facility diminish over time. Ultimately, more research is needed on this topic, and on further measures to minimize wind-farm-related impacts to raptors.

Regan Dohm[1*], Christopher S Jennelle[2], Julie C Garvin[3], and David Drake[4]

*[1]Nelson Institute for Environmental Studies, University of Wisconsin–Madison, Madison, WI *(regan.dohm12@gmail.com); [2]Minnesota Department of Natural Resources, Forest Lake, MN; [3]Tetra Tech Inc, Portland, OR; [4]Department of Forest and Wildlife Ecology, University of Wisconsin–Madison, Madison, WI*

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Doubling demands in programming skills call for ecoinformatics education

Many science disciplines are witnessing marked increases in the volume and variety of data collected, analyzed, and stored (Khoury and Ioannidis 2014). Ecology has also inevitably entered the era of "big data" (Hampton *et al.* 2013), with large datasets from museum collections (Constable *et al.* 2010), citizen-science programs (Sullivan *et al.* 2014), environmental sensors, and remote-sensing platforms (Toth and Jóźków 2016). Ecological science is increasingly asked to make more data-driven predictions at different temporal and spatial scales (Dietze *et al.* 2018).

The shift in data culture necessitates a fundamental change in how ecologists conduct research and train students. Indeed, computational tools like programming languages – especially those designed for data analysis, such as R and Python – have improved the efficiency and reproducibility of ecological research (Lowndes *et al.* 2017). However, it is still unclear how this trend will affect the job market for early-career ecologists (who we define as scholars seeking PhD assistantships or postdoc positions in ecology). The data culture shift in ecology suggests that the nature of ecological jobs may have also fundamentally changed. But has such a shift occurred?

We analyzed how often programming skills were listed as prerequisites for PhD student and postdoc positions in ecology, based on ~56,000 job descriptions posted on the ECOLOG-L listserv between 2006 and 2018 (WebPanel 1). We found that, in 2018, >26% of PhD student positions and >36% of postdoc positions required that applicants have programming skills. Furthermore, from 2006 to 2018, the demand for these skills not only doubled for PhD student positions and more than tripled for postdoc positions (WebTables 2–4) but also steadily increased over time (Figure 1), at a rate of 1% and 2% per year for PhD student positions and postdoc positions, respectively (WebTable 4). There is no indication that the demand has slowed or will slow anytime soon, and we expect that the differences in demand between the two positions will widen over time.

Given the growing need for programming skills, it is important to ask if ecological education is lagging in teaching the skills that are now increasingly required to conduct ecological research. These skills are typically not included in the undergraduate education of ecology students (Strasser and Hampton 2012) but are desired (Barraquand *et al.* 2014).

