Supporting Information

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SI Text

National-Scale Econometric Land-Use Model. A national-level econometric land-use model (1) is used to project land-use changes on all privately owned parcels in the contiguous United States. The model is based on the assumption that landowners will choose the land use that maximizes the present discounted value of the stream of expected net revenues from the land. Furthermore, it assumes that landowners base their expectations of future net revenues on current and historic values of relevant variables. Net revenues are defined as the quantity of the good produced from land multiplied by its price less the opportunity cost of all variable inputs to production. Given these assumptions, a simple decision rule emerges from the related dynamic optimization problem (2). In time t, the landowner chooses the use with the highest expected one-period net revenues at time t minus the current one-period expected opportunity cost of undertaking land-use conversion. Formally, the owner of a parcel in use i will transition from land-use i to k at time t if

$$R_{kt} - C_{ikt} \geq R_{lt} - C_{ilt} \qquad \textbf{[S1]}$$

for all uses $l \neq k$, where R_{kt} and R_{lt} represent the expected net revenues at time t from a parcel of land in uses k and l, respectively, and C_{ilt} is the expected annualized cost of converting from use i to use l at time t where $C_{iit} = 0$. If the current use i satisfies Eq. **S1**, then the parcel remains in that use at time t; otherwise, the landowner will reallocate the land to the use $k \neq i$ that maximizes expected net revenues minus conversion costs.

In practice, private land-use decisions can be influenced by factors other than market returns. For example, landowners may derive nonmarket benefits from their land (e.g., from recreation or aesthetics) or have historical ties to the land in particular uses (e.g., family-owned farms). Data are available to measure the net revenue variables (or construct suitable proxies) in Eq. **S1**; however, these additional nonmarket factors are unobservable. As such, we model them as random disturbances and modify Eq. **S1** as follows:

$$R_{kt} - C_{ikt} + \varepsilon_{kt} \geq R_{lt} - C_{ilt} + \varepsilon_{lt}, \qquad \textbf{[S2]}$$

where ε_{kt} and ε_{lt} are random variables associated with uses k and l, respectively. Because of the unobserved components, we can now make only probabilistic statements about land-use decisions. By imposing distributional assumptions on the random variables ε_{kt} and ε_{lt} (3), we obtain a parametric expression for the probability that a parcel in use i will be allocated to use k conditional on the net revenue and transition cost variables. The goal of the econometric modeling is to estimate the parameters of the land-use transition probabilities that best fit observed land-use change data. The estimation yields response functions indicating the probability of land-use changes conditional on economic variables.

The National Resources Inventory (NRI) is the primary dataset we use to estimate a national land-use model (4). The NRI is a panel survey of land use and land characteristics on nonfederal lands conducted across the periods 1982–1987, 1987–1992, and 1992–1997 over the entire United States, excluding Alaska. Data include ∼844,000 plot-level observations, each representing a land area indicated by a sampling weight. The econometric analysis focuses on land-use change during the final period, 1992–1997, and on the contiguous United States and six major land uses as defined by the NRI: crops, pasture, forest, urban and built-up, range (i.e., grasslands and shrublands), and land enrolled in the federal Conservation Reserve Program. This land base comprises 1.4 billion acres, representing about 74% of the total land area and 91% of nonfederal land in the contiguous United States. Definitions of the land-use categories are provided in ref. 4. For simplicity, we refer to urban and built-up land as urban.

Distributional assumptions imposed on the random terms in Eq. **S2** yield a nested logit model for estimation (3). The dependent variable is the land-use choice in year t = 1997 at each NRI plot. The land-use transition probabilities are given by

$$P_{jikt} = f\left(\boldsymbol{\beta}_{ik}, \mathbf{NR}_{jt}, \mathbf{LQ}_j\right) \qquad \textbf{[S3]}$$

for all j, i, k, and t, where j indexes the parcel, $\boldsymbol{\beta}_{ik}$ is a vector of parameters associated with the transition from use i to k from 1992 to 1997, $\mathbf{NR}_{jt}$ is a vector of net revenue variables for plot j in time t = 1997, and $\mathbf{LQ}_j$ is a vector of plot-level variables measuring land quality. By assembling data from a variety of private and public sources, Lubowski (5) constructed county-level estimates of annual per-acre net revenues for crops, pasture, forest, range, and urban uses for all 3,014 counties in the contiguous United States. Conversion costs are measured implicitly with constant terms specific to each i-to-k transition. The land-quality measure is an indicator variable for the land capability class rating (I to VIII) of NRI plots (6). We combine classes I and II, III and IV, V and VI, and VII and VIII to form four land-quality categories. Land capability class rating variables indicate the productivity of the land for agriculture and are interacted with the net revenue and conversion cost variables to allow for plot-level deviations from the county average net revenue. Details on the estimation procedure and results are provided in refs. 1 and 5.

We use an econometric model of land use change versus sectoral optimization models (e.g., the Forest and Agricultural Sector Model described in ref. 7) because the econometric approach can capture actual landowner behavior (e.g., the continuation of land-use over time that does not maximize expected net revenue) that cannot be represented in optimization models with perfectly rational decision makers.

The advantage of the NRI data for econometric modeling is that it provides comprehensive and consistent data on private land use and plot attributes for the lower 48 states at multiple points in time. The main disadvantage of the NRI is that it does not provide exact information on the location of plots. Therefore, many spatial variables that plausibly affect land use, such as distance to cities and the land-use choices of neighboring parcels, cannot be included in the model. This problem is mitigated somewhat by the fact that plots close to large and growing cities are also likely to be in a county with high urban net revenues, an included variable in our model. Nevertheless, an important extension of our model would be to use national spatial-temporal data on land-use change as a means to model explicit spatial processes.

Land-Use Transition Matrices. The parameter vector $\boldsymbol{\beta}_{ik}$ is estimated with a nested logit model and then is substituted into Eq. **S3** to yield probabilities of land-use transitions among potential land uses as a function of net revenue and land-quality variables. Therefore, when the response functions are evaluated at the economic and plot-level variables, we obtain a transition probability matrix ($\mathbf{P}_{jt}$) for each NRI plot j and time t. Define the vector $\mathbf{A}_{jt}$ as the number of acres in each of the six land uses in

NRI plot j in time $t = 1997$. Then, the number of acres in each use N 5-y time steps hence is given by

$$\mathbf{A}_{jt+N} = \mathbf{A}_{jt} \times \mathbf{P}_{jt}^{N}. \quad \text{[S4]}$$

Each period is 5 y in length to correspond to the time-step in the NRI data. Because we do not observe land moving out of urban uses, the associated transition probabilities for land beginning in urban use always equal 0. Further, all publicly owned land is assumed not to change use over time.

