way than corresponding uniform fractions. While the LOW and HIGH scenarios, respectively, have 60% and 67% of

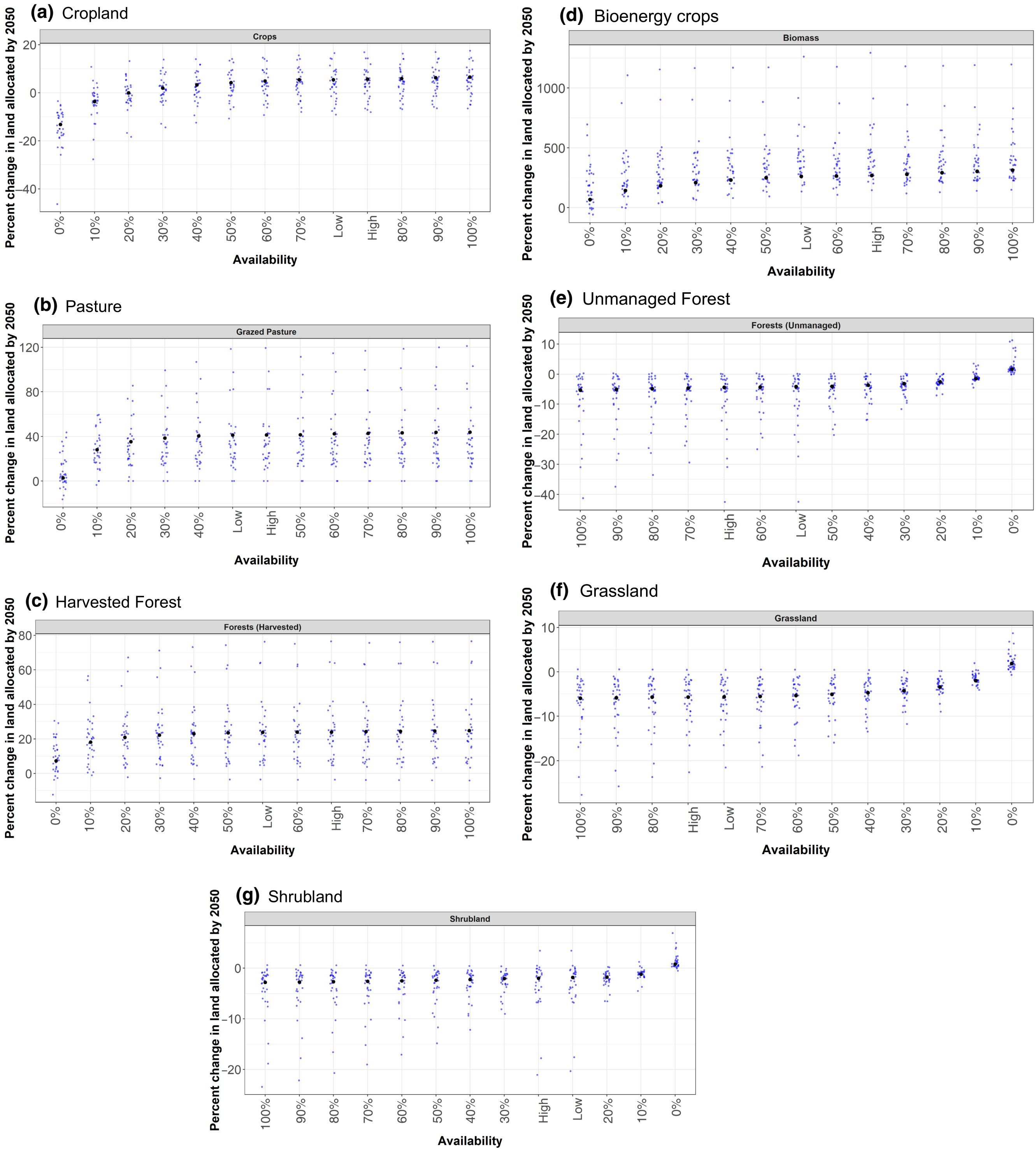

FIGURE 3 Change in land allocation by 2050. (a–c, e–g) Percent change relative to 2015. (d) Percent change relative to 2025 because there is no bioenergy feedstock area in 2015. The blue dots represent each Global Change Analysis Model region, and the black dots represent the global values.

convertible land available globally, their land allocations do not behave like the corresponding uniform scenarios. The following rankings are based on the change in land allocation by 2050 (Figure 3), which are largely consistent with the overall trajectory (Figure 2). The two scenarios behave more like a 70%–80% uniform availability case for crops, like a 40%–50% availability case for grazed pasture, and both near 60% availability for bioenergy feedstock. For managed forest, the LOW scenario is more like a 50%–60% uniform availability case and the HIGH scenario is more like a 60%–70% case. For unmanaged land the LOW (HIGH) scenario behaves like a 50%–60%

(60%–70%) uniform availability case for forest, both scenarios behave similarly to the 80% case for grassland, and both scenarios behave like a 20%–30% case for shrubland. This behavior is not consistent with the global specific land type availability of these scenarios (Table 3), indicating that regional variability of land availability is an important factor in determining land allocation. The main implication here is that the initial distribution of available land is very important for land allocation projection, including the location and type of available land.

The regional variability in behaviors of the LOW and HIGH scenarios is clearly evident in the time series of land allocation (Figure S1). For example, little to no shrubland is lost in the LOW and HIGH scenarios in Canada, Russia, and Central Asia, likely due to relatively low productivity compared with other land types. In addition, the behavior of bioenergy feedstock allocation varies regionally, with most regions allocating more land for the LOW and HIGH scenarios than for the 100% availability case for bioenergy feedstock, while Canada and Russia behave more like the 40% and 20% availability cases, respectively. As stated above, this results from the uneven distribution of unsuitable land that is not available in the LOW and HIGH scenarios. Northern South America and Japan further differentiate feedstock allocation behavior by scenario, indicating that land protection influences allocation in these regions. The HIGH scenario behaves like an 80% (90%) case and the LOW scenario like a 40% (~70%) case in Northern South America (Japan). This regional response has implications for reducing available land through protection, which is discussed below.

3.2 | Commodity production, prices, and energy consumption

Overall, crop and other land commodity production decreases with decreasing land availability (Figures 2 and 4). This is expected because production is the product of yield and allocated area. However, looking at more specific crops highlights an interesting tradeoff between fodder crops and pasture. As pasture decreases with decreasing land availability, fodder crop production and area increase to meet animal feed demand. The only other two crop groups having this inverse relationship with land availability are root tubers and fiber crops, likely because these crops are also used for animal feed in some regions. As pasture increases, less of these crops are needed for feed. The LOW and HIGH scenarios are indistinguishable from each other at the global level with respect to land commodity production and are also consistent with land allocation in their overall behavior relative to the fixed availability constraints. These patterns also hold regionally, including for bioenergy feedstock production, which helps explain why the global production of 96 EJ in 2100 is lower than expected for the LOW and HIGH scenarios compared with 105 EJ for the 60% uniform availability case (Figure 4) that has a comparable 2 million km^2 of bioenergy feedstock land (Figure 2), as opposed to approximately 1.5 million km^2 for the 30% availability case (Figure 2) with bioenergy production comparable to the LOW and HIGH scenarios (Figure 4). Without the designated unsuitable land being available, bioenergy feedstock production moves from seemingly more productive northern areas in Canada and Russia to less productive areas in the rest of the world (Figures S1 and S2). This further illustrates the importance of the spatial distribution of land availability.

Crop producer prices generally are negatively associated with production (e.g., Figures 4–6) and do show regional variability (e.g., Figures 5 and 6) that reflects regional land allocation (Figure S1). This is expected due to supply and demand relationships that cause increases in prices with decreases in supply, especially while demand remains similar across our scenarios, all of which have the same socio-economic constraints. The regional variability is more apparent for bioenergy feedstock (Figure 5) than for other crops (e.g. Figure 6) due to the wide range of biomass productivity across different regions (Figure S2). Again, the crop price behaviors of the LOW and HIGH scenarios are also associated with land allocation and production.

Decreases in bioenergy feedstock production (Figure 4) with decreases in land allocation correspond with decreases in bioenergy consumption and increases in oil consumption (Figure 7). Bioenergy crop feedstock is the dominant bioenergy source by 2050 so bioenergy consumption follows the same pattern as feedstock production. While relative bioenergy consumption decreases can be noticeable by 2050 (7.2% decrease when decreasing land availability by 20% from the bioenergy consumption behavior of the LOW scenario, that is, from 30% to 10% uniform availability), the impacts on consumption of other energy sources are negligible and primarily affect oil (only 0.95% increase in total oil for this same decrease in land availability). This is because most bioenergy feedstock is converted to biofuel in these scenarios and thus serves as a replacement for transportation oil. As such, decreases in bioenergy production have a limited effect on total energy consumption as increased oil mostly compensates for decreased bioenergy feedstock.

