How will climate change affect the potential distribution of Eurasian tree sparrows *Passer montanus* in North America?

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Abstract   Habitat suitability models have been used to predict the present and future potential distribution of a variety of species. Eurasian tree sparrows *Passer montanus*, native to Eurasia, have established populations in other parts of the world. In North America, their current distribution is limited to a relatively small region around its original introduction to St. Louis, Missouri. We combined data from the Global Biodiversity Information Facility with current and future climate data to create habitat suitability models using Maxent for this species. Under projected climate change scenarios, our models show that the distribution and range of the Eurasian tree sparrow could increase as far as the Pacific Northwest and Newfoundland. This is potentially important information for prioritizing the management and control of this non-native species [*Current Zoology* 57 (5): 648–654, 2011].

Keywords   Eurasian tree sparrows, *Passer montanus*, Maxent, Climate change, Distribution model

Invasive species and climate change continue to be two major threats to biodiversity (Butchart et al., 2010), and can also have significant impacts to agricultural systems (Pimentel et al., 2005). Early detection, prediction, and long term monitoring are crucial to the effective management of invasive species to minimize these effects (Stohlgren and Schnase, 2006). Invasive birds in particular can cause damage to buildings, displace native birds, consume agricultural products, and spread disease (Pimentel et al., 2000). Eurasian tree sparrows *Passer montanus* have been viewed as a pest in China because of the large number of seeds they can consume and are a controlled species in western Australia (Blakers et al., 1984) where they damage seed and fruit crops, spoil stored grain with droppings, and may compete with native birds (Massam, 2005). The birds were introduced to the United States in 1870 near Saint Louis, Missouri (Widmann, 1889) and have been gradually increasing their range ever since. Although the birds are non-native to the United States, they are not yet a controlled species nor are they considered invasive.

Eurasian tree sparrows are small birds with a native range expanding throughout central and southern Europe, central Asia and portions of southeast Asia (Sibley and Monroe, 1990). These sparrows are generalists and are adapted to a wide variety of habitat types (Field et al., 2008), but prefer living near wetlands. Eurasian tree sparrows consume insects, seeds, and berries in social groups similar to the diet of the house sparrow *Passer domesticus* (Field and Anderson, 2004). Large flocks can congregate around grain sources such as grain elevators and farms (Barlow et al., 2000). During the 1900s, Eurasian tree sparrows experienced dramatic changes in abundance in portions of their native range (Chamberlain and Fuller, 2001; Gregory et al., 2004). Its spread in the United States has been relatively slow, and its core range is in a three state region around its original introduction. It is believed that its current distribution in the US may be limited in spread by competition with the house sparrow, another non-native species (Barlow et al., 2000).

Species distribution models, also known as habitat suitability models, can provide insight into current and potential distribution of species (Hijmans and Graham, 2006; Franklin, 2009). These models combine data on the observed location of a species with environmental data to predict habitat suitability at unsampled locations. The use of these models has increased in the past decade, due in large part to advancements in geographic information systems and computer technologies (Guisan and Thuiller, 2005; Elith and Leathwick, 2009). The models have been used to predict the potential distribution of

invasive species including the Burmese python *Python molurus bivittatus* (Rodda et al., 2009), the vine kudzu *Pueraria Montana* (Jarnevich and Stohlgren, 2009), and cheatgrass *Bromus tectorum* and the invasive shrub tamarisk (*Tamarix* spp.) (Evangelista et al., 2008).

The conceptual framework behind species distribution models is to find relationships between where a species has been observed and the environmental characteristics, or predictor layers, of those locations (Franklin, 2009). This relationship was defined by Hutchinson as the "niche" of the species (Hutchinson, 1957). The niche for a given species may be limited by temperature, proximity to water, and other variables. There are many methods for creating a model of a species niche which can then be used to predict the potential species distribution, typically on a map (Franklin, 2009). There are also many algorithms available for species distribution modeling including Generalized Linear Models (GLM), Generalized Additive Models (GAM), Genetic Algorithm for Rule-set Production (GARP), boosted regression trees (BRT), and Maxent. These models have been applied to native bird species using GARP (Peterson et al., 2002), while BRTs have been used for modeling the spread of an invasive bird in Europe (Strubbe and Matthysen, 2009). Maxent has been used to model the potential distribution of endangered birds under climate change scenarios (Hu et al., 2010).