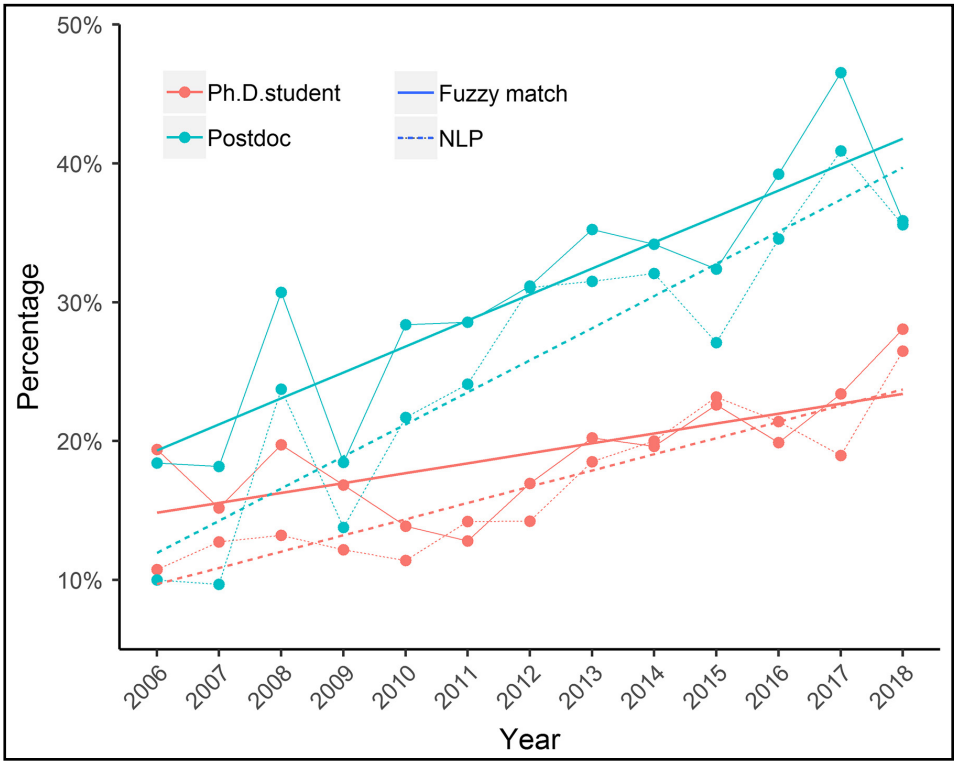

Figure 1. The percentage of PhD student (red) or postdoc (blue) positions that require programming skills. The results based on fuzzy matching and natural language processing (NLP) are depicted as solid and dashed thin lines, respectively. The four straight lines (two solid and two dashed) represent the linear fit of the percentages over time for each position type and processing method.

A survey of undergraduates majoring in environmental or ecological science revealed that over 80% had no formal training in computing or informatics and 74% possessed no skills in any programming language (Hernandez *et al.* 2012). The increased demand for programming skills versus the students' lack of formal training in programming highlights an important disparity between traditional ecological education and emerging expectations in ecological jobs.

The spike in demand for programming skills in the job market is a call to arms. Early-career ecologists should be aware of the changing expectations with respect to skillsets and the type of position – especially when transitioning from a PhD to a postdoc. Increased opportunities to learn programming through workshops or online tutorials, such as Data Carpentry (Teal *et al.* 2015), suggest that more people are developing these skills independently, but we believe that formal training should be implemented much earlier, at the undergraduate level. The University of California–Berkeley is a pioneer in this direction, where introductory data-science classes are offered to undergraduates. However, the rise of data-science classes in some, but not all, institutions suggests that educational quality varies across universities, which may have unequal success in preparing students for the next stage of their careers. Even when available, such courses are usually not oriented toward ecological applications.

Researchers and educators in the field of ecology need to shoulder the responsibility of training the skillsets of ecoinformatics that are demanded by our science. An education in bioinformatics provides a good model to follow; it has transitioned from informal workshops to structured certificates and doctorate programs (Ranganathan 2005). The state of bioinformatics today could represent the state of ecoinformatics in the future. As a discipline, ecology should systematically and strategically adapt the education system to meet this critical need, for example by updating program accreditation requirements and setting a minimum skillset to satisfy informatics needs (Tan *et al.* 2009), incentivizing or hiring technically proficient faculty to develop ecology-focused analytics courses (Pevzner and Shamir 2009), developing integrated dual-degree programs or professional certificates (Hemminger *et al.* 2005), creating paid analytics internship opportunities, providing fellowships structured to support analytics skills development, and establishing and expanding ecoinformatics programs (Recknagel 2011). In light of emerging environmental challenges and the rise of big data, the demand for programming skills and data literacy will undoubtedly continue to increase (Burning Glass Technologies 2016). Offering an ecology curriculum that emphasizes the foundations of data science will therefore better guarantee that ecological science can adequately address future societal and academic needs.

Xiao Feng[1,2*], Huijie Qiao[3], and Brian J Enquist[4,5]

*[1]Institute of the Environment, University of Arizona, Tucson, AZ; [2]School of Natural Resources and the Environment, University of Arizona, Tucson, AZ *(fengxiao@email.arizona.edu); [3]Key Laboratory of Animal Ecology and Conservation Biology, Institute of Zoology, Chinese Academy of Sciences, Beijing, China; [4]Department of Ecology and Evolutionary Biology, University of Arizona, Tucson, AZ; [5]The Santa Fe Institute, Santa Fe, NM*

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Supporting Information

Additional, web-only material may be found in the online version of this article at http://onlinelibrary.wiley.com/doi/10.1002/fee.2179/suppinfo