

Review

An overview of different modeling approaches to prediction of the likely effects of climate change on range shifts of species

Parinaz Rashidi^{1*}, Abdullah Ahmad Makmom¹, Abdolrassoul Salman Mahiny², Hossein Varasteh Moradi², Ramli Mohammad Firuz¹, Jamil Amanollahi¹, Alireza Mickaeili Tabrizi² and Hamidreza Shahbazi²

¹Faculty of Environmental Studies, University of Putra, Malaysia.

²Faculty of Fishery and Environment, University of Agriculture and Natural Resources Sciences, Golestan, Gorgan, Iran.

Accepted 17 February, 2012

Climate change may have noticeable impacts on global biodiversity and can be considered as a huge long-term threat to species survival. To assess the extinction risk of wildlife species and in spatial planning approaches for conservation strategies, it is essential to predict how species respond to climate changes via shift in geographic range. The prediction of species responses to climate change can be done using alternative modeling approaches. This paper provides an overview of five climate-envelope models and their relative benefit to climate change studies.

Key words: Climate changes, biodiversity, modeling approaches, climate-envelope models, geographical range.

INTRODUCTION

Climate change involves, among other effects, changes in the carbon and hydrologic cycles, mean temperature, alterations in distribution of precipitation, and solar radiation and storm severity (Wang and Schimel, 2003; Parry et al., 2007). The alternation in phenology, population density, community structure (Crick et al., 1997; Walther et al., 2002; Parmesan and Yohe, 2003; Root et al., 2003; Edwards and Richardson, 2004; Jonze'n et al., 2006) and species ranges (Parmesan et al., 1999; Beaugrand et al., 2002; Walther et al., 2005; Thomas et al., 2006) are among the most obvious impacts of climate change on biodiversity.

Many recent studies have focused on modelling of impacts of climate changes on species' range to anticipate their future potential geographical distributions

(Pearson and Dawson, 2003; Robertson et al., 2004; Barrio et al., 2006; Lawler et al., 2006; Brooker et al., 2007; Sekercoglu et al., 2008; Virkkala et al., 2008; Anderson, 2010; Sinclair et al., 2010). Climate change has affected species geographical distributions and their persistence (Parmesan, 1996; Walther et al., 2002; Moore, 2003; Parmesan and Yohe, 2003). Pearson and Dawson (2003) investigated on predicting the impacts of climate change on the distribution of species. They questioned the usefulness of the bioclimatic envelope models and evaluated bioclimatic envelope models and argued about their functions for the dissimilar predictive modelling results. These authors proposed that despite the fact that the natural systems are complex; the bioclimatic envelope models can be valuable tools to explore the impacts of climate change on biodiversity. They concluded that spatial scale at each of these models has basic importance and the resultant models should be considered with attention to this limitation. They suggested a hierarchical models framework to be

*Corresponding author. E-mail: parinazrashidi@yahoo.com. Tel: 60172933164.

