ASSESSING THE VISUAL QUALITY OF THE MAXTON PLAINS ALVARS

By

Emily Prieskorn

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ABSTRACT

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This study assesses and documents the visual quality of the Maxton Plains alvar/alvar grassland plant communities found on Drummond Island, Michigan, USA. These small, rare landscape types are not addressed by large-scale visual quality mapping efforts and may differ from predicted scores. Visual quality was assessed using two evolutions of the existing visual quality assessment model to accomplish the study's secondary purpose, which was to compare their performance. Equation (1) produced a score set ranging from 52.70-57.17, with an average of 54.32, a variance of 0.72, and a standard deviation of 0.85. Equation (2) produced a set of scores (hereafter referred to as Set 2) ranging from 47.12-52.67, with an average of 50.55, a variance of 0.84, and a standard deviation of 0.90. The results of the visual quality assessment reveal that the Maxton Plains alvars and alvar grasslands have consistently high-to-moderate visual quality and are visually equivalent. The results also indicated that there are slight differences between evolutions of the model that could play a role in future studies.

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INTRODUCTION

What is Visual Quality?

How do people perceive landscape? What does good landscape look like? What makes it good or bad, and who decides which is which? These questions, and the concepts they represent, are at the heart of professions that seek to change the land for the better.

The assessment of visual quality has traditionally been handled with subjective approaches, but great strides have been made over the last several decades toward quantitative alternatives. A validated model has been developed that can predict the preference level (used interchangeably with 'visual quality') that the general public would be expected to express toward a given landscape (Burley, 1997; Burley & Yilmaz, 2014; Kaplan, 1985; Liu & Burley, 2013; Mo, Le Cleach, Sales, Deyoung, & Burley, 2011; Schafer, Hamilton, & Schmidt, 1969; Schafer & Tooby, 1973). This model has many applications that are currently being explored, one of which is the construction of validated visual quality maps (Burley, Deyoung, Partin & Rokos, 2011; Jin, Burley, Machemer, & Crawford, 2016; Lu, Burley, Crawford, Schutzki, & Loures, 2012; Shafer & Brush, 1977; Yilmaz, Liu, & Burley, 2016). The opportunity exists to improve current maps by documenting the visual quality of uncommon landscape types that large-scale mapping efforts do not capture (Yilmaz, Liu, & Burley, 2016).

Visual Quality Assessment

Visual quality assessment is a quantitative approach to a seemingly qualitative problem. Prior to the development of a quantitative model, many relied on the expert approach to determine visual quality (Daniel, 2001; Ulrich, 1986; Zube, Sell, & Taylor, 1982). This approach, while useful, lacks the empirical data and statistic validation that the visual quality assessment model offers quality (Daniel, 2001; Ulrich, 1986; Zube, Sell, & Taylor, 1982). The model uses an equation to generate a visual quality score based on the physical attributes of a landscape (Schafer, Hamilton, & Schmidt, 1969). This score represents the level of preference that the average member of the general public would be expected to express in response to the landscape.

This model, and the equation that comprises it, have evolved considerably over the last several decades, and several versions with varying levels of accuracy exist. The possible applications of the model as a professional tool are numerous. One such application is the validated mapping of visual quality data, which has recently made great strides in the state of Michigan (Burley, Deyoung, Partin & Rokos, 2011; Jin, Burley, Machemer, & Crawford, 2016; Lu, Burley, Crawford, Schutzki, & Loures, 2012; Yilmaz, Liu, & Burley, 2016).

Visual Quality Mapping: An Opportunity

While there has been significant progress in visual quality mapping (Burley, Deyoung, Partin & Rokos, 2011; Jin, Burley, Machemer, & Crawford, 2016; Lu, Burley, Crawford, Schutzki, & Loures, 2012; Shafer & Brush, 1977; Yilmaz, Liu, & Burley, 2016), the nature of large-scale mapping efforts creates an opportunity for further research. The broad landscape type categories and large cell size necessary to large-scale efforts do not capture small or specialized landscape types. There is very little data about the visual quality of these landscape types (Yilmaz, Liu, & Burley, 2016). This data would not only contribute to the existing body of work regarding visual quality mapping, but to conservation and awareness efforts.

There is also very little data comparing the results of different versions of the model when applied to the same images. The equation used by the validated mapping efforts draws on the same set of variables as more recent, more predictive iterations. A comparison of the results produced by different equations could yield useful information about the equations themselves, which could guide the selection of equation for future studies and assess the feasibility of generating more accurate future maps.

Purpose of Study

The purpose of this study is to assess and document the visual quality of Drummond Island's Maxton Plains alvars. Due to its small size and rarity (Albert, 2006; Albert, Cohen, Kost, & Slaughter, 2008), the alvar plant community does not conform to broad landscape type categories and has not yet been assessed. A secondary purpose of this study is to compare the performance of two equation evolutions in order to gain insight that might guide future studies. This study will use two different versions of the visual quality assessment model: the older version used by visual quality mapping efforts, and a more current version with higher predictive ability.

It is important to note that this study's focus is descriptive in nature. Past work in visual quality has focused on validation and prediction, but the purpose of this study is to describe an area in terms of average visual quality and record the results.

LITERATURE REVIEW

Introduction

The field of landscape visual quality assessment. Over the past 50 years, people have been interested in discovering what makes one landscape visually preferable to another. There are vast amounts of literature available on the topic of visual quality; several excellent endeavors have been made to summarize the body of work available (Daniel, 2001; Zube, Sell, & Taylor, 1982).

Dominant Paradigms

The expert approach. Two major approaches dominate recent work in the field of visual quality: the expert approach and the perception assessment approach. The expert approach is perhaps the more familiar of the two, and relies on the opinion of someone considered an expert to pass judgement based on that expertise. This approach has a number of applications and is especially useful in the design and planning professions, which predicate on the notion that the designer or planner is more qualified than the average person. In historic visual quality assessment, however, the definition of an ‘expert’ is used loosely and may be largely determined by the person seeking expertise. The expert’s field of knowledge may range from the fine arts to the physical sciences, and depending on the method used to collect and evaluate landscape, the information they provide may contain some amount of subjective coloring. The viewpoints that are represented by expert opinion are limited by the number of experts, which may vary significantly from one situation to the next. Expert opinion is difficult to verify, reproduce, or generalize. For the field of landscape visual quality assessment, the expert approach lacks the levels of validity, precision, and reliability necessary for scientific research (Daniel, 2001; Ulrich, 1986; Zube, Sell, & Taylor, 1982).

The perception assessment approach. As the topic of environmental and resource management became more relevant, the perception assessment approach gained ground. This approach focuses on the perceptions of ordinary people, collected and analyzed in objective ways that can be reliably reproduced and verified (Daniel, 2001; (Daniel, 2001; Zube, Sell, & Taylor, 1982). The perception assessment approach offers empirical alternatives to the expert approach, relying on math rather than opinion. One tool that has evolved out of this approach is the visual quality assessment model, which contains an equation that predicts public opinion about visual quality based on the physical attributes of a landscape.

The History of the Model

Origins: Elwood Schafer. The visual quality assessment model is a predictive approach to evaluating a landscape's level of visual appeal from the perspective of the general public. The model involves both a methodology and an equation that generate a visual quality score. The first version of this model was produced by Schafer, Hamilton, and Schmidt (1969).The initial equation had only six variables and explained about 66% of the variance in responses, although others claim that the actual figure is about half that (Burley & Yilmaz, 2014). Their methodology, however, provided groundbreaking insight into how a qualitative assessment method could be developed and effectively applied. A grid system was overlaid onto black and white photographs of landscape (later verified as acceptable substitution for actual landscape). The visual elements present in each landscape were then broken down into 46 variables that could be identified and recorded using the grid system. Once the variables were recorded, preference data was collected for each image using the Q-sort method and two user groups (campers and laypeople). Lastly, statistical methods were applied to determine which, if any, variables were significant predicators of preference. This information was then used to develop a predictive equation, which can be found below (Schafer, Hamilton, & Schmidt, 1969).

$$Y= 184.8 - 0.5436\ X1 - 0.09298\ X2 + 0.002069\ (X1 * X3) + 0.0005538\ (X1 * X4) - 0.002596\ (X3 * X5) + 0.001634\ (X2 * X6) - 0.008441\ (X4 * X6) - 0.0004131\ (X4 * X5) + 0.0006666\ (X1)^2 + 0.0001327\ (X5)^2 \tag{1}$$

X1= perimeter of immediate vegetation
X2= perimeter of intermediate non-vegetation
X3= perimeter of distant vegetation
X4= area of intermediate vegetation
X5= area of any kind of water
X6= area of distant non-vegetation

Schafer went on to apply this equation in a number of subsequent studies (Shafer & Brush, 1977; Schafer & Tooby, 1973). This methodology can still be found in recent work.

Schafer's legacy and subsequent work. Unfortunately, Schafer's work was largely disregarded in his own time due to a lack of theoretical framework and the prevalence and ease of expert opinion (Burley, 1997; Palmer, 2004). However, there was still considerable interest in the field, and others continued to work on different aspects of visual quality assessment, generating new possible variables and versions of Schafer's equation in order to explain more of the variation in responses (Kaplan, 1985).

Aesthetics: a paradigm shift. The successful development of a significantly more predictive equation required a paradigm shift regarding the nature of preference. Schafer's original work dealt primarily in aesthetics- physical attributes of the landscape, such as water or vegetation, which could be observed and recorded. But the original equation's low predictive ability suggested that there was more involved in the way people view landscape, and why they prefer one to another. Burley (1997) credits an environmental checklist included in Carol Smyser's *Nature's Design: A Practical Guide to Natural Landscaping* as the inspiration for a shift away from aesthetics. The book offers practical advice for creating a beautiful, functional home landscape and is geared toward the average homeowner. Its value in terms of visual quality assessment lies in the holistic approach to landscape value that it takes. The book urges the homeowner to consider more than the aesthetic value of the landscape, and offers a fourteen-point environmental checklist as a tool for assessing the landscape's functions (Smyser, 1982; Burley, 1997). This checklist's inherent paradigms became the base for the Smyser index, a scoring system that incorporates environmental, cultural, biological, and economic concerns into one variable of the visual quality assessment equation. The Smyser index first appears in Burley (1997) as one of 27 total variables. This equation nearly doubles Schafer's explained variance value (r^2=66.6%) and relies on the methodological precedents set forth by Schafer, Hamilton, and Schmidt (1969). The

Smyser Index has since been dissected and re-evaluated (Liu & Burley, 2013), but the contributions that it made to the understanding of the model remain invaluable.

The present day. The model has been refined repeatedly through subsequent studies. The most current version explains 98.45% of the variance in viewer preference (Burley & Yilmaz, 2014). The equation's full potential is currently limited to countries with cultural values that are similar to those of the North American respondents it was primarily developed with, which is likely a result of cultural differences the equation does not account for (Mo, Le Cleach, Sales, Deyoung, & Burley, 2011).

Applications

The validation of the visual quality assessment model's predictive ability is only the first step toward the development of a truly useful assessment tool; the next step is to explore how the equation performs in a variety of settings, situations, and purposes. This process is already in motion; variations of the model have appeared in a number of studies with diverse characteristics. A community in Massachusetts has used the core concepts of visual quality assessment to track visual landscape change and resident perceptions over 20 years. The resulting information was used to make vital management decisions (Palmer, 2004). A similar study applied the basic principles of visual quality assessment to rural landscapes to understand how their community viewed not only the land, but some of the visually significant agricultural techniques in use (Arriaza, Canas-Ortega, Canas-Madueno, & Ruiz-Aviles, 2004). The validity and possible uses of remotely sensed data, such as ArcGIS data, has been verified (Crawford, 1994), providing even more tools to expand the field of visual quality.

Visual quality mapping. The application that is most relevant to this study is the mapping of visual quality. The concept of visual quality mapping is nearly as old as the visual quality assessment model (Schafer & Brush, 1977), and involves the generation of visual quality scores based on general land use types. The scores are represented graphically and validated statistically through sampling. The resulting visual quality maps have myriad potential uses. Changes can be tracked in space as well as time, as demonstrated by Jin, Burley, Machemer and Crawford (2016) in their comparison of Detroit, Michigan's current and 1800's visual quality. Burley, Deyoung, Partin and Rokos (2011) demonstrated the planning applications of visual quality maps in a comparison of future and former Detroit to Frank Lloyd Wright's unbuilt Broadacre City.

Large-scale mapping efforts. Recently, great strides have been made toward large-scale mapping. Validated visual quality maps have been generated for areas of various sizes, such as watersheds (Lu, Burley, Crawford, Schutzki, & Loures, 2012) and cities (Burley, Deyoung, Partin, & Rokos, 2011; Jin, Burley, Machemer, & Crawford, 2016). A validated visual quality map of the entire state of Michigan has been produced, confirming the feasibility of mapping efforts on a very large scale as well as the suitability of land uses as markers of visual quality (Yilmaz, Liu, & Burley, 2016).

Opportunities

Visual quality mapping. Despite the extensive body of existing work, there are abundant opportunities for further contribution. The application of the visual quality model to an entire state is certainly impressive and useful. However, there are inherent limitations to large-scale studies. Studies that rely on existing cover type maps are limited by their level of detail, range of classification, and original purpose, but the production of new cover type maps is often beyond the feasible limits of a study. Large cell sizes and broad, general landscape type classifications are not suited to capturing small, unusual landscapes, and may exclude them entirely out of necessity. Yilmaz, Liu, and Burley (2016) note these limitations in their study alongside a call for detailed assessment of these landscape types in order to create a truly comprehensive visual quality prediction map.

Alvars and alvar grasslands. There are many different landscape types not covered by large-scale efforts. This study focuses on the alvar plant community and its sub-community, the alvar grassland. A plant community is a type of ecosystem characterized by its dominant plants (Cohen, Kost, Slaughter, & Albert, 2014). Alvars occur on a thin (<10 inches) layer of soil perched over flat, calcareous bedrock, such as limestone or dolomite. Glacial action during the Ice Ages removed significant portions of existing topsoil from this soft bedrock, depositing foreign rocks and occasionally scoring deeper gouges (called grykes) directly into the bedrock. This resulted in bare patches of exposed rock and a very thin soil profile, which is characteristic of the community. Alvars typically occur near water sources and experience significant seasonal disturbances, such as flooding, drought, scouring winds, and occasionally fire.

Due to the high soil pH, punishing disturbance regimes and thin soil, very few woody plants are able to survive. These harsh conditions create a unique plant community found in only three regions worldwide: Northwest Ireland, the Baltic region, and the Great Lakes region.

An alvar grassland is a subcategory of alvar characterized by slightly larger soil margins and predominately gramanoid (grasses and sedges) cover as opposed to bare patches of ground or exposed substrate (Albert, 2006; Albert, Cohen, Kost, & Slaughter, 2008). For the purposes of this study, it is assumed that the term 'alvar' is inclusive of alvar grasslands unless otherwise specified.

Comparisons and insights. Another opportunity for contribution can be found in the numerous iterations of the visual quality assessment model's equation. These variations were produced as part of the model's evolution, but the development of the most predictive model has not rendered its predecessors obsolete. Many current studies choose to use an older version, which may be due in part to the cumbersome nature of the 99-term final equation. Some studies simply don't require the level of accuracy that the final equation offers, while others may find the length and difficulty prohibitive. However, several older versions exist, and there is little to no research available comparing older models to one another.

Conclusions

The field of visual quality assessment has developed substantially in recent decades. The evolution of a highly predictive model has produced several less predictive but still useful versions of the central equation, many of which are still in use today. The applications of this model are vast and growing as new uses are realized and explored. One of these applications, visual quality mapping, is making considerable progress in increasingly large-scale endeavors at the expense of examining small, rare landscape types. This study will explore the visual quality of an alvar plant community, a landscape cover type found in very small, specific areas of Michigan. The visual quality of the alvar will be assessed using two different versions of the equation, which will then be compared to one another as well as to the validated visual quality map of Michigan. This comparison could yield valuable information about the equations themselves that could influence their future use.

