Spatial-temporal change in water table depth for the conterminous United States over three decades

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ABSTRACT

The subtle equilibrium between supply and demand of freshwater is constantly changing due to anthropogenic activities and shifts in land use and climate. These freshwater resources are crucial for food and water security, and the sustainability of natural and managed systems. The spatial-temporal properties of groundwater are often overlooked, despite these subsurface reservoirs being linked to aboveground water use and ecosystem processes. In this study, we assessed the spatial-temporal changes of water table depth in the conterminous United States (U.S.) over the last three decades (1989-2019). National Ground-Water Monitoring Network water table depth data were paired with climate and terrain features. Interpolated maps were created by combining machine learning (i.e., gradient boosted regression trees) with traditional interpolation methods (i.e., Kriging). Water table depth is shallower in the eastern U.S., as compared to western U.S., except for high elevation locals which consistently had deeper water tables. The overall change in depth to water table for the conterminous U.S. was ~1m indicating that on average the water is getting deeper. Of the 56 aquifer systems, 41 are in areas where the water table has gotten deeper. These results highlight current "hotspots" of possible depletion where water management efforts should focus. Management of this crucial resource is essential for mitigating negative impacts of depletion, which may ultimately feedback further amplifying changes in climate.

Key words: Aquifer, climate change, groundwater, water stress

MAIN

The delicate equilibrium between human activity and freshwater reserves is constantly challenged by the ever-increasing demand for freshwater to meet agriculture, forestry, and urban needs [1]. A significant portion of freshwater is stored below the surface, filling spaces in the soil (i.e., soil moisture) or inside aquifers (i.e., groundwater) [2], from which the latter accounts for roughly 30% of total freshwater reserves [3]. Groundwater is replenished through infiltration from precipitation, snow melt, and surface water seepage (i.e., streams, rivers, lakes, and wetlands). After entering the water table, groundwater can be stored in aquifers, laterally flow between aquifers, discharge into surface water, or is pulled by capillary flux to the root zone for plant use as part of the water cycle [2,4,5]. Anthropogenic activities disrupt this cycle through pumping for human consumption, as well as the indirect effect of agriculture and intensively managed forest crops that increase the pressure for water resources [1,2,6]. Groundwater reserves have received less attention as compared to other resources that are part of the sustainability equation, and its long-term fate has not been traditionally thought of as a limited resource [2]. The water table has become a significant point of concern to ensure sustainable development in areas with low precipitation and high pressure for belowground water resources (e.g., Australia, Spain, and South Africa) [5]. However, forecasted changes in climate patterns are expected to have multiscale impacts on worldwide freshwater reserves making this a global issue. These impacts vary from amplifying freshwater depletion, altering the landscape through effects on vegetative communities, or influencing land-atmosphere water, carbon, and energy exchanges [1,7-11].

Groundwater depletion can have drastic effects on natural and managed land (i.e., agriculture and forestry) in the United States (U.S.) (i.e., ~50% of total land area; ~300 million hectares of forest/woodlands and ~150 million hectares of croplands) [12,13]. Water table depth

strongly influences soil moisture and drainage, evapotranspiration, plant growth, basal area, and foliar nitrogen [14-16]. In fact, water use in some plant species is largely dependent on groundwater resources; for example in some *Eucalytpus* forests, 40-100% of water is obtained from groundwater [17]. Anthropogenic activities in these managed areas create a feedback whereby management practices alter the quality and quantity of groundwater, and the water table depth. Agriculture (e.g., groundwater irrigation; one of the most significant contributors to groundwater depletion) and forest management practices (e.g., harvesting, bedding, thinning, and prescribing fire) also alter water table depth [18-20], especially in areas where rainfall is not enough to cope with the negative inflow of water.