addressed inside a wider scale dependent context. Barrio et al. (2006) proposed a scheme of integrating multiple modelling approaches to predict the potential impacts of climate changes on species distributions in contrasting regions. They combined four models including dispersal model, regional scale bioclimatic and land use suitability model, a connectivity model and a continental scale bioclimatic envelope model in a scale dependent hierarchical framework. They tested an integrating approach to study the effects of climate and land use changes on species distribution. They concluded that climate changes involve the development of temporary situation and fragmentation inside the core of distributions. Likewise, dynamic conservation strategies are needed such that it is made possible to consider current and future arrangement of species and their habitat to support species in their respond to future environmental changes. Lawler et al. (2006) in their study about predicting climate – induced range shift expressed those anticipations of future range shifts are dependent on diversity of modelling methods with different levels of model accuracy. They investigated the potential implication of different modelling methods to show the results about future range shift and extinctions. The authors contrasted six approaches for modelling anticipated future ranges and concluded that the different methods can have different results on forecasted range shift and model – averaging methods seems to have greatest potential on anticipating geographical range shift. Sekercloglu et al. (2008) conducted a study about climate changes, elevation range shifts and bird extinctions. They modelled the impacts of height restrictions on the extinction risk of land birds and for this integrated elevation ranges, a middle estimation of surface warming of 2.8°C, and four millennium evaluation of habitat-lose scenarios. Then, they predicted 400 to 500 land bird extinction likelihoods. They indicated that each degree of warming projected a nonlinear rise in bird extinction of about 100 to 500 species. Besides, they highlighted different scenarios of climate change and habitat loss for land birds. According to their findings, there is an essential requirement for fine resolution evaluations of shift in the elevation range of species to make more accurate climate induced extinction approximations. Anderson (2010) reviewed potential effects of climate changes on biodiversity especially on changes in species geographical range. The author highlighted methods that most broadly used to anticipate the effects of climate changes on geographic range of species. These included maximum entropy method that is used to discover a probability distribution consistent with a set of data via maximizing the information entropy of the selected distribution given the data limitations. Here, we discuss these approaches and some of their limitations.

Nowadays ecologists are more focused on prediction of changes in distribution of species due to climate changes,

because it considerably help to develop the conservation planning and strategies for biodiversity (Thomas et al., 2004; Brooker et al., 2007). Some approaches such as long-period monitoring (Warren et al., 2001; Root et al., 2003; Richardson and Schoeman, 2004) and manipulation experiments (Chapin et al., 1995; Press et al., 1998; Emmett et al., 2004) which are used for current and future responses of ecosystem and species have limitation in their spatial or temporal scopes (Brooker et al., 2007). The modelling has therefore become a key supplementary tool (Brooker et al., 2007). As such, it is necessary to develop models that link species range and different scenarios of climate changes. The majority of anticipation of range shift of species is based on bioclimatic models; so it is essential to know about advantages and disadvantages of these models to choose the model with the best performance.

The goal of this study is to introduce some common alternative modelling approaches to help understand the usefulness and negative sides of the bioclimatic models in predicting the geographic range of species and to quantify the risk affected by climate changes on biodiversity.

APPROACHES

There are various approaches to predict species range based on climatic condition (Table 1). In this paper, five models have been reviewed to describe their usefulness and assess their efficiency which includes: general linear models (GLM), generalized additive model (GAM), genetic algorithms for rule set prediction (GARP), artificial neural network (ANN) and maximum entropy (MAXENT).

Generalized Linear Models (GLMs)

The concept of GLMs is related to a unit theory of estimation and testing (McCullagh and Nelder, 1989). Powerful statistical basis and ability to realistically model ecological relationships are the reasons that generalized linear models are applied widely in species' distribution modelling (Austin, 2002). GLMs permit for the modelling of other distributions in the response variable and impermanent variance functions, so modelling framework of these approaches is more flexible than basic linear regression models (Guisan et al., 2002). They fit parametric terms, usually some combination of linear, quadratic and/or cubic terms (Hastie and Tibshirani, 1990). These techniques use the presence and absence data to predict species range. These approaches can be useful for non-normal data such as binary data (Venables and Dichmont, 2004). They do not constrain data into unnatural scales, so that permit for non-linearity and non-constant variance structures in the data (Hastie and Tibshirani, 1990). GLM models can be executed in a geographic information system (GIS) and there are some packages to run these models in GIS software's (Guisan

Table 1. Different modeling approaches for prediction of climate changes on range shifts of species.