METHODS

Area of Study

Drummond Island, Michigan, is located just off the coast of the state's Upper Peninsula, near the Canadian-American border. The island is accessible by ferry or boat.

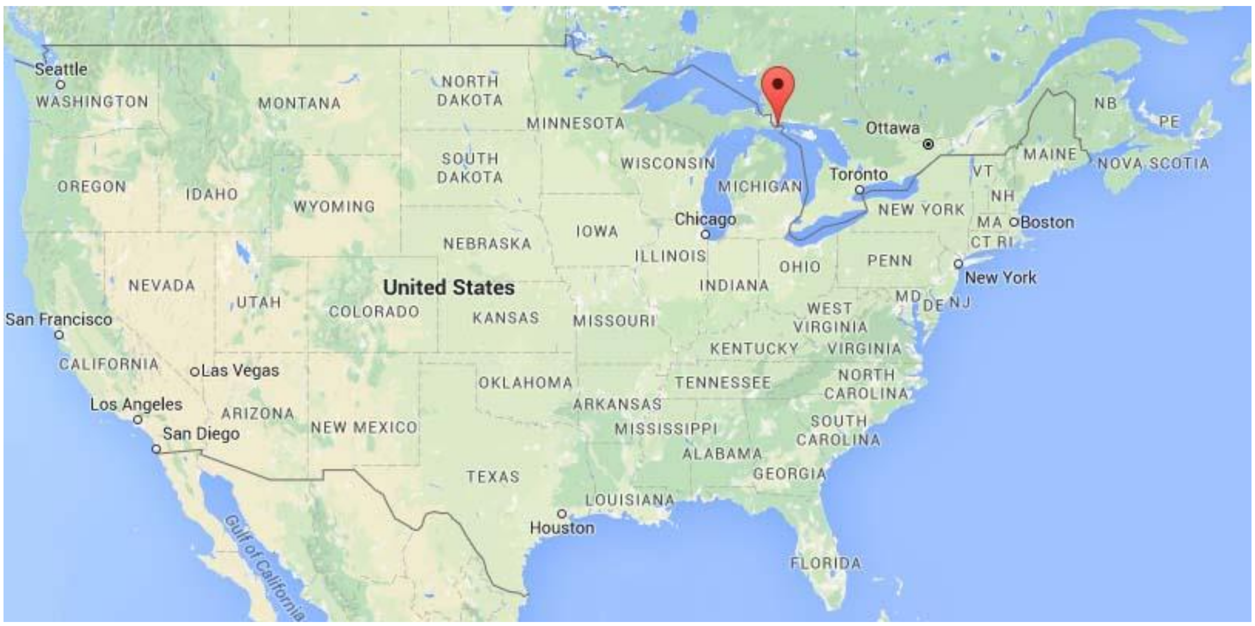


Figure 1: Map of the United States of America, showing Drummond Island, Michigan. Made using Google Maps (2016).

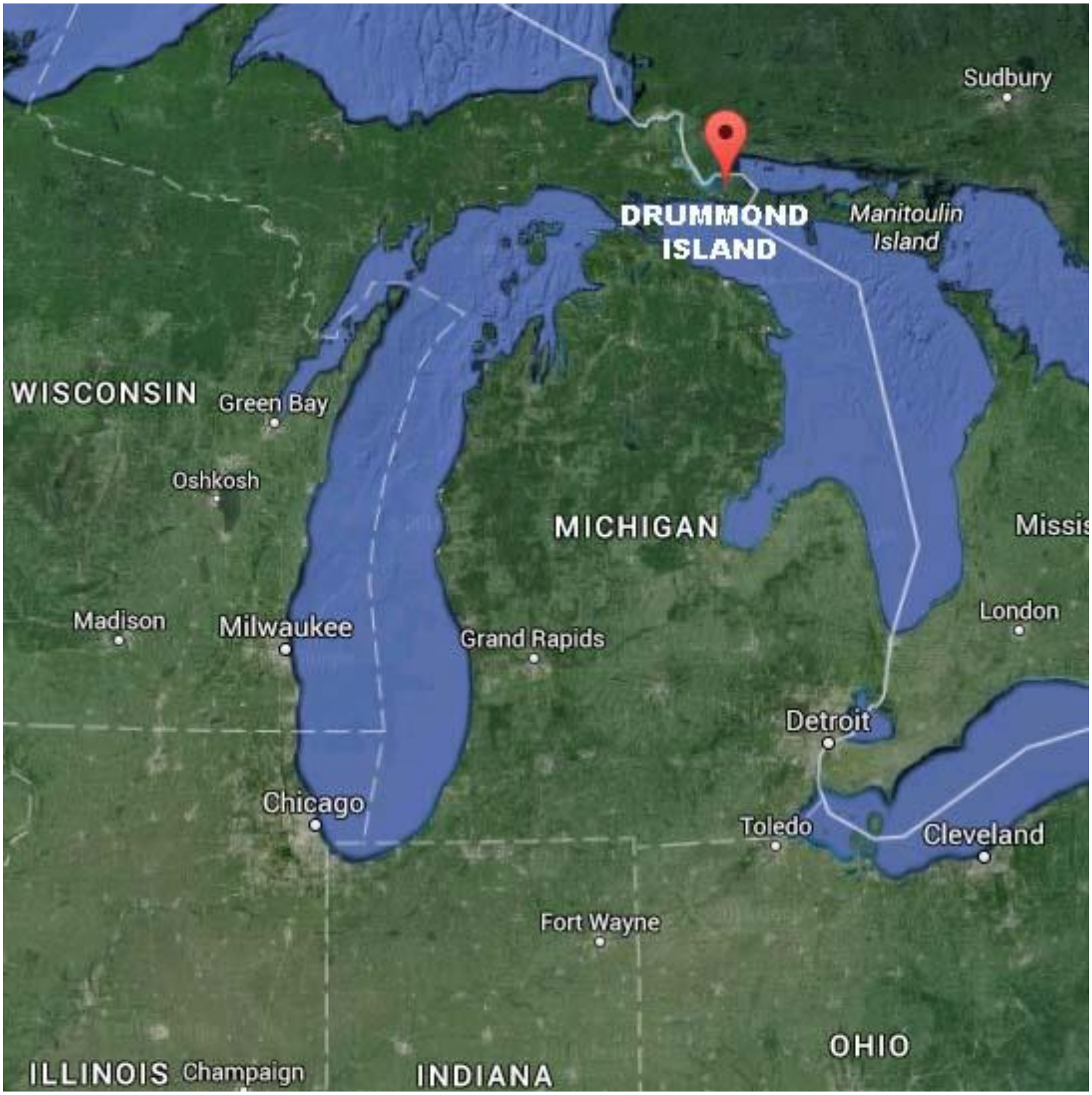


Figure 2: Map of Michigan, showing Drummond Island. Made using Google Maps (2016).

The northern part of the island is home to Maxton Plains, part of The Nature Conservancy. Maxton Plains contains up to 8 square miles of scattered alvar and alvar grassland, and is accessible by car or bicycle (Bailey, 2009).

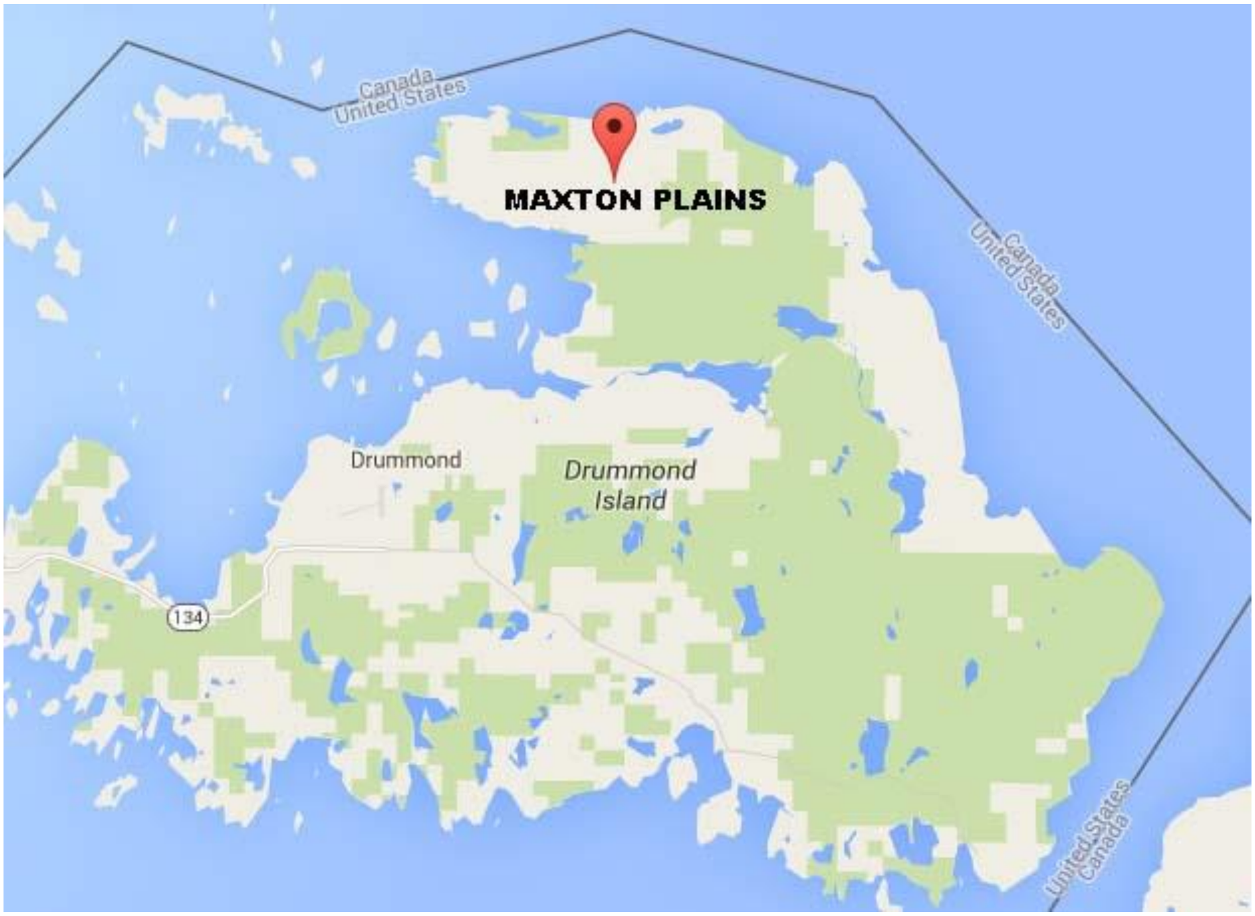


Figure 3: Map of Drummond Island, showing Maxton Plains. Made using Google Maps (2016).

Procedures: Equations and Variables

A set of 60 images, gathered from 31 points, were collected for analysis. All images were gathered on July 31, 2015. Images can be found in Appendix B. These points are spread out over five locations as depicted in Map B. For the purposes of this study, a location consists of a single, contiguous alvar or alvar grassland.

Figure 4: Locations of Points Within Maxton Plains. Made using Google Maps (2016).

The images were then analyzed according to the methodology set forth by other studies. For a complete and exhaustive review of the process, refer to Schafer and Brush (1977) or Burley (1997). The base set of variables that both equations use can be found below.

Table 1: Variables		
Variable	Name	Description
HEALTH/CVQ	Smyser Index	Number derived from the application of the Smyser Index (Table 2)
X1/V1	Perimeter of Immediate Vegetation	Number of boundary edges in which individual leaves, needles, bark, or stems of trees/shrubs are easily distinguishable
X2/V2	Perimeter of Intermediate Non-Vegetation	Number of boundary edges in which individual rocks, snow, or patches of bare ground are distinguishable but lack fine detail
X3/V3	Perimeter of Distant Vegetation	Number of boundary edges in which vegetation is present but individual trees/shrubs are indistinguishable
X4/V4	Area of Intermediate Vegetation	Number of squares in which the outlines of individual trees/shrubs are recognizable, but lack fine detail
X5/V5	Area of Any Kind of Water	Number of squares containing any kind of water
X6/V6	Area of Distant Non-Vegetation	Number of squares in which rocks, bare soil, and snow occur but lack recognizable individual detail
X7/V7	Area of Pavement	Number of squares containing man-made pavement
X8/V8	Area of Buildings	Number of squares containing man-made structures
X9/V9	Area of Vehicles	Number of squares containing any kind of man-made vehicle
X10/V10	Area of Humans	Number of squares containing humans
X11/V11	Area of Smoke	Number of squares containing smoke
X12/V12	Area of Fire	Number of squares containing fire
X13/V13	Area of Herbaceous Foreground Material	Number of squares containing non-woody plant material in the foreground
X14/V14	Area of Wildflowers in Foreground	Number of squares containing wildflowers in bloom in the foreground
X15/V15	Area of Utilities	Number of squares containing utility poles, wires, pipes, etc
X16/V16	Area of Boats	Number of squares containing boats
X17/V17	Area of Dead Foreground Vegetation	Number of squares containing dead woody vegetation in the foreground
X18/V18	Area of Exposed Foreground Substrate	Number of squares containing patches of bare ground in the foreground
X19/V19	Area of Wildlife	Number of squares containing animals, excluding humans
X20/V20	Smoothness (Scale 1-5)	Uniformity and height of ground texture
X30/V30	Open Landscapes (X2 + X4 + 2(X3 + X6))	
X31/V31	Closed Landscapes (X2 + X4 + 2(X1 + X17))	
X32/V32	Openness (X30 – X31)	Amount of space perceivable to viewer
X34/V34	Mystery (X30 * X31 * X7 / 1140)	Promise of new but related information
X44/V44	Complexity (Variables X1-X19 squared, them summed)	Richness or intricacy; number of different elements
X46/V46	Sum of Variables X1-X19	
X51/V51	Wetness (X5/X46)	
X52/V52	Noosphericness (X7 + X8 + X9 + X15 + X16)	Man-made or otherwise non-natural elements
X53/V53	Greenness	
X63/V63	Schafer Index (3, 4, 5, 6)	
X80/V80	X63 * X52	

(Burley, 1997; Burley, Deyoung, Partin, & Rokos, 2011; Kaplan, Kaplan, & Brown, 1989; Schafer, Hamilton, & Schmidt, 1969)

Table 2: Smyser Index				
A	Purifies Air	1	0	-1
B	Purifies Water	1	0	-1
C	Builds Soil Resources	1	0	-1
D	Promotes Human Cultural Diversity	1	0	-1
E	Preserves Natural Resources	1	0	-1
F	Limits Use of Fossil Fuels	1	0	-1
G	Minimizes Radioactive Contamination	1	0	-1
H	Promotes Biological Diversity	1	0	-1
I	Provides Food	1	0	-1
J	Ameliorates Wind	1	0	-1
K	Prevents Soil Erosion	1	0	-1
L	Provides Shade	1	0	-1
M	Presents Pleasant Smells	1	0	-1
N	Presents Pleasant Sounds	1	0	-1
O	Does not Contribute to Global Warming	1	0	-1
P	Contributes to the World Economy	1	0	-1
Q	Accommodates Recycling	1	0	-1
R	Accommodates Multiple Use	1	0	-1
S	Accommodates Low Maintenance	1	0	-1
T	Visually Pleasing	1	0	-1

(Burley, 1997).

