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Modeling in Biology Research and the Biology Classroom

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Modeling in Biology Research and the Biology Classroom

A THESIS

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ABSTRACT OF THESIS

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ABSTRACT:

Over the last few decades, science education has shifted from a focus on knowing facts about science to a focus on carrying out science practice in the classroom. However, few secondary science teachers have first-hand experience with scientific research. To this end, Dr. Beth Allan and Dr. Mike Nelson have suggested a new model for biology teachers seeking a master's degree. In this unique program, students have the opportunity to engage in both a biology research project and an education action-research project. Therefore, my thesis and is made up of two distinct projects: "Projected changes in range

suitability for *Gavia"* & "Implementing Model-based Instruction A Method to Improve Science Instruction."

Chapter 1: Projected changes in range suitability for Gavia

Most species are expected to be impacted by anthropogenic climate change. In the past, studies focused on tracking avian range shifts in response to changing temperatures. However, few studies have examined how avian distributions may change under different climate change scenarios. We used a maximum entropy approach to model the distribution of five loon species (*G. adamsii, G. arctica, G. immer, G. pacifica, and G. stellata)* under four climate change scenarios. We found that suitable habitat for *G. adamsii, G. pacifica, and G. stellata is* expected to decline under every scenario. However, highly suitable habitat will increase for *G. arctica* and remain relatively unchanged for *G. immer*. The centroid for all species shifted northward. Overall, centroids shifted at a median rate of 100.5 km/decade over all scenarios. A range of behavioral and phenological characteristic of loons will likely cause significant shifts in both range and populations across the species.

Chapter 2: Implementing Model-based Instruction A Method to Improve Science Instruction

The implementation of scientific modeling in science curriculum has the potential to improve students' ability to reason scientifically. However, there is little research that examines the impact modeling has on student content knowledge. In this study, we used an experimental design to demonstrate whether a cause and effect relationship exists between the type of curriculum implemented and student outcomes. The study took place over the course of one semester, 90 instructional days, and included two experimental and two control units designed to meet Oklahoma Academic Science Standards. Pre- and post-tests provided the evidence of student learning. Student attitude surveys and records of student work completed provided evidence of student engagement. Data analysis revealed no significant difference in either gains in student content knowledge or student attitudes toward science between treatment and non-treatment units.

INTRODUCTION

Over the last few decades, science education has shifted from a focus on knowing facts about science to a focus on carrying out science practice in the classroom. Years of research on science education culminated in the Next Generation Science Standards (NGSS). NGSS suggests a three-dimensional approach to science education: disciplinary core ideas (science content knowledge), cross-cutting concepts (ideas such as cause and effect that transcend science disciplines), and science and engineering practices. The three dimensions allow students to learn science as science is done. However, few secondary science teachers have first-hand experience with scientific research, making it difficult to teach students to carry out science. To this end, Dr. Elizabeth Allan and Dr. Mike Nelson suggested a new program at the University of Central Oklahoma. In this unique program, students have the opportunity to engage in both a biology research project and an education action-research project. Therefore, my thesis and is made up of two distinct projects: "Projected changes in range suitability for *Gavia*" & "Implementing Model-based Instruction: A Method to Improve Science Instruction."

Chapter 1

Projected changes in range suitability for *Gavia*

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INTRODUCTION

Many studies have shown a link between changes in the phenology and distribution of many organisms and the rise in global mean surface temperature by 0.87±0.12 degrees in the last 165 years (1). Anthropogenic climate change has been linked to changes in abundance and distribution of species (2, 3). In an interspecies study, Thomas (2010) found that between half and two-thirds of species moved their ranges in response to climate change. Climate change has impacted the distribution of avian species through contracting ranges (4), expanding ranges (5), and range shifts (6). Species that are highly vagile, such as migratory birds, may be both most impacted (7) and most successful in moving to new habitats (8, 9). A 2012 study of threats to avian species lists climate change as an important, but lacking, area of focus (10).

The rate of warming is almost twice as great in far northern latitudes compared to the rest of the world due to loss of sea ice and changes in poleward heat transfer (11-13); impacts of warmer temperatures in these ecosystems include glacier retreat, increasing river discharge, decreases in duration and extent of both snow cover and sea ice, and other changes to ecosystem structure and function (14). Ponds, lakes, and wetlands may experience even more dynamic change than rivers and coastline (15). Both the extent and distribution of wetlands are changing as a result of saltwater inundation, permafrost melting, and increased erosion (16). Avian species such as loons *(Gavia)* whose breeding grounds are in far northern latitude wetlands (17) may experience a variety of impacts. There are five extant species of loons: Yellow-billed Loons (*Gavia* *adamsii*), Arctic Loons (*Gavia arctica*), Common Loons (*Gavia immer*), Pacific Loons (*Gavia pacifica*), and Red-throated Loons (*Gavia stellata*). Most species occur in the Arctic and subarctic (17), but Common Loons extend as far south as central Mexico (18).

Loons, or divers in Europe, are migratory water birds similar to seabirds (19). Loons are characterized by medium-sized bodies with thick plumage, thin wings, a short tail short, robust legs, and webbed feet (17, 20). Loons are largely piscivorous, typically overwinter in marine environments, and breed on freshwater lakes (21).

Fossil record of Gaviiformes, which today include only the five *Gavia* species, occurred circumpolarly in the Holarctic since the middle Eocene (22). Recently, the alleged Austrian fossil auk *Petralca austriaca* points toward higher *Gavia* diversity in the Early Miocene of Europe (23). However, during the Cretaceous, Gaviiformes appear to occur only in the Southern Hemisphere (22). It is likely that Gaviiformes from the Late Cretaceous of Vega and Marambio islands dispersed to the Northern Hemisphere in the early Eocene (22). The Northern Hemisphere provided an ecological niche Gaviiformes could fill as competition as competition increased with a growing number of penguin species (22). Though loons have adjusted to climate change in the past, climate change is occurring much faster than in the past.

In the northern United States, the Common Loon *(Gavia immer)* has retracted its range to the north (18) and is ecologically important (24). Because of their trophic position, Common Loons have been proposed as indicators of aquatic health in the northern lake ecosystems they inhabit (25-27). Common Loons have been studied as primary indicators of mercury accumulation and other pollutants (28, 29) and as indicator species when predicting habitat recovery (30). Poor reproductive success in Common Loons is strongly linked to mercury pollution and acid precipitation (27). Thus, loons serve as a proxy species, alerting wildlife managers to potential changes to water quality and species fitness.

Ecological niche modeling has been used to predict changes in range and distribution for a variety of plant (31-33), animal (34, 35), and other species (36); however, studies on the effects of anthropogenic climate change on the projected distribution of loons have only been carried out at the regional scale (37), and there are no studies specifically examining the potential effects of this change on the future distribution of loons across the Northern Hemisphere. However, climate change research for loons consists largely of surveys (38-42) or specific management impacts (43). Much is known about loon nesting habitat requirements, and modeling studies have used that data to predict areas suitable for breeding (24, 44). Some studies have used modeling to predict the impact of climate change on loons. One such study focused on birds of the northeast United States, including loons. (45), and another modeled the distribution of breeding birds in Britain and Ireland, including loons (37).

Ecological niche modeling, also known as species distribution modeling, is widely used to address a variety of issues in biogeography, ecology, and evolution (46). Ecological niche models combine distribution data with environmental variable data to predict species distributions across time and space (47). There are a variety of modeling methods for evaluating the changing distribution of species such as loons through time (47-49). Models that use bioclimatic variables to predict distribution based on ecological niches are well suited to predicting changing distribution in response to climate change (50-53). A maximum entropy approach (Maxent) is particularly well-suited because it uses only presence data rather than presence and absence (pseudo-absence) data to model species distribution (53-55). Many studies have used Maxent to predict the future distributions of a wide range of taxa e.g, (2, 53, 56, 57).

In this study, we used Maxent to predict the ranges of five species of loons in the northern hemisphere. We then attempted to predict the impacts of climate change on these species by modeling their future niches under multiple climate change scenarios.

METHODS

Using methods described by Butler et. al (58), we modeled the current and projected distributions of breeding areas for five loon species (*G. stellata, G. immer, G. pacifica, G. arctica, and G. adamsii*) (54, 59). We download records of these species from eBird and Vertnet (60, 61), eliminated duplicate records, cleaned the data sets of errors, (62) and a incorporated locality data from the literature (63-66). We resampled the locality data so that there was only one record per 25 km^2 (67). We obtained range maps showing each species of loon breeding grounds from NatureServe (68) and then clipped the data to include only points within the breeding ranges for each species. We obtained data for elevation and 19 bioclimatic variables at a resolution of five arc-minutes from Worldclim (69). We clipped the geographic extent of the variables to include only the northern hemisphere (±180° longitude, 30° to 9° latitude) using ArcGIS (70). Only the variables with the highest gain when used in isolation were used because they appeared to have the highest predictive value. Also, those environmental variables that decreased the gain the most when omitted were used, as they seemed to have unique predictive information. We checked variables for high multicollinearity (71). We used the R package ENMEval to optimize regularization parameters to avoid model overfitting. We also used the small sample corrected variant of Akaike's information criterion (AIC_C) scores to evaluate the regularization of models (72) using all possible combinations of the variables that did not exhibit high multicollinearity. Receiver operating characteristic (ROC) curves were created by plotting sensitivity vs specificity, and tenfold cross-validation area under the curve (AUC) scores were used to evaluate the accuracy of the resulting model. Models with an AUC score of 1 indicated a perfect model, and models with an AUC score of 0.5 indicted a model that performs no better than random (54). It has been suggested that AUC scores be used in conjunction with other methods of evaluating models since they are not without limitations (73). Therefore, we determined the models that best describe the current distribution of the five loon species using AIC_C scores and model weights in conjunction with AUC scores. Based on these results, we created models of current and projected distribution of the five loon species using Maxent (54, 59). We used the R package ENMEval to optimize regularization parameters to avoid model overfitting. We used Climate BC as our GCM (74). Then we used that model to predict to the year 2070, using 4 different RCP scenarios. These included RCP 2.6 (projects that carbon dioxide emissions will peak before 2020 and decline after), RCP 4.5 (emissions peak about 2040 then decline), RCP 6.0 (emissions peak around 2080 and then decline), and RCP 8.5 (emissions continue to increase throughout the 21st century) (75).

Results

The best model for Yellow-billed Loons (i.e., with the lowest AIC score) included the variables maximum temperature of warmest month (BIO 5), minimum temperature of the coldest month (BIO 6), and elevation (Table 2). The AUC for this model was 0.951 ± 0.001. Areas that were predicted to have suitability >50% had a maximum temperature of the warmest month of 7.3-14.9°C, a minimum temperature of the coldest month of -37.7–33.1°C, and elevation that was below 200 meters. Areas that are currently shown as >50% suitability were nearly circumpolar, extending from Baffin Island (Canada) through northern Canada, northern Alaska, and northern Russia (Figure 2).

The best model for Arctic Loons included the variables annual mean temperature (BIO 1), mean diurnal range (BIO 2), precipitation of driest month (BIO 14), and elevation (Table 2). The AUC for this model was 0.940 ± 0.007. Areas that were predicted to have suitability >50% had an annual mean temperature of -1.8-7.3°C, a mean diurnal range of 5.2-8.6 °C, precipitation of the driest month between 24.3-61.9mm, and elevation that was below 359 meters. Areas that are currently shown as >50% suitability were nearly circumpolar, extending from Greenland through northern Canada, northern Alaska, northern Russia, and to Svalbard (Norway) (Figure 3).

The best model for the Common Loon included the variables annual mean temperature (BIO 1), precipitation of the driest quarter (BIO 17), and elevation (Table 2). The AUC for this model was 0.743 ± 0.005. Areas that were predicted to have suitability >50% had an annual mean temperature -0.8-6.8°C, precipitation of the driest quarter of 120.2-311.4mm, and elevation that was below 589 meters. Areas that are currently shown as >50% suitability were nearly circumpolar, extending from the Svalbard (Norway), through Iceland, Greenland, Canada, and Alaska (Figure 4).