Given the implications of groundwater depletion and the threat of climate change further amplifying the magnitude of groundwater depletion, development of water table depth data and assessments of temporal fluctuations and change are critical for water resource management. Prior research has used inverse distance weighting (IDW), radial basis functions, and kriging (ordinary, simple, universal, and fuzzy) for water table interpolations [21-26]. These studies have documented water table depth for infrequent and irregularly scattered data, sometimes on smaller spatial and temporal scales, or are not available for the entire U.S. Having a complete picture for changes in depth to water table could allow for a better insight for developing public policies as related to environmental resource uses. Over the last few decades computer algorithms have improved exponentially, allowing for a shift in the interpolation paradigm from traditional kriging to a more contemporary ensemble of machine learning interpolation methods driven by the existing data. These methods, when combined with a large number of auxiliary variables, allow for improved predictions. In this research, we use these contemporary methods; however, since our major objective is to make inference about the phenomena, we still include a traditional evaluation for

the uncertainty present in our estimates. Thus, the objectives of this study were: 1) to create depth to water table maps with estimated prediction uncertainty for the conterminous U.S., and 2) to assess how water table depth has changed over the last three decades (1989-2019) to highlight areas at risk and guide sustainable development of agriculture and/or forestry.

Spatio-temporal Change in Depth to the Water Table

Conterminous U.S. depth to water table data from the National Ground-Water Monitoring Network (NGWMN) indicates that in 1989 the average water table depth was ~15m. This number increased to circa ~30m in 2019, showing a rate of 0.5 meters per year increase over a 30 year period (Fig. 1). Similarly, there have been changes in cumulative annual precipitation (~1.3×10^9 mm rise), temperatures (~ 1^oC increase for minimum, maximum, and average temperatures), and cumulative snow water equivalent (~2.1×10^8 kg/m^2 decrease) (Fig. 1).

The interpolated predictions estimated the average water table depth to be -44.6 m in 1989 and -45.5 m in 2019. In general, the predicted water table was predicted to be deeper in the western U.S. as compared to the eastern U.S. (Fig. 2). Additionally, the predicted depth to water table increased as elevation increased, such as the Appalachian, Cascades, Rocky, and Sierra Nevada mountain ranges (Fig. 2). When assessing the change in water table depth from 1989 to 2019, predictions indicated that on average the water table depth has increased (i.e., gotten deeper) by ~1m or 0.03 m/year. This ~1m drop in the water table over the last 30 years is not as severe as the drop indicated by the raw data (>10 m); however, this discrepancy may be due to spatial variation regarding the direction of change in the water table depth across the U.S., as well as averages from the raw data being more sensitive to individual measurements and locations with only few observations. Overall, maximum water table depth (i.e., furthest subsurface distance) was

relatively similar in 1989 and 2019 (~1600m); however, the minimum depth to water table differed by ~300 m. Since this change (i.e., minimum depth to water table) occurred in areas where the water table depth was >0m, these shifts are likely due to changes in surface water levels. In general, the water table has become shallower in most of the western and northeastern U.S., as well as eastern U.S. coastal areas (Fig. 3; Table 1). This decrease in water table depth is most prominent in parts of Idaho, New Mexico, southeastern Texas, and Utah; however, California Central Valley, Colorado, western Texas, and some high elevation locals are exceptions, as our predictions indicated that these areas have seen a deepening of the water table. Some of these areas have particularly slow groundwater recharge (i.e., low precipitation and increased droughts) and increased human demand [27,28]. Conversely, water table depth has been getting deeper in the midwestern and inland southeastern U.S. (Fig. 3; Table 1). The largest increases in depth occurred in in parts of Alabama, Georgia, Illinois, Indiana, Iowa, Missouri, Michigan, Mississippi, North Carolina, Ohio, South Carolina, Tennessee, West Texas, and Wisconsin. In fact, both Illinois and Indiana were predicted to have seen an average water table depth increase > 20m over the last three decades (Table 1).

Our analysis indicates the water table is becoming deeper in historically wet regions, particularly in areas with high hectarage focused on crops and timberlands (predominately conifers), despite some of these locations receiving the highest amount of rainfall (e.g., southeastern U.S.) [29]. The vegetative systems in the southeastern U.S. are of concern because, 1) water table depth changes may negatively impact economically important crops (i.e., indirectly via reduced ground-fed irrigation) and forests (i.e., directly via reduced root access to groundwater), and 2) these systems may be partial drivers of this water table change. Conifers, the most predominant tree type in the southeastern U.S., are often characterized as isohydric and are thought