Species distribution models are affected by many factors, including the sample size and distribution of sample data in time and space (Wisz et al., 2008), different environmental breadth captured by the occurrence data relative to extent of the study area (Rodda et al., 2011), and whether the species is a habitat specialist versus a habitat generalist (Evangelista et al., 2008). Bias can be strong when there are a small number of points early in an invasion (i.e., where many suitable sites have yet to be invaded). Still, species distribution models have proven accurate and robust for many species (Kumar et al., 2009; Holcombe et al., 2010).

The majority of data available for species distribution modeling include locations where a species was observed at a given location, also known as an "occurrence" or "presence point" (Graham et al., 2004). One of the most popular modeling techniques for modeling species based on presence-only data, and one that consistently performs well (Elith et al., 2006) is Maxent (Phillips et al., 2006; Phillips and Dudik, 2008). Maxent uses principles of maximum entropy to develop relationships between the environment at presence locations and the available environment as described by background data points. Maxent, along with other species distribution modeling techniques, provides the ability to predict species suitable habitats now and in the future.

The Global Biodiversity Information Facility (GBIF) provides an open-access on-line database of occurrence records for species from all over the world (GBIF, 2010), including Eurasian tree sparrows. Because the primary source of GBIF data includes herbariums and museums around the world, there are issues using the data such as taxonomic inaccuracies, spatial bias, and precision in geographic coordinates (Graham et al., 2004). However, these databases provide the potential to model species in almost any region of the world without spending the time and resources to collect new field data. The methods used in this study were designed to alleviate many of the issues related to using this type of data.

The Eurasian tree sparrow has been slowly increasing its range in North American since its introduction, and it is unknown how it may respond to climate change. With climate change, could they cause similar problems in the United States to those being caused in China and Australia? Climate matching based on the native and introduced range can provide information on its climatic tolerance, and we can project these into the future. Therefore, we developed a model to determine the potential change in suitable habitat for Eurasian tree sparrows with current and future climate conditions in North America. Our secondary goal was to determine if data from a large aggregated dataset, like GBIF, could be used effectively to evaluate potential habitats for a species. This is the first example using Maxent to model a non-native bird species under future climate change scenarios.

1 Materials and Methods

1.1 Data sets

We downloaded 179,005 occurrence records for Eurasian tree sparrows from the GBIF web site on the 23rd of September, 2010 that included species' name and location coordinates (latitude, longitude; Fig. 1). The data contained contributions from 465 different datasets. The complete list is available at http://ibis.colostate.edu/ETS. Given the negative effect of spatial errors when modeling distributions (Osborne and Leitao, 2009), we examined all Eurasian tree sparrow coordinates for potential issues. These issues included coordinates with a coarser precision than our predictor layers (e.g., latitude of 40 degrees compared to our resolution of 30 arc sec), coordinates with obvious rounding introduced (e.g.,
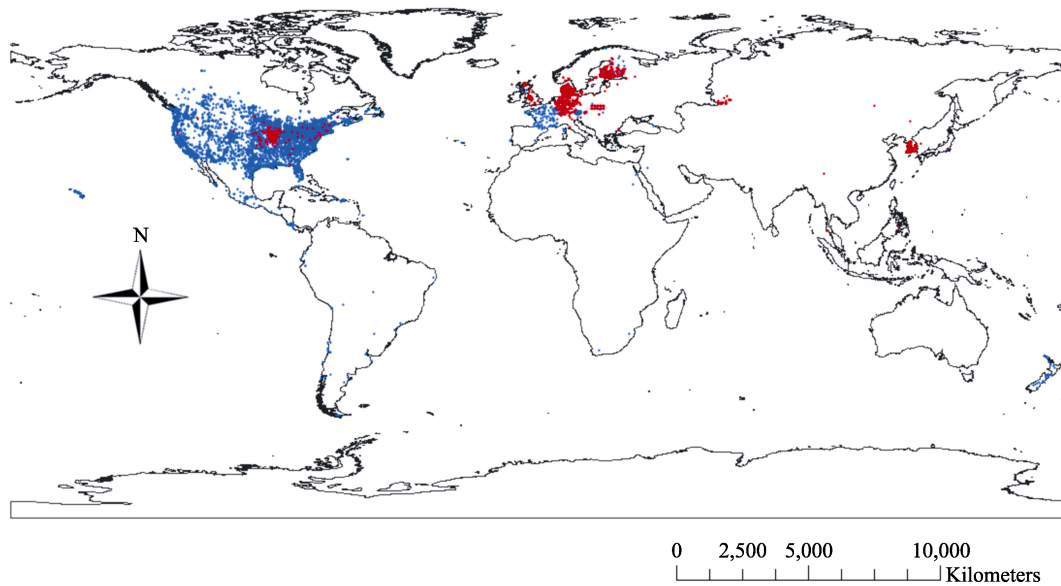
Fig. 1   Global occurrences and background points
The presence points for Eurasian tree sparrows are red; the background points are blue.