The best model for Pacific Loons included the variables mean temperature of wettest quarter (BIO 8), mean temperature of coldest quarter (BIO 11), and elevation (Table 2). The AUC for this model was 0.882 ± 0.010. Areas that were predicted to have suitability >50% had a mean temperature of the wettest quarter of 3.3-11.9°C, a mean temperature of the coolest quarter of -31.6-22.0°C, and elevation that was below 90 meters. Areas that are currently shown as >50% suitability were nearly circumpolar, extending from Baffin Island (Canada) through northern Canada, northern Alaska, and northern Russia (Figure 5).

The best model for the Red-throated Loon included the mean diurnal range (mean of monthly [max temp − min temp]) (BIO 2), maximum temperature of warmest month (BIO 5), and elevation (Table 2). The AUC for this model was 0.855 ± 0.006. Areas that were predicted to have suitability >50% had a mean diurnal range of 4.3-7.8°C, a maximum temperature of the warmest month of

9.1–17.6°C, and elevation that was below 150 meters. Areas that are currently shown as >50% suitability were nearly circumpolar, extending from Baffin Island (Canada) through northern Canada, northern Alaska, and northern Russia (Figure 6).

The median projected change in highly suitable conditions (i.e., those >50% suitability) for all five species was −12.3% (range -66.4%– 15.0%), although there was considerable variation among species (Table 3). The amount of highly suitable habitat for Yellow-billed Loons, Pacific Loons, and Red-throated Loons declined, while the amount of highly suitable habitat for the Common Loon remained largely unchanged, and the amount for the Arctic Loon increased. However, the median amount of currently highly suitable habitat retained in future projections for these five species was only 53.6% (range 23.4%–81.1%).

Under all scenarios, suitable conditions for the Yellow-billed Loon declined precipitously by 2070, with highly suitable areas (i.e., those >50% suitability) reduced by 30.6 – 48.4% (Figure 7). A total of 4,464,047 km^2 was identified as being currently highly suitable (i.e., >50% chance of suitable conditions). By 2070, the amount of highly suitable habitat declined to 2,303,551 – 3,097,627 km^2, of which 42%–60% was shared with the current model (Table 3).

Under all scenarios, suitable conditions for Arctic Loons increased by 2070, with highly suitable areas (i.e., those >50% suitability) enlarged by 4.0 –15% (Figure 8). A total of 4,080,749 km^2 was identified as being currently highly suitable (i.e., >50% chance of suitable conditions). By 2070, the amount of highly suitable habitat increased to 1,572,173 – 2,756,693 km^2, of which 38.5%–67.6% was shared with the current model (Table 3).

Under most scenarios, suitable conditions for Common Loons changed by 2070 (Figure 9). Under three scenarios (RCP 2.6, RCP 4.5, and RCP 6.0), suitable habitat increased (Figure 9). However, under RCP 8.5 suitable habitat decreased. A total of 4,349,863.24 km^2 was identified as being currently highly suitable (i.e., >50% chance of suitable conditions). By 2070, the amount of highly suitable habitat varies from 3,819,417 – 4,724,504 km^2, of which 44.1%–81% was shared with the current model (Table 3).

Under all scenarios, suitable conditions for the Pacific Loon declined considerably by 2070, with highly suitable areas (i.e., those >50% suitability) reduced by 28.8 – 66.4% (Figure 10). A total of 3,778,491.96km^2 was identified as being currently highly suitable (i.e., >50% chance of suitable conditions). By 2070, the amount of highly suitable habitat declined to 1,269,218– 2,689,410 km^2, of which 23.4% – 52.8% was shared with the current model (Table 3).

Under all scenarios, suitable conditions for Red-throated Loons declined by 2070, with highly suitable areas (i.e., those >50% suitability) reduced by 11.7 – 20.2% (Figure 11). A total of 7,083,198.29 km^2 was identified as being currently highly suitable (i.e., >50% chance of suitable conditions). By 2070, the amount of highly suitable habitat declined to 5,651,452 – 6,258,190 km^2, of which 63.4% – 74.7% was shared with the current model (Table 3).

For all five species considered, centroids shifted generally northward (Figure 12). The median projected centroid shift for these five species was 100.5 km per decade, but considerable species-specific variability exists in the response rate. Under all scenarios, the rate of change for Yellow-billed Loons was 25 – 36 km per decade (Table 4). Centroids for Common Loons shifted at a moderate rate of 42–101 km per decade. In contrast, the rate of change was much faster for Arctic Loon centroids (81–187 km per decade) and for Red-throated Loon centroids (120–168 km per decade).

Discussion

Maxent effectively predicted the actual current distributions of all five species. The highest probability of occurrence coincided with the core of the species geographic ranges in general. At the edge of the species geographic ranges projected probabilities decreased. For some species, highly suitable habitat (>50% suitability) was projected to occur outside the geographic range. For example, models for Yellow-billed Loons and Red-throated Loons predicted highly suitable habitat extending across northern Russia, and the model for Pacific Loons predicted highly suitable habitat extending into eastern Russia. It is not surprising that suitable habitat was identified outside the core range of the species because species distribution models like Maxent can be used to predict the distribution of birds in novel habitats (76, 77). However, it is important to note that while ecological niche modeling predicts suitable species habitat, it does not predict whether the species can successfully gain access to the area (78).

Avian species are especially sensitive to climate changes (79-82). Our models project that highly suitable habitat will decline in the coming decades for Yellow-billed Loons, Pacific Loons, and Red-throated Loons under all four climate change models while highly suitable habitat will increase for Arctic Loons and remain relatively unchanged for Common Loons. These findings are consistent with another study predicting that 66-83% of migratory birds breeding in far northern latitudes will lose suitable habitat (83).

Even when the range of the species is predicted to increase, loons may not be able to expand its range accordingly. For the Arctic Loon, only 38%-68% of its current habitat will still be highly suitable by 2070. Though newly created highly suitable habitat will be created and the overall amount of suitable habitat may increase by as much as 15% (Table 3), there may be a lag and even a decrease before Arctic Loons can expand to occupy newly suitable areas. According to the IUCN, Arctic Loon populations are currently in decline with habitat alteration due to climate change listed among the threats (84). The Common Loon is also listed as a species of least concern and is the only member of the genus with a stable population, according to IUCN (85). Our models suggest that the amount of highly suitable habitat Common Loons for will remain largely unchanged.

Under all scenarios, a decline in suitable habitat is expected for Yellow-billed Loons, Pacific Loons, and Red-throated Loons. The Yellow-billed Loon is listed as near-threatened by the IUCN due habitat alternation as a result of climate change, biological resource use, and pollution (85). Our models project a 31%-47% decrease in highly suitable habitat for Yellow-billed Loons. The Pacific Loon is a species of least concern with increasing populations. The main threat to Pacific Loons is pollution (86). However, our models predict that highly suitable habitat for the Pacific Loon may decrease 29%-66% by 2070.

The Red-throated Loon is also listed as a species of least concern. However, Red-throated Loon populations are decreasing. Threats to Red-throated Loons include habitat alternation as a result of climate change, pollution, energy production, transportation, and biological resource use (87). Our models suggest a decrease in highly suitable habitat for Red-throated Loons between 12% and 20%. While our models predict overall decrease in highly suitable habitat, one study focusing on Scottish populations of Red-throated Loons predicts range expansion under a low climate change scenario and range reduction under all other scenarios (37). In Ireland, Red-throated Loons have the potential to increase suitable habitat under all scenarios (37). Despite their different current classifications, it seems likely that the Yellow-billed Loon, the Pacific Loon, and the Red-throated Loon will all decline by 2070 as a result of climate change. As a result, it seems likely that loon populations will decrease.

In contrast, our models predict an increase in highly suitable habitat for Arctic Loons across all scenarios. The IUCN lists the Arctic Loon as a species of least concern, though populations are declining (84). Despite a projected increase in highly suitable habitat, land use issues including energy production, transportation, fishing, and harvesting aquatic resources are likely to limit the amount of occupied suitable habitat. Likewise, our models predict an increase in highly suitable habitat for Common Loons for all but one climate change scenario. A species of least concern according to the IUCN, Common Loon populations are holding steady, and the only current threats are fishing and aquatic resource harvest (85).

The centroid for each species shifted at a median rate of 100.5 km / decade (range= 25 km/decade – 187 km/decade; mean=94.85 km/decade; Table 4). In a 2011 study, Chen et al. found that, overall, species have moved poleward at a median rate of 16.9 km/decade $^{-1}$ (mean=17.6 km/decade $^{-1}$) (88). Species at higher altitudes, like loons, are able to respond to climate change by shifting their ranges along latitudinal climatic gradients, perhaps leading to these greater range shifts (89). Several studies have demonstrated similar responses across different avian species and geographic locations (6, 90-92).

If the rate of climate change is too high, organisms may not be able to adapt quickly enough to persist in current ranges (93). Foden et al. suggest three dimensions to examine when determining a species' vulnerability to climate change: sensitivity (inability to persist in the current range), exposure (the extent to which the physical environment change), and adaptive capacity (ability to adapt through micro-evolutionary changes or dispersal) (94). Based on criteria described by Foden et al., loons have mixed sensitivity to climate change (94). Climate change is a threat to suitable habitat for loons, as much of the breeding are is threatened by changes in Arctic water levels. However, populations, with the exception of the Yellow-billed Loon, populations are stable. Loons have high dispersal capability but have low reproductive rates (18), resulting in mixed adaptive capacity. Both the highest overall warming and highest relative warming are predicted to occur in high latitudes, causing high sensitivity for loons (95, 96). This combination of factors will likely cause significant shifts in both range and populations across the species.

Models of currently suitable habitat allow wildlife managers to identify areas for management priority and develop management plans (46). Ecological niche models have been used to identify and protect critical habitats for threatened species like Yellow-billed Loons to establish wildlife persevere areas (97), and to identify areas for habitat restoration (98). However, these strategies focus on species and habitats as they currently occur. Because we know that species are being impacted by ever-increasing rates of climate change, it is vital to understand changes to species ranges and compositions in order to develop strategies for both long-term management of current sites and network-wide management (99). Specifically, understanding and predicating the variations of bird species in time and space is essential for understating population dynamics and for species conservation (41).

To maintain population objectives and mitigate the impacts of climate change, wildlife managers must understand both the current status of species and forecasts of species response to warming (16). Part of the management plans include identifying species of concern (16). Conserving avian species such as loons at high altitudes is especially important due to low diversity in the region (100). Loons, along with other migratory birds, play an important role in Arctic ecosystems (101) and, therefore must play an important role in Arctic management decisions. Three loon species (Red-throated Loons, Yellow-billed Loons, and Pacific Loons) breed in the Arctica Coastal Plain, Alaska. Understanding loon breeding can inform management decisions to protect loons, help implement protected buffer zones in the region, and inform decisions about offshore development in other areas (102, 103). As managers make decisions to protect loon populations, they can serve as umbrella species, indirectly protecting other species in the area.

To develop the most complete and accurate predictions of range changes, future research should use models integrating other factors which contribute to loon breeding habitat suitability. Interspecific interactions, including niche overlaps, spatial dynamics (104, 105), land-use, and physiology (106) are some important factors to consider. Further, improved survey data of Arctic species, including loons, will improve the accuracy of models. More complete and accurate predictions will be necessary tools for wildlife and managers as they respond to climate change.

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Figure 1 The five species included in this study are the Yellow-billed Loon, Arctic Loon, Common Loon, Pacific Loon, and Red-throated Loon.