3.3 | The effects of marginal decreases in land availability

Changes in land allocation due to incrementally decreasing land availability provide estimates of how additional

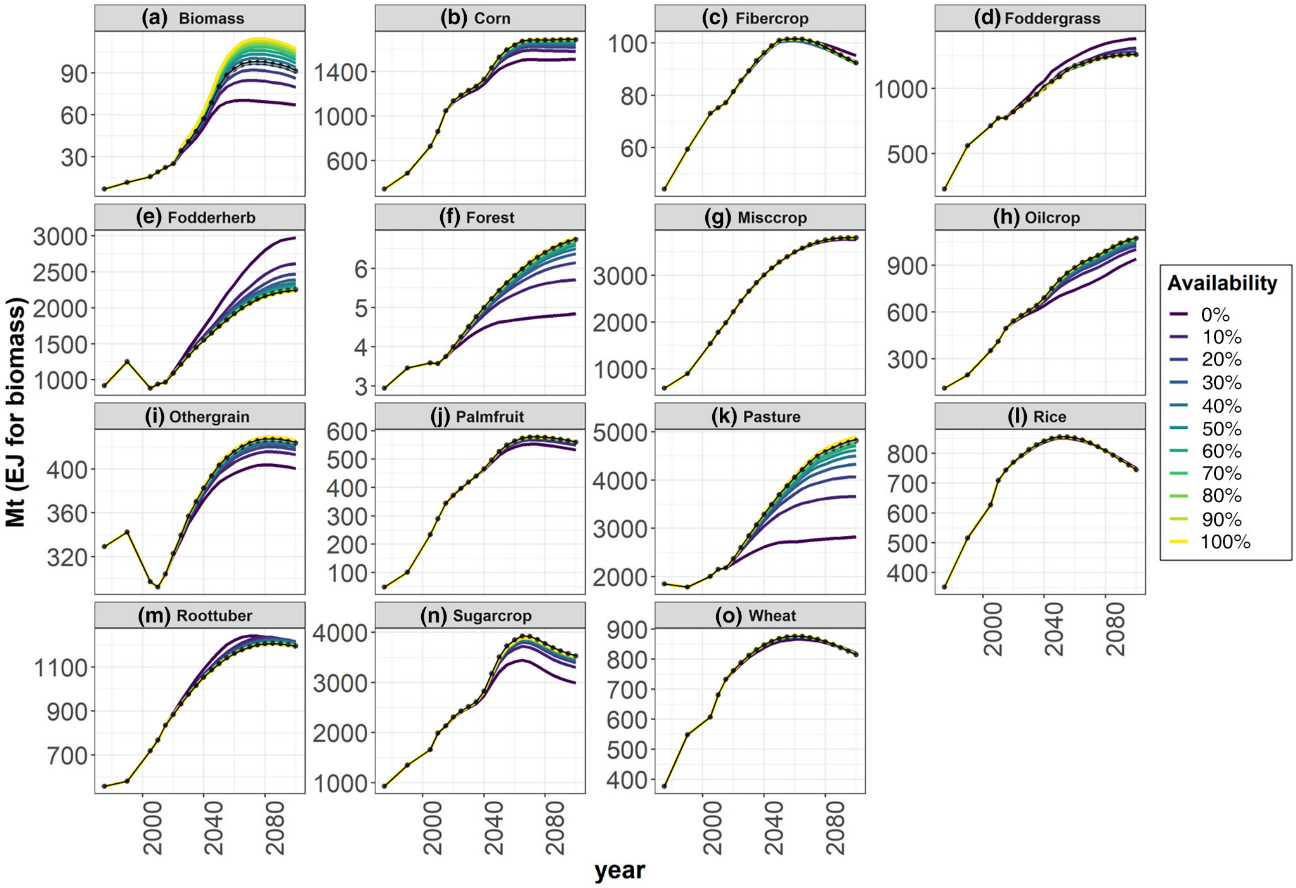

FIGURE 4 Global crop and commodity production (panels (a–o)) under different land availability constraints. Dots represent the LOW availability scenario and diamonds represent the HIGH availability scenario.

land protection may affect future land use and cover (Figures 8 and 9). In general, decreasing land availability decreases agricultural land use and increases undeveloped land (Figure 8), but these two groups do not have the same response pattern with respect to their relative changes (Figure 9). The absolute change in area is more relevant for the undeveloped types as it directly reflects the impact of the amount of newly protected land, while the relative change matters more for the developed types because production changes proportionally with changes in allocation. As the developed land types have a smaller global extent than the undeveloped types, the same change in area can have a much larger relative impact on the developed types than the undeveloped types.

In terms of area, gains in undeveloped types are balanced by losses in developed types, but these gains do not necessarily equal the area of decreased land availability for conversion. This is because unprotected, undeveloped land still exists and can be converted until land availability drops to zero. We quantify this mismatch between the undeveloped area preserved and the area made unavailable as the land protection efficiency, which is defined as the ratio of the change in undeveloped area to the change in available area (Table 4). The geographic distribution of land types plays a large role in the land allocation response to a given percent decrease in land availability (applied uniformly to the three convertible land types; Figure 8; Figure S3). Some regions rapidly gain grassland as availability decreases, while others have strong gains in forest or shrubland, and still, others show little gain in unmanaged land until no land is available for conversion. Globally, and in nearly all regions, cropland decreases the most as availability decreases. The major exceptions are in South Korea and Japan where cropland slightly increases until availability drops to zero. When summed to the globe, this heterogeneity results in an increasing land protection efficiency as the amount of available land decreases. Since land protection efficiencies are less than 100% at high availability (for most regions), there is a low-availability threshold at which efficiencies exceed 100% for the undeveloped land areas to catch up to a zero availability state where they do not change over time (Table 4; Figure 2). For the globe, this threshold occurs at a state between 20% and 10% availability. In a few regions (India, Pakistan, and the European Free Trade Association) where land allocation responds to small initial decreases in availability

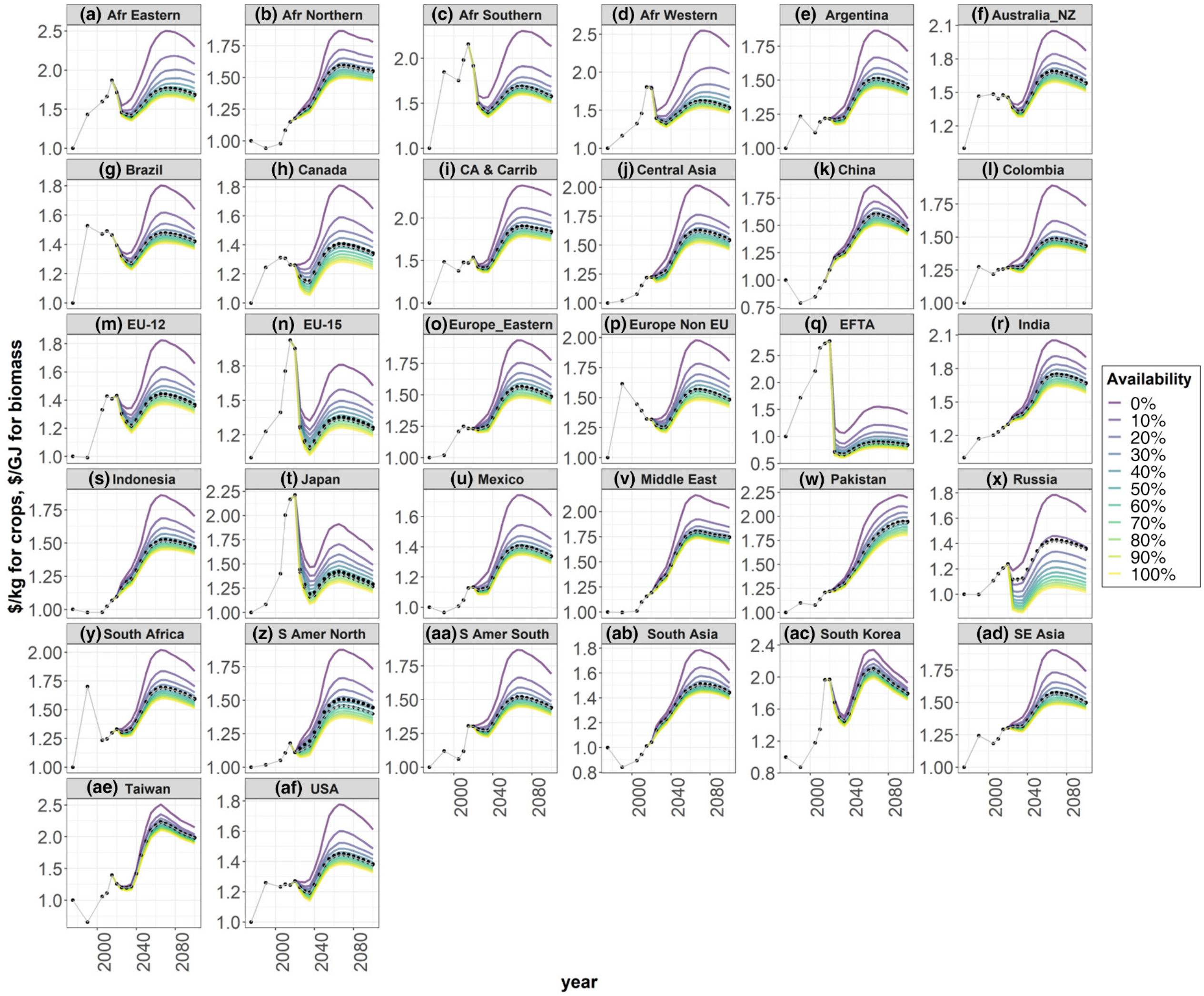

FIGURE 5 Regional crop producer prices for bioenergy feedstock. Panels (a–af) each represent one of 32 Global Change Analysis Model (GCAM) regions.