decimal continues with many repeats of a value such as 0.33333333), and indications that a precisely given data point may have been derived from a larger area (e.g., situations where data points are the centroid of a county). We removed records with questionable coordinates from the dataset, leaving 4,295 unique records at a 30 arc second resolution that were used in our model. Although we were specifically interested in predicting the invaded range in North America, we used global data to train our models. This strengthens the ability of the model to extrapolate to potential future climates because models using locations from both invaded and native ranges capture more of the suitable environment (Bradley et al., 2010),

We obtained the WorldClim bioclimatic variables at 30 arc second resolution to use as predictors in our models (Hijmans et al., 2005). These layers included 19 bioclimatic variables derived from monthly precipitation and minimum and maximum temperature that describe seasonality in climate that may be biologically important. The sparrows are also known to be limited by winter temperatures (Zheng et al., 2008) and prefer areas near water (Field and Anderson, 2004). Based on this, we hypothesized that they may be able to be modeled based on minimum temperature and minimum available precipitation, Min Temperature of Coldest Month (BIO6) and Precipitation of Driest Quarter (BIO17), respectively. We also included Annual Precipitation (BIO12) and Annual Mean Temperature (BIO1) to see if the more general layers correlated bet-

ter than the minimum values. We used current climate (1950 to 2000 average) and future climate projections for 2020 and 2050. The future climate was averaged across three global climate models produced from the Canadian Centre for Climate Modeling and Analysis (CCCMA), Hadley Centre Coupled Model v3 (HadCM3) and Commonwealth Scientific and Industrial Research Organization (CSIRO) for the more liberal emission scenario, b2a.

1.2   Modeling

We used Maxent version 3.3.3a to develop our habitat suitability maps (Phillips et al., 2006). To mimic the sampling bias in our un-statistically collected presence locations, we used the target background approach with Maxent (Phillips et al., 2009). With this procedure, we provided 10,000 randomly selected presence locations for house sparrows also downloaded from GBIF as background locations because these species are sympatric (Anderson, 1978), have similar global distributions, and are both commonly recorded species. We used the default settings in Maxent except for increasing the maximum iterations to 5000 to allow the models to converge. We ran each model 10 times, withholding a different 30% of the data each time for testing to determine the model dependence on the locations used. We used the average prediction from all model runs for our final maps. Maxent also produces maps of novel environments, which highlight predicted locations where the environmental conditions are outside those captured by the presence and background locations used to train the

model (Elith et al., 2010). Extrapolating models beyond the bounds of data used to train the model can lead to over predictions or under predictions in those areas (Peterson et al., 2007). Maxent also provides information on variable importance through the percent contribution and permutation importance. These are two different measures Maxent makes, with percent contribution calculated based on how much the variable contributed to the model dependent upon the path selected for a particular model run. The permutation importance is determined by varying the predictors' values between presence and background points and examining the change in area under the curve (AUC) and is not dependent on the path but only on the final model for a particular model run.

Maxent creates a receiver operator curve and measures the AUC to determine model accuracy. AUC values of 0.5 show no value in the model while values of 1.0 would indicate the model can perfectly distinguish been presence and absence of a species (Swets, 1988). We evaluated AUC (Fielding and Bell, 1997) for the random test partition of data (30% of locations withheld each iteration).