Modelling method	Reference	Data	Advantages	Disadvantages
GLMs	McCullagh and Nelder (1989), Austin (2002), Guisan and Zimmermann (2000)	- Presence and Absence data	Useful for non-normal data like binary data. Do not constrain data into unnatural scales	Needs fine environmental data and lots of valid records. Requires a specific response curve to be fit to the predictor variables
GAMs	Leathwick et al. (1996), Thuiller (2003, 2004), Araújo et al. (2004)	- Presence and Absence data	Do not need a particular response curve to be fit to the forecaster variables. Capability to deal with extremely non-linear and non-monotonic relationships among the response and the set of descriptive variables. Good at regional scales	Causes a better data fit but comes with a lesser amount of clearness and interpretability
ANN	Berry et al. (2002), Thuiller (2003, 2004)	- Presence data	Is capable of managing descriptive variables from various sources. Indicates climatic envelopes that have nonlinear responses to environmental variables	Needs large data to train. Identifies areas that will become climatically suitable for species without taking into account limiting factors of species dispersal
GARP	Stockwell and Noble (1992), Stockwell and Peters (1999), Ancaes and Peterson (2006)	- Presence and Presence/Absence data. - Produces tight models	Data layers easy to prepare	Focused on potential geographical distributions instead of real geographical distribution. Predictive accuracy of GARP is not independent of range size
MAXENT	Phillips et al. (2006), Phillips and Dudik (2008)	- Presence data	Ability to run with presence-only point occurrences. A high performance with few point localities	Smaller number of guideline for its use in general. Hardly can evaluate the amount of error in anticipation

and Zimmermann, 2000). In addition, these models will be suitable for species with relatively simple relationships to environmental gradients (Lawler et al., 2006). These techniques focus on general trends of species' presence/absence response (Segurado and Araújo, 2004) and need fine environmental data and lots of valid records. GLMs require a specific response curve to be fit into the predictor variables (Hastie and Tibshirani, 1990) due to the fact that they are less flexible than GAMs.

Generalized Additive Model (GAMs)

GAMs are popular approach, which have been applied in climate change impact studies on

species range (Leathwick et al., 1996; Thuiller, 2003 and 2004; Araújo et al., 2004). GAMs are non-parametric extensions of GLMs (Hastie and Tibshirani, 1990) that are more flexible than generalized linear models, because the response variable is modelled as the additive combination of independent variables functions and does not need a particular response curve to be fitted into the forecaster variables (Hastie and Tibshirani, 1990; Jeschke and Strayer, 2008). These models offer a better data fit, but come with a lesser amount of clearness and interpretability. GAMs use a link function to create a relation between the mean of the response variable and a 'smoothed' function of the descriptive variable(s) (Guisan et al., 2002). The potency of GAMs is the capability to deal with extremely non-linear and

non-monotonic relationships among the response and a set of descriptive variables (Guisan et al., 2002).

Artificial Neural Network (ANN)

One of the robust rule-based modelling approaches which are used in bioclimatic envelope modelling is Artificial Neural Networks techniques (Berry et al., 2002; Thuiller, 2003, 2004). The real neural networks are fundamental of ANN as a machine-learning approach (Ripley, 1996). A series of interlink neurons make networks which get and process input signals and potentially generate output signals. For recognizing the patterns in the data set, the network

is trained on a data set (Lawler et al., 2006). This method is capable of managing descriptive variables from various sources, like categorical and Boolean data. Besides, it does not assume a normal distribution of the data. This capacity causes the model to be useful for recognizing 'patchy' or scanty distributions. Moreover, it is able to indicate climatic envelopes that have nonlinear responses to environmental variables (Hilbert and Ostendorf, 2001; Pearson et al., 2002, 2004). Meanwhile, there are some limitations (such as the need to numerous quantities of data to train) in this approach (Heikkinen et al., 2006). Identifying areas that are climatically suitable for species without taking into account limiting factors of species dispersal and validation and test of the model's training dataset is according to the assumption that current species' distributions are in equilibrium with the current climate (Pearson et al., 2002). Nonetheless, ANN provides a signal of the amount of the impacts of future climate changes and presents an intuition into potential future trends, including the recognition of those areas and species that are most sensitive to change.