Equations

Equation (1). The first equation (hereafter referred to as Equation (1)) is found in Burley (1997). This equation explains about 67% of the variance in responses, and contains 18 terms. This equation has been utilized in a number of existing visual quality studies, making it a useful baseline for comparisons across studies.

$$Y = 68.30 - 1.878\ HEALTH + 0.131\ X1 - 0.064\ X6 + 0.020\ X9 + 0.036\ X10 + 0.129\ X15 - 0.129\ X19 - .006\ X32 + 0.00003\ X34 + 0.032\ X52 + 0.008\ X1X1 + 0.00006\ X6X6 - 0.0003\ X15X15 + 0.0002\ X19X19 - 0.0009\ X2X14 - 0.00003\ X52X52 - 0.0000001\ X52X34 \quad (2)$$

Equation (2). The second equation (hereafter referred to as Equation (2)) is found in Burley, Deyoung, Partin, & Rokos (2011), and is an updated version based on Equation (1). It has 19 terms and explains about 75% of the variance in responses.

$$Y = 58.98827 + 0.07725\ V2 + 0.03775\ V10 - 1.18505\ CVQ - 0.01074\ V32 + 0.01161\ V52 - 0.00181\ V1V2 - 0.00026\ V1V5 + 0.00134\ V1V10 - 0.00071\ V2V14 + 0.00018\ V5V9 - 0.00092\ V7V18 + 0.00025\ V8V14 + 0.00425\ V8V15 + 0.00023\ V15V18 - 0.00012\ V2V32 + 0.000000613388\ V6V34 - 0.000000783802\ V8V34 + 0.00117\ V11V52 \quad (3)$$

RESULTS

Equation (1) produced a set of scores (hereafter referred to as Set 1) ranging from 52.70-57.17, with an average of 54.32, a variance of 0.72, and a standard deviation of 0.85. Equation (2) produced a set of scores (hereafter referred to as Set 2) ranging from 47.12-52.67, with an average of 50.55, a variance of 0.84, and a standard deviation of 0.90.

DISCUSSION

Understanding Visual Quality Scores

Overview. The Maxton Plains alvars produced two sets of consistently moderate to low scores that reflect the anticipated levels of visual quality and uniformity. While the score sets are numerically close, there are differences between them that allow for meaningful comparison and offer insight into each equation.

Expectations and reasoning. The expectations of this study are based on the application of key concepts found in previous visual quality studies. These concepts are particularly important to the interpretation and comprehension of visual quality data. The first and most important is that visual quality scores are inversely related to the level of preference they represent. High visual quality scores indicate low levels of preference, while low scores indicate high levels of preference. Scores of 30 or lower are highly preferred, 50-60 moderately preferred, 70 less preferred, and scores of 100+ are not preferred (Burley, 2006). It is also helpful to consider the normative theories developed by Burley (1997), which offer insights into why certain landscapes produce the scores that they do. The first is the biospheric preference theory, which states that people tend to prefer natural, nonhuman landscapes that include elements such as vegetation, water, and sky. These landscapes produce mid-to-low scores. Conversely, human or built (noospheric) elements, such as roads, cars, boats, or other humans, tend to lower visual quality and produce higher scores. Finally, temporary natural elements, such as wildflowers or wildlife, raise visual quality and produce lower scores

(Burley, 1997). Alvars are plant communities; by definition, they contain almost no noospheric elements to lower their visual quality, and may even contain quality boosters in the form of wildflowers or wildlife. Therefore, an alvar would be expected to produce neutral to low scores and high visual quality, which is in line with both sets of average results.

Consistency within the plant community. Both score sets also have low standard deviations, which indicate the high levels of visual consistency that are expected in a visually unified plant community. This corroborates the findings of Lu, Burley, Carwford, Schutzki, and Loures (2012), who concluded that landscape type is predictor of visual quality, and therefore an appropriate way to generate visual quality maps. This consistency is also present within each location- even the least consistent location (Location 3) still has a very low standard deviation. Location 3 also contains the highest score for both data sets and the lowest score of Set 2, resulting in the highest ranges of any location and its slightly elevated standard deviation. Interestingly, there is not a most consistent location. All five locations produced very close averages, indicating that the locations are visually similar to one another. This indicates that, at least to the general public, an alvar grassland is visually interchangeable with a true alvar. Initially, this conclusion may sound contradictory to Lu, Burley, Carwford, Schutzki, and Loures (2012)'s findings regarding land use categories. However, it is important to remember that there are major differences in scale and purpose between a plant community and a land use category. A plant community is delineated according to the plants it contains and how they relate to one another. The distinctions that necessitate the creation of different plant communities may have little impact on their overall visual character. Land use categories are determined by much broader criteria for a variety of purposes. The distinction between an alvar and an alvar grassland may be of great use and interest to professionals in the natural sciences, but it is too minute to be visually significant.

Comparing Equations

Score sets. A comparison of the score sets to one another yields some interesting observations about each equation. Set 1's scores are higher than Set 2's, and were produced by an older equation that is less predictive. Set 2's scores are lower and were produced by a newer, more predictive version of Equation (1). The differences in score sets per image are relatively consistent (Table 5). Each image does not necessarily occupy the same relative position within both sets: Image 103 generates the maximum value for both sets, but Image 280 produces Set 1's lowest score, while Image 197 produces Set 2's lowest.

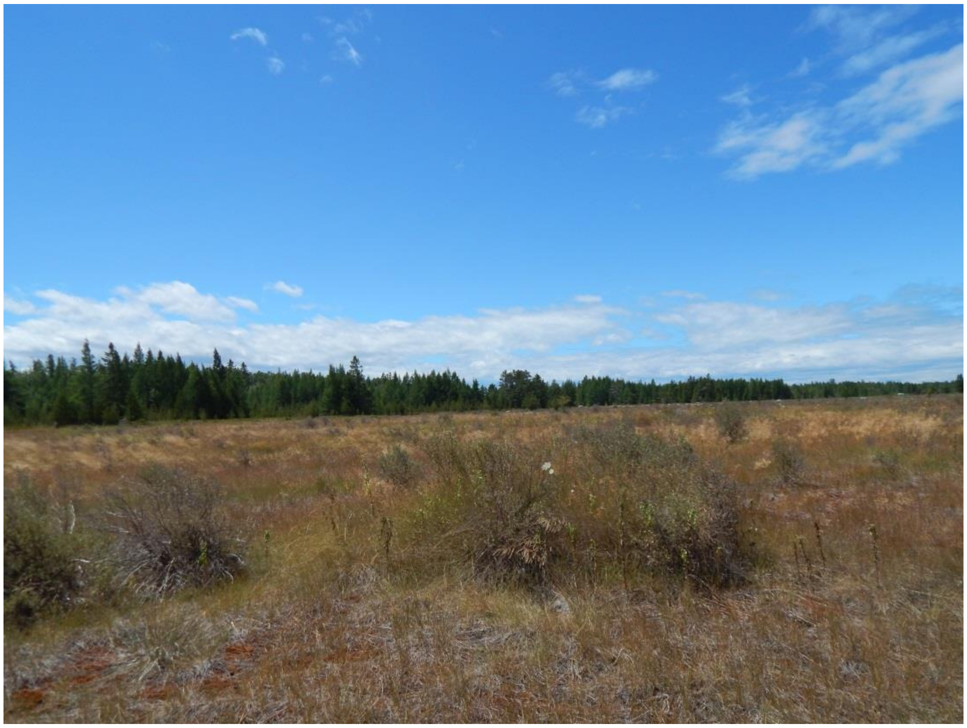


Figure 5: Image 5

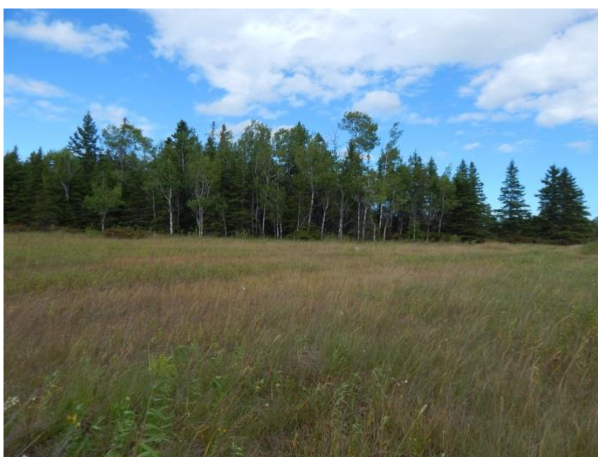


Figure 6: Image 280 Figure 7: Image 197

Interpretation. These results suggest that Equation (1) and Equation (2) are relatively equivalent in terms of performance. Equation (2) generated slightly lower scores than Equation (1). Further comparison of the equations to one another reveals some interesting differences. Both equations draw from the same list of measured variables, but not all of the variables make it into both equations. For instance, Equation (2) relies heavily on the variable X2 (perimeter of intermediate non-vegetation,) which appears once by itself and three times as part of a larger term. However, this variable only appears once in Equation (1), and is multiplied by X14 (area of wildflowers in foreground,) a variable that is frequently 0. In fact, out of 60 images, only one image has nonzero integers for both variables. Altering this value would have significant effects on Equation (2), but almost no effect on Equation (1). Some variables only appear in one equation, such as X11 (area of smoke) and X16 (area of boats.) These variables were not present in this study's images, but could play more significant roles in other landscape types.

Contributions

Visual quality mapping. Our findings contribute to the knowledge base of visual quality mapping efforts by assessing the visual quality of a previously undocumented landscape type that falls outside the purview of previous studies. While the land use classifications mapping studies utilize are far less specific than the plant communities this study focused on, their results provide some context. Yilmaz, Liu, and Burley (2016) found that the average scores of highly noospheric land uses were higher (92 Industrial, 74 Downtown, 68 Commercial, 62 Residential and Farmland) than average scores for more biospheric land uses (55 Forested/Woodland, 57 Water, 58 Savanna, 62 Grassland Dunes.) The Maxton Plains alvars produced an average score that is slightly lower than any of these biospheric land use categories, but the difference is very small. This indicates that the visual quality of the study area is slightly higher than other biospheric categories. The difference in scores is not surprising when the grain and scale of the studies are considered, but it does support Yilmaz, Liu and Burley (2016)'s conclusion that there is value in the continued assessment of smaller, rarer landscape types.

Conservation. These findings may also be of interest to the conservation efforts that protect Michigan's alvars. The high visual quality of the Maxton Plains alvars is due in part to its lack of noospheric elements when viewed from the central road. The preservation of those views is essential to the maintenance of the alvar's high visual quality, and an understanding of this may help conservation efforts plan to retain them. This insight may have value to conservation efforts taking place in other plant communities as well.

CONCLUSION

Summary

Purpose of study. The purpose of this study was to assess and document the visual quality of the Maxton Plains alvar plant community, found on Drummond Island, Michigan. The alvar plant community is a small, rare landscape type that large-scale visual quality mapping efforts have not been able to examine. This study offers information that contributes toward the creation of a more detailed, comprehensive visual quality map of the state of Michigan. The visual quality of the Maxton Plains alvars was assessed using two versions of the visual quality assessment model for comparison purposes, offering new insights about the equations that may prove useful to future visual quality studies.

Procedures and results. The visual quality data of the Maxton Plains alvars was generated from a set of 60 photographs taken from five locations, and includes alvars and alvar grasslands. The images were then scored according to the methods found in Burley (1997) and both equations applied. The first equation, which was also used by the large-scale visual quality mapping efforts of Yilmaz, Liu and Burley (2016), produced an average score of 54.32. The second equation, which is more recent and predictive, produced an average of 50.55. A comparison of equation 1's average score to the average scores of other landscape types reveals that alvars have high to moderate visual quality.

Limitations of Study

While this study came about as a response to the limitations of large-scale mapping endeavors, it invariably has limitations of its own. Some of these limitations result from the design of this specific study, while others are inherent to the nature of the model.

Generalization and applicability. The average visual quality scores generated herein can only be confidently applied to the Drummond Island alvars, and have not yet been replicated and corroborated. Since this study was only interested in the visual quality of the plant community, special care was taken to avoid noospheric elements and other plant communities. It would therefore be inappropriate to apply these findings to all of Maxton Plains or Drummond Island. The process of image collection requires larger alvars that allow for a full image; smaller alvars were excluded out of necessity. Very little data is available regarding the impact of season or time of day on visual quality; for the purposes of this study, it is assumed to be negligible in order to allow comparison between this and other studies.

Further Studies

Visual quality. The field of visual quality is growing and developing rapidly as new applications are explored. This study's success creates many opportunities for future work. Michigan is home to many different rare landscape types that could be examined to contribute toward the creation of a truly comprehensive map. While this study documents one example of one such landscape, future studies are needed to increase sample size and corroborate our findings in other alvars. The impacts of season, weather, and time of day have not yet been studied, but could be relevant in areas with significantly different seasonal views.

This study's secondary purpose was to compare older models of the visual quality assessment models. While this study was able to make some general conclusions, a more extensive study could yield further information. There are numerous evolutions of the model that have not yet been examined.

APPENDICES

APPENDIX A: DATA AND RESULTS

Table 3: Results by Location					
Location	Points	Images	Results	Equation 1	Equation 2
1	5	9	Highest Score	54.54	51.08
			Lowest Score	53.10	48.70
			Range	1.44	2.38
			Average	54.13	50.56
			Variance	0.28	0.67
			Standard Deviation	0.53	0.82
2	6	12	Highest Score	54.44	51.06
			Lowest Score	53.16	49.40
			Range	1.28	1.66
			Average	54.10	50.58
			Variance	0.26	0.40
			Standard Deviation	0.51	0.64
3	8	16	Highest Score	57.17	52.67
			Lowest Score	53.18	47.14
			Range	3.99	5.53
			Average	54.74	50.59
			Variance	1.31	1.46
			Standard Deviation	1.14	1.21
4	5	10	Highest Score	55.22	51.29
			Lowest Score	53.19	49.03
			Range	2.03	2.27
			Average	54.08	50.32
			Variance	0.47	0.78
			Standard Deviation	0.68	0.89
5	6	12	Highest Score	55.84	51.79
			Lowest Score	52.70	48.58
			Range	3.13	3.20
			Average	54.30	50.65
			Variance	0.74	0.71
			Standard Deviation	0.86	0.84

Table 4: Data

Variables		Location 1									Location 2											
		Point 2		Point 3		Point 4	Point 7		Point 8		Point 11		Point 12		Point 13		Point 14		Point 15		Point 17	
Name	Description	5	8	10	12	15	29	33	35	36	50	51	55	58	60	61	66	67	73	74	86	88
HEALTH	Environmental Quality Index	7	7	8	7	7	7	8	7	7	8	8	7	7	7	7	7	7	7	7	7	8
X1	Perimeter of Immediate Vegetation	100	100	96	96	96	96	96	96	96	96	96	96	96	96	96	98	96	96	96	96	96
X2	Perimeter of Intermediate Non-Vegetation	0	0	0	0	0	0	6	0	0	0	0	0	0	6	0	0	0	0	0	0	0
X3	Perimeter of Distant Vegetation	82	94	88	88	82	86	106	82	80	96	82	82	83	82	79	84	82	85	86	82	101
X4	Area of Intermediate Vegetation	345	190	129	197	238	228	112	126	114	190	176	177	142	188	173	114	107	144	131	152	100
X6	Area of Distant Non-Vegetation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X7	Area of Pavement	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X8	Area of Buildings	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X9	Area of Vehicles	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X10	Area of Humans	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X11	Area of Smoke	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X14	Area of Wildflowers in Foreground	0	0	0	0	0	0	0	1	0	0	2	0	0	0	0	0	0	2	0	0	0
X15	Area of Utilities	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X16	Area of Boats	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X17	Area of Dead Foreground Vegetation	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X18	Area of Exposed Foreground Substrate	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X19	Area of Wildlife	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X30	X2 + X4 + 2(X3+X6)	1163	1330	1371	1393	1298	1340	1354	1420	1474	1210	1374	1393	1448	1398	1399	1456	1463	1414	1385	1424	1138
X31	X2 + X4 + 2(X1 + X17)	545	390	321	389	430	420	310	318	306	382	368	369	334	386	365	310	299	336	323	344	292
X32	X30-X31	618	940	1050	1004	868	920	1044	1102	1168	828	1006	1024	1114	1012	1034	1146	1164	1078	1062	1080	846
X34	(X30 * X1*X7)/1140	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
X52	X7+X8+X9 +X15+X16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4 (cont'd)

