# USING CITIZEN SCIENCE TO DEVELOP MAST PRODUCTION INDICES IN MICHIGAN

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ABSTRACT

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Variation in mast production influences wildlife populations. Annual mast production is logistically difficult to measure and thus robust yearly estimates generally do not exist. Hence, wildlife managers rarely have access to information on mast occurrence and production that is spatially extensive and temporally replicated. The purpose of my research was to assess the feasibility of using citizen scientists to collect reliable data that can be used by wildlife managers to produce annual mast production estimates throughout Michigan. In Chapter 1, I present the design, development, and recruitment of a citizen-science program called MI-MAST: Wildlife Food Tracker. Following field validation of volunteer submitted data form 2014-2015, I concluded that untrained volunteers were capable of contributing reliable data on mast occurrence and production. In Chapter 2, I use data collected in 2015 to demonstrate how hard- and soft-mast production indices could be generated using the citizen-science sampling protocol. I describe a process to assess the spatial scale at which mast production variability occurs and suggest how data should be collected and combined into ecoregional units to estimate mast production for wildlife planning. I conclude that using the model described herein, citizen science is capable of producing sustainable annual mast production indices that can likely improve population models used to manage wildlife species. I also recommend that increased communication with account holders and recruitment of new participants will be needed to produce robust annual indices throughout Michigan.

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## INTRODUCTION

Hard and soft mast meet important dietary needs for many wildlife species, such as white-tailed deer *(Odocoileus virginianus)*, black bear *(Ursus americanus)*, and wild turkey (*Meleagris gallopavo*; Feldhamer 2002, Steffen et al. 2002, Ryan et al. 2004, Reynolds-Hogland et al. 2007). Hard mast is defined as a fruit with a hard exterior, and soft mast as a fruit with a fleshy exterior. Individual trees and shrubs produce varying amounts of mast during any given year (Kelly and Sork 2002). This irregular pattern of production is referred to as *masting* and can directly affect populations of wildlife that rely on these food sources (Martin et al. 1951, Elowe and Dodge 1989, Ostfeld et al. 1996, McShea 2000, Inman and Pelton 2002). Quantitative measures of annual food production can improve the utility of statistical models used to estimate wildlife populations and harvest limits (Malcolm and Van Deelen 2010, Bridges et al. 2011). However, mast is highly variable in space and time, and rigorous monitoring efforts are often arduous and outside the logistical capabilities of wildlife management agencies (Koenig and Knops 2000, Greenberg and Warburton 2007, McDonald-Madden et al. 2010). Studies have attempted to identify the mechanisms responsible for mast patterns (Silvertown 1980, Norton and Kelly 1988, Herrera et al. 1998, Levey and Benkman 1999, Kelly et al. 2001), but consensus has yet to be reached (Kelly and Sork 2002). Due to the complexity of masting, accurately estimating mast production requires that many plants be sampled annually.

Citizen science, or the use of untrained volunteers to assist in scientific studies, is a field that has grown immensely in the past decade due largely to the increased accessibility of new technology for data collection and storage (Silvertown 2009). Despite several successful applications, critics remain skeptical about the reliability of data produced by citizen scientists and whether those data should be used to answer scientific questions and manage natural resources (Nichols and Williams 2006, Szabo et al. 2012). Studies are continuing to advance the methods used in citizen science, and educational resources exist that promote best practices in program development. These best practices are intended to instill scientific integrity when using volunteers to collect data (Bonney et al. 2009, Pasrsons et al. 2011). Information derived from citizen scientists that may have otherwise gone unrecorded can assist in answering a new suite of scientific questions (Tulloch et al. 2013). Citizen scientists are proving they can play a valuable and much needed role in ecological monitoring where data at large scales can be more efficiently collected (Tulloch and Szabo 2012, McKinley et al. 2015), expanding the outcomes from limited conservation budgets (Danielsen et al. 2005, Robertson et al. 2010, Aceves-Buneo et al. 2015).

The importance of mast to a variety of wildlife, and the fact that masting is temporally and spatially variable makes citizen science an appealing approach for collecting data on masting. No consistent, large-scale monitoring efforts on mast production existed in the Great Lakes Region when information on masting was requested by Michigan biologists to improve management of wildlife populations. I tested the feasibility of using citizen scientists to generate data on annual mast-production in Michigan. In Chapter 1, I describe the development of a citizen-science program (called MI-MAST: Wildlife Food Tracker) and test the accuracy of data submitted by volunteers. I also comment on techniques for engaging participants and marketing the program. In Chapter 2, I use data collected via the MI-MAST interface to demonstrate how hard- and soft-mast production indices can be generated in Michigan. The findings of my study can be used to guide the development, marketing, and use of a citizen science program for indexing mast production.

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**CHAPTER 1**

# DESIGNING, IMPLEMENTING, AND VALIDATING A CITIZEN-SCIENCE PROGRAM TO QUANTIFY MAST PRODUCTION IN MICHIGAN

## Abstract

Citizen science is increasingly being used as a conservation tool by researchers and managers when extensive monitoring efforts are needed at large spatial or long temporal scales. Estimating annual spatiotemporal variations in hard- and soft-mast production in Michigan could improve wildlife population models currently used to set harvest limits. I investigated whether a citizen-science program relying on volunteers could produce reliable mast production indices. The program was designed with input from the Michigan Department of Natural Resources - Wildlife Division, Michigan State University, and Michigan United Conservation Clubs. I engaged multiple partners to maximize usefulness, effectiveness, and to help increase the likelihood that the program was sustainable. I developed a field sampling protocol for untrained volunteers that could produce accurate mast production indices. I also developed a website equipped with instructional materials, a data submission portal, personal account databases, and mobile phone applications. The focus of technological development was to use readily accessible and easy to use tools that reduced the effort required by MI-MAST participants. In 2014, MI-MAST was introduced to nearly 150 potential participants to test technology and capabilities of volunteers. In 2015, I worked with project partners to market MI-MAST to an additional ~500 potential participants throughout Michigan. In total, 273 people registered for a MI-MAST account and 30 people submitted data. On average, each person that submitted data recorded 4 mast observations. I field validated 60 mast submissions submitted by 15 participants to verify the reliability of data. Of the 60 sites I visited, 100% of the plants were correctly identified and 97% of records describing mast amounts were accurate. 73% of registered users listed hunting as

an activity they were interested in and frequent interactions with participants revealed that using the program tools to track mast production on their own property was a primary attraction for enrollment. My results suggest that with enough participation MI-MAST can produce reliable mast production estimates to inform wildlife population models. The biggest challenge facing natural resource agencies wanting to use MI-MAST is in recruiting and retaining individuals to be able to develop mast production indices that are robust across large spatial and temporal extents.

**Key Words**

Acorns, berries, citizen science, fruits, mast production, Michigan, volunteers, wildlife food

## 1.1. Introduction

Hard and soft mast plays an important dietary role for many wildlife species, such as white-tailed deer *(Odocoileus virginianus)*, black bear *(Ursus americanus)*, and wild turkey (*Meleagris gallopavo*) (Feldhamer 2002, Steffen et al. 2002, Ryan et al. 2004, Reynolds-Hogland et al. 2007). Wildlife populations are affected by varying types and amounts of mast produced each year (Martin et al. 1951, Elowe and Dodge 1989, Ostfeld et al. 1996, McShea 2000, Inman and Pelton 2002). Human-wildlife conflict has also been linked to fluctuations in mast production (Ryan et al. 2007, Howe et al. 2010). Current models estimating wildlife populations used by managers to set harvest limits of game species that rely on mast could be improved with the addition of mast production data. However, quantifying mast production at scales that correspond to wildlife management units can be difficult because mast production exhibits high spatial and temporal variability (Kelly and Sork 2002). Various hypotheses have been proposed to explain masting patterns but no consensus has been reached (Silvertown 1980, Norton and Kelly 1988, Herrera et al. 1998, Levey and Benkman 1999, Kelly et al. 2001).

Extensive sampling is thus required to monitor mast production, but these monitoring requirements often exceed the logistic capabilities of wildlife management agencies.

Recently the use of volunteers lacking formal scientific training to conduct ecological monitoring as a means to achieve research and management goals has increased (Bonney et al. 2009, Aceves-Bueno et al. 2015). However citizen science is not a new idea and was first conducted in the 1800s to report birds striking lighthouses, and was followed by the popular Christmas Bird Count in 1900 that still is conducted today (Droege 2007). Programs now exist in a variety of disciplines such as wildlife biology (Evans et al. 2005), water quality (Ohrel and Register 2006), astronomy (Raddick et al. 2010), criminal justice (Vitos et al. 2013), and oncology (Pharoah 2014). Important large-scale ecological information that would otherwise go unrecorded due to lack of human and monetary resources or data collection restrictions on private lands is now being collected by citizen scientists (Danielsen et al. 2005, Dickinson et al. 2010). For example, using citizen-science data, researchers have investigated long-term abundance and occupancy trends of bird species (Webb at al. 2007), effects of forest fragmentation on wildlife populations (Villard et al. 1999), and the spread of invasive species and infectious disease (Crowl et al. 2008).

Participation in citizen-science programs increases public involvement in natural resource policy, appreciation of the outdoors, and ecological education (Ryan et al. 2001, Newman et al. 2003, Lawrence 2006, Aceves-Buneo et al. 2015). These results are often viewed as secondary to data collection, but often align with state and federal natural resource goals (Stepenuck 2013, McKinley et al. 2015). Citizen science can be an advantageous tool for certain ecological studies; however it has multiple limitations that must be recognized before collecting data to answer new questions. Sampling biases can occur in many forms and standardized sampling protocols may not be appropriate for volunteers (Dickinson et al. 2010). Differences in the amount of time participants dedicate to sampling can result in a bias in detection probability (Link and Sauer 1999), location of sampling can create bias when data is recorded in an area that does not represent the larger landscape (Bart et al. 1995), and differences in the ability of participants to report accurate information can lead to data inconsistencies (Fitzpatrick et al. 2009). Hence, a citizen science program should be easy to use, intuitive, require minimal economic or time investment by participants, and produce tangible benefits to participants.

Developing a successful citizen-science program relies on skills and tools beyond those typically required of a standard scientific study, including broad understandings of institutional collaboration, scientific principles, and public interests (Penrose and Call 1995, Darwall and Dulvy 1996, Ryan et al. 2001, Bonney et al. 2009, Robertson et al. 2010, Rotman et al. 2012). To fulfill the need for mast production data in Michigan, I developed a citizen-science program (MI-MAST: Wildlife Food Tracker) that relies on volunteers to monitor and report annual mast production that can theoretically be used by biologists to improve wildlife population models. Drawing on previous citizen-science successes, my objectives were to 1) create a sustainable and productive collaboration between the Michigan Department of Natural Resources, Michigan State University, Michigan United Conservation Clubs, and other wildlife stakeholder groups, each supplying different expertise, needs, or access to potential volunteers, 2) develop a sampling protocol appropriate for untrained volunteers that produces reliable and usable data on mast production, and 3) understand participant motivations and interests to sustain recruitment and retention of volunteers.

