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RESEARCH ARTICLE

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Key Points:

- We investigated the environmental drivers of massive bird die-offs by combining earth observations with citizen science observations
- We found distance to wildfire and air quality were the major factors that affect the birth mortality events
- Our findings highlight the important impact of extreme weather and natural disasters on bird biology, survival, and migration

Supporting Information:

- Supporting Information S1

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Unprecedented Migratory Bird Die-Off: A Citizen-Based Analysis on the Spatiotemporal Patterns of Mass Mortality Events in the Western United States

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Abstract Extensive, severe wildfires, and wildfire-induced smoke occurred across the western and central United States since August 2020. Wildfires resulting in the loss of habitats and emission of particulate matter and volatile organic compounds pose serious threatens to wildlife and human populations, especially for avian species, the respiratory system of which are sensitive to air pollutions. At the same time, the extreme weather (e.g., snowstorms) in late summer may also impact bird migration by cutting off their food supply and promoting their migration before they were physiologically ready. In this study, we investigated the environmental drivers of massive bird die-offs by combining socioecological earth observations data sets with citizen science observations. We employed the geographically weighted regression models to quantitatively evaluate the effects of different environmental and climatic drivers, including wildfire, air quality, extreme weather, drought, and land cover types, on the spatial pattern of migratory bird mortality across the western and central US during August-September 2020. We found that these drivers affected the death of migratory birds in different ways, among which air quality and distance to wildfire were two major drivers. Additionally, there were more bird mortality events found in urban areas and close to wildfire in early August. However, fewer bird deaths were detected closer to wildfires in California in late August and September. Our findings highlight the important impact of extreme weather and natural disasters on bird biology, survival, and migration, which can provide significant insights into bird biodiversity, conservation, and ecosystem sustainability.

1. Introduction

Extreme weather and natural disasters have increased the rates of disease, degraded habitats of living species on Earth, as well as threatened their survival (Foden & Young, 2016). The population dynamics of bird species are often influenced by extreme weather anomalies and natural hazards, such as droughts, hurricanes, wildfires, and snowstorms (Møller et al., 2008). During August–September 2020, numerous dead birds were found by citizen scientists and were reported on the citizen science platform (Johnson, 2020). The observation of this massive birds' dead-off event includes a large number of avian species, particularly a wide variety of migratory birds (Johnson, 2020). During the same period, a number of large wildfires have occurred across the western and central United States (US). Until October 5, there were 7.8 million acres of burned areas associated with 44,714 wildfires in 2020 (Insurance Information Institute, 2020). The wildfires and summer droughts directly cause tree mortality and result in habitat loss and fragmentations for wildlife species, including the birds, which were often found to have a negative impact on species richness, distribution, and abundance (Martinuzzi et al., 2015). Additionally, the smoke and toxic gases released by wildfires could threaten the health of humans and animals, especially for birds, as their respiratory systems are found sensitive to air pollutions (Sanderfoot & Holloway, 2017). Low visibility caused by the smoke can also disrupt the navigation for the migratory avian species and increase the potential difficulties in finding food sources.

Accompanied with the wildfires, another extreme weather event, an abnormal early winter storm that occurred in early September across the northwestern United States, with temperatures dropped 30–40°C in a few hours, could also disrupt the bird's migration patterns (Newton, 2007). Many studies have suggested the significant effects of the daily climatic variables on bird migration phenology (Richardson, 1978). The sudden cold weather might prompt the migration of many birds before they were physically ready (Schaefer et al., 2008). Moreover, potential food shortage resulting from the snowstorm may severely affect the birds' migration since the metabolic and energetic requirement of flight are the important cost for avian species (Guy Morrison et al., 2007; La Sorte et al., 2016; McCue, 2010; Wikelski et al., 2003). Therefore, it is highly plausible that there exist cause and effect relationships between the sequential occurrences of abnormal ecological and environmental disturbances as mentioned above and the massive migratory bird mortality events across the western United States in summer 2020 (Lee et al., 2017). Yet, it is still unknown about which the environmental factors and how they drive the massive bird mortality across space and time. Identifying the factors that influence the survival of the avian species and disentangling the roles of these factors is, thus, critical for understanding the general biology, ecophysiology of birds, and their responses to ecological disturbance and natural hazards.

In the field of ecological conservation, an observational database is essential for conducting ecological modeling (Tsoar et al., 2007). The traditional ways for collecting and validating ground-based data across a broad spatial extent are costly. Citizen science in species monitoring has emerged as a revolutionary tool to engage people from all places to participate in research. There is also a long history of incorporating citizen science research activities. For example, recent developments in mobile applications increase the potential and ability of citizens to collect and share data (Heggen et al., 2013). One of citizen science representations—Volunteered Geographic Information (VGI) has been widely used in species distribution mapping, which facilitates the enhancement, update, and completion of many spatial data sets for research (Goodchild, 2007). D. Yang, Wan, et al. (2019) studied the environmental drivers impacting Monarch butterflies by incorporating citizen science data with the earth observation data set. Fern and Morrison (2017) modeled the critical areas for migratory songbirds by combining eBird and Landsat 8 OLI database. The integration of citizen science data with diver remote sensing data (e.g., climate, weather, land cover) provides an opportunity to link board-scale patterns of animal behavior with environmental patterns from both time and space. Additionally, citizen science can increase our understanding of land-use patterns and management practices while engaging the public at local, regional, and global scales to study their environment (D. Yang et al., 2017). Involving citizen science to inform conservation practices can usually lead to a more effective outcome of research success because it raises awareness and garners to support the project among the public.

