

Strengths and weaknesses of existing theories for predicting vegetation range shift

Physical measurements of vegetation range shifts

Plant range shift is difficult to measure *in-situ*, since the geographic distributions of plants surpass the limits of physical survey capabilities, as well as difficulties measuring changes temporally due to logistical constraints (Morin and Thuiller, 2009). Small-scale experimental studies where patches of land are manipulated to control for temperature and precipitation go some way to predict the ecological drivers of shifting, but are challenging to upscale to an extent that includes or measures all the potential factors at play. Equally, long-term monitoring studies of forest plots which include re-surveys, and consistently collected data on phenology, do support observed measurements of changes to species abundance, but are not designed to assess range shift *per se*. Therefore, most studies on terrestrial plant range shift to date are conducted by computer modelling (Thuiller, 2007).

Computer modelling of vegetation range shifts

Vegetation shifts are modelled in many ways, and multiple metrics can be used to measure different components of shift distance, shape, and speed. Before any predictions can be made, the species in question must have a quantifiable known range for the current time from which to measure any differences in the future. Yalcin and Leroux (2017), defined six popular methods for measuring current species ranges: observational-based studies, grid-based maps converted from presence data, the drawing of convex hulls around the spatial limit of known points, interpolation techniques such as kriging, species distribution models (SDM) using software like MaxEnt, or hybrid approaches (Yalcin and Leroux, 2017). They showed in their review of range shift predictions for all taxa (2013-14) that SDM usage surpassed all other mentioned methods for studying changes to current and future range limits, size or suitability/probability of occurrence (Yalcin and Leroux, 2017).

Statistical modelling approaches

Statistical modelling approaches such as Maxent have been common since the mid 2000's to support range shift predictions. This correlative approach is straightforward to use, generates almost instantaneous, accurate results and requires no licence fee (Merow et al., 2013). Correlative model limitations are well documented by its authors and users, (Clark et al., 2010, García-Valdés, 2013, Pompe et al., 2008, Zwiener et al., 2018), where a fundamental disadvantage is the assumption that species are in equilibrium with the environment and climate, which is often not the case (García-Valdés, 2013, Svenning and Sandel, 2013, Rohde, 2006). Many correlative-based approaches highlight the effectiveness of process-based (PB) model equivalents due to their ability to incorporate dispersal and other biotic interactions (Fitzpatrick et al., 2008, Shrestha et al., 2018, Zhang et al., 2020), but still neglect to parameterise such a model, citing the difficulties in identifying, quantifying and inclusion in models (Birhane et al., 2020, Vieilledent et al., 2013).

Process-based modelling approaches

The uptake of process-based (PB) models in the context of range shift has been slow. This is likely due to the additional parameters required to build these types of models, when compared with correlative models that can

Strengths and weaknesses of existing theories for predicting vegetation range shift

predict with “top-down” bioclimatic variables such as temperature and precipitation. For PB models to be more widely used, data on phenology, physiology and dispersal need to be available on a mass scale. Initiatives such as the TRY plant traits database (Kattge et al., 2020), go some way to reducing this data gap specifically for traits, but depending on the species, country, or study context, acquiring these data is not always possible. For example, a particular problem with plants (compared to animal shifts) is that ‘dispersal’ as a model parameter is not a straightforward measurement to capture or predict, given a value could be vastly different depending on seed size, environmental conditions, and individual biotic interactions. This is especially true in the case of long-term dispersal events which could be one of the main mechanisms that allow plants to track the current rate of climate change (Cain et al., 2000).

Quantifying measurements of range shift (range shift metrics)

Calculations to measure range shift are inferred from habitat net change (the area difference between the current and future predicted ranges), habitat direction change (the up/downslope travel for elevational shifting), or rate of change, an index for assessing whether species may be able to track climate change velocity (Choe et al., 2017, Radinger et al., 2017, Yesuf et al., 2021). There are also species and habitat specific measurements, such as the Predicted Area of Habitat (PAOH) coined by the International Union for the Conservation of Nature (IUCN) which may be more suitable for individual populations of a selected species (IUCN, 2022). To our knowledge there is no single agreed metric to which all range shift measurements on taxa are made. This makes it difficult to cross-compare studies, species, and geographies to understand trends and wider conservation impacts. Yet, providing a quantitative measure of range shift with one of the aforementioned is more robust than supplying a continuous probability of occurrence. Numbers extracted from calculating range shift metrics can be directly fed into conservation strategies and support decision making surrounding the taxa under investigation.

