Short communication

Explaining harvests of wild-harvested herbaceous plants: American ginseng as a case study

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Keywords: American ginseng, Forest herbaceous plant, Geoadditive model, Open access resource, Social-ecological, Plant conservation, Species distribution model, Time-series

ABSTRACT

Wild-harvested plants face increasing demand globally. As in many fisheries, monitoring the effect of harvesting on the size and trajectory of resource stocks presents many challenges given often limited data from disparate sources. Here we analyze American ginseng (Panax quinquefolius L.) harvests from 18 states in the eastern U.S. 1978–2014 to infer temporal patterns and evidence of population declines, and we test the effects of local environmental and socioeconomic factors on ginseng harvesting at the county level 2000–2014.

Despite rising prices, annual wild ginseng harvests decreased from a high point in the late 1980s to early 1990s, then, in most, increased after 2005 or 2010 - suggesting range-wide overexploitation notwithstanding federal regulations that, since 1999, restrict minimum harvest age. County-level harvest rates increased with available habitat, road density, poverty and unemployment, but decreased when public land formed a large proportion of county area. Harvests were largest in the Southern Appalachian region. Poverty and accessibility were strongly related to high levels of harvesting.

A key implication is that to conserve valuable wild native plant products while also improving local livelihoods, wild cultivation and good stewardship practices must be strongly promoted. Our approach to assessing the condition of wild populations offers a broad template that could be adapted to other wild-harvested plants.

1. Introduction

Global demand for forest herbal products is rising (Schippmann et al., 2002), and is likely causing increased extractive effort in many regions of the world (Belcher and Schreckenberg, 2007; Ghorbani et al., 2014; Chamberlain, 2015; Chamberlain et al., 2018). Many forest herbaceous species collected for the medicinal trade (e.g., ginseng, goldenseal, cohosh) are slow-growing perennials that require many years to reach reproductive maturity (e.g., Sinclair et al., 2005; Nantel et al., 1996). Moreover, whether they occur on public or private lands, forest herb populations are, by default, managed as an open access resource (Ticktin and Shackleton, 2011) such that, in practice, location, timing, and the number of people engaged in harvesting is usually unrestricted (e.g., McGraw et al., 2010). Like other open access resources (e.g., many fisheries), populations are prone to overexploitation and rapid depletion (Gordon, 1954; Hardin, 1968).

Given increasing demand (and/or decreasing supply) that has led to higher prices, harvest pressure on ginseng is likely to increase into the foreseeable future. Historical documentation indicates that wild products gathered in the Southern Appalachians during the 19th century were regarded as a common property resource. Yet, it is unclear how much cultural conventions may have promoted a culture of good stewardship. Since the early 20th century, restrictions on harvesting of ginseng on private land other than one’s own, and outside of the September–October season when fruits have matured have entered the law in many states (Manget, 2013), and since 1999, the U.S. Fish and Wildlife Service (USFWS) imposes a minimum harvest age (Frey et al., 2018). Yet, how effective these measures are in regulating the practices of harvesters is unclear. On public land, in the absence of what would certainly be very costly investments in vastly increased law...
enforcement, ginseng populations do remain a de facto open access resource. In such cases, collectors have little incentive — unless very strong cultural prohibitions prevail - to conserve, manage or monitor a resource that they neither own nor control access to (Ostrom, 2010). Restricting or eliminating collection permits on the national forest may send a signal that ginseng populations are threatened, but, without strong enforcement, a permit program is unlikely to affect harvest rates so long as demand remains high. As such, broad approaches to assessing the status of plant species commercially collected from the wild based on available data on harvest fill a critical knowledge gap in developing conservation policy.

1.1. American ginseng as a case study

American ginseng (*Panax quinquefolius* L. Araliaceae, hereafter ginseng), one of the most widespread and valuable non-timber forest products in eastern North America, offers a useful case study. Within mainly hardwood forest habitats, ginseng is widespread in its occurrence, found from the Coastal Plain of the southeast through the Southern Appalachians, Ozarks, Ouachitas, Northeast, Midwest and riparian forests in the plain states. While tolerating a broad range of environmental conditions, ginseng particularly favors mesic conditions and circumneutral soils (McGraw et al., 2013).