Ecological processes across multiple spatiotemporal scales often result from various factors, including climate and environmental gradients and disjunction, biotic interactions, and anthropogenic impacts (A. Yang et al., 2020). The geospatial models with explicit consideration of spatial autocorrelation are commonly used to understand the ecological processes and events from local to global scales (Skidmore et al., 2011). The geographically weighted regression model is one such tool that can identify spatial heterogeneities in regression models of georeferenced data with the estimation of spatial variability of local regression coefficients. It has been widely used in different fields to address spatially related questions, including public health (Acharya et al., 2018; Gilbert & Chakraborty, 2011), social science (Waller et al., 2007), environmental science (Brown et al., 2012; Jaimes et al., 2010), and conservation ecology (An et al., 2016).

In this study, we aimed to quantify the effects of different environmental and climatic drivers, including wildfires, air quality degradation, summer drought, and the early winter storm, on the massive bird mortality occurrences in the western and central US during summer 2020. Specifically, we used citizen science-based data to estimate and compare the effects of wildfire, air quality, drought, land cover types, and extreme weather on the survival of migratory birds. The combination of citizen science, remote sensing technology, and geospatial models offers an innovative and feasible solution to collect near-real-time data at a global scale and investigate the patterns of ecological processes, which is essential for understanding the effects of natural hazards on ecosystem functions.

2. Materials and Methods

2.1. Study Area and Bird Death Data

Our study area covers most of the western and central US with 12 states included based on the data collection areas of the southwest Avian Mortality Project under iNaturalist: https://www.inaturalist.org/pro-

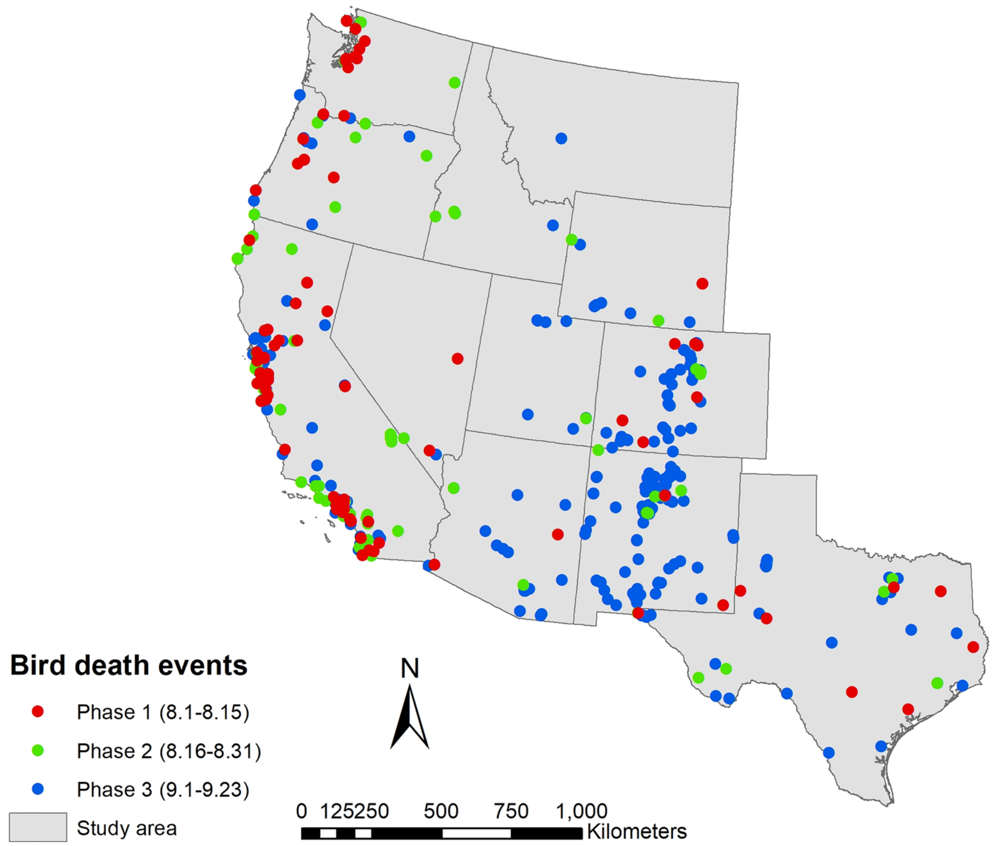

Figure 1. The geography distribution of the citizen science-based bird death observations in three phases.

jects/southwest-avian-mortality-project (Figure 1). The quality grade of the project is "research grade" and "Needs ID." Each observation includes a georeferenced photo with a unique ID. We adopted the georeferenced bird mortality data on August 1 to September 23 from the citizen science database from the Southwest Avian Mortality Project at iNaturalist platform. Major species with observed death in the citizen science database include warblers, tanagers, flycatchers, and swallows. We screened the bird mortality data to only focus on migratory birds based on the species category recorded by citizen scientists and divided the data into three phases: August 1 to August 15 (Phase 1); August 16 to August 31 (Phase 2); and September 1 to September 23 (Phase 3). Finally, there were 94, 80, and 362 observed records in Phase 1, Phase 2, and Phase 3, respectively, which were incorporated in the following analyses (Figure 1). We then generated a 25 km × 25 km gridded surface that covered the study area and aggregated the bird mortality data in each phase based on the gridded surface, such that each cell of the grid indicated the number of migratory bird death events during a specific time period. This 25 km × 25 km gridded surface was selected to (1) filter out the potential clustering patterns of the observed bird mortality data to reduce the spatial autocorrelation effects on explanation of the factors of interest and (2) avoid the zero-inflation problems in the statistical analyses.