Strengths and weaknesses of existing theories for predicting vegetation range shift

References

- E. Birhane, Asgedom, K. T., Tadesse, T., Hishe, H., Abrha, H. & Noulèkoun, F. 2020. Vulnerability of baobab (*Adansonia digitata* L.) to human disturbances and climate change in western Tigray, Ethiopia: Conservation concerns and priorities. *Global ecology and conservation*, 22, e00943 DOI: 10.1016/j.gecco.2020.e00943.
- M. L. Cain, Milligan, B. G. & Strand, A. E. 2000. Long-distance seed dispersal in plant populations. *American Journal of Botany*, 87, 1217-1227 DOI: <https://doi.org/10.2307/2656714>.
- H. Choe, Thorne, J. H., Hijmans, R., Kim, J., Kwon, H. & Seo, C. 2017. Meta-corridor solutions for climate-vulnerable plant species groups in South Korea. *Journal of Applied Ecology*, 54, 1742-1754 DOI: 10.1111/1365-2664.12865.
- J. M. Clark, Gallego-Sala, A. V., Allott, T. E. H., Chapman, S. J., Farewell, T., Freeman, C., House, J. I., Orr, H. G., Prentice, I. C. & Smith, P. 2010. Assessing the vulnerability of blanket peat to climate change using an ensemble of statistical bioclimatic envelope models. *Climate research*, 45, 131-150 DOI: 10.3354/cr00929.
- M. C. Fitzpatrick, Gove, A. D., Sanders, N. J. & Dunn, R. R. 2008. Climate change, plant migration, and range collapse in a global biodiversity hotspot: The Banksia (Proteaceae) of Western Australia. *Global Change Biology*.
- R. García-Valdés, Zavala, M. A., Araújo, M. B., & Purves, D. W. 2013. Chasing a moving target: projecting climate change-induced shifts in non-equilibrium tree species distributions. *Journal of Ecology*, 101, 441-453.
- J. Kattge, Bönsch, G., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., Tautenhahn, S., Werner, G. D. A., Aakala, T., Abedi, M., Acosta, A. T. R., Adamidis, G. C., Adamson, K., Aiba, M., Albert, C. H., Alcántara, J. M., Alcázar, C., Aleixo, I., Ali, H., Amiaud, B., Ammer, C., Amoroso, M. M., Anand, M., Anderson, C., Anten, N., Antos, J., Apgaua, D. M. G., Ashman, T.-L., Asmara, D. H., Asner, G. P., Aspinwall, M., Atkin, O., Aubin, I., Bastrup-Spohr, L., Bahalkeh, K., Bahn, M., Baker, T., Baker, W. J., Bakker, J. P., Baldocchi, D., Baltzer, J., Banerjee, A., Baranger, A., Barlow, J., Barneche, D. R., Baruch, Z., Bastianelli, D., Battles, J., Bauerle, W., Bauters, M., Bazzato, E., Beckmann, M., Biecekman, H., Beierkuhnlein, C., Bekker, R., Belfry, G., Belluau, M., Beloiu, M., Benavides, R., Benomar, L., Berdugo-Lattke, M. L., Berenguer, E., Bergamin, R., Bergmann, J., Bergmann Carlucci, M., Berner, L., Bernhardt-Römermann, M., Bigler, C., Bjorkman, A. D., Blackman, C., Blanco, C., Blonder, B., Blumenthal, D., Bocanegra-González, K. T., Boeckx, P., Bohlman, S., Böhning-Gaese, K., Boisvert-Marsh, L., Bond, W., Bond-Lamberty, B., Boom, A., Boonman, C. C. F., Bordin, K., Boughton, E. H., Boukili, V., Bowman, D. M. J. S., Bravo, S., Brendel, M. R., Broadley, M. R., Brown, K. A., Bruehlheide, H., Brumnick, F., Bruun, H. H., Bruy, D., Buchanan, S. W., Bucher, S. F., Buchmann, N., Buitenwerf, R., Bunker, D. E., Bürger, J., et al. 2020. TRY plant trait database – enhanced coverage and open access. *Global Change Biology*, 26, 119-188 DOI: <https://doi.org/10.1111/gcb.14904>.