Location 3

Point 20		Point 21		Point 25		Point 26		Point 27		Point 29		Point 30		Point 35	
100	103	109	110	129	131	135	136	145	146	155	156	163	164	197	199
8	7	7	7	7	7	7	7	8	7	7	7	7	7	8	7
96	132	96	112	113	112	136	116	100	96	96	110	96	96	96	96
0	0	0	0	8	7	0	12	0	0	0	0	0	0	24	0
99	82	92	84	80	82	86	84	90	84	102	86	74	86	98	84
131	106	114	152	152	111	228	142	163	184	190	121	125	168	177	92
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	42	0	2	0	0	0	0	0	0	0	0	0	0	0	0
0	42	0	2	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1253	1450	1408	1360	1454	1346	1376	1420	1333	1332	1398	1393	1501	1398	1147	1398
323	454	306	380	386	342	500	386	363	376	382	341	317	360	393	284
930	996	1102	980	1068	1004	876	1034	970	956	1016	1052	1184	1038	754	1114
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 4 (cont’d)									
Location 4									
Point 40		Point 43		Point 44		Point 46		Point 48	
221	222	234	238	242	243	257	259	266	270
7	7	7	8	8	8	7	7	8	7
114	107	96	96	96	107	96	96	96	96
0	0	0	0	6	0	0	0	6	0
86	92	91	98	89	96	84	86	91	84
182	211	201	190	197	237	228	228	235	114
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
3	2	5	0	0	0	3	2	4	10
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
1302	1313	1337	1188	1203	1179	1332	1294	1153	1382
410	425	393	382	395	451	420	420	433	306
892	888	944	806	808	728	912	874	720	1076
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

Table 4 (cont'd)

Location 5

Point 49		Point 50		Point 51		Point 52		Point 54		Point 55	
272	276	278	280	284	286	290	291	299	303	306	310
7	8	8	8	7	8	6	7	7	7	7	7
121	100	96	96	104	96	106	96	96	96	96	96
0	4	0	0	0	0	6	0	0	0	0	0
88	52	86	139	92	30	80	86	106	84	80	88
114	254	298	169	227	248	203	190	190	266	266	91
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	5	1	2	4	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
1396	1284	1300	1191	1269	1092	1357	1306	1426	1304	1324	1185
356	458	490	361	435	440	421	382	382	458	458	283
1040	826	810	830	834	652	936	924	1044	846	866	902
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0

Table 5: Visual Quality Score Sets						
Location	Point	Picture number	Visual Quality Score Set 1	Visual Quality Score Set 2	GPS Coordinate (Point)	Difference in Scores
1	2	5	54.54	51.08	46 04 .217	3.46
		8	54.39	50.82	83 35 .451	3.57
	3	10	53.31	49.68	46 04 .231	3.64
		12	54.31	50.86	083 35 .495	3.45
	4	15	54.39	50.99	46 04 .235	3.39
					83 35 .539	
	7	29	54.34	50.91	46 04 .168	3.43
		33	53.10	48.70	83 35 .599	4.40
	8	35	54.39	50.99	46 04 .238	3.39
		36	54.41	51.04	83 35 .583	3.37
2	11	50	53.22	49.51	46 04 .341	3.71
		51	53.39	49.81	83 36 .729	3.58
	12	55	54.39	50.99	46 04 .344	3.39
		58	54.37	50.97	83 36 .823	3.40
	13	60	54.39	50.43	46 04 .382	3.95
		61	54.42	51.06	83 36 .806	3.36
	14	66	54.44	50.99	46 04 .403	3.44
		67	54.39	50.99	83 36 .862	3.39
	15	73	54.35	50.93	46 04 .403	3.42
		74	54.34	50.91	83 36 .903	3.43
	17	86	54.39	50.99	46 04 .347	3.39
		88	53.16	49.40	83 37 .026	3.76
3	20	100	53.18	49.44	46 04 .459	3.74
		103	57.17	52.67	83 39 .260	4.50
	21	109	54.27	50.78	46 04 .467	3.49
		110	55.15	51.34	83 39 .352	3.81
	25	129	55.23	50.45	46 04 .517	4.78
		131	55.15	50.51	83 39 .492	4.64
	26	135	57.00	51.77	46 04 .471	5.24
		136	55.37	49.88	83 39 .506	5.49
	27	145	53.44	49.72	46 04 .475	3.72
		146	54.36	50.95	83 39 .552	3.41
	29	155	54.15	50.56	46 04 .528	3.58
		156	54.98	51.21	83 39 .717	3.77
	30	163	54.48	51.17	46 04 .567	3.32
		164	54.34	50.91	83 39 .775	3.43
	35	197	53.19	47.14	46 04 .520	6.06
		199	54.36	50.95	83 39 .813	3.41

Table 5 (cont'd)						
4	41	221	55.22	51.29	46 05 .220	3.93
		222	54.74	51.02	83 42 .143	3.73
	43	234	54.28	50.80	46 05 .181	3.48
		238	53.19	49.46	83 42 .103	3.73
	44	242	53.30	49.09	46 05 .201	4.21
		243	53.70	49.74	83 41 .978	3.95
	46	257	54.36	50.95	46 05 .161	3.41
		259	54.34	50.91	83 41 .782	3.43
	48	266	53.26	49.03	46 05 .145	4.23
		270	54.36	50.95	83 41 .593	3.41
5	49	272	55.68	51.40	46 05 .074	4.28
		276	53.90	50.17	83 41 .593	3.73
	50	278	53.34	49.72	46 05 .072	3.62
		280	52.70	48.58	83 41 .175	4.12
	51	284	54.59	50.95	46 05 .114	3.64
		286	54.01	50.93	83 41 .182	3.09
	52	290	55.84	51.79	46 05 .064	4.05
		291	54.34	50.91	83 41 .103	3.43
	54	299	54.10	50.48	46 05 .062	3.62
		303	54.36	50.95	83 40 .964	3.41
	55	306	54.41	51.04	46 05 .094	3.37
		310	54.31	50.86	83 40 .936	3.45

Table 6: Descriptive Statistics by Location

Location	1	2	3	4	5
Number of pictures	9	12	16	10	12
Maximum Set 1	54.54	54.44	57.17	55.22	55.84
Maximum Set 2	51.08	51.06	52.67	51.29	51.79
Minimum Set 1	53.10	48.70	53.18	53.19	52.70
Minimum Set 2	48.70	53.16	47.14	49.03	48.58
Range Set 1	1.44	1.28	3.99	2.03	3.13
Range Set 2	2.38	1.66	5.53	2.27	3.20
Average Set 1	54.13	50.56	54.74	54.08	54.30
Average Set 2	50.56	54.10	50.59	50.32	50.65
Variance Set 1	0.28	0.67	1.31	0.47	0.74
Variance Set 2	0.67	0.26	1.46	0.78	0.71
Standard Deviation Set 1	0.53	0.82	1.14	0.68	0.86
Standard Deviation Set 2	0.82	0.51	1.21	0.89	0.84