2.2. Environmental Data

We considered 21 environmental covariates to account for the potential effects of wildfire, air quality, drought, and extreme weather on bird mortality. These covariates were calculated and adopted from multiple sources (Table 1). The data sets we used in this study are all publicly available, which makes this study highly transferable to other geographic regions. For the fire database, we extracted the daily near-real-time fire boundaries from InciWeb, and calculated the Euclidean distance to the closest wildfire events using ArcMap 10.6 (ESRI Inc., Redlands, CA). As the smoke observations were measured every 5 min, we extracted the daily maximum, median, and maximum smoke values within the regions and then averaged

Table 1
Covariates Considered in This Study and Their Sources

Factors	Covariates	Description (units)	Spatial resolution	Data source
Wildfire	Fire	Euclidean distance to the closest wildfire events (m)	25 km	InciWeb
	Mean smoke	Mean of daily smoke level in different phases	25 km	Hazard Mapping System Fire and Smoke Product
	Median smoke	Median of daily smoke level in different phases		
	Maximum smoke	Maximum of daily smoke level in different phases		
Air quality	Carbon monoxide (CO)	Average of CO concentration in different phases	0.01°	Sentinel-5P TROPOMI
	Sulfur dioxide (SO_2)	Average of SO_2 concentration in different phases		
	Nitrogen dioxide (NO_2)	Average of NO_2 concentration in different phases		
Drought	Precipitation	Average of daily amount of precipitation in different phases (mm)	5 km	Gridded Meteorological Data (GridMET) from "climateR" R-package
	Maximum humidity	Average of daily maximum relative humidity in different phases (%)		
	Minimum humidity	Average of daily minimum relative humidity in different phases (%)		
	Pressure	Average of daily mean vapor pressure deficit in different phase (kPa)		
Land cover types	Agriculture, barren, forest, grass, urban, water	Percentage of agriculture land, barren land, forest land, grass land, urban land, water areas (%)	30 m	2016 National Land Cover Database (NLCD)
Extreme weather	Temperature	Average of daily mean temperature in different phases (C)	5 km	Gridded Meteorological Data (GridMET) from "climateR" R-package
	Wind	Average of daily mean wind speed in different phases (m/s)		
	Snow	Maximum of daily snow cover during different phases	500 m	MOD10A1 V6 Daily Snow Cover
Topography	Elevation	Elevation (m)	30 arc-second	GTOPO30

the daily measurements for three phases. The land cover distribution was mapped based on the 2016 USGS Land Cover Database (NLCD), which was constructed from Landsat imagery at 30-m spatial resolution. For mapping the major land cover types, we aggregated 21 classes in NLCD into six classes: forest (class # 41–43), agriculture (class #81, 82), barren (class #31), grass (class #51, 52, 71–74), urban (class #21–24), and water (class #11, 12). For the snow cover database, the minimum, mean, and maximum map of three different phases were computed using the MOD10A1 daily snow cover database on Google Earth Engine, respectively. Other meteorological measurements reflecting summer drought and extreme weather as well as the air quality measurements were directly downloaded from the sources. All remote sensing raster data sets were reshaped to our study area and resampled to a spatial resolution of 25 km to keep it concurrent with the resolution of the aggregated observation data set. The earth observation data sets were also divided and aggregated into three phases: Phase 1 (August 1 to August 15), Phase 2 (August 16 to August 31), and Phase 3 (September 1 to September 23).

2.3. Geographically Weighted Regression (GWR) Models

We employed the Geographically Weighted Regression models to examine the relationships between different ecological and environmental factors and the number of bird deaths at the 25 km× 25 km grid level. The GWR model is a suite of Ordinary Least Squares regression models with the allowance of local variations in rates of changes, such that the coefficients of the model outputs are specific to a location *i* rather than being the global estimates (Brunsdon et al., 1996). The model structure of the GWR can be demonstrated as the following equations (Fotheringham et al., 2003; Mao et al., 2018):

Table 2
Model Performance and Predictive Power for the Best 10 Candidate GWR Models for Phase 1

Model No.	Model structure	ΔAICc	Global R^2
1	Urban + water + distance to fire + CO + pressure	0	0.72
2	Agriculture + barren + forest + urban + water + distance to fire + mean smoke + SO_2	38.7	0.70
3	Agriculture + barren + urban + water + snow + mean smoke + SO_2 + pressure + humidity	42.5	0.70
4	Barren + urban + water + snow + precipitation + CO + SO_2 + wind	186.5	0.69
5	Temperature + barren + urban + water + precipitation + mean smoke + CO + wind	450.2	0.66
6	Temperature + agriculture + barren + urban + water + snow + precipitation + mean smoke + SO_2 + wind	696.1	0.62
7	Temperature + barren + urban + forest + grass + water + snow + precipitation + mean smoke + CO + wind	1006.2	0.61
8	Temperature + barren + water + snow + precipitation + maximum snow + NO_2 + minimum humidity	2347.1	0.50
9	Barren + forest + water + distance to fire + snow + mean smoke + NO_2	2455.1	0.50
10	Barren + water + distance to fire + snow + mean smoke + NO_2 + maximum humidity	2462.9	0.49

$$Y = \beta_{0,i} + \sum_{k=1}^{m} \beta_{k,i} X_{k,i} + \varepsilon$$

where Y is the number of bird death events in each grid cell, $\beta_{0,i}$ is the intercept at the location i. The coordinates of location i are taken and multiplied with the local predictors $X_{k,i}$. The $\beta_{k,i}$ was estimated as the following equation:

$$\beta_{k,i} = \left(X^{\mathrm{T}} W_{i,j} Y\right) / \left(X^{\mathrm{T}} W_{i,j} X\right)$$

$$W_{i,j} = exp\left(-d_{i,j} / h\right)^2$$

where $W_{i,j}$ is the weighting scheme with j represents a specific point in space at which data are observed and i is the point in space for which the parameters are estimated; $d_{i,j}$ is the Euclidean distance between location i and j; and h is the kernel distance decay bandwidth.