The highest reported U.S.-wide ginseng harvest in the last 4 decades (71,393 kg in 1979) was > 40% below the peak recorded in the 19th century (> 400,000 in 1878), but greater than the low point in the early 20th century (125,000, 1905) (Kauffman, 2006). Major declines in ginseng harvests since the 19th century must certainly reflect enormous changes in socioeconomic and environmental conditions throughout the rural East (e.g., fewer people engaged in ginseng harvesting as a livelihood component), but they likely reflect much lower ginseng abundance as well.

Despite stewardship guidelines (e.g. those provided by the American Herbal Products Association) and legal protections (USFWS, 2018) to promote sustainable resource management, data limitations have made assessing long-term, broad-scale ginseng’s population trends an ongoing challenge (McGraw, 2017; McGraw et al., 2013), and by extension have made it difficult to evaluate the effectiveness of these measures. Indirect evidence from herbarium accessions (Case et al., 2007), reduced plant stature (McGraw, 2001), and anecdotal reports (summarized in Kaufman, 2006) as well as data on plant demography (McGraw et al., 2013) suggest regional declines in ginseng abundance as a combined effect of harvest pressure and herbivory by deer (Farrington et al., 2009; McGraw and Furedi, 2005). Also, while rates on and off the national forests cannot be readily quantified, Kauffman (2006) suggests that illegal harvesting may be sizable.

Ginseng has been harvested for the international trade since the early 18th century. However, population conditions prior to commercial exploitation are unknown. Relatively, because population size is difficult to measure, it is typically inferred from harvest data (Robbins, 2000), as in the case of many fisheries. Nantel et al. (1996) estimate stochastic population sizes under several contrasting harvest regimes to calculate extinction thresholds. We use actual harvest data rather than hypothetical harvest regimes to estimate an econometric model rather than to perform simulations of population dynamics. As such, ours is one of the first studies to rigorously assess the status of ginseng at a broad scale, by synthesizing evidence from multiple data sources with broad, high resolution geographic and temporal coverage. We used a 37-year (1978–2014) time series of ginseng harvests from 18 states to quantify temporal trends in harvest rates, and, by inference, ginseng abundance. We then developed a species distribution model (SDM) for ginseng across the eastern U.S. to estimate quality and extent of habitat by county. Finally, we examined 15 years (2000–2014) of county-level harvest data to test, while controlling for the extent and quality of suitable habitat, the relative effects of localized environmental and socioeconomic factors, and the availability of public land on ginseng harvesting levels.

1.2. Objectives

Our objectives were to identify where pressure on the resource is greatest, determine where habitat appears abundant relative to harvests, and investigate the joint effects of social and environmental drivers on ginseng harvesting. While our results are intended to have management implications specific to ginseng, the approach we demonstrate offers a broad template that could be adapted to many similar species facing heavy exploitation.

2. Materials and methods

2.1. Temporal patterns in ginseng harvesting by state

The USFWS is the authority for regulating ginseng export under the Convention on International Trade of Endangered Species of Wild Fauna and Flora (CITES). Ginseng, as a CITES Appendix II species, “may be traded internationally if accompanied by appropriate permits.” Appendix II listing is meant to help “support natural resource management programs in range countries to prevent endangerment,” and is not a “ban or boycott of trade,” but, rather, aims to “regulate and monitor trade for species vulnerable to overuse, and implements measures to attain sustainable harvest and legal trade.” At present, 19 states have wild ginseng export programs, which include harvest rules, and the reporting of harvest and sales volumes, approved by USFWS. As a result, harvest records from 1978 to 2014 are available for 18 states (Alabama, Arkansas, Georgia, Illinois, Indiana, Iowa, Kentucky, Maryland, Missouri, New York, North Carolina, Ohio, Pennsylvania, Tennessee, Vermont, Virginia, West Virginia, and Wisconsin). To assess and compare changes in harvesting pressure on ginseng populations over time, we fit a regression model to the time series for each state using the mgcv package in R (R Development Core Team, 2008) to run generalized additive models (GAMMs, Wood et al., 2016). In generalized additive models (GAMs), linear predictors depend linearly on unknown smooth functions in the case of some predictor variables. We used mixed modeling because time series data consists of repeated measures (i.e., same states), and generalized additive models to incorporate what appeared to be non-linear effects over time (Gelman and Hill, 2006). Temporal autocorrelation was accounted for using a first order autoregressive moving average (ARMA) model and cubic splines (Shumway and Stoffer, 2010).