APPENDIX B: IMAGES

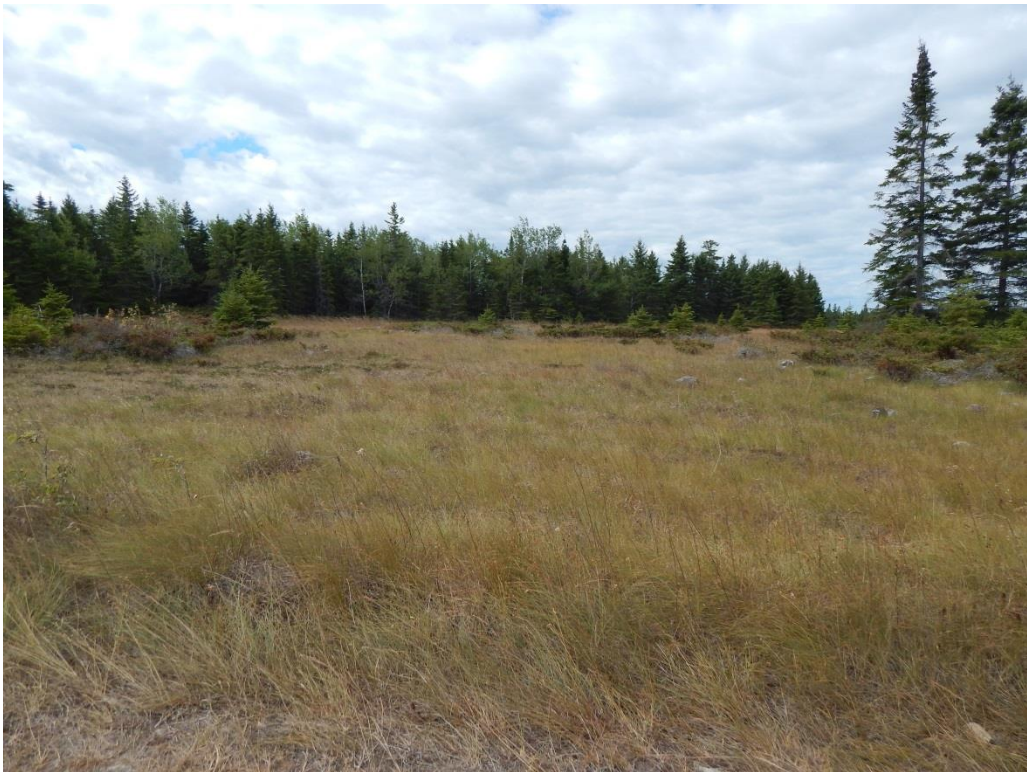


Figure 8: Image 5

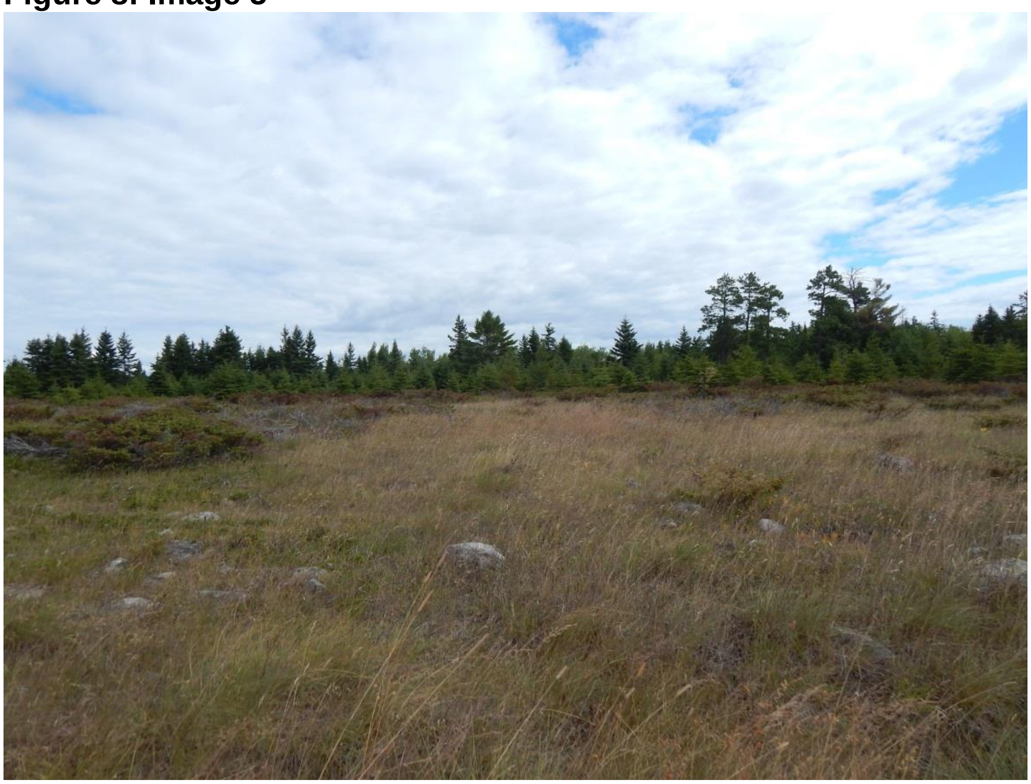


Figure 9: Image 8

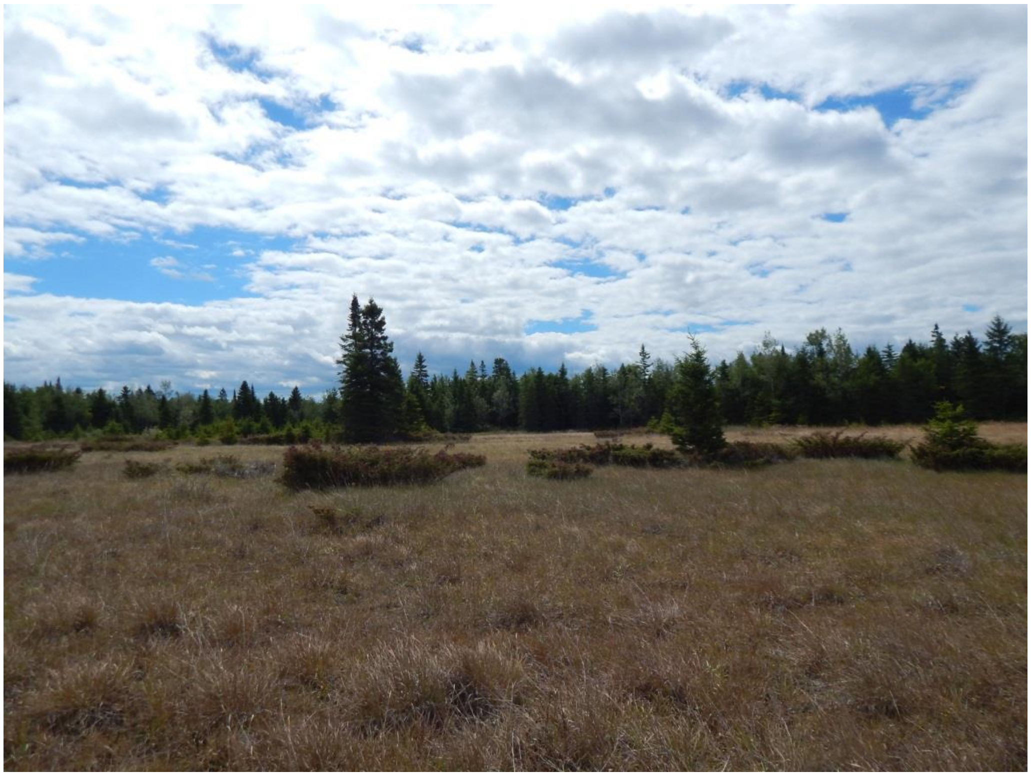


Figure 10: Image 10

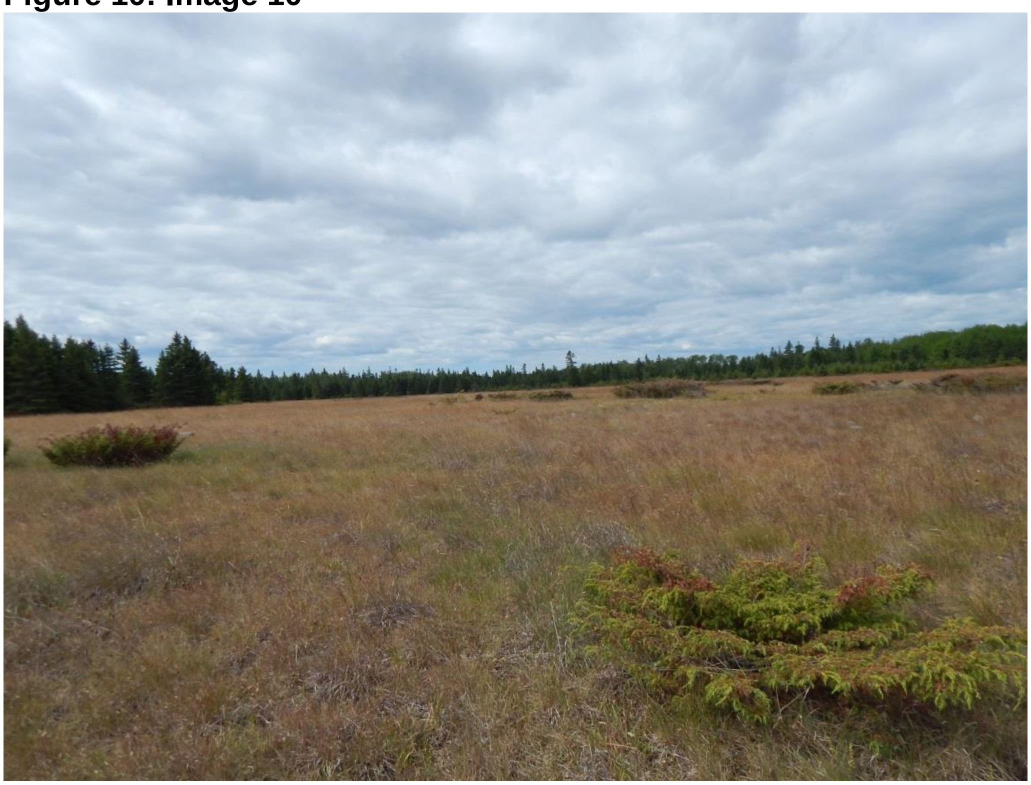


Figure 11: Image 12

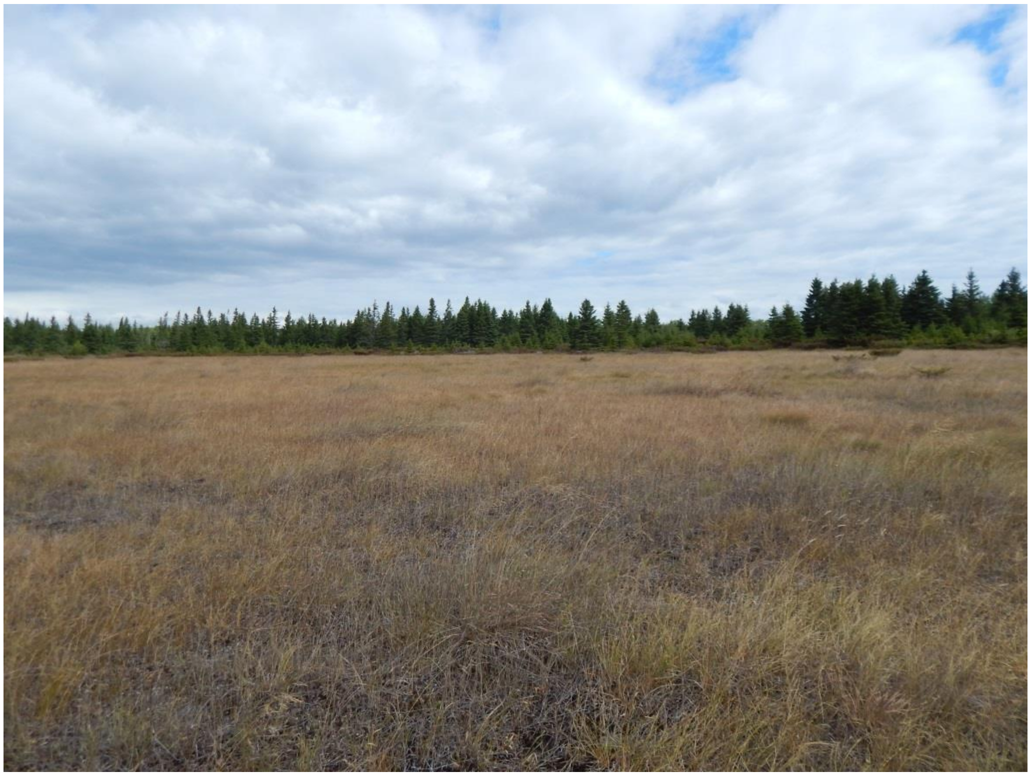


Figure 12: Image 15

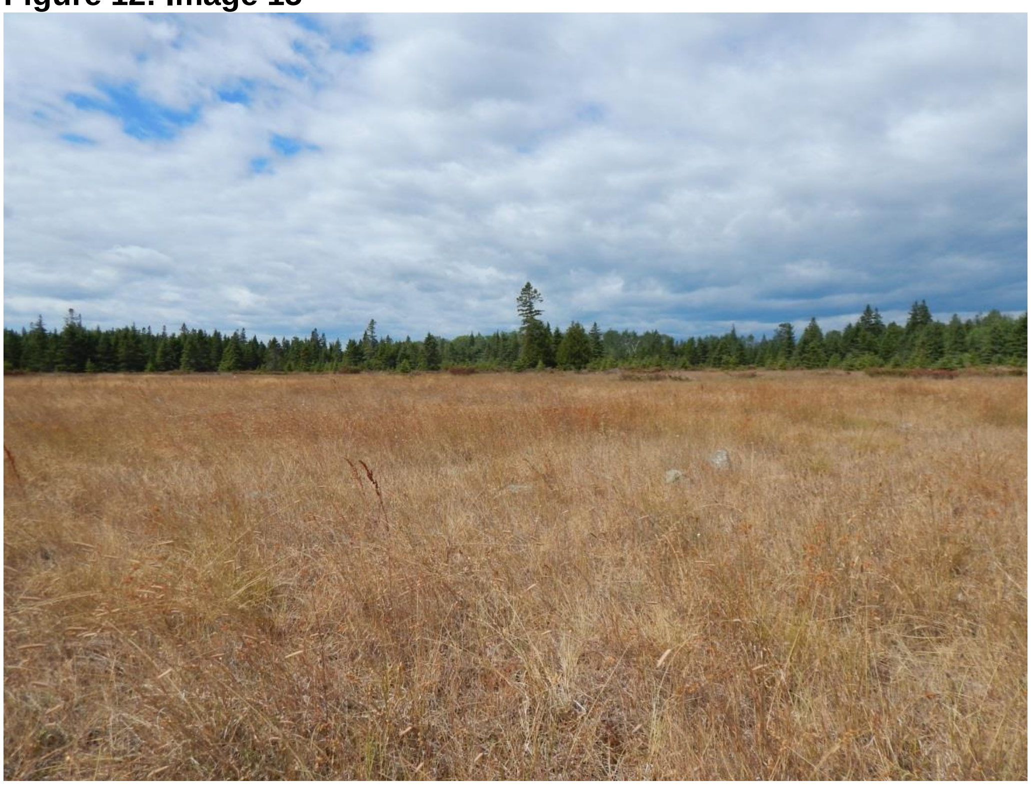


Figure 13: Image 29

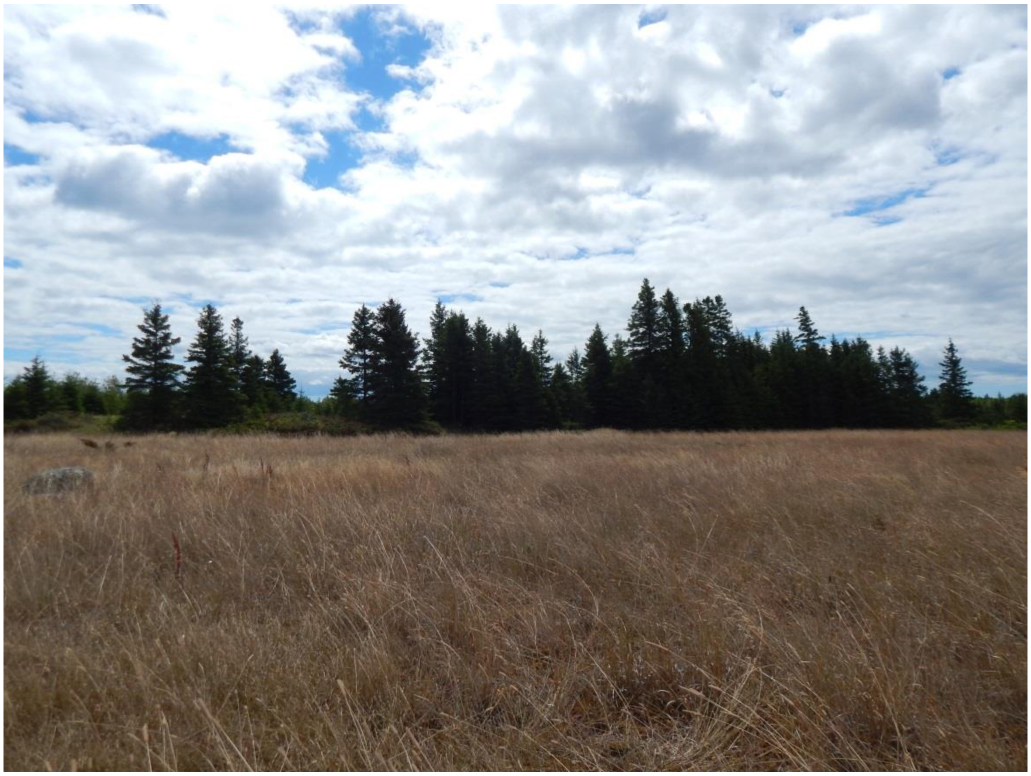


Figure 14: Image 33

