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Original Article

An integrated approach to project environmental sustainability under future climate variability: An application to U.S. Rio Grande Basin

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ABSTRACT

Extreme weather events have been affecting local environmental sustainability. Previous literature in this field evaluates environmental sustainability based mainly on past and current resource consumption and availability, however, knowledge about the status and potential changes of environmental sustainability under future climate extremes is missing. This paper proposes an integrated approach (combining the Ecological Footprint Analysis with econometric regressions) to predict future environmental sustainability under different climate scenarios. Based on the case study of the U.S. Rio Grande Basin, the results show that this region has been sustainable in 1982–2012, although sustainability levels have been declining over time. In addition, projections for the future show that the entire region will most likely move away from sustainability by the end of this century under the high emission scenario (e.g., RCP8.5). These findings are relevant for sustainable resource management and allocation of local environmental resources as well as for decision-making support regarding climate risk adaptation and mitigation strategies.

1. Introduction

Although there are many definitions of environmental sustainability in the literature (Chambers et al., 2014; Goodland, 1995; Moldan et al., 2012), the mainstream defines it as the maintenance of natural capital in a balanced condition. In other words, a system allows the society to satisfy its needs over generations without exceeding the capacity of its ecosystems to continue to regenerate its provisioning, supporting, regulatory, and cultural services (Goodland, 1995). Previous literature has proposed different methods to construct indicators to measure environmental sustainability using both quantitative and qualitative techniques (Cano-Orellana and Delgado-Cabeza, 2015; Heberling and Hopton, 2014; Moldan et al., 2012; Neumayer, 2012). However, existing sustainability indicators mainly focus on the current sustainability status, using trends or reference values generated under historical conditions, and do not consider potential future changes in environmental sustainability subject to climate variability (Milman and Short, 2008). Thus, knowledge of possible patterns of environmental sustainability under future climate extremes is missing. In this paper, we propose an integrated approach to fill the identified research gap in this field. This approach combines the Ecological Footprint Analysis with econometric regressions to predict the conditions of environmental sustainability under future climate variability. While this approach could be applied to different regions and countries, in this paper, we use data from the U.S. Rio Grande Basin as one of the applications.

Many studies have shown that weather variability and climate change can potentially affect the availability of environmental resources, possibly in a negative way, resulting in the status change of environmental sustainability (Field, 2012; IPCC, 2014). For example, some species are threatened with extinction under global warming (Thomas et al., 2004; Urban, 2015); forest area in the tropics has been declining due to the stress from climate change (Geist and Lambin, 2002; Malhi et al., 2008); and water resources stresses have also been increasing because of reduced water availability (Arnell, 2004; Vörösmarty et al., 2000). Many of these changes could have continuous impacts on resource supply, including land use, food and timber production, biodiversity, and consequently on human health and well-being (Metzger et al., 2006). On the other hand, population growth and increasing demand for food, energy, and water resources could result in rising atmospheric carbon dioxide levels in the mid and long term (Galloway, 2001; Metzger et al., 2006). Over time, it is difficult to keep the balance of environmental demand and supply when climate change is taken into account. Moreover, some studies found that the frequency

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and intensity of extreme weather events are likely to increase under future climate change (Huber and Gulledge, 2011), which could further affect the demand and supply of environmental resources and consequently environmental sustainability.

Due to continuous changes in resource demand and supply as well as weather variability, it is important to understand the past, current and potential future conditions and changes of environmental sustainability. This knowledge could help organizations, enterprises, and policy makers track progress towards sustainable development and set policies supporting this progress (Milman and Short, 2008). The integrated approach presented in this paper addresses current decision-making and policy needs in this area and can be used to project changes in future sustainability due to climate variability. To the best of our knowledge, this is the first study to improve understanding of this topic in this discipline and to contribute to scientific and policy discussions on environmental sustainability and sustainable development.

2. Methods

To achieve the research goal as specified above, the following steps were conducted:

1) Application of the Ecological Footprint Analysis (EFA) to determine the status and changes of environmental sustainability under historical conditions from 1982 to 2012.
2) Development of econometric regression models to investigate potential impacts of climate conditions on the determined demand and supply of environmental resources.
3) Projections of future environmental sustainability conditions and changes based on the estimated parameters of the econometric regressions as well as climate projections from 20 global climate models for two emission scenarios.

2.1. Calculation of environmental sustainability indicators

In order to determine indicators of environmental sustainability, the EFA method was applied in this study, which was first introduced by Rees and Wackernagel (1996) and expanded by Chambers et al. (2014). EFA has been applied in numerous studies for different geographic regions and spatial scales, from global to municipal and from industry level to household level (Bagliani et al., 2008; Chambers et al., 2014; Collins et al., 2006; Erb, 2004; Graymore et al., 2008; Lammers et al., 2008; Medved, 2006; Niccolucci et al., 2008; Wackernagel et al., 2004). The application of EFA in this study is highly viable, as it has proven to be especially useful when total national production, import and export data for key sectors are readily available and easier to locate than specific local data, particularly for developed countries (Moore et al., 2013).

EFA measures both the demand (i.e., *ecological footprint*) and supply (i.e., *environmental biocapacity*) of environmental resources in the analyzed region. In the analysis, the demand for environmental resources is expressed with direct and indirect consumption levels of the respective resources, while the supply of environmental resources is the measurement of resource availability.

To calculate the ecological footprint (demand for natural resources) in an exemplary (case study) region, the area of the ecologically productive land was divided into six categories according to their uses, including built land (developed land plus other rural land), forest land, arable land (cropland plus land enrolled in conservation programs), pasture land, surface water areas[1] and energy land. Given the population growth and increasing resource demands in the case study region over time, the ecological footprint indicator was calculated for each year according to Eq. (1):

$$EF = N \times ef = N \times \sum \gamma_i (c_i/p_i) \tag{1}$$

where i is the type of the resources; p_i is the average productivity of producing i^{th} type of a resource; c_i is the per capita quantity of the i^{th} resource consumed; γ_i is the equivalence factor describing productivity of different land types in reference to the reported yields of various plant and animal produce; N stands for the total population in the analyzed area; ef describes per capita ecological footprint; and EF is the total ecological footprint.

