PHILOSOPHICAL TRANSACTIONS B

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Research

Cite this article: Olson JR. 2019 Predicting combined effects of land use and climate change on river and stream salinity. *Phil. Trans. R. Soc. B* **374**: 20180005.
http://dx.doi.org/10.1098/rstb.2018.0005

Accepted: 23 October 2018

One contribution of 23 to a theme issue 'Salt in freshwaters: causes, ecological consequences and future prospects'.

Subject Areas:
environmental science

Keywords:
specific electrical conductivity, salinity, climate change, land use

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Electronic supplementary material is available online at https://dx.doi.org/10.6084/m9.figshare.c.4282559.

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Predicting combined effects of land use and climate change on river and stream salinity

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Agricultural, industrial and urban development have all contributed to increased salinity in streams and rivers, but the likely effects of future development and climate change are unknown. I developed two empirical models to estimate how these combined effects might affect salinity by the end of this century (measured as electrical conductivity, EC). The first model predicts natural background from static (e.g. geology and soils) and dynamic (i.e. climate and vegetation) environmental factors and explained 78% of the variation in EC. I then compared the estimated background EC with current measurements at 2001 sites chosen probabilistically from all conterminous USA streams. EC was more than 50% greater at 34% of these sites. The second model predicts deviation of EC from background as a function of human land use and environmental factors and explained 60% of the variation in alteration from background. I then predicted the effects of climate and land use change on EC at the end of the century by replacing dynamic variables with published projections of future conditions based on the A2 emissions scenario. By the end of the century, the median EC is predicted to increase from 0.319 mS cm^{-1} to 0.524 mS cm^{-1} with over 50% of streams having greater than 50% increases in EC and 35% more than doubling their EC. Most of the change is related to increases in human land use, with climate change accounting for only 12% of the increase. In extreme cases, increased salinity may make water unsuitable for human use, but widespread moderate increases are likely a greater threat to stream ecosystems owing to the elimination of low EC habitats.

This article is part of the theme issue 'Salt in freshwaters: causes, ecological consequences and future prospects'.

1. Introduction

Anthropogenic salinization of rivers and lakes is increasingly recognized as an emerging threat to freshwater resources, biodiversity and ecosystem functions [1]. The 'salinization syndrome' [2] is the result of the combined effects of anthropogenic salt inputs, accelerated geological weathering and weathering of construction materials (i.e. concrete and cement). Humans release salts in the form of a variety of ions (calcium, magnesium, sodium, bicarbonate, sulfate, chloride, etc.) via diverse activities such as industry, agriculture, resource extraction and transportation [3]. In addition to accelerating weathering by releasing strong acids, humans also now move more geological material than natural processes by an order of magnitude [4,5], speeding up weathering by exposing more rock. The problem of increased inputs is further compounded by increased evaporative concentration of salts resulting from human activities. Damming of rivers has been linked to increasing evaporative concentration, causing 12% of the salinization along the Colorado River [6]. As an example, a fourfold increase in salinity along the Rio Grande River has been related to evaporation exacerbated by management and irrigation practices [7]. Human-caused climate change also increases temperatures, which, in turn, increase evaporative concentration [4] and in some regions decrease precipitation,