Genetic Algorithms for Rule set Prediction (GARP)

GARP is one of the most widely used bioclimatic models for modelling species range. GARP employs a genetic algorithm to assemble a set of rules (for example, adaptations of regression and range specifications) to define a species' range (Stockwell and Noble, 1992; Stockwell and Peters, 1999). Suitable conditions are predicted for pixels satisfying a number of set of environmental conditions via positive rules; comparably, unsuitable conditions are predicted by negative rules (Phillips et al., 2006). It is designed to use only presence data (Anciaes and Peterson, 2006) and geo-referenced data on ecological factors to provide predictions of the species' geographical distribution (Heikkinen et al., 2006), but it allowed for creating a set of pseudo-absence points with replacement from the pixels without confirming the presence data in the training (Anderson et al., 2003). GARP works in a repetitive procedure of rule selections, evaluation, testing and incorporation or refusal (Anciaes and Peterson, 2006) for generating a heterogeneous rule set to make summary of species' ecological requirements (Anderson et al., 2002).

Predictive accuracy of GARP is not independent of range size. Hence, widespread species are modelled with less accuracy (Stockwell and Peterson, 2002). GARP may often predict distribution in areas that are not occupied by the species and instead of emphasis on real geographical distributions are focused on potential geographical distributions (Meyer et al., 2004). Inclusion of extra ecological dimensions and even consideration of historical elements that causes the absence of species from areas that is suitable to live, may in some cases decrease these over prediction errors (Peterson et al.,

1999; Peterson and Vieglais, 2001).

Maximum Entropy (MAXENT)

One novel method which has not been widely applied in species geographic range modelling is MAXENT (Phillips et al., 2006; Phillips and Dudik, 2008). MAXENT is a general-purpose machine-learning method that is designed for use with presence-only data, (Phillips et al., 2006) and it can compute probability distributions based on incomplete information (Phillips et al., 2006). This method makes a continual probability field that can be explained as a relative indicator of environmental suitability, where higher values show anticipation of better conditions for the species in the study area (Phillips et al., 2006; Phillips and Dudik, 2008). Possibility distributions are estimated via MAXENT by finding the probability distribution of maximum entropy or uniform given restriction originated from the presence data and functions of the environmental feature (Phillips and Dudik, 2008). Model yield can be elucidated as the probability of presence under a comparable level of sampling effort as needed to get the recognized presence data (Phillips and Dudik, 2008). In addition, MAXENT scored as one of the most accurate in a recent comparison of several widely used models (Elith et al., 2006), but there are some negative points that should be considered in any research involving MAXENT. For example, there are smaller numbers of guidelines for its use in general and the method can hardly evaluate the amount of error in anticipation (Phillips et al., 2006). Meanwhile, the exponential model which is used for probabilities in this approach is not intrinsically bounded above and can give so big anticipated values for environmental conditions that are not inside the range present in a given study area. Therefore, additional care is required when the method is applied to other study areas or to future or past climatic conditions (Phillips et al., 2006).

CONCLUSION

The modelling of current and future arrangement of wildlife species in landscape is essential for conservation and planning purposes to support species in their response to future environmental changes. Araújo and New (2006) have evaluated sixteen approaches of modelling from five continental areas, in relation to climate and species distribution. We described the five models that are more flexible and common with their own strengths and drawbacks. Summarizing credible biogeographic responses of species range for each of the modelling approaches can be different from climatic forecasters (Segurado and Araújo, 2004). In addition, the modelling techniques based on presence data are more