## 1.2. Methods

### 1.2.1. Collaborative Structure

Citizen-science is capable of producing large quantities of accurate data and influencing policy and management decisions (Stepenuck 2013, Fuccillo et al. 2014). However, to effectively utilize the economic and scientific benefits of using a large network of volunteers, standard protocols must exist to recruit, train, and manage volunteers and to collect and compile their data (Bonney et al. 2009, Sullivan et al. 2009). To alleviate these demands from any one organization, strategic collaboration with diverse partners who each play a specific role can build the capacity of the program to grow and adapt. A common strategy in operating a citizen-science monitoring program is to create a semi-independent organization that may appear as its own entity but is operated by personnel from multiple organizations (Bonney et al. 2009, Silvertown 2009, Shirk et al. 2012).

For the program I developed, MI-MAST, an intentional collaboration was formed with three organizations, where each played unique roles in the authoritative center to share responsibility, maximize benefits for all parties, and ensure program sustainability. There are many types of organizational models that been developed to best achieve different types of goals, thus it is important to decide what goals the program intends to achieve and to make that decision process transparent. In my case, the Michigan Department of Natural Resources - Wildlife Division (MIDNR) identified a need to monitor mast production throughout Michigan. The MIDNR recognized that they could not produce this information internally at the spatial and temporal scales that would be meaningful to managers hence they invited the support of local people to contribute information. In this case, local people were not intended to take part in the decisions made with their contributed information, but were recruited knowing that their contributions would be used in the best interest of conservation planning. This structure is best described as top-down participation, where an authoritative center of experts is requesting support from the public (Lawrence 2006). The primary goal of asking the public to monitor mast production was to produce an annual mast report that could be used by biologists to better manage the natural resources of Michigan. This differs from a bottom-up approach where local people identify a problem or question and enlist experts to help guide them through the scientific process (Lawrence 2006). Often these types of programs mimic activist behavior and occur on a smaller scale to produce information to guide local decision making.

Michigan State University researchers supplied expertise in developing and testing a scientifically rigorous sampling protocol that could be used by untrained volunteers. In return, Michigan State University was provided with new data that could be used in future research. To efficiently collect and store data from volunteers scattered throughout Michigan, experience with database management and recent technological developments was necessary. I relied on the Applied Spatial Ecology and Technical Services (ASETS) laboratory at Michigan State University to create and maintain technology for MI-MAST. The ASETS laboratory had experience in developing and managing citizen science web pages, mobile applications, and databases and was compensated for the tools they developed, routine system maintenance, and was given the opportunity to contribute to the advancement of technology that scientists could use for future studies.

Efficiently recruiting volunteers at a large scale requires partnerships with diverse organizations that frequently interact with the public (Bell et al. 2008). Michigan United Conservation Clubs (MUCC) is the largest statewide conservation organization in the United States and provides services to member-affiliated clubs with diverse outdoor interests (MUCC

2015). Partnering with one large umbrella organization, like MUCC, reduces complexity in the authoritative center to allow greater focus on primary goals of the program. MUCC routinely interacts with the portion of the public most interested in conservation topics and possessed the proper communication mechanisms to promote MI-MAST. Recruiting participants gave MUCC an opportunity to involve stakeholders in actionable science, improve education, and improve Michigan conservation.

### 1.2.2. Mast Sampling Protocol

One constraint of using citizen scientists to collect data is that participants commonly lack formal scientific training, and data can become unreliable if requested tasks are beyond the ability or interests of the volunteers (Penrose and Call 1995, Newman et al. 2003, Galloway et al. 2006). In some citizen-science programs, in-person or online training modules are required before volunteers can participate if certain technical skills are needed (Bloniarz and Ryan 1996). Some participants may be interested in the opportunity to learn new things whereas others may not be willing to dedicate the necessary time to go through training (Parsons et al. 2011). Programs requiring little to no technical skills from their volunteers may be in a better position to safely assume that data are reliable; accurate data are capable of being collected regardless of previous training if simple instructions are followed. Data reliability is a concern for all scientific studies even when conducted by professionals and is not limited to citizen-science (Szabo et al. 2012). Citizen-science program designers must find a balance between asking volunteers to perform duties beyond their skill level and requesting over-simplified data that cannot properly answer the scientific questions for which the program was designed (Brandon et al. 2003). This process can result in sampling standards that are more rigorous than traditional studies because extra attention is given to observer error, which is a common concern in almost all ecological studies (Sauer et al. 1994, Kendall et al. 1996). Significant attention should also be given to specifying the required time commitments of volunteers when developing the sampling protocol. Higher effort requirements can lead to obtaining more data per participant, but the associated time commitments may initially deter contributors who would rather play a smaller role (Parsons et al. 2011, Silvertown et al. 2013).

I developed a sampling protocol for MI-MAST by first identifying the amount and type of data necessary to accurately estimate hard and soft mast production in Michigan. A successful target monitoring design is implemented based on *a priori* hypotheses (Nichols and Williams 2006), and often is capable of informing more management decisions than undirected monitoring approaches (McNie 2007, Sarewitz and Pielkejr 2007). Focusing on the capabilities of current scientific methods, rather than volunteer interests or capabilities, ensured that rigorous standards were used and that project goals could be met (Bonney et al. 2009).

Several, often labor-intensive, sampling strategies have long existed to estimate hard and soft mast production (Daubenmire 1959, Whitehead 1969). Recent improvements to these methods suggest estimates of hard mast production can be produced using short visual scans that are highly correlated to estimates from the previous labor-intensive methods (Greenberg and Warburton 2007). I designed the sampling protocol for hard mast by adopting methodologies described in Greenberg and Warburton (2007; described below). Less established protocols existed for soft mast production. Soft mast methods suitable for large areas typically involve the establishment of plots and counting of plant stems and fruits (Shaw et al. 2010, Lashley et al. 2011, 2014). I modified an approach used by the West Virginia Division of Natural Resources (Uhlig and Wilson 1952, Richmond et al. 2015), with the modification providing better alignment to the protocol used for hard mast indexing.

I asked users to identify mast producing plants in locations they frequently visited, report the amount of mast present once a year, and then return to that location in subsequent years to again report the amount of mast. Reporting on the same plants each year produces greater estimation accuracy because the index values are only relative to previous years (Greenberg and Warburton 2007). Participants recorded the amount of mast present on a plant by selecting one of three possible options. If reporting on hard mast, users described it qualitatively as 1) None ‘No nuts are present’, 2) Few ‘<1/3 of the tree canopy is bearing nuts’, or 3) Many ‘>1/3 of the tree canopy is bearing nuts’. If reporting on soft mast, users described it as 1) None ‘No berries are present’, 2) Few ‘Few fruits are present and they may be small or shriveled’, or 3) Many ‘Fruits are abundant and in good condition’. The database for a participant that revisits plants is filled with the locations of their plants and a list of production amounts from previous years.

The MI-MAST sampling protocol was based on scientifically credible processes (i.e., Uhlig and Wilson 1952, Greenberg and Warburton 2007, Richmond et al. 2015), while theoretically remaining simple enough to maximize the number of participants. I did not establish minimum participation requirements (e.g., minimum number of plants) and ensured that the sampling protocol would not require extensive training. Submitting a mast record the first time only takes a few minutes, and submitting subsequent observations on the same plant requires even less time for observing mast amounts and data entry. I also included an individual database that allowed participants to see their monitoring results. This feature was an important marketing function as some participants (e.g., hunters, landowners) informally expressed interest during our interactions in better understanding wildlife food production at locations they were familiar with. I made the individual online database portal (described below) private so participants were comfortable submitting information that may be valuable to other people interested in outdoor activities like hunting.

### 1.2.3. Participant Recruitment

To increase attention to the program, allow all partners to be equally represented, and to make the program appear as established, I designed a unique MI-MAST brand. Because volunteers participate in activities that align with their interests (Rotman et al. 2012), creating a brand that clearly represents the program is important for recruitment. The program was named MI-MAST: Wildlife Food Tracker and a logo incorporating a white-tailed deer, black bear, and wild turkey inside of an acorn was created (Figure 1.1). Popular game species that rely on mast were included to attract hunters, who were identified as a potential primary audience for MI-MAST. Hunters often pay attention to masting patterns to better predict where animals will be, and are the audience that directly associate with the goal of MI-MAST, i.e., to improve management information for game species. The name included ‘MI’ to reinforce that the efforts are specific to Michigan conservation and also paralleled the naming format of other state agency programs. The purpose of ‘Wildlife Food Tracker’ was to appeal to participants that monitor wildlife food abundances to increase viewing or hunting successes. To inform future recruitment strategies, MI-MAST participants were given the option to specify their age, sex, previous experience identifying plants, and primary and secondary interests in outdoor activities when registering for an account (Table 1.1). Using Google Analytics, additional information was collected regarding how visitors interacted with the website (described below).

### 1.2.4. Streamlining Participant Interactions with MI-MAST

To efficiently coordinate volunteers and collect information throughout the state, all instructions and tools necessary to participate in MI-MAST were provided on a website (http://www.mimast.org/). Here participants could find details regarding the purpose of the program, partners, instructional materials, and field identification guides (described below). Within the website users created an account and completed an optional demographic questionnaire (Table 1.1), watched a video tutorial explaining how to use the online features, and accessed a private portal to enter records and manage their personal database. Smartphone applications were developed for iOS 5.1 or later and Android 3.2 or later devices that also included instructional materials, field guides, and a personal database for participants to record, view, and edit their records. The mobile applications were an alternative to submitting data through the website and reduced sampling effort by utilizing the GPS capabilities of smartphones to record locational information. Users were also given the option to use the camera in their phone to include pictures with their data. All records were stored locally on the phone until mobile data or wireless internet connectivity was established, allowing the user to synchronize their records with those of the main database and their website account. This feature enabled data collection in remote areas lacking cellular reception, which is common throughout Michigan.

### 1.2.5. Identifying Plant Species

As mast production can vary among species or genus, it is important to accurately identify plants that are recorded (Kelly and Sork 2002, Lusk et al. 2007). Many mast-producing species found in Michigan can be difficult to accurately identify to species even with formal training. The ability of untrained volunteers to correctly identify plants using structured protocols has been demonstrated, but accuracy decreases when volunteers need to differentiate among similar species (Bloniarz and Ryan 1996, Brandon et al. 2003, Crall et al. 2011, Jordan et al. 2012, Fuccillo et al. 2014). I compiled a list of the most-common mast producing species found in Michigan that were used by game animals (Table 1.2). To help reduce identification errors, I restricted participants to only submitting data on plants in Table 1.2, but I also provided the opportunity for participants to request that new species be added to the database. Field identification guides including pictures of several parts of the plant and non-technical descriptions were provided to assist in identification and included on both the website and smartphone applications.

#### 1.2.6. Data Validation

A subset of mast data submitted by 15 participants in 2014 and 2015 (n=60/82 sites) were field validated for accuracy within 2 weeks of submission. I visited data sites and tested the data submissions for 1) accuracy of GPS location tools by comparing submitted GPS locations with those associated with the plant of interest using a separate GPS handheld device, 2) correct species identification, and 3) correct mast amount classification compared to what I would have recorded based on the data collection protocol.