Environmental biocapacity (supply or availability of natural resources) was calculated with Eq. (2):

$$BC = N \times bc = N \times (1{-}12\%) \times \sum \gamma_i y_i a_i \tag{2}$$

where a_i is the per capita area of the productive land of the i^{th} type of a resource; y_i is the yield factor, which usually stands for the supply-existing national biocapacity (per capita); bc and BC present the per capita and the total ecological biocapacity, respectively. The 12% value in the equation is a correction factor, indicating that 12% of the land area deducted from the ecological supply should be preserved for biodiversity protection. This factor is based on an assumption defined by WCED (1987) and has been consistently applied in the EFA methodology across different studies. Other variables in Eq. (2) are defined the same way as in Eq. (1).

To calculate the demand and supply indicator of environmental resources, we use values of the equivalent factor (γ_i) and the yield factor (y_i) from Chambers et al. (2014), as follows: 2.83 and 1.22 for arable and built land, 0.44 and 1.63 for pastureland, 1.17 and 2.11 for forestland, 0.06 and 1 for surface water areas, and 1.17 and 0 for energy land, respectively. To ensure validity of the results, sensitivity analysis was conducted with different values for each land type. Findings of those analyses showed that trends of the per capita environmental biocapacity and ecological footprint are consistent, although magnitudes vary across different values of these two parameters. Despite the variations in magnitude, the factor values from Chambers et al. (2014) were used for this analysis as they have been widely acknowledged in the literature and applied in many relevant studies in this field (Hopton and Berland, 2015; Hopton and White, 2012; Moore et al., 2013).

Based on Eqs. (1) and (2), environmental sustainability has been calculated as a difference between ef and bc. The value of this indicator denotes if the selected area experienced an ecological deficit (i.e., $ef - bc > 0$, corresponding to positive values) or an ecological reserve (i.e., $ef - bc < 0$, corresponding to negative values). Accordingly, resource use in the selected area would be called sustainable if $ef - bc < 0$, while it would be moving away from sustainability or be called unsustainable if $ef - bc > 0$. By comparing the combined footprint in the selected area with the ecological productive land available in the region over time, EFA will detect if the growing population in the selected area overuses resources, thus exceeding its ecological carrying capacity (Graymore et al., 2008).

2.2. Estimating impacts of climate variability on current environmental sustainability

Using the calculated ecological footprint and per capita environmental biocapacity from Eqs. (1) and (2), we then develop an econometric regression model to examine impacts of climate conditions on the supply and demand of environmental resources. The model was defined with the following equation (Eq. (3)) for each county c in year t:

$$y_{ct} = C_c + \sum_{k=1} \alpha_k W_{kct} + \theta T_{ct} + u_{ct} \tag{3}$$

where y_{ct} is either the ecological footprint (ef) or per capita

[1] According to the National Resource Inventory (https://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/soils/?cid=nrcs143_013913), water area is defined as "a broad land cover/use category comprising water bodies and streams that are permanent open water".

environmental biocapacity (bc), which was calculated with Eqs. (1) or (2). W_{kct} is a vector of climate factors including the mean temperature, annual precipitation, and variables expressing extreme weather events (such as the drought index, precipitation intensity index, the variation of the mean temperature, cold growing season degree-days with temperature less than 8 °C, and hot growing season degree days with temperature higher than 32 °C). T_{ct} is the time trend to control for possible technology improvements. C_c is the county fixed effects to control for county characteristics that are unobservable and do not vary across time. u_{ct} is the error term, while α and θ are parameters to be estimated.

Panel regression with fixed effects was used to estimate Eq. (3).[2] Serial correlation and/or heteroskedasticity were accounted for by clustering the standard errors at the county level.

2.3. Projections of environmental sustainability under future climate variability

The parameters estimated with Eq. (3) were further used to predict future demand and supply of environmental resources under different climate scenarios. For a given climate model or emission scenario, the impact for county c is given by:

$$M_c = \sum_{k=1} \widehat{\alpha_k} \Delta W_{kc} \tag{4}$$

where ΔW_{kc} is the predicted changes in weather variable k from the base period in county c. These changes are specific to a climate model, emission scenario and time scale. $\widehat{\alpha_k}$ are estimated parameters for the weather variable k from Eq. (3). M_c is defined as the impacts from climate change in county c.

When projecting future impacts of climate variability on environmental sustainability, all other non-climate variables were controlled at the historical mean in order to capture effects from all climate variables. Moreover, climate projections from 20 global climate models for two emission scenarios were used in order to capture climate uncertainties (Burke et al., 2015; Flato et al., 2013). Thus, changes of future environmental sustainability could be pinpointed as the average effects of climate change under uncertainty.

3. Study area

To prove the practical applicability of the integrated approach, we use data from the U.S. Rio Grande Basin. The Rio Grande Basin is located in the southwestern United States, and spans over 870,000 km^2 across three U.S. states (Colorado, New Mexico and Texas) and Mexico (Fig. 1 shows the U.S. part of the Rio Grande Basin). The Rio Grande Basin is an appropriate case for analyzing environmental sustainability changes over time due to the variability of ecosystem services in this basin as well as the multitude and intensity of interactions between the ecological and human dimensions, which create many natural resource and sustainability issues (Graymore et al., 2008).

The Rio Grande Basin has been facing many economic, environmental, and social challenges that determine the sustainable use of resources in the region, including water resources. For example, Colorado, New Mexico, and Texas experienced growing population that almost doubled from 19.7 million in 1982 to 33.3 million in 2012, which directly raised demand for environmental resources. Moreover, the region has recorded a significant economic growth over time. According to the U.S. Bureau of Economic Analysis (BEA), the per capita real Gross Domestic Product (GDP) in 1997 in Colorado, New Mexico, and Texas amounted to \$43,558, \$36,297, and \$41,366 (in 2009 dollars), respectively. In 2012, the per capita real GDP increased by 14%, 10%, and 22%, respectively. The economic development and population growth led to increasing withdrawals of groundwater and surface water across Colorado, New Mexico, and Texas from 19 billion gallons per day in 1985 to 39 billion gallons per day in 2010 (USGS, 2017). With reduced streamflow and recharge, water availability (and supply to the respective users for different purposes) in the Rio Grande Basin became an urgent issue affecting not only human well-being but also the provision of ecosystem services.

Future climate in this region is projected to be warming, while precipitation has been decreasing (Fig. 1), which could affect the availability of natural resources (especially water resources) and ecosystem services. For example, the projected increase in temperatures and changes in precipitation are anticipated to reduce spring and early summer stream flows, thus reducing water availability for irrigation and other economic uses. Warmer conditions will also increase evaporation and decrease stream flow, which could eventually reduce natural groundwater recharge. Those conditions are projected to elevate stress on animal and fish species (e.g., silvery minnow), change a constellation of river ecosystems and foster invasive species (Arnell, 2004; Thomas et al., 2004; Urban, 2015; Vörösmarty et al., 2000).