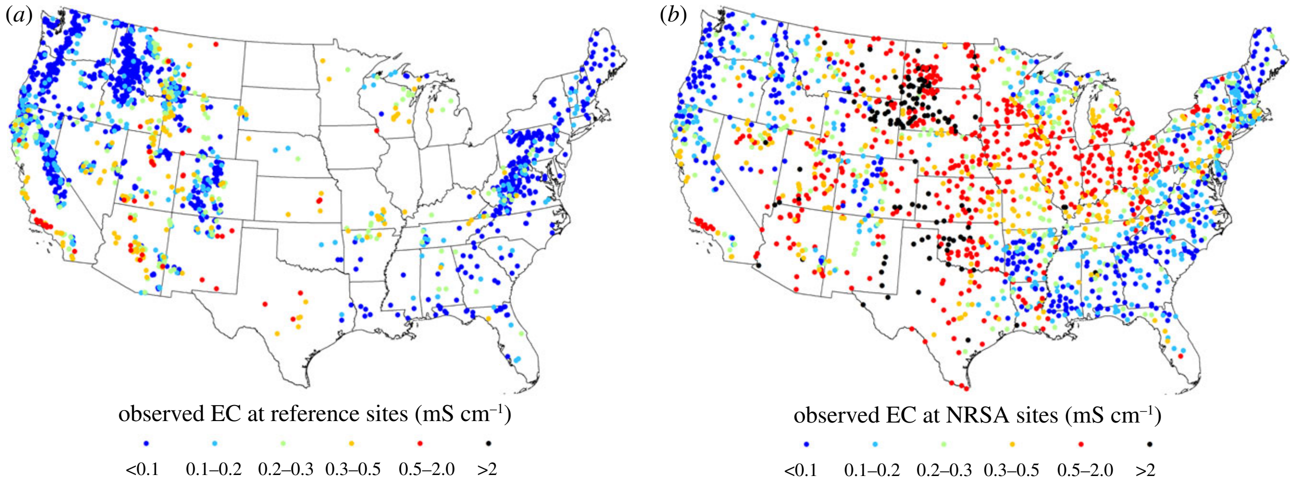

Figure 1. Observations of EC used in this study. (*a*) EC at 1935 reference-quality sites (i.e. determined to be minimally disturbed by human activities affecting EC). (*b*) EC at 2001 probabilistic sites (i.e. sites chosen randomly with respect to size) sampled as part of the National River and Stream Assessment (NRSA).

causing lower dilution and greater salt concentrations. Increased salinity in freshwater systems is expected to cause extensive changes in biota and potentially in ecological function, and some losses of freshwater resources. Ephemeroptera, Plecoptera and Trichoptera are generally sensitive to increased salinity, so salinity increases greater than $1.5\ \mathrm{mS\ cm^{-1}}$ result in them being replaced by Diptera, Coleoptera, Odonata and Hemiptera [8]. This alteration of composition can then result in a shift in ecological function as key organisms like Trichopteran shredders are removed and not replaced by taxa performing similar functions. In the USA, stream salinity (measured indirectly as specific electrical conductivity, EC) naturally varies over four orders of magnitude, from less than 0.01 to greater than $12\ \mathrm{mS\ cm^{-1}}$ [9]. However, human activities can increase EC to over $54\ \mathrm{mS\ cm^{-1}}$ [10], the average concentration of seawater. Increased EC can make freshwater resources no longer suitable for human use. EC above $3\ \mathrm{mS\ cm^{-1}}$ is considered no longer usable for irrigation [11] and above $5\ \mathrm{mS\ cm^{-1}}$ water is no longer suitable for many industrial uses [12].

Although we know salinization is increasing, we lack an estimate of how pervasive it might be, or how much more change is possible given forecasted changes in land use and climate. Long-term monitoring has shown increasing salinity in streams across the USA over the last 25 years [2], but our ability to make inferences about the pervasiveness and severity of salinization is limited by the number of places with a sufficient record of EC. Examining past trends also does not account for the predicted spatial patterns of land use and climate changes. The SPARROW (SPAtially Referenced Regressions on Watershed attributes) model relates salinity to both natural and anthropogenic drivers [13] and could be used to estimate the current loadings derived from human activities, but does not allow estimates of future loads or concentrations. Understanding the extent, severity and locations of future salinization is needed to take steps to manage and protect freshwater resources [1]. To effectively address the challenge of salinization, we specifically need to know how much salinity in streams has already been altered by human activities and how much more alteration is likely with increasing development and climate change.

To better understand how much EC has already changed, and how much more change might be expected, my objectives were to: (1) empirically model background salinity using both static (e.g. geology) and dynamic (e.g. climate) natural environmental factors, (2) determine the amount of current alteration in salinity by comparing current salinity with predicted background, (3) model this alteration as a function of modelled current land use and climate, and (4) replace predictions of current land use and climate with future predictions to estimate EC at the end of the century.

2. Material and methods

(a) Data

I used two datasets of observed stream EC as response variables and an associated set of watershed environmental predictor variables to train the background and alteration models. The background model used a reference dataset measured at sites minimally affected by human activity. The alteration model used a dataset measured at sites probabilistically selected representing the range of effects that human activity has on stream EC. Although high flows and winter road salt applications can result in transport of high loads, I limited both datasets and resulting models to summer base-flow conditions because more data were available for modelling during this period and EC has a high potential to affect both human uses and aquatic life during low base-flows. Predictors used in both models included static (e.g. geology, long-term atmospheric deposition and soils) and dynamic (e.g. climate, vegetation and land use) characterizations of the watershed environments.

(i) Reference dataset

I used EC data collected at base-flow by multiple agencies from 1935 reference-quality sites (figure 1*a*; electronic supplementary material, table S1). Most data were collected during single visits, but in cases where multiple measurements were made, a single sample was chosen at random. I verified that upstream watersheds were only minimally altered by human activities, following Olson & Hawkins [14] (except atmospheric deposition, which was treated as a natural variable because natural and anthropogenic sources cannot be distinguished). From 2449 candidate sites, I removed any site with greater than 10% urban or agricultural land use. I then used aerial photographs and maps to examine the watersheds of all sites with greater than 1% urban or agricultural land use or greater than $1\ \mathrm{mS\ cm^{-1}}$ EC and eliminated any site with evidence of activities that would influence EC (e.g. mining, ranching and forestry). The remaining

Table 1. Potential predictor variables.