The changes in land use over time affect the supply of commodities and commodity prices, which in turn affects the net revenues from each use of the land. Therefore, $\mathbf{P}_{jt}$ for $t = 2002$ does not equal $\mathbf{P}_{jt}$ for $t = 1997$, $\mathbf{P}_{jt}$ for $t = 2007$ does not equal $\mathbf{P}_{jt}$ for $t = 2002$, and so forth. Our mechanism for modeling these price feedbacks works as follows. Landowners with static expectations observe the level of net revenues to all alternative uses in period t. With static expectations, the optimal decision at each point in time is to convert to (or remain in) the use with the highest annual net revenue less conversion costs (2). Therefore, landowners are not assumed to anticipate any changes in net revenues induced by future conversions. In the next decision period ($t + 5$), net revenues are updated to account for price and yield changes that occurred between t and $t + 5$. Price changes occur because of shifts in land use, which change the supply of outputs from the land and, therefore, prices for these outputs. Once net revenues are updated to account for these supply shifts and $\mathbf{P}_{jt}$ is adjusted accordingly, landowners repeat the same decision process that began in period t. This price feedback approach is not a true general equilibrium model because we have no mechanism that simultaneously clears all markets. Rather, our model represents a disequilibrium in land markets together with a price-feedback mechanism that pushes the landscape toward equilibrium. To better understand this feature of our model, consider that landowners respond to the relative levels of net revenues. For example, if there is a large difference between the levels of crop and forest net revenues, landowners may be induced to move more land into crops because this difference signals a more profitable opportunity. Such changes in land uses affect output and prices and, thus, the levels of net revenues, signaling new opportunities for profitable changes in land use. This process continues until such opportunities are exhausted, which implies no further changes in land use or the levels of net revenues. At this point, markets would be in equilibrium. In our simulations, equilibrium is never actually achieved, although the price-feedback mechanism moves the landscape toward equilibrium.

The endogenous adjustments in net revenues are made using econometrically estimated demand elasticities selected after an exhaustive review of the literature. Lubowski et al. (1) discuss the elasticities used for forest and crop prices. For pasture and rangeland, we were unable to find any estimates of forage demand elasticities and assumed that the crop price elasticity used in Lubowski et al. (1) applied to pasture and rangeland revenues. Thus, a 1% increase in a county's pasture or range acreage was assumed to result in a 1.51% decrease in pasture or range revenues in that county. The adjustments to urban net revenues are made using elasticity estimates from Haim (8). Unlike existing studies of urban land markets that used metropolitan area data or focused on single cities, Haim's analysis was conducted using data on all US counties. Because he used a log-level specification, elasticity estimates are proportional to net revenues in each county. For example, in a county with an average urban net revenue of \$10,000/acre, a 1% increase in urban acreage results in 0.47% decrease in the urban net revenue; that is, $0.47 = (0.000212 \times 10{,}000)^{-1}$. With the exception of the elasticity for urban land, all demand elasticities in the model are assumed to remain constant over time. In practice, factors such as income and population growth, changes in substitute goods, and shifting demographics may cause elasticities to change over time. Econometric analysis outside the scope of this study would be needed to accommodate time-varying elasticities. Table S1 shows all elasticity measures and information on how they are used to update prices and net revenues as a function of shifts in the supply of land use.

Two additional modifications to the modeling approach described above are that crop yields increase by 6% each period (which directly affect agricultural rents and create a feedback on prices), reflecting historical patterns (9), and increases in forest are prevented in regions where climatic conditions severely restrict forest growth. To define these regions, we use maps of Holdridge Life Zones (10) to distinguish between forest zones (e.g., cool, temperate, moist forest) and nonforest zones (e.g., warm, temperate, montane steppe). Ideally we would model crop yield as a function of farmer managerial response to crop prices rather than our approach of assuming an exogenous increase in yields. However, adding a model of land use intensity (e.g., how much fertilizer is applied, is irrigation water used, etc.) as a function of crop prices is a nontrivial extension that we leave to future work.

After Eq. **S4** has been used to estimate area of land by use and land quality class in each NRI plot j at each 5-y time step ($\mathbf{A}_{jt+1}, \mathbf{A}_{jt+2}$, etc.), the area in each land-use and land-quality category combination are aggregated to the county level for each time step. Land in crops and the Conservation Reserve Program (CRP) are combined into one category at this stage, cropland, because the land use map used for grid-cell level projections of land use (discussed below) does not separately identify these categories. Finally, all of the modeled changes in land use from 1997 to 2047, now aggregated at the county level, are used to construct 50-y transition probability matrices for each county and land-quality combination.

The NRI dataset does not give the exact location of land use. Therefore, to create spatially explicit maps of future land use at the grid-cell level, a level of detail necessary for many ecosystem models including our habitat model, we apply the transition probability matrices to a baseline map that defines land use and land quality for every grid cell in the United States. Unfortunately, a contiguous US grid-cell map of land use is not available for $t = 1997$, the beginning point of our estimated transition matrices. Grid-cell maps of national land cover data (NLCD) for the contiguous United States are only available for the years 1992, 2001, and 2006 (a time-invariant grid cell-level map of land quality can be used in combination with any of these maps). We use the 2001 NLCD (11) map as our base year for two reasons: (*i*) The 2006 map is temporally more distant from the land-use change data (1992–1997) used to estimate the econometric model than the 2001 map and (*ii*) the US public land map we use is available for the early 2000s but not 1992 (http://protectedareas.databasin.org/).

To summarize, we use the two different data sets (NRI 1992–1997 and NLCD 2001) for two different purposes. We use the NRI to estimate the econometric model of land-use change (Eqs. **S3** and **S4**) and then to construct the 50-y transition matrices. We then apply these transition matrices to the 2001 NCLD to define a grid cell-level map of US land use in 2051.

Policy Scenarios. We use the projection model described above to simulate several land-use policies. Market-based incentives, including subsidies and taxes, are introduced by modifying the net revenue measures in Eq. **S3**. For example, to simulate a per-acre subsidy S for afforestation, we add S to the net revenue from forests in the case of all transitions from nonforest uses (crop, pasture, CRP, and range) to forest. An afforestation subsidy increases the amount of land in forest. However, this increase in timber supply also depresses timber prices slightly. In addition, this subsidy engenders reductions in the supply of commodities from cropland, pasture, and ranges, raising the net revenues from these uses. Thus, the model captures policy feedbacks on market prices, and therefore, the incentives for changes in land use.