The unbalanced supply and demand relations of environmental resources in the basin generate a research need to investigate the past, current, and future conditions and changes of environmental sustainability. Understanding those changes and variations will provide valuable information to identify adaptation and mitigation strategies to potential climate risks and to design programs to maintain environmental sustainability in the short and long term.

4. Data and sources

4.1. Data for ecological footprint analysis

The following data from counties in the Rio Grande Basin were collected: (1) population, (2) the amount of food and energy consumed per capita, (3) the amount of biologically productive land types, and (4) the average productivity of each biologically productive land type in the region. The period of the analysis spanned the years from 1982 to 2012. In a case of missing county-level data, state-level or national-level data were used based on the assumption of homogenous patterns across the state or nation. This procedure was also found in other studies (Hopton and White, 2012). In addition, for variables with missing values in some years (e.g., land use data are available only every five years), values for the missing annual data points were linearly interpolated based on the long term trend of the available data, following the approach by Heberling and Hopton (2014).

Data of county-level population were extracted from BEA.[3] Data of land acres for built land, forest land, arable land, pasture land, and surface water areas were collected from the 2012 National Resource Inventory.[4] Energy land was calculated based on the forest land according to the approach in Chambers et al. (2014), which presumes that the energy land is the area of the forest land used to sequestrate CO_2 originating from energy consumption (Hopton and White, 2012). Specifically, the parameter of 0.62 was applied based on the translation rate between the capability of forests to sequester greenhouse gas emission and the total amount of emissions from energy consumption.

Average land productivity was calculated using data from multiple sources. County-level crop yield data for main field crops produced in the Rio Grande Basin (wheat, barley, corn, hay, soybeans, sorghum, oats, and sugarcane) were collected from the U.S. Department of Agriculture (USDA)'s National Agricultural Statistics Services (NASS).[5] National per acre production of livestock and fish were used for this

[2] The reason for using fixed effects in this analysis is the need to control for some unobservables that are not included in Eq. (3) due to data paucity.

[3] The county-level population data can be found here: https://www.bea.gov.
[4] These data were collected through a direct request.
[5] https://www.ers.usda.gov/data-products.

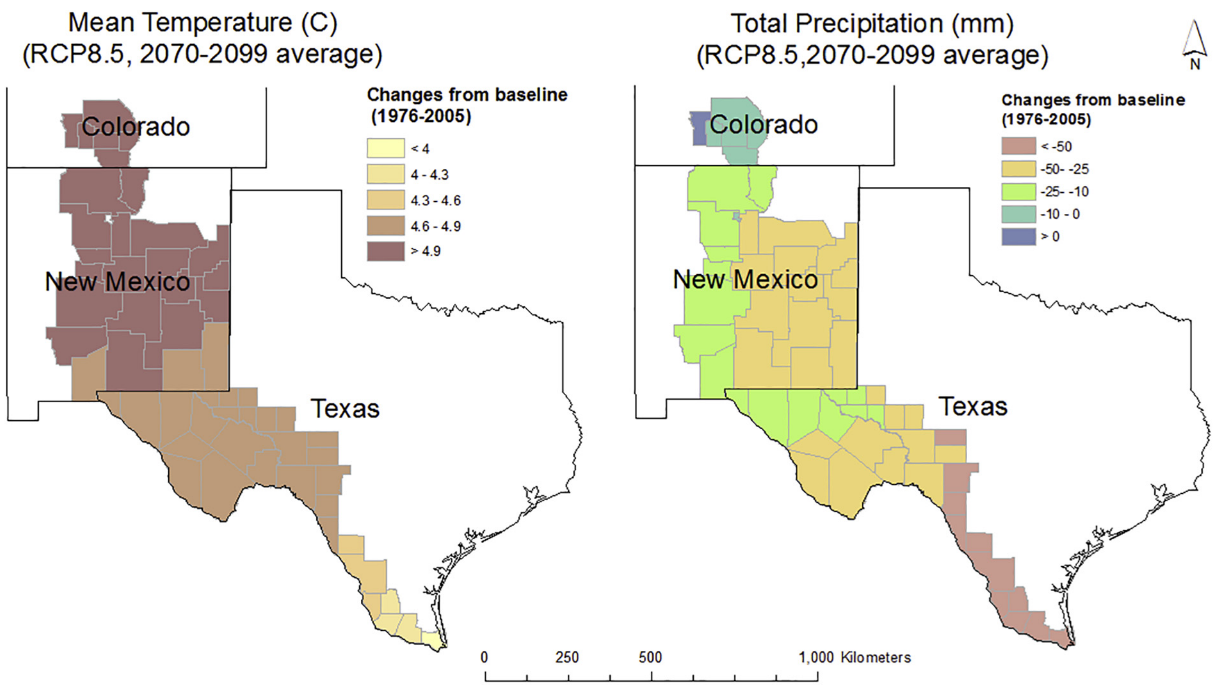

Fig. 1. Changes in mean temperature and total precipitation in the late period (2070–2099 average) from the baseline (1976–2005 average) in the high emission scenario (RCP8.5) in the Rio Grande Basin (Note: All values are aggregated across 20 global climate models).

analysis as approximation values of county-level production per acre because regional (i.e., state-wide) crop production data are not available. The statistics were obtained from the USDA's Economic Research Service (ERS), with livestock production including the production totals of red meat, poultry, and dairy products. The total production levels of crops, livestock and fish were used to calculate the average productivity for pastureland, arable land, and surface water areas.

The average productivity and per capita consumption of timber products and energy were calculated using data of the available national forest land and state energy land, respectively. National timber production and consumption data were drawn from Howard and Jones (2016), while state energy production and consumption data were derived from the State Energy Data System maintained by the U.S. Energy Information Administration.

Per capita food consumption data were also collected from USDA's ERS at the national level due to missing statistical data at the county level. Food consumption data include fish, dairy, fruits and vegetables, grain and meat products, which, for the purpose of this analysis, were aggregated into three categories of livestock, crop, and fish consumption.