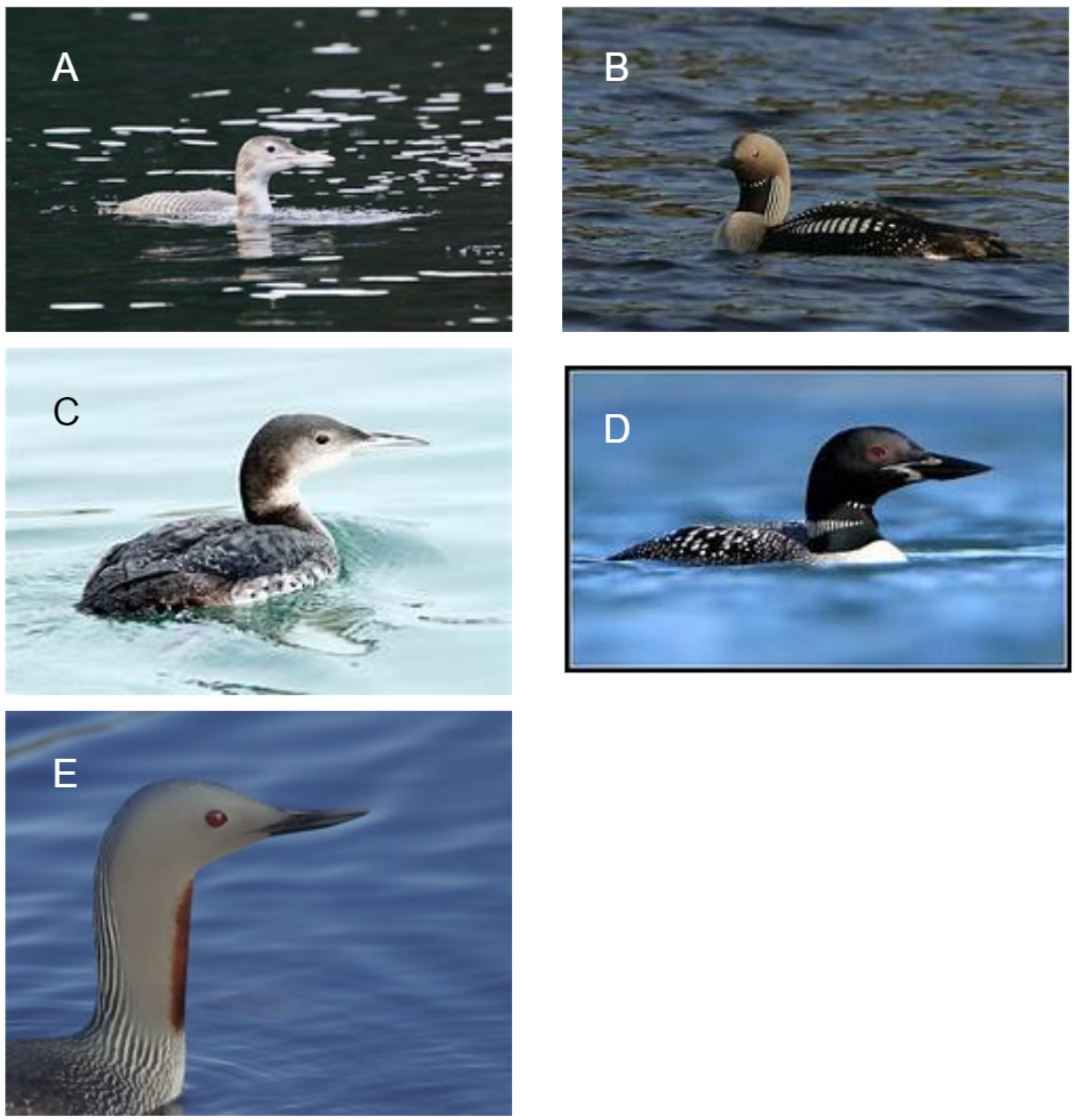

Figure 2. Locations where Yellow-billed Loons were recorded as present based on data retrieved are shown with stars (A). The modeled current distribution of Yellow-billed Loons (B). The probability is shown in grey scale in the legend; the darkest shade shows an area with >.5 probability of occurrence.

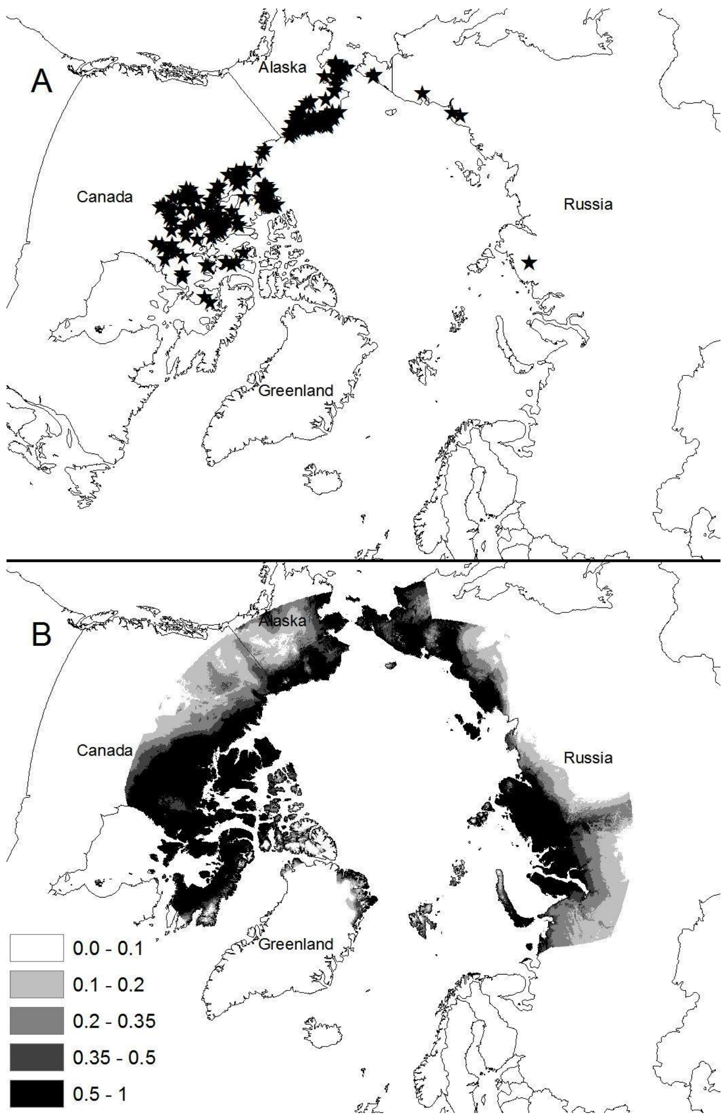

Figure 3. Locations where Arctic Loons were recorded as present based on data retrieved are shown with stars (A). The modeled current distribution of Arctic Loons (B). The probability is shown in grey scale in the legend; the darkest shade shows an area with >.5 probability of occurrence.

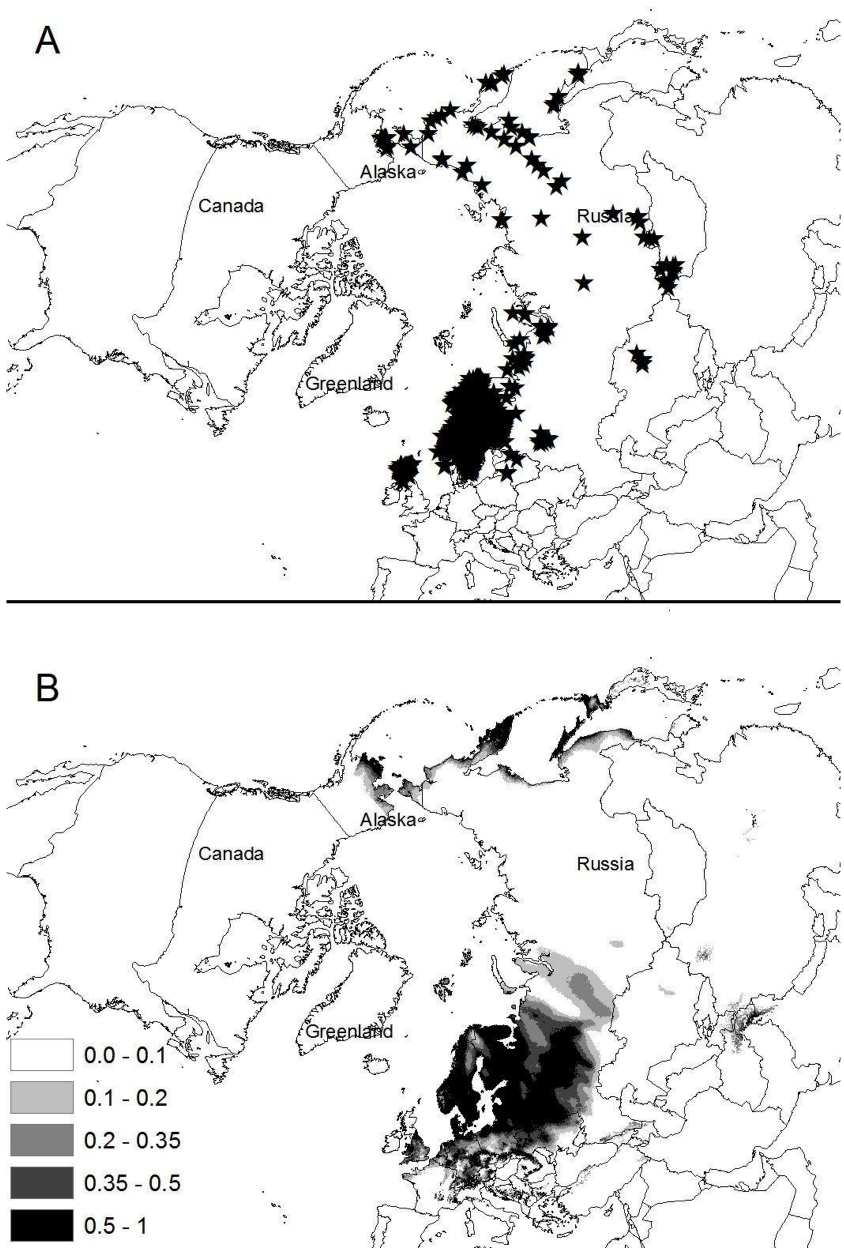

Figure 4. Locations where Common Loons were recorded as present based on data retrieved are shown with stars (A). The modeled current distribution of Common Loons (B). The probability is shown in grey scale in the legend; the darkest shade shows an area with >.5 probability of occurrence.

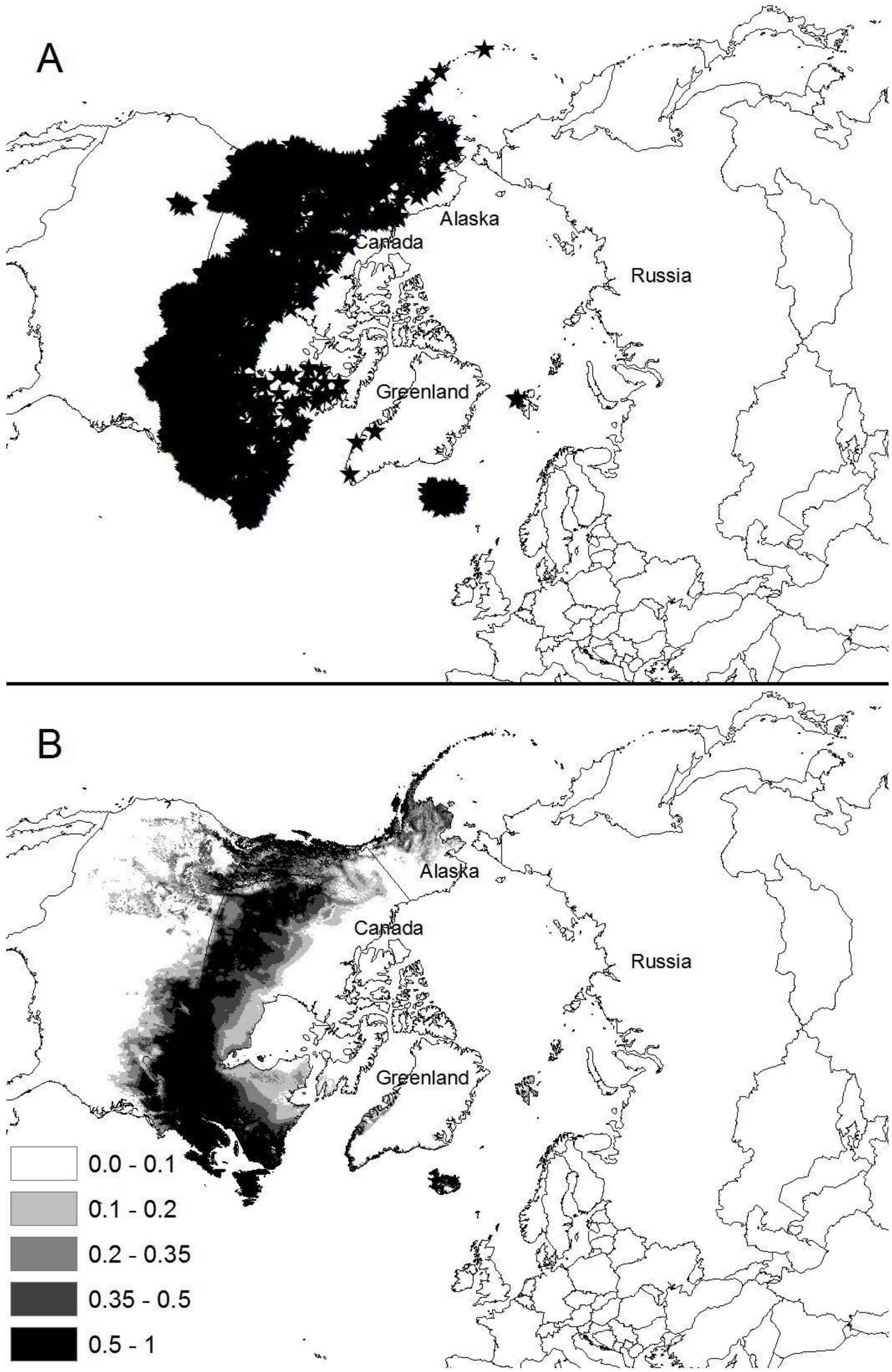

Figure 5. Locations where Pacific Loons were recorded as present based on data retrieved are shown with stars (A). The modeled current distribution of Pacific

Loons (B). The probability is shown in grey scale in the legend; the darkest shade shows an area with >.5 probability of occurrence.

