Importance of Understanding Landscape Biases in USGS Gage Locations: Implications and Solutions for Managers

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ABSTRACT: *Flow and water temperature are fundamental properties of stream ecosystems upon which many freshwater resource management decisions are based. U.S. Geological Survey (USGS) gages are the most important source of streamflow and water temperature data available nationwide, but the degree to which gages represent landscape attributes of the larger population of streams has not been thoroughly evaluated. We identified substantial biases for seven landscape attributes in one or more regions across the conterminous United States. Streams with small watersheds (<10 km²) and at high elevations were often underrepresented, and biases were greater for water temperature gages and in arid regions. Biases can fundamentally alter management decisions and at a minimum this potential for error must be acknowledged accurately and transparently. We highlight three strategies that seek to reduce bias or limit errors arising from bias and illustrate how one strategy, supplementing USGS data, can greatly reduce bias.*

La importancia de comprender el sesgo inducido por el paisaje en el posicionamiento de sensores USGS: implicaciones y soluciones para los administradores

RESUMEN: *la temperatura y flujo de agua son propiedades fundamentales de los ecosistemas fluviales, sobre los cuales se toman diversas decisiones de manejo en cuanto a recursos dulceacuícolos. Los sensores del Estudio Geológico de los Estados Unidos de Norte América (EGEU) son la fuente disponible más importante de datos de flujo de agua y temperatura a nivel nacional, pero el grado al cual los sensores son representativos de los atributos paisajísticos de una población más grande de ríos, no ha sido analizado a profundidad. Se identificaron sesgos sustanciales en siete atributos paisajísticos en una o más regiones a lo largo de las zonas limítrofes de los Estados Unidos de Norte América. Los ríos de cauce pequeño (<10 km²) y aquellos localizados en regiones elevadas no estuvieron adecuadamente representados, y los mayores sesgos se observaron en los sensores que miden la temperatura del agua y en las regiones áridas. Los sesgos tienen el potencial de alterar de manera fundamental las decisiones de manejo, y como mínimo este error tiene que reconocerse de forma precisa y transparente. Se plantean tres estrategias que buscan tanto reducir el sesgo o limitar los errores que surgen de dicho sesgo, como ilustrar cómo una estrategia, suplementando los datos EGEU, puede reducir el sesgo de manera importante.*

INTRODUCTION

Streamflow and water temperature are fundamental properties of fluvial systems that structure aquatic communities, determine environmental services, and are susceptible to human activity and climatic processes. Streams are often characterized by flow regime (Poff et al. 1997), which determines the movement of energy within stream channels (Leopold et al. 1964), connectivity to floodplains (Tockner et al. 2000), availability and diversity of instream habitats (Jowett and Duncan 1990), and ultimately the structure of lotic communities (Poff and Allan 1995). Water temperature is a key determinant of ecological processes, such as stream metabolism (Demars et al. 2011) and organism bioenergetics (Kitchell et al. 1977), and plays a primary role in influencing distributions of aquatic organisms due to varied thermal tolerances of individual species (Magnuson et al. 1979).

Just as streamflow and water temperatures influence distribution and abundance of fluvial fishes, flow and temperature regimes are themselves influenced by both natural and anthropogenic landscape attributes (Frissell et al. 1986; Poff et al. 1997). Climatic and landscape attributes that influence streamflow and temperature regimes include precipitation and air temperature, catchment area, soil and bedrock permeability, valley constraint, catchment aspect and elevation, and vegetative cover over multiple spatial extents (Isaak and Hubert 2001; Morris et al. 2009; McManamay et al. 2011). Similarly, anthropogenic activities can confound influences of natural controls, and their effects on streamflow and temperature have been widely documented (e.g., Paul and Meyer 2001; Poole and Berman 2001; Poff et al. 2006).

Management of stream and river ecosystems and fisheries, along with their interconnected lake and reservoir systems, often relies on our ability to characterize both streamflow and temperature regimes throughout regions of interest. To achieve this end, streamflow and water temperature data must be monitored using a statistically valid sampling strategy that ensures representation of regional variation in natural and anthropogenic landscape attributes (e.g., U.S. Environmental Protection Agency Environmental Monitoring and Assessment Program, USEPA 2010), if the goal is to characterize hydrologic and thermal properties of all streams in a region of interest. However, this goal may be difficult to achieve in many regions, because streamflow and water temperature data are rarely collected in such a systematic manner.