4.2. Historical climate data and future projections

Historical climate data and future climate projections were derived from the climate data hub at the University of Idaho.[6] For the analysis presented in this paper, the following climate variables were selected: mean temperature (°C), total precipitation measured in 100 mm, cold and hot growing season degree-days, precipitation intensity, drought index, and standard deviation of the mean temperature. To determine the best set of variables for the model analysis of Eq. (3), the Least Absolute Shrinkage and Selection Operator (LASSO) regression analysis was conducted in order to enhance the prediction accuracy and interpretability of the final regression model. The LARS module in STATA 14.0 was used to perform this analysis.

Among the selected variables, precipitation intensity was calculated as a fraction of annual cumulative precipitation that occurred from daily precipitation exceeding the 95th percentile of the climatological distribution for wet days (Tebaldi et al., 2006). Cold and hot growing season degree-days were calculated using thresholds of 8 °C and 32 °C for each day and summing them over the calendar year from January to December, respectively. In addition, we constructed a binary measure of the drought index when the average Palmer Drought Severity Index (PDSI) in a growing season was less than -2. Table 1 shows the summary statistics of the climate variables used in this paper.

Historical weather observations were obtained from Abatzoglou (2013), by aggregating gridded ~4-km spatial resolution surface meteorological datasets to the county level. For future weather projections, we used statistically downscaled climate model simulations for 20 global climate models from the Coupled Model Intercomparison Project Phase 5 (CMIP5). These climate models were also used in the 2012 Intergovernmental Panel on Climate Change (IPCC) report. Daily surface meteorological data were statistically downscaled to 4-km resolution using the observed surface meteorological dataset from Abatzoglou (2013) and used the Multivariate Adaptive Constructed Analogs method (Abatzoglou and Brown, 2012). Downscaling of climate projections was conducted for both historical (1950–2005) and future (2006–2099) model experiments, considering two Representative Concentration Pathways (RCPs), RCP4.5 and RCP8.5, which represent medium and high atmospheric greenhouse gas emission levels. According to the IPCC Fifth Assessment Report (AR5 WG1), relative to temperature levels in the late 20th to early 21st centuries (1986–2005 average), global warming projections from RCP4.5 and RCP8.5 show an increase in temperature by around 1.8 °C and 3.7 °C, respectively, by the late 21st century (2081–2100 average).

Using the RCP8.5 emission scenario in the Rio Grande Basin as an example, Fig. 1 shows changes in the mean temperature and total precipitation compared to the baseline scenario (1976–2005 average). For the late-period (2070–2099 average), the scenario predicts increased mean temperature across the entire region and reduced precipitation in most of the Rio Grande Basin counties. This suggest that this region will become warmer and dryer by the late 21st century under future climate projections for the high emission scenario.

[6] https://climate.northwestknowledge.net/.

Table 1
Summary statistics.

Variables	Mean	Std. Dev.	Min	Max
Per capita biological capacity	77.04	187.31	0.40	2071.42
Per capita ecological footprint	11.21	12.72	1.16	92.89
Mean temperature (C)	15.00	5.95	−1.86	24.48
Annual precipitation	42.64	18.50	0	124.14
Drought index	0.02	0.14	0	1
Variation of mean temperature	3.11	0.37	2.25	4.6
Precipitation intensity index	0.17	0.11	0	0.59
Degree-days with mean temperature less than 8 C	602.32	803.58	0	3764.8
Degree-days with mean temperature higher than 32 C	0.92	4.07	0	75.1
Time trend	15.50	8.66	1	30
Observations	1710			

Note: Data cover 58 counties in the Rio Grande Basin from 1982 to 2011.

5. Results and discussions

5.1. Current environmental sustainability in the Rio Grande Basin

Trends of the calculated per capita environmental biocapacity, ecological footprint, and the sustainability indicator (measured in hectares/capita) for the entire Rio Grande Basin are shown in Fig. 2. These regional environmental indicators were calculated based on indicators in each county and further aggregated using each county's total land area as the weight. Results of the ecological footprint analysis revealed two main outcomes. First, per capita biocapacity (supply, i.e. availability of natural resources) has been declining over the analyzed period from 24 ha/capita in 1982 to 14 ha/capita in 2012. A possible reason for this trend is the rapid population growth and increased demand for resources due to economic development. Second, the values of the per capita ecological footprint indicator remained relatively steady over time, with a slight increase from 0.2 ha/capita in 1982 to 0.4 ha/capita in 2012. This trend can possibly be explained by the calculation of this indicator as a ratio of average per capita productivity and consumption, while its relative change over time was determined by changes in both the denominator and numerator. In the developed countries, the average per capita productivity for each land type has generally been increasing due to technological progress (Heinemann et al., 2014). Meanwhile, the average per capita consumption is affected by income and higher per capita consumption with rising income (Storey and Anderson, 2014).

Based on those outcomes, the environmental sustainability indicator was calculated as the difference between ecological footprint and environmental biocapacity ($ef-bc$), with negative values denoting sustainability in the region and positive values indicating unsustainable conditions. Accordingly, results show that the Rio Grande Basin has been generally sustainable in the analyzed time frame as the per capita ecological footprint (demand for natural resources) is lower than the biocapacity (supply/availability of natural resources) (i.e., $ef-bc < 0$). However, this region has become less sustainable over time, with changes of the environmental sustainability indicator from -9.6 ha/capita in 1982 to −5.6 ha/capita in 2012, due to the declining trend of per capita biocapacity and the relatively stable trend of per capita ecological footprint. These results are consistent with findings by Hopton and White (2012) who analyzed regional environmental sustainability in south Colorado.

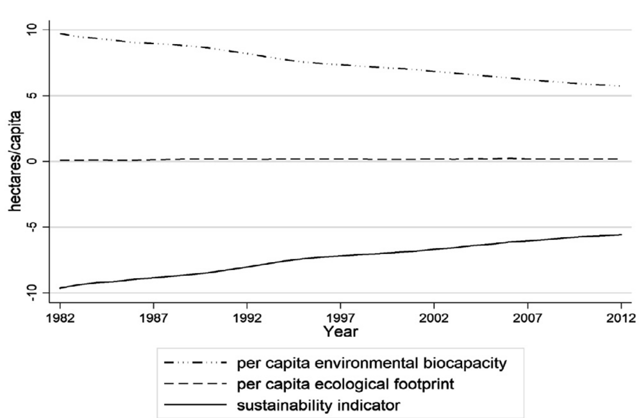

Fig. 2. Per capita biocapacity and per capita ecological footprint in the Rio Grande Basin from 1982 to 2012. (Note: The sustainability indicator is defined as the difference between the per capita ecological footprint and the per capita biocapacity. Negative values show sustainable conditions, while positive values indicate unsustainable conditions).