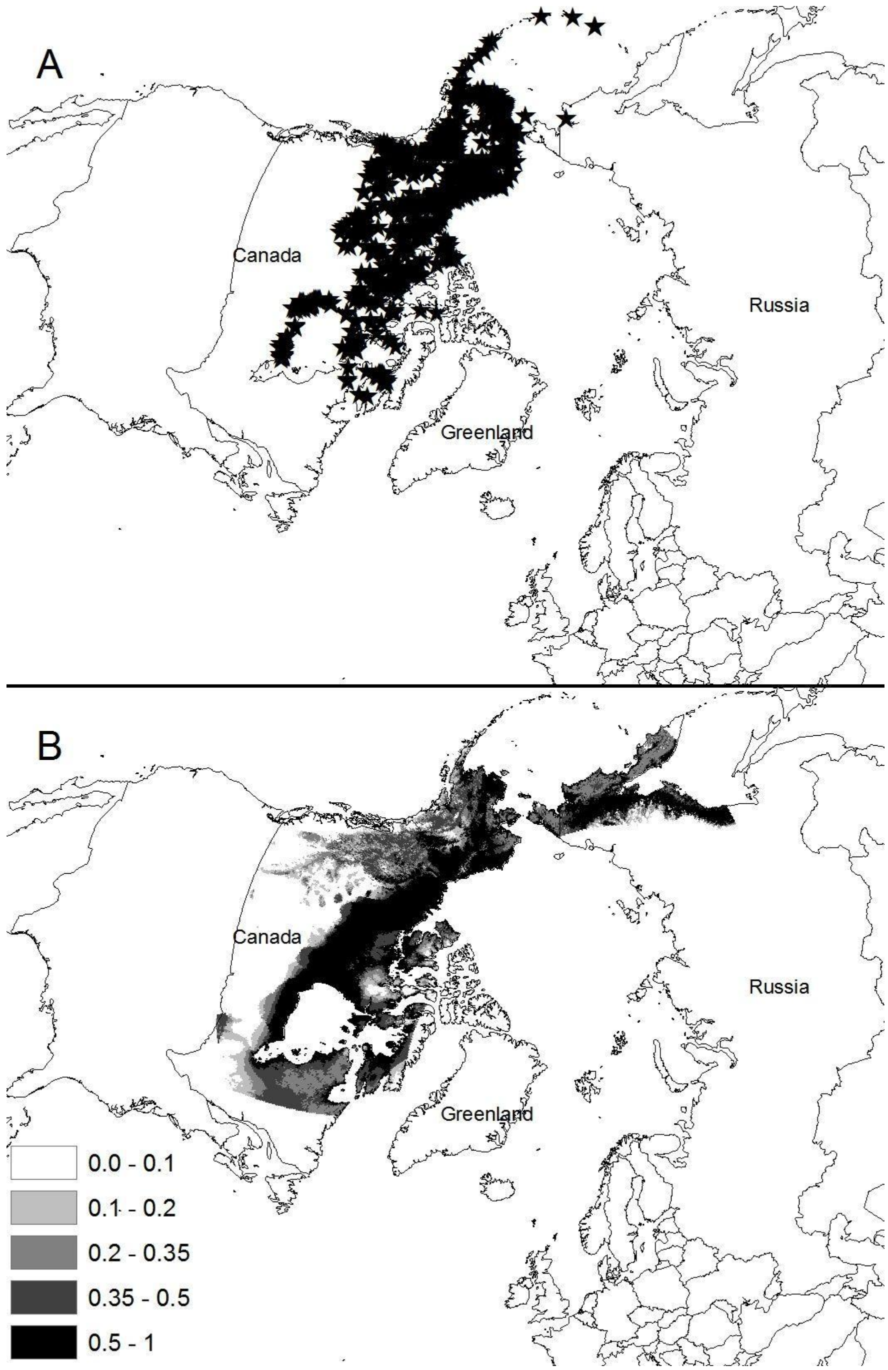

Figure 6. Locations where Red-throated Loons were recorded as present based on data retrieved are shown with stars (A). The modeled current distribution of

Red-throated Loons (B). The probability is shown in grey scale in the legend; the darkest shade shows an area with >.5 probability of occurrence. Locations where Red-throated Loons were recorded as present based on data retrieved are shown with stars (A).

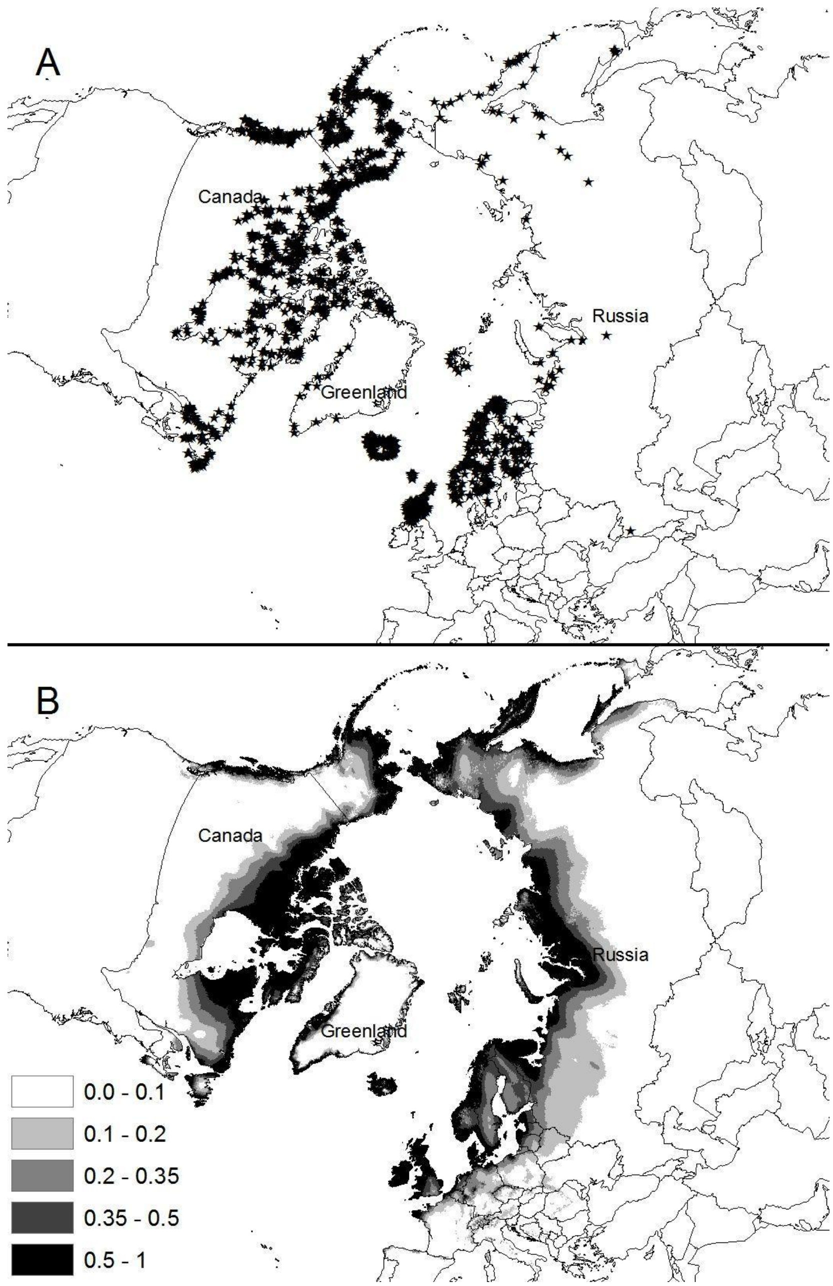

Figure 7. Projected distribution of Yellow-billed Loons under RCP 2.6 (A), RCP 4.5 (B), RCP 6.0 (C), and RCP 8.5 (D).

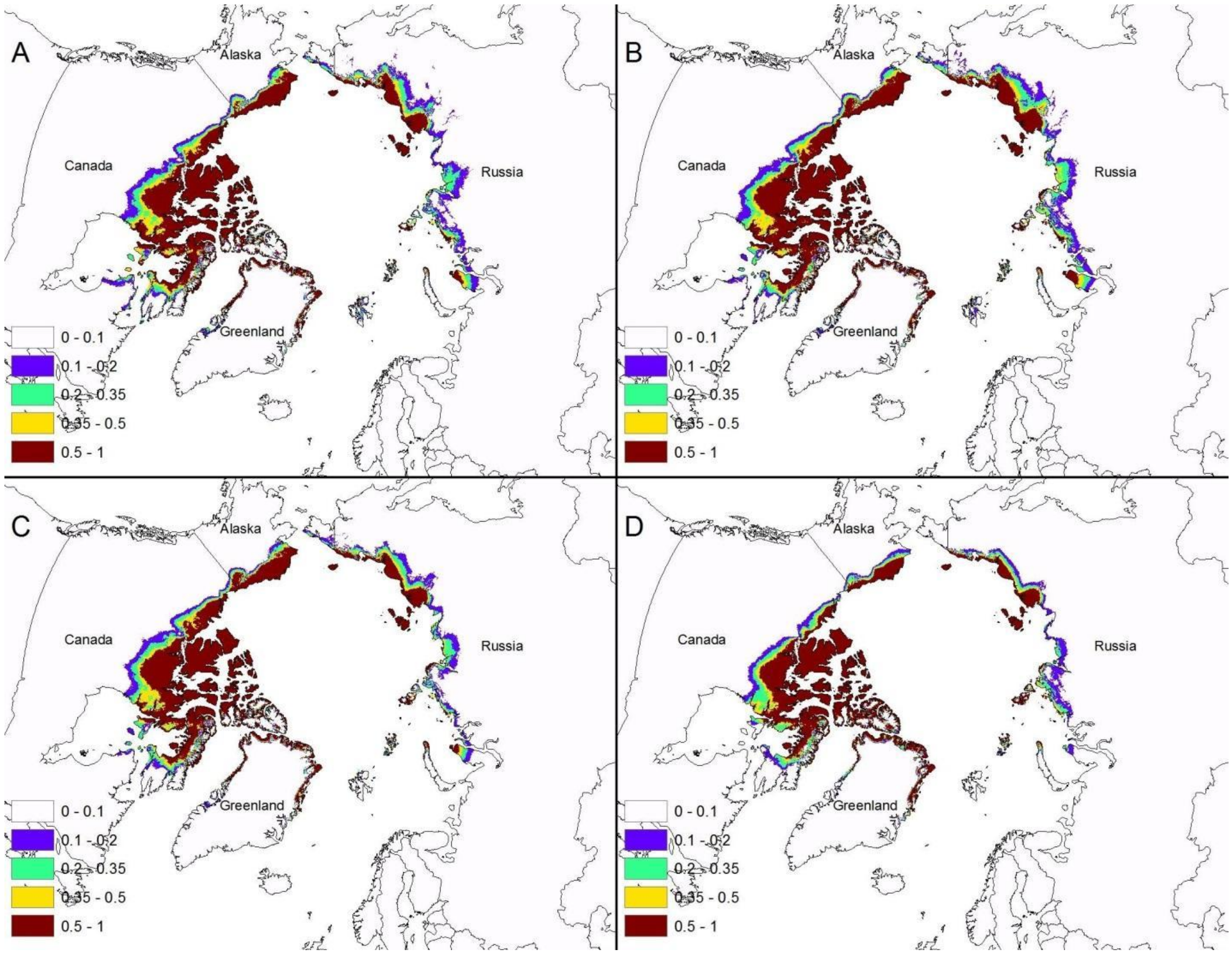

Figure 8. Projected distribution of Arctic Loons under RCP 2.6 (A), RCP 4.5 (B), RCP 6.0 (C), and RCP 8.5 (D).