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environmental factor	data source	predictors	
static predictors			
geology	geochemical and geophysical characteristics of the conterminous USA (www.sciencebase.gov/catalog/folder/53481333e4b06f6ce034aae7)	% rock CaO	% rock Na_2O
		% rock MgO	% rock N
		% rock P_2O_5	% rock SiO_2
		% rock Al_2O_3	% rock Fe_2O_3
		% rock K_2O	rock strength
		rock hydraulic conductivity	
soil	NRCS STATSGO Database (soils.usda.gov/survey/geography/statsgo/)	bulk density	permeability
		soil erodibility (*K* factor)	
	Soil Data Task Group	soil organic carbon	
atmospheric deposition	National Atmospheric Deposition Program 10 year average concentration of wet deposition (nadp.sws.uiuc.edu/NTN/maps.aspx)	Ca^{2+}	SO_4^{2-}
		Mg^{2+}	
topography	National Elevation Database digital elevation models (DEMs) (http://ned.usgs.gov/)	relief ratio	elevation
		shape factor	watershed area
geography		latitude	longitude
dynamic predictors			
vegetation and land use	USGS, land carbon conterminous United States land-use/land-cover mosaics 1992–2100, for A2 emission scenario (http://landcover-modeling.cr.usgs.gov/projects.php)	% evergreen	% developed
		% deciduous	% mine
		% canopy	% crop
		% clear cut	% hay/pasture
climate	dynamically and statistically downscaled GCM data from NCAR Community Climate System Model v. 3.0 using A2 mid-high scenario	minimum temperature	
		maximum temperature	
		annual precipitation	
		minimum precipitation	
	Hawkins *et al.* [16]	dryness index	

1935 sites were well-distributed geographically (figure 1*a*), although more sites were located in mountains than lowlands.

(ii) Probabilistic dataset

I used EC data collected by the U.S. Environmental Protection Agency (EPA) from 2001 sites that were sampled in support of the National River and Stream Assessment (NRSA, [15], figure 1*b*). These sites were selected using a spatially balanced sample representative of the range of perennial streams across the contiguous USA designed to provide statistically representative assessments of the physical, chemical and biological conditions of streams and rivers. A total of 146 sites from the NRSA dataset had little to no human activity upstream and were, therefore, also included in the reference condition dataset. I excluded sites with contributing areas greater than 1×10^6 km^2 (i.e. sites on the lower Missouri and Mississippi Rivers) because of the excessive computational time needed for analysis of these watersheds.

(iii) Potential environmental predictors

For each site in the reference and probabilistic datasets, I calculated watershed averages of 36 predictors (table 1) representing natural and human environment using ArcGIS [17]. Potential predictors were chosen based on observed importance in previous modelling [14,18]. I used model estimates of the current conditions for the dynamic predictors (i.e. climate and land use) instead of more direct observations so estimates of both current and future conditions would be based on data derived in the same manner. The background and alteration models were both trained using climate and land use model hindcasts as dynamic predictors. End of the century EC predictions were then made using climate and land use model forecasts for 2100 based on the A2 emissions scenario developed by the Intergovernmental Panel on Climate Change (IPCC) *Special report on emissions scenarios* [19] as dynamic predictors. Estimates of current and future climate were derived from the National Center for Atmospheric Research (NCAR) Community Climate System Model v. 3.0, which were bias corrected and downscaled to 4 km^2 by applying a combination of dynamic and statistical downscaling methods (see [20] for details). Current and future land use estimates were based on the US Geologic Survey Earth Resources Observation and Science (EROS) Center's FORE-SCE model, which spatially allocates land use change associated with the A2 emission scenario to create rasters of projected land use at a 250 m resolution [21]. These land use allocations were based on logistic regression models that used biogeophysical and socioeconomic conditions as predictors.