### 1.3. Results

In 2014, the first year of the program, 10 conservation groups were visited in Michigan and given a presentation introducing MI-MAST and inviting them to participate (~ 150 individuals). A small audience was purposely targeted to test the program's instructional materials, technology, and sampling protocol before marketing it to a larger audience. In 2015, additional outreach to conservations groups occurred (~ 200 individuals), and hyperlinks directing people to the MI-MAST website were featured on MIDNR webpages, MUCC hosted multiple blog posts featuring MI-MAST, and MI-MAST was featured on MIDNR and MUCC social media outlets. MI-MAST was also featured using a booth at two large outdoor expositions (~ 150 individuals interacted with the booth). MIDNR staff was also incentivized to participate in the program by being entered into a drawing to win wildlife memorabilia. Throughout these informal interactions common themes of potential participants included 1) interests in keeping a private database to track mast production on their own property, 2) interests in what sort of products would be publicly available, and 3) how the data would be used by the MIDNR. During this time little interest was expressed in helping the MIDNR or being involved in scientific inquiry.

Based on results from Google Analytics, during 2014-2015, 7,725 people visited the website and 608 returned to the website at least once (8%). Most web-site visitors (55%) connected to MI-MAST via a link from an MIDNR web page, with most (44%) of the other visitors engaged by direct communication or email. Most individuals on the MI-MAST web page were located in the southern portion of the Lower Peninsula of Michigan, even though recruitment efforts specifically focused on northern Michigan (Fig. 1.2). The MI-MAST smartphone application had 239 iOS and 199 Android downloads, pointing to the importance of providing both mobile platforms. I had 273 users register for an account and 222 of those users completed a demographic questionnaire (Table 1.1). Of those users who completed the questionnaire, 75% were male and the majority (35%) of respondents were 45-54 years old (Fig. 1.3). About one-third of the respondents received formal plant identification training, 43% had identified plants before, and 25% had never identified plants before (Fig. 1.4). Most (93%) of the participants in the youngest age group (14-24 years old) had some experience identifying plants (Fig. 1.5). The majority (61%) of respondents listed hunting as their primary outdoor interest (Fig. 1.6).

After arriving at the website homepage, 52% of users next visited the mast species fact sheets, 22% the program description page, and 13% the registration page. During these visits users spent an average of 31 seconds on the homepage, 32 seconds on the fact sheets, 46 seconds on the program description, and 3 minutes and 44 seconds on the registration page.

Overall 30 users submitted at least one record. Those 30 users submitted 82 plant records in total and recorded 70 mast amounts (12 plants were identified earlier in the year but were not revisited to report mast amounts). I visited 60 of the 82 locations (73%) that were submitted by 15 participants. All 60 of the plants were correctly identified to 19 different genera or species (depending on the plant) by MI-MAST participants. All 23 hard mast amounts were correctly recorded and 29 out of 32 (91%) soft mast amounts were correctly recorded, based on the amount I would have recorded following the sampling protocol instructions. The most common soft mast error was over-reporting mast amounts on dwarf red raspberry (*Rubus pubescens*).

### 1.4. Discussion

In developing MI-MAST my first objective was to create a sustainable and productive collaboration among the founding organizations and between wildlife stakeholder groups. During program creation I found the collaboration between the MIDNR, MUCC, and MSU to be well-balanced in regard to devotion of time spent on program objectives. Relying on the ASETS laboratory to develop and maintain the technology behind the program proved to be most beneficial. Although tools exist for novices to create their own websites, mobile applications, and databases (Hartung et. al 2010); the program would have taken much longer to develop if a team was not entirely devoted to technical development and maintenance. The ASETS laboratory also had previous experience building tools for conservation programs, and thus I assumed they were able to better handle budgetary constraints while maintaining basic functionality than were potentially offered by private technical development companies.

During initial recruitment I attempted to present MI-MAST to other conservation organizations not affiliated with MUCC, and was seldom successful at recruiting new participants. Common responses included shortage of staff time to organize a presentation meeting, or no upcoming planned member activities that were relevant to the topic of MI-MAST. Building new relationships with volunteer organizations often already overwhelmed with duties takes more time than is often available when trying to beta test a new program. Relying on the trust MUCC has built with their organizations proved to be beneficial when needing to arrange presentations and gain confidence from large new audiences. All MUCC affiliated organizations that I contacted were willing and enthused to have MI-MAST introduced to their members, and allowed me to successfully beta test the program in 2014. Similar initial interests were observed with MIDNR biologists and during several of those meetings the biologists provided comments on how the beta program could be improved and insights on how the public may react to certain features.

My second objective was to develop a sampling protocol appropriate for untrained volunteers that produced reliable and usable data on mast production. I found no indications that the design of MI-MAST impeded the effective collection of data that could be used to calculate mast production indices in Michigan. My field validation showed that MI-MAST participants correctly identified mast-producing plants and accurately portrayed hard (100% correct) and soft (91% correct) mast amounts. My results were consistent with other citizen science programs that have shown volunteers can correctly identify plants when given the appropriate resources and simple instructions (Brandon et al. 2003, Crall et al. 2011, Fuccillo et al. 2014). All locations that were field validated proved to have recorded accurate coordinates based on a separate GPS reading on the plant of interest and suggested users could properly use the interactive online map and mobile applications when submitting data.

I caution that my validation results are only based on data submitted by 15 different volunteers who came from a population of predominantly hunters, who generally had experience in identifying plants. If a broader audience is engaged to participate in the program the accuracy of data may be different than what I found in this study. I recommend data validation be conducted in future years when more users participate to ensure data are reliable for producing accurate mast production estimates.

A limitation in the sampling protocol was that participants were not given a specific time to record their data to account for temporal variations in mast ripening throughout Michigan, and instead were instructed to report mast amounts at a time when mast was ripe. If participants collect data on a plant too early, mast may have not developed yet and it would be underreported. However, if the plant is visited too late, soft mast may have been eaten. McCarty et al. (2002) found that ripe fruit survived predation ranging anywhere from 3-165 days. Providing additional information in the field guides suggesting ripe periods for each species could reduce this temporal bias without having to set a firm data collection time requirement for all soft or hard species, potentially reducing participation interest.

Continued use of this sampling protocol may also require additional investigation of participant sampling behavior that may influence production estimates. I found that participants could correctly identify species and mast amounts, but I did not place any restrictions on where participants should record data or how many plants to sample in an area. This was done to make submitting data to the program easier for participants (Parsons et al. 2011). Using opportunistic data instead of data collected on fixed transects may result in collection bias in the first few years.  Participants may be more likely to begin monitoring a plant that was producing mast in the initial year because it caught their attention as a mast-producing plant (Kendall et al. 1996, Fitzpatrick et al. 2009).  However, asking participants to revisit the same plants in subsequent years should eliminate this bias in the future. Although data submitted by MI-MAST participants did not reveal this pattern, year one observations should still be used with caution when comparing production amounts to following years. Similar "first-year participant" effects have been documented in other citizen-science programs where data collection behavior of the participants changes once they become more comfortable with the methods (Kendall et al. 1996, Sauer et al. 1994). In such instances coordinators often choose not to use those data.

My third objective was to understand participant motivations and interests to sustain recruitment and retention of volunteers. Even after extensive marketing and recruiting, only a small percentage (11%) of account holders submitted data. I predicted that creating an account would be the largest impediment to getting volunteers to participate in MI-MAST. I assumed that once participants created an account they would likely submit mast observations because of the little effort needed to participate. Silvertown et al. (2013) also found low participation rates in a citizen science program, but their program required greater sampling effort. In the Silverton et al. (2013) program, few participants submitted data and an even smaller group produced the majority of data. In my study, notifications were sent to account holders twice via email reminding them it was an appropriate time to collect mast data. My results suggest that other and more frequent communication methods may be needed to ensure more account holders are submitting data.

Bell et al. (2008) found that participants highly valued social experiences and communication amongst other participants, and suggested more frequent communication may be necessary. This communication strategy may be particularly effective for engaging a younger cohort of MI-MAST participants as these individuals are known to rely on social connectivity (Lenhart et al. 2010). Another strategy for improving participation may be to appeal to the competitive tendencies of individuals. Sullivan et al. (2009) tripled the number of individuals who submitted data to a citizen science program immediately after implementing features that allowed participants to view their own reports and compare them with the reports of other participants. Creating a community culture among participants throughout Michigan that communicate and share experiences may increase participant interest and hold users more accountable. Creating an online message board or forum may serve this purpose.

The demographics of MI-MAST account holders aligned with our marketing audience. Generally, hunters in Michigan are middle-to-late aged males (Frawley 2004). I recognize that many conservation organizations without hunting interests consist of members who frequently volunteer to support wildlife conservation. Members from these organizations often are already participating in citizen-science programs (e.g., stream monitoring, bird surveys, invasive species reporting). Ryan et al. (2001) found that participants of this demographic were most motivated by helping the environment and learning. The interests of conservation or stewardship members may make them more willing to participate if they know the data are being used by managers for conservation purposes, whereas the interest among hunters may be more directed towards individual benefits that will ultimately increase their own hunting success or preserving hunting values. This was observed when recruiting participants, where hunters were more interested in the way they could apply our tools for their own hunting purposes.

I noticed that at initial presentations of MI-MAST, many attendees appeared to be >60 years old. It is commonly accepted that this generation lacks technological skills or access to smartphones or tablets (Roupa et al. 2010). However, many attendees had smartphones and proved capable of operating both the website portal and mobile applications. Considering that roughly one-third of volunteers in America are 55 years or older, they should not be overlooked as an important demographic in technology-based citizen science programs (Bureau of Labor Statistics 2015).

The majority of conservation organizations that were introduced to MI-MAST with an in-person presentation were located in the northern Lower Peninsula, and coincided with the majority of volunteer data locations (Figure 1.2). The majority of webpage views occurred in large urban areas in the southern Lower Peninsula and is likely related to the larger resident population of these areas (Figure 1.2). The two outdoor expositions where MI-MAST was marketed were located in the southern portions of Michigan and may have contributed to more webpage views, but did not correlate to the amount of data submitted near these locations. These findings showed that members of the conservation organizations visited in the northern Lower Peninsula were less likely to view the webpages than audiences in the southern portion of the state, but may have been more likely to submit data. This could suggest that two different audience types exist in Michigan; one that is more likely to visit the webpage and learn about the program but less likely to get involved, and another that participates more readily but may be less concerned about new online tools or features.

I found no indications that features of the sampling protocol or collaboration among organizations would inhibit a sustainable and successful citizen-science program. MI-MAST was only marketed in 2015 and continued recruitment will be necessary in future years to increase participation and data collection to produce mast production indices throughout Michigan. I suggest the additional recruitment strategies and new insights into audience behavior as found in this study be used to guide program development and participation in future years.

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**APPENDIX**

Table 1.1.
Optional demographic questionnaire participants were prompted to complete when creating an account on www.mimast.org.