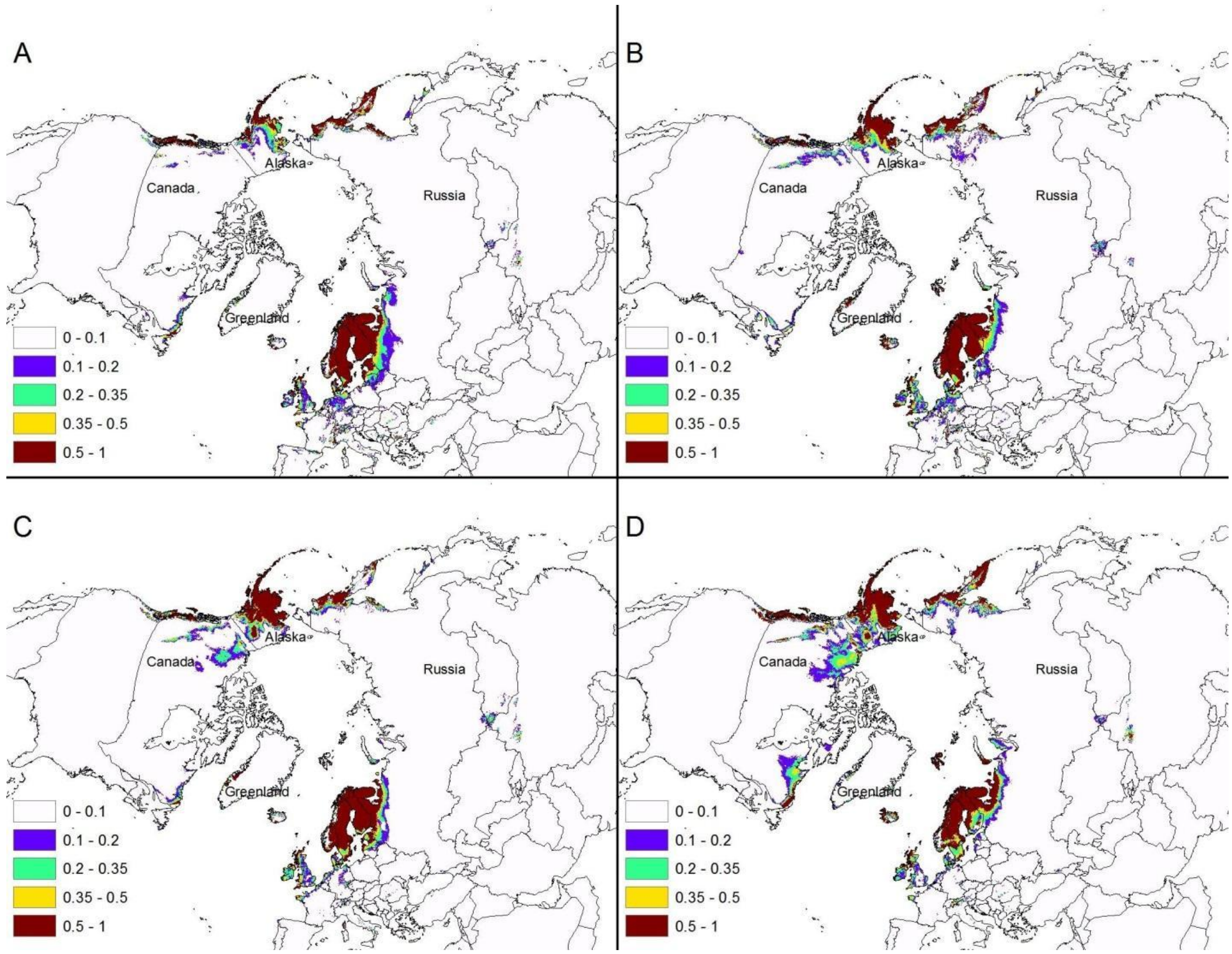

Figure 9. Projected distribution of Common Loons under RCP 2.6 (A), RCP 4.5 (B), RCP 6.0 (C), and RCP 8.5 (D).

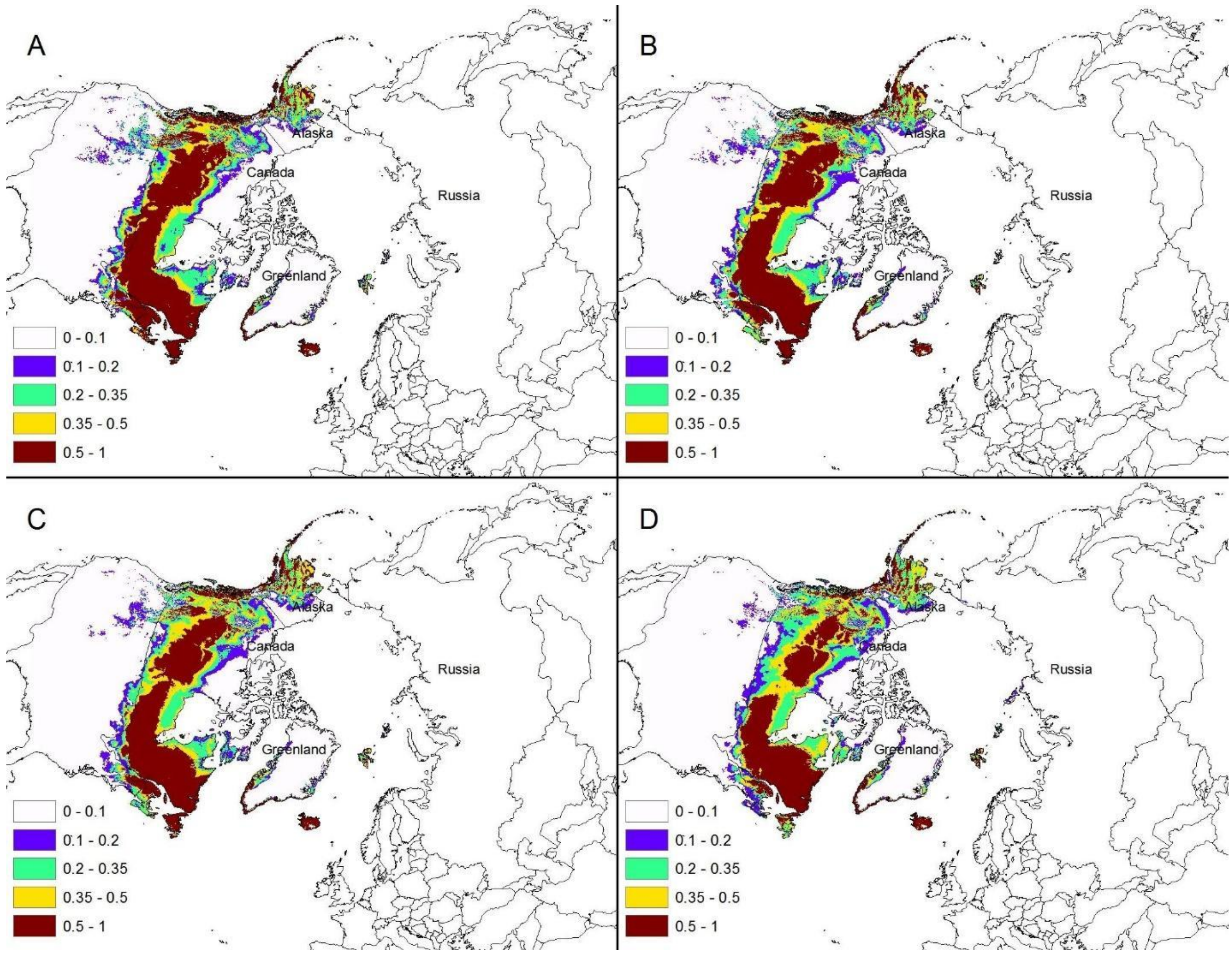

Figure 10. Projected distribution of Pacific Loons under RCP 2.6 (A), RCP 4.5 (B), RCP 6.0 (C), and RCP 8.5 (D).

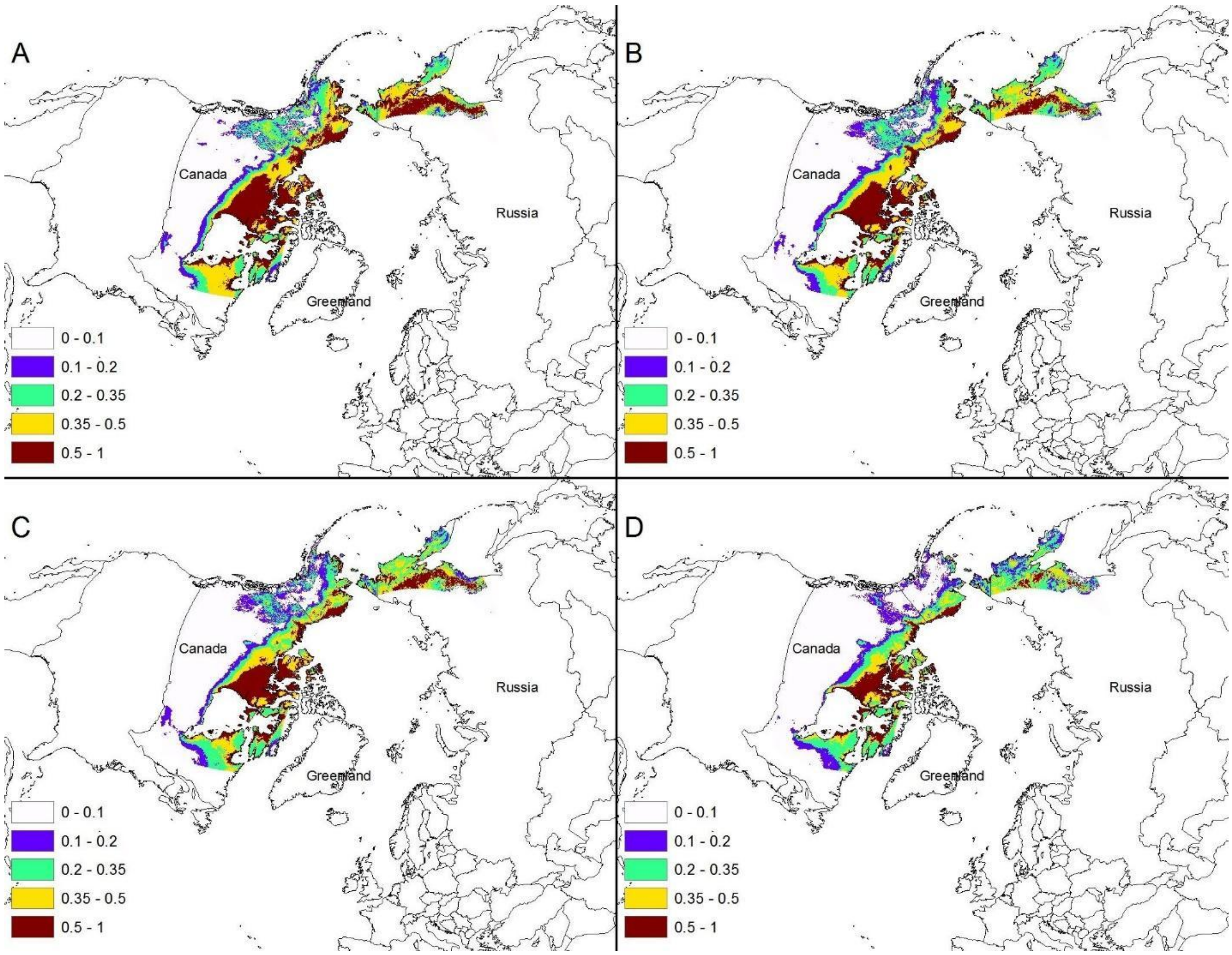

Figure 11. Projected distribution of Red-throated Loons under RCP 2.6 (A), RCP 4.5 (B), RCP 6.0 (C), and RCP 8.5 (D).