(b) Modelling and analysis steps

1. Empirically model background salinity (Objective 1). To estimate site-specific background EC expected to naturally occur in streams across the USA, I constructed a random forest model [22] that related EC observed at minimally disturbed reference streams to upstream watershed environmental attributes (following [14]). Because I developed this model to predict natural background EC, I excluded human land uses from the potential predictors evaluated for this model.
2. Determine the amount of current alteration in salinity (Objective 2). I estimated background EC at probabilistic sites by applying their watershed environmental attributes to the background model. To assess how well the reference dataset used to train the background model represented the range of naturally occurring environments observed in the probabilistic dataset (following Vander Laan & Hawkins [23]), I: (1) calculated the average Euclidian multidimensional environmental distance (using the predictors selected for the background model) between each reference site and its 10 nearest neighbours in the reference dataset to produce a distribution of nearest-site distances, (2) calculated the multidimensional environmental distance between each probabilistic site and its 10 nearest reference sites and then (3) classified probabilistic sites as within the reference site environmental space if the average distance to its 10 nearest reference sites was within the 99th percentile of nearest-neighbour distances observed for all reference sites. Based on this analysis, 95% of the probabilistic sites were classified as within the same environmental space as the reference sites. I then estimated the amount of current alteration in EC by subtracting the estimated background EC at probabilistic sites from the EC observed at these sites. See also electronic supplementary material, table S2 for comparison of the distributions of environmental predictors in each dataset.
3. Empirically model current salinity alteration (Objective 3). I developed a second random forest model to relate site-specific alterations in EC (i.e. differences between observed and predicted background EC at probabilistic sites) as a function of upstream human land uses (e.g. % crops or developed land) and the same natural factors used in the background model. EC expected in the presence of anthropogenic land use was estimated by adding EC predicted by the background model to the change in EC due to human land use predicted by the alteration model.
4. Estimate the salinity at the end of the century (Objective 4). I estimated values of EC expected at the end of the twenty-first century at each of the probabilistic sites by adding future changes in EC predicted by the alteration model to the future EC predicted by the background model. Predictions of future ECs were derived by replacing the FORE-SCE land use and NCAR Community Climate System Model climate hindcasts with end of century values in the background and alteration models. I also assessed the relative impacts of climate versus land use by comparing the amount of change expected by predictions based on only future climate change, only future land use change, and both combined.

(c) Model development and performance assessment

The background and alteration models were constructed using a forward selection method described in Hill & Hawkins [24]. This variable selection method adds predictors one at a time until no improvement is seen in model performance. Models were built with the 'randomForests' package in R with default settings except I built 1500 trees and used the bias correction feature. I assessed model performance by calculating R^2 and root mean squared error (RMSE) of the data not selected for the construction of each individual tree (out-of-bag data), which is analogous to cross-validation [25]. Although estimates of predictive ability using external validation would also be valuable in assessing model performance, previous comparisons of the performance of similar models evaluated with both out-of-bag and external validation data showed R^2 values for external data within 0.1 of the R^2 values calculated from out-of-bag data [14]. It is also not clear how informative external validation based on current conditions would be for predictions of future conditions. Therefore, to maximize the amount of environmental variation in the training datasets (and thus the generality of the resulting models), I used all data to train models, and sacrificed the ability to assess model performance using external validation data.

3. Results

(a) Empirically model background salinity

The model predicting background EC used 10 predictors, including variables associated with watershed geology, climate, vegetation and soils. The relationships of these natural factors to background EC (electronic supplementary material, figure S1) are similar to those relationships seen in earlier models (see [14]). This model had an R^2 of 0.78 and an RMSE of 0.067 mS cm^{-1} (electronic supplementary material, figure S2). Figure 2*a* shows the background expected at the probabilistic NRSA sites derived from the background model.

(b) Determine the amount of current alteration in salinity

Comparing background EC at probabilistic sites (figure 2*a*) to that currently observed (figure 1*b*) shows that EC has been altered greatly in parts of the USA (figure 2*b*). EC increased by more than 50% over background levels at 34% of probability sites. The largest relative increases occur in the highly developed Northeast and the agricultural Midwest. The greatest ECs and absolute increases tend to occur in the central Great Plains, which is affected by a combination of agriculture, groundwater pumping and resource extraction (i.e. oil, gas and coal). A minority of sites had lower ECs than predicted, although except for sites in the Great Plains and western mountains these differences were less than 0.1 mS cm^{-1}. A portion of these differences are likely due to model error, but groundwater pumping and inter-basin transfer likely contribute to the largest decreases. Many sites showed little to no absolute change from background conditions (the mode of the distribution in figure 3*a* is near 0), but 17% of sites showed greater than 0.5 mS cm^{-1} increase in EC. Comparing the distribution of background EC with current EC (figure 3*b*) shows a shift from low EC conditions (less than 0.2 mS cm^{-1}) to much higher ECs (greater than 1 mS cm^{-1}), with the median increasing from 0.214 mS cm^{-1} to 0.319 mS cm^{-1}.