(Figure S3) the land protection efficiencies are over 100% at high availability as land use is allocated elsewhere in response to market forces.

With respect to relative changes in land type area, it is clear that developed land, and particularly bioenergy feedstock land, has greater declines in allocation with decreases in land availability than undeveloped land (Figure 9). Changes from a given availability state are fairly constant at high levels of land availability (with the exceptions of bioenergy feedstock and some undeveloped types in a few specific regions), but as availability decreases the responses across land types begin to diverge with respect to both the onset of increasing change and the magnitude of change. Agricultural land use tends to decline sooner (at higher land availability) and at higher rates (a greater percent change from the previous state) than undeveloped land. Overall, bioenergy feedstock allocation has the largest decrease in comparison with other land types and also has the earliest onset of an increasing rate of decline, partly because it has the smallest area of those compared. There are a few regional exceptions (e.g., Northern Africa, Central America, Central Asia), likely due to regional land availability, bioenergy crop productivity, and international trade, where bioenergy feedstock allocation has a slight increase initially but eventually declines dramatically at very low levels of land availability (Figures S2 and S4). Also, in India and Pakistan initial decreases in land availability cause noticeable increases in undeveloped land as well as decreases in agricultural land. As land becomes less available, however, the relative impacts on agricultural land become comparable with or greater than those on undeveloped land.

3.4 | The potential implications of achieving 30% land protection

The potential impacts of proposed land protection depend on the current levels of land use (Figure 2) and availability

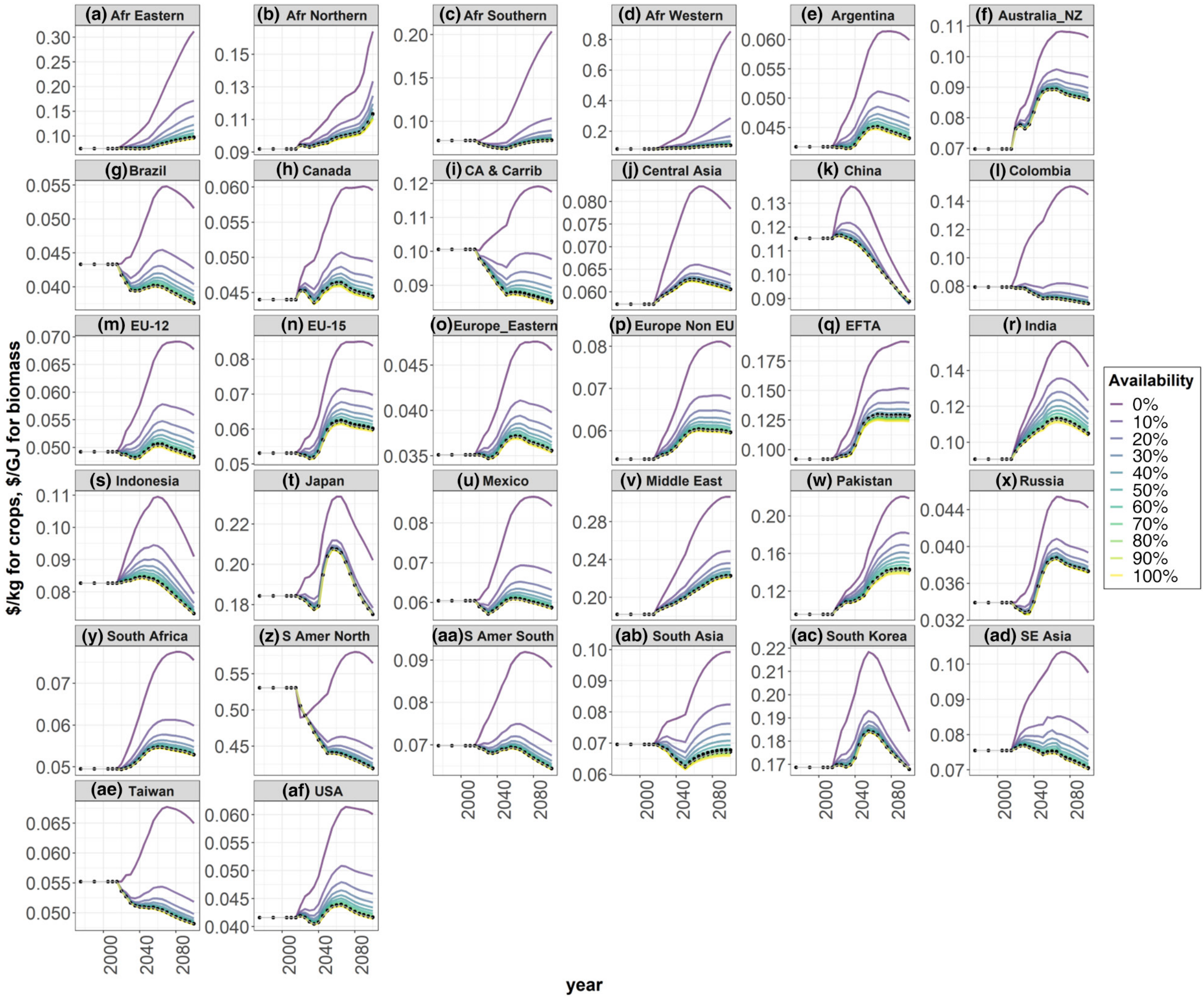

FIGURE 6 Regional crop producer prices for corn. Panels (a–af) each represent one of 32 Global Change Analysis Model (GCAM) regions.

(Table S5), how land allocation may change as availability decreases (Figures 8 and 9) and which land becomes protected (Table 5). To apply our results to current calls for 30% land protection we have to translate 30% of all land into a value corresponding with GCAM's definition of land availability. According to the primary source on protected areas (UNEP-WCMC & IUCN, 2022), 15.73% of terrestrial land and water are in a protected area. GCAM considers only actual land area, as water is not available for land use. As a result, only 9.37% of GCAM land area is protected (based on corresponding source data), with a little over half of this protected area considered suitable for agriculture (Table 5; Figure 10). Furthermore, this GCAM value includes all land types to account for land classification inconsistencies between the protected area data and the rest of the Moirai land data. Since 30% protection is about double the currently reported amount, we explore the implications of approximately doubling GCAM's global protected area to 20% of land in 2015, both globally and by region. The resulting impacts are estimated as differences in land type area by 2050.

To estimate the potential impacts of added protection in GCAM the desired protected area needs to be determined as a percentage of convertible land, which is the basis for availability. The percent of total land required to meet 20% protection is converted to area and then divided by the amount of convertible land to determine the percent decrease in GCAM land availability required to meet the protection target (Table 5). Only three regions have already met this protection goal (EU-15, Japan, and Northern South America), and two others would need to protect 1% or less of their convertible land (Australia/New Zealand and Taiwan) to meet this target. This does not mean that these regions do not have additional sensitive areas that would benefit from being protected. Another interesting result is that Northern Africa would need to protect 118% of its convertible land to meet the goal. This results from 84.7% of its undeveloped land falling in the unconvertible