precious (Anderson et al., 2003), because absence data are seldom available, in particular for poorly sampled tropical areas where modelling is potentially so precious and important for conservation (Anderson et al., 2002; Ponder et al., 2001; Soberón, 1999). In addition, absence data in many situations may be of doubtful value (Anderson et al., 2003). Alternative approaches provide different results for modelling climate changes on species range and these results describe different range shift and different extinction risks. Every bioclimatic envelope modelling techniques have their capabilities, and are different in their ability to summarise credible biogeographic reaction of species distributions to climatic forecasters (Segurado and Araújo, 2004). Comparability of modelling approaches on climate change is more new (Thuiller, 2003, 2004; Araújo et al., 2005a, b; Pearson et al., 2006). Some of comparative studies have tested the act of diverse bioclimatic envelope modelling approaches (Franklin, 1995; Manel et al., 1999; Bio et al., 2002; Elith et al., 2002; Moisen and Frescino, 2002; Olden and Jackson, 2002; Thuiller, 2003; Muñoz and Felicísimo, 2004; Segurado and Araújo, 2004). For example, the conclusions of the follow-up study by Thuiller (2003) expressed ANN indicated inclination, to overfit for the duration of the calibration procedure, whereas, GAMs and GLMs does not appear to overfit, and their accuracy were higher than ANN in various cases. Bio et al. (2002) in their study on bioclimatic modelling, reported GAMs to be than GLMs for modelling more than half of the species, demonstrating that species' reaction are often complicated and hard to fit using simple symmetric response shapes. Elith et al., (2002) stated an obvious trend in relation to better model discriminatory performance from GAMs and GLMs compared to GARP. These authors reported that performance of GARP appears better than the other two techniques when original data was used for testing, otherwise it showed an ambiguous results and distinctions with different accuracy. These results are inconsistent with optimistic statements of Peterson and Cohoon (1999) and Anderson et al. (2003), who recommended that GARP is particularly victorious in predicting species' distributions under a broad variety of situations (Heikkinen et al., 2006). To evaluate the overall model performance there are some measures like AUC: Area under the receiver-operating characteristic (ROC) curve and Kappa index. Assessments of modelling success using ROC showed MAXENT model has first and the highest performance of the modelling in comparison to other four modelling approaches (Elith et al., 2006). However, the method generally cannot account for some processes like dispersal, biotic interaction and adaptation. It is clear that there is no single approach that works best for all species. Multiple modelling approaches can be integrated to study the impact of climate changes on species distributions (Barri et al., 2006). In conclusion, the choice of method will always depend on the focal species, data

set and the question raised, and a range of factors including the breadth of ecological knowledge, existing distribution data, spatial and temporal scale as well as goals of the modelling (Pearson and Dawson, 2003).

