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Projecting effects of land use change on human well-being through changes in ecosystem services

Susan H. Yee[1], **E. Paulukonis**[1,2], **C. Simmons**[3], **M. Russell**[1], **R. Fulford**[1], **L. Harwell**[1], **L.M. Smith**[1]

[1.]Gulf Ecosystem Measurement and Modeling Division, Center for Environmental Measurement and Modeling, US Environmental Protection Agency, Gulf Breeze, FL 32561

[2.]Current address: Ecosystem Processes Division, Center for Environmental Measurement and Modeling, Athens, GA 30602

[3.]General Dynamics Information Technology, 109 T.W. Alexander Drive, Research Triangle Park, NC27711

Abstract

Changing patterns of land use, temperature, and precipitation are expected to impact ecosystem services, including water quality and quantity, buffering of extreme events, soil quality, and biodiversity. Scenario analyses that link such impacts on ecosystem services to human well-being may be valuable in anticipating potential consequences of change that are meaningful to people living in a community. Ecosystem services provide numerous benefits to community well-being, including living standards, health, cultural fulfillment, education, and connection to nature. Yet assessments of impacts of ecosystem services on human well-being have largely focused on human health or monetary benefits (e.g. market values). This study applies a human well-being modelling framework to demonstrate the potential impacts of alternative land use scenarios on multi-faceted components of human well-being through changes in ecosystem services (i.e., ecological benefits functions). The modelling framework quantitatively defines these relationships in a way that can be used to project the influence of ecosystem service flows on indicators of human well-being, alongside social service flows and economic service flows. Land use changes are linked to changing indicators of ecosystem services through the application of ecological production functions. The approach is demonstrated for two future land use scenarios in a Florida watershed, representing different degrees of population growth and environmental resource protection. Increasing rates of land development were almost universally associated with declines in ecosystem services indicators and associated indicators of well-being, as natural ecosystems were replaced by impervious surfaces that depleted the ability of ecosystems to buffer air pollutants, provide habitat for biodiversity, and retain rainwater. Scenarios with increases in indicators of ecosystem services, however, did not necessarily translate into increases in indicators of well-being, due to covarying changes in social and economic services indicators. The approach is broadly transferable to other communities or decision scenarios and serves to illustrate the potential impacts of changing land use on ecosystem services and human well-being.

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Keywords

Human Well-Being Index; scenario analysis; ecosystem services; relationship functions; land use change

1. Introduction

People often think about the more obvious market benefits of ecosystem goods and services, such as harvestable fish or timber, but ecosystem services can have more subtle benefits that are equally important to community well-being, including wealth (Escobedo et al. 2015), physical and mental health (Bell et al. 2008, Hendryx and Innes-Wimsatt 2013), culture and spirituality (Schaich et al. 2010), education (Louv 2005), and social connections (Kuo and Sullivan 2001). Changing patterns of land use, temperature, and precipitation, for example, are expected to impact the ability of ecosystems to regulate water quality and quantity, reduce the ability of ecosystems to buffer extreme events, result in loss and degradation of soil and water assets for agriculture, and lead to alterations in biodiversity (Groffman et al. 2014), with potential consequences for human well-being. Yet, studies that have attempted to quantify well-being impacts of future development, temperature, or precipitation scenarios have primarily focused toward economic losses (Speers et al. 2016; Tol 2018) or human health impacts (McMichael et al. 2003; Luber et al. 2014), with consideration of cultural, social, safety, education or other well-being impacts largely inferred, such as through expert working groups (MEA 2005). Scenario models that link decision alternatives to human well-being, including those that impact ecosystem services, may be valuable in estimating potential benefits and trade-offs that are meaningful to people living in a community (Summers et al. 2016).

To be able to project human well-being outcomes, scenarios of changing ecological condition can be linked to changing ecosystem services through the application of ecological production functions (EPFs; Wainger and Mazzotta 2011). In turn, EPFs are commonly linked to market and non-market economic valuations through the application of economic and household production functions, which translate metrics of ecosystem service production to monetary values of benefit (Bruins et al. 2017). Conceptually similar, the relative changes in ecosystem services can also be linked to changes in human well-being through ecological benefits functions (EBFs). Several efforts have been undertaken to connect the provisioning of ecosystem services to indicators of well-being, paving the way for EBFs to project potential changes in human well-being (Gordon and Folke 2000; Pereira et al. 2005; Pinto et al. 2014; Summers et al. 2016).

Measures of human well-being can be represented as composite indices that attempt to provide a comprehensive non-monetary measure of human welfare by integrating metrics of wealth and health alongside other factors such as culture, safety, and social cohesion (Smith et al. 2012; Ferrara and Nistico 2015; Dyrbye et al. 2016). The advantages of considering multiple types of well-being benefits is that such an approach may be more closely aligned with what stakeholders care about rather than monetary measures (Fulford et al. 2016), and

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provides a flexible approach for simultaneously examining trade-offs across multiple objectives.

Here we apply a modelling framework based on a composite well-being index (Human Well-being Index, HWBI; Summers et al. 2016) to demonstrate the potential impacts of alternative land use scenarios on indicators of human well-being through projected changes in a suite of ecosystem services indicators. The HWBI modelling framework quantitatively defines these relationships in a way that can be used to project the influence of ecosystem service flows on indicators of human well-being, alongside social service flows and economic service flows (Fig. 1; Smith et al. 2014b; Summers et al. 2016). We use a suite of EPFs to quantify likely changes in ecosystem services indicators resulting from changes in ecological condition. We assess which components of changing ecological condition have the strongest influence on a suite of well-being indicators, and explore how uncertainty in model relationships translates into uncertainty in well-being outcomes. Though demonstrated for two future land use scenarios in a Florida watershed, the approach is broadly transferable to other communities or decision scenarios and serves to illustrate the potential impacts of changing land use on ecosystem services and human well-being.

2. Methods

2.1. Human Well-Being Framework

The HWBI modelling framework describes the relationships between indicators of ecosystem services, social services, economic services, and indicators of human well-being (Summers et al. 2016). Human well-being is quantified as a multidimensional composite index (Human Well-being Index, HWBI; Smith et al. 2012) representing eight domains of well-being—Connection to Nature, Cultural Fulfillment, Education, Health, Leisure Time, Living Standards, Safety and Security, and Social Cohesion—that are considered globally applicable to human well-being (Smith et al., 2012, 2013) and broadly resonate with community sustainability goals (Fulford et al. 2016). Social, economic, and ecosystem services all influence human well-being.

Social services, ecosystem services, economic services, and eight domains of well-being are each quantified by suites of indicators composed of representative metrics (Smith et al. 2014a). Although originally developed at a county scale with nationally available data, the HWBI framework was designed to be broadly applicable and flexible. Integrity is maintained at the indicator-level, but metrics within each ecosystem service or HWBI indicator can be customized to suit data availability or specific community context (Smith et al., 2012, 2014a), including for example, American Indian Alaska Natives (Smith et al., 2014c), children (Buck et al. 2018), and Puerto Rico (Orlando et al. 2017).

Both service and well-being metric data were previously developed for counties within the United States from 2000–2010 and used to develop quantitative models describing the relationships between aggregated indices of economic, social, and ecosystem services and domains of well-being (Table 1; Smith et al. 2014b; Summers et al. 2016). The regression models can be used to project potential outcomes for human well-being domain scores as indicators of ecosystem services, economic services, or social services are modified through the actions of decision-makers (Summers et al. 2016). Because the HWBI framework is based on aggregated indicators, the goal of the model is not to provide precise predictions of change, but instead is intended as a decision-making tool to investigate potential linkages between decision levers and overall well-being to stimulate conversation.

In addition to the direct actions of decision-makers to modify service availability, ecosystem services, in particular, may be impacted by longer-term natural processes and anthropogenic decisions that alter the condition of the natural and built environment. Here, we use the HWBI framework to explore how longer-term processes, such as changing land use or weather patterns, may impact human well-being through changes in ecosystem services. For an example set of future scenarios, we apply ecological production functions (EPFs; Fig. 1; Wainger and Mazzotta 2011) to model changes in ecosystem services in response to changing land use/land cover and changing weather patterns over a 40 year period. We then use the projected ecosystem services indicators as input into ecological benefits functions (EBFs; Fig. 1), namely the services to domain regression models (Summers et al. 2016), to link the changes in ecosystem services indicators to changes in human well-being domain scores.

2.2. Future Scenarios of Environmental Conditions

As an example demonstration study to develop the approach, we investigated the potential impacts of changing land use/land cover, precipitation, and temperature on ecosystem services and human well-being for the Pensacola Bay watershed, Florida. In a prior workshop, Escambia County residents developed community sustainability goals, well-aligned with the eight HWBI domains of human well-being, and identified strategies to achieve those goals (Fulford et al. 2016). Availability of ecosystem services is often overlooked compared to economic or social strategies, despite ecosystem services being linked to economic stability, sense of place, human health, and safety (Smith et al. 2013). It is largely unknown how specific future development scenarios might impact ecosystem services and well-being for the local community. Here, we demonstrate how the application of the HWBI framework to investigate potential impacts of ecosystem services on well-being under alternative development scenarios. We modeled changes in ecosystem services and human well-being for a set of existing scenarios of land use change and climate from 2010–2050, as developed by the FOREcasting Scenarios of Land use Change modeling framework (FORE-SCE; Sohl et al. 2016; USGS 2016). Several models exist for modeling future land use/land cover change (e.g., integrated climate and land-use scenarios (ICLUS)), but most are limited to only few types of land use, such as urban development, or are more appropriate for specific local applications (Sohl et al. 2012), limiting our ability to connect projected changes in future environmental condition to ecosystem services at watershed scales. By comparison, the FORE-SCE projects spatially explicit maps of future land use/land cover, including forest, developed space, wetlands, grassland, crops, pasture, and water, based on extrapolations of historical change and nationally-relevant scenarios of future socioeconomic and environmental conditions.

The FORE-SCE framework uses the Intergovernmental Panel on Climate Change (IPCC) A2 and B1 scenarios to describe and model socio-economic and biophysical drivers of land use change. Each scenario implements a set of statistical and deterministic modeling techniques to project future land use change. The A2 scenario describes regionally oriented economic development, slow and fragmented technological change, reliance on fossil fuel energy, increasing population growth, and low resource protection (Cubasch et al. 2001). The B1 scenario describes globally oriented solutions to economic, social, and environmental sustainability, introduction of resource-efficient and renewable energy technologies, lower population growth, and a greater emphasis on environmental protection. For each scenario, A2 or B1, we downloaded forty-one raster maps representing each year from 2010–2050 of projected land use/land cover that were used as input into our EPF models to calculate ecosystem services indicators.

Projected effects of future precipitation and temperature on land cover are already integrated into FORE-SCE projected land use/land cover maps through statistical relationships used to forecast land cover change (Sohl and Sayler 2008). In addition, in order to model changes in surface water flow with projected changes in land cover, we obtained projected daily weather data, including precipitation, temperature, windspeed, and humidity, from available projected data sets of future climate conditions (Multivariate Adaptive Constructed Analogs, MACA; Abatzoglou and Brown 2012; www.climatologylab.org). MACA uses a statistical methodology to downscale a common set of Global Climate Models to a 4 km resolution. From 2010–2050, precipitation and temperature patterns are assumed to be reasonably similar between the A2 and B1 scenarios (Cubasch et al. 2011), therefore we used a single time series of projected climate data for both scenarios.

We applied a suite of EPFs (e.g., Russell et al. 2013; Tallis et al. 2013; Fulford et al. 2016) to model how two alternate scenarios, A2 or B1, of changing land use and future weather patterns might impact production of ecosystem services, and then used these relative changes in ecosystem services as input into EBFs described by the HWBI services to domains regression models (Table 1; Summers et al. 2016) to assess potential impacts on human well-being under each scenario. Each scenario consisted of the forty-one FORE-SCE land use/land cover maps, representing each year from 2010–2050, and corresponding projected daily weather data from 2010–2050.

2.3. Spatially-Explicit Modeling Platform

We used the Envision spatially-explicit modeling platform (Bolte and Vache 2010; Bolte 2014) to run model simulations for each scenario. Envision uses polygon-based GIS maps to model landscape change processes and calculate yearly evaluative metrics. We developed the EPFs and EBFs (i.e., HWBI services to domain regression models, Summers et al. 2016) as model plug-ins to Envision to calculate yearly changes in ecosystem services and human well-being in each spatial polygon. Each polygon represents an integrated decision unit (IDU), which is the relevant spatial scale at which decisions or environmental processes are assumed to act. Models are run and evaluative metrics calculated at the scale of each IDU. For our analysis, we identified an IDU as a census tract, but split census tracts that were contained within separate sub-watersheds. For Envision applications with a hydrological component, IDU polygons may be grouped into hydrological response units (HRU), based on their connectivity to the same stream reach, for implementing EPFs related to hydrological processes.

To conform with Envision's polygon-based GIS maps, yearly FORE-SCE raster maps were converted to IDU polygons representing census tracts in the Escambia Bay watershed of Florida (Fig. 2). The landuse/landcover class covering the majority of area in each IDU polygon was assigned to that IDU polygon. In addition to majority land use, FORE-SCE raster maps were used to calculate area of water and area of forest for each IDU polygon for each year of the simulation period. Because population growth is not explicitly modeled by FORE-SCE, but is instead inferred through specified changes in developed area, we estimated population change with changing land use by calculating an average population density for each land use/land cover type in the year 2010 (US Census) and projecting forward to subsequent years. The study area comprised 33,250 IDUs within four counties in Florida: Escambia, Okaloosa, Santa Rosa, and Walton. IDU polygons were assigned to one of 3006 HRU polygons, defined by catchments obtained from the National Hydrography Dataset (NHD+). The IDU census tract polygons were split as needed to assure that an IDU did not belong to more than one HRU, but an HRU could contain multiple IDUs (Fig. 2).