114 to be less susceptible to drought due to their water-use strategy and increased wood density helping
115 to prevent xylem cavitation [30,31]. However, severe reductions in available water interrupts water
116 transport, and this loss of hydraulic conductance ultimately kills roots and can lead to mortality,
117 along with other inciting factors (e.g., biotic agents), regardless of carbon reserves [30,32]. Since
118 hydraulic traits shift somewhat for a given species based on water availability, it is difficult to
119 determine whether species-level plant responses are due to environment, genotype or both [33].
120 Increased ground-fed irrigation in this region is likely a contributing factor and is widely discussed
121 in the literature [34], but forest plantations may play a larger role. Forests typically use more water
122 than agricultural cropland, especially conifers, and possess root systems that are deep enough to
123 access shallow water tables (*discussed in Benyon et al. 2006*). Further compounding this increase
124 in water use, increased growth rates in forest plantations due to genetic engineering may also result
125 in increased groundwater use. Future research should quantify the drivers and consequences of
126 this water table drop and develop plans for the sustainable management of these resources.

127

128 **Water Table Depth Change by Aquifer**

129 Interestingly, some of the most significant water table depth changes aligned with principal
130 aquifers in the U.S. Based on the 56 aquifer systems in the conterminous U.S. identified by the
131 U.S. Geological Survey (2003), the interpolated predictions indicate that the water table has gotten
132 deeper in 41 systems over three decades (Table 2). Of these aquifers, water table depth has gotten
133 deeper by >10 m for 12 systems (Ada-Vamoosa, Cambrian-Ordovician, Central Oklahoma,
134 Denver Basin, Jacobsville, Marshall, Northern Rocky Mountains, Pacific Northwest, Seymour,
135 Southeastern Coastal Plain, Upper Tertiary, and Valley and Ridge Carbonate-rock) (Table 2). The
136 largest increases in water table depth occurred in Denver Basin (21.4±1.00), Jacobsville

(20.9±0.35), and Pecos River Basin Alluvial (24.8±0.294) aquifer systems. Many of these aquifers have experienced significant groundwater withdrawals over the last few decades, primarily for agricultural irrigation [34,35].

Prior work quantifying groundwater reserves and depletion for specific aquifers have identified "hot spots" for depletion and raised concerns about local and/or regional sustainability of water resources [28]. California Central Valley groundwater reserves have helped mitigate the impacts of drought, but depletion has occurred due to increased water use at a rate faster than groundwater recharge [36]. Prior work has also predicted severe groundwater declines in the High Plains aquifer, particularly in the southern portion [28,37,38], and has the largest volume of groundwater extracted every year of any major aquifer system [34,39]. The spatial variation in depletion within this aquifer may partially be due to groundwater recharge rates, as Scanlon and others (2012) found that southern recharge rates are significantly slower than the northern portion of the aquifer. These differences may be further amplified under future climate changes [39]. The southern portion of the High Plains aquifer coincides with one of the largest predicted water table depth drops in our study. The predicted drop in water table follows the aquifer north until Nebraska, at which point there are a few areas with significant drops but is primarily dominated by a rise in water table (*also discussed in McGuire 2017*).

Implications

Existing knowledge and characterization of vertical subsurface geology and available water is lacking in current literature but is critical when assessing plant-water relationships and the feedbacks that occur under water stress. Knowledge on groundwater systems will add to current

hydrologic and hydraulic models, allowing for a more comprehensive understanding of these relationships. Our study provides the first comprehensive assessment of depth to water table in the conterminous U.S., as well as the temporal difference in depth from 1989-2019. We found that water table depth has changed significantly over the last three decades. Subsurface freshwater reserves in these areas may be at risk for depletion if the process of groundwater recharge is slower than the rate of anthropogenic use. If water table depth continues to move deeper, as the trends in our predictions show, this may further reduce the rate of groundwater recharge, with important consequences for water resource sustainability.

The urgent need for groundwater management and monitoring extends beyond the aforementioned hydrological systems, as research has shown that groundwater depletion results in reduced water quality, lowering of the water table, land subsidence, sea-level rise, depletion of surface freshwater, contamination in coastal aquifers from saltwater intrusion, and climate feedbacks [7,8]. This study may be built on with the inclusion of aquifer characteristics (e.g., depth and volume) and satellite data (i.e., soil moisture and surface water levels) to increase the precision of estimates. Additionally, this work serves as the foundation for future research aimed to fill gaps in knowledge, such as quantifying and evaluating, 1) the role of groundwater in plant physiology, 2) impacts of the temporal changes in water table depth on vegetation, 3) the complex interactions and/or additive effects of climate change, 4) how current water use is influencing these critical freshwater reserves, and 5) the role of groundwater in water, energy, and carbon land-atmosphere exchanges at a national scale.