REFERENCES

- Anciaes M, Peterson AT (2006). Climate Change Effects on Neotropical Manakin Diversity Based on Ecological Niche Modeling. *Condor*, 108: 778-791.
- Anderson RP, Lew D, Peterson AT (2003). Evaluating predictive models of species' distributions: Criteria for selecting optimal models. *Ecol. Model*, 162: 211-232.
- Anderson RP, Gomez-Laverde M, Peterson AT (2002). Geographical distributions of spiny pocket mice in South America: insights from predictive models. *Glob. Ecol. Biogeogr.*, 11(2): 131-141.
- Anderson MC (2010). Predicting impacts of climate change on biodiversity geographic range shifts. Forum on Public Policy.
- Araújo MB, Cabeza M, Thuiller W, Hannah L, Williams PH (2004). Would climate change drive species out of reserves? An assessment of existing reserve-selection methods. *Glob. Change Biol.*, 10: 26-1618.
- Araújo MB, Pearson RG, Thuiller W, Erhard M (2005a). Validation of species-climate impact models under climate change. *Glob. Change Biol.*, 11(9): 1504-1513.
- Araújo MB, Whittaker RJ, Ladle RJ, Erhard M (2005b). Reducing uncertainty in projections of extinction risk from climate change. *Glob. Ecol. Biogeogr.*, 14(6): 529-538.
- Araujo M, New M (2006). Ensemble forecasting of species distributions. *Trends Ecol. Evol.*, 22(1): 42-47.
- Austin MP (2002). Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. *Ecol. Model*, 157: 101-118.
- Barrio GD, Harrison PA, Berry PM, Butt N, Sanjuan ME, Pearson RG, Dawson T (2006). Integrating multiple modelling approaches to predict the potential impacts of climate change on species' distributions in contrasting regions: Comparison and implications for policy. *Environ. Sci. Pol.*, 9: 129-147.
- Beaugrand G, Reid PC, Ibanez F, Lindley JA, Edwards M (2002). Reorganization of North Atlantic marine copepod biodiversity and climate. *Science*, 296(5573): 1692-1694.
- Berry P, Dawson T, Harrison P, Pearson R (2002). Modelling potential impacts of climate change on the bioclimatic envelope of species in Britain and Ireland. *Glob. Ecol. Biogeogr.*, 11: 453-462.
- Bio AMF, De Becker P, De Bie E, Huybrechts W, Wassen M (2002). Prediction of plant species distribution in lowland river valleys in Belgium: Modelling species response to site conditions. *Biodivers. Conserv.*, 11(12): 2189-2216.
- Brooker RW, Travis JMJ, Clark EJ, Dytham C (2007). Modelling species' range shifts in a changing climate: The impacts of biotic interactions, dispersal distance and the rate of climate change. *J. Theor. Biol.*, 245(1): 59-65.
- Chapin FS, Shaver G, Giblin A, Nadelhoffer K, Laundre JA (1995). Responses of arctic tundra to experimental and observed changes in climate. *Ecology*, 76(3): 694-711.
- Crick HQP, Dudley C, Glue DE, Thomson DL (1997). UK birds are laying eggs earlier. *Nature*, 388(6642): 526.
- Edwards M, Richardson AJ (2004). Impact of climate change on marine pelagic phenology and trophic mismatch. *Nature*, 430: 881-884.
- Elith J, Burgman MA, Regan HM (2002). Mapping epistemic uncertainties and vague concepts in predictions of species distributions. *Ecol. Model*, 157: 29-313.
- Elith J, Graham CH, Anderson RP (2006). Novel methods improve prediction of species' distributions from occurrence data. *Ecography*, 29: 129-151.
- Emmett BA, Beier C, Estiarte M, Tietema A, Kristensen HL, Williams D, Penuelas J, Schmidt I, Sowerby A (2004). The response of soil processes to climate change: Results from manipulation studies of shrublands across an environmental gradient. *Ecosystems*, 7(6): 625-637.