The stream gage network of the U.S. Geological Survey (USGS) is the main source of nationally available standardized data for characterizing streamflow and temperature regimes. The USGS gage network was designed to collect continuous streamflow data to serve a number of purposes, which include water management, flood monitoring, recreation, and scientific studies (National Hydrologic Warning Council 2006). Water temperature is also monitored at a smaller subset of gages. Although water temperature data are often collected by other agencies or researchers, those data are often not readily available, because they must be compiled into standardized formats (e.g., Isaak 2011). Though USGS gages provide data that characterize large numbers of streams throughout a variety of large spatial units (e.g., basins, entire states, and ecoregions), the gage network was not designed to support statistically valid, regional inferences. For example, at the national scale, gages are disproportionately located near dams, in areas dominated by human influences, and on larger rivers (Poff et al. 2006; Falcone et al. 2010). Such biases in gage locations may compromise opportunities to extrapolate from gage data to all streams in a region. However, these *landscape biases* have not been formally quantified for USGS gage locations and there has been little systematic discussion of related implications for research and management.

To address these challenges and facilitate the use of streamflow and water temperature data across large regions, we assess and quantify landscape biases for the complete USGS gage network within the conterminous United States. Our decision to focus on the conterminous United States stems from a growing federal interest in identifying and prioritizing management actions to address landscape-scale changes (e.g., National Fish Habitat Partnership, www.fishhabitat.org; U.S. Fish and Wildlife Landscape Conservation Cooperatives, www.fws.gov/landscape-conservation/lcc.html). We also assess landscape biases among different ecoregions. We then discuss implications for using gage data to make inferences in a research and management context in light of landscape biases. Finally, we highlight three strategies to address landscape bias and demonstrate how one of these strategies, compiling supplemental data, can greatly reduce landscape bias.

METHODS—IDENTIFYING BIASES

We assessed the distribution of USGS gages throughout the conterminous United States (national extent) and within the nine ecoregions of Herlihy et al. (2008): Coastal Plains (CPL), Northern Appalachians (NAP), Northern Plains (NPL), Southern Appalachians (SAP), Southern Plains (SPL), Tall Grass Plains (TPL), Upper Midwest (UMW), Western Mountains (WMT), and Xeric West (XER; Figure 1). These physiographically diverse ecoregions were selected for use in this study because they have been used in prior investigations to characterize the current condition of lotic fish habitats (Esselman et al. 2011) as well as an ongoing investigation to identify potential effects of climate and land use changes on these habitats (FHCLC 2011). We used the 1:100,000 NHDPlusV1 as the base spatial layer or "census population" for data management and analyses, where the finest spatial unit was the individual stream reach (USEPA and USGS 2005). Data sets linking stream reaches to physical or anthropogenic landscape attributes were previously compiled as part of the National Fish Habitat Partnership–National Fish Habitat Assessment (Esselman et al. 2011). Landscape attributes were summarized at the watershed scale, which includes all land area draining to a given stream reach.

The locations of USGS gages were obtained in October 2010 from the National Water Information System (http://waterdata.usgs.gov/nwis). Water temperature gages for the nation and nine ecoregions were the subset of USGS gages with recorded water temperatures. We included all gages where streamflow or water temperature data have ever been collected. It is important to note that our results may not reflect current landscape bias in USGS gages because some gages included in our study are no longer operational. However, historic gage data are still used for some objectives and including all gages enables our study to provide a baseline assessment of bias that is likely lower than all other subsets (e.g., currently active gages).

We selected three physical landscape attributes to describe natural variation among stream reaches: watershed area (km^2), mean watershed elevation (m), and mean watershed slope (degree; Table 1). We also selected three percentage measures of land cover as metrics of human disturbance: natural (as sum of forest, grassland, and shrubland), agricultural, and urban (Table 1). These physical and land cover metrics can influence water temperature, streamflow, and distributions of fishes (e.g., Brenden et al. 2008), macroinvertebrates (e.g., Tsang et al. 2011), and algae (e.g., Cao et al. 2007) throughout the conterminous United States. We followed methods in Wagner et al. (2008) to identify potential sampling biases for each of the landscape attributes by comparing cumulative frequency distributions (CFDs) of the sample of reaches containing streamflow or water temperature