2.4. Ecological Production Functions (EPFs)

Ecological production functions were applied to translate projected changes in land use and weather data to a suite of ecosystem services indicators (Wainger and Mazzotta 2011; Russell et al. 2013; Tallis et al. 2013). The ecological production functions, described in the following sections, were implemented as model plug-ins within Envision (Bolte 2014). Output from these models was then used as input into EBFs described by the HWBI services to domains regression models (Fig. 1; Summers et al. 2016).

The EPFs included in the model were selected based on their input variable requirements aligning with projected environmental condition in future scenarios, and their output aligning with input needs for EBFs. In many cases, EPFs were not available to model the exact ecosystem services metrics in the original national HWBI (Smith et al. 2014a), either because no known EPF model with that specific metric as output was available, or because the necessary input data could not be connected to the condition metrics described in future scenarios. When an EPF could not be identified, we replaced the original ecosystem services metrics with alternative surrogates that were i) comparable, or reasonably assumed to be correlated, with metrics in the HWBI (Table 2), and ii) could be modelled with changing environmental conditions in the FORE-SCE scenarios (Table 3). To further ensure surrogate estimates of services were on the same scale as the original services, we calibrated our modelled estimates of ecosystem services relative to the known services score values in 2010 (Appendix Table A1; Smith et al. 2014a; Ignatius et al. 2016; EPA 2018). As such, the relative changes in modelled ecosystem services should provide a reasonable surrogate for assigning relative changes in ecosystem services scores as input into HWBI regression models.

Ecosystem services metrics were modelled for each IDU using EPFs and then scaled between zero and one, using the minimum and maximum IDU value across the entire watershed at the start of the simulation period to bound the range of outcomes and prevent extreme outliers from skewing scaled scores in future years. An average scaled metric value was then calculated across all IDU within each county. Following the HWBI indicator calculation procedure (Smith et al. 2012, 2014a,b), scaled metrics were averaged to calculate a yearly indicator score for each county, with indicators then averaged to create an aggregated ecosystem service score for each county (Table 2). We fixed the start year 2010 to the known ecosystem service score values from 2000–2010 for each county (Appendix Table A1; Smith et al. 2014a; EPA 2018), and adjusted yearly modelled ecosystem scores relative to that start year based on year-to-year differences in scores.

2.4.1. Air quality—Air quality, originally measured in the HWBI as the fraction of days each year with good to moderate air quality (Table 2), is assumed to be related to changes in pollution over time, as well as the ability of trees to buffer that pollution. Rates of air pollutant removal depend on the downward flux of particles intercepted by the tree canopy (Lovett et al. 1994; Nowak et al., 2008), which can be used to calculate the reduction in pollution concentration as:

$$\text{rate of air pollutant removal} = \frac{\%\ \text{canopy cover}}{100} \times \text{area} \times \text{deposition velocity} \times \text{pollutant concentration} \tag{1}$$

Because atmospheric pollutant concentration and types of pollutants can vary widely across time and space, we standardized the rates of pollutant removal per unit of pollutant (i.e., per $1g/m^3$ of pollutant throughout the watershed). We focused on removal rates for particulate matter greater than 2 μm, and assumed a deposition velocity of 1.25 cm/s (range=0.5–2 cm/s; Lovett, 1994). Canopy cover per IDU was modelled as a changing function of land use, based on calculating an average canopy cover (NLCD 2011) across IDUs assigned to each land use/land cover class in 2010 (Appendix Table A1).

2.4.2. Food, Fiber, and Fuel—The HWBI indicator of food, fiber, and fuel comprises three indicators describing food production, raw material reserves, and energy reserves (Table 2). Raw material reserves and energy reserves were set to their average 2000–2010 values at the start of simulations and assumed to decline at a fixed rate over time. Referring to the FORE-SCE scenarios, material and energy reserves were assumed to decline at a slightly faster rate for the A2 scenario (1% per year) than the B1 scenario (0.5% per year), the latter of which was assumed to implement more renewable energy technologies. The commercial fishery landings component of food production was set to the average 2000–2010 value and assumed to be constant over time as projected vulnerability under both A2 and B1 scenarios has been estimated to be low and uncertain, as projected impacts are highly species specific and could be both negative and positive (Porter et al. 2014). Timber production was assumed to be a constant percentage (2.15% per year) of available forest cover, based on published rates of timber production for the area (USFS 2016), such that FORE-SCE scenarios producing greater forest cover would also have greater potential for timber production. Agricultural productivity was calculated as a composite index of indicators of soil quality, including carbon burial into soil, nitrogen fixation in soil, and soil water content. Rates of carbon burial and nitrogen fixation were calculated as the mean for each land use/land cover type, derived from a scientific literature review (Fulford et al. 2016;

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Smith et al. 2017; Appendix Table A2). Depth of soil water content was modelled as percolation of moisture through the soil, depending on changing weather patterns for precipitation and temperature, with the HBV hydrologic model (Bergström 1995; Abebe et al. 2010), depending on soil moisture storage capacity and evapotranspiration coefficients (Allen et al. 1998; Appendix Tables A2, A3).

2.4.3. Greenspace—Greenspace is comprised of two indicators: i) extent of natural areas and ii) usage of nature through recreation and aesthetics (Table 2). Acreage and visitation rates to designated natural areas, such as National Parks or wildlife areas, and non-consumptive activity rates, were fixed to their original 2000–2010 levels, under the assumption that they would not predictably differ between the A2 or B1 scenarios. Fraction of unclassified land areas was modelled by assigning barren, forest, grassland, and wetlands as unclassified land and calculating coverage relative to total land cover. Wildlife observation activity was assumed to be correlated with biodiversity (i.e., species richness) of amphibians, reptiles, birds, and mammals. Species richness data was obtained from the Gap Analysis Project, which generates species distribution maps based on best available data (USGS 2011). Each land use/land cover class was assigned an average species richness based on the average richness across all IDUs assigned to that class. Blue space was calculated as the area designated as water per person in each IDU.

2.4.4. Water Quality—Water quality, is measured in the national HWBI by the percent of water bodies assessed as ‘good’ and percent days under beach action, is assumed to be associated with the capacity of different land cover classes to retain nutrients, sediment, and fecal coliforms (Table 2). Sediment loading, nutrient loading, and fecal coliform loading from each IDU was modelled by first using the HBV hydrological model (Bergström 1995; Abebe et al. 2010) to calculate daily surface water runoff volume. Surface water runoff depends on the capacities of different land cover classes for retaining water, depending on soil moisture storage capacity and evapotranspiration coefficients (Appendix Table A2, A3). Each IDU’s contribution to nutrient runoff depends on the contribution of that IDU to surface runoff within an HRU (hydrologic sensitivity score, HSS), the area weighted average nutrient export from each land use within an HRU (E_{nut}), and the percent efficiency of land cover vegetation in an IDU at removing nutrients (RE_{nut}), and was calculated as:

$$\text{nutrient loading} = \text{HSS} \times E_{nut} \times (1 - RE_{nut}/100)/\text{area} \tag{2}$$

where HSS is the relative contribution of surface runoff from a given IDU relative to all IDU within an HRU (Tallis et al. 2013). Sediment loading from each IDU was estimated by applying the modified Universal Soil Loss Equation (USLE; Williams 1975) less the percent of sediment retained by vegetation (Tallis et al, 2013):

$$\begin{aligned}\text{sediment loading} = {} & 11.8 \times \left(Q * q_p\right)^{0.56} \times K_{sed} \times ls \times C_{sed} \times P_{sed} \\ & \times (1 - RE_{sed}/100)\end{aligned} \tag{3}$$

Here, sediment loading is dependent on surface runoff volume (Q), peak runoff rate (q_p), cover and management factor (C_{sed}), management practice factor (P_{sed}), land slope factor (ls), soil erodibility factor (K_{sed}), and the percent efficiency of land cover vegetation in retaining sediment (RE_{sed}). To approximate downslope movement of water within an IDU polygon, retention efficiencies (RE_{nut}, RE_{sed}) were assumed to be 0% for the portion of an IDU's area within 50 meters of a stream, and 90% for the portion of area greater than 500 meters distance from a stream (CRWQCB 2013). Fecal coliform loading was modelled as the fraction of bacterial coliforms accumulating in each IDU that are susceptible to wash-off by surface runoff (SURO), and is calculated as:

$$\mathrm{SOQUAL} \ = \left(\mathrm{N}_{\mathrm{accum}} + \mathrm{N}_0\left(10^{-\mathrm{k}}\right)\right) \times (1 - \exp(-1 \times \mathrm{SURO} \times 2.30/\mathrm{WSQOP}) \qquad (4)$$

where N_{accum} is the daily accumulation rate of bacteria colonies, N_0 is the number of colonies the prior day, k is the rate of colony die-off, and WSQOP is the rate of surface runoff needed in each land cover type to wash-off 90% of bacterial colonies (Moyer and Hyer 2003).

2.4.5. Water Quantity—

In the national HWBI, water quantity comprises two indicators representing water sustainability and drought potential (Table 2). Drought potential is assumed to be related to the capacity of the landscape to store rainwater. The maximum rainwater storage capacity of the landscape during a precipitation event (in^3/in^2) depends on soil moisture retention (*S*) and initial abstraction of water by vegetation (*Ia*), and can be estimated by the curve number method (USDA and NRCS, 1986; Lim et al., 2006):

$$Maximum\ retained\ volume = S + Ia = 1.05 \times \left(\frac{1000}{CN} - 10\right) \qquad (5)$$

Curve numbers (*CN*) were calculated based on the mean distribution of hydrologic soil groups for each region in each land use/land cover class at a resolution of $30 \times 30m^2$ (Appendix Table A2). Retention was then converted from inches to mm^3/mm^2. The water sustainability index already incorporates 2050 projections of water demand under future scenarios, and was therefore set to the original calculated county values (NRDC 2005).

2.4.6. EPF Model Uncertainty—

Parameterization of EPF models was derived from a combination of literature values or estimates of mean production per land use type from available data. In total, the full suite of connected EPF models had over 35 model parameters, many of which had separate parameters for each land use/land cover type. Because uncertainty in model parameters can potentially influence outcomes, we investigated the degree to which uncertainty in ecosystem services estimates influence uncertainty in results. We ran 20 simulations for each of the two FORE-SCE scenarios, drawing all EPF model parameters from truncated normal distributions, based on the literature derived mean, standard deviation, minimum, and maximum (Appendix Tables A2, A3). We limited our uncertainty investigation to the EPF parameterization, such that only the EPF model parameters were allowed to vary between each simulation run. The yearly FORE-SCE raster maps and projected weather data coefficients were consistent with each simulation. We note these both could be additional sources of uncertainty, but because the primary focus of this article is leveraging EPFs to connect environmental condition to well-being, we focused our uncertainty analysis on the EPFs. Twenty stochastic simulations for each scenario was determined to be sufficient to produce stable estimates of mean ecosystem services and confidence intervals, while balancing limitations in model run-time that made large numbers of simulations prohibitive.

2.5. Ecological Benefits Functions (EBFs)

Projected county-scale ecosystem services indicators (air quality, food/fiber/fuel, greenspace, water quality, and water quantity) in each scenario simulation year were used as input into HWBI services to domain regression models (Table 1; Summers et al. 2016) in order to estimate corresponding changes in eight domains of well-being. In addition to ecosystem services indicators, the HWBI services to domain regression models (Summers et al. 2016) include the effects of economic services indicators and social services indicators on human well-being domain scores (Fig.1; Appendix Table A4). Initial data for economic and social services indicators were obtained as the 2000–2010 averages for each county (Appendix Table A1; Smith et al. 2014a; Ignatius et al. 2016; EPA 2018). Because our primary focus was on the role of ecosystem services in projected land use development scenarios, we did not directly model projected changes in economic or social services indicators. However, the potential covarying effects of economic or social services indicators can still contribute to uncertainty in model outcomes. Therefore, in addition to the 20 stochastic simulations capturing uncertainty in ecosystem services models (EPFs), we also investigated uncertainty driven by covarying social and economic services indicators.

The HWBI services to domain regression models supply three approaches for adjusting projected domain scores based on covariances among services and domains (Summers et al. 2016). First, we assumed social and economic services indicators were constant over the 40 year simulation time period. Second, we adjusted economic and social services indicators yearly based on their covariances with ecosystem services indicators in the US national data set (Appendix Table A4; Summers et al. 2016). Third, after applying services covariances, we further adjusted domain scores based on covariances among domains in the US national data set (Appendix Table A5; Summers et al. 2016). The three approaches provide three separate calculations of domain and HWBI scores, which, combined with the 20 simulations of EPF parameters, we used to estimate the mean and 90% confidence interval of projected outcomes.

Modelled indicator scores for ecosystem services, economic services, and social services for each county each year were input into HWBI regression models (Table 1; Summers et al. 2016) to calculate scores with or without covariance adjustments for each domain of human well-being. We calibrated modeled HWBI domain scores to known county values by looking at the relative change in scores each year, setting the start year to the known 2010 scores (Appendix Table A1; Smith et al. 2014a; Ignatius et al. 2016; EPA 2018). Composite HWBI was calculated as the geometric mean of domain scores (Smith et al. 2012). The HWBI framework allows the option to differentially weight domain scores depending on their perceived importance to a community through relative importance values (Smith et al. 2012; Fulford et al. 2016). For simplification, however, we assumed the relative importance of domains were equally weighted. To calculate service, domain, and HWBI scores for the entire study area, county scores were averaged and weighted by the population density in each county.

2.6. Sensitivity Analysis and Scenario Comparisons

Because indicator scores for both services and well-being domains are calculated on a relative scale between zero and one, it may not be apparent what range of scores is considered to be good or poor. Therefore, we used the US national average scores 2000–2010 to set a baseline for comparison (Smith et al. 2014a; Ignatius et al. 2016; EPA 2018). Scores below the US national average, either for a particular county or over time, were generally considered “below average”, with scores above the US national values considered “above average”.