We evaluate two alternative reference scenarios and three policy scenarios. The first reference scenario (1990 trends) reflects a continuation of economic conditions during the 1990 decade, the period of the data used to estimate the econometric model. The alternative reference scenario (high crop demand) assumes an exogenous increase in crop prices of 10% every 5 y for every crop type. The scenario also assumes continued support for the CRP at current levels, and so no land is allowed to enter or exit this program. In the forest incentives policy scenario, we provide a subsidy of $100 per acre per year for afforestation and levy a tax of $100 per acre per year on land leaving forest. Such a policy can be motivated by a policy goal of increasing carbon sequestration in forests. Based on results in ref. 1, this translates into a carbon tax/subsidy of about $50/ton of carbon. The Native Habitats policy is designed to retain land in less-intensive uses (forest and range, because the NRI category "range" includes native grasslands and shrublands). A tax of $100 per acre per year is levied on land leaving forest and range, including transitions between these two uses. The tax remains with the parcel that leaves forest or range until it afforests or becomes rangeland again. Finally, the urban containment scenario limits urban expansion to metropolitan counties (counties that form a metropolitan statistical area, as defined by the US Office of Management and Budget). This policy mimics zoning regulations that limit urban expansion in rural areas.

Finally, the use of scenarios allows us to gauge the sensitivity of our results to different assumptions about the underlying drivers of land-use change on the provision of ecosystem services. Scenarios are used in place of a formal treatment of parameter and data uncertainty, which is infeasible given the scale of the modeling exercise.

Biomass Carbon Storage in Private Forests. For each forest stand type m found in county c we use the US Forest Inventory Analysis (FIA) datatset to find the Faustmann volume, given by V_{cm}^F. The economic value from harvesting a stand is maximized if it occurs at the stand's Faustmann volume. The function $V_{cm}(t)$ gives the volume in an acre of stand type m in county c at stand age t (12). Let t_{cm} be the stand age that solves $V_{cm}(t)=V_{cm}^F$. If an exact t that solves $V_{cm}(t)=V_{cm}^F$ cannot be found we set t_{cm} equal to the t that minimizes $V_{cm}(t)-V_{cm}^F$ subject to the difference being positive.

Let $B_{cm}(t)$ indicate the metric tons of biomass carbon found in an acre of stand type m at age t in county c (a stand's biomass carbon includes carbon stored in live aboveground, live belowground, and dead woody biomass and detritus on the forest floor) (12). Let $\Delta B_{cm}=B_{cm}(t_{cm})-B_{cm}(0)/t_{cm}$ indicate the average annual gain in carbon storage in an acre of c, m over t_{cm} years of growth.

If a stand of type m in county c is in even-age rotation then $1/t_{cm}$ of the stand's area has just been harvested, $1/t_{cm}$ of the stand is composed of 1-y-old trees, $1/t_{cm}$ of the stand is composed of 2-y-old trees, and so on. The last $1/t_{cm}$ of the stand is composed of $1/t_{cm}$ – 1-y-old trees. Assume each $1/t_{cm}$ portion of the stand is 1 acre. The total biomass carbon stored over the t_{cm}-acre even-age rotation stand of type m in county c at any point in time is given by S_{cm},

$$S_{cm}=\sum_{i=0}^{t_{cm}-1}\left(i\times\Delta B_{cm}(t_{cm})+B_{cm}(0)\right), \qquad \textbf{[S5]}$$

and the average per-acre storage in the stand is $\overline{S}_{cm}=S_{cm}/t_{cm}$. If we assume all private forest land in a county is in even-age rotation then the tons of biomass carbon stored in a representative hectare of private forest land in county c, given by $\overline{S}_c$, is equal to the weighted average of $\overline{S}_{cm}$ values across all stand types found in county c,

$$\overline{S}_c=2.471\frac{\sum_{m=1}^{M}A_{cm}\overline{S}_{cm}}{\sum_{m=1}^{M}A_{cm}}, \qquad \textbf{[S6]}$$

where A_{cm} is the area of stand type m found in county c during the period of US FIA dataset compilation and 2.471 is the constant that converts per-acre to per-hectare measures.

Let $A_{c,f,2001}$ and $A_{c,f,2051}$ indicate the hectares of private forest in county c in 2001 and 2051, respectively. We set biomass carbon stored in private forest land in each county in 2001 and 2051 equal to $A_{c,f,2001}\overline{S}_c$ and $A_{c,f,2051}\overline{S}_c$, respectively. Note that we credit each hectare of private forest in 2001 and 2051 with its county's even-age rotation biomass carbon measure.

Biomass Carbon Storage in Public Forests. In public forests we do not assume trees are managed in a rotation system. Instead, we assume that every stand of public forest has trees with an average age of t. Recall that $B_{cm}(t)$ is the function that gives the biomass carbon expected in an acre of stand type m at age t in county c. Therefore, the biomass carbon stored in a hectare of public forest in county c, given by $\overline{E}_c$, is equal to the weighted average of $B_{cm}(t)$ values across all stand types found in county c,

$$\overline{E}_c=2.471\frac{\sum_{m=1}^{M}A_{cm}B_{cm}(t)}{\sum_{m=1}^{M}A_{cm}}, \qquad \textbf{[S7]}$$

where A_{cm} the area of stand type m found in county c during the period of US FIA dataset compilation. In Eq. **S7** we set t = 70 y for all c and m combinations.

Let $A_{c,pf,2001}$ and $A_{c,pf,2051}$ indicate the hectares of public forest in county c in 2001 and 2051, respectively. In our model, $A_{c,pf,2001}=A_{c,pf,2051}$. Therefore, biomass carbon stored in public forest land in each county in 2001 and 2051 is given by $A_{c,pf,2001}\overline{E}_c$.

Biomass Carbon Storage in Other Land-Use Types. We assume that a hectare of private urban land use in county c has biomass carbon equal to 10% of the biomass carbon found in a hectare of the county's even-age rotation private forests,

$$\overline{U}_c=0.1\overline{S}_c. \qquad \textbf{[S8]}$$

Let $A_{c,u,2001}$ and $A_{c,u,2051}$ indicate the hectares of urban land in county c in 2001 and 2051, respectively. Therefore, biomass carbon stored in urban land in each county in 2001 and 2051 is given by $A_{c,u,2001}\overline{U}_c$ and $A_{c,u,2051}\overline{U}_c$, respectively.

We assume cropland and pasture have biomass carbon steady-state values of 0. Although annual crops sequester carbon over the growing season, most of this storage is lost to the atmosphere at or soon after harvest. Some of the crop biomass may be cycled into the soil, but this dynamic is accounted for in the soil carbon pool (discussed below). Perennial crop operations, especially woody perennial crops such as apple or orange farms, could reach a rotational biomass carbon steady state similar to private forests. However, we do not have a nationwide database that describes the carbon dynamics of the various perennial crop operations in the United States. Therefore, we do not include perennial crop biomass carbon processes in our model.