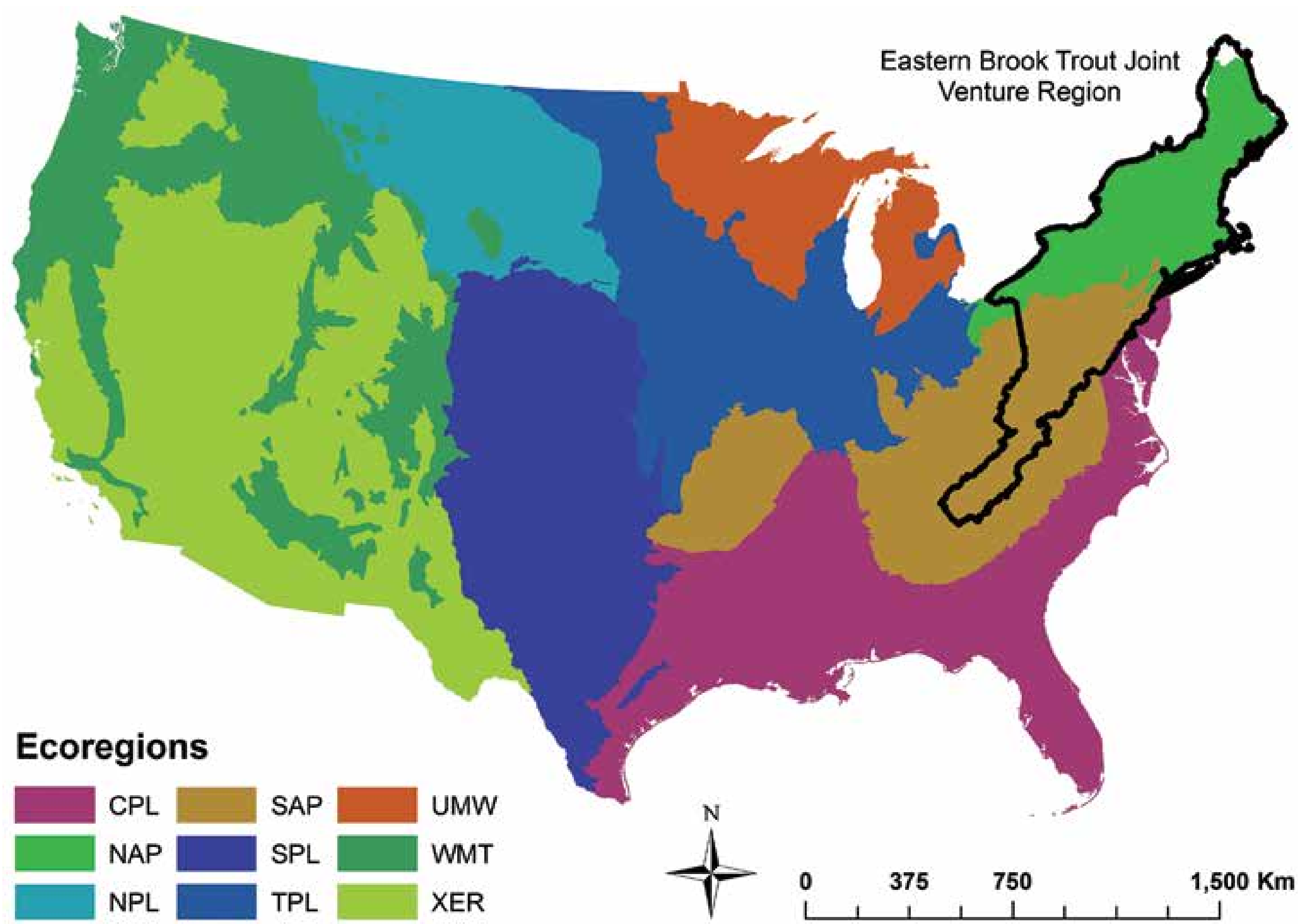

Figure 1. Map of the conterminous United States showing the nine ecoregions and one focused management region used in analyses: the Coastal Plains (CPL), Northern Appalachians (NAP), Northern Plains (NPL), Southern Appalachians (SAP), Southern Plains (SPL), Tall Grass Plains (TPL), Upper Midwest (UMW), Western Mountains (WMT), Xeric West (XER), and the Eastern Brook Trout Joint Venture region.

Table 1. Names and sources of natural and anthropogenic landscape attributes that were used in analyses. The land cover code column lists the reference numbers from the source data set used to calculate land cover types used in our analyses.

Attribute	Resolution	Units	Source	Land cover code
Watershed area	1:100,000	km^2	Calculated using NHDPlusV1[1]	NA
Mean slope	30 m	degrees	National Elevation Dataset[2]	NA
Mean elevation	30 m	m	National Elevation Dataset[2]	NA
Urban land cover	30 m	% of network catchment	NLCD 2001 Version 1[3]	21 + 22 + 23 + 24
Agricultural land cover	30 m	% of network catchment	NLCD 2001 Version 1[3]	81 + 82
Natural land cover	30 m	% of network catchment	NLCD 2001 Version 1[3]	41 + 42 + 43 + 52 +71

[1] USEPA and USGS (2005).
[2] USGS (2006).
[3] Homer et al. (2007).

gages to those of the census population of all stream reaches in each region. We performed statistical analyses and created plots within the R programming environment (R Development Core Team 2012).