**Age**

Select Age:

- 14-24
- 25-34
- 35-44
- 45-54
- 55-64
- 65+

**Gender**

Select Gender:

- Male
- Female

**Plant Identification**

Select ID Experience:

- None
- I have identified plants before
- I have received formal training in identifying plants

**Primary Interests**

Select your primary outdoor interest:

- Hunting
- Bird Watching
- Hiking/Walking
- Natural Areas
- Outdoor Sports
- Other

**Secondary Interests**

Select your secondary outdoor interest:

- Hunting
- Bird Watching
- Hiking/Walking
- Natural Areas
- Outdoor Sports
- Other

Table 1.2.
Hard and soft mast species and genera included in MI-MAST: Wildlife Food Tracker. Mast species were included based on intensity of use by large game animals in Michigan, USA, based on MIDNR biologist recommendations and Martin et al. 1951.

| | Species | Common Name |
|---|---|---|
| **Hard Mast** | | |
| | *Quercus bicolor* | Swamp white oak |
| | *Quercus alba* | White oak |
| | *Carya cordiformis* | Bitternut hickory |
| | *Corylus cornuta* | Beaked hazelnut |
| | *Carya ovata* | Shagbark hickory |
| | *Fagus grandifolia* | American beech |
| | *Juglans cinerea* | Butternut |
| | *Juglans nigra* | Black walnut |
| | *Quercus macrocarpa* | Bur oak |
| | *Quercus palustris* | Pin oak |
| | *Quercus rubra* | Northern red oak |
| | *Quercus velutina* | Black oak |
| **Soft Mast** | | |
| | *Amelanchier arborea* | Serviceberry |
| | *Cornus spp.* | Dogwood |
| | *Crataegus spp.* | Hawthorn |
| | *Elaeagnus umbellata* | Autumn Olive |
| | *Gaylussacia baccata* | Huckleberry |
| | *Malus coronaria* | Crabapple |
| | *Malus pumila* | Apple |
| | *Phytolacca americana* | Pokeweed |
| | *Prunus serotina* | Black cherry |
| | *Prunus virginiana* | Chokecherry |
| | *Rubus allegheniensis* | Blackberry |
| | *Rubus pubescens* | Dwarf red raspberry |
| | *Sambucus canadensis* | Elderberry |
| | *Vaccinium myrtilloides* | Blueberry |
| | *Viburnum acerifolium* | Mapleleaf viburnum |

Figure 1.1.
MI-MAST: Wildlife Food Tracker logo.

Figure 1.2.
Locations of recruitment events, volunteer data submissions, and webpage views (provided by Google Analytics) for MI-MAST: Wildlife Food Tracker in Michigan, USA, 2014-2015.

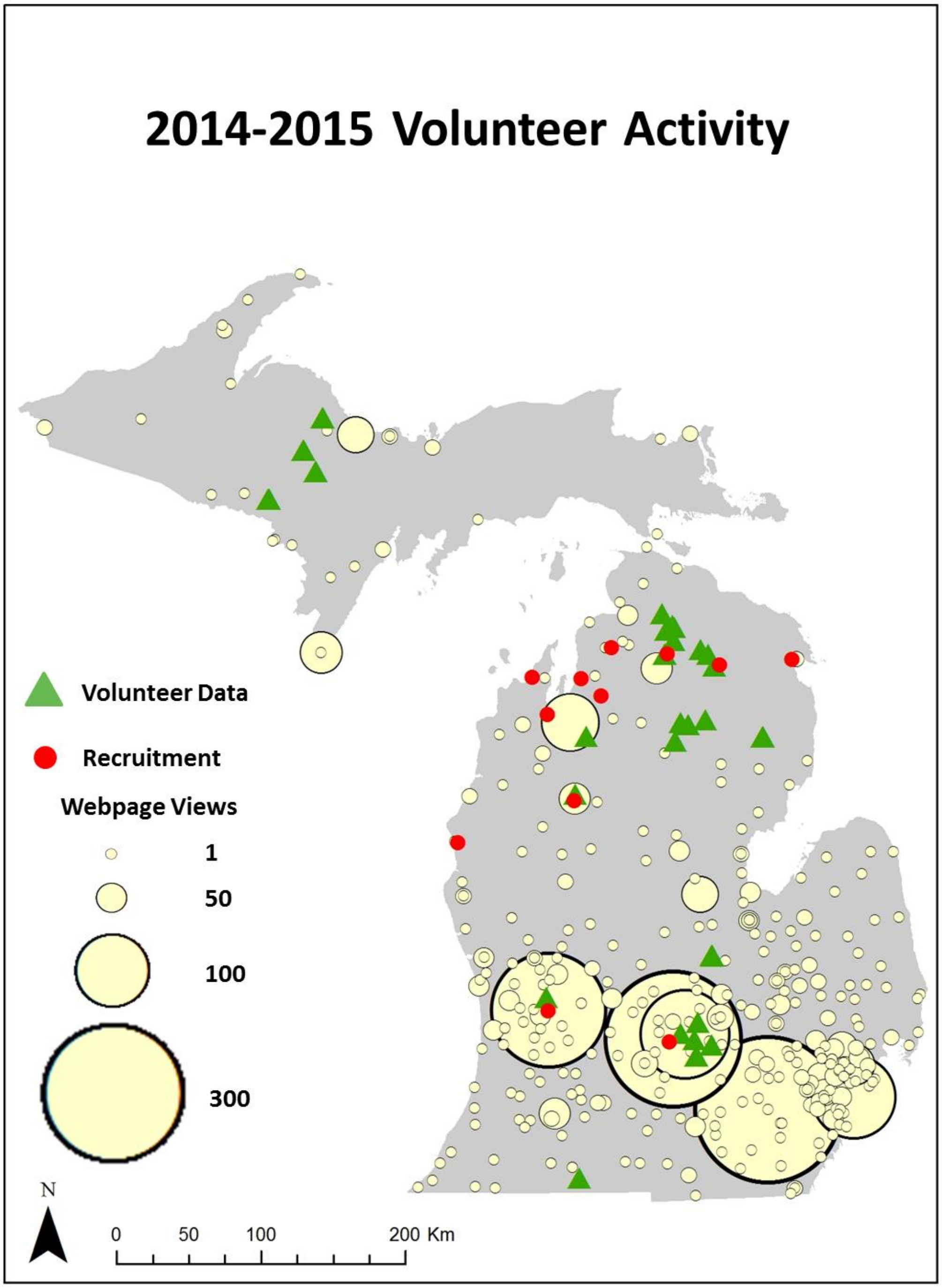


Figure 1.3.
Ages of MI-MAST: Wildlife Food Tracker account holders who completed the demographic questionnaire upon registration, 2014-2015.

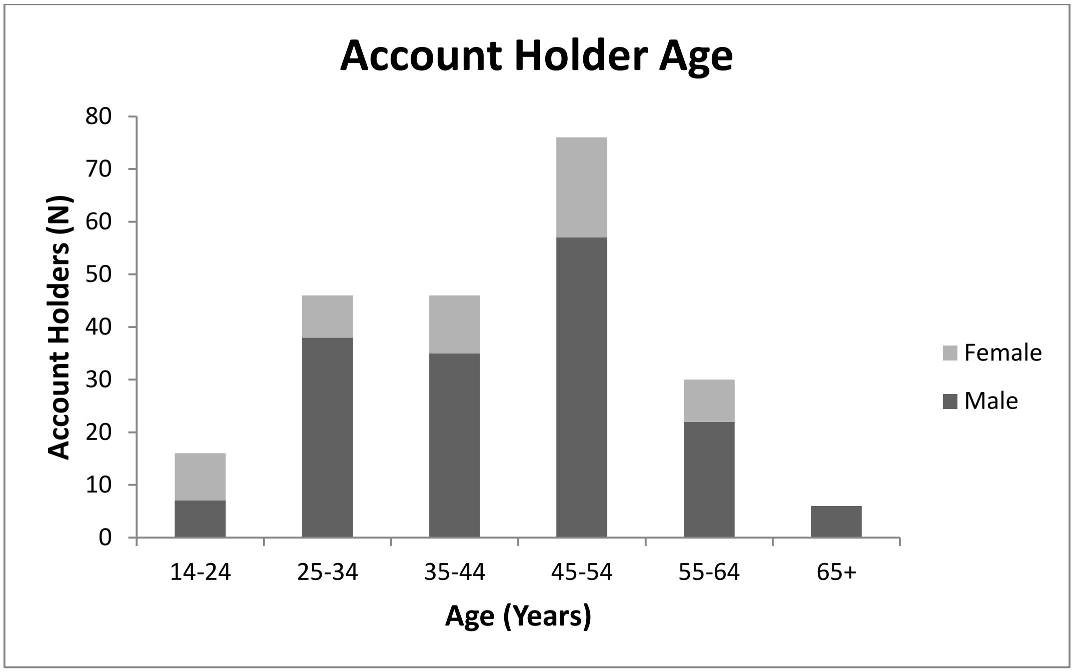



Figure 1.4.
Previous experience identifying plants of MI-MAST: Wildlife Food Tracker account holders who completed the demographic questionnaire upon registration, 2014-2015.

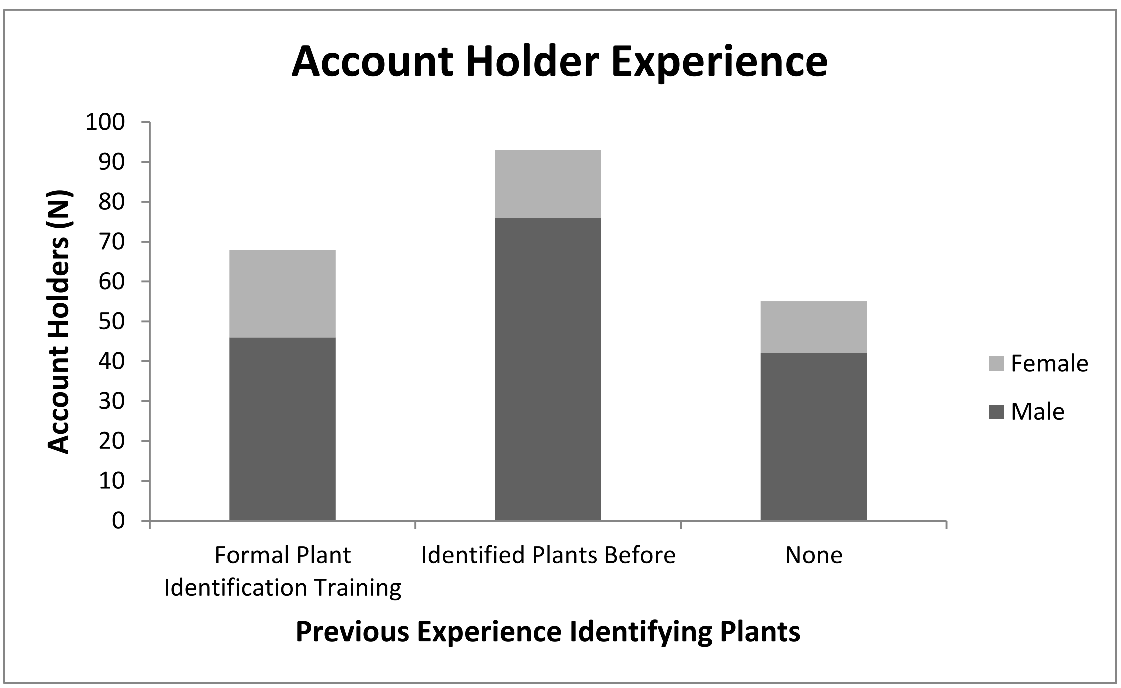


Figure 1.5.
Age and previous experience identifying plants of MI-MAST: Wildlife Food Tracker account holders who completed the demographic questionnaire upon registration, 2014-2015.