Before the development of the GWR models, we first screened all the environmental covariates for multicollinearity (Pearson's correlation coefficient $|r| \geq 0.3$) (Mollalo et al., 2020). Please find the correlation matrices figures for each phase in the supporting information (Figures S1–S3). We standardized the continuous variables using the "scale" function in R v 3.6.4 (R Core Team, 2019) to allow the direct comparison across different covariates. We then developed separate GWR models for three different phases using the Geographically Weighted Regression tool in ArcMap 10 with a default bandwidth setting (i.e., 1,000 nearest neighbor locations were considered by using a kernel function). For each phase, we generated all possible addictive combinations of environmental covariates and selected the best model based on the corrected Akaike Information Criterion (AICc). Additionally, we estimated the model predictive performance of the best models in different phases based on the global and local R-square (R^2). GWR models were built using factors that were significant at the 90% confidence level.

3. Results

3.1. GWR Results in Phase 1

We selected Model 1 in Table 2 with the lowest AICc (the corrected Akaike information criterion) and highest global R^2 as the best model to describe the effects of different environmental and climatic environmental drivers on bird mortality in the western and central US in Phase 1. The differences in the AICc values between the best model with the lowest AICc and other candidate models (i.e., ΔAICc) were used as a measure of relative performance of each model for model selection. The overall predictive power of the top-selected model was pretty well with a global R^2 of 0.72 and the local R^2 ranging from 0 to 0.93 (Figure 2).

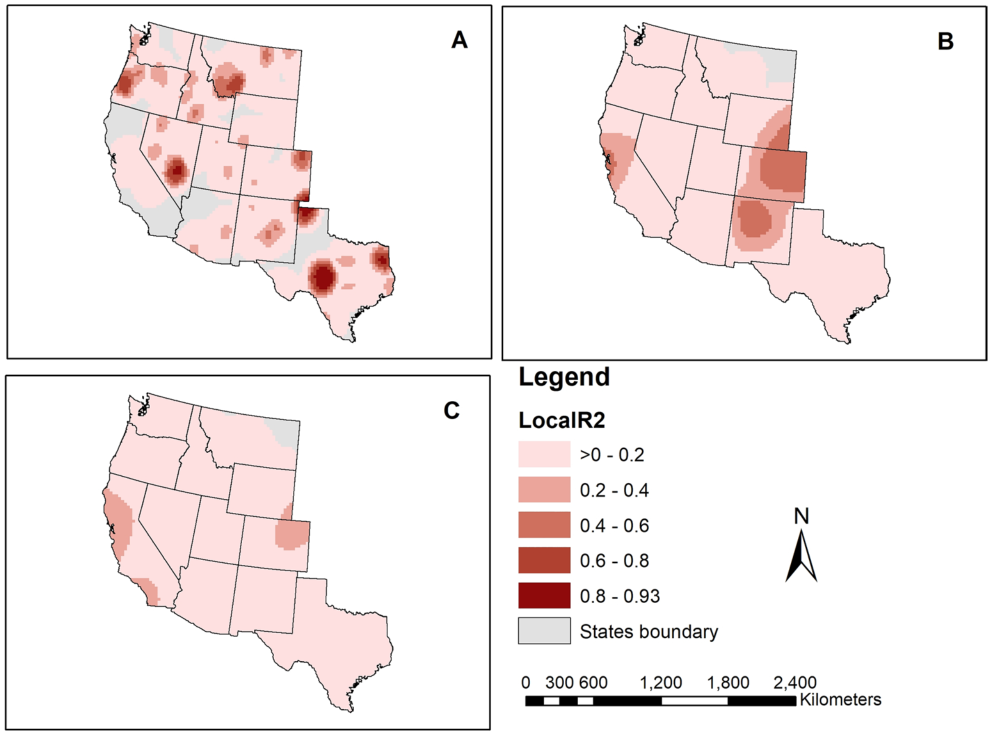

Figure 2. The local R^2 for the top-selected GWR models in different phases: (a) Phase 1, (b) Phase 2, and (c) Phase 3. GWR, Geographically Weighted Regression.

The local R^2 values of GWR result were not homogeneously distributed in western side of the United States with 12 states. Urban areas showed a positive correlation with the number of bird mortality events, while most water areas showed a negative correlation (Figure 3). In most circumstances, the further the bird mortality location was to the wildfires, the smaller the number of death events was found. The locations with higher CO concentration often led to more bird deaths except in some areas in central Texas, central Oregon, and northeastern Montana.

3.2. GWR Results in Phase 2

Model 1 in Table 3 was the top-selected model to describe the spatial patterns of bird mortality events in Phase 2. The overall model predictive performance is fairly good with the global R^2 of 0.31 and the local R^2 varying from 0 to 0.54 (Figure 2). Distance to wildfire was negatively correlated with the bird mortality events except for coastal California (Figure 4). In California, there were fewer bird mortality cases in the place where the average daily minimum humidity was lower. The NO_2 concentration was positively correlated with the number of bird deaths in the west of the study area but showed a negative correlation in Colorado and New Mexico. The increasing number of open water areas decreased the bird death events in California but increased the cases in New Mexico. Overall, the increasing number of urban areas in the region increased the number of bird mortality detections. Most of the agriculture land was negatively correlated with bird mortality, while barren land was positively correlated with bird mortality in areas surrounding California.