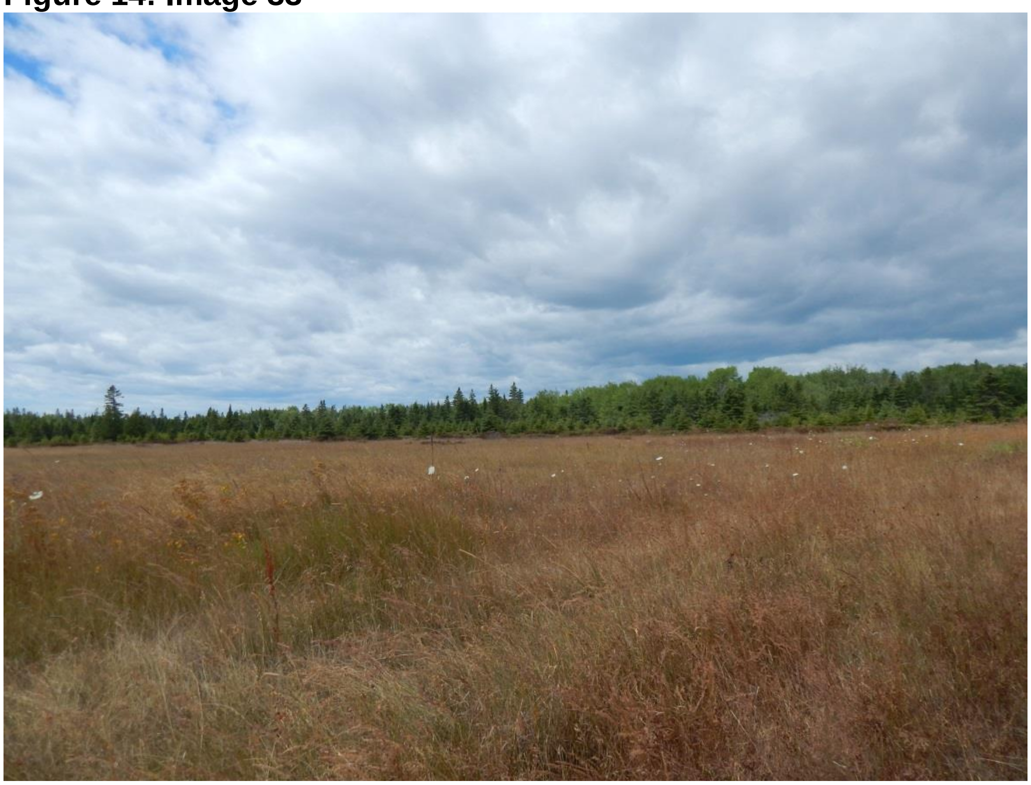


Figure 15: Image 35

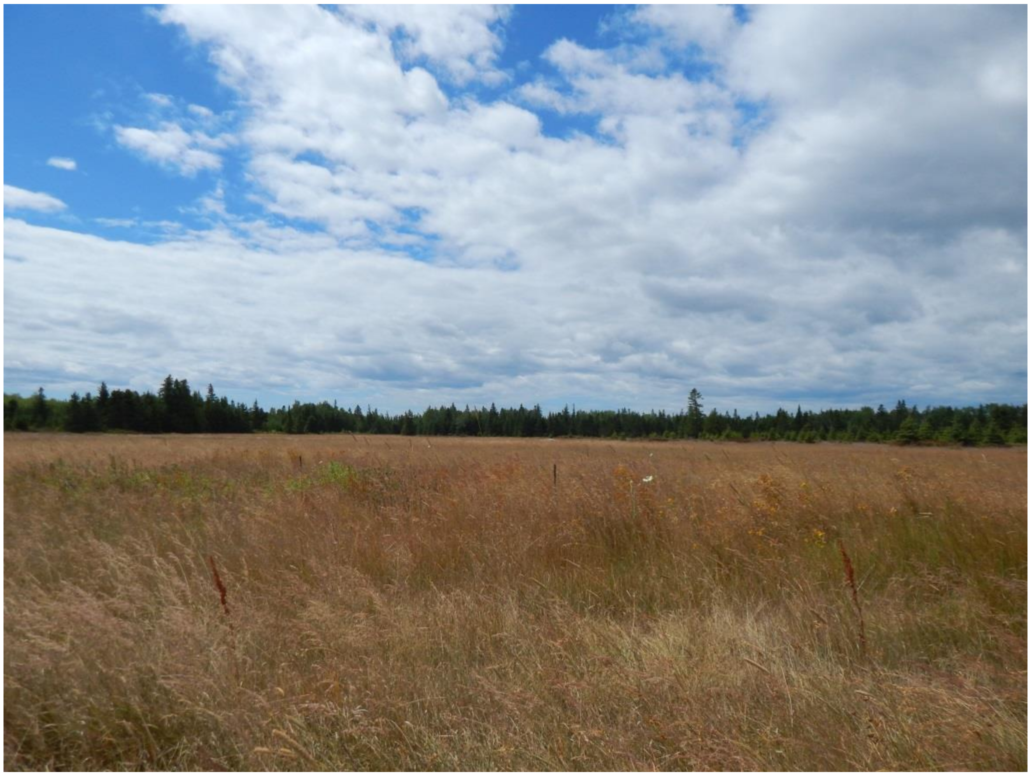


Figure 16: Image 36

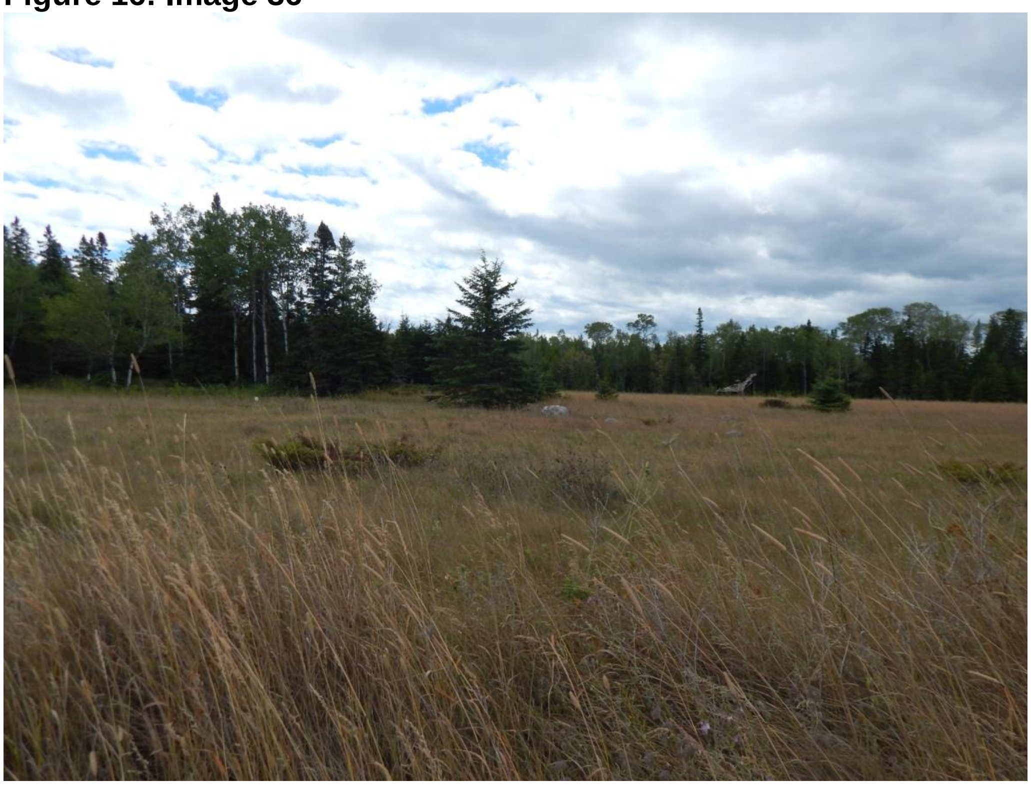


Figure 17: Image 50

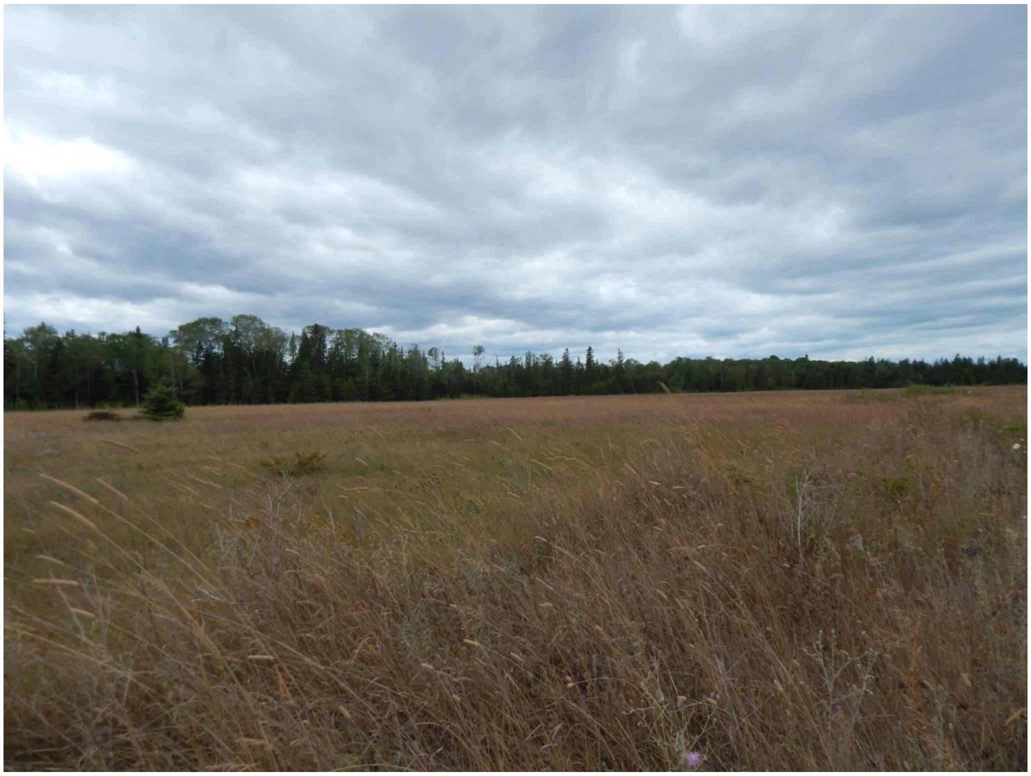


Figure 18: Image 51

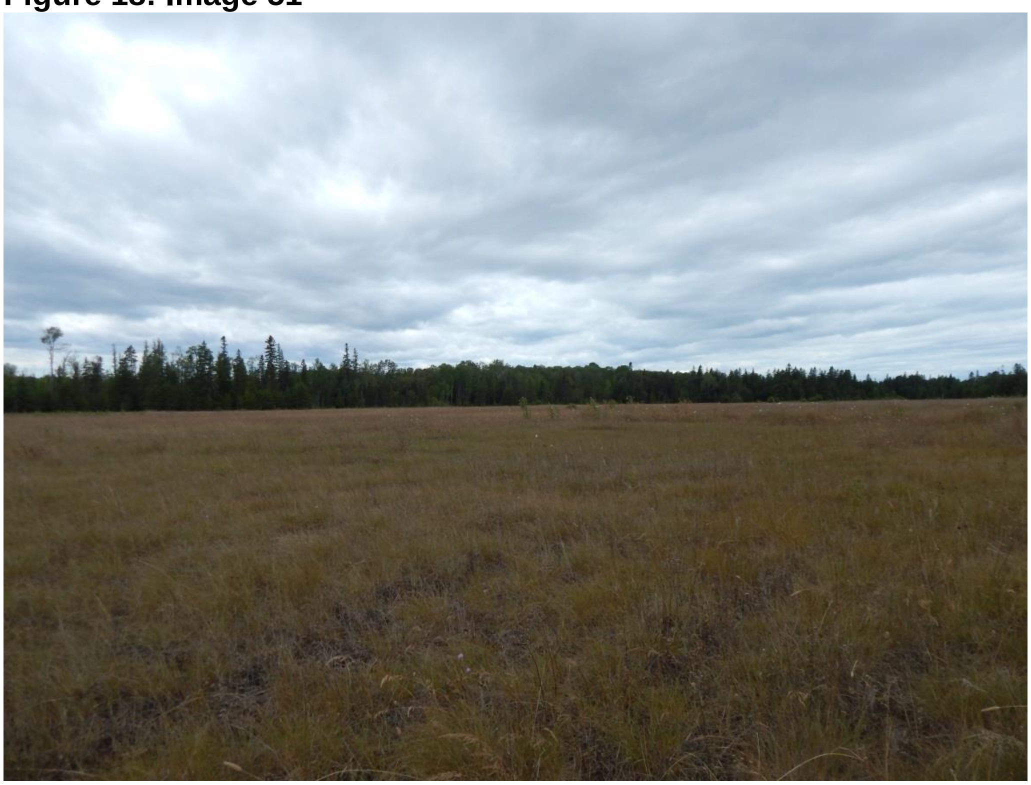
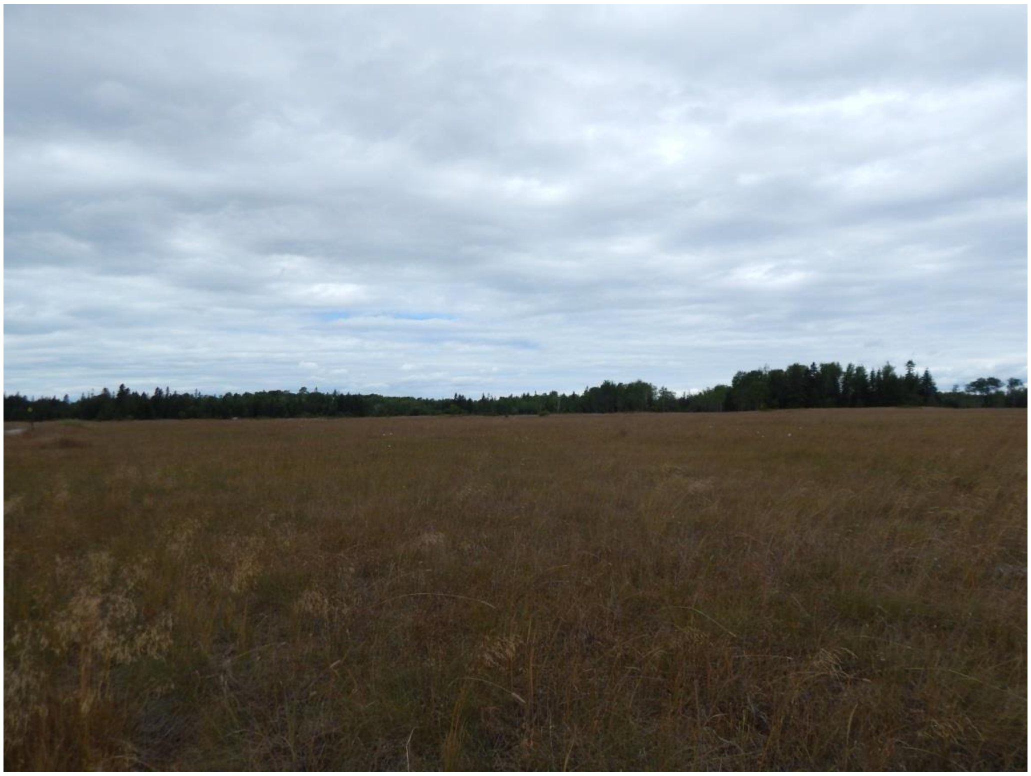


Figure 19: Image 55



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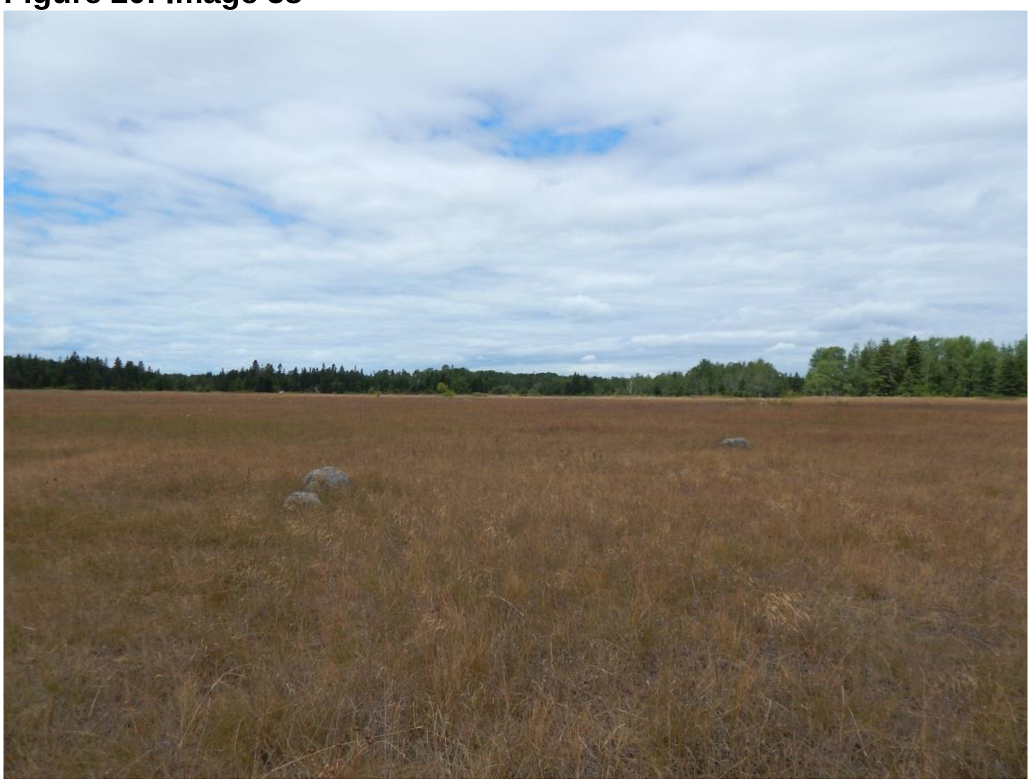