Similarly, pasture will produce grasses that sequester carbon. However, this storage may be temporary because the grass is eaten by animals or converted to hay that is fed to animals soon after harvest. Further, leftover grass will die in winter in some areas of the United States. Some carbon stored in the grass will migrate to the soil carbon pool; however, this process is accounted for in our soil carbon model (discussed below). We do not account for carbon stored in the root systems of pasture. On some pasture types this storage capacity can be substantial.

We also assume rangeland has a biomass carbon storage steady-state value of 0. This assumption is problematic given that rangeland includes land with scrub–shrub covers and other woody biomass features. However, because we do not have a nationwide database that describes the carbon dynamics of the various covers that make up the rangeland category we do not include rangeland biomass carbon processes in our study. Again we do not account for carbon stored in the root systems of grasslands in the rangeland category.

Soil Carbon Storage. We overlaid the 2001 NLCD (11) and a US county map on a map of soil carbon data (13) to determine the average mass of soil carbon stored on a hectare of each NLCD land use/land cover (LULC) category in each US county. Soil carbon is measured to a depth of 30 cm. We then cross-walked the NLCD LULC categories with the NRI land-use categories to create a county-level dataset of average soil carbon mass stored in a hectare of each of the five modeled land uses (see Table S2 for cross-walk). Let L_{ck} indicate the average mass of carbon stored in the first 30 cm of soil on a hectare of land use k in county c.

Let $A_{c,k,2001}$ and $A_{c,k,2051}$ indicate the number of hectares (private and public) in county c in land use k in 2001 and 2051, respectively. The carbon stored in 30 cm of soil in county c in 2001 is given by $\sum_{k=1}^{5} A_{c,k,2001}L_{ck}$, where k indexes cropland (k = 1), pasture (k = 2), forest (k = 3), urban (k = 4), and range (k = 5). The carbon stored in 30 cm of soil in county c in 2051 is given by $\sum_{k=1}^{5} A_{c,k,2051}L_{ck}$. We do not dynamically track the sequestration of carbon in soil. Instead, we assign each 2051 ha of land use type k the average level of carbon storage observed in that land use type circa 2001.

Kilocalorie Production. Let the 2001 per acre yield of crop type j in county c be given by Y_{jc} (8). Let the constant that converts a unit of crop yield k into grams be given by G_j (www.futures101.ru/wp-content/uploads/2010/03/conversion.pdf). For example, wheat yield is given in bushels. A bushel of wheat has a mass of 27,216 g. Therefore, G_{wheat} = 27,216 g. Let K_j measure the kilocalories in a gram of crop j. For example, each gram of wheat contains 3.39 kcal. See Table S3 for the list of crop types and G_j and K_j for each crop type (14). Let O_{jc} indicate the millions of kilocalories produced per acre of crop j in county c in 2001,

$$O_{jc,2001} = \frac{Y_{jc}G_jK_j}{1{,}000{,}000}. \quad \textbf{[S9]}$$

Next we calculate an average per hectare kilocalorie production value in 2001 for each county. Let F_{jc} indicate the fraction of county c's private cropland in crop j (9). Therefore, O_c, county c's weighted average kilocalorie production per hectare of private cropland in 2001, is given by

$$O_{c,2001} = 2.471\sum_{j=1}^{J} F_{jc}O_{c,2001}, \quad \textbf{[S10]}$$

where the constant 2.471 converts per-acre values to per-hectare values and $O_{c,2001}$ is measured in millions of kilocalories.

We assume a 6% increase in crop yield every 5 y from 2001 to 2051 across all crop types and all counties in the United States. We assume F_{jc} stays fixed for each j and c combination from 2001 to 2051. Therefore, 2051 kcal production per hectare of private cropland in county c be given by

$$O_{c,2051} = O_{c,2001}1.06^{10}, \quad \textbf{[S11]}$$

where $O_{c,2051}$ is measured in millions of kilocalories.

Let $A_{c,c,2001}$ and $A_{c,c,2051}$ indicate the hectares of private cropland in county c in 2001 and 2051, respectively. Therefore, kilocalorie production in each county in 2001 and 2051 is given by $A_{c,c,2001}O_{c,2001}$ and $A_{c,c,2051}O_{c,2051}$, respectively.

Timber Production. Let D_c indicate the expected yield of timber in county c where yield is measured in thousand cubic feet (mcf) per hectare (6). We assume that D_c does not change over time. Let R_c indicate the weighted average rotation length of private forest in county c. R_c is a function of A_{cm} and t_{cm} over all m,

$$R_c = \frac{\sum_{m=1}^{M} A_{cm}t_{cm}}{\sum_{m=1}^{M} A_{cm}}, \quad \textbf{[S12]}$$

where A_{cm} and t_{cm} are defined in *SI Text*, *Biomass Carbon Storage in Private Forests*. Timber production in county c in any given year is equal to $P_c = D_c/R_c$ where we divide by R_c to account for the fact that each year only $1/R_c$ of forest area in county c is harvested (recall our assumption that all private forests are in steady-state rotation at all times).

Let $A_{c,f,2001}$ and $A_{c,f,2051}$ indicate the hectares of private forest in county c in 2001 and 2051, respectively. Therefore, total timber production in each county in 2001 and 2051, measured in thousands of cubic feet, is given by $A_{c,f,2001}P_c$ and $A_{c,f,2051}P_c$, respectively. Note that we credit each hectare of private forest in 2001 and 2051 with its even-age rotation timber harvest.

We do not track timber harvest on public land. By 2002 harvest on public lands had fallen to less than 8% of the country's annual harvest (15). Therefore, we do not think our estimates of alternative trends in timber harvest across the contiguous United States are invalidated by ignoring public land harvest over time.

Finally, note that we do not account for the carbon dioxide fertilization effect in our study. If this phenomenon is real, then we underestimate timber production.

Species Habitat. To assess species responses to land-use change we quantify changes in the amount of habitat for 194 terrestrial vertebrate species. All of the chosen species have ecological or social importance. The chosen species represent four major groups: amphibians (n = 56), influential species (including top carnivores and ecosystem engineers, n = 81), game species (n = 34), and at-risk birds [categorized by the American Bird Conservancy (16) as "vulnerable" or "potential concern," n = 47; see Dataset S1 for the complete species list]. We quantify potential habitat area for each species on the 2001 and 2051 maps by using species' geographic range maps and known habitat associations. We assume that species' geographic ranges and habitat associations will remain static despite the potential of climate change to alter both (17). For each species and species group, we compare the projected change in habitat area from 2001 to 2051 under the 1990 Trends and high crop demand scenarios and differences in 2051 habitat across policy scenarios.

We obtained digital range maps for 42 mammals (18), 108 birds (19), and 56 amphibians (data available online at www.iucnredlist.org/technical-documents/spatial-data). For bird ranges, we only use the portions that supplied breeding or year-round residency. For amphibians, we use only species that had significant use of uplands (terrestrial) habitat during their life cycle (i.e., not exclusively aquatic species or wetlands specialists).