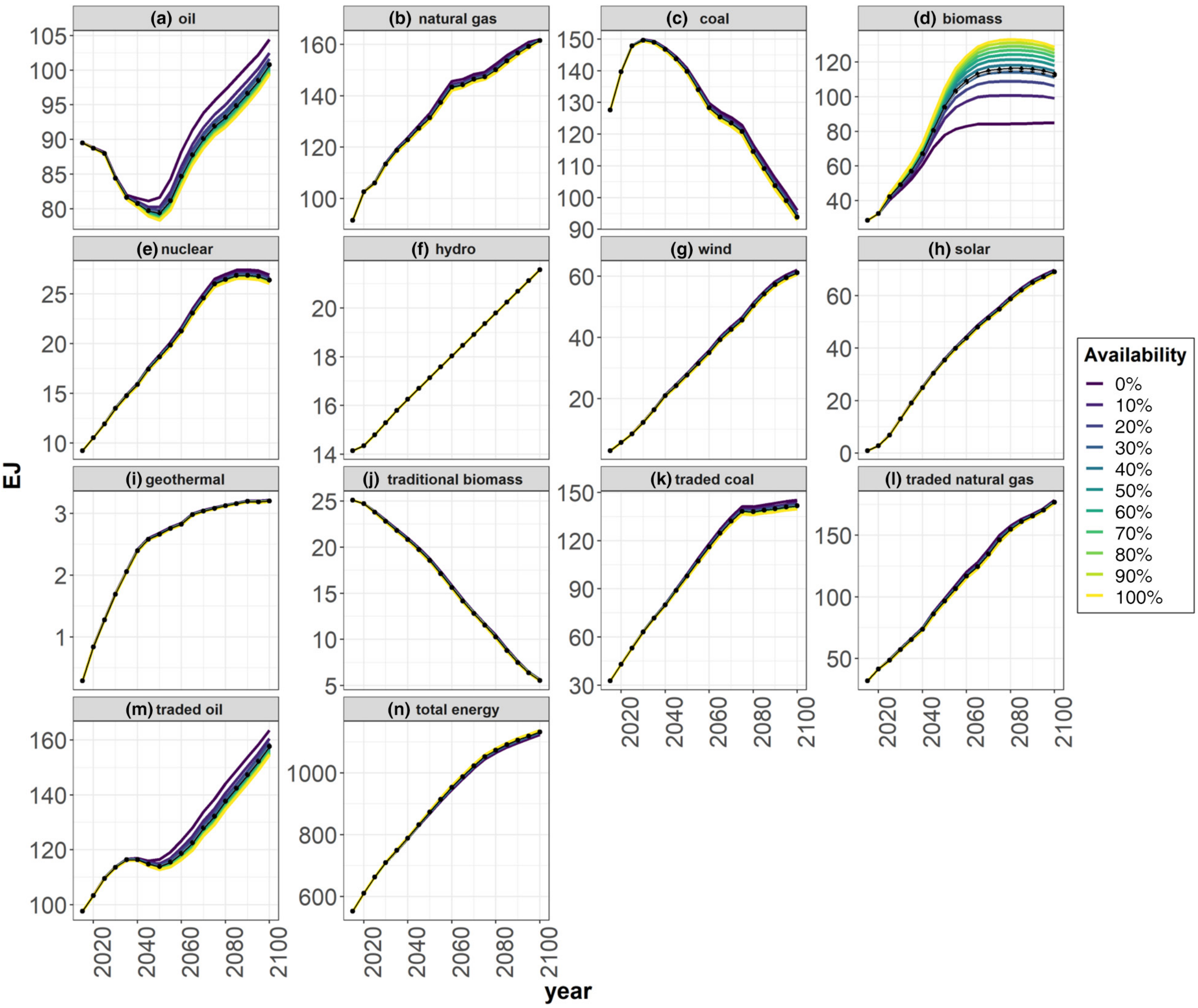

FIGURE 7 Primary energy consumption under different land availability constraints. Panels (a–n) each represent a primary energy source in the Global Change Analysis Model (GCAM).

"Other" land type category (which in this case is all desert). It is also important to note that many GCAM regions include multiple countries and that a regional value does not necessarily represent the state of an individual country.

Applying the estimated additional protection to the current availability in the context of our 2050 marginal impact analysis demonstrates how reaching the protection target may impact both developed and undeveloped land (Figures 8 and 9). The respective availabilities of convertible unmanaged forest, shrubland, and grassland in the LOW scenario (Table S5) can be superposed on the marginal impact plots (Figures 8 and 9) to represent their current states from which availability will be reduced. The managed land types can be converted from any of the unmanaged types, so their current states are represented by the availability of all convertible land, regardless of type. The additional protected area is defined as the percent of all convertible land and is applied uniformly to all land types by moving along each land type line from the current availability to the new desired availability (Figures 8 and 9; Table S6). Since the current state in the LOW scenario considers only suitable, unprotected land as available, this desired availability effectively estimates the effects of protecting only suitable, unprotected land (because protected land and unsuitable land are already unavailable). The slope between two points on a line (in terms of the change in land type area due to the reduction in available area) represents the impact of a particular land type of added protection, relative to the initial point. This slope between the LOW case starting point and the target availability is calculated as a sum of the weighted piecewise-linear area changes along the land type lines, which are derived from the 10% availability interval cases. Using the change in available convertible area as the reference allows for direct comparison between impacts on different land types.

Low protection efficiencies combined with considerable regional shifts in land allocation highlight the need for carefully selected land protection over area-based

GCB-BIOENERGY BIOPRODUCTS FOR A SUSTAINABLE BIOECONOMY Open Access

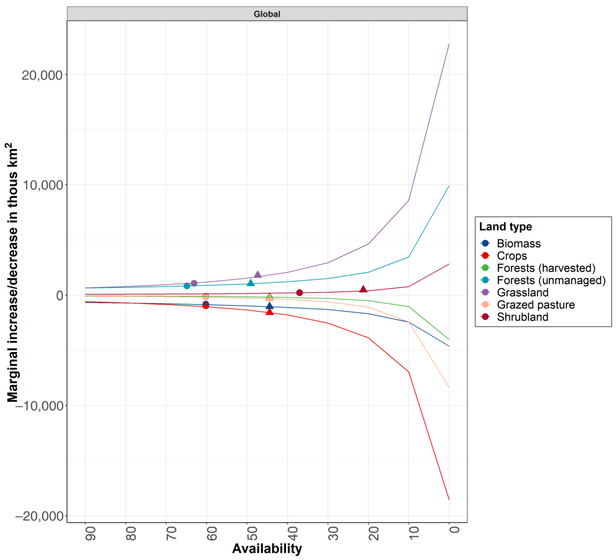

FIGURE 8 Marginal absolute changes in land allocation in 2050 due to incremental decreases in land availability, globally. The *x*-axis denotes a 10% decrease in land availability from the previous tic, starting at 100% availability. The *y*-axis values are absolute change in area relative to that at the previous availability level. Circles indicate the current availability and extent of unmanaged forest, grassland, and shrubland, respectively, and of these three types combined (on the managed land type lines), based on the 2015 Global Change Analysis Model initial state. The triangles indicate land type availability and extent when protected area is approximately doubled. The absolute change in land allocation of a particular type due to meeting the new protection target is estimated by moving from the circle to the triangle along a given line.

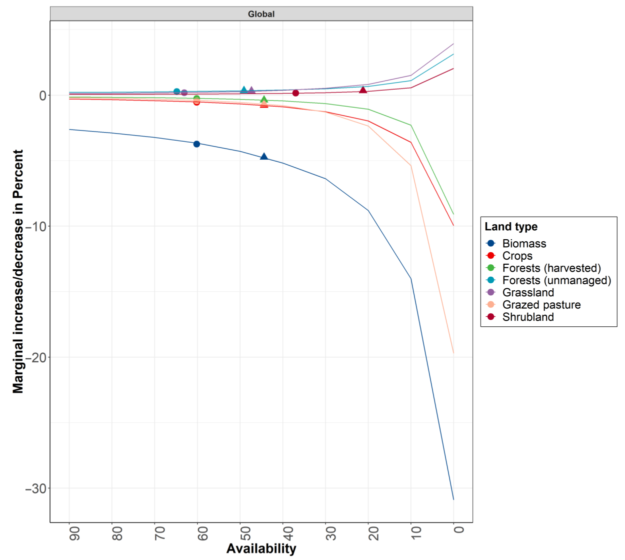

FIGURE 9 Marginal relative changes in land allocation in 2050 due to incremental decreases in land availability, globally. The *x*-axis denotes a 10% decrease in land availability from the previous tic, starting at 100% availability. The *y*-axis values are percent changes in land type area relative to that at the previous availability level. Circles indicate the current availability and extent of unmanaged forest, grassland, and shrubland, respectively, and of these three types combined (on the managed land type lines), based on the 2015 Global Change Analysis Model initial state. The triangles indicate land-type availability and extent when protected area is approximately doubled. The relative change in land allocation of a particular type due to meeting the new protection target is estimated by moving from the circle to the triangle along a given line.

protection targets due to asymmetric impacts between developed and undeveloped land. Approximately doubling protected area exhibits low protection efficiencies globally (25%–39%) and in most regions, with only Northern Africa, India, Pakistan, European Free Trade Association, EU-15, and South Asia reaching at least 100% efficiency for one or more intervals (Table 4). This indicates that land protection is not very effective at reducing land conversion, suggesting that protected land should be carefully selected to maximize the desired benefits, rather than be selected to meet area targets. Relative changes in land use (and corresponding production) can be substantial regionally while global changes are more stable due to the need to meet demands (Figure S4; Table S6). Globally, less than 2% of undeveloped land is gained by achieving the protection target while 10.4% of bioenergy feedstock land, 3.2% of cropland, 1.7% of harvested forest, and 3.5% of grazed pasture are lost. Regional shifts in bioenergy feedstock allocation are greater than 10% for 10 of the regions with Russia losing 46%, Canada losing 39% and northern South America gaining 36%. Northern Africa loses 61% of cropland, 35% of harvested forest, and 100% of grazed pasture, with other regions also showing considerable losses of these land types. Regional gains in undeveloped land can be relatively substantial in India, Pakistan, and Northern Africa. Unmanaged forest increased by 31% in India and 26% in Pakistan; grassland increased by 34% in Northern Africa, 26% in India, and 36% in Pakistan; and shrubland increased by 24% in Northern Africa, 21% in India, and 31% in Pakistan. Corresponding shifts in production and prices will be felt regionally, while the benefits of protection will depend on which land is protected. In other words, protecting land can have substantial impacts on human systems while not avoiding conversion of an equivalent amount of land, and also not providing the desired benefits if the land is not selected properly.