The interpretation of sampling bias from CFD curves is as follows: (1) generally unbiased samples have a CFD that matches closely with the census population CFD; (2) sample CFD deviations above the population CFD represent oversampling; and (3) CFD deviations below the population CFD represent undersampling. Sample CFDs may begin at higher or end at lower values of a landscape attribute than the census population, which signifies that some values of the attribute are not represented by USGS gages (i.e., these extreme attribute values are entirely unsampled). Erratic, step-like CFDs result whenever the addition of one or a few gages results in a large increase in cumulative frequency and are usually associated with a small number of gages.

For each landscape attribute, we assessed the magnitude of biases for streamflow and water temperature gages. First, we calculated the maximum difference in cumulative frequency between the population and the sample for each landscape attribute (i.e., the greatest vertical difference between population and sampling CFDs). We then summarized the magnitude of bias by classifying the maximum difference using arbitrarily defined cutoffs: "low" (maximum difference between population and sample CFDs < 0.1), "moderate" (maximum difference between population and sample CFDs ≥ 0.1 and < 0.3), and "high" (maximum difference between population and sample CFDs ≥ 0.3). Second, we identified CFDs where the sample range was less than 90% of the population range and refer to these as "notably unsampled."

We found that the greatest landscape bias existed for watershed area.

RESULTS—IDENTIFIED BIASES

Of the 2,607,304 census population stream reaches in the conterminous United States, USGS gaging stations monitored streamflow for 20,362 (0.78%) reaches and water temperature for 1,673 (0.06%) reaches. The UMW had the greatest percentage of stream reaches with streamflow gages (2.66%) and the SAP had the lowest (0.25%). The percentage of stream reaches with temperature gages was much lower, with the SPL having the highest (0.13%) and the NPL the lowest (0.02%). Landscape characteristics of all census population stream reaches, including gaged reaches, are provided in Table A1 for the national extent and all ecoregions (see http://fisheries.org/appendices).

We present a subset of CFDs to illustrate typical biases for each landscape attribute; the full set of CFD plots for each attribute and all regions is available online (Figures A1–A6, see http://fisheries.org/appendices). Streamflow and water temperature sampling CFDs indicated that small (i.e., <10 km^2) and intermediate (i.e., ≥10 and <500 km^2) sized watersheds were highly underrepresented or notably unsampled at the national extent and in most ecoregions (Figure 2a, Table 2). Large watersheds (i.e., >10,000 km^2) were well represented in all regions (Figure A1, see http://fisheries.org/appendices), and biases were higher for water temperature gages than for streamflow gages in all regions.

Mean watershed elevation was generally better represented than watershed area for both streamflow and water temperature gages (Table 2; Figure 2b). However, relatively higher elevations were notably unsampled by streamflow gages in all regions, except the national and TPL, and by water temperature gages in all regions (Table 2). For example, the NPL had the highest magnitude of biases for both streamflow and water temperature gages, and high elevations (>2,200 m) were notably unsampled by water temperature gages (Figure 2b).

Urban land cover CFDs for streamflow gages showed moderate biases in nearly all regions and high bias in only the XER ecoregion, whereas biases for water temperature gages were high in four ecoregions (Table 2). Biases in most regions were due to undersampling of all but the highest percentages of urban land cover, and this tendency was greater for water temperature gages (see national, Figure 2c). The magnitude of undersampling was lowest in the NPL, but intermediate to high urban land cover was notably unsampled by streamflow and water temperature gages in this ecoregion (Figure 2c).

Biases for natural land cover were moderate in most regions for both streamflow and water temperature gages (Table 2). No region had low bias for streamflow gages, but the UMW had low bias for water temperature gages. The most common bias was oversampling areas with relatively high natural land cover, but the magnitude differed among regions. For example, at the national extent, streamflow gages oversampled natural land cover greater than 80%, whereas in the SAP streamflow gages oversampled natural land cover greater than 20% (Figure 2d). In contrast, only natural land cover greater than 85% was oversampled in the SPL, while almost all of the range was undersampled (Figure 2d).

Most regions had low or moderate landscape bias for agricultural land cover for streamflow gages and moderate or high bias for water temperature gages (Table 2). Biases in most regions were due to oversampling across a wide range of intermediate to high agricultural land cover (e.g., SPL), undersampling low agricultural land cover (e.g., XER), or a combination of these two (e.g., national; see Figure 2e). Stream reaches with higher values of agricultural land cover (>80%) were notably unsampled by streamflow gages in the NAP ecoregion and by water temperature gages in four ecoregions (e.g., SPL; Figure 2e).