1.3   Change in distribution

We used a 10% training presence logistic threshold to identify suitable and non-suitable habitat for current and future predictions for the Eurasian tree sparrow. The 10% training presence threshold means that 10% of the presence locations used to develop the model (training data) will be misclassified. We used this metric as it is available by Maxent, and is less conservative than the minimum training presence where all training locations would be correctly classified, that is very sensitive to outliers. For highly mobile species such as birds, we feel the minimum training presence may over-predict the suitable habitat because it is sensitive to "highly occasional" bird sightings. The potential change in species distribution under climate change was computed by classifying current and future suitable (current=1, future=4) and non-suitable habitat (current=0, future=2) for each prediction and then adding current predictions to future predictions. This allowed us to identify areas

that were unsuitable (current and future), stable (suitable currently and in the future), increasing suitability in the future, and decreasing suitability in the future (unsuitable=2, stable=5, increasing=4, decreasing=3) under future climate scenarios.

2   Results

The AUCs from the 10 iterations ranged from 0.8451 to 0.8479, with Precipitation of the Driest Quarter as the largest contributing predictor at 58%. Minimum Temperature of the Coldest Month and Annual Precipitation contributed 18%, while Precipitation of Driest Quarter contributed 6% (Table 1). The permutation importance supported this order of importance.

The model predicted suitable habitat near St. Louis, Missouri where the original population was introduced (Fig. 2). The model also showed suitable habitat along the inner coast of British Colombia and in Southern Alaska. Northern Canada and Greenland were largely novel environments that were not represented in the sample data, so we did not consider these regions.

The prediction for 2020 showed the Eurasian tree sparrow's suitable habitat expanding and moving to the northeast within the United States, to the north in Alaska, and beginning to develop in Newfoundland (Fig. 3). The 2050 prediction showed the same trend with a large habitat developing in Newfoundland (Fig. 4).

3   Discussion

The GBIF data appeared to perform well according to the AUC evaluation metric and represented a subset of the distribution of Eurasian tree sparrows as documented in the literature. This is promising for future efforts to map continental distributions of invasive species. Databases aggregating occurrence data such as GBIF can play crucial roles in providing global data to develop species distribution models. While we were able to create accurate models using GBIF data, similar studies have cautioned about issues related to those described related to integrated data (Graham et al., 2004, Loiselle et al., 2008). By evaluating the quality and accuracy of the data we downloaded as described in our

Table 1   Percent contribution for each environmental layer from the WorldClim-BioClim dataset

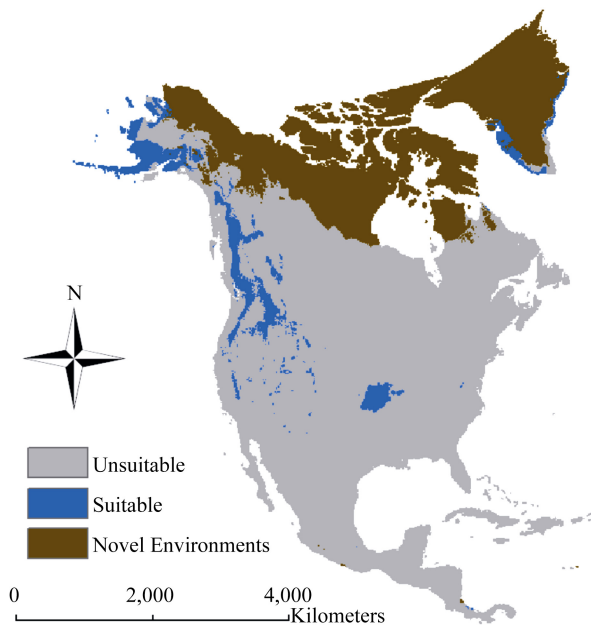| Environmental Layer	Description	Percent Contribution	Permutation Importance
Bio17	Precipitation of driest quarter (mm)	58	43
Bio6	Min temperature of coldest month(°C * 10)	18	30
Bio1	Annual mean temperature(°C * 10)	18	19
Bio12	Annual precipitation (mm)	6	8