3.3. GWR Results in Phase 3

We selected Model 1 in Table 4 as the best model to demonstrate the effects of various factors on bird mortality across the landscape in Phase 3. The predictive power of the best model had a global R^2 of 0.22 and local R^2 ranging from 0 to 0.48 (Figure 2). When the locations were closer to wildfires, there were a smaller number of bird deaths (Figure 5). Most of the other covariates, including maximum humidity, SO_2, CO, water,

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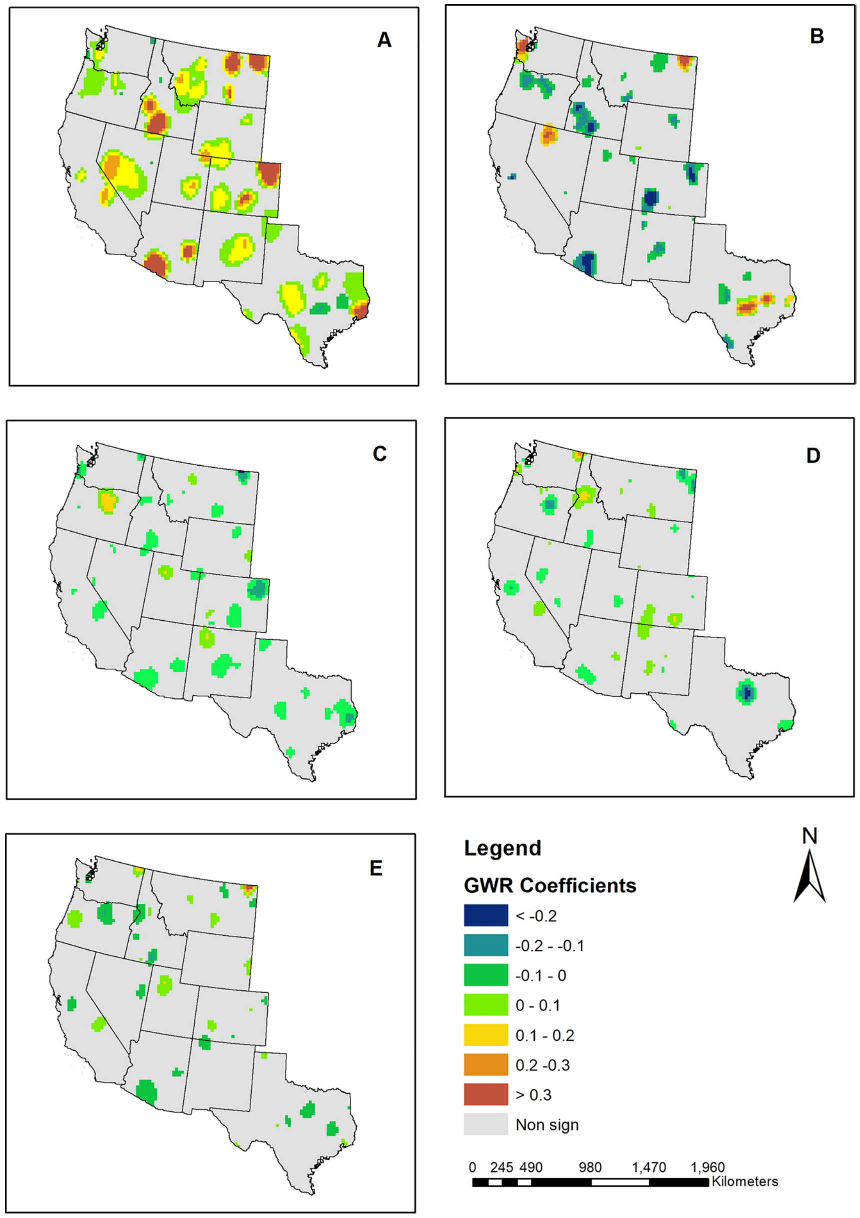

Figure 3. The coefficients of the top-selected GWR model for Phase 1. (a) urban; (b) water; (c) distance to wildfires; (d) CO; and (e) pressure. GWR, Geographically Weighted Regression.

urban, grassland, forest, barren land, and mean smoke, were positively correlated with the bird mortality events in most of the study area, especially in California, while wind speed was negatively correlated with the bird deaths in California (Figure 5).

4. Discussion

Extreme weather and natural hazards often pose significant threats to wildlife population and ecosystem sustainability, including habitat loss/fragmentation, forest loss, and species mortality (Dang et al., 2018; Gardner et al., 2017; Harris et al., 2018). The occurrence of two major crises, wildfires and the early snowstorm event, in the late summer of 2020, has been hypothesized to be the major factor that causes the massive mortality events of migratory avian species across the western United States. From the dead birds' lab report, all the birds were severely emaciated (New Mexico Department of Game & Fish, 2020). This

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Table 3
Model Performance and Predictive Power for the Best 10 Candidate GWR Models for Phase 2

Model No.	Model structure	ΔAICc	Global R^2
1	Agriculture + barren + urban + water + distance to fire + NO_2 + minimum humidity	0	0.31
2	Agriculture + barren + urban + water + distance to fire + snow + NO_2 + minimum humidity	14	0.31
3	Barren + grass + urban + water + distance to fire + maximum smoke + CO + pressure	502.5	0.25
4	Temperature + barren + grass + water + distance to fire + NO_2	694.1	0.23
5	Agriculture + barren + water + distance to fire + snow + precipitation + NO_2 + SO_2 + pressure	864.9	0.21
6	Barren + grass + water + distance to fire + snow + CO + wind + maximum humidity	877.6	0.21
7	Agriculture + barren + forest + urban + water + maximum smoke + wind + maximum humidity	894.5	0.21
8	Forest + urban + water + maximum smoke + CO + wind + maximum humidity	920.1	0.20
9	Forest + urban + water + average smoke + CO + SO_2 + wind	938.0	0.22
10	Agriculture + barren + water + distance to fire + precipitation + maximum smoke + CO + SO_2	1157.8	0.17