(c) Empirically model alteration of current salinity

The alteration model (developed using deviations from background shown in figure 2*b*) included 11 predictors (electronic supplementary material, figure S3) associated with land use, but also climate, soils and geology. The inclusion of natural factors in the alteration model was necessary to incorporate

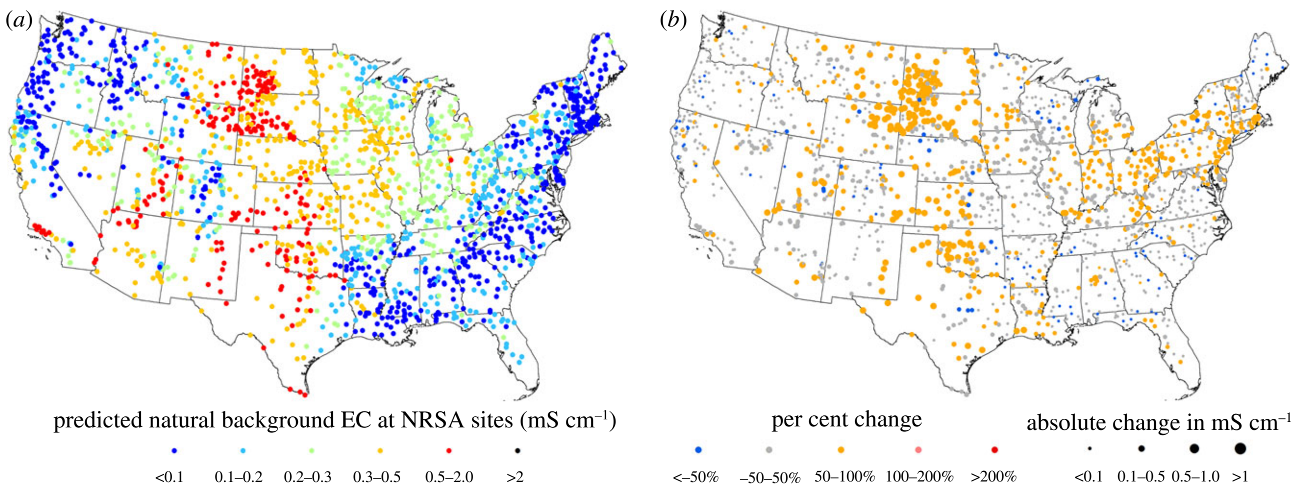

Figure 2. Predicted natural and altered EC at 2001 probabilistic sites sampled as part of the NRSA programme. (*a*) Predicted background EC at each site. (*b*) Change in EC from background shown as per cent change (colour gradient) and absolute change (symbol size). Both the relative and absolute changes are characterized using the same scale as figure 4*b* to allow for easy comparisons.

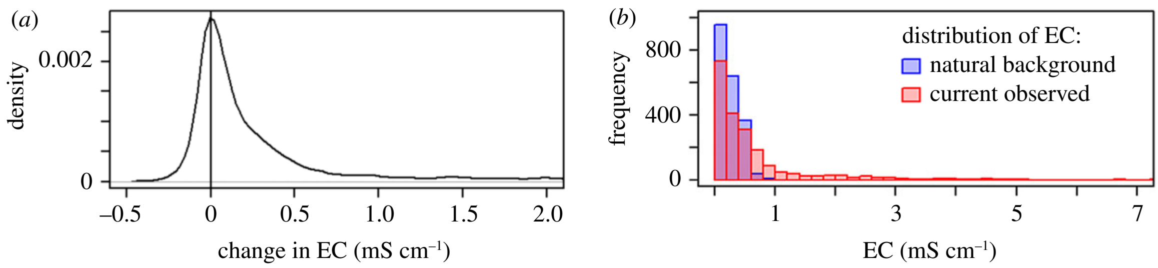

Figure 3. Comparisons of current observed EC with background. (*a*) Kernel density plot showing the distribution of the differences in EC (current observed − natural background). (*b*) Histogram comparing the distributions of background EC to that currently observed (in 2008–2010).

the effects of interactions between natural factors and land use (e.g. agriculture has a larger effect on EC in arid areas than in humid areas, see electronic supplementary material, figure S4 for an example of this interaction). Human land uses (i.e. % crops, % pasture/hay, % developed and % mining) were all associated with increasing EC (electronic supplementary material, figure S3), but were of lower importance than the interacting climatic and geological factors. The alteration model had an R^2 of 0.60 and an RMSE of 0.604 mS cm^{-1} (electronic supplementary material, figure S5). The predicted current EC at probabilistic sites (derived by adding expected alteration to background) had an R^2 of 0.66 (electronic supplementary material, figure S6).