To derive species–habitat associations we use a land-cover classification of 144 ecological systems from NatureServe (20), generalized from 30-m to 100-m pixels to match our other spatial datasets, in conjunction with expert opinion. Ecological systems represent "recurring groups of biological communities that are found in similar physical environments and are influenced by similar dynamic ecological processes, such as fire or flooding" (20). Descriptions of the ecological systems and data layers for the conterminous United States are available online (www.natureserve.org). We do not use the finest-level classification of ecological systems available ($n = 544$) but rather groupings of those systems at the macrogroup level as provided by NatureServe (Table S4).

To model transitions from one land-use type to a new forest or range land-use type based on the coarse NRI classes used in the econometric model, we use a potential vegetation dataset known as "biophysical settings" from NatureServe. Biophysical settings represent "the vegetation that may have been dominant on the landscape prior to Euro-American settlement," taking into account historical disturbance regimes (www.landfire.gov). Because the biophysical settings vegetation classification is based on NatureServe's ecological systems, we used the same groupings of ecological systems at the macrogroup level (Table S4) for potential vegetation as we did for current land cover.

To be compatible with the outputs of the econometric model, we had to ensure that each NRI class (water, crops, pasture, forest, urban and built-up, and range) could be mapped as an appropriate ecological system. First we assign each NRI class (0:5) to the appropriate NLCD Anderson level-1 class (1:8) and NLCD 2001 land-cover class (11:95). This is done by examining current land cover under each classification (Table S5). The NRI class "water" includes both wetlands classes as well as "barren lands" in the NLCD 2001 classification. Given the cross-walk shown in Table S5 it is relatively straightforward to assign each of our 144 land-cover classes to one of the NLCD 2001 classes, and therefore the appropriate NRI class. A potential problem arises with clear-cut forests, which are likely to be classified as forest in the NRI and as shrub/scrub or grassland/herbaceous in the NLCD. As indicated in Table S2, shrub/scrub and grassland/herbaceous are matched to the NRI rangeland category. Thus, in some cases we will apply the transition probabilities for land starting in rangeland to land that is properly categorized as forest. If there is any ambiguity we use the ecological systems definition(s) to determine the appropriate NLCD 2001 class. We use the NLCD 2001 grid as the basis for our "current" land-cover layer, but with one of our 144 land-cover codes assigned to each 30-m-resolution grid cell. To be consistent with land-use and carbon modeling layers, we built a 100-m resolution by taking the most common land-cover code in the 30-m cells that a single 100-m cell overlapped.

We use expert opinion (the authors and NatureServe staff) to identify the ecological systems considered to be "prime habitat," defined as those ecological systems use for foraging and/or reproduction and expected to support population growth over time on its own. Our estimates of habitat area and habitat change in this paper are based on prime habitat only.

We quantify the species' habitat area in 2001 using the following calculation:

$$HV_s^P = \sum_1^j P_j, \qquad \textbf{[S13]}$$

where HV_s^P is the current prime habitat area for species s, and P_j is the total area (in the range of species s) of land-cover type j of the list of land-cover types considered to be prime habitat for species s.

For habitat area in 2051 we use

$$HV_s^P = \sum_1^y \left\{ \sum_{i=1}^5 \sum_1^j p_i C_j + \sum_{i=1}^5 \sum_1^j p_i T_j \right\}, \qquad \textbf{[S14]}$$

where HV_s^P is the scenario-specific prime habitat value for species s, y is the total of all pixels in the range of species s, p_i is the probability of land cover at a pixel being type i 50 y in the future, $C_j = 1$ if i is the current land cover type at pixel y and land-cover type j is on the prime habitat list for species s, whereas $T_j = 1$ if i represents a transition to a new land-cover type and land-cover type j is on the prime habitat list for species s and is assigned to pixel y according to the rule for new land cover.

The 100-m grid with ecological system values described above are used to calculate the current amount of habitat available to each species on our list, based on a simple sum of the area of all macrogroups on the prime habitat list for each species. Because future land cover is based on the probability of any given grid cell staying the same (NRI-based) land cover, or transitioning to another land-cover type, if the land cover stayed the same we used the habitat value (if any) assigned to the ecological system in the current land-cover grid. If the land cover represented a transition to a new land cover we use the rules shown in Table S6 to assign a habitat value to the grid cell.

For each scenario of projected land-use change, any individual pixel y in the range of species s can have a potential habitat value from 0 to 1 (the term inside the brackets in Eq. **S14**). We create a grid with continuous pixel values of 0–1 across a species' range for projected habitat values to calculate overall habitat amounts and changes. Changes in habitat are calculated for each species comparing the scenario-specific habitat values to current values and comparing those changes under each policy scenario to the amount of change under the baseline scenario.

A Note on Climate Change. In our analyses, changes in land use and land use productivity (e.g., crop yield, timber yield, and biomass carbon sequestration rates) are not a function of expected climate change. Haim et al. (9) found that land-use choices will not be greatly affected by climate change between 2001 and 2051 across the United States. However, it is fairly clear that land-use productivity and vegetative cover will be affected by climate change (21, 22). There is also evidence to suggest that many tree species will migrate and forest productivity in the United States will change owing to climate change. For example, Kirilenko and Sedjo (23) suggest that productivity in many forests will increase as a result of CO_2 fertilization. We do not account for the fertilization effect in our study, which would raise our estimates of timber production and carbon sequestration in forests. However, increases in productivity owing to fertilization could be offset by climate change factors such as increasing frequency of forest fires (24). Finally, species ranges will change as the climate changes, with many species shifting their distributions to track suitable climates (25). Incorporating climate-change impacts is an important next step in providing more realistic future projections.

A Note on Carbon Storage Estimates. Our analyses simplify carbon sequestration dynamics by using a steady-state analysis. We assume that the carbon stored in vegetation and soil is in steady-state equilibrium on the landscape in 2001 and that the carbon storage between 2001 and 2051 only changes when land use changes. Further, we assume that carbon stocks in land that changes between 2001 and 2051 reaches its steady-state storage by 2051. To the extent that not all carbon adjustments to land-use change have been made by 2051, our carbon estimates may overestimate their actual 2051 values. Nonetheless, our estimate of future carbon storage by 2051 is similar to a US Forest Service estimate (26). An increase of 1.1 billion Mg of carbon storage over the 50-y period (projected by our 1990s trend scenario) amounts to an increase in the annual sink of 80 MM t carbon dioxide equivalents. This is a little less than 10% of the total estimated US annual sink in the years from 2007 to 2011 (27).