Fig. 2   The predicted suitable and unsuitable habitat for Eurasian tree sparrows based on the available occurrences
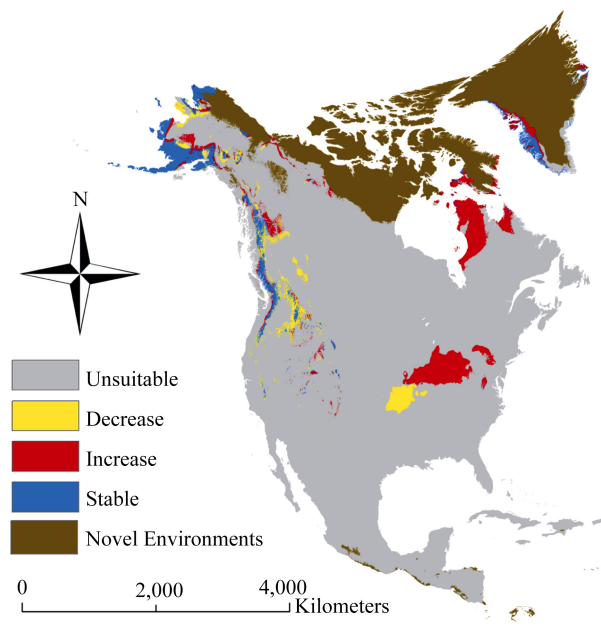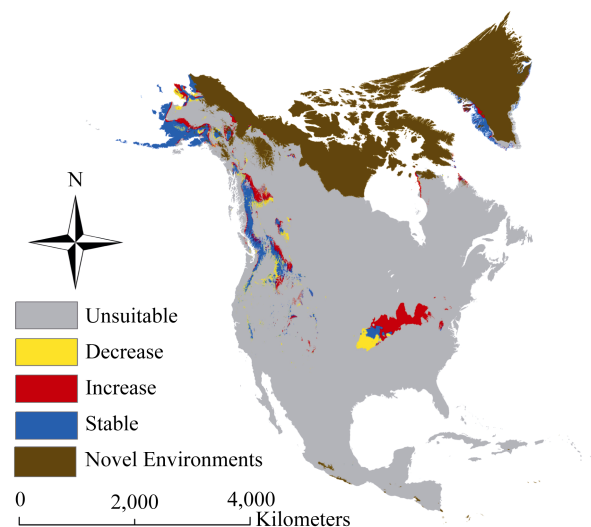

Fig. 3   Predicted change in suitable habitat for Eurasian tree sparrows for the year 2020

methods, we were able to remove some data of questionable utility and accuracy. We also employed the 'target background' approach to try to alleviate sampling bias in the dataset. However, the locations data we used may still have affected the models. As an additional check of data completeness, we downloaded the available data from the Avian Knowledge Network (http://www.avianknowledge.net) and compared it with the data from GBIF. The Avian Knowledge Network data showed a similar distribution in North America but additional data in Asia. Neither dataset showed points in

Fig. 4   The predicted change in habitat for Eurasian tree sparrows between 2010 and 2050

British Columbia or Alaska. It is possible that the birds have not reached this area or that the model is missing a predictor variable that would exclude these areas such as competition with house sparrows or other bird species, disease, or predation.

Our results indicate that precipitation is strongly associated with Eurasian tree sparrow distribution at continental scales. Precipitation of the Driest Quarter contributed more than three times as much to the final model than any other predictor variable. Flieg (1971) hypothesized that the Eurasian tree sparrows lack of westward spread from Saint Louis was related to the drier climate to the west. This could be due to the sparrow's preference for wetlands (Field et al., 2008), much of which has been altered by agriculture.

Assuming the climate projections are accurate, our preliminary predictions for Eurasian tree sparrows show suitable habitat along the western coast of North America. These predictions are best viewed as "hypotheses," which can be refined with new data and better models (Stohlgren and Schnase, 2006). We suggest that resource managers of potentially suitable habitat should place these sparrows on early detection lists. While no sightings have been reported in these areas, our model suggests that the western coast of North America is at a high risk of invasion. In addition, house sparrows are competitors with Eurasian tree sparrows and are hypothesized to restrict their invasion (Anderson, 1978; Barlow et al., 2000). Because house sparrows are not

found in the area predicted suitable for Eurasian tree sparrows in Alaska and northern Canada, these northern areas may be especially susceptible to invasion and rapid expansion.