COMPETING INTEREST DECLARATION: The authors declare no competing interests.

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Table 1. Average water table depth change (m) (±SE) from 1989 to 2019 by state in the conterminous United States

State	Water table depth (m)	±SE	State	Water table depth (m)	±SE
Alabama	11.0	0.01	Nebraska	0.04	0.01
Arizona	-30.8	0.04	Nevada	-7.36	0.04
Arkansas	2.24	0.01	New Hampshire	-5.02	0.04
California	-7.13	0.05	New Jersey	5.71	0.01
Colorado	9.76	0.03	New Mexico	-1.79	0.03
Connecticut	4.12	0.02	New York	-4.83	0.02
Delaware	-0.34	0.01	North Carolina	5.08	0.02
Florida	2.32	0.00	North Dakota	6.33	0.01
Georgia	6.24	0.01	Ohio	10.4	0.01
Idaho	-20.3	0.01	Oklahoma	5.84	0.01
Illinois	27.6	0.01	Oregon	-5.07	0.05
Indiana	22.0	0.01	Pennsylvania	0.55	0.02
Iowa	15.5	0.01	Rhode Island	6.52	0.01
Kansas	4.80	0.01	South Carolina	3.89	0.01
Kentucky	7.94	0.01	South Dakota	4.37	0.01
Louisiana	5.92	0.01	Tennessee	10.3	0.02
Maine	-5.80	0.02	Texas	5.43	0.02
Maryland	-2.03	0.02	Utah	-10.5	0.04
Massachusetts	0.32	0.02	Vermont	-3.71	0.04
Michigan	18.5	0.01	Virginia	2.69	0.02
Minnesota	4.46	0.01	Washington	-8.94	0.07
Mississippi	11.7	0.01	West Virginia	1.44	0.02
Missouri	11.3	0.01	Wisconsin	14.6	0.01
Montana	-5.38	0.05	Wyoming	0.82	0.03

* Calculations were based on maps produced using a multistep interpolation technique (gradient boosting and kriging). Positive values indicate the water table is becoming deeper and negative values indicate the water table is becoming shallower.

Table 2. Average change (±SE) in water table depth for aquifers in the United States from 1989 to 2018

Aquifer System	Change (m)	±SE	Aquifer System	Change (m)	±SE
Ada-Vamoosa	13.3	0.28	New York Sandstone	-9.19	0.22
Arbuckle-Simpson	-6.07	0.79	Northern Atlantic Coastal Plain	-0.20	0.05
Basin and Range Basin-fill	-1.75	0.17	Northern Rocky Mountains	12.0	0.39
Basin and Range (CAR)	-43.4	0.29	Ordovician	9.85	0.17
Biscayne	0.873	0.03	Ozark Plateaus	5.83	0.12
Blaine	9.61	0.34	Pacific Northwest	11.9	0.17
California Coastal Basin	9.41	0.20	Pacific Northwest (BAS)	-10.5	0.21
Cambrian-Ordovician	13.7	0.08	Paleozoic	-6.67	0.22
Castle Hayne	-4.71	0.07	Pecos River Basin Alluvial	24.8	0.29
Central Oklahoma	13.8	0.45	Pennsylvanian	4.58	0.08
Central Valley	3.91	0.17	Piedmont / Blue Ridge (CAR)	9.19	0.10
Coastal Lowlands	3.64	0.04	Piedmont / Blue Ridge (CRY)	7.82	0.10
Colorado Plateaus	-4.89	0.28	Puget Sound	4.38	1.74
Columbia Plateau (BAS)	-12.7	0.62	Rio Grande	3.90	0.27
Columbia Plateau Basin-fill	1.07	0.40	Roswell Basin	4.19	0.79
Denver Basin	21.4	1.00	Rush Springs	5.15	0.42
Early Mesozoic Basin	1.69	0.08	Seymour	12.2	0.19
Edwards-Trinity	7.46	0.13	Snake River Plain	-8.91	0.25
Floridan	1.67	0.04	Southeastern Coastal Plain	11.0	0.06
High Plains	2.09	0.09	Southern Nevada (VOL)	-32.9	2.13
Jacobsville	20.9	0.34	Surficial	1.64	0.02
Lower Cretaceous	5.65	0.05	Texas Coastal Uplands	-6.81	0.09
Lower Tertiary	3.32	0.08	Upper Carbonate	4.05	0.25
Marshall	17.9	0.17	Upper Cretaceous	4.14	0.19
Mississippi Embayment	9.70	0.07	Upper Tertiary	12.1	0.33
Mississippi River Valley	5.70	0.09	Valley and Ridge	5.06	0.13
Mississippian	9.79	0.06	Valley and Ridge (CAR)	12.5	0.09
New York/ New England (CAR)	-1.04	0.13	Willamette Lowland	-1.67	0.65