DISCUSSION

Our analyses identified substantial landscape biases in streamflow and water temperature gages across several landscape attributes in one or more regions. Landscape biases were lower for flow gages than for temperature gages across all landscape attributes, partly because streamflow data are collected at more USGS gages than water temperature data. Biases were also generally greater within arid ecoregions of the western United States, where a lower percentage of streams were gaged. We found that the greatest landscape bias existed for watershed area, and this bias toward sampling larger rivers has been previously noted (e.g., Poff et al. 2006; Falcone et al. 2010). Higher elevation streams were entirely unsampled in some regions (e.g., NPL), which may be particularly important because shifts in air temperature and precipitation resulting from climate and land use changes may have pronounced effects on small, high elevation stream systems (Beniston et al. 1997). Large biases in the arid ecoregions of the western United States (e.g., XER) are also concerning because many of these streams contain endemic fishes of conservation concern and are already impaired from dams, water extraction, and nonnative fishes (Olden and Poff 2005).

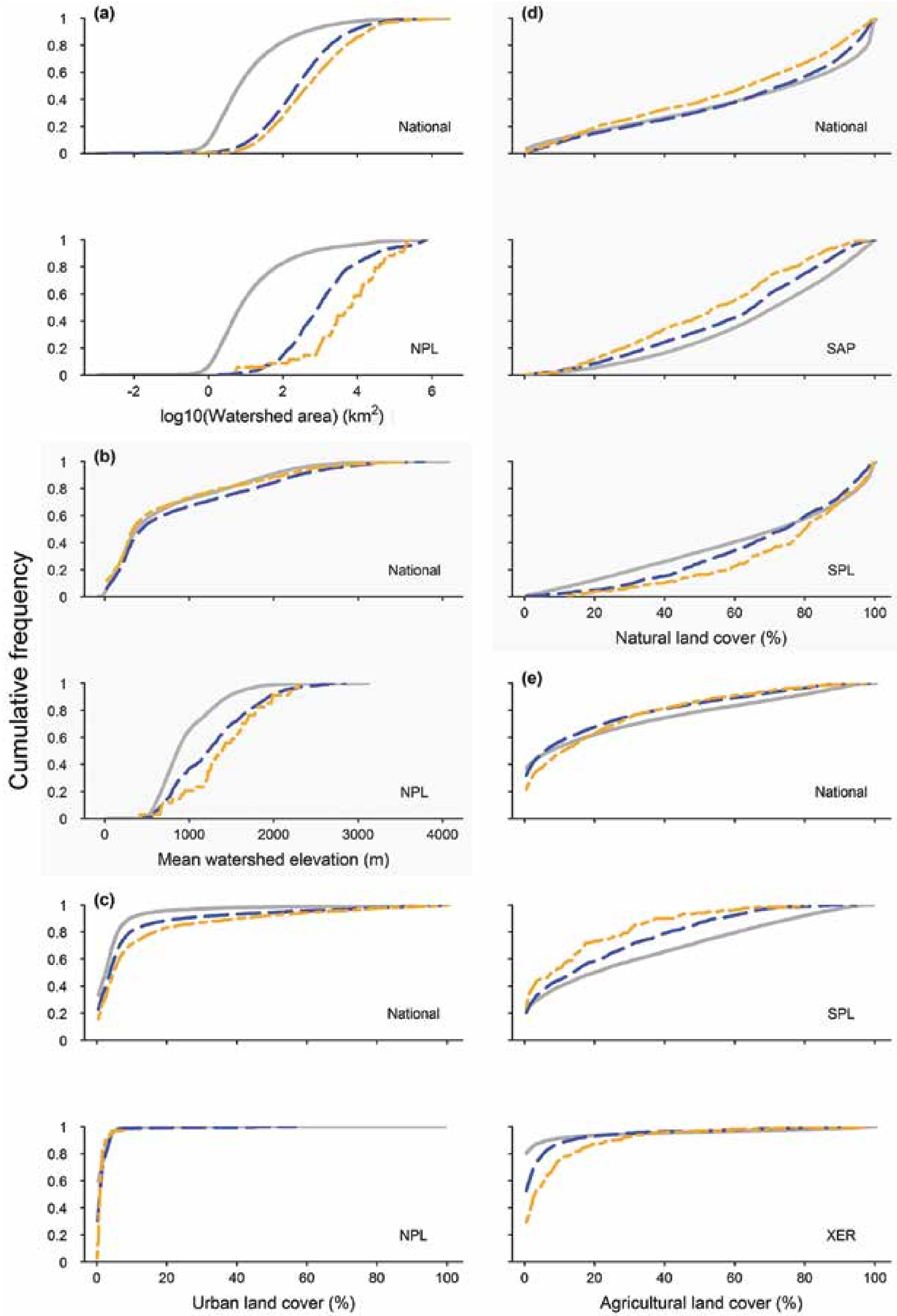

Figure 2. Cumulative frequency distributions for the national extent and selected ecoregions illustrating typical landscape biases for (a) watershed area (log10 (km²)), (b) mean elevation (m), (c) urban land cover (%), (d) natural land cover (%), and (e) agricultural land cover (%). The solid grey line represents the population of stream reaches, the dashed blue line represents reaches with streamflow gages, and the orange dash-dot line represents reaches with water temperature gages.

Table 2. Summary of the landscape biases observed for each landscape attribute by region for streamflow and water temperature gages. We calculated the magnitude of bias as the maximum difference in cumulative frequency across all values in the sampling data and classified bias as low (maximum difference between population and sample CFDs < 0.1), moderate (maximum difference between population and sample CFDs ≥ 0.1 and < 0.3), and high (maximum difference between population and sample CFDs ≥ 0.3). Regions are listed in order of increasing bias for each landscape attribute. Bold font denotes regions where the landscape attribute sample range was < 90% of the population range.

Landscape attribute	Landscape bias		
	Low	Moderate	High
Streamflow data			
Watershed area	None	None	**UMW, CPL, NAP, WMT,** National, **SAP, XER, TPL, SPL, NPL**
Mean elevation	**NAP, UMW, WMT,** National, TPL, **SAP, CPL**	**SPL, XER, NPL**	None
Mean slope	**SAP, CPL, WMT, NAP, TPL, UMW**	**SPL, National, XER, NPL**	None
Natural land cover	None	SPL, UMW, SAP, National, CPL, NAP, TPL, NPL	WMT, XER
Urban land cover	SPL	**NPL**, National, UMW, WMT, NAP, TPL, SAP, CPL	XER
Agricultural land cover	SAP, National, CPL, UMW	WMT, SPL, NAP, TPL, **NPL, XER**	None
Water temperature data			