Future predictions indicate that the Eurasian tree sparrow's range may move northward, expanding from its existing range and developing a new range in Newfoundland. Our current model does not represent non-climatic factors such as the impact of humans or biotic interactions. Eurasian tree sparrows compete with house sparrows, and may be limited in their occupied range in North America by competition with this species. A change in house sparrow distribution or abundance, which has been observed in Europe (Gregory et al., 2004), could be an important driver to Eurasian tree sparrow distribution in addition to climate change. It is unknown how house sparrows may respond to climate change. Climatically suitable habitat may be occupied by the Eurasian tree sparrow if these areas are no longer suitable for the house sparrow. Additional research could further refine these predictions and investigate if this sparrow could pose a potential problem in the future. The combination of effects and the variability in future climate models make modeling future species distribution, especially for birds, very complicated.

The models showed a potential change in the climatically suitable habitat and thus potential distribution of Eurasian tree sparrows in North America for 2020 and 2050. This information may be valuable in planning future control efforts for non-native species. Resource managers can use these models to help inform management decisions while recognizing the uncertainty of these predictions. These models should continue to be refined, especially as biotic interactions limiting species distributions may change with changing climate. The alterations in climate and associated biotic interactions could allow non-native species with a low level of concern to be elevated to species of greater concern.

References

Anderson TR, 1978. Population studies of European Sparrows in North America. Occas. Pap. Mus. Nat. Hist. Univ. Kans. 1–58.

Barlow JC, Sheridan N, Leckie, 2000. Eurasian tree sparrow *Passer montanus*. In: Poole A ed. The Birds of North America Online. Ithaca, New York: Cornell Lab of Ornithology.

Blakers M, Davies SJJF, Reilly PN, 1984. Tree Sparrow *Passer montanus*. Brunswick, Victoria, Australia: The Atlas of Australian Birds. Melbourne University Press, 345.

Bradley BA, Blumenthal DM, Wilcove DS, Ziska LH, 2010. Predicting plant invasions in an era of global change. Trends in Ecology & Evolution 25: 310–318.

Butchart SHM, Walpole M, Collen B, van Strien A, Scharlemann JPW et al., 2010. Global biodiversity: Indicators of recent declines. Science 328: 1164–1168.

Chamberlain DE, Fuller RJ, 2001. Contrasting patterns of change in the distribution and abundance of farmland birds in relation to farming system in lowland Britain. Global Ecology and Biogeography 10: 399–409.

Elith J, Graham CH, Anderson RP, Dudik M, Ferrier S et al., 2006. Novel methods improve prediction of species' distributions from occurrence data. Ecography 29: 129–151.

Elith J, Kearney M, Phillips SJ, 2010. The art of modeling range-shifting species. Methods in Ecology and Evolution 1: 330–342.

Elith J, Leathwick JR, 2009. Species distribution models: Ecological explanation and prediction across space and time. Annual Review of Ecology Evolution and Systematics 40: 677–697.

Evangelista PH, Kumar S, Stohlgren TJ, Jarnevich CS, Crall AW et al., 2008. Modelling invasion for a habitat generalist and a specialist plant species. Diversity and Distributions 14: 808–817.

Field RH, Anderson GQA, 2004. Habitat use by breeding tree sparrows *Passer montanus*. Ibis 146: 60–68.

Field RH, Anderson GQA, Gruar DJ, 2008. Land-use correlates of breeding performance and diet in tree sparrows *Passer montanus*. Bird Study 55: 280–289.

Fielding AH, Bell JF, 1997. A review of methods for the assessment of prediction errors in conservation presence/ absence models. Environmental Conservation 24: 38–49.

Franklin J, 2009. Mapping Species Distributions: Spatial Inference and Prediction. Cambridge: Cambridge University Press.

GBIF, 2010. Global Biodiversity Information Facility. www.gbif.org.

Graham CH, Ferrier S, Huettman F, Moritz C, Peterson AT, 2004. New developments in museum-based informatics and applications in biodiversity analysis. Trends in Ecology & Evolution 19: 497–503.

Gregory RD, Noble DG, Custance J, 2004. The state of play of farmland birds: Population trends and conservation status of lowland farmland birds in the United Kingdom. Ibis 146: 1–13.

Guisan A, Thuiller W, 2005. Predicting species distribution: Offering more than simple habitat models. Ecology Letters 8: 993–1009.

Hijmans RJ, Cameron SE, Parra JL, Jones PG, Jarvis A, 2005. Very high resolution interpolated climate surfaces for global

land areas. International Journal of Climatology 25: 1965–1978.

Hijmans RJ, Graham CH, 2006. The ability of climate envelope models to predict the effect of climate change on species distributions. Global Change Biology 12: 2272–2281.