* Calculations were based on maps produced using a multistep interpolation technique (gradient boosting and kriging). Positive values indicate the water table is becoming deeper and negative values indicate the water table is becoming shallower. Aquifer shapefile was obtained from the U.S. Geological survey.

** Basaltic rock (BAS), carbonate rock (CAR), crystalline rock (CRY), and volcanic rock (VOL).

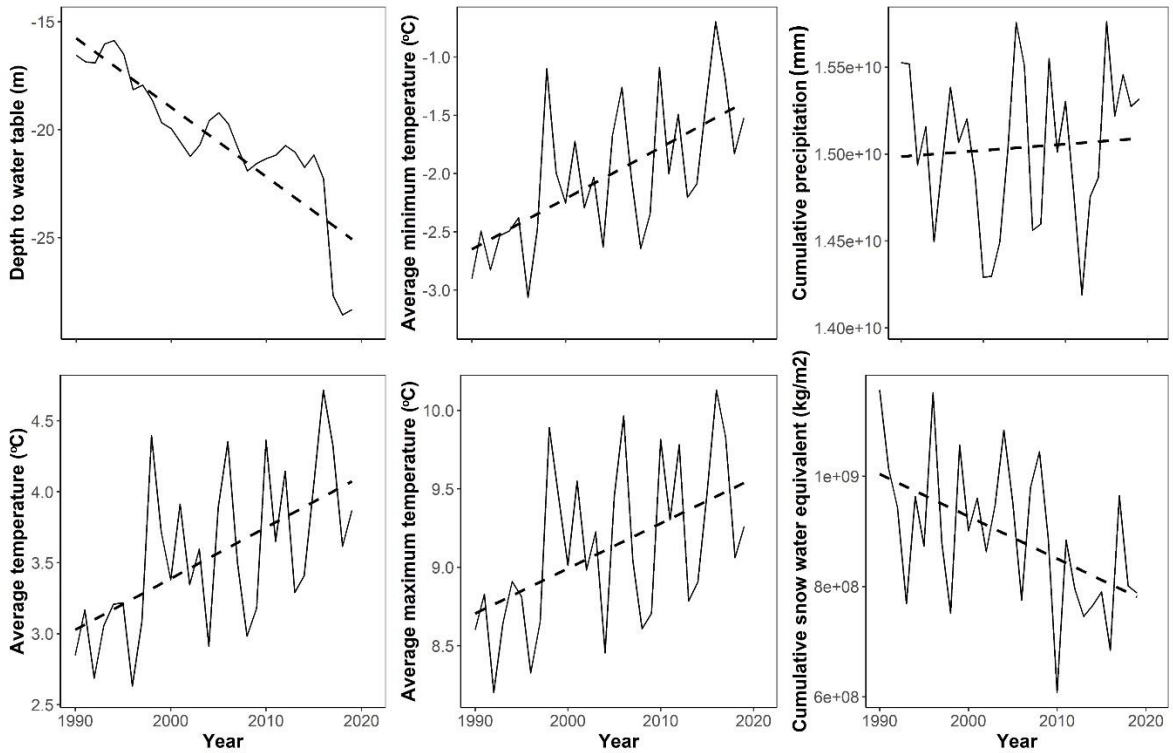

Figure 1. The 30-year trend in water table depth (m), temperature (°C) (i.e., minimum, maximum, and mean annual temperatures), cumulative precipitation (mm), and cumulative snow water equivalent (kg/m^2) for the conterminous United States. Water table depth data were obtained from National Ground-Water Monitoring Network (NGWMN). Climate data were obtained from Daymet Daily Surface Weather and Climatological Summaries (Version 4).