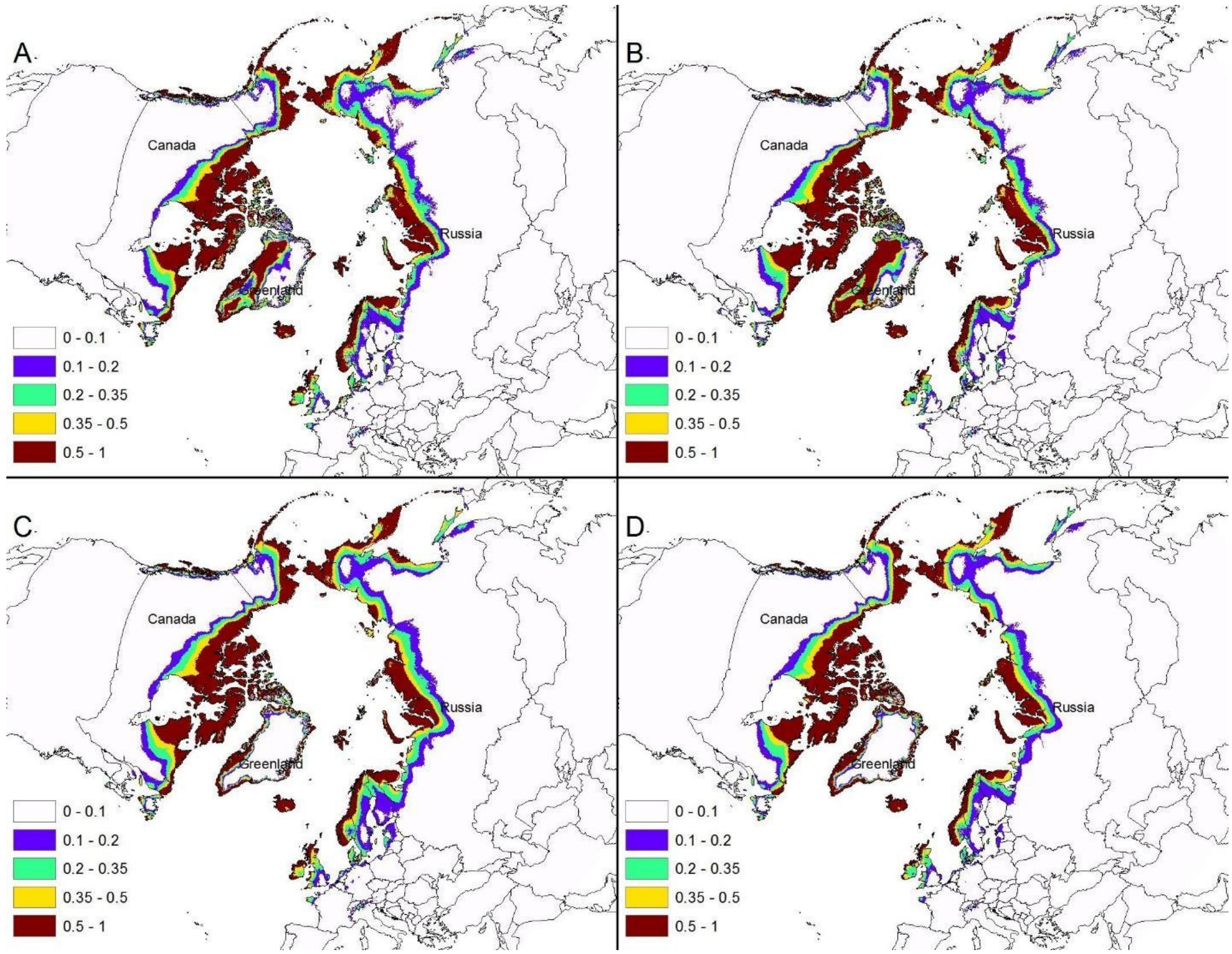

Figure 12. Projected centroids for each species (Common Loons (A), Arctic Loons (B), Common Loons (C), Pacific Loons (D), and Red-throated Loons (E)) under RCP 2.6, RCP 4.5, RCP 6.0, and RCP 8.5.

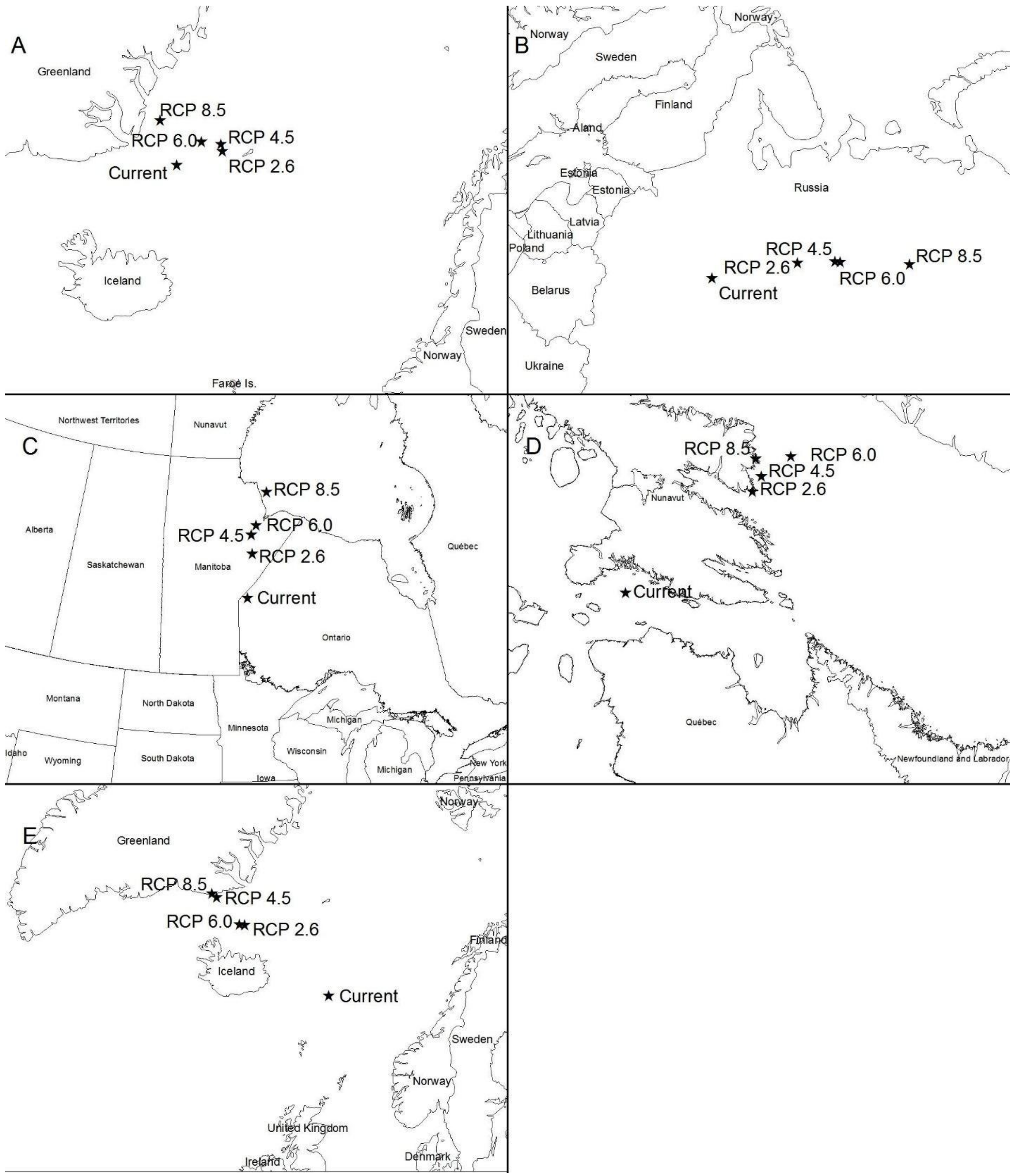

TABLE 1 Summary of bioclimatic variables used in this study

Variable	Definition
BIO 1	Annual mean temperature
BIO 2	Mean diurnal range (Mean of monthly [max temp – min temp)
BIO 3	Isothermality (BIO 2 / BIO 7) × 100
BIO 4	Temperature seasonality (standard deviation × 100)
BIO 5	Max temperature of warmest month
BIO 6	Min temperature of coldest month
BIO 7	Temperature annual range (BIO 5–BIO 6)
BIO 8	Mean temperature of wettest quarter
BIO 9	Mean temperature of driest quarter
BIO 10	Mean temperature of warmest quarter
BI0 11	Mean temperature of coldest quarter
BIO 12	Annual precipitation
BIO 13	Precipitation of wettest month

BIO 14	Precipitation of driest month
BIO 15	Precipitation seasonality (coefficient of variation)
BIO 16	Precipitation of wettest quarter
BIO 17	Precipitation of driest quarter
BIO 18	Precipitation of warmest quarter
BIO 19	Precipitation of coolest quarter
Elevation	Elevation above sea level

TABLE 2 A comparison of top model runs for each species

Species	Variables	Log-likelihood	AIC_C score	Δ AIC_C	$wAIC_C$	Mean AUC
G. adamsii	BIO 5, BIO 6, elevation	-14431.207	29027.274	0	.674	.951
G. arctica	BIO 1, BIO 2, BIO 14, elevation	-25462.013	51049.625	0	0	.940
G. immer	BIO 1, BIO 17, elevation	-105035.415	210187.613	0	1	.743
G. pacifica	BIO 8, BIO 11, elevation	-12616.02585	25341.43451	0	.991	.882
G. stellata	BIO 2, BIO 5, elevation	-23812.214	47708.165	0	1	.855

TABLE 3 The total area predicted to have >50% probability of suitable conditions for each species under each climate change scenario by 2070

Species	Scenario	Area (km²)	% change in area	Area common to current (km²)	% current distribution retained
G. adamsii	Current	4,464,047.26			
	RCP 2.6	3,097,626.61	-30.61%	2,663,998.59	59.68%
	RCP 4.5	2,303,551.06	-48.40%	1,885,270.10	42.23%
	RCP 6.0	2,887,704.81	-35.31%	2,395,157.62	53.65%
	RCP 8.5	2,380,758.26	-46.67%	1,946,023.68	43.59%
G. arctica	Current	4,080,749.00			
	RCP 2.6	4,243,962.84	4.00%	2,756,693.67	67.55%

	RCP 4.5	4,409,866.43	8.07%	2,164,197.80	53.03%
	RCP 6.0	4,632,738.07	13.53%	2,187,990.79	53.62%
	RCP 8.5	4,692,232.54	14.98%	1,572,173.20	38.53%
G. immer	Current	4,349,863.24			
	RCP 2.6	4,724,504.69	8.61%	3,526,816.77	81.08%
	RCP 4.5	4,642,348.73	6.72%	3,086,796.61	70.96%
	RCP 6.0	4,387,156.87	0.86%	2,789,457.10	64.13%
	RCP 8.5	3,819,417.25	-12.19%	1,919,215.44	44.12%
G. pacifica	Current	3,778,491.96			
	RCP 2.6	2,689,410.49	-28.82%	1,995,140.28	52.80%