To determine which environmental conditions were primarily driving changes in ecosystem services indicators, we calculated several environmental condition metrics for each scenario, including percent area of different land use types, human population density, mean precipitation, and mean temperature. We conducted a multiple linear regression for each ecosystem service indicator, with stochastic runs as a random effect, to determine the degree to which year-to-year change in ecosystem services scores could be explained by year-to-year changes in environmental condition. Years within a given stochastic simulation were treated as repeated measures. All statistical analyses were conducted in R (www.r-project.org) using ‘lm’ for standard linear regressions or ‘lme’ for models with random effects.

Across the entire watershed, we used analysis of covariance (ANCOVA), with stochastic runs as a random effect, to assess whether ecosystem service scores, domain scores, or HWBI scores changed over time for the A2 and B1 scenarios (year × scenario). To evaluate upward or downward temporal trends by county, we used linear regressions to calculate the slopes of scores over time as a measure of the average yearly rate of change for the watershed study area or each county. We then conducted two-way analysis of variance (ANOVA) to assess whether calculated rates of change differed significantly between scenario A2 and B1, and whether there were differences between counties (county × scenario).

3. Results

3.1. Sensitivity Analysis and Model Uncertainty

We examined the results of twenty simulations of two future land use scenarios to assess which environmental changes were primarily driving changes in ecosystem services indicator scores (Table 4). Year-to-year changes in air quality scores decreased as land dedicated to either development or agricultural uses increased (Table 4). Increases in open space were positively associated with higher air quality scores. Food/fiber/fuel scores tended to decrease with corresponding declines in pasture lands and forest cover, and greater availability of developed open spaces (Table 4). Greenspace scores tended to decrease with increasing coverages of agricultural or developed lands (Table 4). Water quantity scores tended to decrease with increasing coverages of agricultural lands, but increased with forest cover. Unlike the other four ecosystem services, water quality scores were more strongly driven by year to year variability in precipitation and temperature, with declines in water

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quality scores in years with higher mean daily precipitation or higher mean temperature (Table 4).

Parameter uncertainty in EPF models led to the greatest uncertainty in projections for food/fiber/fuel scores or water quality scores, with 90% of projected scores across simulations differing by as much as 0.1 by the end of the simulation period (year 2050) on a standardized scale from 0.0 to 1.0 for services scores (Fig. 3). Uncertainty was the lowest for greenspace scores (90% differing by less than 0.02) and water quantity scores (90% differing by less than 0.04). Air quality scores differed by as much as 0.07 by the end of the simulation period. However, with the exception of food/fiber/fuel scores differences between stochastic simulations due to parameter uncertainty were still far less than known range of variability in services scores between counties (Appendix A5). Similarly, uncertainty in projections of domain scores, which also incorporated uncertainty from contributions of social and economic services, produced scores that differed by as little as 0.07 for health domain scores and as much as 0.2 for connection to nature domain scores and social cohesion domain scores by the end of the simulation period, on a standardized scale of 0.0 to 1.0 (Fig. 4). Differences, however, were again within or below the known range of variability across county domain scores in 2010 (Appendix A5).

3.2. Scenario Comparisons

3.2.1. Projected Changes in Environmental Condition—Projected future land use and weather trends for the Pensacola Bay watershed were obtained from external sources (USGS 2016; Abatzoglou and Brown 2012) and are briefly summarized here. Under scenario A2, the counties in Pensacola Bay watershed were projected to have increases in developed lands and agriculture, with declines in forest and wetland cover (Fig. 5a). Under the B1 FORE-SCE scenario, development increased only slightly, with fewer conversions of forest or wetland to developed lands than the A2 scenario (Fig. 5b). The B1 scenario also projected declines in agriculture, pasture, barren lands, and open space, as these lands are left to transition to forest. As a result, forest cover was projected to increase in most counties. Yearly transitions to developed space tended to be smoother in scenario A2, as development increased at a fairly steady pace, whereas in B1 development was somewhat more episodic to minimize impacts to protected natural areas. In scenario B1, land cover changes tended to stabilize roughly half-way through simulations as space to add more developed areas became increasing limited. Projected precipitation and temperature were variable day to day (Fig. 5e, f), with a slight increasing trend in mean annual temperature (0.015°C increase from 2010–2050) and decreasing trend in mean annual precipitation (0.002 mm decrease from 2010–2050) over the forty-year simulation time period.

We modeled the estimated population density over time based on the mean population density per land use/land cover class in 2010 and projected it forward based on the FORE-SCE projected land use types. Population density was projected to increase in both scenarios, but at much faster rates in the A2 scenario (Fig. 5c, d). Our population estimates were consistent with the FORE-SCE descriptions of higher rates of population growth in the A2 scenario, represented by increased developed space in the FORE-SCE land use maps.

3.2.2. Ecosystem Services Indicators—The indicators for air quality, greenspace, and water quantity across the bay watershed were relatively stable under the B1 scenario, but declined significantly under the A2 scenario (Fig. 3, left column; ANCOVA: Air quality, Scenario × Year, $F=1386.1$, $p<0.001$; Greenspace, Scenario × Year, $F=5020.3$, $p<0.001$; Water quantity, Scenario × Year, $F=1794.8$, $p<0.001$). Rates at which the three changed over time differed among the four counties, with the fastest projected declines for each in the most urbanized county under scenario A2 (Fig. 3, right column; ANOVA, Scenario × County, $F=5.89$, $p<0.001$; Greenspace, Scenario × County, $F=8.32$, $p<0.001$; Water quantity, Scenario × County, $F=16.5$, $p<0.001$). Year-to-year changes in air quality, greenspace, or water quantity indicators were primarily related to projected changes in developed, agricultural, and pasture lands, which tended to replace forest and wetland canopy cover in the A2 scenario (Table 4). Under the B1 scenario, for counties where agricultural and pasture lands transitioned to forest at rates faster than urban land development, air quality scores, greenspace scores, and water quantity scores were projected to have marginal increases over time (Fig. 3, right column).

At the start of simulations, food/fiber/fuel scores across the bay watershed was relatively close to the US national average, but was projected to decline substantially under both scenarios, particularly A2 (Fig. 3c; ANCOVA, Scenario × Year, $F=679.6$, $p<0.001$). Rates of decline in food/fiber/fuel scores were similar across counties, and were consistently lower in scenario A2 than B1 across all counties (Fig. 3d; ANOVA: Scenario, $F=78.5$, $p<0.001$; County, $F=2.6$, $p=0.05$; Scenario × County, $F=0.36$, $p=0.78$). Projected declines in food/fiber/fuel scores were primarily related to declines in pasture lands, declines in timber-providing forest cover, and increases in developed open spaces (Table 4).

The water quality indicator was variable from year to year, but did not differ significantly between scenarios (Fig. 3g; ANCOVA: Scenario, $F=0.087$, $p=0.77$; Year, $F=29.7$, $p<0.001$; Scenario × Year, $F=1.99$, $p=0.16$). Water quality scores were projected to increase slightly for most counties under both scenarios, but particularly with increasing urbanization under the A2 scenario (Fig. 3h; ANOVA, Scenario × County, $F=3.37$, $p<0.001$). For both scenarios, the water quality indicator remained consistently above the US national average, with the exception of declines in water quality scores in years with higher mean daily precipitation or higher mean temperature (Table 4).

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3.2.3. Human Well-being Indicators—For most domains of well-being, scores across the Pensacola bay watershed declined over time for both scenarios, but at faster rates for scenario A2 (Fig. 4, left column). Education, leisure time, living standards, and social cohesion domain scores across the watershed were initially close to the US national average, but fell to levels below that over time, particularly in scenario A2 (Fig. 4; ANCOVA: Education, Scenario × Year, $F=58.1$, $p<0.001$; Leisure time, Scenario × Year, $F=178.5$, $p<0.001$; Living standards, Scenario × Year, $F=185.8$, $p<0.001$; Social cohesion, Scenario × Year, $F=128.9$, $p<0.001$). Cultural fulfillment and health domain scores remained at levels close to the US national average, with slight declines over time for the A2 scenario (Fig. 4; ANCOVA: Cultural fulfillment, Scenario × Year, $F=13.5$, $p=0.002$; Health, Scenario × Year, $F=6.6$, $p=0.01$). Safety and security domain scores started and remained below the US

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national average throughout the simulation period (Fig. 4m; ANCOVA: Cultural fulfillment, Scenario × Year, $F=5.1$, $p=0.03$).

Domain scores for cultural fulfillment, education, health, living standards, safety and security, and social cohesion declined at the fastest rates for the most urbanized county under the A2 scenario, with almost no change over time for the least urbanized county under the B1 scenario (Fig 4, right column; ANOVA: Cultural fulfillment, $F=7.5$, $p<0.001$; Education, $F=6.5$, $p<0.001$; Health, $F=10.8$, $p<0.001$; Living standards, $F=2.2$, $p=0.08$; Safety, $F=14.4$, $p<0.001$; Social cohesion, $F=7.5$, $p<0.001$). Leisure time scores declined over time for all counties, with A2 consistently lower than B1 (Fig. 4j; ANOVA: Scenario, $F=70.3$, $p<0.001$; County, $F=3.9$, $p=0.01$; Scenario × County, $F=0.66$, $p=0.57$).

Connection to nature was the only domain of well-being projected to have increasing scores over time, with scenario A2 showing higher rates of increase than B1 (Fig. 4a; ANCOVA, $F=132.2$, $p<0.001$). The most urbanized county was projected to have the highest rates of increase in connection to nature scores, particularly under scenario A2, while the least urbanized county was projected to be more stable over time, particularly under scenario B1 (Fig. 4b; ANOVA, $F=8.3$, $p<0.001$).

The composite well-being index score for the watershed, HWBI, was below the US national average and was projected to decline over time for the A2 scenario, with slight declines for the B1 scenario (Fig. 6a; ANCOVA, $F=94.1$, $p<0.001$). HWBI was projected to decline at the fastest rates for the most urban county under scenario A2 (Fig. 6b; ANOVA, $F=5.9$, $p<0.001$). The least urbanized county had mean rates of change closer to zero under the B1 scenario, with some stochastic simulations projecting increases in well-being (Fig. 6b).

4. Discussion

4.1. Pensacola Bay Watershed Demonstration Study

This study developed a modeling approach to estimate the potential impacts of long-term changes in environmental condition on components of human well-being through changes in ecosystem services. We demonstrated our approach for the Pensacola Bay, Florida watershed. Under the A2 scenario of increasing population growth, slow technological change, increasing reliance on fossil fuels, and low resource protection (Cubasch et al. 2001), projected declines were observed for our indicators of air quality, food/fiber/fuel, greenspace, and water quantity over the 40 year simulation period. The declines in ecosystem services indicators were primarily related to replacement of forest and wetland by development and agriculture, particularly in the most urbanized counties, as well as high rates of depletion of raw materials and energy resources. In contrast, our water quality indicator, defined by sediment, nutrient, and fecal coliform loading, tended to increase in the most urbanized county as development outpaced greater contributors of non-point source runoff under model assumptions, such as agriculture. Projected declines in ecosystem services indicators translated to declines in most human well-being domain scores for the A2 scenario, particularly in counties with the highest rates of urbanization. Only connection to nature domain scores were projected to increase under the A2 scenario.

The B1 scenario, which has a greater emphasis on environmental protection and resource efficiency (Cubasch et al. 2001), was projected to produce fairly stable levels for our ecosystem services indicators across the watershed over the 40 year simulation period. Counties with the slowest rates of development and fastest transitions of barren, pasture, or agricultural lands to forest were projected to have increases in ecosystem services indicators. Only food/fiber/fuel scores were projected to have consistent declines as raw material and energy resources were used, albeit at slower rates than the A2 scenario. Well-being domain scores were also fairly stable for most counties over the B1 simulation, although the most urbanized county was projected to have slight declines over time. Leisure time was the only domain of well-being projected to have declining scores across all counties, largely due to its strong correlations with declines in food/fiber/fuel scores.

This scenario analysis, though a demonstration, was motivated by a prior workshop with Escambia County residents to identify sustainability goals and strategies for achieving them (Fulford et al. 2016). Ecosystem services value (usable air, usable water, stable climate, and flood protection) was previously estimated to be lower for Escambia County than nearby similar coastal counties (Fulford et al. 2016), and our results broadly indicate that failing to implement land use development practices to account for maintaining and improving ecosystem services could lead to declines in community well-being. Moreover, in prior workshops, Pensacola community members identified goals related to living standards and social cohesion as most important to them, with connection to nature being among the least important goals (Fulford et al. 2016). For simplification, we weighted domain scores equally in our simulations, but note that weighting domain scores in alignment with community goals may have resulted in even greater declines in overall aggregate measures of well-being.

4.2. Impacts of Land Use and Changing Weather Patterns on Well-being

Although our analysis focused on the Pensacola Bay watershed, the results serve to illustrate a number of points about how ecosystem services may impact well-being that are broadly transferable to other communities. First, increasing rates of developed lands were almost universally associated with declines in ecosystem services indicators and domain scores of well-being, as natural ecosystems were replaced by impervious surfaces. Declines in forest cover, in particular, depleted the ability of ecosystems to buffer air ollutants, provide habitat for biodiversity, and retain rainwater. Second, increases in ecosystem services indicators did not necessarily translate into increases in domain scores for well-being. In our simulations, projected changes in domain scores could remain generally flat over time, despite increases in ecosystem services indicators over the same time period. In the HWBI services to domain regression models (Summers et al. 2016), some ecosystem services indicators were negatively correlated with domain scores for well-being, or had effects that were small relative to other social or economic services indicators.