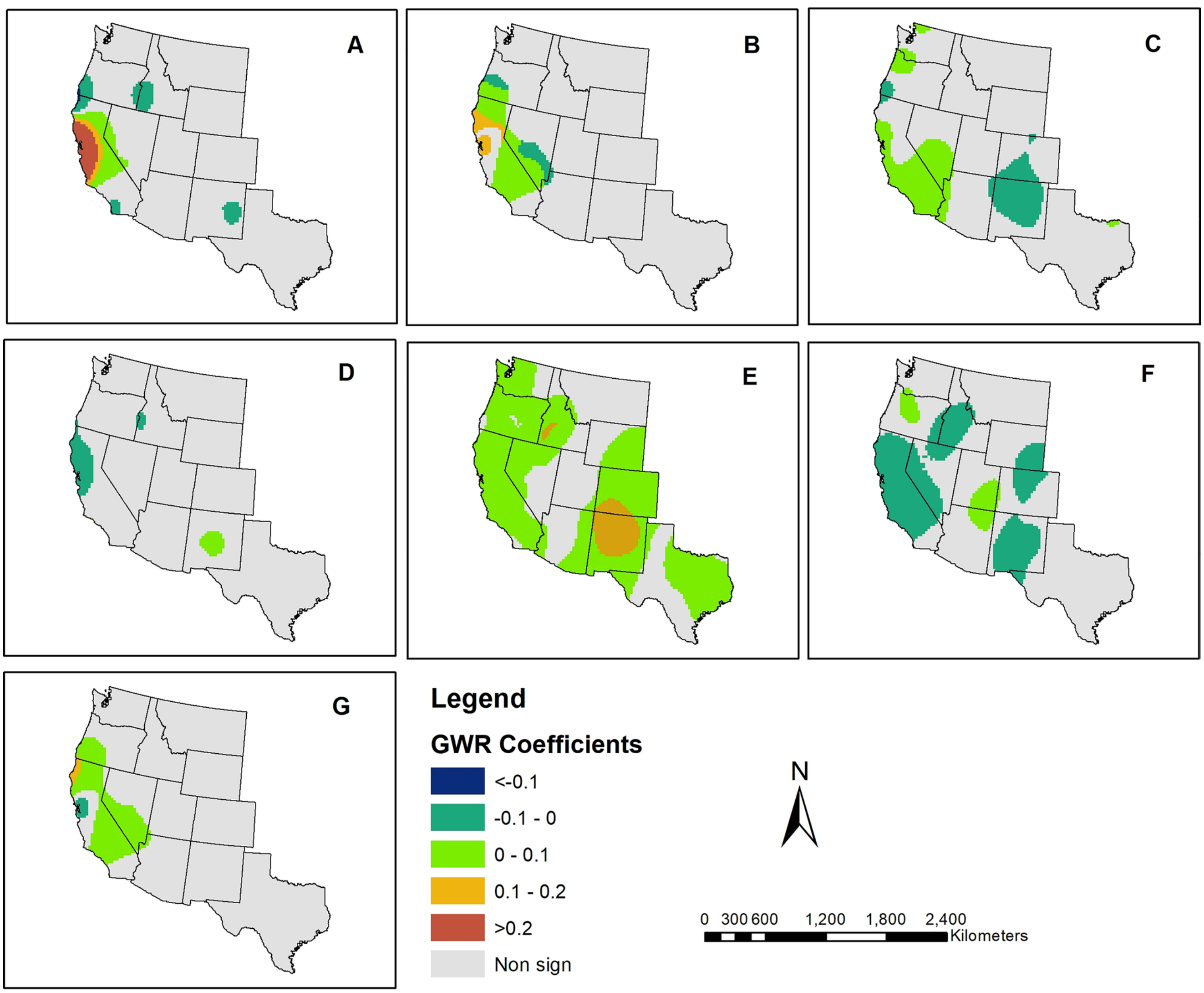

Figure 4. The coefficients of the top-selected GWR model for Phase 2. (a) distance to fire; (b) minimum humidity; (c) NO_2; (d) water; (e) urban; (f) agriculture (g) barren. GWR, Geographically Weighted Regression.

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Table 4
Model Performance and Predictive Power for the Best 10 Candidate GWR Models for Phase 3

Model No.	Model structure	ΔAICc	Global R^2
1	Barren + forest + grass + urban + water + distance to fire + mean smoke + CO + SO_2 + wind + maximum humidity	0	0.22
2	Barren + grass + water + distance to fire + snow + average smoke +	181.2	0.21
3	Agriculture + barren + water + distance to fire + NO_2 + SO_2 + wind + pressure	197.2	0.19
4	Temperature + agriculture + barren + urban + water + snow + CO + SO_2	268.2	0.20
5	Temperature + precipitation + urban + water + maximum smoke + CO + SO_2	381.7	0.18
6	Agriculture + barren + water + distance to fire + snow + average smoke + NO_2 + minimum humidity	458.9	0.15
7	Agriculture + barren + urban + water + distance to fire + snow + median smoke + SO_2 + maximum humidity	465.2	0.14
8	Barren + grass + urban + water + snow + average smoke + SO_2 +wind	652.3	0.12
9	Agriculture + barren + water + distance to fire + snow + average smoke + NO_2 + SO_2 + minimum humidity	656.9	0.12
10	Barren + forest + water + snow + median smoke + NO_2 + wind	980.5	0.08

research, to our best knowledge, is the first study to investigate and disentangle the effects and interplay of different environmental and climatic drivers on the spatial patterns of massive bird mortality at a continental scale. Here, we used the citizen science data set of bird mortality and compiled 21 potential environmental variables, which covers the factors of wildfire, air quality, land cover, and extremely cold weather, to examine the causes of the migratory avian deaths in the western United States in the late summer from August 1 to mid-September. Our results suggested that distance to wildfire and air quality were the major factors that influence the number of bird mortality over the study period. However, we did not find a significant effect of snow cover on bird deaths. Also, most mortality events detected were associated with the increasing urban areas in the study region.