4 | DISCUSSION

4.1 | Bioenergy

Bioenergy crop production in the LOW and HIGH scenarios is reasonable, even though other studies allocate more of it

TABLE 4 Land protection efficiency calculated as the ratio (%) of marginal, undeveloped (unmanaged forest, grassland, shrubland), convertible area change by 2050 to the change in the available area. Shaded ranges indicate the efficiencies spanned when going from the LOW scenario to 20% protection. Numbers have been rounded for readability.

	Available convertible land									
Region	**100%–90%**	**90%–80%**	**80%–70%**	**70%–60%**	**60%–50%**	**50%–40%**	**40%–30%**	**30%–20%**	**20%–10%**	**10%–0%**
Eastern Africa	24	31				108	166	280	519	903
Northern Africa	19	22	27	33	41	51	67			
Southern Africa	2			6	9	14	23	46	118	491
Western Africa	17				50	72	107	180	359	812
Argentina	8	9	11	13				51	101	374
Australia_NZ	0	0	0	1		4	8	16	45	288
Brazil	4			9	12	18	27	47	97	340
Canada	21	22	24	26	29	33	38			243
Central America and Caribbean	11	14			31	44	65	106	200	474
Central Asia	−1	−1	−1	−1	−1	0				214
China	2	2	2	3					67	335
Colombia	0	0		1	1	2	4	9	33	376
EU-12	65				106	128	160	211	304	524
EU-15	83			114	130	153	187	241	334	529
Eastern Europe	69					113	133	166	243	432
Europe—non-EU	33					74	99	141	230	454
European Free Trade Association	169	178	190	205			285	345	456	709
India	160							497	615	765
Indonesia	14				31	41	57	86	151	383
Japan	40	42			48	51	53	54	51	99
Mexico	3	5			14	22	38	72	167	501
Middle East	−1	0	0	0	1					292
Pakistan	151	172							527	644
Russia	27	29	32	35	39	44	51			235
South Africa	3	4					27	53	132	468
Northern South America	2	2			2	2	2	2	3	87
Southern South America	1	1			2	3	6	13	44	289
South Asia	40	49	60	76					449	733

TABLE 4 (Continued)

Region	Available convertible land 100%–90%	90%–80%	80%–70%	70%–60%	60%–50%	50%–40%	40%–30%	30%–20%	20%–10%	10%–0%
South Korea	−1	−1			−4	−5	−8	−11	−13	68
Southeast Asia	10				24	33	48	77	148	426
Taiwan	−2	−3	−4	−5		−8	−11	−16	−17	156
USA	12	14	17			34	48	75	138	393
Global	16	18	21				53	80	144	399

to electricity or heat than this study does. In 2050 the LOW scenario (our best estimate of current land availability) produces 80 EJ of crop-derived bioenergy, which is about 9% of the total energy consumption and 85% of total bioenergy consumption. Total bioenergy consumption in 2050 is projected to be 94 EJ due to the presence of non-crop bioenergy sources (municipal waste, forest residues, and crop residues). A review by Searle and Malins (2015) estimates sustainable bioenergy crop production in 2050 of 40–110 EJ with only 25%–29% of total bioenergy consumption being biofuel and 50%–57% being electricity (the remainder being direct heat). On the other hand, Gielen et al. (2019) estimate about 67 EJ of bioenergy consumption in 2050 with 22 EJ of biofuel, 7 EJ of electricity, and 38 EJ of direct heat/use. These total bioenergy estimates are remarkably similar considering the variety of feedstocks, technologies, costs, and other factors that models can incorporate. For example, Daioglou et al. (2020) report that the wide ranges of available technologies and costs in models are consistent with those in the bioenergy literature and that costs, including feedstock costs, tend to dominate modeling results. Rose et al. (2022) further conclude that feedstock production costs drive biomass supply in models and that there is little consensus among models as to the location and amount of biomass supplied due to variability in feedstocks, land conversion and management, emissions, and markets. Overall, the final energy use type is likely influenced by and also influences the magnitude of primary bioenergy crop production due to the various cost and efficiency differences among available feedstocks and conversion technologies.

4.2 | Further implications of decreasing land availability

Based on the relationships described in previous sections, agricultural production and prices in most of the globe would be negatively affected much sooner (at higher availability levels) when reducing land availability than would the extent of undeveloped land as a whole be preserved. This indicates that land protection must target specific land if its goal is to minimize agricultural impacts while maximizing the benefits of land protection. Otherwise, achieving blanket target projections (e.g., 30%) could have considerable, negative consequences for agriculture and food security while having relatively little impact on the extent or benefits of undeveloped land. To select protected land that generates environmental benefits while maintaining agricultural production, the environmental benefits must be clearly defined and should reflect a relative change in metrics that are more comparable with agricultural production than simply the effective area of avoided conversion.

TABLE 5 Percent of convertible land needed to reach 20% total protected area. Note that the total land here includes the unknown land type, while Global Change Analysis Model (GCAM) excludes unknown land type from its land area (GCAM global land area is 131,719 thousand km^2). Numbers have been rounded for readability.

Region	Total land (th km^2)	Suitable protected (% total)	Unsuitable protected (% total)	Needed for 20% protected (% total)	Convertible land (thous km^2)	Need protected in GCAM (% conv)	Suitable unprotected (% convertible)	Unsuitable unprotected (% convertible)	Need suitable unprot after unsuit (% conv)
Eastern Africa	5825	6	0	13	3840	20	73	18	3
Northern Africa	5764	0	3	17	822	118	28	71	47
Southern Africa	5594	10	2	7	4833	8	83	4	5
Western Africa	11,335	5	2	13	7004	20	87	4	16
Argentina	2763	3	4	13	2023	18	56	37	0
Australia NZ	7936	13	6	1	7160	1	56	23	0
Brazil	8440	14	0	6	6945	7	80	3	4
Canada	9121	2	8	10	6015	15	29	61	0
Central America and Caribbean	715	14	1	5	492	7	76	4	3
Central Asia	5625	1	5	14	4870	16	33	61	0
China	9297	0	0	20	6205	30	55	45	0
Colombia	1138	11	2	7	1050	7	79	7	0
EU-12	1074	7	1	12	574	22	83	5	17
EU-15	5243	6	18	−4	1919	−11	71	13	0
Eastern Europe	825	3	0	17	352	39	89	5	34
Europe—non-EU	1037	1	0	19	655	30	86	12	18
European Free Trade Association	471	5	12	3	232	6	53	36	0
India	3140	3	1	16	1062	48	85	10	38
Indonesia	1894	8	1	11	1311	15	81	6	9
Japan	404	13	10	−3	308	−5	66	9	0
Mexico	1939	6	3	10	1555	13	80	9	4
Middle East	5162	1	4	14	3040	24	42	52	0
Pakistan	869	3	1	16	259	53	75	19	34
Russia	16,349	2	6	13	11,676	18	28	64	0
South Africa	1220	0	0	20	1016	24	73	26	0
Northern South America	1350	23	8	−12	1266	−12	61	6	0
Southern South America	3925	6	2	12	3056	15	79	12	3
South Asia	1027	3	3	14	658	22	50	43	0
South Korea	104	8	3	9	77	12	77	11	1
Southeast Asia	3225	9	1	11	2257	15	83	5	10
Taiwan	35	7	12	1	27	1	59	17	0
USA	9137	4	8	8	6550	11	65	22	0
Global	131,979	5	4	11	89,109	16	60	29	0