5.2. Impacts of climate on demand and supply indicators of natural resources

The calculated biocapacity and ecological footprint indicators in each county of the Rio Grande Basin were further used to investigate impacts of historical climate conditions on natural resources. In the estimation model, socio-economic variables were not included due to a possible endogeneity problem. Only climate-related variables were used in this model, assuming that socio-economic variables are indirectly included as the function of climate-related variables.

In order to determine the most robust model for further interpretation and predictions, estimation results of per capita biocapacity and ecological footprint are reported in Table 2 for three model specifications. Model 1 is defined as the baseline model with no squared terms of temperature and precipitation and no extreme weather variables. Model 2 adds squared terms of temperature and precipitation to the baseline model (without extreme weather variables), while Model 3 includes variables specified in Model 2 plus extreme weather variables. Results from Model 1 and Model 2 are consistent with outcomes from Model 3, however, they have a relatively smaller goodness of fit (R^2) in the regression of per capita ecological footprint. These findings suggest that Model 3 is the most robust model as it is not sensitive to the selection of climate-related variables. For this reason, estimates from Model 3 were selected for the following simulation analyses to determine potential future changes in environmental sustainability.

As shown in Table 2 (results from Model 3 in column three and column six), the estimated parameters of the squared mean temperature are positive, while mean temperature values are negative, suggesting that temperature has U-shape effects both on per capita environmental biocapacity and ecological footprint. These findings indicate that both per capita biocapacity and ecological footprint would decrease to a certain threshold and then increase as temperature keeps rising. According to the estimated parameters in Table 2, the turning points of the mean temperature for per capita biocapacity and ecological footprint were found to be around 11 °C and 16 °C, respectively. With the current mean temperature of 15 °C (as shown in Table 1), the county-averaged per capita environmental biocapacity will be 80 ha/capita, which is higher than the county-averaged per capita ecological footprint (45 ha/capita), suggesting that the Rio Grande Basin is sustainable at the regional mean temperature.

Furthermore, the estimated results suggest that extreme weather variables would influence environmental sustainability in the Rio Grande Basin. For example, precipitation intensity was found to have a statistically and significantly negative impact on the per capita biocapacity, while the drought index and cold growing season degree-days both have significantly negative effects on per capita ecological footprint. Other extreme climate variables have also been found to affect environmental sustainability; however, they are statistically insignificant. These results indicate that extreme weather events could reduce the demand and supply of natural resources, for instance, through their negative impacts on food production and land use allocations, as has

Table 2
Estimation results of the supply and demand of natural resources.

Variables	Per capita biocapacity (supply)			Per capita footprint (demand)		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
Mean temperature, square		0.2860*	0.3931**		0.1820***	0.2389***
		(0.1596)	(0.1907)		(0.0373)	(0.0516)
Mean temperature	1.5067	−5.9552**	−8.3967**	0.4723	−4.7536***	−7.7934***
	(2.0352)	(2.4879)	(3.4666)	(0.4837)	(1.1039)	(2.1126)
Annual precipitation, squared		−0.0033	−0.0037		0.0007	0.0011*
		(0.0031)	(0.0034)		(0.0006)	(0.0005)
Annual precipitation	0.1954	0.5925	0.6856	0.0400	−0.0182	−0.0629
	(0.1564)	(0.5028)	(0.5543)	(0.0245)	(0.0685)	(0.0700)
Trend	0.3511	0.3523	0.3612	0.0858	0.0776	0.0921
	(0.3321)	(0.3349)	(0.3345)	(0.0596)	(0.0622)	(0.0634)
Drought index			2.7549			−2.4343**
			(1.9433)			(1.1792)
Variation of mean temperature			0.8091			0.2294
			(1.4147)			(0.7446)
Precipitation intensity index			−9.0456*			−1.9070
			(5.3471)			(2.1534)
Degree-days with mean temperature less than 8 C			−0.0036			−0.0100***
			(0.0092)			(0.0037)
Degree-days with mean temperature higher than 32 C			−0.5124			0.0658
			(0.4794)			(0.0635)
Constant	−4.9292	21.3249	34.9416	19.1458***	44.7153***	79.6575***
	(20.5941)	(13.8956)	(41.6973)	(3.5024)	(5.3589)	(16.2215)
County fixed effects	Y	Y	Y	Y	Y	Y
R^2	0.96	0.96	0.96	0.72	0.73	0.74
Observations	1710	1710	1710	1710	1710	1710

been confirmed by other studies (IPCC, 2014; Lawler et al., 2014; Metzger et al., 2006; Mu et al., 2018, 2017).

5.3. Sustainability under future climate scenarios in the Rio Grande Basin

To simulate future demand and supply of environmental resources (and further environmental sustainability) in the Rio Grande Basin, we use the estimated parameters from Model 3 in combination with climate projections from 20 global climate models for two emission scenarios, including RCP4.5 and RCP8.5. For this purpose, we first projected the demand and supply of environmental resources for the baseline period (1976–2005 average) and then for three future time scales as follows: early-period (labeled '2030' as the 2010–2039 average), mid-period (labeled '2050' as the 2040–2069 average), and late-period (labeled '2070' as the 2070–2099 average). The projected values for all three future time scales were further expressed as the percent change from the baseline. In a next step, the environmental sustainability indicator was calculated as the difference between the predicted demand and supply of environmental resources ($ef-bc$) and expressed as a percent change from the baseline for each future time scale.

The results show that under future climate projections and emission scenarios, the per capita environmental capacity is expected to decline, while the per capita ecological footprint will possibly increase by the late-period of the 21st century (Fig. 3). The projection results also show visible variations of climate change impacts across different emission scenarios and time scales. For example, changes in both per capita ecological footprint and environmental biocapacity have a larger range under the high emission scenario (RCP 8.5) than changes under the medium emission scenario (RCP 4.5). In addition, percent changes in both per capita ecological footprint and environmental biocapacity are relatively small in the early-period (i.e., 2030), while they become more significant in the late-period (i.e., 2070). These findings suggest that severe changes in temperature, precipitation, and weather extremes in the high emission scenario by the late-period could more severely affect the demand and supply of environmental resources than those changes in the medium emission level scenario by the early-period.