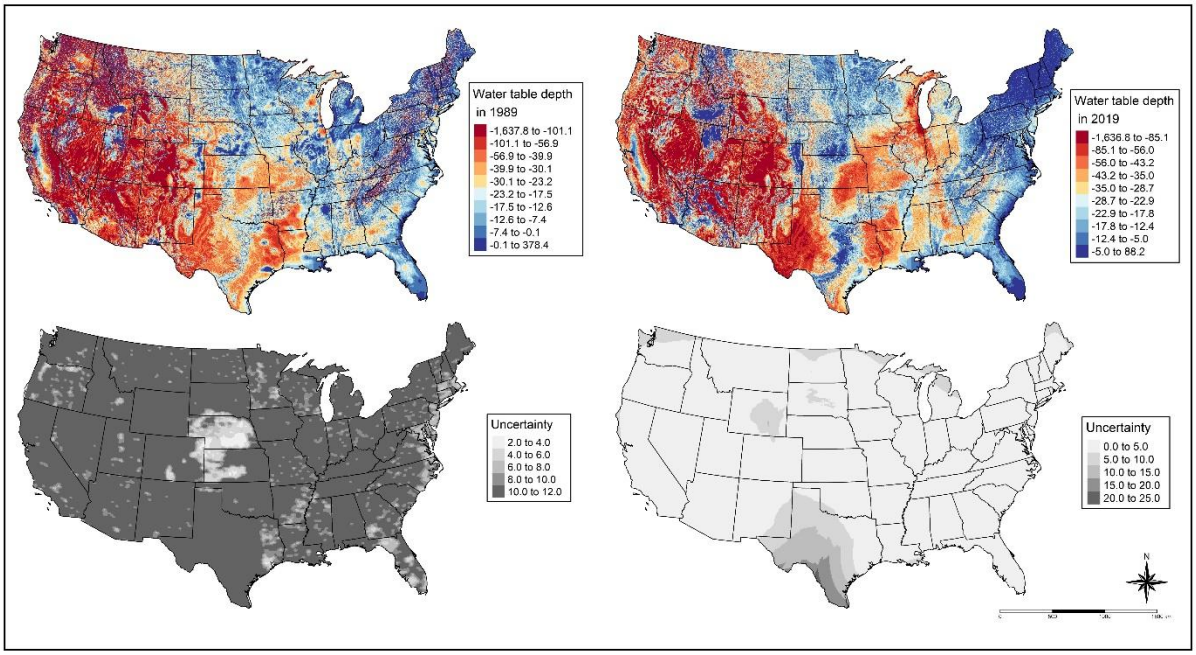

Figure 2. Water table depth (m) predictions and uncertainty for the conterminous United States for 1989 (left) and 2019 (right). Predictions were developed via a combination of stochastic gradient boosted regression tree models (GBRT) and kriging interpolation. Predictions were estimated from the GBRT using climatic variables (i.e., temperature, precipitation, and snow water equivalent), digital elevation model, compound topographic index, and distance to west and east coast as features, and then the extracted residuals were interpolated via Kriging to account for spatial autocorrelation. The GBRT prediction and Kriging interpolation were combined to produce the final prediction maps. Prediction uncertainty (bottom row) was developed from the kriging interpolation of the residuals.