Greenspace has been shown to have positive benefits on education, including test scores, problem solving skills, and interpersonal skills (Lieberman and Hoody 1998, Louv 2005, Guhn et al. 2010). Similarly, our study found declines in our indicator of greenspace, particularly in scenarios and counties with higher development, to be associated with declines in our composite education component of well-being. In contrast, in our simulations, declines in our indicator of greenspace were associated with increases in connection to nature domain scores, driven by a significant negative correlation between the two in the HWBI regression models (Summers et al. 2016). This seems counterintuitive, as the ability to interact with nature has been shown to strengthen one's appreciation for it (Nisbet 2009). However, in developed areas in particular, greenspace may be associated with fear of crime (Schroeder & Anderson 1984). Alternatively, increasing scarcity of indicators describing greenspace and biodiversity may increase appreciation for it (Smith et al. 2014b). The HWBI regression models are built on data for the whole United States at a county-scale, and whether these relationships hold regionally, or at finer spatial scales (e.g., census tracts) is worth further exploration (Summers et al. 2016).

Changing land use/land cover and changing climate are anticipated to have impacts on human health through disruptions to pollen seasons (Ziska et al. 2011), urban heat islands (Wilby 2008), and weather hazard related illnesses (Curriero et al. 2001; Ahern et al. 2005). However, our results found a fairly small impact of future land use or weather patterns under the IPCC scenarios on human health domain scores as a component of well-being. In the HWBI services to domain models, the water quantity indicator explained a small portion (15%; Summers et al. 2016) of variability in health outcomes, and in our models water quantity scores were largely driven by the ability of changing land cover classes to retain rainwater (e.g., drought and flood mitigation). Heat islands and allergens related to pollen were not metrics explicitly modelled within the HWBI framework (Smith et al. 2014a).

Shifts in precipitation, temperature, and extreme weather events are projected to impact agricultural productivity, including crop and livestock production (Luber et al. 2014), resulting in greater efforts needed to maintain food production and security. Our analysis found leisure time domain scores to decrease over time, particularly in scenarios and counties with greater development. Leisure time scores were positively correlated with indicators of food/fiber/fuel production (Summers et al. 2016), which in our models was explained primarily by agricultural productivity.

Weather hazards and loss of natural resources are expected to have impacts on job security and the ability to obtain basic necessities, as well as cultural opportunities (Cutter et al. 2014; Groffman et al. 2014). In our study, the indicators for water quantity and food/fiber/fuel provisioning were positively correlated with living standards scores, and we found counties and scenarios with greater development to have small corresponding declines in living standards domain scores, and to a lesser extent for cultural fulfillment scores. However, in the HWBI regression models (Summers et al. 2016), the biggest driver of living standards was employment, explaining roughly 48% of variability in scores, and something not explicitly modeled in our scenarios. Variability in cultural fulfillment scores were primarily driven by community and faith-based social initiatives (49%; Summers et al. 2016).

Natural hazards, impacts on food supply, and susceptibility to pathogens or contaminants are anticipated to have impacts on human safety and security (MEA 2005). In our analysis, indicators of food/fiber/fuel and water quantity were also projected to have small positive effects on safety (Summers et al. 2016). However, overall our study found only small decreases on safety and security domain scores, particularly in the scenarios and counties with high development and higher water quality, driven primarily by negative correlations between water quality and safety in the HWBI regression models. In our models, water quality is primarily related to nutrient, sediment, and pathogen runoff (e.g., from agricultural areas), such that developed areas, which may be prone to higher crime, tended to have higher relative water quality.

Community cohesion and sense of identity, particularly for rural communities, is tightly linked to local natural systems and may be vulnerable to loss of natural resources (Hales et al. 2014). Weather hazards or inequities in natural resource availability can also exacerbate tensions in a community (Corell et al. 2014). In our analysis, the strongest impacts of land use change, in particular scenarios with high development, were on social cohesion domain scores. Our indicators of air quality and greenspace were positively correlated with social cohesion (Summers et al. 2016), and loss of these ecosystem services indicators with increasing development was projected to have negative impacts on social cohesion domain scores.

4.3. Modeling Approach and Limitations

This study demonstrates a modeling approach to project the impacts of changing ecosystem condition on ecosystem services and benefits to human well-being. In developing the approach, we leveraged data and models that are broadly available and highly transferable. For purposes of demonstration, we used the broadly available FORE-SCE future land use scenarios and MACA future weather projections. A more detailed analysis could substitute locally derived land use scenarios for the watershed of interest. The key is that environmental condition data must match, or be convertible to, the input data needed for EPFs.

Our approach leverages existing EPF models for quantifying ecosystem services production, identified based on their ability to bridge both environmental condition scenario data needed as input, and to generate output compatible as input into HWBI services to domains regression models. Good EPFs rely on data that is broadly available and can be modified and parameterized according to user needs (Bruins et al. 2017). The approaches we used to parameterize models for Pensacola Bay watershed are easily transferable to other locations. Our analysis was fairly coarse, in that our estimates of ecosystem services provisioning were primarily based on changing coverages of land use/land cover. At the scale of our study, a census-tract was essentially treated as a uniformly developed surface. Smaller-scale decisions, such as development of rain gardens, riparian buffers, or parks may help to mitigate some of the negative impacts of development on ecosystem services in ways that are not captured in our coarser analysis. Additionally, we restricted our analysis to ecosystem services metrics that aligned closely with the HWBI services to domain regression models and could be linked to changing land use/land cover, which limited our interpretation of results.

We leveraged the HWBI framework as an EBF to link changes in ecosystem services to domains of well-being because it is a comprehensive and flexible approach (Smith et al.

2012; Smith et al. 2014a) that resonates with the goals of communities (Fulford et al. 2016). Our approach provides an alternative to more common approaches to link ecosystem services to health outcomes (e.g., Jackson et al. 2013; Oosterbroek et al. 2016) or to monetary measures of well-being (e.g., Birol et al. 2006; Johnston and Wainger 2015; Yoskowitz et al. 2016), which tend to be biased toward market-based goods and services that are more straightforward to quantify (Tuya et al. 2014). Although we weighted domains to have equal importance, the HWBI framework included the ability to assign relative importance values to differentially weight domain scores in line with how stakeholders perceive their importance, which can be highly variable among communities (Smith et al. 2012; Fulford et al. 2016). The HWBI services to domain regression models are built off nationally available data, to identify broad characterizations most likely outcomes (Summers et al. 2016). We restricted our demonstration to county-scale interpretations, to match county-scale data used to develop the original HWBI regression models. If alternative local community data or finer-scale interpretation is desired or available, the regression models could be re-parameterized using local-scale data to better reflect specific local conditions. Additionally, because HWBI models are based off composite indicators representing domains of well-being and services, interpretations are limited to a broad interpretation of relationships, and may not be appropriate when specific metrics (e.g., educational test scores, employment) need to be considered.

A key challenge with applying production functions and benefits functions is dealing with uncertainties associated with our choice of EPFs and model parameterization. We allowed model parameters to vary within ranges we obtained from a literature review and ran stochastic simulations to quantify the uncertainty in projections. The indicator food/fiber/fuel had the greatest variability in projected outcomes, but produced consistent downward trends across multiple stochastic simulations, driven in large part by the assumed constant rate of decline in raw material and energy reserves. In contrast, air quality and water quality indicators also had high variability in projected outcomes but led to greater uncertainty as some simulations indicated positive change while others indicated negative. Despite the variability in ecosystem services scores, however, projected upward or downward trends in human well-being domain scores and composite HWBI scores were consistent when comparing scenarios, and within or below the range of known variability. To some degree, the use of aggregated indices to measure ecosystem services provisioning may help dampen out uncertainty in modelled estimates of individual metrics.

Although several efforts have been undertaken to connect the provisioning of ecosystem services to measures of human well-being (Gordon and Folke 2000; Pereira et al. 2005; Pinto et al. 2014), the relative importance of ecosystem services compared to economic or social services is largely unknown. Land use changes over time that may produce greater ecosystem services occur in concert with changes in other social or economic services, in ways that are often hard to disentangle. For example, land that is allowed to transition to forest may provide positive effects through air quality or greenspace, but is countered by tradeoffs in that the land may no longer be for economic or social services, e.g. such as building a school or roads to improve emergency access. The HWBI framework assumes changes in well-being are driven by environmental, economic, and social factors, and presents an approach that explicitly considers ecosystem services within the context of economic and social services (Summers et al., 2016).

The projections from the HWBI regression models are not intended to provide precise predictions of future well-being. Instead, scenario analysis should be interpreted as a potential direction and magnitude for highlighting potential trade-offs, and provides a starting point for further discussion (Summers et al. 2016). The use of a comprehensive well-being framework, such as the HWBI, helps ensure commonly overlooked services and elements of well-being are considered as part of that discussion. The scenarios examined here serve to demonstrate how differences in population growth, land development, and resource protection may impact ecosystem services and well-being. Such an analysis can raise awareness of potential unforeseen consequences, so that communities and decision-makers can be pro-active in enacting decisions that improve well-being goals and consider the role of natural resources in achieving those goals.

4.4. Conclusions

Well-being is a concept that broadly resonates with community goals for health, education, or social cohesion (Fulford et al. 2016), yet land use planning efforts often largely focus on social or economic decision levers, and less often consider the potential benefits of managing natural resources. In addition to the HWBI framework, other efforts have been undertaken to connect the provisioning of ecosystem services to measures of well-being, paving the way for well-being assessments (Gordon and Folke 2000; Pereira et al. 2005; Pinto et al. 2014). Although the analysis presented here is highly quantitative, the goal of a tradeoff analysis should not be to obtain a mathematically optimal solution (Failing et al. 2007; Gregory et al. 2012). Instead, ecosystem services and well-being assessments serve to complement more traditional planning efforts by facilitating discussion, helping identify potential unintended consequences, helping identify common goals, and identifying areas of uncertainty where more information is needed (Yee et al. 2017). An examination of the direct links from environmental conditions to social and economic benefits, can help ensure that key well-being objectives and creative alternatives to achieve them are not overlooked.

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APPENDIX

Appendix Table A1.

Data-based 2000–2010 indicator values for ecosystem services, human well-being domains, and composite HWBI for the four counties in the study area (Smith et al. 2014; EPA 2018).

	Escambia	Okaloosa	Santa Rosa	Walton
Ecosystem Services				
Air Quality	0.31	0.72	0.29	0.90
Food, Fiber, Fuel	0.41	0.41	0.40	0.44
Greenspace	0.51	0.51	0.52	0.55
Water Quality	0.41	0.39	0.73	0.67
Water Quantity	0.40	0.48	0.41	0.38
Economic Services				
Capital investment	0.59	0.59	0.58	0.58
Consumption	0.52	0.52	0.51	0.52
Employment	0.61	0.64	0.62	0.62
Finance	0.49	0.48	0.44	0.51
Innovation	0.39	0.40	0.58	0.60
Production	0.51	0.47	0.48	0.50
Re-distribution	0.40	0.42	0.35	0.49
Social Services				
Activism	0.59	0.55	0.49	0.59
Communication	0.49	0.56	0.48	0.48
Community Initiatives	0.19	0.18	0.31	0.34
Education	0.44	0.41	0.39	0.46
Emergency Preparedness	0.31	0.59	0.61	0.54
Family Services	0.48	0.54	0.53	0.57
Healthcare	0.35	0.41	0.41	0.44
Justice	0.48	0.4	0.42	0.55
Labor	0.46	0.44	0.44	0.47
Public works	0.45	0.45	0.46	0.56
Human Well-Being				
Connection to Nature	0.49	0.49	0.47	0.85
Cultural Fulfillment	0.51	0.49	0.49	0.36
Education	0.46	0.52	0.51	0.31
Health	0.57	0.58	0.60	0.53
Leisure Time	0.60	0.57	0.59	0.56
Living Standards	0.50	0.55	0.54	0.50
Safety and Security	0.50	0.59	0.65	0.57
Social Cohesion	0.43	0.49	0.51	0.38
Composite HWBI	0.50	0.53	0.54	0.48

Appendix Table A2.

Mean and standard deviation of parameters for each land cover type used to calculate ecosystem services metrics. Canopy cover, impervious surface, species richness, and population density were calculated as the average among IDU polygons where a given land cover type was the majority land cover.