2.2. Correlates of recent (2000–2014) county-level ginseng harvesting

2.2.1. Ginseng species distribution model

Species distribution models (SDM, sometimes referred to as habitat suitability models or niche models) are computational approaches that make use of known presence points, random background points where the species in question may or may not occur, and data for a set of pertinent environmental variables at each point, to predict probability of ginseng occurrence.

Presence points (1200 locations of historic and current ginseng populations) were compiled from a number of sources: University of Georgia Herbarium, Georgia Natural Heritage Program, South Carolina Natural Heritage Program, US Forest Service ginseng monitoring plots, other National Forest data, data from the American Ginseng Society (range-wide), and data provided by USGS (mostly Midwestern). Importantly, the occurrence points used to develop the SDM were independent of ginseng harvest data. Table S2 in the supplementary materials gives the number of point locations by state.

Selecting appropriate background geography is essential to assessing model accuracy. In this case, we narrowed the geographic background to The Nature Conservancy’s terrestrial ecoregions (TNC, 2009), based on Olson and Dinerstein (2002), within which at least one
The ginseng population is reported to have occurred historically (Fig. 1). Using these ecoregions, we then restricted background habitat to deciduous and mixed forests as classified by the National Landcover Database (NLCD, Homer et al., 2015) as the class from which 100,000 background points were randomly generated.

We used a variety of geographic data sources to capture parent material, landform, climate, and soil taxonomy. From the Natural Resources Conservation Service, the Soil Survey Geographic Databases (SSURGO, Soil Survey Staff, 2017) for all states overlapping ginseng ecoregions were used to generate a set of binary predictors identifying soil taxonomic subgroups at a 1:2.5 × 10^6 scale. Using the USGS topographic moisture potential raster (30 m pixel, Cress et al., 2009a), each point was placed in one of the following categories: wetland, mesic upland, dry upland, or very dry upland. From USGS land surface forms raster (30 m pixel, Cress et al., 2009b), each point was assigned to one of the following: flat plains, smooth plains, irregular plains, escarpments, low hills, hills, breaks/toothills, low mountains, high mountains/deep canyons, and drainage channels. And from the USGS isobioclimatic raster (1 km pixel, Rivas-Martínez et al., 1999), of climate/vegetation zones.

Species distribution modeling methods given in the Supplementary materials.

2.2.2. Geoadditve regression models of county-level harvest size

For the years 2000–2014, the only years for which harvest data disaggregated to county level were available, we were interested in the relative importance of ecological factors (e.g. available habitat), socioeconomics (population, poverty, unemployment), and governance and infrastructure (public land area, road density) in explaining variation in harvests between counties.

For the period 2000–2014, we compiled harvest amounts by county of wild-harvested ginseng from reports by states to the USFWS for states permitting wild ginseng harvest for export (excluding Minnesota). Note that ginseng also grows wild in a number of states that do not permit wild harvest for export (Connecticut, Delaware, Kansas, Maine, Massachusetts, Michigan, Nebraska, New Hampshire, New Jersey, Oklahoma, Rhode Island, South Carolina).