- Franklin J (1995). Predictive vegetation mapping: geographic modelling of biospatial patterns in relation to environmental gradients. *Prog. Phys. Geogr.*, 19: 474-499.
- Guisan A, Zimmermann NE (2000). Predictive habitat distribution models in ecology. *Ecol. Model.*, 135: 147-186.
- Guisan A, Edwards TC, Hastie T (2002). Generalized linear and generalized additive models in studies of species distributions: Setting the scene. *Ecol. Model.*, 157: 89-100.
- Hastie TJ, Tibshirani RJ (1990). *Generalized Additive Models*. Chapman & Hall, London.
- Heikkinen RK, Luoto L, Miguel B, Virkkala R, Thuiller W, Sykes MT (2006). Methods and uncertainties in bioclimatic envelope modelling under climate change. *Prog. Phys. Geogr.*, 30(6): 751-777.
- Hilbert DW, Ostendorf B (2001). The utility of artificial neural networks for modelling the distribution of vegetation in past, present and future climates. *Ecol. Model.*, 146(1-3): 311-327.
- Jeschke JM, Strayer DL (2008). Usefulness of Bioclimatic Models for Studying Climate Change and Invasive Species. *Ann. Ny. Acad. Sci.*, 1134(1): 1-24.
- Jonze'n N, Linde'n A, Ergon T, Knudsen E, Vik JO, Rubolini D, Piacentini D, Brinch C, Spina F, Karlsson L, Stervander M, Andersson A, Waldenstro'm J, Lehtikoinen A, Edvardsen E, Solvang R, Stenseth NC (2006). Rapid advance of spring arrival dates in long-distance migratory birds. *Science*, 312: 1959-1961.
- Lawler JJ, White D, Nelson RP, Blaustein AR (2006). Predicting climate-induced range shifts: Model differences and model reliability. *Glob. Change Biol.*, 12: 1568-1584.
- Leathwick JR, Whitehead D, McLeod M (1996). Predicting changes in the composition of New Zealand's indigenous forests in response to global warming: a modelling approach. *Environ. Softw.*, 11: 81-90.
- Manel S, Dias JM, Ormerod S (1999). Comparing discriminant analysis, neural networks and logistic regression for predicting species distribution: A case study with a Himalayan river bird. *Ecol. Model.*, 120(2-3): 337-347.
- Meyer EM, Peterson AT, Hargrove WW (2004). Ecological niches as stable distributional constraints on mammal species, with implications for Pleistocene extinctions and climate change projections for biodiversity. *Glob. Ecol. Biogeogr.*, 13: 305-314.
- McCullagh P, Nelder JA (1989). *Generalized Linear Models*. Chapman & Hall, London.
- Parmesan C, Ryrholm N, Stefanescu C, Hill J K, Thomas C D, Descimon H, Huntley B, Kaila L, Kullberg J, Tammaru T, Tennent WJ, Thomas JA, Warren M (1999). Poleward shifts in geographical ranges of butterfly species associated with regional warming. *Nature*, 399: 579-583.
- Moisen G, Frescino T (2002). Comparing five modelling techniques for predict forest characteristics. *Ecol. Model.*, 157: 209-225.
- Muñoz J, Felicísimo AM (2004). Comparison of statistical methods commonly used in predictive modelling. *J. Veg. Sci.*, 15: 285-292.
- Olden JD, Jackson DA (2002). A comparison of statistical approaches for modelling fish species distributions. *Freshwater Biol.*, 47(10): 1976-1995.
- Parmesan C, Yohe G (2003). A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, 421: 37-42.
- Parry ML, Canziani OF, Palutikof JP, Hanson CE, Vander Linden PJ (2007). Impacts, adaptation and vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.
- Pearson RG, Dawson TP, Berry PM, Harrison PA (2002). SPECIES: A spatial evaluation of climate impact on the envelope of species. *Ecol. Model.*, 154: 289-300.
- Pearson RG, Dawson TP (2003). Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Glob. Ecol. Biogeogr.*, 12(5): 361-371.
- Pearson RG, Dawson TP, Liu C (2004). Modelling species distributions in Britain: a hierarchical integration of climate and land-cover data. *Ecography*, 27: 98-285.
- Pearson RG, Thuiller W, Araújo MB, Martinez-Meyer E, Brotons L, McClean C, Miles L, Segurado P, Dawson TE, Lees DC (2006). Model-based uncertainty in species range prediction. *J. Biogeogr.*, 33(10): 1704-1711.
- Peterson AT, Cohoon KP (1999). Sensitivity of distributional prediction algorithms to geographic data completeness. *Ecol. Model.*, 117: 159-164.