In addition, the Rio Grande Basin is anticipated to become less sustainable under future climate projections and emission scenarios (Fig. 4). The left graph in Fig. 4 shows the environmental sustainability levels across time scales for two emission scenarios, while the right graph displays the percent changes of environmental sustainability from the baseline period. Compared to the baseline, the Rio Grande Basin would be sustainable in most of the analyzed years, with the sustainability indicator less than zero; however, the region could become less sustainable by the end of the 21st century. More importantly, the projected results show that the Rio Grande Basin could become unsustainable under the high emission scenario (i.e., RCP8.5), with the sustainability indicator greater than zero, due to projected warmer and dryer climate conditions in this region (Fig. 1). Both graphs in Fig. 4 show a large variability of the projected sustainability in different emission scenarios and time scales. This suggests high uncertainty of climate impacts and the importance to consider different emission scenarios and time scales for climate change impact assessments (Burke et al., 2015).

In order to determine counties that are most vulnerable to the projected climate variations, we mapped the geographic distribution of the sustainability levels across the U.S. Rio Grande Basin for three future time scales and two emission scenarios (Fig. 5). The regional analysis shows that sustainability level changes in most Rio Grande counties do not vary considerably over time regardless of the emission scenario. For example, counties in south Texas are projected to remain unsustainable in both emission scenarios and three time scales. However, large variations have been found within the same time scale across the entire Rio Grande region suggesting that some counties might become less sustainable than others in this region. For instance, the Crane, Crockett, Pecos, Reagan, Reeves, Schleicher, Sutton, and Upton counties in northwestern Texas are projected to become less sustainable or even unsustainable. At the same time, the Socorro, Lincoln, and Lea counties in central and eastern New Mexico are projected to become more sustainable by the end of the 21st century under the higher emission scenario.

5.4. Discussion

In summary, this study found that the Rio Grande Basin would most

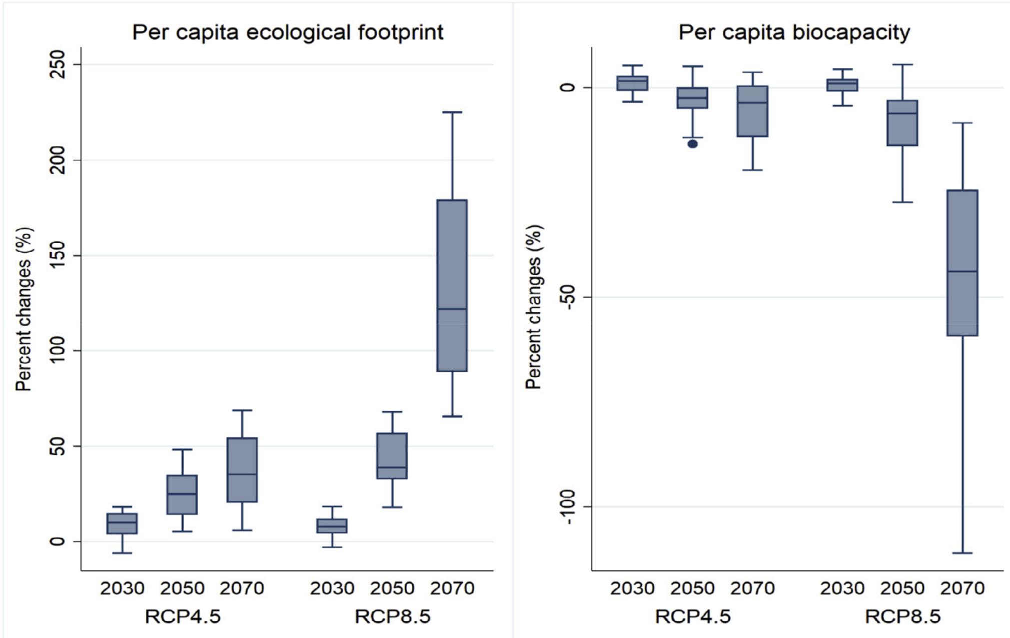

Fig. 3. Percent changes in per capita ecological footprint and biocapacity under future climate (Note: All values are aggregated across 20 global climate models for all counties in the Rio Grande Basin).

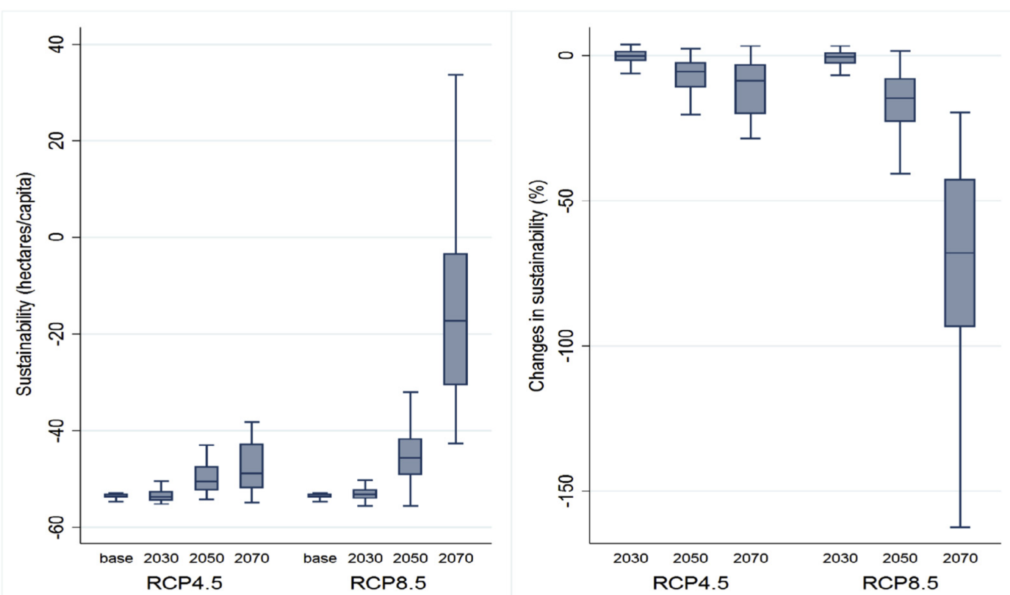

Fig. 4. Changes in sustainability from the baseline under future climate (Note: Values are aggregated across 20 global climate models for all counties in the Rio Grande Basin; the sustainability indicator is defined as the difference between the per capita ecological footprint and the per capita biocapacity. Negative values show sustainable conditions, while positive values indicate unsustainable conditions).

likely remain sustainable under future climate scenarios in the short term; however, it might become less sustainable or even unsustainable in the long term. In addition, the projected environmental sustainability indicator shows large variations due to different climate model projections, emission scenarios and time scales, with some counties indicating lower sustainability levels and other counties showing higher sustainability levels under future climate scenarios.