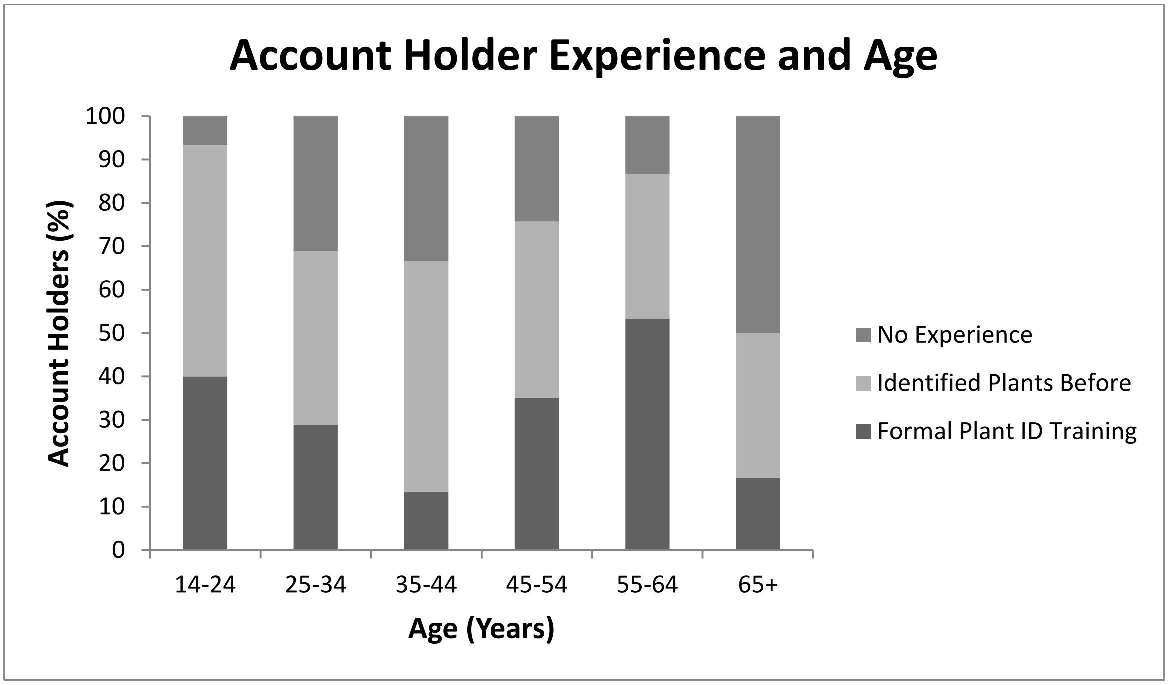
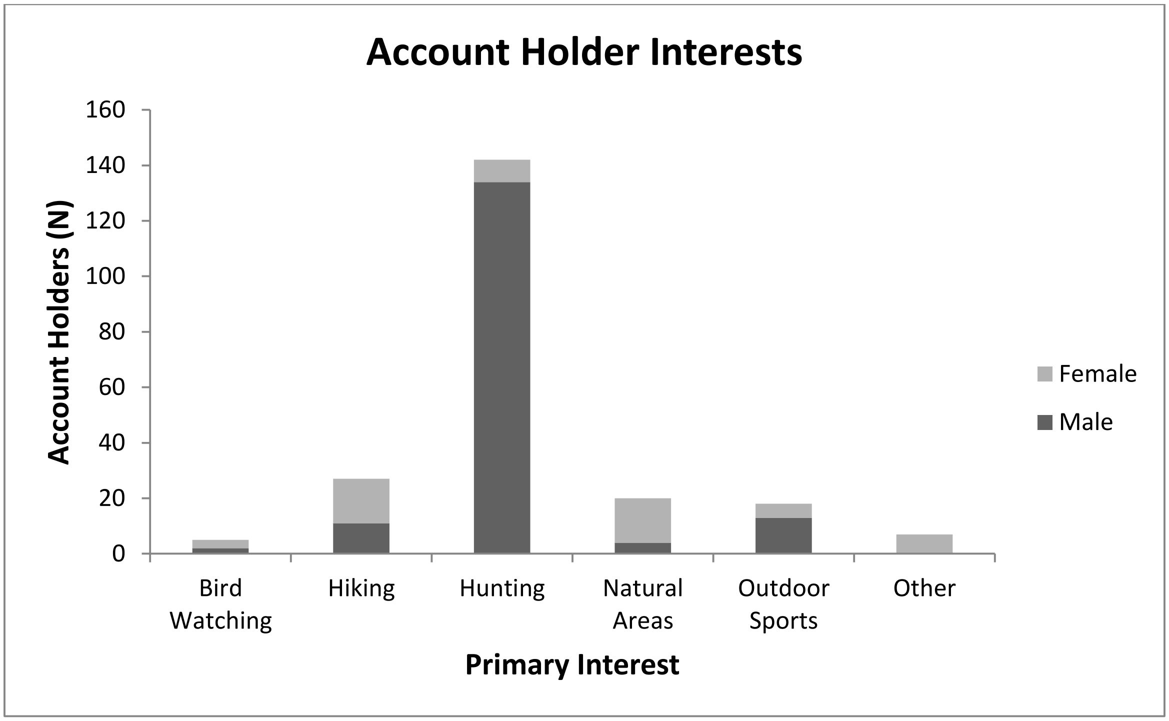


Figure 1.6.
Primary outdoor interests of MI-MAST: Wildlife Food Tracker account holders who completed the demographic questionnaire upon registration, 2014-2015.



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**CHAPTER 2**

# USING CITIZEN-SCIENCE DATA TO DEVELOP ANNUAL MAST PRODUCTION INDICES IN MICHIGAN

## Abstract

Some animals rely on mast production for a significant portion of their diet. Patterns of mast are often variable, producing a large crop some years and scarce amounts in others. This large fluctuation in food availability can affect wildlife populations. Including quantitative information about annual mast production into wildlife population models may produce more accurate estimates of population demographics. However, annual statewide monitoring efforts would not be feasible for most wildlife management agencies. I show how point-based data collected by citizen scientists can be used to generate hard- and soft-mast production indices. These indices, if based on data that are spatially and temporally extensive, could be used to compare relative crop sizes among regions and years. In 2015, I collected 673 records of hard mast production and 218 records of soft mast production in several locations throughout Michigan. I introduce a process to identify spatial scales of production variability that can inform how data should be distributed and combined into similar ecoregional units. Using these results, I calculated a hard and soft mast index based on previously developed empirical equations for 1 ecoregion for 3 combined species of oak (*Quercus alba*, *Q. palustris*, and *Q. rubra*) and black cherry *(Prunus serotina*). Indices can be used to compare differences in production amounts among years. Based on previous long term studies on mast production indices and associated subjective crop rankings, the indices I calculated for both oak (0.54) and cherry (0.71) suggested near crop failure in the ecoregion I selected for this analysis. The accuracy of calculated mast indices is directly related to the number of records and the spatial and temporal extents of those records within an assessment area. I caution that my results are based on data from relatively few

species and concentrated in only one portion of the state; however the process I describe can be replicated when more data are collected. Given sufficiently detailed and properly distributed data, I show that a simple data collection protocol compatible with citizen science programs can produce relative estimates of hard and soft mast production that are spatially explicit and potentially useful for managing wildlife.

**Key Words**
Acorns, berries, fruits, hard mast, soft mast, citizen science, Michigan, wildlife foods

## 2.1. Introduction

Some plants exhibit a behavior of masting, or the bimodal pattern of seed production, where many seeds are produced some years and few in others (Kelly 1994, Koenig and Knops 2000, Kelly and Sork 2002). This behavior is more commonly associated with hard-mast producing trees like oak (*Quercus* spp.) and beech (*Fagus grandifolia*) (Gysel 1971, Greenberg and Parresol 2002). Trees closer in proximity often show synchrony and produce large mast crops in unison, yet a consistent spatial scale at which synchrony occurs has not been observed (Kelly and Sork 2002).

Several hypotheses have been proposed to explain why this pattern in seed production exists, yet researchers have struggled to provide overwhelming evidence in support of a single hypothesis (Kelly and Sork 2002). One hypothesis, the resource-matching hypothesis, suggests that temperature and precipitation determine mast production patterns. The hypothesis suggests that it is less costly for trees to reproduce in years with abundant water and favorable temperatures than in years with unfavorable weather, and as a result natural selection has favored producing mast during favorable conditions (Norton and Kelly 1988, Sork 1993, Kelly 1994, Houle 1999, Pearse et al. 2014). Since variation in weather alone does not reflect the bimodal pattern observed in mast production, other factors are likely influencing production (Koenig and

Knops 2000). Another hypothesis, the predator satiation hypothesis, suggests that crop production is determined by predators, where producing more seeds at once and synchronizing production with neighbors overwhelms seed predators and thereby creates a higher probability of seedling survival (Janzen 1971, Silvertown 1980). If this were the case, synchrony of mast production should occur at a scale comparable to the geographic extents of seed predator movements (Janzen 1971), with synchrony being less defined among trees that attract multiple types of predators with varying ranges (Kelly and Sork 2002). Plant communities lacking tree species diversity exhibit stronger masting behavior (Janzen 1971, Boucher 1981), which may be a product of single or similar types of predators living in those communities. No single explanation has yet accounted for the spatiotemporal variation in masting patterns, leading to the conclusion that multiple interacting factors influence the behavior (Herrera et al. 1998, Kelly and Sork 2002).

Masting is less common in small trees or shrubs that produce fleshy fruits (Silvertown 1980). These soft-mast species are more likely to reproduce in regular intervals and yield similar amounts of fruits (Kelly and Sork 2002). However spatiotemporal variability can still occur among soft mast species and appears most correlated with large temperature and precipitation fluctuations during the summer when fruits are ripening and during autumn when flower buds are forming (Selas 2000). A variety of growing patterns exist among soft mast species, suggesting that weather effects are most likely species specific (Martin et al. 1951).

Hard and soft mast is an important source of food for many wildlife species (Martin et al. 1951, Wolff 1996). Masting can cause changes in body condition, reproduction, and ultimately population size and distribution in game species such as the white-tailed deer *(Odocoileus virginianus)*, black bear *(Ursus americanus)*, and wild turkey (*Meleagris gallopavo*) (Feldhamer

2002, Steffen et al. 2002, Ryan et al. 2004, Reynolds-Hogland et al. 2007). A proper understanding of wildlife population dynamics is needed by managers to set seasonal harvest limits that are sustainable. Population models of wildlife species that rely on mast could be improved with the addition of quantitative information describing the annual amount of mast available on the landscape relative to previous years.

To produce a dataset that portrays mast production at scales corresponding to harvest management of wildlife would require extensive sampling over space and time to collect enough data to understand the spatiotemporal variability of mast production (Greenberg and Warburton 2007). Methods for estimating the size and extent of acorn production exist, including direct measurement with seed traps (Greenberg and Parresol 2002), qualitative rankings based on visual surveys (Sharp 1958, Graves 1980), and laborious quantitative surveys counting acorns or tree stems (Whitehead 1969, Koenig et al. 1994). Seed traps can best describe actual crop sizes but they are impractical to implement across large scales. Labor intensive quantitative visual surveys as described by Whitehead (1969) produce hard-mast indices that can be used to compare crop production to previous years and are highly correlated with density estimates calculated by seed traps (Perry and Thill 1999, Greenberg and Warburton 2007). By using a greater quantity of qualitative visual surveys, Greenberg and Warburton (2007) found that high production years were correlated with the amount of trees producing acorns.