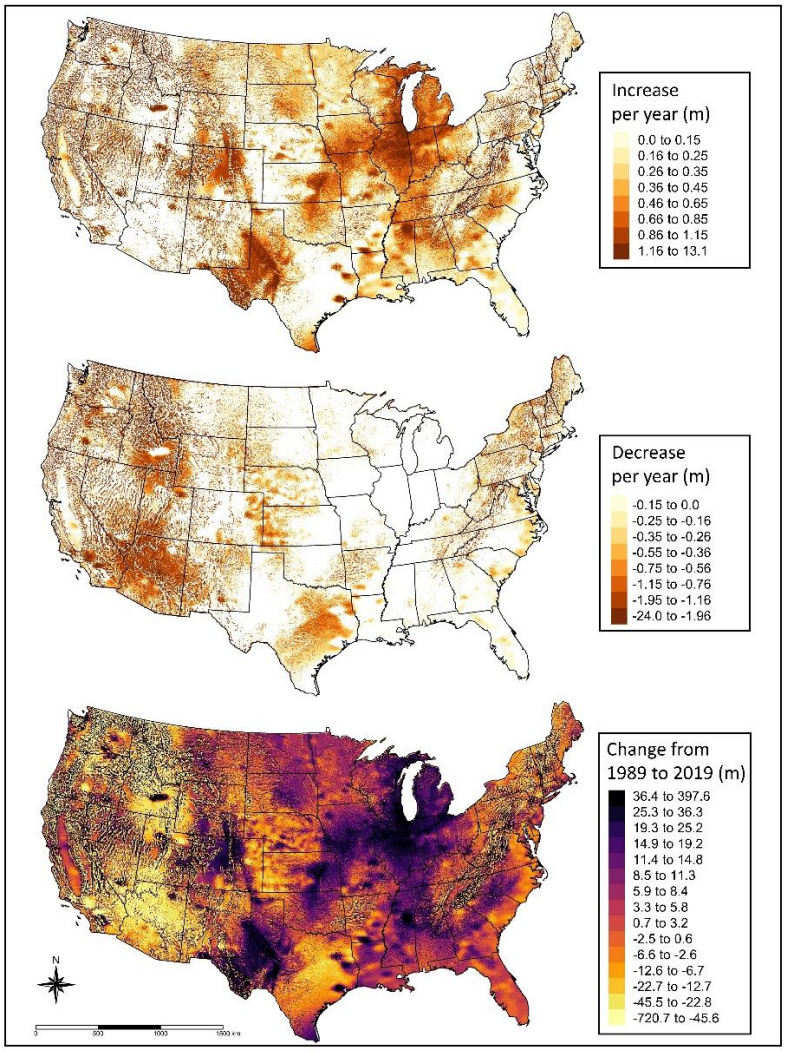

Figure 3. (Top) Annual change for areas predicted to have an increase in water table depth (m). (Middle) Annual change for locations predicted to have a decrease in water table depth (m). (Bottom) Total predicted change in water table depth (m) over the last three decades (1989 to 2019). Negative values indicate the water table is getting more shallow and positive values indicate the water table is becoming deeper. Maps were generated via a multistep approach using gradient boosted regression trees and kriging interpolation of the residuals using the National Ground-Water Monitoring Network data and climatic variables (i.e., temperature, precipitation, and snow water equivalent obtained from Daymet), digital elevation model, compound topographic index, distance to west coast, and distance to east coast as features.

METHODS

Data Acquisition

To create depth to water table maps and their corresponding uncertainty estimates, as well as assess change over time, point estimates for the conterminous U.S. were obtained from the National Ground-Water Monitoring Network (NGWMN). NGWMN is a collection of principal and major aquifer data from local, state, and federal organizations, which includes information on quality and quantity of groundwater reserves. Data included 14,351 sites and 17,632,047 observations for the years 1989-2019 (Supplemental Figure 1). Across locations, this dataset was recorded at different temporal resolutions: yearly, monthly, and daily, so for our study every location was coerced into yearly values. In this research, instead of estimating depth to water table as the dependent variable, we used the elevation of the water table, as this value should allow for a smoother transition between adjacent sampling points, similar to [1]. Height of water table was converted back to depth to water table for visualization.

To improve our inference a set of auxiliary variables proven to have a relation with depth to water table were included [2-7]. We paired point estimates of depth to water table data with environmental data, as well as terrain variables derived out of a base digital elevation model (DEM) created by NASA at 1x1km resolution. Climatic layers (temperature, precipitation, and snow melt equivalent) for 1989-2019 were obtained from Daymet (Version 4), which provides a continuous grid of historical monthly and annual weather data, with a 1x1km spatial resolution [8]. These climatic variables were chosen due to their role in the water cycle, as temperature, precipitation, and snow water equivalent influence evapotranspiration, soil moisture, and the infiltration of water to the water table [9-13]. Out of the DEM, primary (slope, aspect) and secondary terrain attributes (curvatures, upslope contributing areas) were used to calculate a compound

topographic index (CTI). These variables have shown to be important components in catchment hydrology and water table assessments, particularly in the TOPMODEL [14-16].