Holcombe TR, Stohlgren TJ, Jarnevich CS, 2010. From points to forecasts: Predicting invasive species habitat suitability in the Near Term. Diversity 2: 738–767.

Hu JH, Hu HJ, Jiang ZG, 2010. The impacts of climate change on the wintering distribution of an endangered migratory bird. Oecologia 164: 555–565.

Hutchinson GE, 1957. Population studies - animal ecology and demography - concluding remarks. Cold Spring Harbor Symposia on Quantitative Biology 22: 415–427.

Jarnevich CS, Stohlgren TJ, 2009. Near term climate projections for invasive species distributions. Biological Invasions 11: 1373–1379.

Kumar S, Spaulding SA, Stohlgren TJ, Hermann KA, Schmidt TS et al., 2009. Potential habitat distribution for the freshwater diatom *Didymosphenia geminata* in the continental US. Frontiers in Ecology and the Environment 7: 415–420.

Loiselle BA, Jorgensen PM, Consiglio T, Jimenez I, Blake JG et al., 2008. Predicting species distributions from herbarium collections: Does climate bias in collection sampling influence model outcomes? Journal of Biogeography 35: 105–116.

Massam M, 2005. Farmnote: Sparrows. South Perth: Information Services, Agriculture Western Australia.

Osborne PE, PJ Leitao, 2009. Effects of species and habitat positional errors on the performance and interpretation of species distribution models. Diversity and Distributions 15: 671–681.

Peterson AT, Ball LG, Cohoon KP, 2002. Predicting distributions of Mexican birds using ecological niche modelling methods. Ibis 144: E27–E32.

Peterson AT, Papes M, Eaton M, 2007. Transferability and model evaluation in ecological niche modeling: A comparison of GARP and Maxent. Ecography 30: 550–560.

Phillips SJ, Anderson RP, Schapire RE, 2006. Maximum entropy modeling of species geographic distributions. Ecological Modelling 190: 231–259.

Phillips SJ, Dudik M, 2008. Modeling of species distributions with Maxent: new extensions and a comprehensive evaluation. Ecography 31: 161–175.

Phillips SJ, Dudik M, Elith J, Graham CH, Lehmann A, et al., 2009. Sample selection bias and presence-only distribution models: Implications for background and pseudo-absence data. Ecological Applications 19: 181–197.

Pimentel D, Lach L, Zuniga R, Morrison D, 2000. Environmental and economic costs of nonindigenous speces in the Unites States. Bioscience 50: 53–65.

Pimentel D, Zuniga R, Morrison D, 2005. Update on the environmental and economic costs associated with alien-invasive species in the United States. Ecological Economics 52: 273–288.

Rodda GH, Jarnevich CS, Reed RN, 2009. What parts of the US mainland are climatically suitable for invasive alien pythons spreading from Everglades National Park? Biological Invasions 11: 241–252.

Rodda GH, Jarnevich CS, Reed RN, 2011. Challenges in identifying sites climatically matched to the native ranges of animal invaders. PLoS ONE 6: e14670.

Sibley CG, Monroe BL, 1990. Ditribution and Taxonomy of Birds of the World. New Haven and London: Yale University Press, 577.

Stohlgren TJ, Schnase JL, 2006. Risk analysis for biological hazards: What we need to know about invasive species. Risk Analysis 26: 163–173.

Strubbe D, Matthysen E, 2009. Establishment success of invasive ring-necked and monk parakeets in Europe. Journal of Biogeography 36: 2264–2278.

Swets JA, 1988. Measuring the accuracy of diagnostic systems. science 240: 1285–1293.

Widmann O, 1889. History of the House Sparrow *Passer domesticus* and the European Tree Sparrow *Passer montanus* at Saint Louis, Mo. Washington DC: U.S. Department of Agriculture, Division of Economic Ornithology and Mammology.

Wisz MS, Hijmans RJ, Li J, Peterson AT, Graham CH et al., 2008. Effects of sample size on the performance of species distribution models. Diversity and Distributions 14: 763–773.

Zheng WH, Li M, Liu JS, Shao SL, 2008. Seasonal acclima tization of metabolism in Eurasian tree sparrows *Passer montanus*. Comparative Biochemistry and Physiology A–Molecular & Integrative Physiology 151: 519–525.