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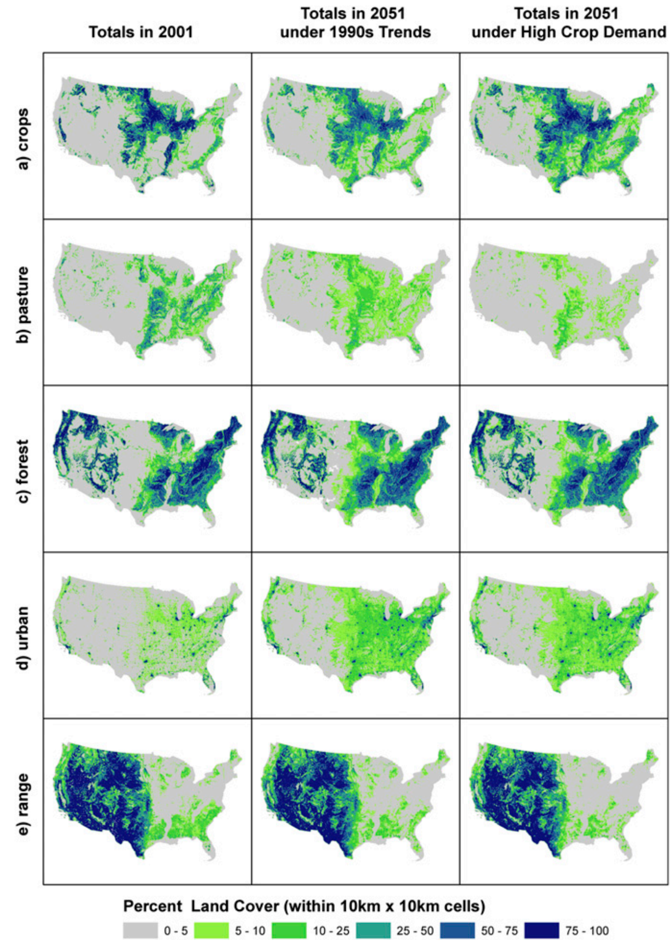

Fig. S1. (*A–E*) Spatial patterns in land cover in 2001 and in 2051. Future projections were made for two baseline scenarios, 1990s trends and high crop demand.

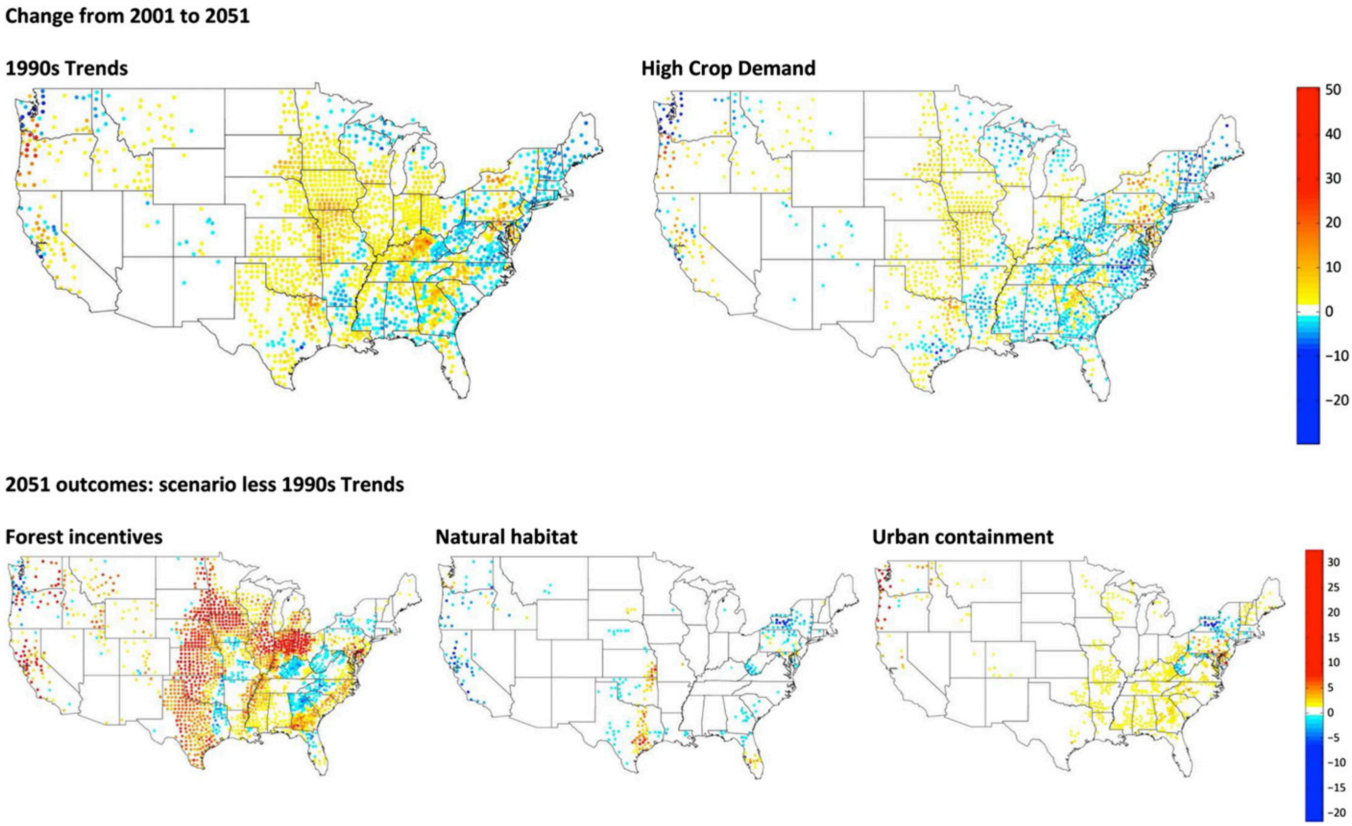

Fig. S2. Change in biomass carbon stock (megagrams per hectare). Each dot represents a county (the dot is placed at its county's centroid). The top row of maps gives change over time for the two reference scenarios. The bottom row of maps gives differences as of 2051 when a scenario outcome is compared with the 1990s trends outcome. In the bottom row of maps a positive (negative) number for a county means that the scenario value for that county is higher (lower) than the 1990s trends value for that county. In all maps white space indicates no change for that county over time or between a scenario and the 1990s trends as of 2051.