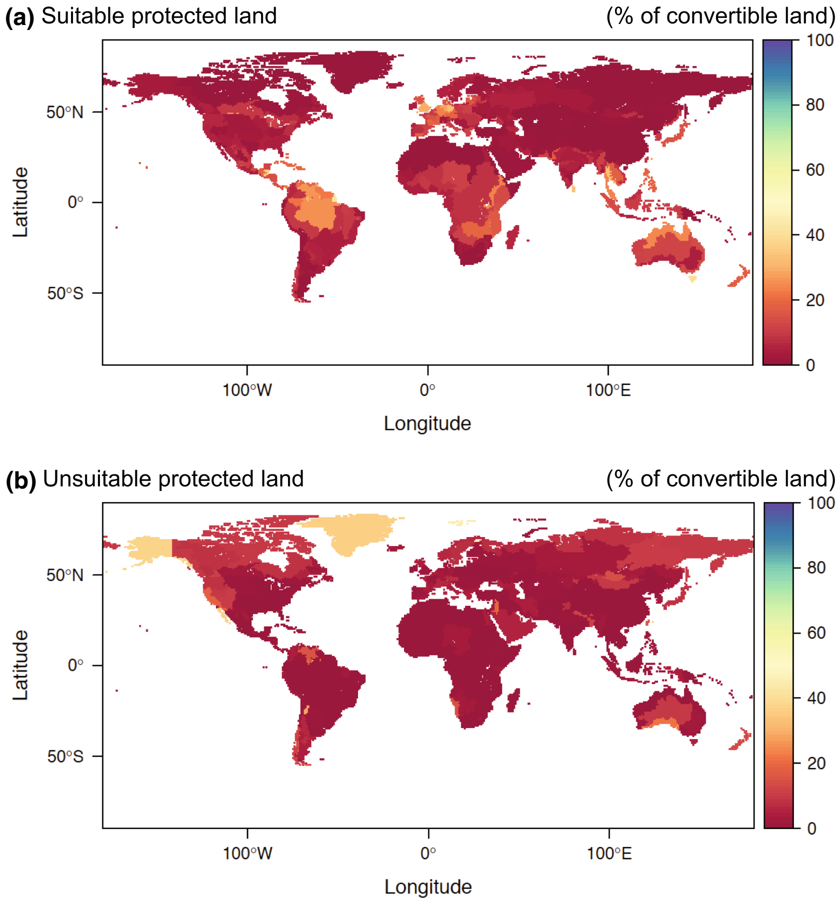

FIGURE 10 Current percent of Global Change Analysis Model (GCAM) convertible land that is protected, by water basin within each GCAM region. The values are determined by the 2015 GCAM initial state. Panels represent land that is (a) suitable or (b) unsuitable for agricultural expansion. Map lines delineate study areas and do not necessarily depict accepted national boundaries.

4.3 | The implications of protecting land that is not suitable for agriculture

Our results raise the following questions: what are the goals of protecting land, where are the areas that meet these goals, and how much do they overlap with suitable, convertible land? If the main goal is to increase the extent of unmanaged land or decrease the expansion of land use, then a 30% target is likely not high enough because there is still enough unprotected land to meet land use needs. If the goal is to protect specific areas for ecological reasons (e.g., wildlife habitat/connectivity, biodiversity, environmental services), then a blanket area target may not be sufficient. It seems that the primary challenge is to protect land that would meet conservation goals while having a minimal impact on agriculture. The results presented above represent the maximum impact on agriculture as only suitable land is selected for additional protection (because only suitable land is available in the LOW case). If all suitable, unprotected, convertible land were protected first then all but one region would not need to protect unsuitable land to meet the protection target (the exception being Northern Africa, which would also need to protect non-convertible land to meet the target; Table 5). On the other hand, if all unsuitable, unprotected, convertible land were protected first then only 16 regions would not have to protect any suitable land (including Columbia and the three that do not need additional protection), which may limit the negative impacts of land protection to agriculture, but also may limit benefits of land protection. Some of the remaining regions would still have to protect substantial portions of suitable land (Table 5). Additionally, GCAM's non-convertible land could be protected to meet area targets. This land is the least likely to be converted for human use as it includes desert, rock, ice, tundra, and other relatively barren areas. For example, Northern Africa could meet the protection target by protecting just a fraction of its desert, which may not affect agricultural expansion at all, but it may not meet ecological conservation goals either. Further combined analysis of potential agricultural expansion and ecologically sensitive areas is required to determine the appropriate selection of potential protected areas. For example, Molotoks et al. (2017) have shown high spatial variability in the overlap of food security/expansion indices and multiple biodiversity indicators. Delzeit et al. (2017) and Zabel et al. (2019) identify specific areas of high species riches and high agricultural intensification potential. Our results also show a high degree of spatial variability for agricultural impacts resulting from decreasing land availability. But none of these studies define protection goals or provides a clear method for selecting protected area, largely because these are likely to be determined at a local level. The main implication of these findings is that a globally uniform area protection target may not be sufficient to meet only conservation goals or only agricultural needs, let alone both.

5 | CONCLUSION

By combining an incremental approach to investigating the impacts of land availability with estimates of current availability we show that agriculture, and particularly bioenergy feedstock, is more likely to have greater negative impacts than the land preservation benefits gained by approximately doubling existing land protection globally. This is because extending protected area from the current state immediately impacts land use while being inefficient at preserving undeveloped land. Furthermore, the selection of protected land can have more or less impact on agriculture depending on the suitability of the protected land. Thus, if the overarching goal is to maximize conservation benefits while minimizing impacts on agriculture, protected land must be carefully selected to achieve well-defined conservation goals, rather than being selected to meet a blanket area target. A previous study on energy development supports this finding through its conclusion that excluding protected land from development may increase the threat to biodiversity by requiring more land to meet the same energy production (McManamay et al., 2021).

A major caveat of our study is that we are applying changes in uniform availability to a spatially heterogeneous initial state of land availability. We show that this initial state is a critical factor in estimating land use projection because regional variability generates land use behavior that is different from that obtained with a similar level of uniform land availability. Furthermore, the protected area is effectively increased fully in 2015 in our analysis, rather than being added over time. Nonetheless, this approach gives an initial estimate showing the significance of decreasing land availability from a spatially explicit current state, and provides the motivation to implement the capability to do more detailed experiments. Thus, we intend to work toward applying spatially explicit, additional protection to our newly developed initial state. This will enable a more rigorous, flexible, and targeted approach to estimating the effects of decreasing land availability on agriculture and land preservation.

ACKNOWLEDGMENTS

This research was supported by the U.S. Department of Energy (DOE), Office of Science, Office of Biological and Environmental Research, as a part of research in the Multi-Sector Dynamics, Earth and Environmental System Modeling Program. Work at Lawrence Berkeley National Laboratory was performed under contract DE-AC02-05CH11231, and work at Battelle-operated Pacific Northwest National Laboratory was performed under contract DE-AC05-76RL01830. Dr. Katherine Calvin, Earth Scientist, Pacific Northwest National Laboratory, is currently detailed to the National Aeronautics and Space Administration. Dr. Calvin's contributions to this article occurred prior to her detail. The views expressed are her own and do not necessarily represent the views of the National Aeronautics and Space Administration or the United States Government.

CONFLICT OF INTEREST

The authors declare that they have no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study and detailed instructions to replicate this analysis are openly available on GitHub (https://github.com/JGCRI/Di_Vittorio_et_al_2022_GCB), as referenced by http://doi.org/10.5281/zenodo.6927245. Note that this DOI points to the most recent release of the GitHub metarepo listed above.

ORCID

Alan V. Di Vittorio https://orcid.org/0000-0002-8139-4640
Katherine Calvin https://orcid.org/0000-0003-2191-4189

REFERENCES

Alexander, P., Prestele, R., Verburg, P. H., Arneth, A., Baranzelli, C., Batista e Silva, F., Brown, C., Butler, A., Calvin, K., Dendoncker, N., Doelman, J. C., Dunford, R., Engström, K., Eitelberg, D., Fujimori, S., Harrison, P. A., Hasegawa, T., Havlik, P., Holzhauer, S., ... Rounsevell, M. D. (2017). Assessing uncertainties in land cover projections. *Global Change Biology*, *23*, 767–781.

Baillie, J., & Zhang, Y.-P. (2018). Space for nature. *Science*, *361*, 1051. https://doi.org/10.1126/science.aau1397

Ball, T. S., Vaughan, N. E., Powell, T. W., Lovett, A., & Lenton, T. M. (2022). C-LLAMA 1.0: A traceable model for food, agriculture, and land use. *Geoscientific Model Development*, *15*, 929–949.

Breach, P. A., & Simonovic, S. P. (2021). ANEMI3: An updated tool for global change analysis. *PLoS One*, *16*, e0251489.

Calvin, K., Patel, P., Clarke, L., Asrar, G., Bond-Lamberty, B., Cui, R. Y., Di Vittorio, A., Dorheim, K., Edmonds, J., Hartin, C., Hejazi, M., Horowitz, R., Iyer, G., Kyle, P., Kim, S., Link, R., McJeon, H., Smith, S. J., Snyder, A., ... Wise, M. (2019). GCAM v5.1: Representing the linkages between energy, water, land, climate, and economic systems. *Geoscientific Model Development*, *12*(2), 677–698. https://doi.org/10.5194/gmd-12-677-2019

Calvin, K., Wise, M., Kyle, P., Patel, P., Clarke, L., & Edmonds, J. (2014). Trade-offs of different land and bioenergy policies on the path to achieving climate targets. *Climatic Change*, *123*, 691–704.