Parameter	Water	Developed Open Space	Developed	Barren	Deciduous Forest	Evergreen Forest	Mixed Forest	Grassland	Hay and Pasture	Agriculture
Air Quality										
Canopy Cover[1] (%)	43.92	44.98	33.11	12.86	43.06	59	51.08	18.04	40.7	38.82
Std Dev	*22.41*	*21.09*	*19.33*	*18.04*	*20.7*	*21.58*	*20.81*	*18.76*	*23.31*	*23.92*
Food, Fuel, Fiber										
Nitrogen Fixation[11] (g N/m^2/yr)	3.86	0.98	0.98†	0	6.06	0.54	2.91	1.83	17.92	11.86
StdDev	*3*	*0.51*	*0.51*†	*0*	*3.57*	*0.35*	*3.6*	*3*	*5.87*	*7.56*
Carbon Burial[10] (g C/m^2/yr)	103.3	91.75	98.5†	0	7.97	47.14	27.56	30.11	48.65	43.48
StdDev	*61.63*	*29.9*	*29.9*†	*0*	*2.8*	*40.7*	*36.9*	*38.6*	*10.1*	*46.1*
Impervious Surface[1] (%)	4.74	12.38	30.87	23.82	8.09	7.1	7.65	26.46	8.45	9.19
StdDev	*9.99*	*14.65*	*19.38*	*24.07*	*10.4*	*10.12*	*10.17*	*17.26*	*10.2*	*11.34*
Evapotranspiration[2]	0.9	0.5	0.25	0.5	1	1	1	0.79	0.82	0.92
StdDev	*0.21*	*0.11*	*0.16*	*0.21*	*0.11*	*0.11*	*0.11*	*0.15*	*0.11*	*0.21*
Greenspace										
Species Richness[12]	113.8	113.2	100.5	104.1	115.8	115.8	116.3	101.5	117.9	118.0
StdDev	*22.4*	*23.4*	*25.6*	*29.2*	*20.6*	*21.5*	*20.4*	*31.4*	*20.8*	*20.8*
Population Density[13] (number/km^2)	3	623	1658	1180	285	549	579	102	399	306
StdDev	*39*	*1909*	*51068*	*290*	*1908*	*29390*	*23775*	*211*	*9200*	*4480*
Water Quality										
Nutrient Export[3] (kg/km^2/yr)	0	325	1141	100	317	317	317	854	854	43300
StdDev	*0*	*15*	*46*	*7*	*7*	*7*	*7*	*161*	*161*	*41500*
Nutrient Retention[4] (%)	0	0	0	0	90	90	90	90	90	50
StdDev	*0*	*0*	*0*	*0*	*5.48*	*5.48*	*5.48*	*5.48*	*5.48*	*5.48*
Soil Erodibility[5] (tons/km^2)	0	99	99	22	160	160	160	240	10	160
StdDev	*0*	*11*	*11*	*2*	*18*	*18*	*18*	*26*	*1*	*18*
Management Factor[6]	0	0	0	0	0.076	0.076	0.076	0.050	0.050	0.186
StdDev	*0*	*0*	*0*	*0*	*0.008*	*0.008*	*0.008*	*0.006*	*0.006*	*0.020*
Practice Factor[7]	0	0	0	0	0	0	0	0	1	0.5
StdDev	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0*	*0.05*	*0.05*
Sediment Retention[4] (%)	0	0	0	0	90	90	90	90	90	50

Parameter	Water	Developed Open Space	Developed	Barren	Deciduous Forest	Evergreen Forest	Mixed Forest	Grassland	Hay and Pasture	Agriculture
StdDev	*0*	*0*	*0*	*0*	*5.48*	*5.48*	*5.48*	*5.48*	*5.48*	*5.48*
Wash-off rate[8] (mm/hr)	0	49.02	36.58	49.02	44.96	44.96	44.96	47.5	47.5	47.5
StdDev	*0*	*30.99*	*43.94*	*30.99*	*20.57*	*20.57*	*20.57*	*26.67*	*26.67*	*26.67*
Daily accumulation[8] (billions/km^2/day)	0	7.90	0.01	7.90	7.88	7.88	7.88	7.98	7.98	7.98
StdDev	*0*	*11.12*	*0.01*	*11.12*	*11.14*	*11.14*	*11.14*	*11.07*	*11.07*	*11.07*
Surface decay rate[8] (per day)	0	0.295	0.41	0.295	0.295	0.295	0.295	0.295	0.295	0.295
StdDev	*0*	*0.261*	*0.22*	*0.261*	*0.261*	*0.261*	*0.261*	*0.261*	*0.261*	*0.261*
Water Quantity										
Curve Number[10]	100[†]	35.95	58.35	94.99	25.42	26.59	23.69	37.75	41.73	59.07
StdDev	*1.53*	*4.98*	*6.72*	*1.53*	*18.39*	*10.5*	*15.59*	*5.62*	*1.53*	*3.42*

[1.] NLCD 2011;

[2.] Allen et al. 1998;

[3.] Reckhow et al. 1980;

[4.] Tallis et al. 2013;

[5.] USDA & NRCS 2004; Stone and Hilborn 2012;

[6.] Wischmeier and Smith, 1978;

[7.] Stone and Hilborn 2012;

[8.] Gregory & Frick 2000, Yagow et al. 2001, Paul et al. 2002, Moyer & Hyer 2003, Im et al. 2012;

[9.] USDA and NRCS, 1986; USDA & NRCS 2004;

[10.] Fulford et al. 2016;

[11.] Augusto et al. 2005, Barber et al. 1976, Bell and Wright 1994, Boring et al. 1988, Bormann and Gordon 1984, Burns and Hardy 2012, Buresh et al. 1980, Busse 1999, Capone and Carpenter 1982, Casselman et al. 1981, Cleveland et al. 1999, Danso et al. 1992, DeLaune et al. 1986, Dierberg and Brezonik 1981, Dierberg and Scheinkman 1987, Galal et al. 2000, Giddens 1982, Grant and Binkley 1987, Gu et al. 2009, Hungate et al. 1999, Jensen 1986, Jorgensen 1975, Khanna 1998, Ley and D’Antonio 1998, Peoples and Baldock 2001, Permar and Fisher 1983, Rochester et al. 2001, Zahran 1999, Zuberer and Silver 1978;

[12.] USGS Gap Analysis Program 2011;

[13.] US Census 2010

[†] Value is lawn rate, which was multiplied by (1-impervious surface)

[††] Open water and wetland soils are assumed to be 100% saturated.

Appendix A3.

Range of parameters for HBV hydrology and evapotranspiration (ET) models (Abebe et al. 2010; Huntington and Allen 2010).

Variable	Description	Minimum	Maximum	units
TT	Threshold temperature	−1	1	°C
CFMAX	Degree day factor for snowmelt	1	10	mm/°C day
SFCF	Snowfall correction factor	0	2	
CFR	Refreezing coefficient	0	0.1	
CWH	Snowpack water retention fraction	0	0.2	

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Variable	Description	Minimum	Maximum	units
FC	Field capacity	100	300	mm
LP	Soil moisture value above which actual ET reaches potential ET	20	100	mm
BETA	Shape coefficient	1	6	
PERC	Percolation to groundwater	0	2	mm
UZL	Reservoir threshold	0	100	mm
K0	Recession coefficient	0.05	0.5	1/day
K1	Recession coefficient	0.01	0.3	1/day
K2	Recession coefficient	0.001	0.1	1/day
WP	Permanent wilting point	0	20	mm
Planting Threshold T30	Temperature at which crops are planted	5	12	°C
Killing Frost Temp	Temperature at which frost kills vegetation	−12	−2	°C
Min Growing Season	Minimum crop growing season	100	220	Days
CGDD P to T	Cumulative growing degree days	740	3600	°C days

Table A4.

Directionality of covariances between ecosystem services indicators and social or economic services calculated from national indicator data (from Summers et al. 2016), used to adjust yearly values of economic and social services based on modelled changes in ecosystem services.

	Air Quality	Food/Fiber	Greenspace	Water Quality	Water Quantity
Economic Services					
Capital investment		+	+	+	
Consumption		+	+	+	
Employment		+	+		
Finance		−	−	−	
Innovation					
Production		−			
Re-distribution	+				
Social Services					
Activism		+	+	+	
Communication					
Community Initiatives					+
Education		−	−	−	+
Emergency Preparedness		−	−	−	
Family Services		−	−	−	
Healthcare		+			−
Justice			+	+	
Labor			−		
Public works					

Table A5.

Directionality of covariances between domains calculated from national indicator data (from Summers et al. 2016), used to adjust yearly domain scores.

	Cultural Fulfillment	Education	Health	Leisure Time	Living Standards	Safety and Security	Social Cohesion
Connection to Nature	−	−	−	+	−	−	−
Cultural Fulfillment		+	+	−	+	+	+
Education			+	+	+	+	+
Health				+	+	+	+
Leisure Time					−	0	0
Living Standards						+	+
Safety and Security							+

References

Abatzoglou JT and Brown TJ A comparison of statistical downscaling methods suited for wildfire applications, International Journal of Climatology (2012), 32, 772–780

Abebe NA, Ogden FL, Pradhan NR.. 2010. Sensitivity and uncertainty analysis of the conceptual HBV rainfall-runoff model: Implications for parameter estimation. Journal of Hydrology 389:301–310.

Ahern M, Kovats RS, Wilkinson P, Few R, and Matthies F, 2005: Global health impacts of floods: Epidemiologic evidence. Epidemiologic Reviews, 27, 36–46 [PubMed: 15958425]

Allen RG, Pereira LS, Raes D, Smith M, 1998. Crop evapotranspiration – guidelines for computing crop water requirements – FAO irrigation and drainage paper 56. FAO – Food and Agriculture Organization of the United Nations, Rome.

Bell JF, Wilson JS, Liu GC. 2008. Neighborhood greenness and 2-year changes in Body Mass Index of children and youth. American Journal of Preventive Medicine 35(6):547–553 [PubMed: 19000844]

Bergström S, 1995. The HBV model. In: Singh VP (Ed.), Computer Models of Watershed Hydrology. Water Resources Publications, Highlands Ranch, CO

Birol E, Karousakis K, Koundouri P. 2006. Using economic valuation techniques to inform water resources management: A survey and critical appraisal of available techniques and an application. Science of the Total Environment 365:105–122.

Bolte J, Vache K. 2010. Envisioning puget sound alternative futures: PSNERP Final Report. Puget Sound Nearshore Ecosystem Restoration Project.

Bolte J 2014. Envision (Version 7): A Guide to Application Development. Biological and Ecological Engineering Department, Oregon State University, Corvallis, OR.

Bruins RJF, Canfield TJ, Duke C, Kapustka L, Nahlik AM, Schäfer RB. 2017. Using ecological production functions to link ecological processes to ecosystem services. Integrated Environmental Assessment and Management 13(1):52–61. [PubMed: 27541951]

Buck K, Summers K, Smith L, and Harwell L. Application of the Human Well-Being Index to Sensitive Population Divisions: A Children's Well-Being Index Development. Child Indicators Research. SpringerNetherlands, , Netherlands, 11(4):1249–1280, (2018) [PubMed: 30220939]

Corell RW, Liverman D, Dow K, Ebi KL, Kunkel K, Mearns LO, and Melillo J, 2014: Ch. 29: Research Needs for Climate and Global Change Assessments. Climate Change Impacts in the United States: The Third National Climate Assessment, Melillo JM, Richmond Terese (T.C.), and Yohe GW, Eds., U.S. Global Change Research Program, 707–718.

CRWQCB (California Regional Water Quality Control Board) 2013. Total Maximum Daily Loads for Nitrogen Compounds and Orthophosphate for the Lower Salinas River and Reclamation Canal Basin, and the Moro Cojo Slough Subwatershed, Monterey County, California: Appendix F: Export Coefficient Model. CRWQCB Central Coast Region, San Luis Obispo, CA.

Cubasch U, Meehl G, Boer G, Stouffer R, Dix M, Noda A, Senior C, Raper S, and Yap K, 2001: Projections of future climate change. In: Climate Change 2001: The Scientific Basis, Houghton JT, Ding Y, Griggs DJ, Noquer M, Van der Linden PJ, Dai X, Maskell K, and Johnson CA, Eds., Cambridge University Press, 525–582.

Curriero FC, Patz JA, Rose JB, and Lele S, 2001: The association between extreme precipitation and waterborne disease outbreaks in the United States, 1948–1994. American Journal of Public Health, 91, 1194–1199 [PubMed: 11499103]

Cutter SL, Solecki W, Bragado N, Carmin J, Fragkias M, Ruth M, and Wilbanks TJ, 2014: Ch. 11: Urban Systems, Infrastructure, and Vulnerability. Climate Change Impacts in the United States: The Third National Climate Assessment, Melillo JM, Richmond Terese (T.C.), and Yohe GW, Eds., U.S. Global Change Research Program, 282–296

Dyrbye LN, Satele D, Shanafelt T. 2016. Ability of a 9-item well-being index to identify distress and stratify quality of life in US workers. Journal of Occupational and Environmental Medicine 58: 810–817. [PubMed: 27294444]

Environmental Protection Agency (EPA) 2018. Human Well-Being Index Map Server. https://gispub.epa.gov/arcgis/rest/services/ORD/HumanWellBeingIndex/MapServer/

Escobedo FJ, Clerici N, Staudhammer CL, and Corzo GT. 2015. Socio-ecological dynamics and inequality in Bogota, Columbia's public urban forests and their ecosystem services. Urban Forestry and Urban Greening 14:1040–1053.

Energy Information Administration. 2000–2010. Annual Coal, Crude Oil, Natural Gas, and Uranium Reports. US Department of Energy, Washington D.C.

Failing L, Gregory R, Harstone M. 2007. Integrating science and local knowledge in environmental risk management: A decision-focused approach. Ecological Economics 64:47–60.

Ferrara AR, and Nistico R. 2015. Regional well-being indicators and dispersion from a multidimensional perspective: evidence from Italy. Annals of Regional Science 55: 373–420.

Fulford RS, Russell M, Harvey J, and Harwell MC. 2016. Sustainability at the Community Level: Searching for Common Ground as a Part of a National Strategy for Decision Support. U.S. Environmental Protection Agency, Gulf Breeze, FL, EPA/600/R-16/178.

Gordon L, and Folke C. 2000. Ecohydrological landscape management for human well-being. Water International 25: 178–184.

Gregory R, Failing L, Harstone M, Long G, McDaniels T, Ohlson D. 2012. Structured Decision-making: A Practical Guide to Environmental Management Choices. West Sussex, UK: Wiley-Blackwell.

Groffman PM, Kareiva P, Carter S, Grimm NB, Lawler J, Mack M, Matzek V, and Tallis H. 2014. Ch. 8: Ecosystems, Biodiversity, and Ecosystem Services. Climate Change Impacts in the United States: The Third National Climate Assessment, Melillo JM, Richmond Terese (T.C.), and Yohe GW, Eds., U.S. Global Change Research Program. DOI:10.7930/J0TD9V7H.

Guhn M, Gadermann AM, and Zumbo BD. 2010. Education: A report of the Canadian Index of Wellbeing (CIW). University of British Columbia, Kelowna, British Columbia, Canada.