(d) Estimate the salinity at the end of the century

EC predicted to occur at the probabilistic sites by the end of the twenty-first century (figure 4*a*) indicates that salinity is expected to continue to increase, with EC values greater than 0.5 mS cm^{-1} becoming common. The relative and absolute differences from current observed EC (figure 4*b*) are predicted to be even larger than changes seen between background and current conditions (figure 2*b*). The estimated EC in 2100 was more than double current observed EC at 700 sites (35%) and increased by greater than 50% at just over half of sites. The most extensive relative and absolute EC increases occurred in the South, although large relative and absolute increases also occur throughout the Southwest and the Great Plains. Areas that have already been heavily altered like the Midwest and Northeast showed the least amount of change in the future. However, areas where EC has changed little like the arid Southwest and Pacific Northwest show large relative increases by 2100, with many sites increasing by more than 100%. In the arid Southwest, many sites are expected to have EC greater than 1 mS cm^{-1}. Absolute changes in the Pacific Northwest are much smaller (less than 0.1 mS cm^{-1}), but fewer sites now have EC values less than 0.1 mS cm^{-1} normally expected in this region. EC was predicted to decrease by more than 50% at 32 sites, owing to increased precipitation (median increase of 47 mm yr^{-1} for these sites). Most sites showed increases by 2100 (figure 5*a*), with the estimated EC increasing at 20% of sites by greater than 0.5 mS cm^{-1}. Comparing the current distribution of EC to that expected at the end of the century (figure 5*b*) shows that low EC conditions (i.e. less than 0.2 mS cm^{-1}) may no longer be the most frequent. The median EC is expected to increase from its current value of 0.319 mS cm^{-1} to 0.524 mS cm^{-1}.

The amount of change in EC calculated by changing only climate values, only land use values, and both (figure 6), showed that on average land use changes accounted for more of the predicted change in EC than did climate. Future EC changes predicted from only changes in climate on average accounted for 12% of the total amount of change expected by 2100 whereas land use alone accounted for 55%. Mean EC increased 0.035 mS cm^{-1} (5%) when only changes in climate were applied, compared with 0.049 mS cm^{-1} (8%) applying only land use changes.

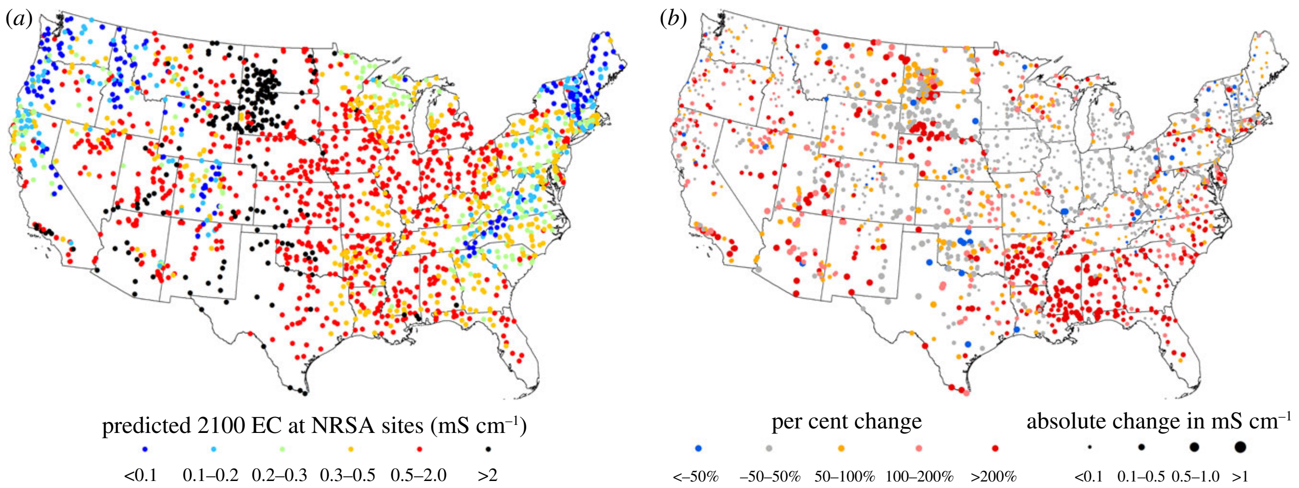

Figure 4. Modelled changes in low-flow, stream EC at probabilistic sites in 2100. (*a*) Site-specific predictions of stream EC in 2100. (*b*) Relative (% change indicated by colours) and absolute (indicated by bubble size) changes in EC between modelled future (2100) and current EC.

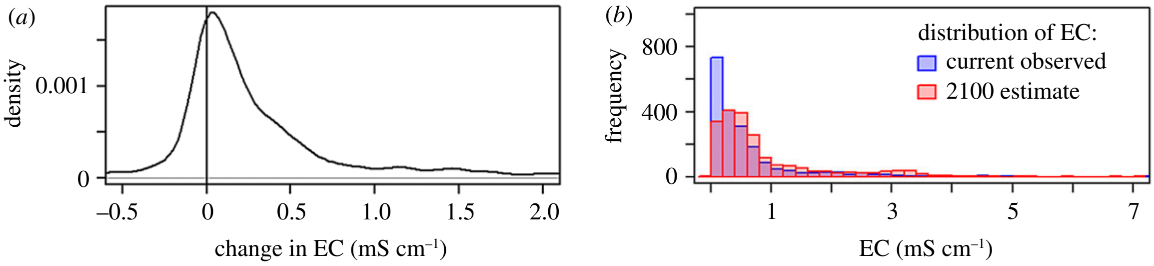

Figure 5. Comparisons of current observed EC with predicted end of century EC. (*a*) Kernel density plot showing the distribution of the differences in EC (2100 EC − current observed). (*b*) Histogram comparing the distributions of EC currently observed (in 2008–2010) to EC distribution expected in 2100.