	RCP 4.5	2,143,632.32	-43.27%	1,475,657.12	39.05%
	RCP 6.0	1,980,846.88	-47.58%	1,357,217.50	35.92%
	RCP 8.5	1,269,218.01	-66.41	883,027.49	23.37%
G. stellata	Current	7,083,198.29			
	RCP 2.6	6,202,179.42	-12.44%	5,236,576.43	73.93%
	RCP 4.5	6,227,185.44	-12.09%	4,794,968.88	67.69%
	RCP 6.0	6,258,190.04	-11.65%	5,293,588.82	74.73%
	RCP 8.5	5,651,452.59	-20.21%	4,487,733.08	63.36%

TABLE 4 A summary of the distance from each centroid for each scenario to the current centroid and the rate per decade

Species	Scenario	Distance (km) and direction from current	Rate per decade
G. adamsii	RCP 2.6	206 (ENE)	34 km/decade
	RCP 4.5	213 (ENE)	36 km/decade
	RCP 6.0	148 (NE)	25 km/decade
	RCP 8.5	206 (NNW)	34 km/decade
G. arctica	RCP 2.6	486 (ENE)	81 km/decade
	RCP 4.5	700 (ENE)	117 km/decade
	RCP 6.0	729 (ENE)	122 km/decade
	RCP 8.5	1122 (ENE)	187 km/decade
G. immer	RCP 2.6	250 (N)	42 km/decade
	RCP 4.5	358 (N)	60 km/decade
	RCP 6.0	413 (N)	69 km/decade
	RCP 8.5	607 (N)	101 km/decade
G. pacifica	RCP 2.6	546 (NE)	91 km/decade

	RCP 4.5	602 (NE)	100 km/decade
	RCP 6.0	722 (NE)	120 km/decade
	RCP 8.5	627 (NE)	105 km/decade
G. stellata	RCP 2.6	717 (NW)	120 km/decade
	RCP 4.5	967 (NW)	161 km/decade
	RCP 6.0	746 (NW)	124 km/decade
	RCP 8.5	1007 (NW)	168 km/decade

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Chapter 2

Implementing Model-based Instruction: A Method to Improve Science Instruction

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Introduction

As citizens of modern society, today's students will face a life permeated with science, engineering, and technology ideas. From making medical decisions to evaluating science-related political issues, it will be important for 21st century citizens to be proficient consumers of scientific information. Students with a strong STEM background will have a career advantage; a 2012 report from the President's Council of Advisors on Science and Technology reported that a million more STEM graduates will be needed to meet career demands in the next decade (National Council of Teachers of Mathematics, 2018).

Even before the need for scientifically skilled workers and for students graduating with those skills began to grow so quickly, historical events like the beginning of the space race highlighted the need to re-examine science education in the United States. In 1982, the National Commission for Excellence in Education saw a "rising tide of mediocrity" in science education and called for improved instructional standards (Michaels, 2008). Published in 1989, Science for All Americans was the seminal work in the progression toward current science teaching recommendation (Rutherford, 1990). In this work, Rutherford and Algren defined science literacy, outlined what all students should learn in school, and listed the steps the US must take to reform science education (Rutherford, 1990). In 1993, Benchmarks for Science Literacy took the work further, giving educators a suggested sequence of learning goals on which they should build their core curriculums ("Benchmarks for science literacy: Project 2061, American Association for the Advancement of Science," 1994). 2007's study Taking Science to School expanded on this work. In this work, researchers answered three questions: how is science learned, how should science be taught, and what other research is needed for us to understand how students learn science (Duschl et al., 2007). These decades of research culminated in the recommendations set forth by A Framework for K-12 Science Education. Central to these recommendations is that students should be engaged in doing science rather than learning about science (National Research Council . Committee on a Conceptual Framework for New K-12 Science Education Standards, 2012). The science and engineering practices outlined in the framework, including developing and using models, are the means by which students will do science in the classroom (Figure 1).

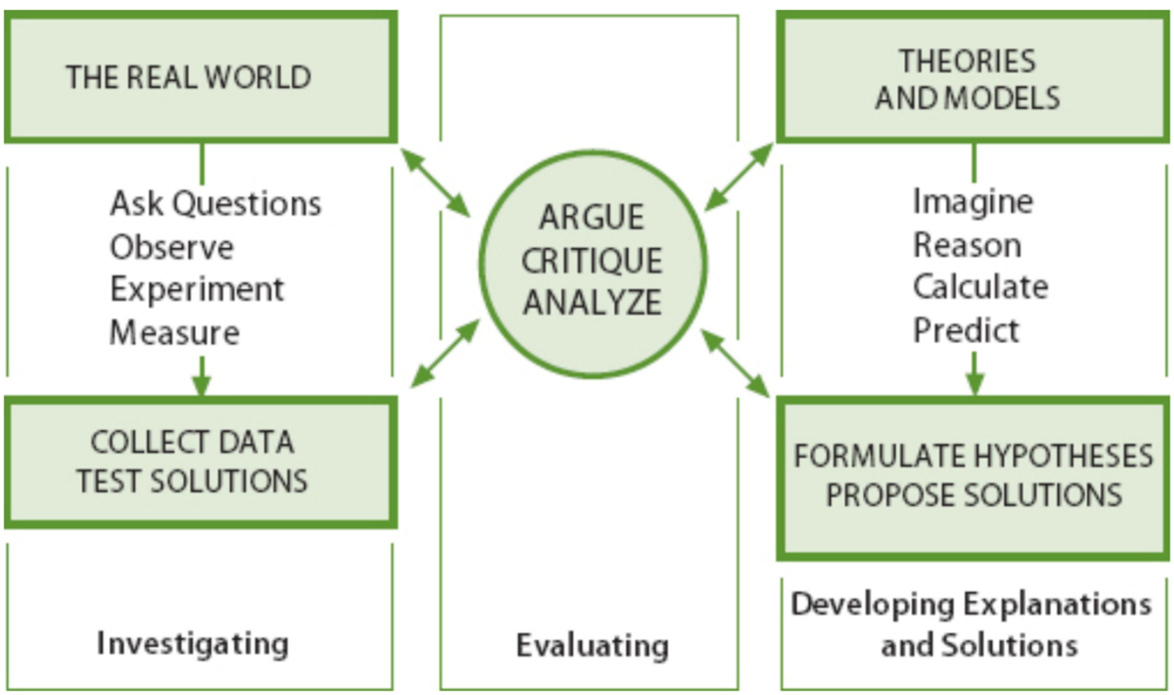


Figure 1—The three spheres of activity for scientists and engineers include the use of models (National Research Council . Committee on a Conceptual Framework for New K-12 Science Education Standards, 2012).

Overall, Harrah High School students consistently fail to meet college readiness standards in science reasoning. The ACT Aspire test sets the college readiness benchmark for science reasoning at 164 of a possible 175 points. On the spring 2018 test, Harrah sophomore students' average score was 155, and the national average was 161. The area these students struggled the most with was evaluation of models and results; their average score on the subset was 55%. Nationally, only 36% of students taking the ACT met the college readiness benchmark for science in 2016. Meanwhile, the most popular choice among the same group of students was health science / technologies, a STEM field ("Condition of", 2016). Evidence suggests that current educational practices are not meeting students' needs and that we should consider a shift in science instructional practices. Engaging students in real-world scientific modeling is an integral part of that process.

The implementation of scientific modeling in science curriculum has the potential to improve students' ability to reason scientifically and to increase their understanding of science content. It is imperative that members of modern society have this tool, not only for their professions, but also to make critical decisions as citizens.

As teachers work to integrate modeling into the curriculum, studies have investigated how students and teachers understand models (Aktamis & Caliskan, 2011; Torres, Moutinho, & Vasconcelos, 2015). Other studies have examined how teachers' implementation impacts student learning (Carrejo & Reinhartz, 2014; Schwarz et al., 2009). However, more research is needed to demonstrate the impact of modeling on student learning.

Understanding of Models and Modeling

Central to understanding how implementing models can improve instruction is understanding what students know and believe about models. In a 2011 study, researchers found that students had a good understanding of the criteria necessary for good models. The same study categorized student understanding of and beliefs about models into five categories: goals of models, characteristics of models, communicative elements of models, evidence in models, and epistemic elements of models (Pluta, Chinn, & Duncan, 2011).

For students to have a deep and flexible understanding of models, they should understand their purpose. However, students often hold very limited beliefs about this. Researchers have found that students believe models have several goals, but most of these understood goals are aimed at simply educating the model's audience. Among the goals named by students are giving explanations, providing information, giving descriptions, and answering a question (Pluta et al., 2011). Other students see models as idealized representations of reality or research tools, more ideas that are linked to educating the model's audience (Krell, Upmeier zu Belzen, & Krüger, 2014). In most studies, students did not indicate that models could be used to make predictions though this is a goal that many models actually have. One study addressed this idea by examining student beliefs about different kinds of models.

Researchers found that students see biology models as descriptive while physics and chemistry models are predictive (Krell, Reinisch, & Krüger, 2015).

Students tend to hold accurate, though limited, views about the characteristics of models. These are closely linked to their beliefs about models' purposes. Students believe that models can be diagrams, figures, maps, graphics, or pictures, which are all ways of communicating information (Aktamis & Caliskan, 2011; Pluta et al., 2011). Students also believe that models can be abstract, helping to provide an explanation (Aktamis & Caliskan, 2011). It is important to students that models communicate with clarity, focus, and appropriate details and that they are based on good evidence (Pluta et al., 2011). All of these characteristics students look for in models relate closely to their belief that models are primarily a way of sharing information.

Like their beliefs about model characteristics, student beliefs about models' epistemic elements are tied to their belief that models should be informative. One study listed several elements students believe make good models: quantity of evidence, descriptions, and information; creativity; interest; accuracy; and realism (Pluta et al., 2011). While some students rightly believe models are the result of inference, others believe that they are simply a copy of reality (Aktamis & Caliskan, 2011; Torres et al., 2015). Just over half of students believe models can change based on new evidence (Aktamis & Caliskan, 2011).

Teachers' views of models are similar in many ways to student beliefs and are likewise limited. Like students, they believe that models are the result of inference (Torres et al., 2015) and that the goals of models include providing explanations, information, and answers to questions (Pluta et al., 2011). However, many of their beliefs about models relate to instruction. Teachers believe that models contribute to better learning of science, about science, and how to do science (Torres et al., 2015).

Implementing Models in the Classroom

Though scientific modeling is frequently used in the classroom, it is rarely used to its best advantage. Scientific models are often a secondary resource for providing information rather than a primary tool for developing understanding and content knowledge. Based on findings about student and teacher understanding of models, researchers suggest the inclusion of more explicit introduction to scientific models and their uses to promote better understanding of science content (Krell et al., 2015). Specifically, they suggest students should learn about major scientific models, the nature of models and modeling, and how to use models (Krell et al., 2015). When models are used in these ways, students will be better able to develop their own understanding of science processes and content rather than relying on teachers to simply deliver information.

When students are given the opportunity to discover content and ideas for themselves, they have a deeper, more flexible, and longer-lasting understanding. Evidence suggests that science modeling and inquiry may transfer to science content learning (Schwarz & White, 2005). In one study though, students taught with a traditional lecture method initially showed a greater gain in content understanding; the difference between those students and students taught using a model-based inquiry method was smaller in delayed assessments (Campbell, Zhang, & Neilson, 2011). If the goal of science education is to equip students to be good consumers of scientific information, long-term understanding, which can be measured using delayed assessments, is more important than short term content knowledge.

The goal of equipping students as competent science consumers is best met when they are taught to reason scientifically. A good measure of student scientific reasoning is the ability to construct and use original models (Carrejo & Reinhartz, 2014). Studies show that implementing modelling in the classroom can result in an improvement in students' ability both to reason scientifically and also to construct models. One study demonstrated that through a model-based unit, students acquired several specific skills related to modeling including: constructing abstract models from specifics given, using models to make predictions, evaluating and comparing models, choosing which aspects to include in a model, and revising their models as their understanding changed (Schwarz et al., 2009). Model-based inquiry promotes student understanding of the nature and purpose of models and of abstract models and that multiple models can be used for the same phenomenon (Schwarz et al., 2009). Overall, model-based inquiry was more effective than traditional methods at improving students' science process skills (Ogan-Bekiroğlu & Arslan, 2014).