Watershed area	None	None	**UMW, SAP, NAP,** National, **CPL, TPL,** WMT, **SPL, XER, NPL**
Mean elevation	National, SAP	XER, SPL, WMT, UMW, NAP, TPL	CPL, NPL
Mean slope	National, WMT	SAP, TPL, SPL, UMW, CPL, XER	NPL
Natural land cover	UMW	TPL, National, **NAP,** SPL, **CPL,** SAP	**NPL,** WMT, XER
Urban land cover	None	**NPL,** SPL, TPL, National, **WMT, NAP**	CPL, SAP, UMW, XER
Agricultural land cover	SAP	**NAP,** CPL, UMW, National, WMT, SPL, **TPL**	**NPL, XER**

Are Biases Relevant?

Our results show that streamflow and water temperature data from USGS gages do not adequately represent key landscape attributes throughout the nation and in one or more ecoregions. The resulting landscape biases will be relevant to research and management efforts that attempt to characterize streamflow or water temperature within ungaged streams (i.e., to extrapolate from gaged to ungaged streams). If inferences are restricted to gaged streams, then the landscape biases reported here are irrelevant. However, many research and management efforts seek to draw inferences regarding large regions, and these inferences can be fundamentally altered by landscape bias.

When landscape biases are determined to be relevant, the next step is to assess the magnitude of biases for landscape attributes of interest. We have provided an example of how CFDs and selected landscape attributes can be used to characterize landscape bias in a rigorous and quantitative manner. However, we caution that our results may not be representative of other regions or of other landscape attributes.

Addressing Bias

At a minimum, landscape biases and their potential for introducing error must be acknowledged accurately and transparently when gage data are used to inform management decisions. However, a simple acknowledgement of bias may not always be sufficient. Thus, we also discuss three approaches that seek to reduce biases or limit associated errors in light of existing biases.

1. *Limit or qualify inferences.* The first strategy for addressing biases in USGS gage data is to limit or qualify inferences for regions or types of streams with large landscape biases. To illustrate this strategy, consider the biases and CFDs for agricultural land cover (Figure 2e). For example, landscape biases in water temperature data may be considered "too great" for the entirety of the NPL and XER ecoregions, and analyses could be limited to other ecoregions where data are more representative of agricultural land cover. Alternatively, inferences in the NPL and XER regions could be qualified to incorporate potential errors arising from bias in these regions. Similarly, this strategy can also be employed within a single region to limit or qualify inferences to subsets of streams based on magnitudes of bias. For example, in the XER ecoregion one may decide that water temperature gage biases are too great for streams with less than 30% agricultural land cover (Figure 2e) and either qualify inferences for this subset of streams or limit inferences to streams with more agricultural land cover.