Methods exist to estimate soft-mast yield at small spatial scales, but these also require individual fruit or stem counts making it difficult to apply to large areas (Daubenmire 1959, Lashley et al. 2014). Since soft mast production exhibits less variability than does hard mast, qualitative measures of production can describe patterns at large scales. These types of qualitative assessments are performed by several state wildlife agencies (Uhlig and Wilson 1952, Richmond et al. 2015).

To demonstrate how spatially explicit mast production indices could be calculated from relatively simple data like those collected by citizen science, my objectives were to 1) identify the spatial scale where regional differences in mast production occur, 2) delineate ecoregional mast production units in accordance with the regional spatial scale, 3) identify the spatial scale where mast production varies within regions to estimate how data should be dispersed within units, and 4) calculate hard- and soft-mast production indices for select areas in Michigan based on field data collection.

## 2.2. Methods

### 2.2.1. Mast Sampling Protocol

The hard-mast sampling protocol I used was based on Greenberg and Warburton (2007), who showed that reliable hard-mast indices could be produced by sampling the proportion of trees bearing acorns in a specified area. By using a relatively fast, visual survey of the tree canopy, Greenberg and Warburton (2007) suggested that a tree with acorns on >33.5% of the canopy be designated as high production. Although the study was limited to oak, I assumed that this observation could apply to other hard mast species (e.g., beech, walnut (*Juglans* spp.), hickory (*Carya* spp.). In my study, I asked volunteers to opportunistically select potential mast producing trees and describe mast production as: 1) None 'No nuts are present', 2) Few ' <1/3 of the tree canopy is bearing nuts', or 3) Many '>1/3 of the tree canopy is bearing nuts'.

I used a similar three-choice rating system for soft-mast data collection. Considering that soft-mast species exhibit a greater variety of life forms (i.e., individual trees, shrubs, patches of plants) than do hard-mast species, I developed a rating system similar to the hard mast scheme, but applicable to all life forms. I asked volunteers to opportunistically select individual plants or patches of plants and rate each as: 1) None ‘No berries are present’, 2) Few ‘Few fruits are present and they may be small or shriveled’, or 3) Many ‘Fruits are abundant and in good condition’.

#### 2.2.2. Regional Variation

Mast production can vary at both coarse and fine spatial scales (Kelly and Sork 2002). I first assessed regional variation in mast production, as constrained by a sample limited to disparate areas of the northern Lower Peninsula of Michigan (Figure 2.1). Here, I define a region as an area with clustered samples where mast production significantly differs from other clusters of samples. I first used a Ripley’s K-function test to determine the scale(s) at which my point data exhibited clustering (Dixon 2002). Given that the point data I was using exhibited clustering, I subsequently tested for variability in mast production by classifying all of my point data into different sized clusters using the K-means classification algorithm (Jain 2010). This algorithm partitions data points into a user-specified number of clusters by randomly placing centroids throughout the study area, and subsequently assigning points to the nearest centroid that reduces the squared error (distances between points and their assigned centroids). This process is iterated until the algorithm converges to a local minimum (Jain 2010). I evaluated 3 different regional scales by inputting 2, 3, and 4 different clusters into the K-means algorithm. For each cluster classification, I used 1,000 centroid initializations and 100,000 iterations to ensure convergence occurred, in program *R* 3.1.2 (R Core Team 2014). The proportion of trees bearing nuts in >33% of the canopy and the proportion of soft mast plants producing abundant fruits in each cluster were calculated and tested for differences among other clusters at the same scale using a Fisher’s exact test (McDonald 2009). Fisher’s exact test was used in place of a

Chi-square test because it is more accurate when expected values are < 5, which occurred in this analysis because data representing abundant mast observations were relatively rare (McDonald 2009) (Table 2.1). Regions were identified and mapped as the smallest scale (most clusters) that showed significant variation in mast production among the point clusters.

I performed the clustering and comparison process for each genus, subgenus, and species with >30 observations in a localized area, with those localized areas separated by >50 km. Only enough data from the oak genus, red oak subgenus (*Q. rubra* and *Q. palustris*), and black cherry (*Prunus serotina*) were available to implement the regionalization procedures.

### 2.2.3. Within-region Variation

Regional clusters can account for larger scale variation in mast production, but variability can also exist at smaller scales (Kelly and Sork 2002). To identify the scale that mast production varied within regions, I used methods similar to the regional classification process. Data points within a region were classified into smaller clusters again using the K-means method (Figure 2.2). Each region was partitioned into 2, 3, 4, 5, and 6 clusters. Subsequently, the proportion of trees bearing nuts on > 33% of the canopy and the proportion of soft mast plants producing abundant fruits in each cluster were calculated. I again tested for differences among clusters within a region using a Fisher's exact test. Fisher's exact tests were conducted within each of the 5 different scales, and the largest scale (fewest clusters) showing significant differences in mast production among clusters was deemed the optimal spatial configuration within a region. I averaged the distances separating the centroids of the optimal configuration to estimate the spacing of the masting pattern as a guide to the minimum distance that data collection should be distributed within a region.

### 2.2.4. Using Ecoregions to Index Mast Production

Variability in mast production among species is partially determined by weather patterns (Norton and Kelly 1988, Sork 1993, Kelly 1994, Houle 1999, Pearse et al. 2014). For example, Pearse et al. (2014) found temperatures during the previous two spring flowering periods to be correlated with production amounts. Thus, mast production indices should be calculated for regions with similar biotic and abiotic characteristics (Kelly and Sork 2002). Michigan ecoregions represent areas with similar climate, physiography, soil, and biotic communities (Albert 1995). The hierarchical classification of Albert (1995) includes 4 levels: Section - primarily driven by long-term climatic records (n = 5 in Michigan, mean = ~42,500 $km^2$), Subsection - climate and physiography (n = 21, mean = ~6,800 $km^2$; excluding Lac Veaux Desert Outwash Plain), and Sub-subsection - physiography and soil (n = 38, mean = 3,400 $km^2$; Albert 1995). Based on results from the regional and within-region spatial variation of mast production, I used the subsection level of the hierarchy to demonstrate calculation of a mast production index using a land classification scheme that might help account for among region variability.

The size of an ecoregion for calculating mast production indices should be small enough that variation among major vegetation cover types (e.g., mast producing species richness) is minimized but large enough to represent broad-scale phenomenon known to affect mast (e.g., precipitation, temperature). Ecoregions that are too large may yield average mast indices that fail to accurately portray the entire area, whereas ecoregions that are too small may result in over-delineation of similar mast producing areas and thus require more total data (i.e., not an efficient sampling strategy). Given the results of my regional analysis, I selected the Subsection level of the Albert (1995) hierarchy because 1) it was comprised of units that had an area most similar to the regional scale of mast production variability in my study, and 2) was comprised of units that were large enough to accommodate the minimum separation distance among sample points that was identified during my within region analysis.

### 2.2.5. Mast Index Calculation

Using data collected by volunteers and researchers, I calculated one hard-mast index and one soft-mast index in one ecoregional unit. To estimate a hard-mast index using data collected by quick visual surveys, I used the predictive equation shown to calculate an index comparable to that calculated using a more labor-intensive sampling scheme (e.g., Whitehead 1969) developed in a 20-year study of 5 oak species (*Quercus alba*, *Q. prinus*, *Q. coccinea*, *Q. rubra, and Q. velutina*) in western North Carolina (Greenberg and Warburton 2007):

$$\hat{y} = b_0 + b_1 \hat{x}$$

Where $\hat{y}$ is the predicted hard-mast index, $b_0$ is the model intercept resulting from a reduced major axis regression model in their study (0.403), $b_1$ is the coefficient estimated from that model (0.069), and $\hat{x}$ is the percentage of trees bearing nuts in a given year. I used the Whitehead (1969) equation because a time series of mast production data (15-20 years; Greenberg and Warburton 2007) did not exist for Michigan. Greenberg and Warburton (2007) recommend that >165 observations per area (~7,500 $km^2$ in their study) and per species or genus are needed to produce hard mast production indices that are within the 80% confidence level.

To calculate a soft-mast index, I adapted a technique from the West Virginia Division of Natural Resources (Richmond et al. 2015). To my knowledge, no studies have evaluated the sample sizes required to accurately describe soft mast production. I generated the soft mast index on a 0 - 10 scale (where 0 represents poor and 10 represents high production) as:

$$\text{Soft-Mast Index (SMI)} = ((\text{'Many' observations} \div \text{total observations}) + (\text{'Few' observations} \times 0.5 \div \text{total observations}) \times 10)$$

Lastly, to estimate the minimum amount of data needed throughout the state to accurately produce mast indices, I tested the maximum percentage of data needed from the original dataset to calculate an index value that did not significantly differ from the original value. I randomly removed data at 10% intervals (10,000 iterations), calculated a new index, and tested these values to the original index value using a one-sample t-test (McDonald 2009).

### 2.3. Results

In 2015, volunteers submitted 40 mast production observations and I supplemented these data with 843 observations in the northern Lower Peninsula concentrated in the Gladwin State Forest, Manistee National Forest, and Benzie County (Figure 2.1). I used 617 of these points to assess regional and within-region variation for the oak genus, 433 points for red oak subgenus, and 89 points for black cherry (Table 2.1).

The average area of regional clusters ranged from 70,518-313,211 ha for hard mast and 6,518-51,877 ha for black cherry (Table 2.2). Significant differences (Fisher's Exact Test, $p < 0.05$) among clusters were only observed for all oaks combined (Table 2.2). All oaks combined partitioned into 3 clusters, with an average area of 127,298 ha as the smallest scale where significant variability in mast production occurred (Table 2.2). Four clusters for all oak ($p = 0.052$) and 2 clusters for red oak ($p = 0.058$) also warrant evaluation once more data are collected (Table 2.2).

The average area of within-region clusters ranged from 1,187-18,140 ha for hard mast and 441-3,858 ha for black cherry (Table 2.3). Significant differences (Fisher's Exact Test, $p < 0.05$) of mast production within a regional cluster were only detected for the oak genus and red oak subgenus groups, but not in every region (Table 2.4). The largest scale where I detected significant within region variability occurred with 4 clusters and an average area of 4,034 ha for all oaks combined (Tables 2.3; 2.4). The average distance between the 4-cluster centroids was 31.87 km and this was the shortest average distance of all oak genus cluster scales (Table 2.3).

The smallest regional scale that showed significant variability (3 clusters, mean=127,298 ha) most closely corresponded to the Albert (1995) sub-subsection scale (mean=337,363 ha). However, within-region variability in mast production from my sample occurred at distances (31.87 km) larger than the linear dimensions of several sub-subsection boundaries, suggesting that the hierarchical level of 'subsection' may provide more appropriate mast production boundaries. The subsection was subsequently used to calculate mast index values. Only one subsection (Newaygo Outwash Plain) contained enough hard- or soft-mast observations that were dispersed at distances of at least 31.87 km throughout the majority of the area. This area contained 21 pin oak, 149 northern red oak, 128 white oak, and 70 black cherry observations. Resultant index values were 0.54 for oak and 0.71 for black cherry production. No significant difference (One Sample T-test, $p < 0.05$) was observed in either index value when compared to values calculated with lesser amounts of data.