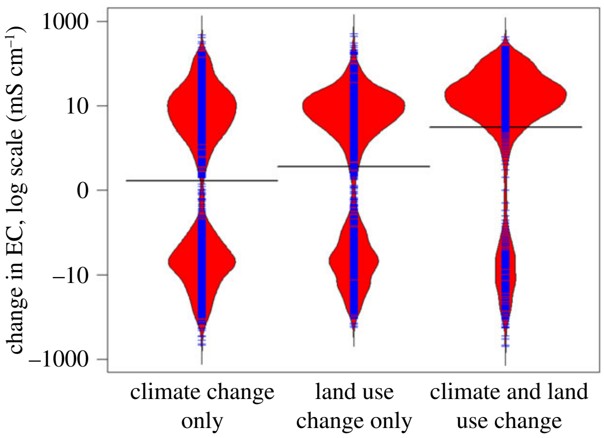

Figure 6. Comparison of the amount of change between current and end of century EC if only climate variables are changed (left), if only land use is changed (centre), and if both climate and land use change (right). Red areas indicate the density of the data, blue lines are a 1-D scatter plot, and black lines indicate group means. Note that the apparent bimodal nature of the data is an artefact of plotting on a log scale.

4. Discussion

The background model had similar performance to that observed in previous EC models developed for the western and contiguous USA [14,18]. However, the explanatory power of the alteration model was relatively low because I used only per cent land use as a measure of the effects of human activities on stream EC. Other models predicting regional stream EC from land use have also reported low R^2 (i.e. 0.49 [26] and 0.23 [27]). Factors like impervious surface cover or population density may have more explanatory power than the per cent land use, but projections of how these factors might change in the future were not available. Because I developed this model to explore how EC might change in the future, I restricted explanatory variables to those with future predictions. The R^2 between log observed and log predicted EC was 0.72, similar to results obtained by the SPARROW model [13] for predicting salinity at 2560 water quality monitoring stations in the USA ($R^2 = 0.67$). The ability of the combined background and alteration models to predict current EC conditions suggests that although future predictions based on these two models may be reasonable, they are not very precise. These predictions do provide a better understanding of how EC might potentially change in the future, and increased precision in these estimates should be pursued only after a better understanding of the full range of possible changes in EC have been determined.

These models represent a first step in quantifying the amount of salinization that might be expected given forecasted changes in climate and land use, but estimates of the range of possible salinities are still needed. This study only develops a single model, using a single set of future climate and land use forecasts, all based on a single emission scenario. To better understand the possible range of future salinities, additional work is needed to develop estimates based on a suite of other emission scenarios, using other forecasts of climatic conditions (i.e. other global climate models and other downscaling approaches), and other forecasts of land use (e.g. Future Land-Use Simulation system [28] and Integrated Climate Land Use Scenario [29]). Examining the array of combinations of models and scenarios would better establish both the most probable change expected and the range of future salinities that might occur. Because land use was the predominant factor driving changes in future salinity (figure 6) and land use models can vary greatly in their predictions [30], quantifying the amount of uncertainty in predictions of future salinity is certainly needed. However, understanding of how much salinity might change in the future is also needed now to provide time to adapt and plan for these changes. Although this study only provides single estimates of future salinity, these estimates are still useful in understanding how much change in salinity is possible and how changes in salinity vary spatially.

The estimates of recent changes in EC (from background to the present) from this study (figure 2*b*) matched well the measured trends in EC observed by Kaushal *et al*. [2], but provided a more spatially complete view of how EC is changing across the USA. Both maps showed the greatest increases in EC occurring in the Northeast and Great Plains regions. Both studies showed most streams in the arid Southwest with decreasing or stable EC. Kaushal *et al*. [2] showed increasing EC also occurring frequently across the Southeast, but the estimated changes from background EC in this study were generally small (i.e. increases were generally less than 50% and 0.1 $\mathrm{mS\,cm^{-1}}$).

The amount of current and future alteration in stream ECs due to climate and land use change varies greatly among individual streams, but has generally increased nationwide and is expected to increase more this century. The median EC has already increased approximately 0.1 $\mathrm{mS\,cm^{-1}}$ from that predicted by the background model, and the median is expected to increase an additional 0.2 $\mathrm{mS\,cm^{-1}}$ by 2100. Stream ECs in the Southeast and some parts of the Northwest showed relatively little alteration of EC currently (figure 2*b*), but had some of the largest expected increases in EC by 2100 (figure 4*b*), resulting in additional losses of low EC habitats over the century.