2. *Compile supplemental data.* The second strategy is to compile supplemental streamflow and water temperature data from sources other than USGS gages. These supplemental data will help to reduce landscape bias when additional landscape variation is represented. Potential sources of supplemental data include Federal Energy Regulation Commission–licensed hydropower projects, National Pollutant Discharge Elimination System permit compliance monitoring data, U.S. EPA STORET, universities, watershed organizations, and state agencies. To illustrate the use of supplemental data, we appended the USGS water temperature data with data from federal, state, university, watershed organization, and two previously published (Gardner et al. 2003; Martin and Petty 2009) sources for a focused management region, the Eastern Brook Trout Joint Venture region (EBTJV; Figure 1). We included all

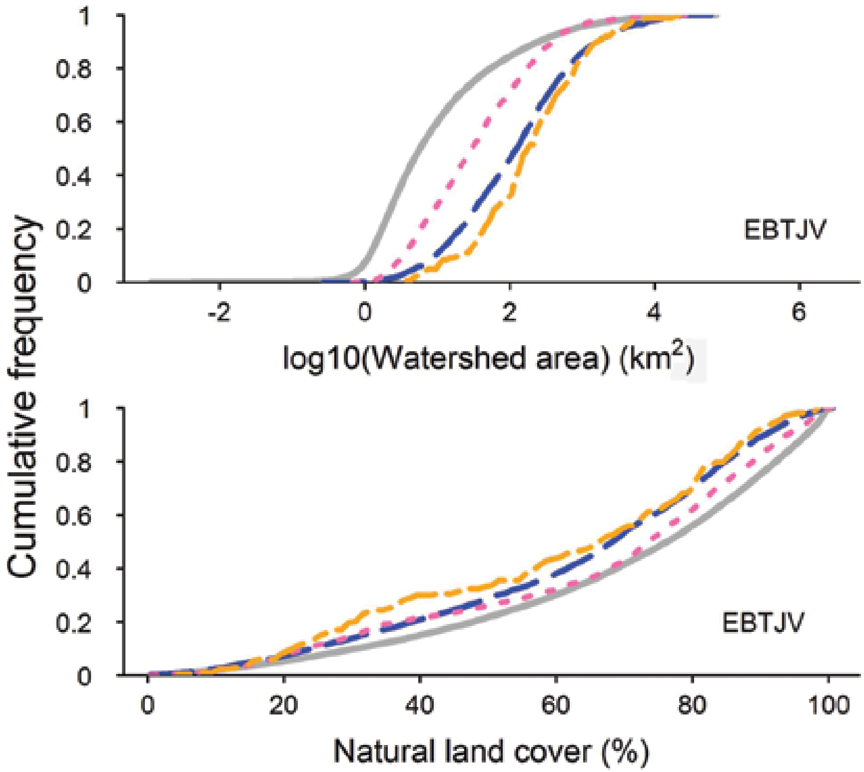

Figure 3. Cumulative frequency distributions illustrating the influence of including supplemental data on landscape biases for watershed area (km²) in the Eastern Brook Trout Joint Venture (EBTJV) region. The solid grey line represents the population of stream reaches, the long dashed blue line represents reaches with streamflow gages, the orange dash-dot line represents reaches with water temperature data from USGS gages only, and the short dashed pink line represents reaches where supplemental temperature gages were included in addition to USGS gages.

water temperature sampling locations where data were collected at a repetitive, systematic interval (hourly, bi-hourly, etc.) and used the same methods described above to create new CFD plots. A total of 1,480 additional stream reaches with temperature data were available for the EBTJV, and landscape biases for some landscape attributes were greatly reduced (e.g., watershed area; Figure 3).