Hales D, Hohenstein W, Bidwell MD, Landry C, McGranahan D, Molnar J, Morton LW, Vasquez M, and Jadin J, 2014: Ch. 14: Rural Communities. Climate Change Impacts in the United States: The Third National Climate Assessment, Melillo JM, Richmond Terese (T.C.), and Yohe GW, Eds., U.S. Global Change Research Program, 333–349.

Hendrix M and Innes-Wimsatt KA. 2013. Increased risk of depression for people living in coal mining areas of Central Appalachia. Ecopsychology 5:179–187

Ignatius A, Wolfe K, Parmar R, Flaishans J, Harwell L, Yee S, Purucker Tom, AND Galvin M. Design and Implementation of a REST API for the Human Well Being Index (HWBI). In Proceedings, 8th International Congress on Environmental Modelling and Software, Toulouse, FRANCE, July 10 – 14, 2016. International Environmental Modelling and Software Society, Manno, Switzerland, 17, (2016).

Jackson LE, Daniel J, McCorkle B, Sears A, Bush KF. 2013. Linking ecosystem services and human health: The Eco-Health Relationship Browser. International Journal of Public Health 58:747–755. [PubMed: 23877533]

Johnston RJ, and Wainger LA. 2015. Benefit Transfer for Ecosystem Service Valuation: An Introduction to Theory and Methods. In Benefit Transfer of Environmental and Resource Values: A Guide for Researchers and Practitioners, ed. Johnston RJ, Rolfe J, Rosenberger RS and Brouwer R, 237–273.

Kuo FE, and Sullivan WC. 2001. Environment and crime in the inner city, does vegetation reduce crime? Environment and Behaviour 33:343–367

Lieberman GA, and Hoody LL. 1998. Closing the achievement gap: Using the environment as an integrating context for learning. State Education and Environment Roundtable. Poway, California, USA.

Lim KJ, Engel BA, Muthukrishnan S, Harbor J, 2006. Effects of initial abstraction and urbanization on estimated runoff using CN technology. J. Am. Water Resour. Assoc 42, 629–643.

Louv R 2005. Last Child in the Woods: Saving our Children from Nature-deficit Disorder. Algonquin Books of Chapel Hill, Chapel Hill, North Carolina, USA

Lovett GM, 1994. Atmospheric deposition of nutrients and pollutants in North America: an ecological perspective. Ecol. Appl 4, 629–650.

Luber G, Knowlton K, Balbus J, Frumpkin H, et al. 2014. Chapter 9: Human Health. Climate Change Impacts in the United States: The Third National Climate Assessment, Melillo JM, Richmond Terese (T.C.), and Yohe GW, Eds., U.S. Global Change Research Program

McMichael AJ, Campbell-Lendrum DH, Corvalan CF, Ebi KL, Githeko AK, Scheraga JD, and Woodward A. 2003. Climate Change and Human Health Risks and Responses. World Health Organization, Geneva, Switzerland.

Millennium Ecosystem Assessment (MEA) 2005. Ecosystems and Human Well-being: Synthesis. Island Press, Washington, D.C.

Moyer DL and Hyer KE. 2003. Use of the Hydrological Simulation Program – FORTRAN and Bacterial Source Tracking for Development of the Fecal Coliform Total Maximum Daily Load (TMDL) for Christians Creek, Augusta County, Virginia. Water Resources Investigations Report 03–4162. US Geological Survey, Richmond, Virginia.

Nisbet EK, Zelenski JM, Murphy SA, 2009. The nature relatedness scale: linking individuals' connection with nature to environmental concern and behaviour. Environment and Behavior 41, 715–740

NLCD (National Land Cover Database), 2011. NLCD 2001 Land cover (2011 Edition). Multi-Resolution Land Characteristics Consortium (MRLC) www.mrlc.gov.

Nowak DJ, Crane DE, Stevens JC, Hoehn RE, Walton JT, Bond J, 2008. A ground-based method of assessing urban forest structure and ecosystem services. Arboriculture & Urban Forestry 34, 347–358.

NRDC (Natural Resource Defense Council) 2005. Evaluating Sustainability of Projected Water Demands in 2050 under climate change scenarios. NRDC.

Oosterbroek B, de Kraker J, Huynen MM, Martens P. 2016. Assessing ecosystem impacts on health: a tool review. Ecosystem Services, 17, 237–254.

Orlando JL, Yee SH, Harwell LC, and Smith LM. 2017. Technical Guidance for Constructing a Human Well-being Index (HWBI): A Puerto Rico Example. U.S. Environmental Protection Agency, Gulf Breeze, FL, EPA/600/R-16/363.

Pereira E, Queiroz C, Pereira HM, Vicente L. 2005. Ecosystem services and human well-being: a participatory study in a mountain community in Portugal. Ecology and Society 10: 14-article 14.

Pinto R, de Jonge VN, Marques JC. 2014. Linking biodiversity indicators, ecosystem functioning, provision of services and human well-being in estuarine systems: Application of a conceptual framework. Ecological Indicators 36: 644–655.

Porter JR, Xie L, Challinor AJ, Cochrane K, Howden SM, Iqbal MM, Lobell DB, and Travasso MI, 2014:Food security and food production systems. In: Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Field CB, Barros

VR, Dokken DJ, Mach KJ, Mastrandrea MD, Bilir TE, Chatterjee M, Ebi KL, Estrada YO, Genova RC, Girma B, Kissel ES, Levy AN, MacCracken S, Mastrandrea PR, and White LL (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 485–533.

Russell M, Teague A, Alvarez F, Dantin D, Osland M, Harvey J, Nestlerode J, Rogers J, Jackson L, Pilant D, Genthner F, Lewis M, Spivak A, Harwell M, Neale A, 2013. Neighborhood scale quantification of ecosystem goods and services. EPA/600/R-13/295. U.S. Environmental Protection Agency, Office of Research and Development, Gulf Ecology Division, Gulf Breeze, Florida

Schaich H, Bieling C, Plieninger T. 2010. Linking Ecosystem Services with Cultural Landscape Research. GAIA-Ecological Perspectives for Science and Society 19:269–277

Smith A, Yee SH, Russell M, Awkerman J, Fisher WS. 2017. Linking ecosystem services supply to stakeholder values in Guánica Bay Watershed, Puerto Rico. Ecological Indicators 74:371–383.

Smith LM, Case JL, Smith HM, Harwell LC, Summers JK. 2013. Relating ecosystem services to domains of human well-being: Foundation for a US index. Ecological Indicators 28: 79–90.

Smith LM, Smith HM, Case JL, Harwell LC, Summers JK, Wade C. 2012. Indicators and Methods for Constructing a U.S. Human Well-being Index (HWBI) for Ecosystem Services Research. EPA/600/R-12/023

Smith LM, Wade CM, Straub KR, Harwell LC, Case JL, Harwell M, and Summers JK. 2014a. Indicators and Methods for Evaluating Economic, Ecosystem, and Social Services Provisioning. EPA/600/R-14/184

Smith LM, Harwell L, Summers JK, Smith HM, Wade CM, Straub KR, and Case JL 2014b. A U.S. Human Well-being Index (HWBI) for multiple scales: linking service provisioning to human well-being endpoints (2000–2010). EPA/600/R-14/223.

Smith LM, Wade CM, Case JL, Harwell LC, Straub KR, and Summers JK. 2014c. Evaluating the Transferability of a U.S. Human Well-Being Index (HWBI) Framework to Native American Populations. Social Indicators Research 124: 157 – 182.

Sohl TL, Sleeter BM, Sayler KL, Bouchard MA, Reker RR, Bennett SL, Sleeter RR, Kanengieter RL, Zhu Z. 2012. Spatially explicit land-use and land-cover scenarios for the Great Plains of the United States. Agriculture, Ecosystems, and Environment 153:1–15.

Sohl TL, Wimberly MC, Radeloff VC, Theobald DM, Sleeter BM. 2016. Divergent projections of future land use in the United States arising from different models and scenarios. Ecological Modelling 337:281–297.

Speers AE, Besedin EY, Palardy JE, and Moore C. 2016. Impacts of climate change and ocean acidification on coral reef fisheries: an integrated ecological-economic model. Ecological Economics 128:33–43.

Summers JK, Harwell LC, Smith LM. 2016. A model for change: An approach for forecasting well-being from service-based decisions. Ecological Indicators 69:295–309.

Tallis HT, Ricketts T, Guerry AD, Wood SA, Sharp R, Nelson E, Ennaanay D, Wolny S, Olwero N, Vigerstol K, Pennington D, Mendoza G, Aukema J, Foster J, Forrest J, Cameron D, Arkema K, Lonsdorf E, Kennedy C, Verutes G, Kim CK, Guannel G, Papenfus M, Toft J, Marsik M, Bernhardt J, and Griffin R, Glowinski K, Chaumont N, Perelman A, Lacayo M Mandle L, Griffin R, Hamel P, Chaplin-Kramer R, 2013. InVEST 3.0.0 User's Guide. The Natural Capital Project, Stanford.

Tol RSJ 2018. The economic impacts of climate change. Review of Environmental Economics and Policy 12:4–25.

Tuya F, Haroun R, Espino F. 2014. Economic assessment of ecosystem services: Monetary value of seagrass meadows for coastal fisheries. Ocean & Coastal Management 96: 181–187.

US Census Bureau. 2010. American FactFinder. http://factfinder.census.gov

USDA & NRCS, 1986. Urban hydrology for small watersheds. United States Department of Agriculture, Natural Resources Conservation Service, and Conservation Engineering Division, Technical Release 55.

USFS (US Forest Service) 2016. Forest Inventory Data Online. https://apps.fs.fed.us/fia/fido/index.html

USGS (US Geological Survey) 2000–2010. Mineral commodity summaries. US Geological Survey, Washington, D.C.

USGS (US Geological Survey) Gap Analysis Program. 2011. National GAP vertebrate species distribution model. http://gapanalysis.usgs.gov/species

USGS 2016. Land cover Modeling Methodology - The FORE-SCE Model. https://landcover-modeling.cr.usgs.gov/methods.php

Wainger L and Mazzotta M. 2011. Realizing the potential of ecosystem services: A framework for relating ecological changes to economic benefits. Environmental Management 48(4):710–733. [PubMed: 21786182]

Wilby RL, 2008: Constructing climate change scenarios of urban heat island intensity and air quality. Environment and Planning B: Planning and Design, 35, 902–919

Williams JR, 1975. Sediment-yield prediction with Universal Equation using runoff energy factor, present and prospective technology for predicting sediment yield and sources. ARS-S-40. Brooksville, FL: US Department of Agriculture, Agricultural Research Service, 244–252.

Yee S, Bousquin J, Bruins R, Canfield TJ, DeWitt TH, de Jesús-Crespo R, Dyson B, Fulford R, Harwell M, Hoffman J, Littles CJ, Johnston JM, McKane RB, Green L, Russell M, Sharpe L, Seeteram N, Tashie A, and Williams K. 2017. Practical Strategies for Integrating Final Ecosystem Goods and Services into Community Decision-Making. U.S. Environmental Protection Agency, Gulf Breeze, FL, EPA/600/R-17/266.

Yoskowitz DW, Werner SR, Carollo C, Santos C, Washburn T, and Isaksen GH. 2016. Gulf of Mexico offshore ecosystem services: Relative valuation by stakeholders. Marine Policy 66: 132–136.

Ziska L, Knowlton K, Rogers C, et al. Recent warming by latitude associated with increased length of ragweed pollen season in central North America. Proc Natl Acad Sci U S A. 2011;108(10):4248–4251. [PubMed: 21368130]

Appendix References

Abebe NA, FL Ogden NR Pradhan. 2010. Sensitivity and uncertainty analysis of the conceptual HBV rainfall-runoff model: Implications for parameter estimation. Journal of Hydrology 389:301–310.

Allen RG, Pereira LS, Raes D, Smith M, 1998. Crop evapotranspiration – guidelines for computing crop water requirements – FAO irrigation and drainage paper 56. FAO – Food and Agriculture Organization of the United Nations, Rome.

Augusto L, Crampon N, Saur E, Bakker MR, Pellerin S, Lavaissiere CD, & Trichet P (2005). High rates of nitrogen fixation of Ulex species in the understory of maritime pine stands and the potential effect of phosphorus fertilization. Canadian Journal of Forest Research, 35(5), 1183–1192.

Barber LE, Tjepkema JD, Russell SA, & Evans HJ (1976). Acetylene reduction (nitrogen fixation) associated with corn inoculated with Spirillum. Applied and environmental microbiology, 32(1), 108–113. [PubMed: 970933]

Bell MJ, & Wright GC (1994). The N2-fixing capacity of peanut cultivars with differing assimilate partitioning characteristics. Australian journal of agricultural research, 45(7), 1455–1468.

Boring LR, Swank WT, Waide JB, & Henderson GS (1988). Sources, fates, and impacts of nitrogen inputs to terrestrial ecosystems: review and synthesis. Biogeochemistry, 6(2), 119–159.

Bormann BT, & Gordon JC (1984). Stand density effects in young red alder plantations: productivity, photosynthate partitioning, and nitrogen fixation. Ecology, 65(2), 394–402.

Buresh RJ, Casselman ME, & Patrick WH Jr (1980). Nitrogen fixation in flooded soil systems, a review. Advances in Agronomy, 33(19801), 149–192.

Burity HA, Ta TC, Faris MA, & Coulman BE (1989). Estimation of nitrogen fixation and transfer from alfalfa to associated grasses in mixed swards under field conditions. Plant and Soil, 114(2), 249–255.

Burns RC, & Hardy RW (2012). Nitrogen fixation in bacteria and higher plants (Vol. 21). Springer Science & Business Media.

Busse MD (1999). Out of Sight, but Not Out of Mind: Soil Microorganisms in Moisture-limited Forests. UNITED STATES DEPARTMENT OF AGRICULTURE FOREST SERVICE GENERAL TECHNICAL REPORT PNW, 146–155.