In Phase 1 (August 1 to August 15), we found the covariate combination reflecting land cover composition, wildfire, summer drought, and air quality can be used to explain the bird death incidence distribution in the western United States. The proportion of the urban area within the region was a major factor that influences bird mortality. There were some degree of regional clustering of bird death detections in urban areas since the movement radius of most citizens are often limited to urban and suburban areas. This is especially true in 2020 under the emergence of two major crises, COVID-19 pandemics and air pollution caused by wildfires. Human mobility, physical activities, and travels were limited given the concerns of COVID-19 infection, social distancing COVID-19 control strategy, and unhealthy outdoor air quality (Archer et al., 2020; Huang et al., 2020). Thus, a clear positive relationship between urban areas and bird mortality has been suggested in all three phases. Additionally, most areas with less water body and away from the wildfire locations were associated with fewer bird death occurrences. However, some areas with water bodies in the middle of Texas, northwest of Washington have a positive association with bird mortality. Surface water and wetland systems often have important effects on reducing air pollution, balancing water cycles between atmosphere and land surface, and improving ecosystem functions (Cong et al., 2020; Qiu et al., 2019). Open water areas have been found to increase the richness and abundance of avian species, especially for shorebirds and water birds (Webb et al., 2010).

In Phase 2 (August 16 to August 31), predictors including the land cover types, distance to wildfires, minimum humidity, and NO_2 were selected to explain a relatively high variability of the death incidence in the western United States. The occurrence of very large wildfires has increased dramatically over the recent decades, causing significant social and ecological impacts (Barbero et al., 2015). The variable distance to wildfires contributed significantly to explaining the spatial patterns of bird deaths in Phase 2. However, in California, we found the distance to wildfires and minimum humidity were positively correlated with the bird deaths, which indicated that there were more bird death events when the location is further to wildfires and the average of minimum humidity is higher. This might result from the geographical distributions of bird death events in California. Most mortality events were located along the coastal shoreline which is away from the wildfires, since most of the large size wildfires that happened in California are in forest areas in Phase 2 and the fire patterns moved to the Mountain West in Phase 3. Additionally, some coastal

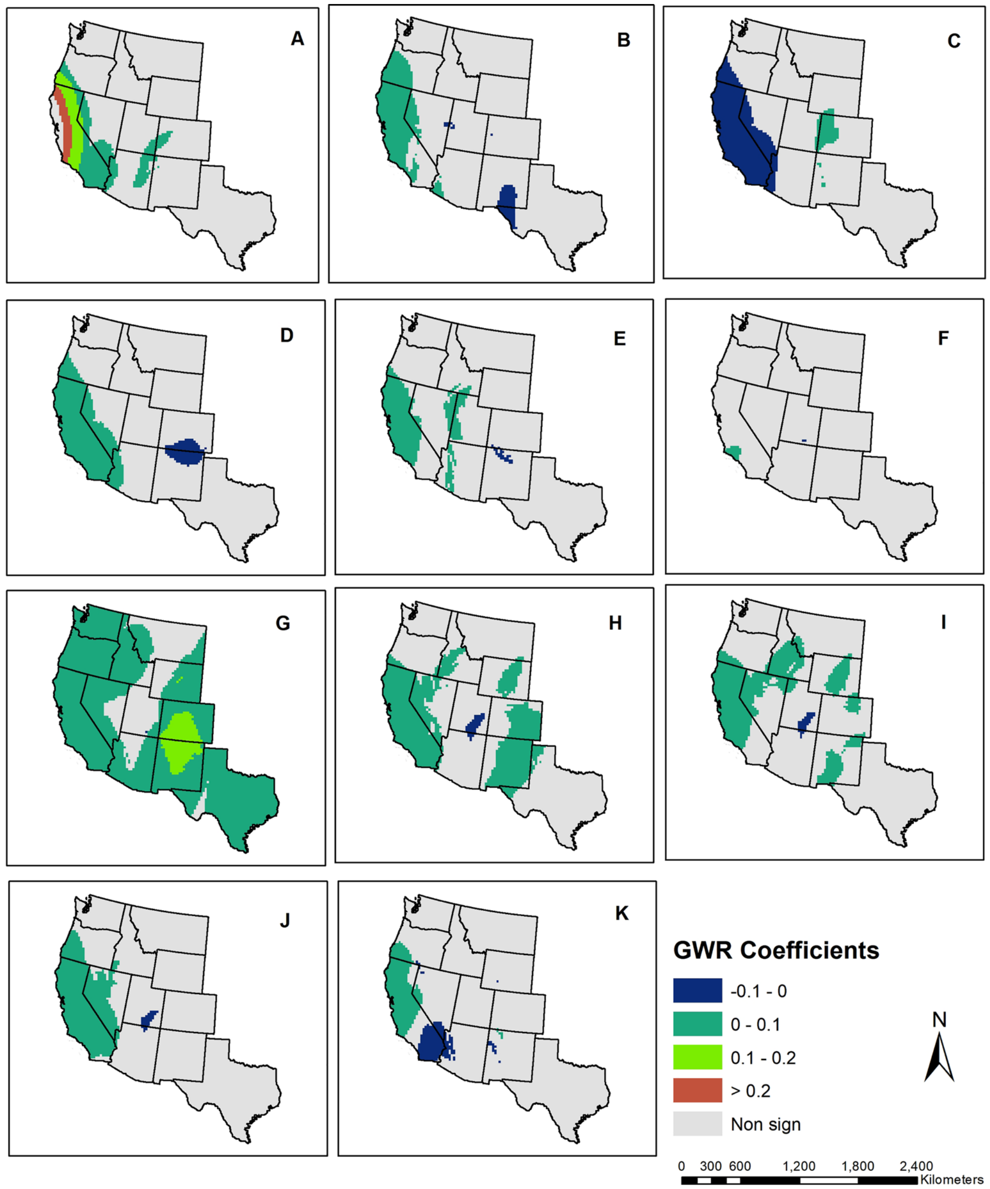

Figure 5. The coefficients of the top-selected GWR model for Phase 3. (a) distance to wildfires; (b) maximum humidity; (c) wind; (d) SO_2; (e) CO; (f) water; (g) urban; (h) grassland; (i) forest; (j) barren land; (k) mean smoke. GWR, Geographically Weighted Regression.