Modeling Framework

Water table depth analyses were conducted using a three-step interpolation approach: 1) we utilized gradient boosted regression trees (GBRT) to make predictions, 2) we used kriging interpolation on GBRT residuals to reduce bias from spatial autocorrelation, to incorporate a spatial correlation structure and to create uncertainty maps, and 3) we then combined the GBRT and kriging predictions for the final map. This method is equivalent to a Universal Kriging, where in our case, we evaluated the trend using GBRT. First, a stochastic GBRT was used to create interpolated depth to water table maps. GBRT is a nonparametric supervised machine learning technique that contains three main components, an optimized loss function, weak learner decision trees, and an additive model of constructed trees that uses gradient descent [17,18]. GBRT is a forward learning process that sequentially adds new models (i.e., trees) to provide an improved estimate of the response variable, as the addition of each tree maximizes the negative descent of the loss function (i.e., minimizes the loss function). Our GBRT was trained on 80% of the data and the remaining data was used for validation. To allow for increased model performance, the response variable (i.e., depth to water table) was converted to the height of the water table by subtracting the depth to water table from the elevation prior to running the model. Model predictors included elevation, distance from the west coast, distance from the east coast, CTI, minimum annual temperature, maximum annual temperature, average annual temperature, precipitation, and snow water equivalent. GBRT is based on boosting (i.e., number of trees and learning rate) and specific tree (i.e., tree depth and a number of observations in terminal nodes) hyperparameters and can be

tuned to increase model performance. The h2o package used for stochastic GBRT, contains additional hyperparameters that allow for subsampling rows and columns before creating trees and new splits. Our GBRT was based on 50 trees with a tree depth of 5, learning rate of 0.1, and row and column sampling rate of one without replacement. Stochastic GBRT allows for random sampling of training data during each iteration where the sampling rate can be set from zero to one. Higher values have shown to reduce overfitting and increase training performance [19]; thus, we utilized the highest available sampling rate of one. GBRT was used to create annual interpolated maps for the U.S. from 1989 to 2019 using the predictors as base layers (1x1km spatial resolution). Model metrics were calculated for the training and validation datasets to evaluate overall performance. To reduce possible biases arising from spatial autocorrelation, as well as to account for the spatial dependency between observations, the residuals were extracted from the GBRT predictions and interpolated using Kriging. The Kriging model used a type of function that included anisotropy to account for a south west-north east trend in the data. Nugget was included as part of the model to account for within site variations from the expected mean. Once the residuals were interpolated this map was combined with the map produced from the GBRT to create a final map with reduced bias. Uncertainty was extracted from the Kriging interpolation to visualize uncertainty in space (i.e., pixel) and time.

Gradient boosted regression tree analyses and visualizations were completed using R statistical software version 3.6.2[20] and RStudio[21] using the packages ggplot2, h2o, raster, rgdal, sf, sp, tidyverse, tmap, and viridis [22-30]. Kriging interpolation and prediction uncertainty were completed using ArcGIS Pro 2.7.

Model Performance

Model using machine learning interpolation (Gradient boosted regression trees) performed well, as the training (RMSE=17.4; MAE=11.7; R^2=0.99) and validation data (RMSE=17.4; MAE=11.7; R^2=0.99) had comparable evaluation metrics. All features (i.e., climatic variables, digital elevation model (DEM), compound topographic index (CTI), distance to west coast, and distance to east coast) held weight in the model (feature importance is calculated based on how much the squared error is reduced if it is included in a split), and thus, were included in the final prediction (Table 1). DEM held the highest importance (99.7%), while distance to west coast was second most important (0.10%). All other features (minimum, maximum, and average temperature, CTI, precipitation, and snow water equivalent) held a <0.01% importance in the model, and thus their contributed weight in the predictions were low (Table 1).

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