For each of the 1387 counties overlapping ecoregions with recorded ginseng populations, we summarized the area and quality of available habitat (deciduous and mixed forest pixels) to create a habitat index (HI)

$$HI_{\text{county}} = \sum_{i=1}^{n} \text{rank}_i \times \text{pixels}_i,$$

where rank is the percentile $i = 1 - n$, of the probabilities generated by the SDM, and pixels are the number of pixels at that rank within the county. To capture habitat quality relative to the total area of potential habitat, we also calculated a relative habitat index (RHI) by dividing HI by the total number of deciduous and mixed forest pixels per county. For statistical analyses, HI was log_{10}-transformed.

From the US Census Bureau’s Small Area Income and Poverty Estimates (SAIPE) program we collated data on total population and percent of households in poverty in 2016 (log_{10}-transformed), and, averaged over the entire period 2000–2014, unemployment, and median income. Using shapefiles of roads from ESRI (2010), we calculated road density (km km^{-2}) by county using the protocol developed by the National Park Service (2013).

Lastly, we overlaid county boundaries on the Protected Areas Database of the United States (USGS, 2003) to calculate the number of acres of non-military public land by county (Fig. 1). Public lands, because they provide habitat for ginseng, are likely subject to some level of illegal harvesting. Although permitted in some national forests (mostly in the southeastern US), ginseng harvesting is not allowed on most types of state and federal lands.

Fig. 1. Public lands (excluding military installations) overlaid on the TNC ecoregions within which at least one ginseng record exists in the occurrence data.
Because counties in geographic proximity are likely to be similar in ways not captured by our covariates, we adopted a geoadditive (Kammann and Wand, 2003) modeling approach using the mgcv package in R (R Development Core Team, 2008). Geoadditive models combine generalized additive models (GAMs, Wood, 2006) with spatial variables (i.e., x-y coordinates of county centroids as covariates) to account for spatial autocorrelation when significant spatial dependencies between data points are expected. Residual spatial autocorrelation is captured by a smooth function of spatial coordinates. Because neighboring counties may fall into different states each with distinct legal, social, cultural or economic factors that could affect ginseng harvesting, we included a smooth term in the model for state as a factor variable.

Finally, of the 1387 counties overlapping the ginseng ecoregions, ginseng harvesting was reported from only 626 in any of the 14 years. Because of the large number of zeros, we chose a hurdle method. First, we used logistic regression to predict if any harvesting was reported in a county. Then, for counties with reported harvesting, we predicted the mean harvest (dry kg) as a normally distributed continuous variable.

3. Results

3.1. State-level patterns of ginseng harvest and habitat

Overall, states with the largest total harvests (Kentucky, Tennessee, Virginia, West Virginia) were those with the largest statewide habitat indices. However, Alabama, Arkansas, Georgia, North Carolina, Maryland, New York, Vermont, and, particularly, Missouri and Pennsylvania registered low total harvests relative to SDM estimates of habitat abundance, while harvests in Illinois, Iowa, Wisconsin, and, particularly, Indiana, were quite large relative to habitat estimates (Table 1).