shoreline area in California can be hot and humid because of the wildfire radiation, oceanic evaporation, and the increasing precipitation in Phase 2, which might cause heat stress for avian species and lead to death (Arjona et al., 1988).

In Phase 3 (September 1 to September 23), the major factors explaining the increased distribution of dead birds include land cover types, wildfire, air quality, and drought. Similar to Phase 2, we found the variable distance to wildfire and maximum humidity was positively correlated with the number of bird death events. Air quality (CO and SO_2) was also positively correlated with bird mortality, which confirmed that toxic components (e.g., CO, NO_2, and SO_2) in the air often considerably threaten the survival of birds, since these pollutants could harm some organisms of birds such as kidney, lung, and liver. (Llacuna et al., 1993). Most of the observation records of bird deaths were collected at urban and park areas with public access, which makes the land cover type of forest, glass, urban, and water the major contributors of the best model in Phase 3. Land cover types of forestland and grassland may also supply habitats and food sources for avian insectivores. Thus, the areas with increasing forestland and grassland away from wildfires were associated with fewer bird mortality events.

Over the study period, we did not find a significant relationship between the snow cover and bird mortality, although we may expect that (1) the snow covers food supply on the migratory birds' pathways, (2) the unexpected cold temperatures affect the naive migratory birds (Newton, 2007), and (3) snow and wind reduce visibility and can cause the migratory birds to be disoriented (Alerstam, 1990). One possible reason is that some areas which are highly packed by snow are often not accessible for a while, and people tend not to travel much during the snowstorms. Some southern study areas like New Mexico, Texas, and California were not impacted by the snowstorms. Moreover, we did find that air quality has a positive relationship with the bird mortality in California within three phases. It is highly possible that the heavy wildfires degraded air quality, thus causing respiratory distress and illness in birds (Sanderfoot & Holloway, 2017).

The variables only explained about 22% of variances in the observed data in Phase 3, indicating that other factors that influence the mortality of avian species might be ignored in our study. For instance, there could be emissions of other toxic components except for CO, NO_2, and SO_2. Some bird mortality may result from the avian collision with human-made structures, including flights, lighted towers, and their guy wires, which annually killed millions of migrating birds based on the report (Longcore et al., 2013). Additionally, as we only tested the spatial patterns under one aggregated scale (25 m × 25 km), there could be some missing patterns after aggregations. The modifiable unit areal problems are the known critical issues that affect the spatial patterns and explanations in ecological studies (Fotheringham & Wong, 1991). Thus, future studies on how the spatial patterns change under different scales would be helpful to better understand the responses of avian species to natural hazards and rapid changes in the environment. Moreover, the GWR models in this study were developed based on one type of bandwidth. Further investigation is needed to explore how the selections of different bandwidths would affect the edge effects and result interpretations.

Although the citizen science database is a useful tool to benefit the study of ecological conservation, the data quality of iNaturalist and public participatory geospatial database remain considerable uncertainties (Haklay, 2013). iNaturalist contributors are often based on perceptions rather than scientific measurements, which could reduce the mapping quality and positional accuracy. Additionally, given that some citizen scientists are not experts in avian biology and ecology, there could be missing identifications or classifications of the species in the field. There are some strategies to overcome the credibility challenges of these participatory mapping databases (Haklay, 2013; Jiménez et al., 2019). First, there are a large number of “superusers” in citizen science mapping projects. These “superusers” make tremendous contributions by providing a large amount of near-real-time accurate information. Second, the quality control of iNaturalist is also a multiuser environmental validation process. Based on the “wiki” principle of most citizen science projects, the community of iNaturalist contributors can act as quality filters, which means the data set is self-validated by the other contributors' numerous times (D. Yang, Yang, et al., 2019). In this study, we applied this strategy, which to the point of self-validation; an extremely large proportion of our birds' databases has the quality mark of “research grade.” Finally, because of the vast amount of citizen scientist data, mapping effects are mostly aggregated based on the ground truth data provided by citizen scientist mappers (Cooper et al., 2007). This strategy can also be highly transferrable to other citizen science platforms such as eBirds and Journey North.

5. Conclusions

This study investigated bird migration and survival from the perspective of global climate change, natural disasters, and ecological disturbance. We employed citizen scientist contributed observation data and the geospatial models to explore the effects of potential environmental drivers on the spatiotemporal patterns of massive migratory bird mortality events across the western United States in 2020. Overall, our findings suggested that air quality and distance to wildfire were two major drivers that caused the severity of bird mortality events. The closer distance to wildfires indicated a smaller number of bird deaths, except in Phases 2 and 3 in California. Also, our results indicated that different land cover compositions affect bird mortality divergently over space and time, but with an increasing number of detections in urban areas. Our findings support calls for the efforts of the bird conservation program and Migratory Bird Treaty Act program to better take into consideration the interactions between environmental change and ecosystem sustainability.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All the data being used in this study can be archived from figshare at https://doi.org/10.6084/m9.figshare.13697434.

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