Even if students have adequate science content knowledge and the ability to reason scientifically, their attitudes toward science education and science education may be poor. Students may see science as less interesting than other subjects and not see science as leading to career opportunities (Sjøberg &

Schreiner, 2010). These attitudes can lead students away from pursing science once their requirements are filled (Gilbert & Gilbert, 2016). Lack of student engagement may lead to these poor attitudes. In many science classrooms, teachers dominate the talk, and students have few opportunities to actively contribute (Mortimer & Scott, 2003). Student-centered approaches like modeling provide opportunities to engage students and improve attitudes.

The body of research shows that model-based learning can be an effective tool for developing both content knowledge and reasoning skills in students as well as improving attitudes toward science. When model-based inquiry was used, students showed gains in their ability to use models which is a good measurement of their science reasoning skills. Therefore, it stands to reason that the use of models can also increase students' understanding of science content.

Study Design

An experimental design was used to demonstrate whether a cause and effect relationship exists between the type of curriculum implemented and student outcomes. The study took place over the course of one semester, 90 instructional days, and included two experimental and two control units designed to meet Oklahoma Academic Science Standards and Next Generation Science Standards (Table 1). Pre- and post-tests provided the evidence of student learning. Student attitude surveys and records of student work completed provided evidence of student engagement.

Control Units		Treatment Units	
Unit	**Oklahoma / NGSS Standarads**	**Unit**	**Oklahoma / NGSS Standards**
Natural Selection	HS-LS2-8 HS-LS3-2 HS-LS3-3 HS-LS4-1 HS-LS4-2 HS-LS4-3 HS-LS4-4	Biochemistry	HS-PS1-7
Ecology	HS-LS2-1 HS-LS2-2 HS-LS2-3 HS-LS2-4 HS-LS2-5	Cellular Energy	HS-LS1-5 HS-LS1-7 HS-LS2-5

Table 1—Control and treatment units were designed to meet Oklahoma Academic Science Standards.

Sample

A convenience sample was drawn from Biology I students at Harrah High School. Harrah High School is a rural high school in central Oklahoma. Though the population is not ethnically diverse, student abilities and socioeconomic levels are. About one-third of the students in the sample have an individualized education plan, and nearly half of the student body qualifies for free and reduced lunches. The biology students were high school students, primarily sophomores, ages 14-17; there were 140 participants.

Curriculum

A total of three control and three experimental units were taught over the course of the semester. Units in the experimental group focused on phenomenon-based scientific modeling to introduce students to the science content.

One lesson in the model-focused biochemistry unit was meant to reinforce and reteach the law of conservation of matter and the important concepts involved in balancing chemical equations. Though most biology students have previous experience with this material in previous courses, few demonstrate a working understanding of the ideas. We began with a class discussion of the basics: matter, elements, atoms, molecules and the basics of chemical bonds.

Next, I introduced the model. Each student was given a set of pony beads, each color representing an atom of a different element. Working on a felt square to prevent rolling and bouncing, the students arranged the beads into groups to represent the different molecules that are the reactants and products of a chemical equation. With the molecules created, the students observed that there were not necessarily the same number of each atom on both sides of the equation. This allowed them to see the need to balance the equations.

The next step was using the beads to balance. I explained to the students that balancing their equations required adding entire molecules, not just individual atoms. They had time to try adding molecules to each side of the equation, making adjustments and exploring solutions until the number of atoms was equal. Students then went on to practice balancing several other equations using the beads as a model.

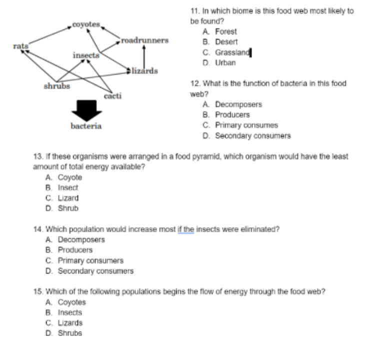
Units in the control group were not phenomenon-based and did not emphasize modeling. Instead, these units were taught under a more typical model including lecture, videos, and worksheets. Each unit was assessed using the NGSS Lesson Scanner, based on the EQUIP rubric to measure its adherence to NGSS standards (Achieve & Association, 2014). The control units met no more than two of the criteria; the treatment units met five of six criteria.

Measurement Tools

Before beginning the study, I developed pre and post assessments for each unit in the study. Each assessment had between 29 and 32 multiple choice questions designed to measure unit-specific content goals and followed this framework:

- 15-25% DOK question level 1
- 55-65% DOK question level 2
- 15-25% DOK question level 3.

As much as possible, assessment included cluster questions which include a stem and two to three questions each (Figure 2).



11. In which biome is this food web most likely to be found?
    A. Forest
    B. Desert
    C. Grassland
    D. Urban

12. What is the function of bacteria in this food web?
    A. Decomposers
    B. Producers
    C. Primary consumes
    D. Secondary consumers

13. If these organisms were arranged in a food pyramid, which organism would have the least amount of total energy available?
    A. Coyote
    B. Insect
    C. Lizard
    D. Shrub

14. Which population would increase most if the insects were eliminated?
    A. Decomposers
    B. Producers
    C. Primary consumers
    D. Secondary consumers

15. Which of the following populations begins the flow of energy through the food web?
    A. Coyotes
    B. Insects
    C. Lizards
    D. Shrubs

Figure 2—Cluster questions such as these are included as much as possible in science content pre and post assessments.

At the end of each unit, I administered a student survey to measure student attitudes towards science along with the content assessment. This instrument has fifteen items designed to measure overall science interest, interest in science careers, and the perceived importance of scientific knowledge. This survey was adapted from the BRAINS instrument (Summers & Abd-El-Khalick, 2018).

I gathered and collected all assessment and survey via ZipGrade, a web-based classroom grading tool. Students responded to survey and assessment questions on the company-provided answer sheets which were scored electronically.

Data Analysis

All statistics were run using IBM SPSS Statistics (Pallant, 2007). Paired samples t-tests compared pre and post-assessment scores, attitude surveys, and absence data. A mixed methods ANOVA compared growth in science content knowledge between control and treatment units. For the ANOVA, the pre and post-test scores were the within-subjects variable, and type of unit (treatment or control) was the between groups-variable. All data sets met the required statistical assumptions of normality and homogeneity of variance.

Results

For both treatment and control units, student content knowledge increased between the pre and post tests. In the control units, the average pre-test score was 37%, and the average post-test score was 50%. There is a significant difference between control unit pre and post test scores ($t(175) = -7.48$, $p < .001$). In the treatment units, the average pre-test score was 60%, and the average post-test score was 73%. The difference between these scores is significant ($t(80)=-8.12$, $p<.001$).

Though students showed growth in content knowledge for both treatment and control units, a mixed-design ANOVA demonstrated no significant difference in the amount of growth between the two types of units ($F(1, 1) = 1.81$, $p= .278$).

During the control units, there was an average of 1.9 students absent per day. During the treatment units 1.53 students were absent per day, on average. There is not a significant difference in attendance between control and treatment units ($t(1) =3.86$, $p=.161$). The mean attitude scores for control units was 48.84 (of 75 possible points), and the mean attitude scores for treatment units was 48.87. A paired samples t-test showed no significant difference in the attitude survey scores between control and treatment units ($t(172) = -.037$, $p=.970$).

Discussion

Over the last several decades our understanding of how students learn science and, therefore, how science should be taught have gone through radical shifts. The culmination of these changes, A Framework for K-12 Science Education, suggests that students should learn to do science rather than learn a large body of science facts. The main tenets of what doing science should look like in the classroom are the Science and Engineering Practices outlined in the framework (National Research Council . Committee on a Conceptual Framework for New K-12 Science Education Standards, 2012). Through these practices, students have the opportunity to engage in science at their own level and to learn to think scientifically, a skill necessary for the 21st century workforce and for citizenship in a world that ever more dependent on science and technology in everyday life.

Developing and using models, one of the eight science and engineering practices, is a way for both scientists and science students to visualize and understand a phenomena (National Research Council . Committee on a Conceptual Framework for New K-12 Science Education Standards, 2012). When students learn to use models, they are learning to think like scientists.

Content knowledge

The focus on modeling in the Biology I curriculum had no significant impact on content knowledge growth compared to other curriculum. Though the research demonstrates that an emphasis on modeling can have significant impact on students' understanding of models and science reasoning skills, pre and post-test data show that the impact is not the same for content knowledge. These findings are in line with previous research that demonstrated little difference in the short term (Campbell et al., 2011). It is possible that a second set of assessments, farther removed from the initial units, would have showed that model-based teaching improved long-term content knowledge gain, as other have previously demonstrated (Campbell et al., 2011).

Students did gain content knowledge in treatment units, though the growth was not significantly more than in control units. However, during modeling activities, students were more engaged and their discussions demonstrated more sophisticated understanding than during control units. During a unit on biochemistry, students used felt and bead models to explore chemical reactions and the law of conservation of matter. Though most of the students had experience with these concepts in previous courses, many students expressed either a deepened understanding of the concepts or that they truly grasped the ideas for the first time when they were given a model. This understanding, and the confidence it produced, carried forward into the second model-based unit, cellular energy. As students worked with various models of photosynthesis and cellular respiration, they drew on their understanding of chemical reactions to create their own models of photosynthesis and cellular respiration.

Student attitudes toward science

A focus on modeling produced no significant difference in student attitudes toward science as reported in science attitude surveys. However, like with content knowledge, there is anecdotal evidence to the contrary. When given the opportunity to use models, student comments and willingness to participate in class activities demonstrated increased confidence in their ability to do science. Some students even shared their modeling activities with students outside of my classroom to help them understand similar concepts in other science courses. A possible explanation for the discrepancy between the surveys and my own observations is survey fatigue. The students completed the same survey multiple times over the course of the study; it seems likely that many students simply chose answers flippantly rather than taking the time to think about them well.

Student absenteeism was also used to examine student engagement. There was no significant difference in the number of unexcused absences between control and treatment units.

The Student Perception of Science survey indicated little to no difference in treatment and control units in impacting student attitudes. It is unlikely that such limited experiences are capable of drastically altering a student's perception of science. Therefore, future research will need to conduct a measurement following a more intensive integration of modeling into currently curriculum to determine whether a greater emphasis is capable of impacting a student's perception. Also, a novel method for gauging student attitudes is needed to replace or augment the instrument, in order to reduce or eliminate survey fatigue.

Future research

A primary goal of this project was to determine whether an emphasis on modeling as an instructional strategy could effectively increase student content knowledge. Towards this goal, our model produced no significant results. However, the study did raise some additional questions.

- Does an emphasis on modeling have a greater impact on students' long-term retention of content knowledge than traditional instruction?
- What impact does an emphasis on modeling have on student ability to answer higher-order questions?
- Is modeling equally effective for all groups of students, including those at different ability levels (special education, honors, etc.) and from underrepresented groups?
- Would a longer model-based curriculum have a greater impact on student attitudes toward science?
- How might the efficacy of implementation of the intervention as well as control be related to the findings?

Conclusion

Though the increase in student content knowledge and student attitudes toward science was not significantly greater for model-based units than for traditional units, a focus on modeling is still a useful tool in the science classroom. When students were given the opportunity to work with models, they were more engaged with the content, showing more interest and having longer, more involved discussions. The enthusiasm for the modeling activities carried on outside the units and even the classroom, as students referred back to them at different times and in different contexts. If student learning continues, even at the same rate as with other methods, there is value in implementing methods that create high student engagement.

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Conclusion

The opportunities I had to do research during the course of the program will have long-lasting impacts on me both as a scientist and as a science educator. Having a background in scientific research has given me the tools to conduct research in the future and to translate those research skills into my classroom. Doing educational research will allow me to formalize the research I do in my classes as I implement new techniques and evaluate their impact. I am also now prepared to advocate for research-based teaching in my classroom, my school, my district, my state, and the nation.