These findings provide valuable information for sustainable resource management and allocation of local environmental resources. They also emphasize the need to protect the capacity of local environmental resources and to mitigate greenhouse gas emissions from local economic activities. Understanding changes in environmental sustainability has important practical implications. In this regard, it is crucial to develop measures, like regulations, incentive programs, and tax credits that can promote sustainable development and define priorities for resource conservation in different sectors, different economic activities, and different regions. This could support not only the environmental but also economic and social aspects of sustainability, which in turn could promote economic growth in local communities while fostering resource conservation.

6. Conclusions

This paper presented an integrated approach to predict the conditions and changes in environmental sustainability under future climate projections for different emission scenarios and time scales. The empirical application of the presented approach suggests that the Rio Grande Basin has been sustainable and the environmental sustainability indicator has been affected by historical climate conditions. In addition, the basin is projected to be moving away from sustainability or even

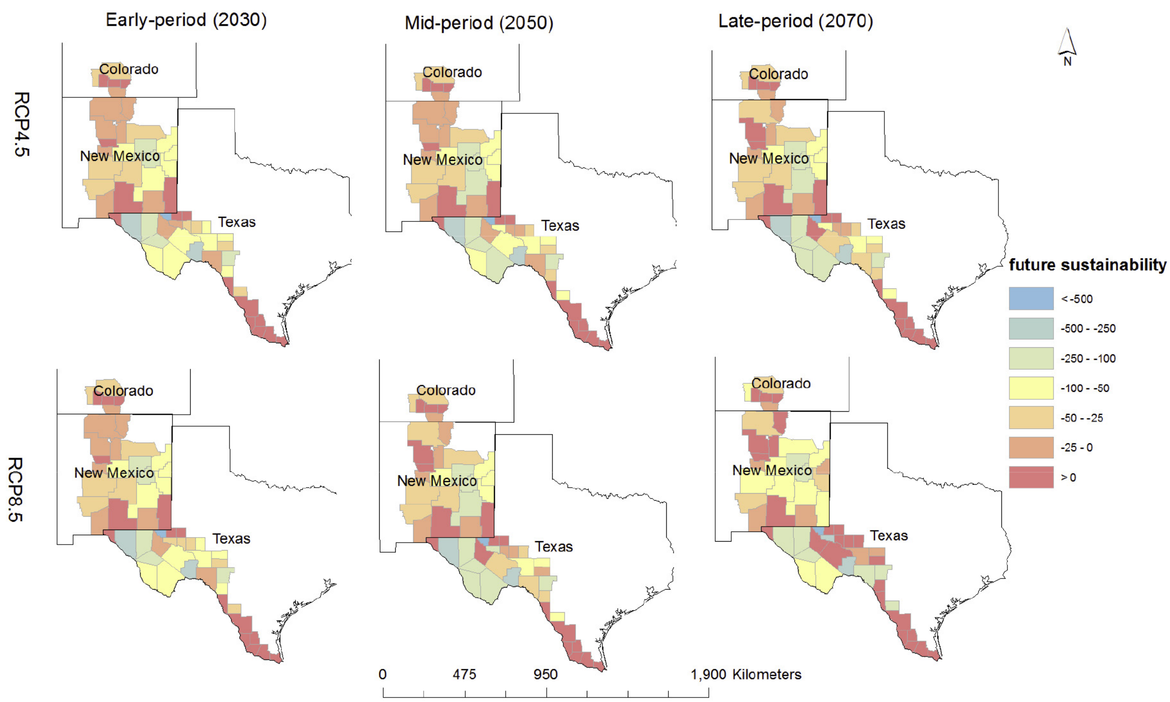

Fig. 5. Geographic distribution of the future sustainability levels in the Rio Grande Basin (Note: Values are aggregated across 20 global climate models in the Rio Grande Basin; the sustainability indicator is defined as the difference between the per capita ecological footprint and the per capita biocapacity. Negative values show sustainable conditions, while positive values indicate unsustainable conditions).

become unsustainable under future projected climate scenarios. These outcomes denote that the rate of natural resource consumption will be greater than the rate of resource production/provision by local ecosystems in the U.S. Rio Grande Basin.

A particular strength of the presented integrated approach is that it includes analyses of climate impacts on the supply and demand of environmental resources, which has not been found or demonstrated in the existing sustainability literature before. More importantly, this approach could be replicated and applied to different spatial scales, including local, regional or national analyses, to examine changes in environmental sustainability under future climate scenarios.

In this specific application, the national/state level data used as a substitute for the county level data as well as the use of linear interpolation for missing data diminish the regional specificity of the analysis to some degree. The approach and models could be fine-tuned if local data were available. However, the presented procedure is necessary because the calculated sustainability indicators are indispensable for the following evaluation of the environmental sustainability trends under future climate scenarios. On the other hand, however, it needs to be emphasized that from a policy perspective, information about long-term trends of environmental sustainability as presented here could be more meaningful for decision-making processes than specific values, particularly considering future climate variability.