Convention on Biological Diversity (CBD). (2021). *First draft of the post-2020 global biodiversity framework*. https://www.cbd.int/doc/c/abb5/591f/2e46096d3f0330b08ce87a45/wg2020-03-03-en.pdf

COP26. (2021) *Glasgow leaders' declaration on forests and land use*. https://ukcop26.org/glasgow-leaders-declaration-on-forests-and-land-use/

Daioglou, V., Rose, S. K., Bauer, N., Kitous, A., Muratori, M., Sano, F., Fujimori, S., Gidden, M. J., Kato, E., Keramidas, K., Klein, D., Leblanc, F., Tsutsui, J., Wise, M., & van Vuuren, D. P. (2020). Bioenergy technologies in long-run climate change mitigation: Results from the EMF-33 study. *Climatic Change*, *163*(3), 1603–1620. https://doi.org/10.1007/s10584-020-02799-y

Delzeit, R., Zabel, F., Meyer, C., & Václavík, T. (2017). Addressing future trade-offs between biodiversity and cropland expansion to improve food security. *Regional Environmental Change*, *17*, 1429–1441.

Di Vittorio, A. V., Mao, J., Shi, X., Chini, L., Hurtt, G., & Collins, W. D. (2018). Quantifying the effects of historical land cover conversion uncertainty on global carbon and climate estimates. *Geophysical Research Letters*, *45*, 974–982.

Di Vittorio, A. V., Vernon, C. R., & Shu, S. (2020). Moirai version 3: A data processing system to generate recent historical land inputs for global modeling applications at various scales. *Journal of open research software*, *8*, 1.

Dietrich, J. P., Bodirsky, B. L., Humpenöder, F., Weindl, I., Stevanović, M., Karstens, K., Kreidenweis, U., Wang, X., Mishra, A., Klein, D., Ambrósio, G., Araujo, E., Yalew, A. W., Baumstark, L., Wirth, S., Giannousakis, A., Beier, F., Chen, D. M.-C., Lotze-Campen, H., & Popp, A. (2019). MAgPIE 4—A modular open-source framework for modeling global land systems. *Geoscientific Model Development*, *12*(4), 1299–1317. https://doi.org/10.5194/gmd-12-1299-2019

Doelman, J. C., Stehfest, E., Tabeau, A., Van Meijl, H., Lassaletta, L., Gernaat, D. E. H. J., Hermans, K., Harmsen, M., Daioglou, V., Biemans, H., van der Sluis, S., & Van Vuuren, D. P. (2018). Exploring SSP land-use dynamics using the IMAGE model: Regional and gridded scenarios of land-use change and land-based climate change mitigation. *Global Environmental Change*, *48*, 119–135.

Dolan, F., Lamontagne, J., Calvin, K., Snyder, A., Narayan, K. B., Di Vittorio, A. V., & Vernon, C. R. (2022). Modeling the economic and environmental impacts of land scarcity under deep uncertainty. *Earth's Futures*, *10*, e2021EF002466.

Edmonds, J. A., Link, R., Waldhoff, S., & Cui, R. (2017). A global food demand model for the Assessment of complex human-earth systems. *Climate Change Economics*, *8*, 1750012.

Eitelberg, D. A., van Vliet, J., & Verburg, P. H. (2015). A review of global potentially available cropland estimates and their consequences for model-based assessments. *Global Change Biology*, *21*(3), 1236–1248. https://doi.org/10.1111/gcb.12733

Engström, K., Rounsevell, M. D. A., Murray-Rust, D., Hardacre, C., Alexander, P., Cui, X., Palmer, P. I., & Arneth, A. (2016). Applying Occam's razor to global agricultural land use change. *Environmental Modelling & Software*, *75*, 212–229.

ESA. (2017). *Land cover CCI product user guide version 2*. Technical Report. https://maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf

Fujimori, S., Masui, T., & Matsuoka, Y. (2014). Development of a global computable general equilibrium model coupled with detailed energy end-use technology. *Applied Energy*, *128*, 296–306.

Fuss, S., Lamb, W. F., Callaghan, M. W., Hilaire, J., Creutzig, F., Amann, T., Beringer, T., de Oliveira Garcia, W., Hartmann, J., Khanna, T., Luderer, G., Nemet, G. F., Rogelj, J., Smith, P., Vicente, J. L. V., Wilcox, J., del Mar Zamora Dominguez, M., & Minx, J. C. (2018). Negative emissions-part2: Costs, potentials, and side effects. *Environmental Research Letters*, *13*, 063002.

GCAM. (2022). *Global Change Analysis Model version 5.4*. https://doi.org/10.5281/zenodo.7057561

GCAM6. (2022). *GCAM v6 documentation: GCAM model overview*. https://jgcri.github.io/gcam-doc/overview.html; https://github.com/JGCRI/gcam-core

Gielen, D., Boshell, F., Saygin, D., Bazilian, M. D., Wanger, N., & Gorini, R. (2019). The role of renewable energy in the global energy transformation. *Energy Strategy Reviews*, *24*, 38–50.

Hannah, L., Roehrdanz, P. R., KC, K. B., Fraser, E. D. G., Donatti, C. I., Saenz, L., Wright, T. M., Hijmans, R. J., Mulligan, M., Berg, A., & Van Soesbergen, A. (2020). The environmental consequences of climate-driven agricultural frontiers. *PLoS One*, *15*, e0228305.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-resolution global maps of 21st-century forest cover change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

Havlík, P., Schneider, U. A., Schmid, E., Böttcher, H., Fritz, S., Skalský, R., Aoki, K., Cara, S. D., Kindermann, G., Kraxner, F., Leduc, S., McCallum, I., Mosnier, A., Sauer, T., & Obersteiner, M. (2011). Global land-use implications of first and second generation biofuel targets. *Energy Policy*, *39*(10), 5690–5702. https://doi.org/10.1016/j.enpol.2010.03.030

Havlík, P., Valin, H., Mosnier, A., Obersteiner, M., Baker, J. S., Herrero, M., Rufino, M. C., & Schmid, E. (2012). Crop productivity and the global livestock sector: Implications for land use change and greenhouse gas emissions. *American Journal of Agricultural Economics*, *95*(2), 442–448. https://doi.org/10.1093/ajae/aas085

Henry, R. C., Engström, K., Olin, S., Alexander, P., Arneth, A., & Rounsevell, M. D. A. (2018). Food supply and bioenergy production within the global cropland planetary boundary. *PLoS One*, *13*, e0194695.

Hof, C., Voskamp, A., Biber, M. F., Böhning-Gaese, K., Engelhardt, E. K., Niamir, A., Willis, S. G., & Hickler, T. (2018). Bioenergy cropland expansion may offset positive effects of climate change mitigation for global vertebrate diversity. *Proceedings of the National Academy of Sciences of the United States of America*, *115*, 13294–13299.

Houghton, R. A. (1999). The annual net flux of carbon to the atmosphere from changes in land use 1850–1990. *Tellus B: Chemical and Physical Meteorology*, *51*, 298–313.

Humpenöder, F., Popp, A., Bodirsky, B. L., Weindl, I., Biewald, A., Lotze-Campen, H., Dietrich, J. P., Klein, D., Kreidenweis, U., Müller, C., Rolinski, S., & Stevanovic, M. (2018). Large-scale bioenergy production: How to resolve sustainability trade-offs? *Environmental Research Letters*, *13*(2), 024011. https://doi.org/10.1088/1748-9326/aa9e3b

IUCN. (2018). *World database on protected areas, version WDPA_Mar2018_Public*. www.protectedplanet.net

Kim, S. H., Hejazi, M., Liu, L., Calvin, K., Clarke, L., Edmonds, J., Kyle, P., Patel, P., Wise, M., & Davies, E. (2016). Balancing global water availability and use at basin scale in an integrated assessment model. *Climatic Change*, *136*(2), 217–231. https://doi.org/10.1007/s10584-016-1604-6

King, A. W., Post, W. M., & Wullschleger, S. D. (1997). The potential response of terrestrial carbon storage to changes in climate and atmospheric CO_2. *Climatic Change*, *35*, 199–227.

King, M., Altdorff, D., Li, P., Galagedara, L., Holden, J., & Unc, A. (2018). Northward shift of the agricultural climate zone under 21st-century global climate change. *Scientific Reports*, *8*, 7904.

Koberl, A. C. (2019). The value of BECCS in IAMs: A review. *Current Sustainable/Renewable Energy Reports*, *6*, 107–115.