Capone DG, & Carpenter EJ (1982). Nitrogen fixation in the marine environment. Science, 217(4565), 1140–1142. [PubMed: 17740970]

Casselman ME, Patrick WH, & DeLaune RD (1981). Nitrogen Fixation in a Gulf Coast Salt Marsh 1. Soil Science Society of America Journal, 45(1), 51–56.

Cleveland CC, Townsend AR, Schimel DS, Fisher H, Howarth RW, Hedin LO, … & Wasson MF (1999). Global patterns of terrestrial biological nitrogen (N2) fixation in natural ecosystems. Global biogeochemical cycles, 13(2), 623–645.

Danso SKA, Bowen GD, & Sanginga N (1992). Biological nitrogen fixation in trees in agro-ecosystems. In Biological Nitrogen Fixation for Sustainable Agriculture (pp. 177–196). Springer, Dordrecht.

DeLaune RD, Smith CJ, & Sarafyan MN (1986). Nitrogen cycling in a freshwater marsh of Panicum hemitomon on the deltaic plain of the Mississippi River. The Journal of Ecology, 249–256

Dierberg FE, & Brezonik PL (1981). Nitrogen fixation (acetylene reduction) associated with decaying leaves of pond cypress (Taxodium distichum var. nutans) in a natural and a sewage-enriched cypress dome. Applied and environmental microbiology, 41(6), 1413–1418. [PubMed: 16345796]

Dierberg FE, & Scheinkman MM (1987). Contribution from nitrogen fixation (acetylene reduction) to the nitrogen budget of Lake Tohopekaliga (Florida). Hydrobiologia, 154(1), 61–73.

Environmental Protection Agency (EPA) 2018. Human Well-Being Index Map Server. https://gispub.epa.gov/arcgis/rest/services/ORD/HumanWellBeingIndex/MapServer/

Fulford RS, Russell M, Harvey J, and Harwell MC. 2016. Sustainability at the Community Level: Searching for Common Ground as a Part of a National Strategy for Decision Support. U.S. Environmental Protection Agency, Gulf Breeze, FL, EPA/600/R-16/178.

Galal YGM, El-Ghandour IA, Aly SS, Soliman S, & Gadalla A (2000). Non-isotopic method for the quantification of biological nitrogen fixation and wheat production under field conditions. Biology and Fertility of Soils, 32(1), 47–51.

Giddens JE (1982). Nitrogen fixation in soil crusts of tall fescue sods. Soil Science, 133(5), 295–297.

Grant D, & Binkley D (1987). Rates of free-living nitrogen fixation in some piedmont forest types. Forest Science, 33(2), 548–551.

Gregory MB and Frick EA. 2000. Fecal-coliform bacteria concentrations in streams of the Chattahoochee River National Recreation Area, Metropolitan Atlanta, Georgia, May–October 1994 and 1995. U.S. Geological Survey Water-Resources Investigations Report 00–4139, Atlanta, Georgia.

Gu B, Chang J, Ge Y, Ge H, Yuan C, Peng C, & Jiang H (2009). Anthropogenic modification of the nitrogen cycling within the Greater Hangzhou Area system, China. Ecological Applications, 19(4), 974–988. [PubMed: 19544738]

Hungate BA, Dijkstra P, Johnson DW, Hinkle CR, & Drake BG (1999). Elevated CO2 increases nitrogen fixation and decreases soil nitrogen mineralization in Florida scrub oak. Global Change Biology, 5(7), 781–789.

Huntington JL and Allen RG. 2010. Evapotranspiration and net irrigation water requirements for Nevada. State of Nevada, Department of Conservation and Natural Resources, Division of Water Resources, Carson City, NV.

Im S, Brannan KM, Mostaghimi S, and Cho J. 2012. Simulating Fecal Coliform Bacteria Loading from an Urbanizing Watershed. Journal of Environmental Science and Health Part A 39:663–679

Jensen ES (1986). The influence of rate and time of nitrate supply on nitrogen fixation and yield in pea (Pisum sativum L.). Fertilizer Research, 10(3), 193–202.

Jorgensen JR (1975). Nitrogen fixation in forested coastal plain soils. FAO Report.

Khanna PK (1998) Nutrient cycling under mixed-species tree systems in Southeast Asia Agrof. Syst, 38, pp. 99–120

Ley RE, D’Antonio CM, 1998. Exotic grass invasion laters potential rates of N fixation in Hawaiian woodlands. Oecologia 113, 179–187. [PubMed: 28308195]

Moyer DL and Hyer KE. 2003. Use of the Hydrological Simulation Program – FORTRAN and Bacterial Source Tracking for Development of the Fecal Coliform Total Maximum Daily Load (TMDL) for Christians Creek, Augusta County, Virginia. Water Resources Investigations Report 03–4162. US Geological Survey, Richmond, Virginia.

NLCD (National Land Cover Database), 2011. NLCD 2001 Land cover (2011 Edition). Multi-Resolution Land Characteristics Consortium (MRLC). www.mrlc.gov.

Paul S, Matlock M, Haan P, Mukhtar S, and Pillai S. 2002. Uncertainty analysis as a first step of developing a risk-based approach to nonpoint source modeling of fecal coliform pollution for total maximum daily load estimates. Texas Water Resources Institute SR-2002–014, College Station, TX

Peoples MB, & Baldock JA (2001). Nitrogen dynamics of pastures: nitrogen fixation inputs, the impact of legumes on soil nitrogen fertility, and the contributions of fixed nitrogen to Australian farming systems. Australian Journal of Experimental Agriculture, 41(3), 327–346.

Permar TA, & Fisher RF (1983). Nitrogen fixation and accretion by wax myrtle (Myrica cerifera) in slash pine (Pinus elliottii) plantations. Forest Ecology and Management, 5(1), 39–46.

Reckhow KH, Beaulac MN, Simpson JT, 1980. Modeling phosphorus loading and lake response under uncertainty: a manual and compilation of export coefficients. EPA/440/5/80/011, U. S. Environmental Protection Agency, Washington, D.C.

Rochester IJ, Peoples MB, Hulugalle NR, Gault R, & Constable GA 2001. Using legumes to enhance nitrogen fertility and improve soil condition in cotton cropping systems. Field crops research, 70(1), 27–41.

Schroeder HW, Anderson LM. 1984. Perception of personal safety in urban recreation sites. Journal of Leisure Research 16:178–194.

Smith LM, Harwell L, Summers JK, Smith HM, Wade CM, Straub KR, and Case JL 2014. A U.S. Human Well-being Index (HWBI) for multiple scales: linking service provisioning to human well-being endpoints (2000–2010). EPA/600/R-14/223.

Stone RP, Hilborn D, 2012. Universal Soil Loss Equation (USLE). Ontario Ministry of Agriculture, Food and Rural Affairs Factsheet, Order No. 12–051.

Sohl T and Sayler K. 2008. Using the FORE-SCE model to project land-cover change in the southeastern United States. Ecological Modelling 219:49–65.

Summers JK, Harwell LC, Smith LM. 2016. A model for change: An approach for forecasting well-being from service-based decisions. Ecological Indicators 69:295–309.

Tallis HT, Ricketts T, Guerry AD, Wood SA, Sharp R, Nelson E, Ennaanay D, Wolny S, Olwero N, Vigerstol K, Pennington D, Mendoza G, Aukema J, Foster J, Forrest J, Cameron D, Arkema K, Lonsdorf E, Kennedy C, Verutes G, Kim CK, Guannel G, Papenfus M, Toft J, Marsik M, Bernhardt J, and Griffin R, Glowinski K, Chaumont N, Perelman A, Lacayo M Mandle L, Griffin R, Hamel P, Chaplin-Kramer R, 2013. InVEST 3.0.0 User's Guide. The Natural Capital Project, Stanford

US Census Bureau. 2010. American FactFinder. http://factfinder.census.gov

USDA & NRCS, 1986. Urban hydrology for small watersheds. United States Department of Agriculture, Natural Resources Conservation Service, and Conservation Engineering Division, Technical Release 55.

USDA & NRCS, 2004. Soil Survey of Escambia County, Florida. United States Department of Agriculture, Natural Resources Conservation Service Technical Report.

USGS (US Geological Survey) Gap Analysis Program. 2011. National GAP vertebrate species distribution model. http://gapanalysis.usgs.gov/species

Wischmeier WH, Smith DD, 1978. Predicting rainfall erosion losses – a guide to conservation planning. U. S. Department of Agriculture, Agriculture Handbook No. 537.

Yagow G, Dillaha T, Mostaghimi S, Brannan K, Heatwole C, Wolfe ML. 2001. TMDL Modeling of fecal coliform bacteria with HSPF. American Society of Agricultural Engineering Paper 01:2066, Sacramento, CA.

Zahran HH (1999). Rhizobium-legume symbiosis and nitrogen fixation under severe conditions and in an arid climate. Microbiology and molecular biology reviews, 63(4), 968–989. [PubMed: 10585971]

Zuberer D, & Silver WS (1978). Biological dinitrogen fixation (acetylene reduction) associated with Florida mangroves. Applied and environmental Microbiology, 35(3), 567–575. [PubMed: 637550]

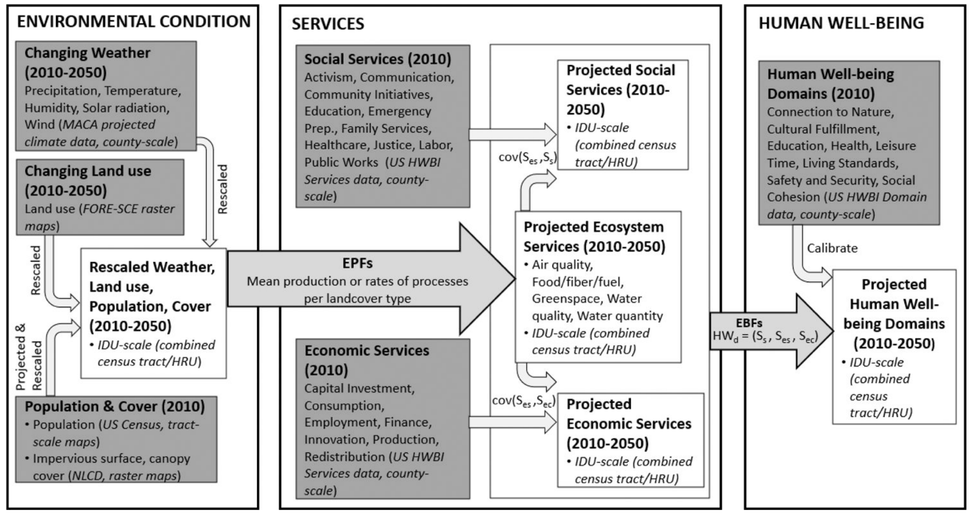

Figure 1.

Conceptual diagram of modeling approach, with available input data in grey boxes and modeled components in white boxes, connected by arrows representing modeling functions. Ecosystem services are modelled as a function of forecast changes in environmental condition using ecological production functions (EPFs). Human well-being domains (HW_d) are modelled as a function of ecosystem (S_{es}), social (S_s), and economic (S_{ec}) services using ecological benefits functions (EBFs). Social and economic services are adjusted relative to changing ecosystem services through a covariance matrix. Data sources and spatial scale are in italics.

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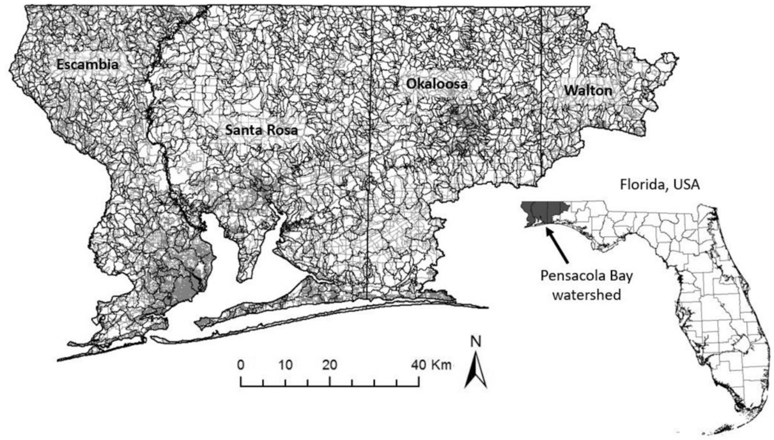

Figure 2.

Four counties within Florida's Pensacola Bay watershed. Hydrological processes were modelled at the scale of stream catchment HRU polygons (fine black lines). Ecosystem services metrics were calculated within IDU polygons (fine grey lines), scaled between zero and one, and then averaged to calculate a metric score for each county.

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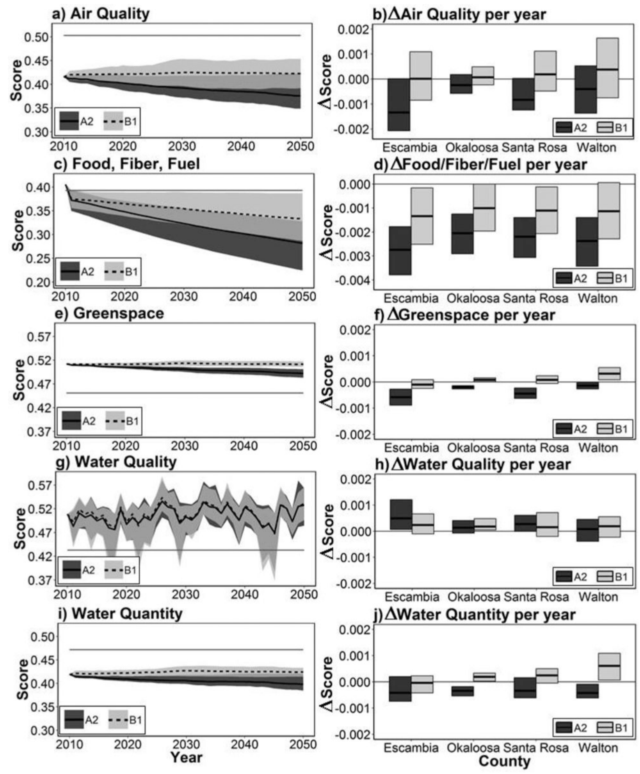

Figure 3.