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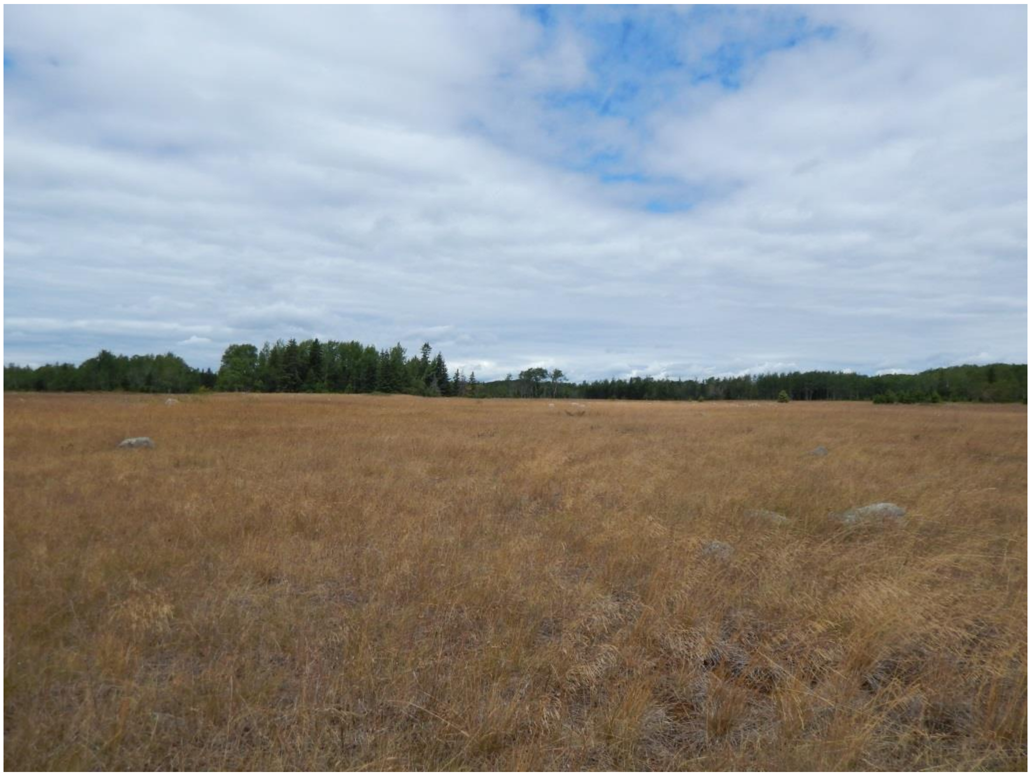
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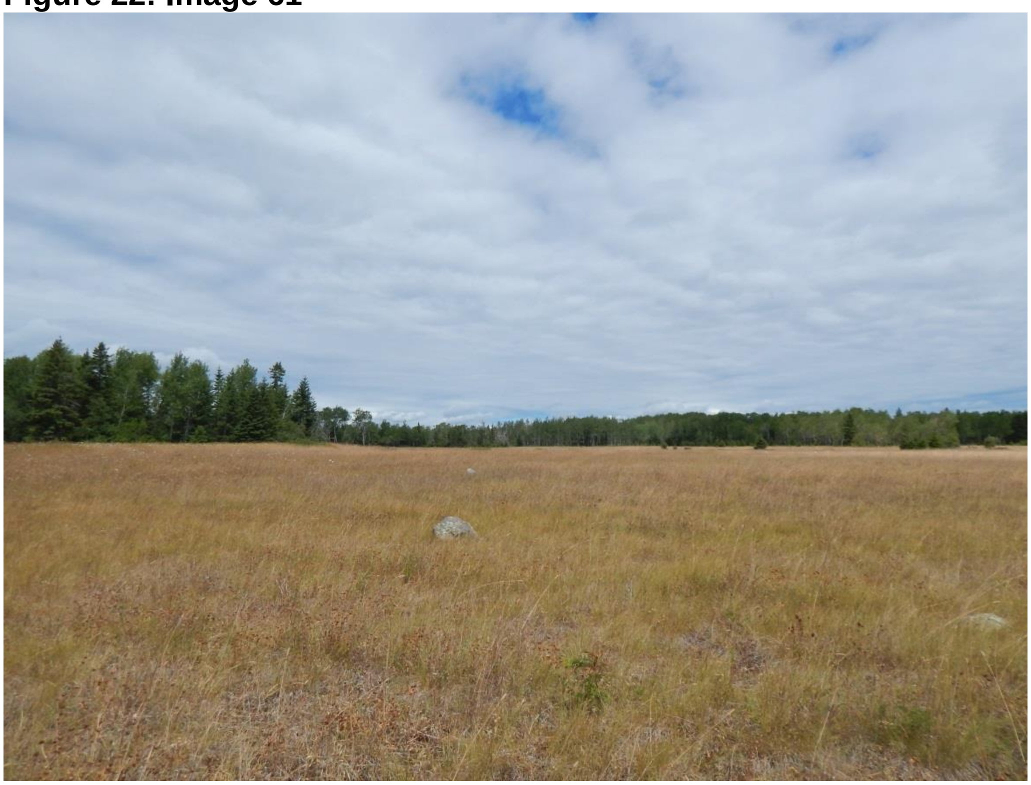
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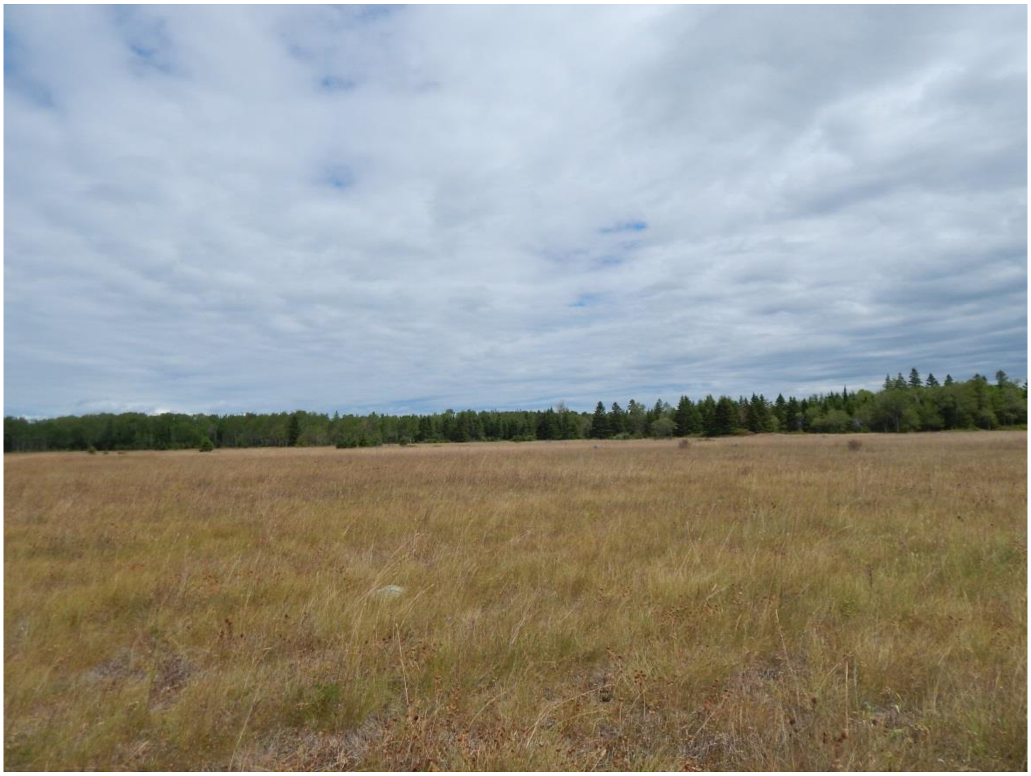
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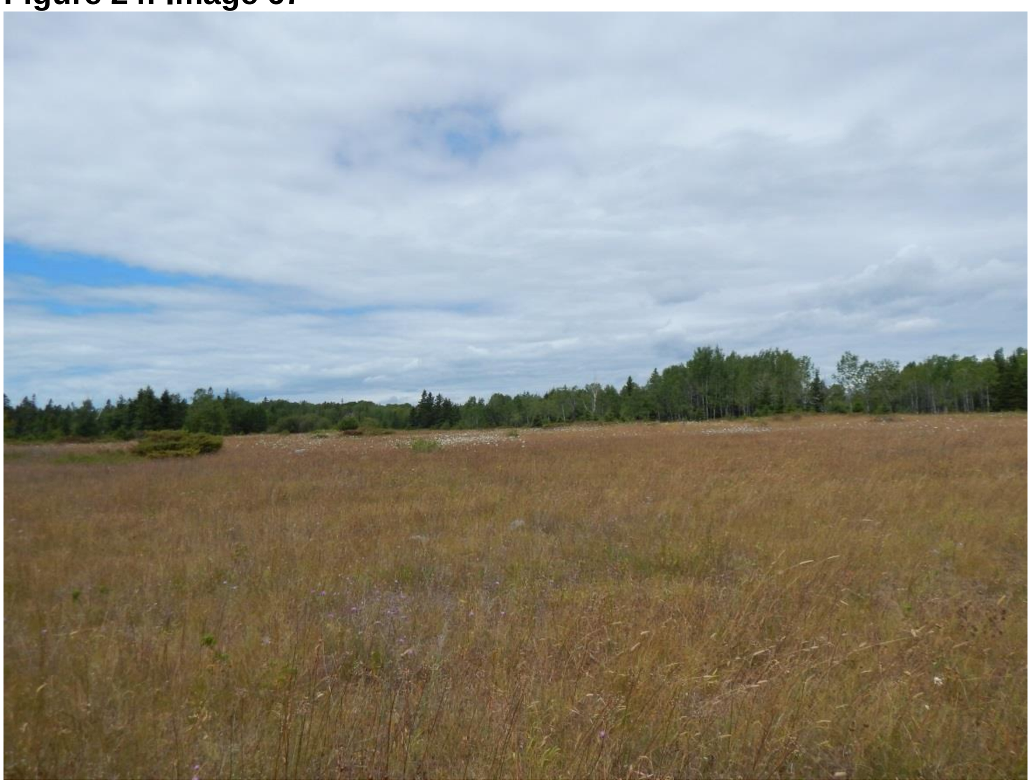
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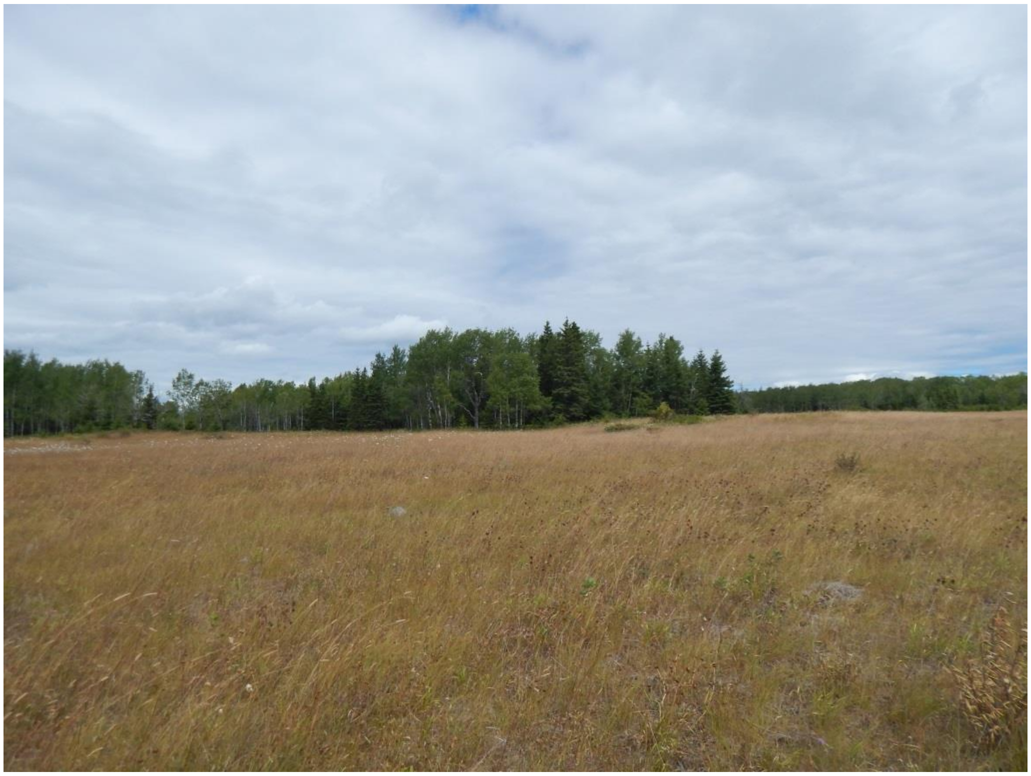

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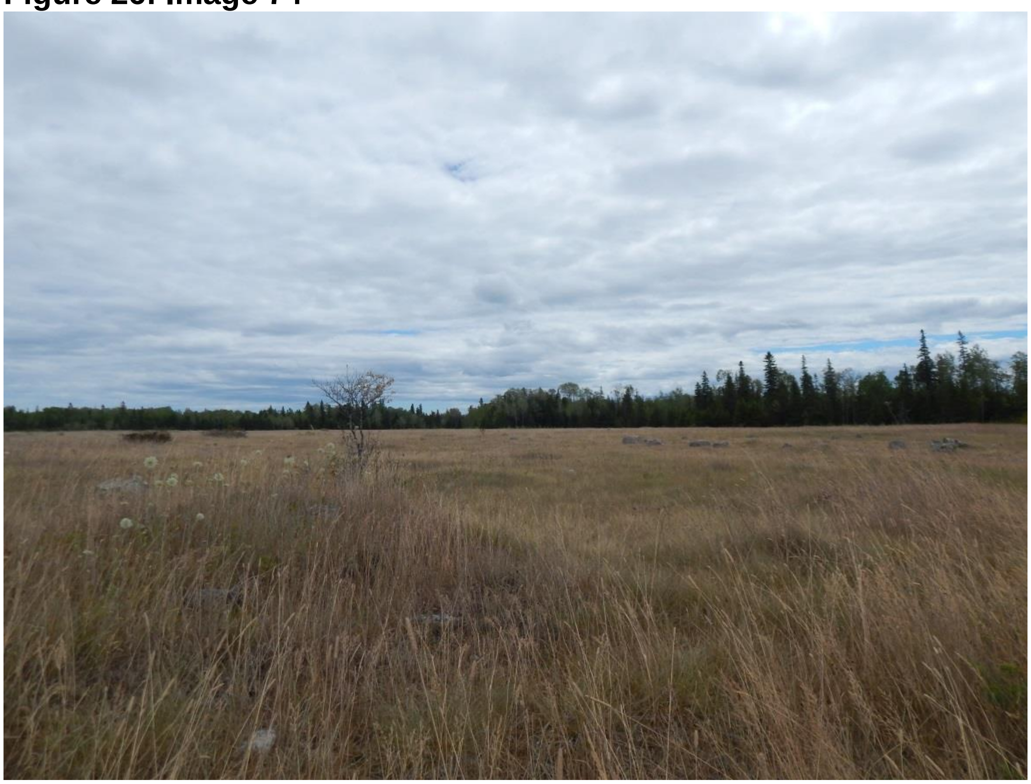

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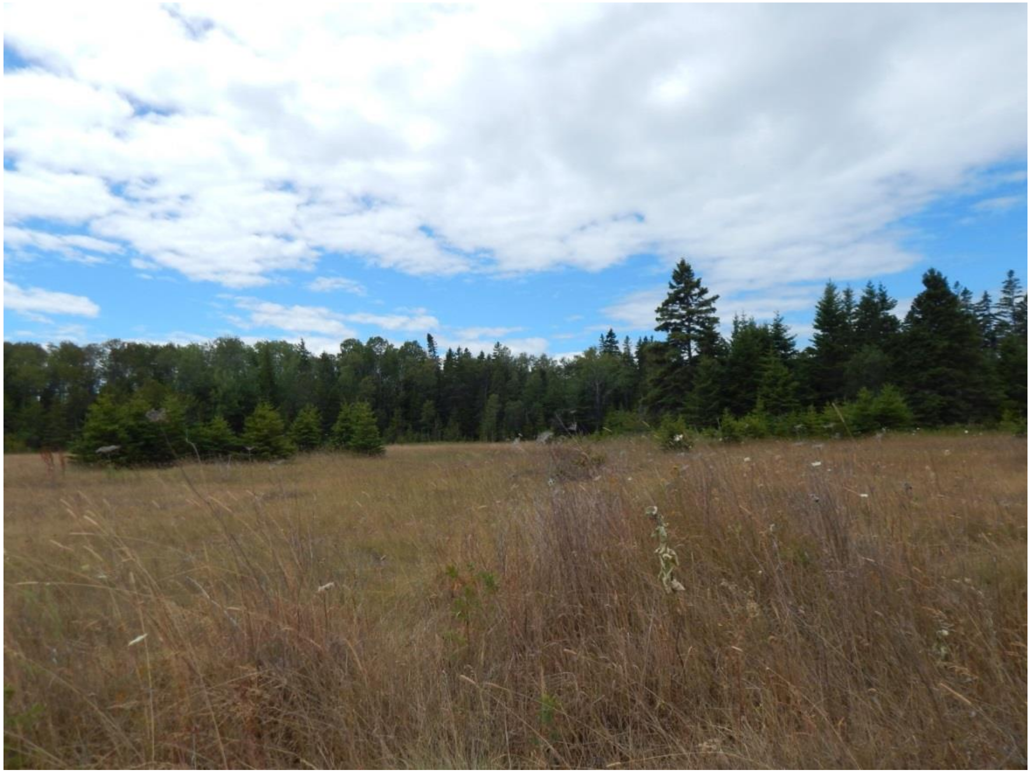

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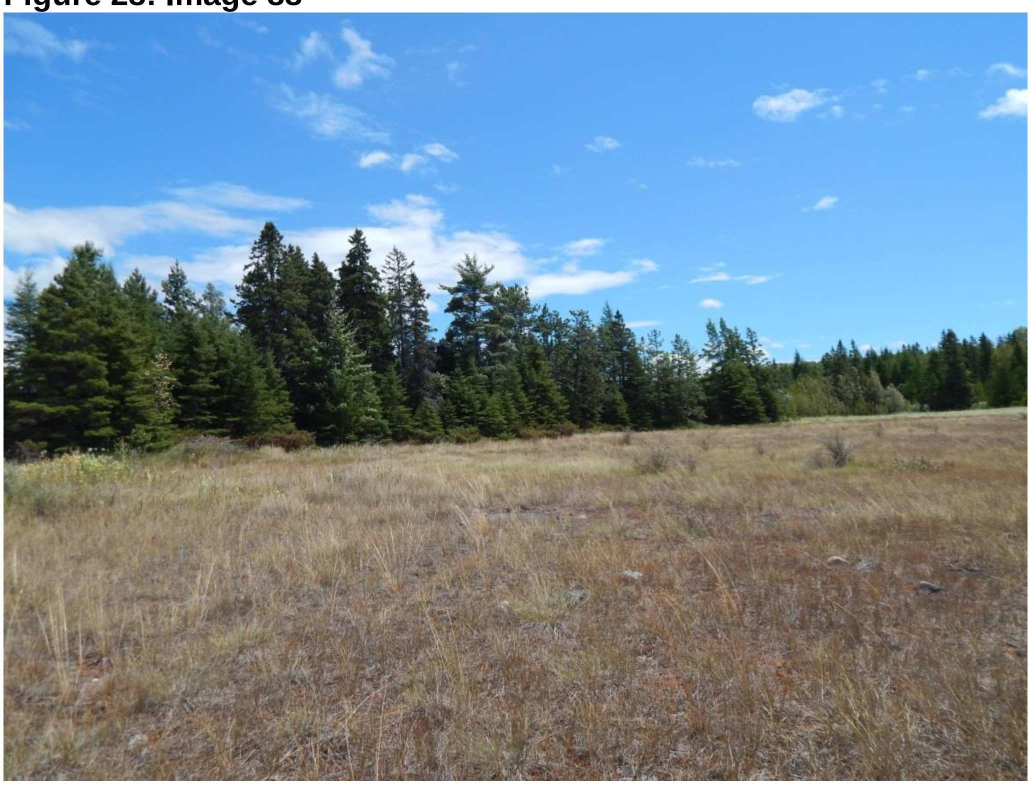