Kraxner, F., Nordström, E.-M., Havlík, P., Gusti, M., Mosnier, A., Frank, S., Valin, H., Fritz, S., Fuss, S., Kindermann, G., McCallum, I., Khabarov, N., Böttcher, H., See, L., Aoki, K., Schmid, E., Máthé, L., & Obersteiner, M. (2013). Global bioenergy scenarios—Future forest development, land-use implications, and trade-offs. *Biomass and Bioenergy*, *57*, 86–96. https://doi.org/10.1016/j.biombioe.2013.02.003

McManamay, R. A., Vernon, C. R., & Jager, H. I. (2021). Global biodiversity implications of alternative electrification strategies under the shared socioeconoimc pathways. *Biological Conservation*, *260*, 109234.

Meiyappan, P., Dalton, M., Oäôneill, B. C., & Jain, A. K. (2014). Spatial modeling of agricultural land use change at global scale. *Ecological Modelling*, *291*, 152–174.

Moirai v3.1. (2021). *The Moirai v3.1 land data system*. https://doi.org/10.5281/zenodo.4973631

Moirai v3.1.1. (2022). *The Moirai v3.1.1 land data system*. https://doi.org/10.5281/zenodo.6632745

Molotoks, A., Kuhnert, M., Dawson, T. P., & Smith, P. (2017). Global hotspots of conflict risk between food security and biodiversity conservation. *Land*, *6*(4), 67.

NGO. (2021). *NGO concerns over the proposed 30% target for protected areas and absence of safeguards for indigenous peoples and local communities*. https://assets.survivalinternational.org/documents/1972/en-fr-es-it-de-200928.pdf

Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., Bodirsky, B. L., Dietrich, J. P., Doelmann, J. C., Gusti, M., Hasegawa, T., Kyle, P., Obersteiner, M., Tabeau, A., Takahashi, K., Valin, H., Waldhoff, S., Weindl, I., Wise, M., … van Vuuren, D. P. (2017). Land-use futures in the shared socio-economic pathways. *Global Environmental Change*, *42*, 331–345. https://doi.org/10.1016/j.gloenvcha.2016.10.002

Popp, A., Rose, S. K., Calvin, K., van Vuuren, D. P., Dietrich, J. P., Wise, M., Stehfest, E., Humpenoder, F., Kyle, P., Van Vliet, J., Bauer, N., Lotze-Campen, H., Klein, D., & Kriegler, E. (2014). Land-use transition for bioenergy and climate stabilization: Model comparison of drivers, impacts and interactions with other land use based mitigation options. *Climatic Change*, *123*, 495–509.

Reid, W. V., Ali, M. K., & Field, C. B. (2020). The future of bioenergy. *Global Change Biology*, *26*(1), 274–286.

Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., Bauer, N., Calvin, K., Dellink, R., Fricko, O., Lutz, W., Popp, A., Cuaresma, J. C., Samir, K. C., Leimbach, M., Jiang, L., Kram, T., Rao, S., Emmerling, J., … Tavoni, M. (2017). The shared socioeconomic pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009

Rose, S. K., Popp, A., Fujimori, S., Havlik, P., Weyant, J., Wise, M., van Vuuren, D., Brunelle, T., Cui, R. Y., Daioglou, V., Frank, S., Hasegawa, T., Humpenöder, F., Kato, E., Sands, R. D., Sano, F., Tsutsui, J., Doelman, J., Muratori, M., … Yamamoto, H. (2022). Global biomass supply modeling for long-run management of the climate system. *Climatic Change*, *172*, 3.

Santangeli, A., Toivonen, T., Pouzols, F. M., Pogson, M., Hastings, A., Smith, P., & Moilanen, A. (2016). Global change synergies and trade-offs between renewable energy and biodiversity. *GCB Bioenergy*, *8*, 941–951.

Schleicher, J., Zaehringer, J. G., Fastre, C., Vira, B., Visconti, P., & Sandbrook, C. (2019). Protecting half of the planet could directly affect over one billion people. *Nature Sustainability*, *2*, 1094–1096. https://doi.org/10.1038/s41893-019-0423-y

Seabra, J. E. A. (2021). *Chapter 1 biofuels in the global energy mix. Roadmap to 2050: The land-water-energy nexus of biofuels*. Sustainable Development Solutions Network and Fondazione Eni Enrico Mattei. https://roadmap2050.report/biofuels/biofuels-in-the-global-energy-mix/

Searle, S., & Malins, C. (2015). A reassessment of global bioenergy potential in 2050. *GCB Bioenergy*, *7*, 328–336.

Stehfest, E., Van Vuuren, D., Kram, T., Bouwman, L., Alkemade, R., Bakklenes, M., Biemas, H., Bouwman, A., Den Elzen, M., Janse, J., Lucas, P., Van Minnen, J., Muller, C., & Prins, A. (2014). *Integrated assessment of global environmental change with IMAGE 3.0. Model description and policy applications*. Netherlands Environmental Agency.

Steinbuks, J., & Hertel, T. W. (2016). Confronting the food–energy–environment trilemma: Global land use in the long run. *Environmental and Resource Economics*, *63*, 545–570.

Strapasson, A., Woods, J., Chum, H., Kalas, N., Shah, N., & Rosillo-Calle, F. (2017). On the global limits of bioenergy and land use for climate change mitigation. *GCB Bioenergy*, *9*, 1721–1735.

Thenkabail, P. S., Teluguntla, P. G., Xiong, J., Oliphant, A., Congalton, R. G., Ozdogan, M., Gumma, M. K., Tilton, J. C., Giri, C., Milesi, C., Phalke, A., Massey, R., Yadav, K., Sankey, T., Zhong, Y., Aneece, I., & Foley, D. (2021). *Global cropland-extent product at 30-m resolution (GCEP30) derived from Landsat satellite time-series data for the year 2015 using multiple machine-learning algorithms on Google Earth Engine Cloud*. U.S. Geological Survey Professional Paper 1868, 63 pp. https://doi.org/10.3133/pp1868

Turner, P. A., Field, C. B., Lobell, D. B., Sanchez, D. L., & Mach, K. J. (2018). Unprecedented rates of land-use transformation in modelled climate change mitigation pathways. *Nature Sustainability*, *1*, 240–245.

UNEP-WCMC & IUCN. (2022). *Protected planet: Main page statistics*. UNEP-WCMC and IUCN. https://www.protectedplanet.net/en

USGS & NASA. (2017). *Release of GFSAD 30 meter cropland extent products*. U.S. Geological Survey–National Aeronautics and Space Administration Land Processes Distributed Active Archive Center. https://lpdaac.usgs.gov/news/release-of-gfsad-30-meter-cropland-extent-products/

Van Asselen, S., & Verburg, P. H. (2013). Land cover change or land-use intensification: Simulating land system change with a global-scale land change model. *Global Change Biology*, *19*, 3648–3667.

Wade, C. M., Austin, K. G., Cajka, J., Lapidus, D., Everett, K. H., Galperin, D., Maynard, R., & Sobel, A. (2020). What is

GCB-BIOENERGY BIOPRODUCTS FOR A SUSTAINABLE BIOECONOMY Open Access —WILEY

threatening forests in protected areas? A global assessment of deforestation in protected areas, 2001–2018. *Forests*, *11*, 539.

Wise, M., Calvin, K., Kyle, P., Luckow, P., & Edmonds, J. (2014). Economic and physical modeling of land use in GCAM 3.0 and an application to agricultural productivity, land, and terrestrial carbon. *Climate Change Economics*, *05*, 1450003.

Woltjer, G. B., & Kuiper, M. H. (2014). *The MAGNET model: Module description*. LEI report 14-057, Wageningen, The Netherlands. https://library.wur.nl/WebQuery/wurpubs/fulltext/310764

Zabel, F., Delzeit, R., Schneider, J. M., Seppelt, R., Mauser, W., & Vaclavik, T. (2019). Global impacts of future cropland expansion and intensification on agricultural markets and biodiversity. *Nature Communications*, *10*, 2844. https://doi.org/10.1028/s41467-019-10775-z

Zabel, F., Putzenlechner, B., & Mauser, W. (2014a). Global agricultural land resources—A high resolution suitability evaluation and its perspectives until 2100 under climate change conditions. *PLoS One*, *9*, e107522.

Zabel, F., Putzenlechner, B., & Mauser, W. (2014b). Data: Global agricultural land resources—A high resolution suitability evaluation and its perspectives until 2100 under climate change conditions. Version 2.0 data set. *Zenodo*. https://doi.org/10.5281/zenodo.3748350

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Di Vittorio, A. V., Narayan, K. B., Patel, P., Calvin, K., & Vernon, C. R. (2023). Doubling protected land area may be inefficient at preserving the extent of undeveloped land and could cause substantial regional shifts in land use. *GCB Bioenergy*, *15*, 185–207. https://doi.org/10.1111/gcbb.13016