3. *Modeling.* The final strategy is to use correlative, spatial, or mechanistic models in place of empirical streamflow and water temperature data. These models can then be used to support resource management decisions for many or all streams throughout a given region. Correlative models have been used widely to predict streamflow (e.g., Vogel et al. 1999) or water temperature (e.g., Mohseni et al. 1998; Wehrly et al. 2009) at unsampled locations based on empirical relationships with variables that are known and typically easy to measure (e.g., precipitation, air temperature). Spatial models incorporate distance and spatial connectivity between sample locations to predict streamflow or water temperature and may also include correlative relationships with other predictors (e.g., Peterson et al. 2007). For example, a spatial stream temperature model may accurately generalize to undersampled headwater reaches by interpolating upstream temperatures based on data from downstream gages. Finally, mechanistic (also referred to as deterministic or process-based) models may reduce landscape bias by predicting streamflow or water temperature based upon physical relationships with landscape attributes and other controlling factors (e.g., Soil & Water Assessment Tool, Arnold et al. 2012; heat budget analysis, Johnson 2004). Each of these types of models can, in some instances, be a powerful tool for estimating flow and/or temperature in ungaged stream reaches. However, it is important to note that landscape bias may be retained in model predictions if biased gage data are used for model calibration or validation purposes. Further, sufficient streamflow and/or water temperature data may not always be available to develop models that can generate accurate predictions in unsampled streams. In such cases, models that use climatic and/or landscape attributes as surrogates of water temperature and/or streamflow can inform management decisions in place of gage data. For example, thermally suitable habitat for Trout has been estimated from correlative models using mean July air temperature in Wyoming (Keleher and Rahel 1996) and elevation in the southern Appalachians (Flebbe et al. 2006) as surrogates of water temperature.

Strategies to Reduce Bias

Acknowledging and addressing existing landscape biases are only temporary, objective-specific solutions for using USGS streamflow and water temperature data sets. In the long term, a strategy to increase the representativeness of landscape attributes is needed to increase the utility of available data for addressing pressing objectives, such as predicting climate and land use change effects on stream hydrologic and thermal regimes. Construction of additional USGS gages is unlikely to greatly reduce landscape bias because financial resources are limited and gage locations are usually not selected solely to capture variation in landscape attributes. However, if the construction of new or redistribution of existing USGS gages becomes feasible, underrepresented streams identified herein could be targeted as one way of reducing landscape bias. A more cost-effective way to reduce landscape biases in available water temperature data is to expand water temperature monitoring to a greater proportion of existing USGS gages. A second cost-effective way to reduce landscape bias and increase the utility of available data is to coordinate supplemental data collection efforts and offer these data in standardized formats. Efforts of this type are already underway for water temperature data in some regions (e.g., Isaak 2011) and can greatly reduce landscape biases as we demonstrated in the EBTJV region.

CONCLUSIONS

We found that streamflow and water temperature data from USGS gages do not adequately represent key landscape attributes throughout the conterminous United States or within select ecoregions, which can lead to errors when attempting to infer or predict hydrologic or thermal properties of all streams in a region of interest. The greatest source of bias was undersampling of small (i.e., <10 km^2) to intermediate sized (i.e., ≥10 and <500 km^2) watersheds, but all landscape metrics showed large biases in one or more regions. Biases in USGS gage data were generally greater in arid regions of the Western United States and were almost always greater for water temperature data than streamflow data, in part because fewer USGS gages monitor water temperature. Our study provides a useful overview of landscape bias throughout the conterminous United States but likely underestimates landscape biases in currently active USGS gages because we used all gages where any streamflow or water temperature data had ever been collected. More restrictive subsets (e.g., currently active gages) are likely to have greater biases, and these biases must be quantified on a case-by-case basis. Reducing landscape biases in USGS data will require a comprehensive strategy, and our results suggest that making data from supplemental sources available in standardized formats can reduce biases and could be one part of this strategy. Despite inherent landscape biases, uniformly collected and reported USGS data remain the most valuable source of streamflow and water temperature data for the United States and will continue to be used widely to support resource management efforts. Nevertheless, landscape biases can fundamentally alter inferences and must be acknowledged as a potential source of error when gage data are used to support management decisions.

ACKNOWLEDGMENTS

We thank James McKenna; Robert Carline; all members of the Fish Habitat, Climate, and Landuse Change project team; two anonymous reviewers; and the Science Editor for helpful comments on earlier versions of this work. Supplemental water temperature data were generously provided by Andrew Dollof, Anthony Raburn of the Georgia Departement of Natural Resources, Joan Trial of the Maine Department of Marine Resources, John Sweka of the U.S. Fish and Wildlife Service Northeast Fishery Center, Mark Hudy, the Maryland Department of Natural Resources Monitoring and Non-tidal Assessment Division, Neal Hagstrom of the Connecticut Department of Energy and Environmental Protection, the New Hamphsire Fish and Game Commission, Rich Kern of the Vermont Fish and Wildlife Department, Roy Martin, Steve Means of the Pennsylvania Department of Environmental Protection, the Susquehana River Basin Commission, Tamara Smith, and the Wood-Pawcatuck Watershed Association.

FUNDING

Funding for this research was provided by the U.S. Geological Survey National Climate Change and Wildlife Science Center. Use of trade names does not imply endorsement by the United States Government.

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