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References

Abatzoglou, J.T., 2013. Development of gridded surface meteorological data for ecological applications and modelling. Int. J. Climatol. 33, 121–131.
Abatzoglou, J.T., Brown, T.J., 2012. A comparison of statistical downscaling methods suited for wildfire applications. Int. J. Climatol. 32, 772–780.
Arnell, N.W., 2004. Climate change and global water resources: SRES emissions and socio-economic scenarios. Global Environ. Change 14, 31–52.
Bagliani, M., Galli, A., Niccolucci, V., Marchettini, N., 2008. Ecological footprint analysis applied to a sub-national area: the case of the Province of Siena (Italy). J. Environ. Manage. 86, 354–364.
Burke, M., Dykema, J., Lobell, D.B., Miguel, E., Satyanath, S., 2015. Incorporating climate uncertainty into estimates of climate change impacts. Rev. Econ. Stat. 97, 461–471.
Cano-Orellana, A., Delgado-Cabeza, M., 2015. Local ecological footprint using Principal Component Analysis: a case study of localities in Andalusia (Spain). Ecol. Ind. 57, 573–579.
Chambers, N., Simmons, C., Wackernagel, M., 2014. Sharing Nature's Interest: Ecological Footprints as an Indicator of Sustainability. Routledge.
Collins, A., Flynn, A., Wiedmann, T., Barrett, J., 2006. The environmental impacts of consumption at a subnational level. J. Ind. Ecol. 10, 9–24.
Erb, K.-H., 2004. Actual land demand of Austria 1926–2000: a variation on ecological footprint assessments. Land Use Policy 21, 247–259.
Field, C.B., 2012. Managing the risks of extreme events and disasters to advance climate change adaptation: special report of the intergovernmental panel on climate change. Cambridge University Press.
Flato, G., Marotzke, J., Abiodun, B., Braconnot, P., Chou, S.C., Collins, W.J., Cox, P., Driouech, F., Emori, S., Eyring, V., 2013. Evaluation of climate models. In: climate change 2013: the physical science basis. Contribution of working group I to the fifth assessment report of the intergovernmental panel on climate change. Climate Change 5, 741–866.
Galloway, J.N., 2001. Acidification of the world: natural and anthropogenic. Water Air Soil Pollut. 130, 17–24.
Geist, H.J., Lambin, E.F., 2002. Proximate causes and underlying driving forces of tropical deforestation: Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. Bioscience 52, 143–150.
Goodland, R., 1995. The concept of environmental sustainability. Annu. Rev. Ecol. Syst. 26, 1–24.
Graymore, M.L., Sipe, N.G., Rickson, R.E., 2008. Regional sustainability: how useful are current tools of sustainability assessment at the regional scale? Ecol. Econ. 67, 362–372.
Heberling, M.T., Hopton, M.E., 2014. Assessing sustainability when data availability limits real-time estimates: using near-time indicators to extend sustainability metrics. Clean Technol. Environ. Policy 16, 739–748.
Heinemann, J.A., Massaro, M., Coray, D.S., Agapito-Tenfen, S.Z., Wen, J.D., 2014. Sustainability and innovation in staple crop production in the US Midwest. Int. J. Agric. Sustain. 12, 71–88.
Hopton, M.E., Berland, A., 2015. Calculating Puerto Rico's ecological footprint (1970–2010) using freely available data. Sustainability 7, 9326–9343.
Hopton, M.E., White, D., 2012. A simplified ecological footprint at a regional scale. J. Environ. Manage. 111, 279–286.
Howard, J.L., Jones, K.C., 2016. U.S. timber production, trade, consumption, and price

statistics, 1965-2013, Madison, WI, p. 91.
Huber, D.G., Gulledge, J., 2011. Extreme weather and climate change: understanding the link, managing the risk. Pew Center on Global. Climate Change Arlington.
IPCC, 2014. Climate Change 2014–Impacts, Adaptation and Vulnerability: Regional Aspects. Cambridge University Press.
Lammers, A., Moles, R., Walsh, C., Huijbregts, M.A., 2008. Ireland's footprint: a time series for 1983–2001. Land Use Policy 25, 53–58.
Lawler, J.J., Lewis, D.J., Nelson, E., Plantinga, A.J., Polasky, S., Withey, J.C., Helmers, D.P., Martinuzzi, S., Pennington, D., Radeloff, V.C., 2014. Projected land-use change impacts on ecosystem services in the United States. Proc. Natl. Acad. Sci. 111, 7492–7497.
Malhi, Y., Roberts, J.T., Betts, R.A., Killeen, T.J., Li, W., Nobre, C.A., 2008. Climate change, deforestation, and the fate of the Amazon. Science 319, 169–172.
Medved, S., 2006. Present and future ecological footprint of Slovenia – the influence of energy demand scenarios. Ecol. Model. 192, 25–36.
Metzger, M.J., Rounsevell, M.D.A., Acosta-Michlik, L., Leemans, R., Schröter, D., 2006. The vulnerability of ecosystem services to land use change. Agric. Ecosyst. Environ. 114, 69–85.
Milman, A., Short, A., 2008. Incorporating resilience into sustainability indicators: an example for the urban water sector. Global Environ. Change 18, 758–767.
Moldan, B., Janoušková, S., Hák, T., 2012. How to understand and measure environmental sustainability: indicators and targets. Ecol. Ind. 17, 4–13.
Moore, J., Kissinger, M., Rees, W.E., 2013. An urban metabolism and ecological footprint assessment of Metro Vancouver. J. Environ. Manage. 124, 51–61.
Mu, J.E., McCarl, B.A., Sleeter, B., Abatzoglou, J.T., Zhang, H., 2018. Adaptation with climate uncertainty: an examination of agricultural land use in the United States. Land Use Policy 77, 392–401.
Mu, J.E., Sleeter, B.M., Abatzoglou, J.T., Antle, J.M., 2017. Climate impacts on agricultural land use in the USA: the role of socio-economic scenarios. Clim. Change.
Neumayer, E., 2012. Human development and sustainability. J. Human Dev. Capab. 13, 561–579.
Niccolucci, V., Galli, A., Kitzes, J., Pulselli, R.M., Borsa, S., Marchettini, N., 2008. Ecological footprint analysis applied to the production of two Italian wines. Agric. Ecosyst. Environ. 128, 162–166.
Rees, W., Wackernagel, M., 1996. Urban ecological footprints: why cities cannot be sustainable – and why they are a key to sustainability. Environ. Impact Assess. Rev. 16, 223–248.
Storey, M., Anderson, P., 2014. Income and race/ethnicity influence dietary fiber intake and vegetable consumption. Nutr. Res. 34, 844–850.
Tebaldi, C., Hayhoe, K., Arblaster, J.M., Meehl, G.A., 2006. Going to the extremes. Clim. Change 79, 185–211.
Thomas, C.D., Cameron, A., Green, R.E., Bakkenes, M., Beaumont, L.J., Collingham, Y.C., Erasmus, B.F., De Siqueira, M.F., Grainger, A., Hannah, L., 2004. Extinction risk from climate change. Nature 427, 145–148.
Urban, M.C., 2015. Accelerating extinction risk from climate change. Science 348, 571–573.
USGS, 2017. USGS Water Data for the Nation. accessed 6 Sep, 2017. https://waterdata.usgs.gov/nwis.
Vörösmarty, C.J., Green, P., Salisbury, J., Lammers, R.B., 2000. Global water resources: vulnerability from climate change and population growth. Science 289, 284–288.
Wackernagel, M., Monfreda, C., Erb, K.-H., Haberl, H., Schulz, N.B., 2004. Ecological footprint time series of Austria, the Philippines, and South Korea for 1961–1999: comparing the conventional approach to an 'actual land area'approach. Land Use Policy 21, 261–269.
Wced, U., 1987. Our common future. World Commission on Environment and. DevelopmentOxford University Press.