- C. Merow, Smith, M. J. & Silander Jr, J. A. 2013. A practical guide to MaxEnt for modeling species' distributions: what it does, and why inputs and settings matter. *Ecography*, 36, 1058-1069 DOI: <https://doi.org/10.1111/j.1600-0587.2013.07872.x>.
- X. Morin & Thuiller, W. 2009. Comparing niche- and process-based models to reduce prediction uncertainty in species range shifts under climate change. *Ecology*, 90, 1301-1313 DOI: <https://doi.org/10.1890/08-0134.1>.
- S. Pompe, Hanspach, J., Badeck, F., Klotz, S., Thuiller, W. & Kuehn, I. 2008. Climate and land use change impacts on plant distributions in Germany. *Biology Letters*, 4, 564-567 DOI: 10.1098/rsbl.2008.0231.
- J. Radinger, Essl, F., Hölker, F., Horký, P., Slavík, O. & Wolter, C. 2017. The future distribution of river fish: The complex interplay of climate and land use changes, species dispersal and movement barriers. *Global Change Biology*, 23, 4970-4986 DOI: 10.1111/gcb.13760.
- K. Rohde 2006. *Nonequilibrium Ecology*, Cambridge, Cambridge University Press.
- U. B. Shrestha, Sharma, K. P., Devkota, A., Siwakoti, M. & Shrestha, B. B. 2018. Potential impact of climate change on the distribution of six invasive alien plants in Nepal. *Ecological Indicators*.
- J.-C. Svenning & Sandel, B. 2013. Disequilibrium Vegetation Dynamics Under Future Climate Change. *American Journal of Botany*, 100, 1266-1286 DOI: 10.3732/ajb.1200469.
- W. Thuiller 2007. Biodiversity: Climate change and the ecologist. *Nature*, 448, 550-2 DOI: <http://dx.doi.org/10.1038/448550a>.
- G. Vieilledent, Cornu, C., Cuní Sanchez, A., Leong Pock-Tsy, J.-M. & Danthu, P. 2013. Vulnerability of baobab species to climate change and effectiveness of the protected area network in Madagascar: Towards new conservation priorities. *Biological Conservation*, 166, 11-22 DOI: <https://doi.org/10.1016/j.biocon.2013.06.007>.
- S. Yalcin & Leroux, S. J. 2017. Diversity and suitability of existing methods and metrics for quantifying species range shifts. *Global Ecology and Biogeography*, 26, 609-624 DOI: <https://doi.org/10.1111/geb.12579>.
- G. U. Yesuf, Brown, K. A., Walford, N. S., Rakotoarisoa, S. E. & Rufino, M. C. 2021. Predicting range shifts for critically endangered plants: Is habitat connectivity irrelevant or necessary? *Biological Conservation*, 256, 109033 DOI: <https://doi.org/10.1016/j.biocon.2021.109033>.
- X. Zhang, Wei, H., Zhang, X., Liu, J., Zhang, Q. & Gu, W. 2020. Non-Pessimistic Predictions of the Distributions and Suitability of *Metasequoia glyptostroboides* under Climate Change Using a Random Forest Model. *Forests*, 11, 62 DOI: 10.3390/f11010062.
- V. P. Zwiener, Lira-Noriega, A., Grady, C. J., Padial, A. A. & Vitule, J. R. S. 2018. Climate change as a driver of biotic homogenization of woody plants in the Atlantic Forest. *Global Ecology and Biogeography*, 27, 298-309 DOI: 10.1111/geb.12695.