Table 1

<table>
<thead>
<tr>
<th>State</th>
<th>Total harvest</th>
<th>HI</th>
<th>RHI</th>
<th>Harvest/HI</th>
</tr>
</thead>
<tbody>
<tr>
<td>KY</td>
<td>299,412</td>
<td>418,178</td>
<td>0.7</td>
<td>1.58</td>
</tr>
<tr>
<td>WV</td>
<td>225,061</td>
<td>408,133</td>
<td>0.73</td>
<td>1.22</td>
</tr>
<tr>
<td>TN</td>
<td>212,307</td>
<td>404,870</td>
<td>0.67</td>
<td>1.16</td>
</tr>
<tr>
<td>VA</td>
<td>133,660</td>
<td>401,924</td>
<td>0.64</td>
<td>0.73</td>
</tr>
<tr>
<td>NC</td>
<td>125,367</td>
<td>321,803</td>
<td>0.64</td>
<td>0.86</td>
</tr>
<tr>
<td>IN</td>
<td>122,437</td>
<td>112,176</td>
<td>0.49</td>
<td>2.41</td>
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<tr>
<td>OH</td>
<td>100,940</td>
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<td>0.48</td>
<td>1.27</td>
</tr>
<tr>
<td>IL</td>
<td>65,607</td>
<td>113,184</td>
<td>0.49</td>
<td>1.28</td>
</tr>
<tr>
<td>WI</td>
<td>44,395</td>
<td>98,559</td>
<td>0.19</td>
<td>0.99</td>
</tr>
<tr>
<td>MO</td>
<td>36,144</td>
<td>429,349</td>
<td>0.61</td>
<td>0.19</td>
</tr>
<tr>
<td>AR</td>
<td>34,663</td>
<td>305,192</td>
<td>0.67</td>
<td>0.25</td>
</tr>
<tr>
<td>PA</td>
<td>23,787</td>
<td>395,866</td>
<td>0.51</td>
<td>0.13</td>
</tr>
<tr>
<td>IA</td>
<td>17,186</td>
<td>47,511</td>
<td>0.47</td>
<td>0.80</td>
</tr>
<tr>
<td>NY</td>
<td>13,069</td>
<td>276,332</td>
<td>0.38</td>
<td>0.10</td>
</tr>
<tr>
<td>AL</td>
<td>10,115</td>
<td>254,647</td>
<td>0.41</td>
<td>0.09</td>
</tr>
<tr>
<td>GA</td>
<td>9809</td>
<td>229,361</td>
<td>0.51</td>
<td>0.09</td>
</tr>
<tr>
<td>MD</td>
<td>3274</td>
<td>44,262</td>
<td>0.56</td>
<td>0.16</td>
</tr>
<tr>
<td>VT</td>
<td>2751</td>
<td>96,126</td>
<td>0.5</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Table 1: Total ginseng harvest (dry kg) for the years 1979–2014, habitat index (HI), relative habitat index (RHI), and the ratio of harvest to HI for states reporting ginseng harvests to the USFWS.

3.2. State-level temporal patterns in ginseng harvesting

Across states a general pattern emerged. Annual wild ginseng harvests decreased from a high point in the late 1980s to early 1990s, then, in some, increased after 2005 or 2010. However, this trend was very variable. Because neighboring counties may fall into different states each with distinct legal, social, cultural or economic factors that could affect ginseng harvesting, we included a smooth term in the model for state as a factor variable.

3.3. Species distribution model results

The final SDM predicted likelihood of ginseng occurrence with moderate to high accuracy; the area under receiver operator curve (AUC, a measure of predictive accuracy 0–1 that compares the rate of false positives to false negatives) was estimated at 0.84 on training data, and 0.83 on holdout test data. Actual accuracy is likely to be higher given that false positive rates may be underestimated as many background locations (0 labels) may currently, or in the past, have supported ginseng populations.

As expected, ginseng habitat suitability was positively associated with cooler climate zones, drainage channels (landforms such as coves and ravines), and soil taxonomic subgroups corresponding to limestone or other more basic parent materials. See appendix Table S1 for a summary of important predictors.

3.4. Habitat and recent (2000–2014) county-level ginseng harvesting

The geoadditive logistic model predicted counties with ginseng harvests with high accuracy (AUC = 0.95). Likelihood of ginseng harvest increased linearly with HI, decreased with population after a threshold at ~50,000, and increased linearly with road density (Fig. 4). There was also an unknown effect of effect of space (coordinates of county centroid) and of state (Table S3). We were able to explain nearly two-thirds of the variation ($r^2 = 0.63$) among the subset of counties with any reported ginseng harvesting in mean harvest size over the period as a function of HI, RHI, percent in poverty, mean unemployment rate, ha of public land, and an unexplained effect of space (Table S4). State, however, did not have a significant effect. Mean ginseng harvest increased at HI values > 3 and increased sharply at RHI values > 0.7 (Fig. 5). Harvest rate increased linearly with poverty, and increased at unemployment rates between 9% and 11%. Because GAMs are sensitive to outliers, effects of HI at values < 2.5 and of unemployment at rates > 11%, where only a few counties fall, cannot be interpreted with confidence (Fig. 5). The effect of availability of public land showed a small but significant decline in counties with significant public landholdings > 10,000 ha (Fig. 5). Maps of significant covariates across the counties included in the analyses highlight the Southern Appalachians (eastern Kentucky especially) and the Ozarks as regions of abundant habitat and large harvests (Fig. 3).