- Peterson AT, Soberon J, Sanchez-Cordero V (1999). Conservatism of ecological niches in evolutionary time. *Science*, 285: 1265-1267.
- Peterson AT, Vieglais DA (2001). Predicting species invasions using ecological niche modelling. *Bioscience*, 51: 363-371.
- Phillips SJ, Anderson RP, Schapire RE (2006). Maximum entropy modelling of species geographic distributions. *Ecol. Model.*, 190: 231-259.
- Phillips SJ, Dudik M (2008). Modelling of species distributions with Maxent: New extensions and a comprehensive evaluation. *Ecography*, 31: 161-175.
- Press MC, Callaghan TV, Lee JA (1998). How will European arctic ecosystems respond to projected global environmental change? *Ambio*, 27: 306-311.
- Richardson AJ, Schoeman DS (2004). Climate impact on plankton ecosystems in the Northeast Atlantic. *Science*, 305: 1609-1612.
- Ripley BD (1996). *Pattern Recognition and Neural Networks*. Cambridge University Press.
- Root TL, Price JT, Hall KR, Schneider SH, Rosenzweig C, Pounds JA (2003). Fingerprints of global warming on wild animals and plants. *Nature*, 421: 57-60.
- Segurado P, Araujo MB (2004). An evaluation of methods for modelling species distributions. *J. Biogeogr.*, 31: 1555-1568.
- Sekercoglu CH, Schneider SH, Fay JP, Loarie SR (2008). Climate Change, elevational range shifts, and bird extinctions. *Conserv. Biol.*, 22(1): 140-150.
- Stockwell DRB, Nobel IR (1992). Induction of sets of rules from animal distribution data: A robust and informative method of analysis. *Math Comput. Simul.*, 33: 385-390.
- Sinclair AJ, Elizabeth AW, Michael AB, van Beek AP, Kema IP, Hughes BA, Murray PI, Nightingale PG, Stewart PM, Saaeha R, Tomlinson JW (2010). Cerebrospinal Fluid Corticosteroid Levels and Cortisol Metabolism in Patients with Idiopathic Intracranial Hypertension: A Link between 11(beta)-HSD1 and Intracranial Pressure Regulation? *J. Clin. Endocrinol. Metab.*, 95: 5348-5356.
- Stockwell DRB, Peters DP (1999). The GARP modelling system: problems and solutions to automated spatial prediction. *Int. J. Geogr. Inf. Syst.*, 13: 143-158.
- Stockwell DRB, Peterson AT (2002). Effects of sample size on accuracy of species distribution models. *Ecol. Model.*, 148: 1-13.
- Thomas D, Cameron A, Green RE, Bakkenes M, Beaumont LJ, Collingham YC, Erasmus BFN, Ferreira de Siqueira M, Grainger A, Hannah L, Hughes L, Huntley B, van Jaarsveld AS, Midgley GF, Miles L, Ortega-Huerta MA, Peterson AT, Phillips OL, Williams SE (2004). Extinction risk from climate change. *Nature*, 427: 145-148.
- Thomas CD, Franco AMA, Hill JK (2006). Range retractions and extinction in the face of climate warming. *Trends Ecol. Evol.*, 21: 415-416.
- Thuiller W (2003). BIOMOD — Optimizing predictions of species distributions and projecting potential future shifts under global change. *Glob. Change Biol.*, 9: 1353-1362.
- Thuiller W (2004). Patterns and uncertainties of species' range shifts under climate change. *Glob. Change Biol.*, 10: 2020-2027.
- Virkkala R, Heikkinen RK, Leikola N, Luoto M (2008). Projected large-scale range reductions of northern-boreal land bird species due to climate change. *Biol. Conserv.*, 141: 1343-1353.
- Venables WN, Dichmont CM (2004). GLMs, GAMs and GLMMs: an overview of theory for applications in fisheries research. *Fish Res.*, 70: 319-337.
- Wang G, Schimel D (2003). Climate change, climate modes, and climate impacts. *Ann. Rev. Env. Resour.*, 28: 1-28.
- Walther GR, Post E, Convey P, Menzel A, Parmesan C, Beebee TJC, Fromentin JM, Hoegh-Guldberg O, Bairlein F (2002). Ecological responses to recent climate change. *Nature*, 416: 389-395.
- Walther GR, Berger S, Sykes MT (2005). An ecological "footprint" of climate change. *Proc. R. Soc. Lond.*, B272: 1427-1432.
- Warren MS, Hill JK, Thomas JA, Asher J, Fox R, Huntley B, Roy DB, Telfer MG, Jeffcoate S, Harding P, Jeffcoate G, Willis SG, Greatorex-Davies JN, Moss D, Thomas CD (2001). Rapid response of British butterflies to opposing forces of climate and habitat change. *Nature*, 414(6859): 65-69.