Spatially explicit mapping of ecological similarity across a large region using matching techniques.

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Abstract

ABSTRACT

Plain Language Summary

Probably am not doing a plain language summary

1 Introduction

A global biodiversity crisis is currently underway, driven by anthropogenic changes and pressures such as climate change, land-use changes, and invasive species, among others (Dirzo & Raven, 2003). Protected areas have been demonstrated to be one of the most effective potential safeguards against these biodiversity losses (Chape et al., 2005). To assess the effectiveness of protected areas, it is necessary to collect data across entire jurisdictions and compare them to similar ecosystems that are not protected. However, collecting direct, field-derived information on biodiversity across large regions is simply not feasible due to financial and temporal constraints.

Remote sensing data, however, can provide a time-efficient, cost-effective alternative to field data, and can be used to generate Essential Biodiversity Variables (EBVs) which are comparable, standardized datasets capable of measuring biodiversity change across large spatial extents through time (Pereira et al., 2013; Skidmore et al., 2021). Two EBV classes are particularly well suited to be used at regional to national scales; ecosystem structure and ecosystem function. Ecosystem structure is defined as the physical organization of biotic and abiotic materials in the system, and is commonly assessed as land cover and forest structural attributes using remote sensing (Noss, 1990). Ecosystem function are attributes related to ecosystem performance, such as the inflows or outflows of energy/nutrients (Pettorelli et al., 2018). Remote sensing of ecosystem function commonly includes productivity metrics such as GPP (Pettorelli et al., 2005, 2018). Remote sensing-derived EBVs provide suitable spatial coverage, temporal depth, and temporal frequency to be used for biodiversity monitoring (Skidmore et al., 2021), and thus, protected area effectiveness assessments.

The use of impact assessment techniques such as matching is becoming increasingly prevalent in studies of the effectiveness of protected areas (Ferraro, 2009). Matching methods generally work by creating a counterfactual scenario in which conservation outcomes are compared between the protected area and what those outcomes would be if the given area were not protected (Ribas et al., 2021). This is achieved by comparing a given protected area to an unprotected area with similar covariates, such as climate, topography, and various anthropogenic data. Propensity score matching uses the covariates and protected status with a logit regression to create a propensity score, which is then used to match the protected area to an unprotected area (Austin, 2011). Coarsened exact matching (CEM) initially coarsens the covariates into bins (percentiles) and then performs exact matching on these bins, while retaining the original, uncoarsened data (Iacus et al., 2012). Other matching methods exist (see Schleicher et al., 2020), but one common issue common to these methods is that many data samples are dropped because there is no suitable match to be found. This can be problematic when attempting to create spatial counterfactuals, such as when evaluating the efficacy of protected areas across large regions, as it can lead to a loss of spatial coverage.

In this study, we seek to enhance the spatial coverage of CEM using a two-step approach. Firstly, we coarsen the covariates into bins, and then perform exact matching on these bins. In the event that no suitable match can be found, a KNN (k = 1) approach is used to identify the nearest match. This two-step approach allows for a more comprehensive assessment of the effectiveness of protected areas, where no observations are discarded. This method is applied to the forested regions of

British Columbia, Canada, and the effectiveness of protected areas to is compared to similar ecosystems that are not protected. We compare the spatial coverage of standard CEM method and our expanded CEM method, and also apply both methods for assessing protected area effectiveness at conserving two EBV classes; ecosystem structure and ecosystem function. Further, we generate bootstrap confidence intervals for each CEM bin for our two EBV classes and compare every forested area in BC to their respective confidence interval. This allows for the respatialization of the results, allowing for managers to identify regions in need of restoration (outside the confidence interval, in protected areas), or protection (inside the confidence interval, outside of protected areas).

2 Data & Methods

3 Results

4 Conclusion

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