As a marginal effect of the full model, mean ginseng harvest increased sharply with poverty and unemployment (Fig. 5), and population and road density were significant predictors in the logistic regression model. When public lands covered a large proportion of a county, the amount of ginseng harvested decreased, but public land area was not highly correlated with either RHI ($r^2 = 0.07$) or HI ($r^2 = 0.21$), or road density ($r^2 = 0.04$). While large portions of the Southern Appalachians and the Ozarks are managed as national forests
Fig. 2. Ginseng price ($ dry kg\(^{-1}\) ) and non-linear fits to time-series of ginseng harvests (dry kg) by state for the years 1978–2014. Light gray bounds indicate 95% confidence intervals. Note that the scale of graph y-axes decreases from top to bottom. (Al = Alabama, AR = Arkansas, GA = Georgia, IL = Illinois, IN = Indiana, IA = Iowa, KY = Kentucky, MD = Maryland, MO = Missouri, NY = New York, NC = North Carolina, OH = Ohio, PA = Pennsylvania, TN = Tennessee, VT = Vermont, VA = Virginia, WV = West Virginia, and WI = Wisconsin).
or national parks, at the county level, the effect of public landholdings on ginseng harvesting is weakly negative. Thus, the geographic regions with the largest ginseng harvests (Southern Appalachians, Ozarks) stand out for the abundance of ginseng habitat, high poverty rates, and the size of public land holdings, all of which were determinants ($r^2 = 0.63$) of the level of ginseng harvesting in regression analyses (Fig. 5).

4. Discussion

4.1. Harvest patterns and the condition of ginseng stocks

Despite rising prices, ginseng harvests in all states but North Carolina have declined over the last 3 decades. Consistent with a backward bending supply curve for open access resources (Frey et al., 2018; Hartwick et al., 1986, p. 263), this suggests that the resource is being overexploited in many regions. Harvests were greatest in the
Southern Appalachians where the extent and quality of ginseng habitat is highest and where there are large blocks of unfragmented forest exist. Eastern Kentucky stands out as a region of extremely large harvests, apparently a result of habitat abundance coupled with very high levels of rural poverty, and perhaps a very strong local tradition of ginseng collecting. While county and state harvest levels broadly coincide with SDM estimates of the quantity and quality of available habitat - given sufficient habitat, socioeconomic conditions appear to be a key driver of harvest pressure. Importantly, and contrary to expectations, we found only a minor effect of public land, and a negative one, on ginseng harvesting. While not strongly correlated with one another, the negative effect of public landholdings and positive effect of road density on ginseng harvesting suggest the importance of accessibility, and perhaps the deterrent affect of law enforcement in national parks. The best conserved ginseng populations are likely to be the most remote. An unexplained effect of space and (in predicting likelihood of any ginseng harvesting) state on county-level harvests may be related to geographic differences in culture and access to buyers. Vermont, Alabama, Georgia, and New York, which had the lowest harvests relative to HI (Table 1), are also at the periphery of the range of ginseng where productivity of the plant, as a function of climate and soils, may be relatively low.

Fig. 3. (continued)
Fig. 4. Marginal effects in the logistic regression model of (top to bottom) habitat index (HI), population in 2016, and road density on the probability that ginseng harvesting was reported in a county for the years 2000–2014 (n = 1387). Light gray bounds are 95% confidence intervals, jittered rug at the bottom indicate the distribution and density of data.
4.2. Historical context

Larger harvests in 1979 than in 1905 (Kauffman, 2006) may merely reflect increasing demand, but could also, indicate the potential for ginseng stocks to recover (van der Voort et al., 2003). During the 20th century, the return of deciduous forests to formerly agricultural lands probably increased the extent of ginseng habitat across the eastern U.S. Nonetheless, the potential for ginseng expansion has likely become increasingly limited by harvest pressure, surging deer populations (McGraw and Puredi, 2005), mining, urbanization, and perhaps climate change (McGraw et al., 2013). Given the long-term dynamics in ginseng harvesting, an intriguing question is whether ginseng populations may be exhibiting (as suggested by Fig. 2) cycles similar to those of heavily exploited fisheries (Anderson et al., 2008), where prices are negatively related to harvests in the long run as stocks decrease in a backward-bending supply curve (Frey et al., 2018).