Mean ecosystem service scores over the simulation period for scenarios A2 and B2 for the bay watershed (a, c, e, g, i), with the US national average score from 2000–2010 included as a reference point (grey horizontal line). Mean yearly rates of change for each county (b, d, f, h, j), with the no change zero line for reference (horizontal line). Dark or light grey fill indicate 90th percentile range across 20 stochastic simulations.

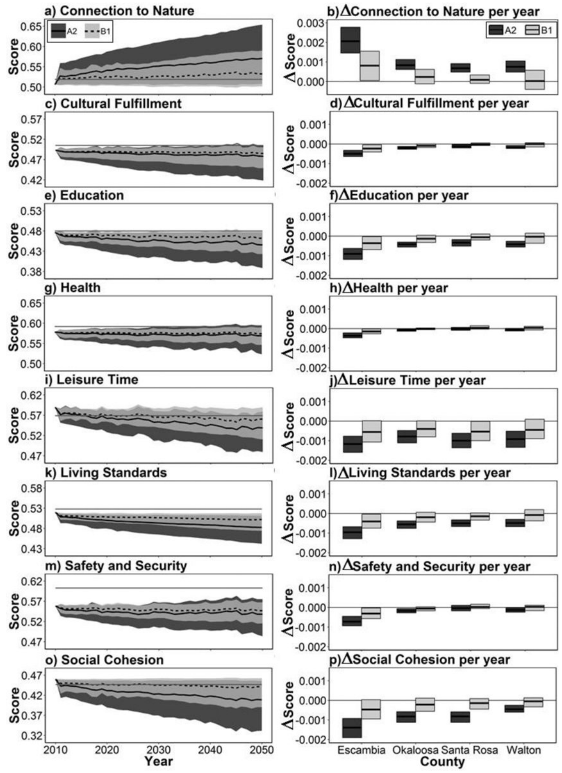

Figure 4.

Mean well-being domain scores over the simulation period for scenarios A2 and B2 for the bay watershed (a, c, e, g, i, k, m), with the US national average score 2000–2010 included as a reference point (grey horizontal line). Mean yearly rates of change for each county (b, d, f, h, j, l, n), with the no change zero line for reference (horizontal line). Dark or light grey fill indicate 90th percentile range across 20 stochastic simulations.

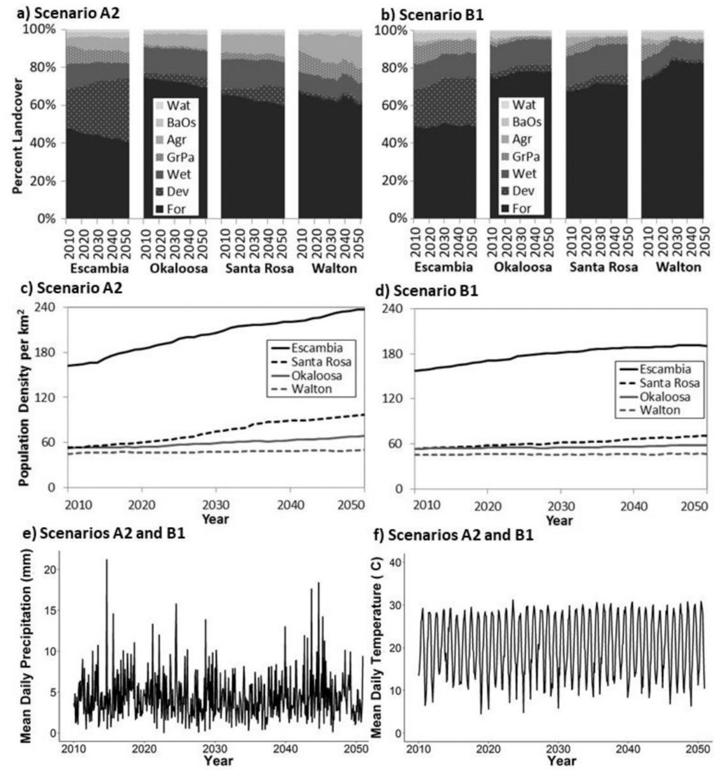

Figure 5.

Change in land cover (a,b), population density (c,d), precipitation (e), and temperature (f) for the two modelled scenarios over the simulation period 2010–2050. Land cover types in order from bottom to top are Forest (For), Developed (Dev), Wetland (Wet), Grassland or Pasture (GrPa), Agriculture (Agr), Barren or Developed Open Space (BaOs), and Water (Wat).

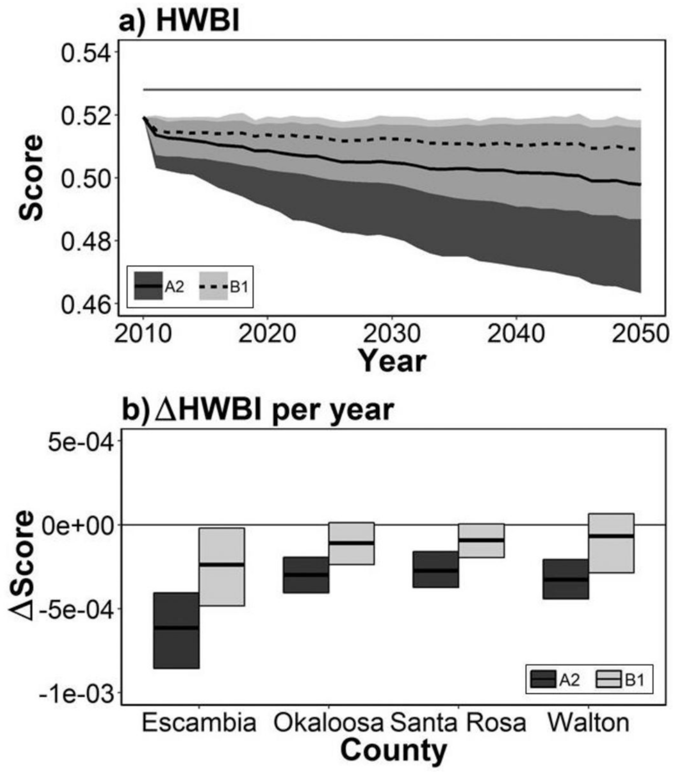

Figure 6.

Mean composite human well-being index (HWBI) over the simulation period for scenarios A2 and B2 for the bay watershed (a), with the US national average score 2000–2010 included as a reference point (grey horizontal line). Mean yearly rates of change for each county (b), with the no change zero line for reference (horizontal line). Dark or light grey fill indicate 90th percentile range across 20 stochastic simulations.

Table 1.

Relationships between services indicators and domains of human well-being (EBFs), based on partial least squares regression models fitted to national indicator data (from Summers et al. 2016). Where interactions among variables were significant in fitted models, variable relationships might be either positive or negative depending on the magnitude of interacting variables.

	Connection to Nature	Cultural Fulfillment	Education	Health	Leisure Time	Living Standards	Safety & Security	Social Cohesion
Ecosystem Services								
Air Quality		+ / −						+
Food/Fiber/Fuel					+	+	+	
Greenspace	−		+		+		−	+ / −
Water Quality	+				−	−	+ / −	−
Water Quantity		−		+	+ / −	+	+	
Economic Services								
Capital Investment						−		+
Consumption	+		−		−			−
Employment					−	+		−
Finance					+	+ / −	−	
Innovation		+		+	−			
Production		−	−				−	−
Redistribution	−		+					+ / −
Social Services								
Activism	+ / −		+	+	+ / −	+	−	
Communication		+ / −		+	+	+		
Community Initiatives	+ / −	+ / −	+	+ / −	−		+	+ / −
Education	+	+		+	−			
Emergency Preparedness	−	+		+			−	
Family Services			+	+				+
Healthcare	−						−	

Table 2.

Modelled metrics used as surrogates for the original HWBI ecosystem services metrics used in developing services to domains regression models (Summers et al. 2016).

HWBI Service Indicator	Original HWBI Services Metrics	Surrogate Modelled Metric
Air Quality		
Usable Air	- % days with good or moderate air quality[1]	- Rate of air pollutant removal
Food, Fiber, and Fuel Provisioning		
Raw Materials	- Copper reserves[2]	- Same metric as original HWBI
	- Gold reserves[2]	- Same metric as original HWBI
	- Lead reserves[2]	- Same metric as original HWBI
	- Silver reserves[2]	- Same metric as original HWBI
	- Zinc reserves[2]	- Same metric as original HWBI
Food & Fiber	- Commercial fishery landings[3] - Saw-timber tree volume on forest land[4] - Agricultural productivity[5]	- Same metric as original HWBI - Forest area allocated for timber removal - Index of nitrogen fixation, carbon sequestration, soil water content
Energy	- Recoverable coal reserves[6] - Crude oil proved reserves[6] - Natural gas proved reserves[6] - Uranium reserves[6]	- Same metric as original HWBI - Same metric as original HWBI - Same metric as original HWBI - Same metric as original HWBI
Greenspace		
Recreation & Aesthetics	- % of people who did non-consumptive activity within a mile of their home[7] - % of people who took a wildlife observation trip within their state[7] - Area of blue space per person[7]	- Same metric as original HWBI - Biodiversity - Modelled area of blue space per person
Natural Areas	- National Parks acreage[8] - % area designated rural park or wildlife area[5] - Number of National Park visitors within a state[8] - Unclassified land use acres (e.g., marsh, swamp, bare rock, tundra)[5]	- Same metric as original HWBI - Same metric as original HWBI - Same metric as original HWBI - Modelled area of natural lands
Water Quality		
Usable Water	- % of water bodies assessed as 'Good'[1] - % days under a beach action (e.g., closure)[1]	- Index of sediment load, nutrient load - Fecal coliform load
Water Quantity		
Available Water	- Average monthly Palmer Hydrological Drought Index[3] - Water Sustainability Index[9]	- Rainwater retention capacity by soil - Same metric as original HWBI

Data Sources:

1. U.S. EPA Air Quality Index Report;

2. U.S. Geological Survey Mineral Commodity Summaries;

3. National Oceanic and Atmospheric Administration National Marine Fisheries Service;

4. U.S. Department of Agriculture Forest Inventory and Analysis Data Base;

5. U.S. Department of Agriculture Economic Research Service;

6. U.S. Energy Information Administration;

7. U.S. Census Bureau;

8. National Park Service;

9. Natural Resources Defense Council

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Table 3.

Input variables into ecological production function models (EPFs) to model ecosystem services metrics.

Ecosystem Service	Input Environmental Condition Variables	Output Ecosystem Service Metric
Air Quality		
	Canopy cover	Rate of air pollutant removal
Food, Fiber, and Fuel Provisioning		
	None (decline at fixed rate over time)	Raw material reserves
	None (constant over time)	Commercial fishery landings
	Area of forest cover	Forest area allocated for timber removal
	Area of each land use/land cover class	Nitrogen fixation
	Area of each land use/land cover class	Carbon sequestration
	Precipitation, temperature, area of each land use/land cover class	Soil water content
	None (decline at fixed rate over time)	Energy reserves
Greenspace		
	None (constant over time)	% of people who did non-consumptive activity within a mile of their home
	Area of each land use/land cover class	Biodiversity
	Area of water, population density	Modelled area of blue space per person
	None (constant over time)	National Parks acreage
	None (constant over time)	% area designated rural park or wildlife area
	None (constant over time)	Number of National Park visitors within a state
	Area of each barren, forest, grassland, wetland classes	Modelled area of natural lands
Water Quality		
	Precipitation, temperature, area of each land use/land cover class	Sediment load
	Precipitation, temperature, area of each land use/land cover class	Nutrient load
	Precipitation, temperature, area of each land use/land cover class	Fecal coliform load
Water Quantity		
	Area of each land use/land cover class	Rainwater retention capacity by soil
	None (constant over time)	Water Sustainability Index

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Table 4.

Environmental variables explaining greatest variability in year to year changes in ecosystem service scores, determined by step-wise multiple linear regressions.

	Variable	Value	T-value	r^2
Δ Air quality	Intercept	1.06E-05	0.12^{NS}	0.12
	Δ Developed	−1.60E-04	−14.02***	
	Δ Agriculture	−1.53E-04	−13.79***	
	Δ Pasture	−1.03E-05	−7.20***	
	Δ Developed Open Space	4.83E-05	5.16***	
Δ Food, Fiber, Fuel	Intercept	−0.00212	−12.07***	0.07
	Δ Pasture	0.00026	9.58***	
	Δ Developed Open Space	−0.00013	−7.01***	
	Δ Deciduous Forest	0.00020	5.54***	
Δ Greenspace	Intercept	−2.61E-05	-1.39^{NS}	0.39
	Δ Developed Open Space	−7.66E-05	−32.02***	
	Δ Agriculture	−9.31E-05	−33.10***	
	Δ Developed	−9.20E-05	−31.70***	
	Δ Pasture	−7.77E-05	−21.28***	
Δ Water quality	Intercept	0.00012	0.34^{NS}	0.34
	Δ Mean Daily Precipitation	−0.02123	−57.57***	
	Δ Mean Daily Temperature	−0.00164	−4.52***	
Δ Water Quantity	Intercept	−2.40E-05	−5.52***	0.28
	Δ Agriculture	−1.94E-04	−31.20***	
	Δ Herbaceous Wetland	−1.31E-04	−18.33***	
	Δ Pasture	−1.22E-04	−15.55***	
	Δ Evergreen Forest	3.65E-05	11.90***	