## 2.4. Discussion

To demonstrate how mast production indices could be calculated from relatively simple data like those collected by citizen science, I quantified the spatial scales where differences in mast production could be detected to help guide how these data should be summarized to support wildlife management. Recognizing that these results may vary by year, I found that mast production significantly differed for all oaks among areas that averaged 127,299 ha. I failed to detect a significant region effect for the red oak subgenus or black cherry. Other studies have failed to find a consistent distance at which mast synchrony occurs, with distances ranging between 135 km (Koenig et al. 1994) and 1,000 km (Koenig and Knops 1998). Within these areas, I found that oak (all oaks combined and the red oak subgenus) production varied on average every 3,500 – 4,000 ha. Additionally, the average distance between clusters of points that were producing different amounts of hard mast was ~32 km (oak genus) and 33 km (red oak subgenus), suggesting that mast samples can be collected from relatively dispersed locations within regions. These results may prove useful in allocating sampling effort.

Mast production varies with factors like soils, temperature, and precipitation which are components of ecological land classification schemes (Kelly and Sork 2002). Given that I detected significant patterns in large- and mid-scale hard mast production in Michigan, I used my results to help identify a scale of the Albert ecoregional classification scheme (Albert 1995) that might prove useful for mast data collection. Although my region-level analysis suggested that the 'sub-subsection' of the Albert classification was most appropriate, the linear distances over which differences in hard mast production were detected suggested that the 'subsection' level was more appropriate for sampling efficiency. Sub-subsections are smaller than subsections and many sub-subsections are not large enough to sample at distances beyond 33 km. Choosing the larger subsection of the ecoregional hierarchy would not necessarily result in sampling less total area, but would allow more optimal placement of sample locations.

The process of calculating mast production indices demonstrated here was only based on 1,137 data points collected in 2015 and not evenly dispersed throughout the state. Only 5% of the total records indicated that mast production was abundant, suggesting that 2015 was a low producing year. The resultant HMI of 0.54 in my study indicated a crop failure based on the interpretation of values provided by Greenberg and Warburton (2007). However, to best interpret the results from using their equations, long term mast production data (15-20 years) is needed to know what the true maximum proportion of trees bearing acorns is in the study area. It is unrealistic to assume it is possible for 100% of trees to bear acorns in a given year, meaning an index range of 0-10 may not be accurate. By knowing this maximum potential percentage witnessed over a long period of time, results can be standardized by dividing the percentage of trees bearing acorns in a given year, by the maximum percentage witnessed. By doing so, a subjective rating of mast production (Failure, Poor, Average, Good, Bumper) can be assigned to this standardized value as well as the historically used HMI value (Warburton and Greene 2007). Until the maximum potential percentage is identified, using the percentage of trees bearing acorns as the hard-mast index will be the value most easily interpreted and accurate in comparing production amounts amongst years.

In years when production is better, variation among different spatial scales is likely to be greater. When comparing within region variability in mast production, I found that masting differences occurred at smaller scales depending on the region. This relatively fine-scale variability in masting is common (Kelly and Sork 2002), and is why more data over longer periods of time are needed to more precisely determine the proper scale at which data should be sampled. I suggest that more data be collected at the scales I have identified in this study, and that this analysis be replicated each year until consistent results are found among years.

A sensitivity analysis using my data found that the hard and soft mast production indices were invariant to changes in sample sizes. I suspect that this result most likely relates to the preponderance of plants in my data that did not produce mast in 2015. Greenberg and Warburton (2007) showed that less data are required to accurately estimate hard mast indices in boom or bust years due to the synchrony observed across large scales, meaning more data are required during moderate production years. I recommend that mast amounts be recorded on multiple nearby plants at each location where data is collected to produce a fine-scale estimate of mast production relative to that local area.

I present a sampling protocol that can be used by untrained volunteers to produce data to develop relative hard- and soft-mast production indices in Michigan. Using citizen scientists to collect data can make monitoring statewide wildlife food sources attainable with limited resources. This protocol can easily be adapted to surrounding states to expand data collection to further the understanding of masting patterns in the Midwest.

**2.5. Acknowledgements**

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# APPENDIX

Table 2.1.
Total mast observation amounts by species and genera in Michigan, USA, 2015.

| Hard Mast | Amount | | | |
|---|---|---|---|---|
| | None | <33% | >33% | Total |
| American beech | 44 | 1 | 0 | 45 |
| Beaked hazelnut | 2 | 3 | 0 | 5 |
| Bitternut hickory | 1 | 0 | 0 | 1 |
| Black walnut | 0 | 2 | 1 | 3 |
| Bur oak | 0 | 0 | 1 | 1 |
| Northern red oak | 284 | 103 | 24 | 411 |
| Pin oak | 9 | 11 | 2 | 22 |
| Shagbark hickory | 0 | 0 | 1 | 1 |
| Swamp white oak | 5 | 3 | 0 | 8 |
| White oak | 151 | 24 | 1 | 176 |
| | | Grand Total | | 673 |

| Soft Mast | Amount | | | |
|---|---|---|---|---|
| | None | Few | Many | Total |
| Apple | 0 | 3 | 1 | 4 |
| Autumn olive | 6 | 12 | 5 | 23 |
| Black cherry | 66 | 15 | 8 | 89 |
| Blackberry | 7 | 7 | 5 | 19 |
| Blueberry | 18 | 6 | 1 | 25 |
| Chokecherry | 8 | 8 | 0 | 16 |
| Crabapple | 0 | 0 | 1 | 1 |
| Dogwood | 1 | 2 | 10 | 13 |
| Dwarf red raspberry | 2 | 5 | 0 | 7 |
| Elderberry | 0 | 1 | 0 | 1 |
| Hawthorn | 7 | 2 | 1 | 10 |
| Highbush cranberry | 0 | 1 | 2 | 3 |
| Pokeweed | 0 | 0 | 1 | 1 |
| Serviceberry | 0 | 1 | 1 | 2 |
| Wild grape | 2 | 2 | 0 | 4 |
| | | Grand Total | | 218 |

Table 2.2.
Average size (ha) of regional clusters classified by the K-means method for 2, 3, and 4 clusters. *p*-value from Fisher's exact test for mast production variability among clusters.

| Regional Clusters (n) | Oaks | | Red Oaks | | Black Cherry | |
|---|---|---|---|---|---|---|
| | Area (ha) | p-value | Area (ha) | p-value | Area (ha) | p-value |
| 2 | 313,211 | **0.011** | 312,614 | 0.058 | 51,877 | 0.185 |
| 3 | 127,298 | **0.034** | 126,787 | 0.180 | 13,533 | 0.275 |
| 4 | 71,068 | 0.052 | 70,518 | 0.161 | 6,518 | 0.195 |

Table 2.3.
Average size (ha) of within-region clusters and average distance (km) from centroids (when regions are classified into 3 clusters).

| Within-region Clusters(n) | Oaks | | Red Oaks | | Black Cherry | |
|---|---|---|---|---|---|---|
| | Area (ha) | Distance (km) | Area (ha) | Distance (km) | Area (ha) | Distance (km) |
| 2 | 18,140 | 48.65 | 17,889 | 48.90 | 3,858 | 18.07 |
| 3 | 6,878 | 39.05 | 6,692 | 39.02 | 1,780 | 15.34 |
| 4 | 4,034 | 31.87 | 3,446 | 33.00 | 950 | 12.81 |
| 5 | 2,351 | 32.72 | 2,229 | 32.68 | 679 | 72.94 |
| 6 | 1,437 | 89.45 | 1,187 | 30.05 | 441 | 80.47 |

Table 2.4
Within-region clusters (when regions are classified into 3 clusters) classified by the K-means method for 2, 3, 4, 5 and 6 clusters. *p*-value from Fisher's exact test for mast production variability among clusters.

| | | ***p*-value** | | | | |
|---|---|---|---|---|---|---|
| | | Within-region Clusters (n) | | | | |
| | **Region** | **2** | **3** | **4** | **5** | **6** |
| **All Oaks** | **A** | 1.000 | 1.000 | 0.707 | 0.707 | 0.787 |
| | **B** | 0.381 | 0.080 | **0.039** | **0.001** | **0.004** |
| | **C** | 0.224 | 0.388 | **< 0.001** | **< 0.001** | **< 0.001** |
| **Red Oaks** | **A** | 0.603 | 0.733 | **< 0.001** | **< 0.001** | **< 0.001** |
| | **B** | 1.000 | 1.000 | 0.839 | 0.839 | 0.859 |
| | **C** | 0.366 | 0.204 | 0.211 | **0.004** | **0.018** |
| **Black Cherry** | **A** | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |
| | **B** | 0.187 | 0.259 | 0.389 | 0.478 | 0.589 |
| | **C** | 1.000 | 1.000 | 1.000 | 1.000 | 1.000 |

Figure 2.1.
Mast production data used in cluster classification (*Quercus bicolor*, *Q. alba*, *Q. palustris*, *Q. rubra*, and *Prunus serotina*; n=704) and subsection ecoregional (n=22) in Michigan, USA, 2015.