4.3. Advantages and limitations of our approach

The accuracy of the county-level harvest data is dependent on information supplied by diggers and dealers. In some cases, the digger’s county of residence or the dealer’s location, rather than the harvest county, may be reported. Because roots can be stored, whether summarized by state or county, roots harvested may not always be reported during the year in which they were harvested as required by states (Robbins, 2000). Because wild-harvested ginseng commands a premium price, 10–25 times that of field-cultivated ginseng (Frey et al., 2018), there is little incentive for sellers to distinguish wild-simulated cultivated ginseng from wild-harvested ginseng possibly inflating reported wild harvest levels (Burkhart and Jacobson, 2009).

More broadly, harvest size alone may not adequately capture the health of ginseng populations. In the short run, for a fixed stock of ginseng, harvests will increase with harvesting effort. In the long run, however, that is not necessarily the case if harvest increases lead to stock decreases (Frey et al., 2018). And, since illegal harvesting frequently occurs outside the harvest season and is otherwise associated with poor stewardship, population growth rates can be further reduced (van der Voort and McGraw, 2006). Thus, the impact of increasing harvests on ginseng stocks may be magnified by the degree of illegal harvesting. Population matrix modeling of medicinal species (Rock et al., 2004; Nantel et al., 1996) point to the critical importance of stochastic events in understanding the effects of harvesting on populations. This stochasticity is implicit in the harvest rates. However, dealing with stochastic processes explicitly was beyond the scope of this study.

Ginseng occurrence points used to develop the SDM may not capture potentially large differences in ginseng abundance between presence points and among regions. Further, geographic biases in the availability of occurrence data (relatively few from the Midwest) may have led to differing levels of accuracy in habitat suitability estimates across the range of ginseng. However, the large amount of variation explained by habitat indices derived from SDM predictions provides good independent validation.

4.4. Conclusions and management recommendations

The declines we infer for ginseng reflect an increasing trend across many wild-harvested, especially medicinal, plants (Liu et al., 2018), and are consistent with a backward bending supply curve (Frey et al., 2018). The multi-evidence approaches we have adopted here are intended to be broadly applicable. Geographic data on hunting yields could be handled similarly. However, the harvest data available for ginseng as a CITES Appendix II species may be lacking for many other species particularly those that have only recently begun to experience heavy exploitation.

Evidence suggests that at least part of the current increase in ginseng harvesting is generated from cultivation on private lands (Thatcher et al., 2006). Globally, non-timber forest products are generally subject to resource depletion in the absence of active management such as wild-cultivation (Kusters et al., 2006), and support for wild cultivation was favored, for example, in surveys of rural collectors in China (Huber et al., 2010). Efforts to promote cultivation and stewardship are clearly needed to conserve and expand populations of ginseng on both private (Schippmann et al., 2006) and public lands. In fact, supporting cultivation, particularly with locally sourced genetic stock, to mitigate potentially negative effects of mixing genotypes (Young et al., 2012), may be the best policy option for increasing ginseng populations range-wide while at the same time improving local livelihoods.

Acknowledgments

None of the authors have any conflicts of interest. The Southern Region of the U.S. Forest Service funded this project. Joanne Baggs and Duke Rankin assisted in providing ginseng occurrence data National Forest lands. USFWS shared harvest data compiled from state reports to the agency. Gary Kauffman of the Pisgah-Nantahala National Forest provided data and expertise as did Lisa Kruse of the Georgia Department of Natural Resources.

Appendix A. Supplementary methods and results

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2019.01.006.

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