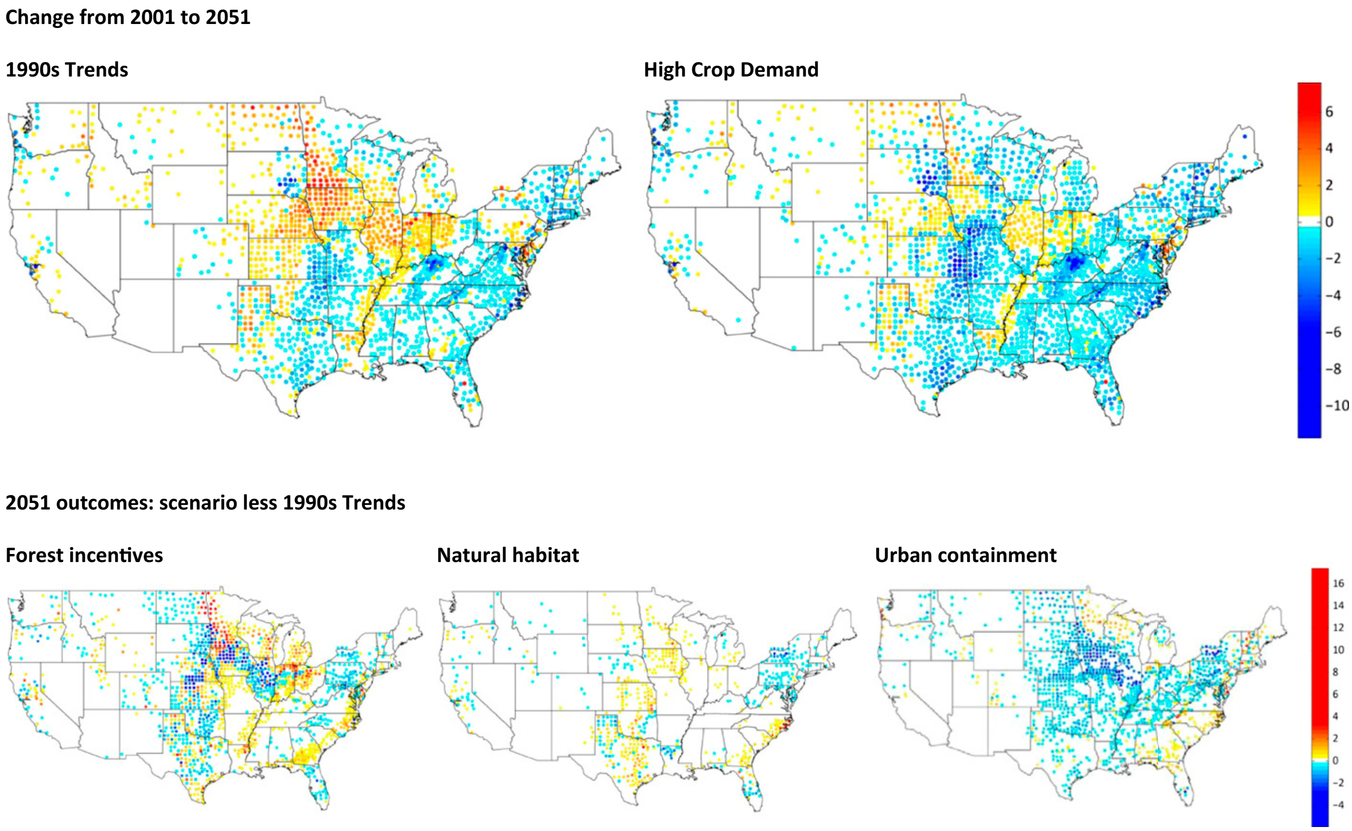

Fig. S3. Change in soil carbon stock (megagrams per hectare of first 30 cm of soil profile). Each dot represents a county (the dot is placed at its county's centroid). The top row of maps gives change over time for the two reference scenarios. The bottom row of maps gives differences as of 2051 when a scenario outcome is compared with the 1990s trends outcome. In the bottom row of maps a positive (negative) number for a county means that the scenario value for that county is higher (lower) than the 1990s trends value for that county. In all maps white space indicates no change for that county over time or between a scenario and the 1990s trends as of 2051.