As EC increases, the increasing salt concentrations will lower the quality, and in some cases the quantity, of our water resources. The EC model predicts that by 2100 12% of streams will have ECs greater than 2 $\mathrm{mS\,cm^{-1}}$ (figure 5*b*), making them of 'doubtful quality' for irrigation [11]. Increasing chloride and sulfate concentration (often the anions associated with increasing salinity) can also cause corrosion of water distribution systems, releasing lead or copper into water supplies [31]. The 3% of streams that are currently unusable for irrigation because their ECs are greater than 3 $\mathrm{mS\,cm^{-1}}$ is expected to double by 2100, compounding losses of water resource availability caused by increasing droughts and other climate change effects.

The effects of the predicted increases in EC on aquatic biota are likely to be even greater than the expected effects on water resources. Biota are adapted to the range of salinities that occurred naturally, and as EC values of streams increase from this background range those taxa adapted to low EC will be increasingly disadvantaged. Low EC streams (i.e. streams with EC less than 0.2 $\mathrm{mS\,cm^{-1}}$) were the dominant EC habitat under natural conditions (figures 1*a*, 2*a* and 3*b*). Currently, 27% of these low EC habitats that likely existed in the past now have ECs greater than 0.2 $\mathrm{mS\,cm^{-1}}$. The future EC predicted in 2100 indicates losses of an additional 42% of this habitat, for a total loss of 69% of low EC habitat in which most taxa evolved. Loss of these low EC habitats would stress the biota in these systems adapted to low salinity environments [32,33], leading to taxa losses, shifts in composition and potentially changes in ecosystem processes [34].

Because both the sensitivity of different taxa to increasing EC [8,33] and the background EC vary widely, predicting how biota might respond to EC increases must be evaluated on a case by case basis. Taxa in streams with naturally low ECs will respond differently to a 0.1 $\mathrm{mS\,cm^{-1}}$ increase compared with taxa found in a naturally high EC stream [33]. For example, sites in the Southeast with background ECs of less than 0.1 $\mathrm{mS\,cm^{-1}}$ (blue dots in figure 2*a*) are expected to have ECs at the end of the century greater than 0.3 $\mathrm{mS\,cm^{-1}}$ (orange and red dots in figure 4*a*). Cormier *et al*. [33] predicted losses of 5% of freshwater invertebrate taxa when streams with current ECs of less than 0.1 $\mathrm{mS\,cm^{-1}}$ increase to over 0.243 $\mathrm{mS\,cm^{-1}}$ (equation (1) from [33]).

In addition to extirpation of taxa from individual streams due to increased EC, the region-wide changes in EC predicted may result in regional extirpations. Many of the increases in salinity shown in figures 2*b* and 4*b* are spatially aggregated, as the agricultural, urban or mining causes of these changes are also aggregated. Increases of EC for all streams in a region may end up having disproportionate effects on taxa by disrupting meta-populations through the elimination of refugia from temporary disturbances or source populations that maintain meta-population dynamics. Changes in mean EC due to climate change alone were associated with 5% increases, compared with 10–15% increases in the mean seen by Dieu Hien *et al*. [35]. Predictions of changes in macroinvertebrate distributions also show larger responses to land use than climate change alone [36]. However, the effects of climate change will be much more pervasive, affecting even streams protected from anthropogenic impacts. Increased EC in all streams in a region including protected streams could potentially lead to local extirpation of salinity sensitive taxa [37].

These predictions help illustrate the extent and severity of future salinization of rivers and streams. Because model predictions are site-specific, they can be used to identify sites that are already degraded, vulnerable, or resistant to increasing EC, and appropriate plans made to protect them or to mitigate damage. The predictions of increasing salinization of streams and rivers highlight the need for effective management and regulation to ensure we protect water resources and freshwater ecosystems [1,33].

Data accessibility. The datasets supporting this article are available from the Dryad Digital Repository at: http://dx.doi.org/10.5061/dryad.jt1kt04 [38] and are detailed in the electronic supplementary material.

Competing interests. I have no competing interests.

Funding. This work was funded by the Sulo and Aileen Maki Endowment at the Desert Research Institute.

Acknowledgements. I am indebted to the work of field and laboratory personnel who generated the primary data. Megan Dettenmaier, Ben Poulsen and Nate McPherron helped with GIS analyses. Chuck Hawkins and Susan Cormier commented on earlier versions of this manuscript, and constructive comments from two anonymous reviewers helped to substantially improve it.

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