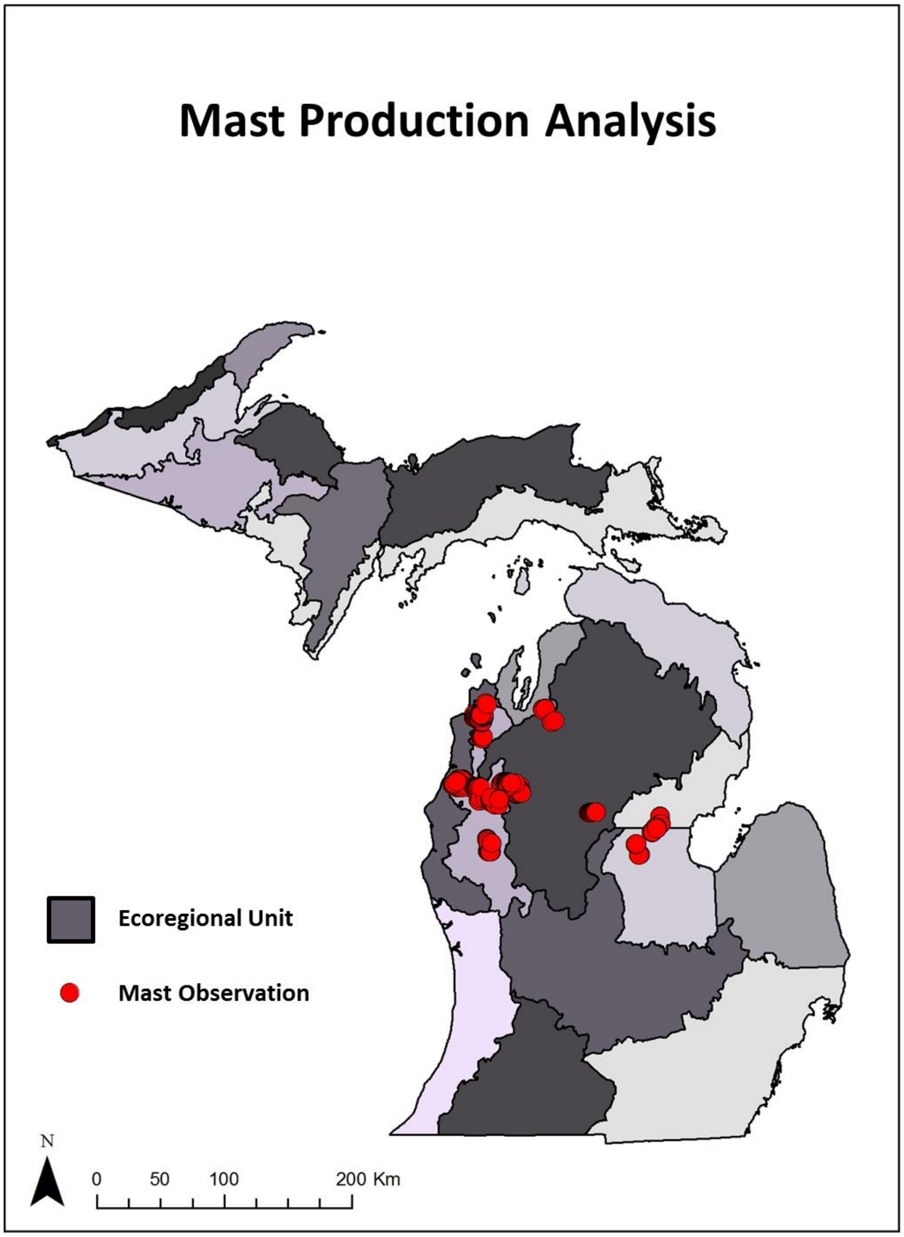


Figure 2.1. (cont'd)
Mast production data used in cluster classification (*Quercus bicolor*, *Q. alba*, *Q. palustris*, *Q. rubra*, and *Prunus serotina*; n=704) and subsection ecoregional units (n=22) in Michigan, USA, 2015.

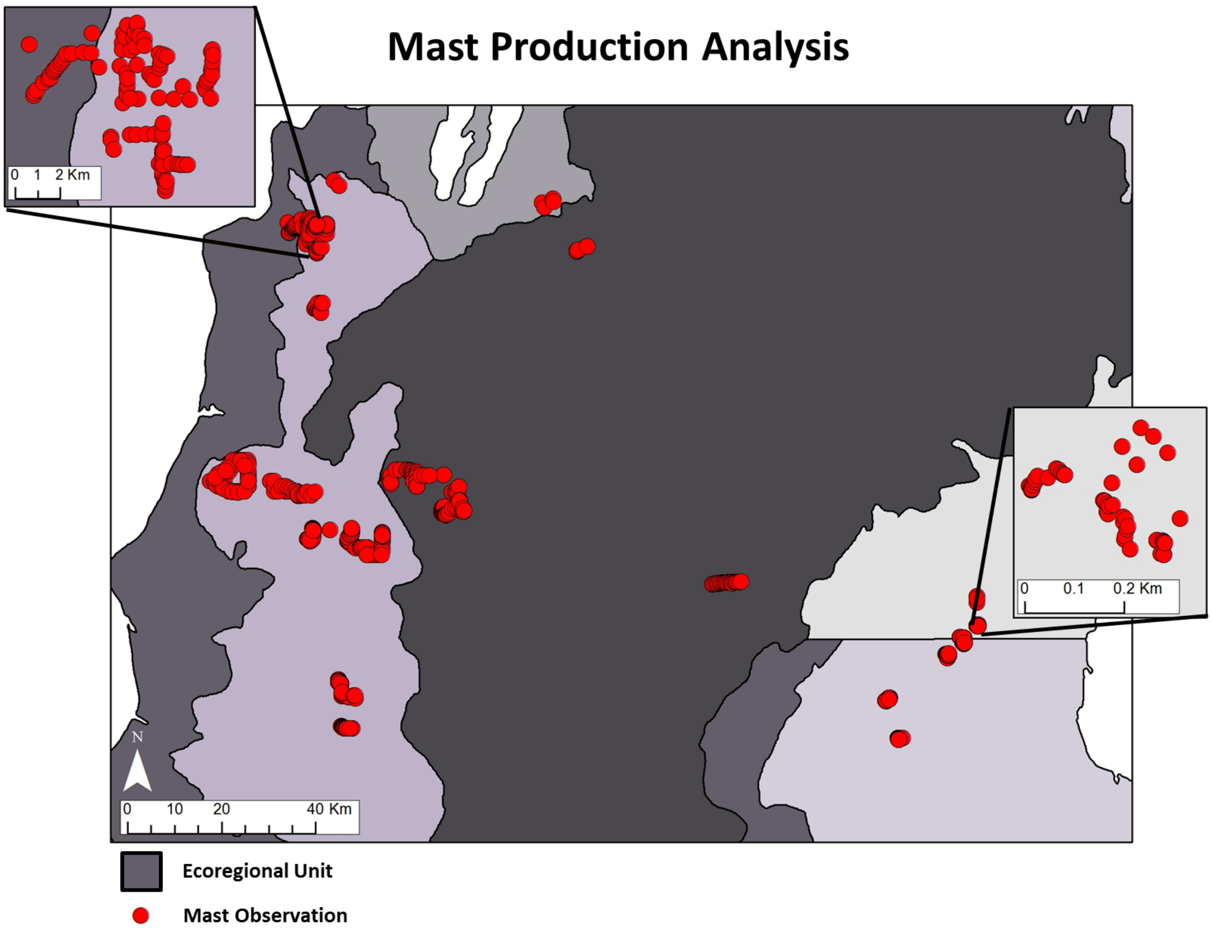
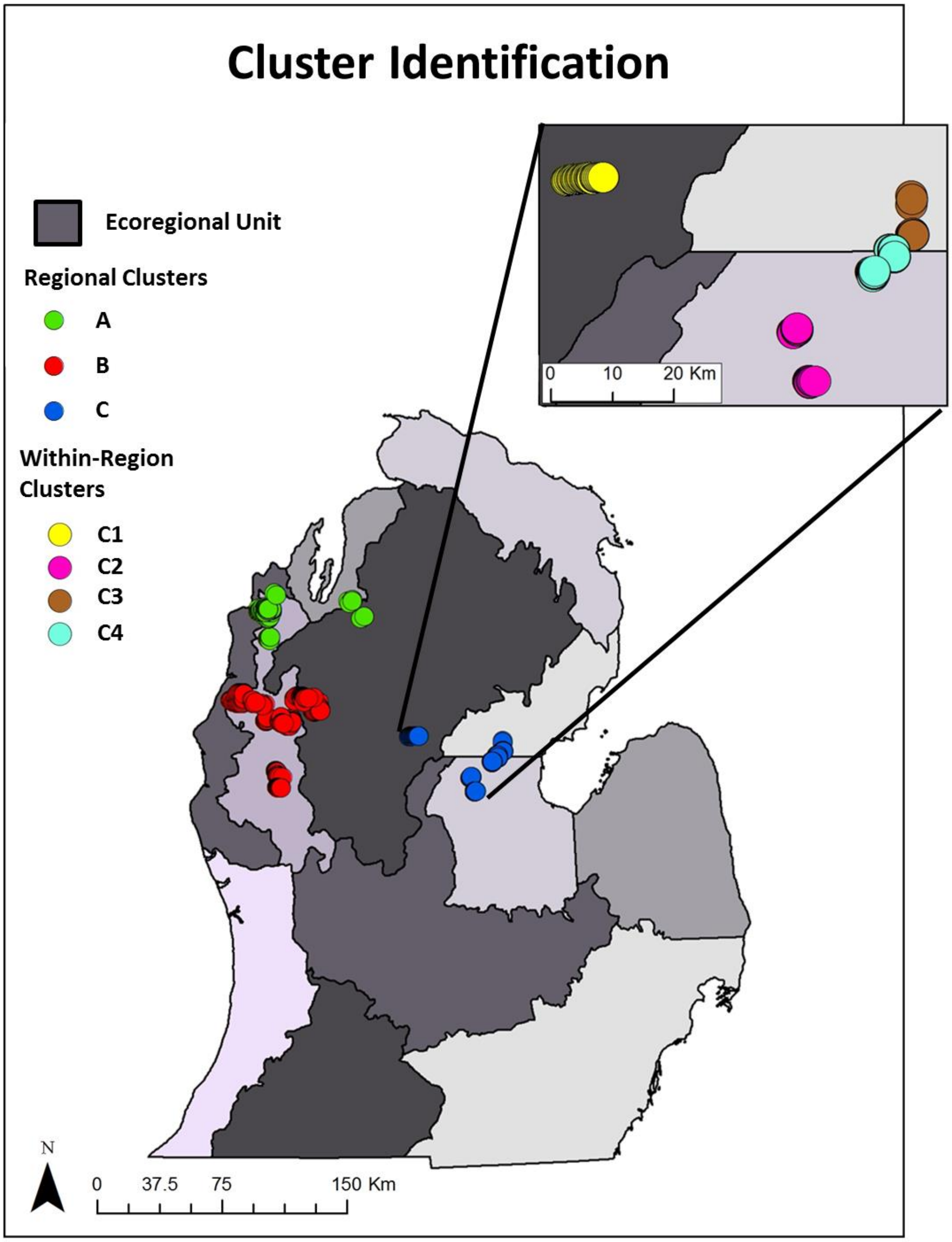


Figure 2.2.
Regional clusters of all oak (*Quercus*) observations and within-region clusters for regional cluster C, Michigan, USA, 2015.



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## CONCLUSIONS

The purpose of this thesis was to describe the feasibility of using citizen scientists to develop annual mast-production indices in Michigan, and to describe a process for analyzing citizen science data to identify scales of variability in mast production. My work can be used to assess the effectiveness of the methods deployed and to inform decisions as to how to best move forward with the coordination of the program. I developed a sampling protocol based on previous scientific findings and adopted the established techniques to ensure accurate data reporting from untrained volunteers. Results from field-validating an initial subset of participant data suggests that data produced by the program can be assumed to be reliable and can be used to accurately estimate mast production indices. Subsequently, I used data collected with this protocol to introduce a process capable of identifying the spatial scales at which hard and soft mast is variable, and how to use this information to estimate production indices at a statewide scale. In the initial years of mast production analyses, the percentage of trees bearing acorns may be the most easily interpreted value of hard mast production by region until a maximum potential production amount has been identified.

Limitations of this work that should be considered are 1) that field validated data were submitted by only 15 volunteers and may not be an accurate representation of data collection capabilities of all participants and 2) mast production indices created in Chapter 2 were created for the purpose of demonstrating the process one would use in the future once adequate data have been obtained. Additional efforts may need to be taken to ensure data is collected for species other than oaks to account for inter-genus production variability. Considering the complimentary working relationships of the partners, the effectiveness of database tools, and accuracy of data submitted by participants thus far, I recommend the continuation of this citizen-science program with an emphasis on recruitment and retention of volunteers.