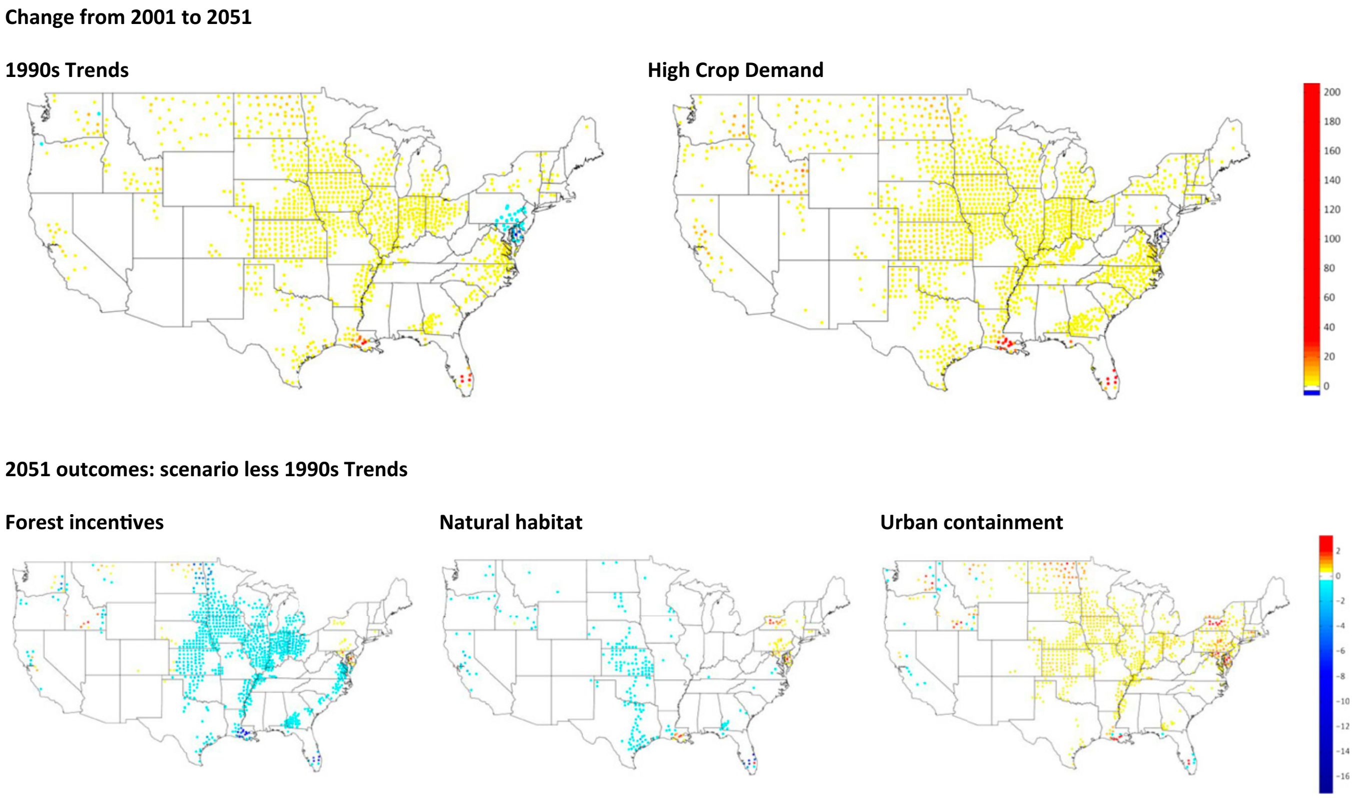

Fig. S4. Change in food production (millions of kilocalories per hectare). Each dot represents a county (the dot is placed at its county's centroid). We assume crop yields for all crops and locations increase 6% every 5 y. The top row of maps gives change over time for the two reference scenarios. The bottom row of maps gives differences as of 2051 when a scenario outcome is compared with the 1990s trends outcome. In the bottom row of maps a positive (negative) number for a county means that the scenario value for that county is higher (lower) than the 1990s trends value for that county. In all maps white space indicates no change for that county over time or between a scenario and the 1990s trends as of 2051.

Table S1. Elasticity measures used to update commodity prices or net revenues to land use

Land use	Elasticity
Crops	−0.661
Pasture	−0.661
Forest	
Region 1	−0.300
Region 2	−0.497
Region 3	−0.054
Region 4	−0.141
Region 5	−0.029
Region 6	−0.193
Region 7	−0.285
Urban	−0.000212
Rangeland	−0.661

The price of crop m at period t is given by $P_{mt-1} \times (1 + (Z_{mt}/\mu_{crop}))$ where P_{mt-1} is the national level price of crop m in period $t-1$, Z_{mt} is the percentage change in the national-level production of m from $t-1$ to t, and μ_{crop} is the elasticity measure of crops. The price of forest in region r at period t is given by $P_{rt-1} \times (1 + (Z_{rt}/\mu_r))$, where P_{rt-1} is the price of forest in region r at period $t-1$, Z_{rt} is the percentage change in the region-level production of timber from $t-1$ to t, and μ_r is the elasticity measure of forest in region r. Net revenues on pasture and rangeland in county c in period t is given by $NR_{jct-1} \times (1 + Q_{jct}/\mu_j)$, where NR_{jct-1} is the return to land use j in county c at period $t-1$ and Q_{jct} is the percentage change in land use j in county c from $t-1$ to t. Net revenues on urban use in county c in period t is given by $NR_{jct-1} + Q_{jct}/\mu_j$.

Table S2. Cross-walk table used for NLCD 2001 land cover in the conterminous United States

NLCD	Definition	Anderson level 1	Our land-use categories
11	Open water	1	0
12	Perennial ice/snow	8	0
21	Developed – open space	2	4
22	Developed – low intensity	2	4
23	Developed – medium intensity	2	4
24	Developed – high intensity	2	4
31	Barren land	3	0
41	Deciduous forest	4	3
42	Evergreen forest	4	3
43	Mixed forest	4	3
52	Shrub/scrub	5	5
71	Grassland/herbaceous	5	5
81	Pasture/hay	6	2
82	Cultivated crops	6	1
90	Woody wetlands	7	0
95	Emergent herbaceous wetlands	7	0

Table S3. Conversion rates for translating crop yield units into grams (G_j) and grams of yield into kilocalories (K_j)

Crop name	Yield unit*	Grams per yield unit	Kilocalories per gram of yield
Winter wheat	bu	27,216	3.39
Durum wheat	bu	27,216	3.39
Other spring wheat	bu	27,216	3.39
Rye	bu	25,401	3.38
All rice	cwt	45,360	3.70
Corn for grain	bu	25,401	0.86
Corn for silage	bu	25,401	0.86
Oats	bu	14,515	3.89
Barley	bu	217,720	3.52
All sorghum	cwt	25,401	3.39
All cotton	lb	453.6	0.00
Sugarcane for sugar	ton	907,000	3.87
Sugarcane for seed	ton	907,000	0.00
Sugarbeets	ton	907,000	0.43
All tobacco	lb	453.6	0.00
Flaxseed	bu	25,401	0.00
Peanuts for nuts	lb	453.6	5.67
Soybeans for beans	bu	27,216	1.47
Sunflower seed	cwt	45,360	5.84
All dry edible beans	cwt	45,360	3.33
Alfalfa hay	ton	907,000	0.00
All other hay	ton	907,000	0.00
All potatoes	cwt	45,360	0.58
Sweet potatoes	cwt	45,360	0.86

Conversion rates for translating crop yield units into grams are available from ref. 14, and conversion rates for translating grams of yield into kilocalories are available at www.futures101.ru/wp-content/uploads/2010/03/conversion.pdf.

*bu, bushel; cwt, hundredweight; lb, pound; ton, US ton.

Table S4. An example of the hierarchical land-cover classification created by NatureServe (18)

Name of classification	*N*	Example	Area of example in conterminous United States, thousands of square kilometers
Class	17	Forest and woodland	2,476
Division	49	Western North American cool temperate forest	567
Macrogroup	144	Rocky Mountain subalpine and high montane conifer forest	163
Ecological system	544	Rocky Mountain lodgepole pine forest	28

The classification used in our study for habitat is the macrogroup level. *N* is the number of different types (of each class) in the conterminous United States.

Table S5. Rules used to assign the appropriate ecological system values (1 of 144) to projected land cover, for projected land cover that represented a transition to a different land-cover type than the current type

NRI code	Transition	Ecological system to use
1	To cropland	Use "agriculture – cultivated crops and irrigated"
2	To pasture	Use "agriculture – pasture/hay"
3	To forest	Use forest system from biophysical settings
4	To urban	Use "developed – medium intensity"
5	To rangeland	Use grassland/shrubland system from biophysical settings

For the transitions to natural land-cover types (forest and rangeland), from the location of the pixel the algorithm looked for the closest system in the biophysical settings layer (see www.landfire.gov) that belonged to the appropriate classification, for example, forest for NRI code 3 and grassland/shrubland for NRI code 5.

Dataset S1. Data file with the 194 vertebrate species used for estimating changes in amounts of wildlife habitat owing to projected land-use change

Dataset S1

The species are in taxonomic order with their membership in the species groups used in our analysis are shown: amphibians, influential species (top carnivores and ecosystem engineers), game (hunted species), and declining birds [categorized by the American Bird Conservancy (16) as "vulnerable" or "potential concern"]. In addition we show each species' International Union for Conservation of Nature status (EN, endangered; LC, least concern; NT, near-threatened; and VU, vulnerable) and whether their prime habitat associations show a specialization ("forest," all forest macrogroups; "none," both forest and range macrogroups, may also include human-dominated land uses; and "range," all range macrogroups).