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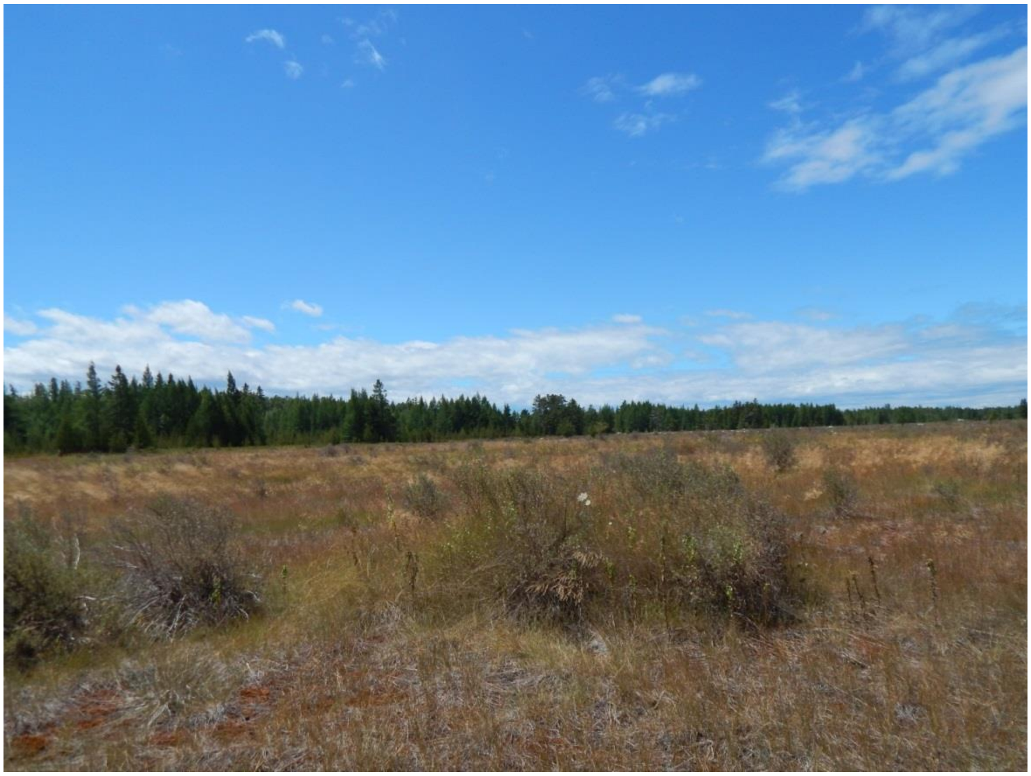

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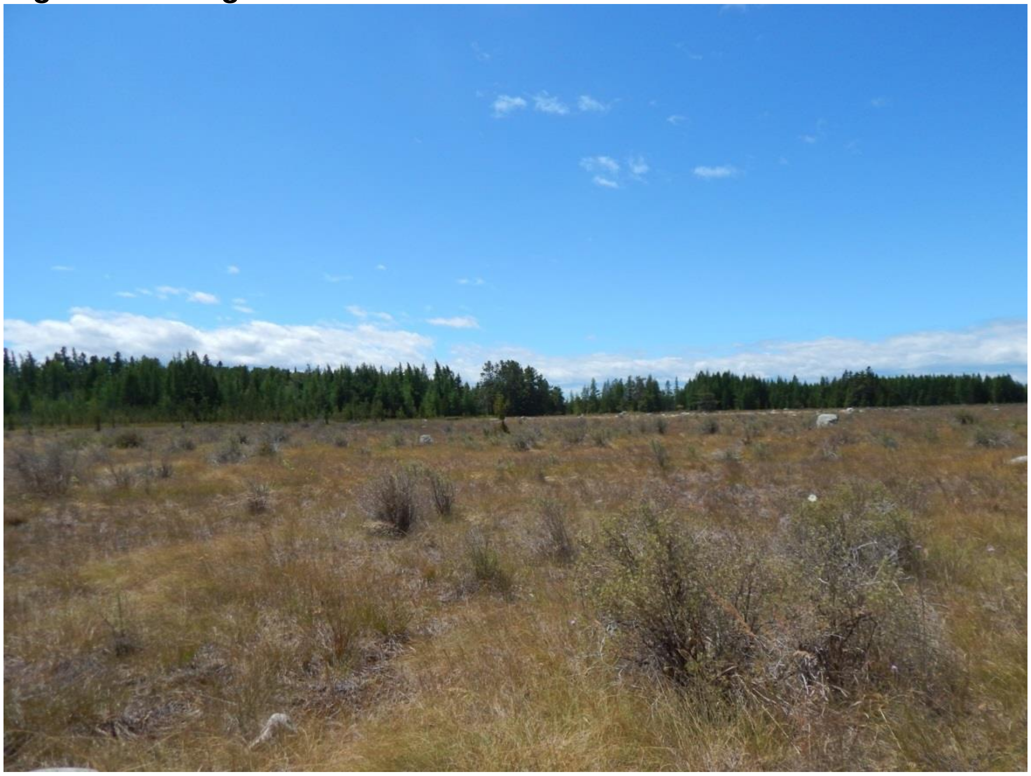

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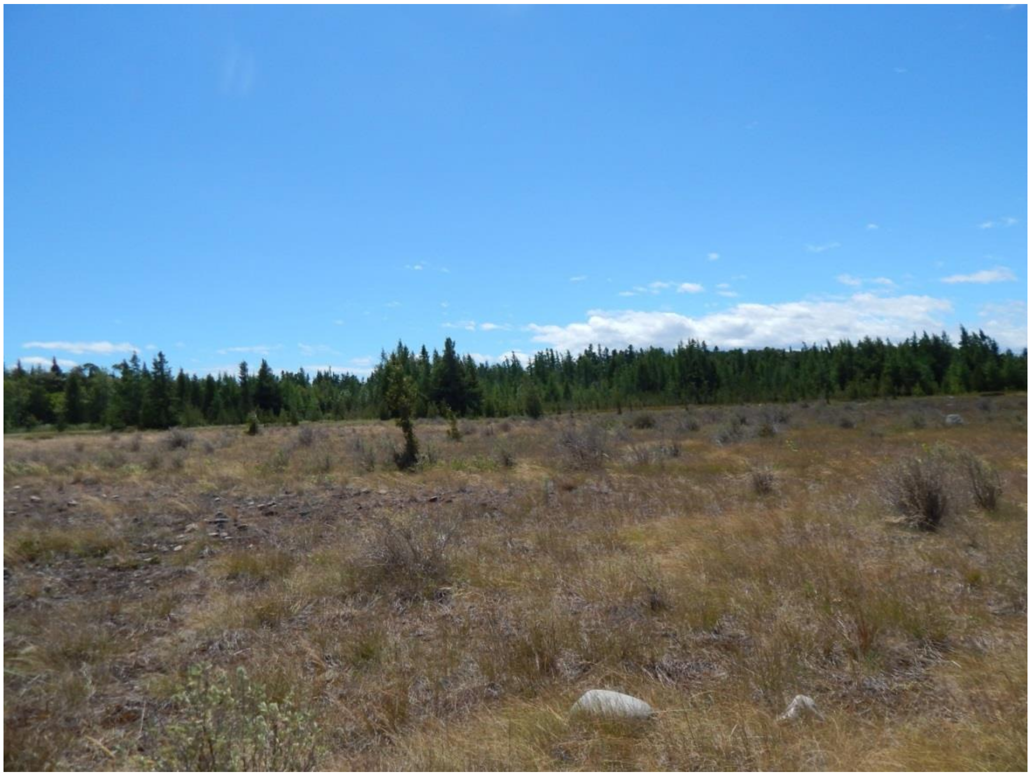

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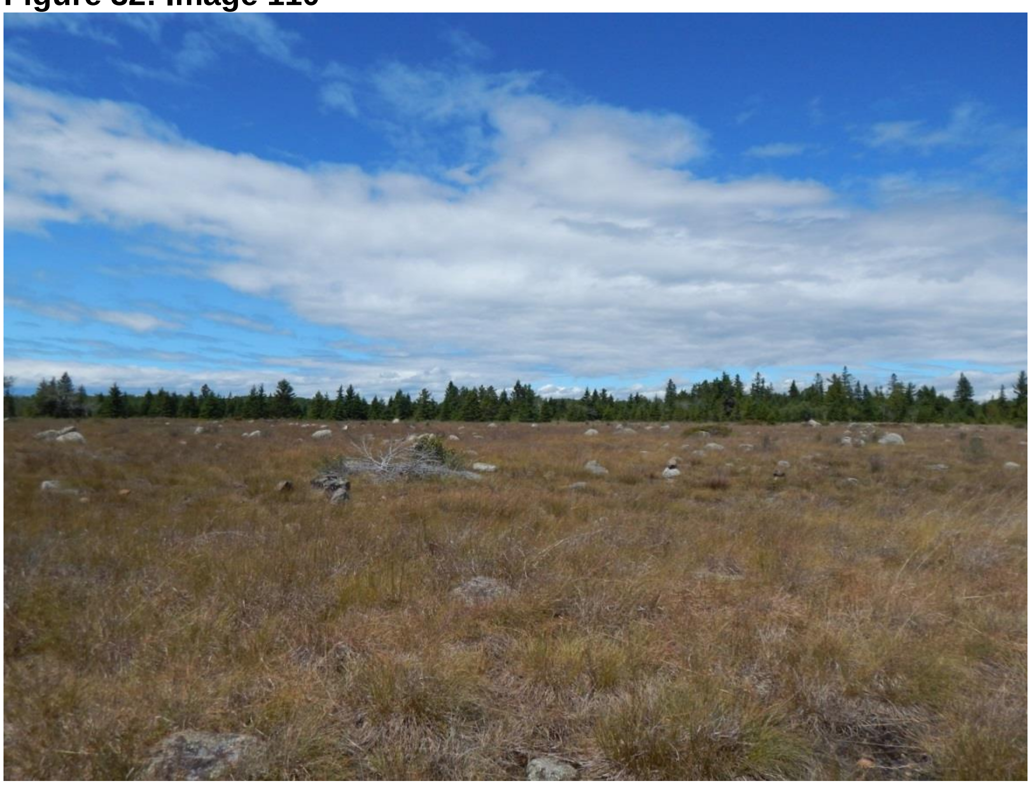

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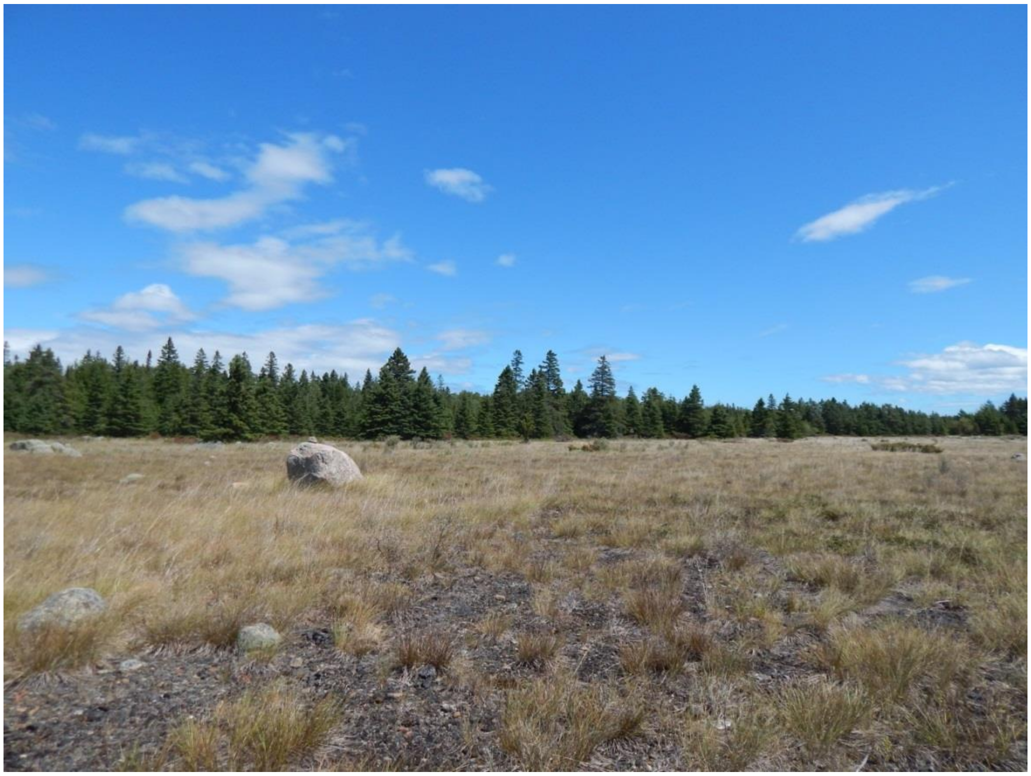

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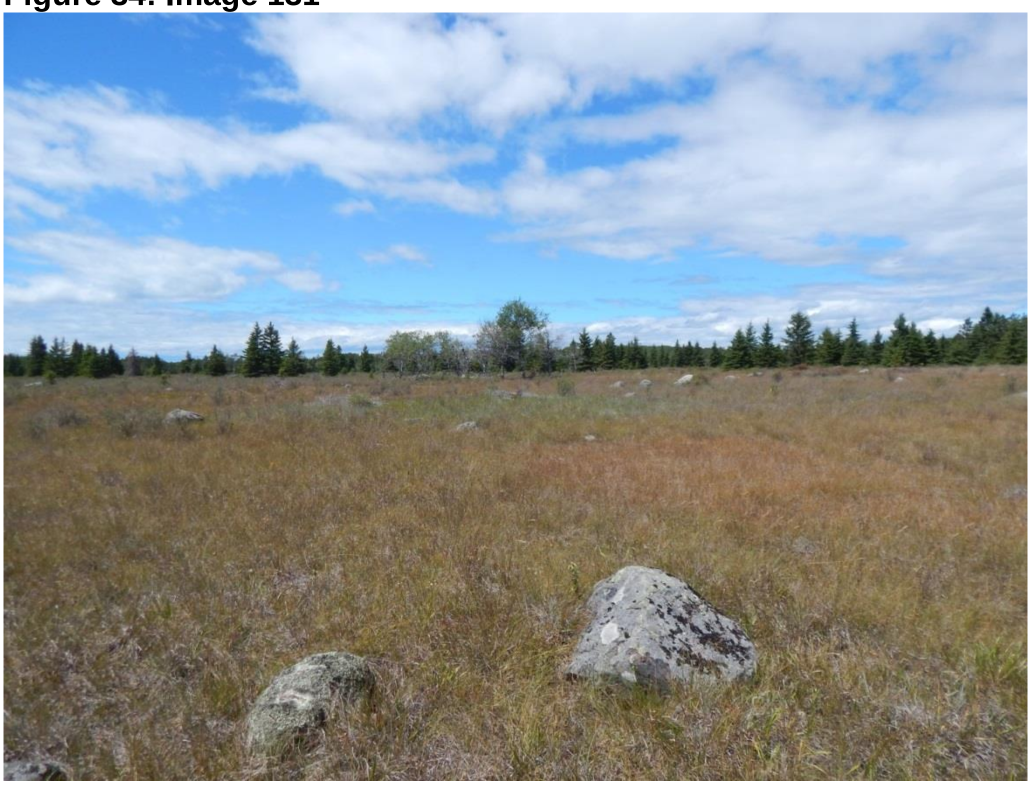

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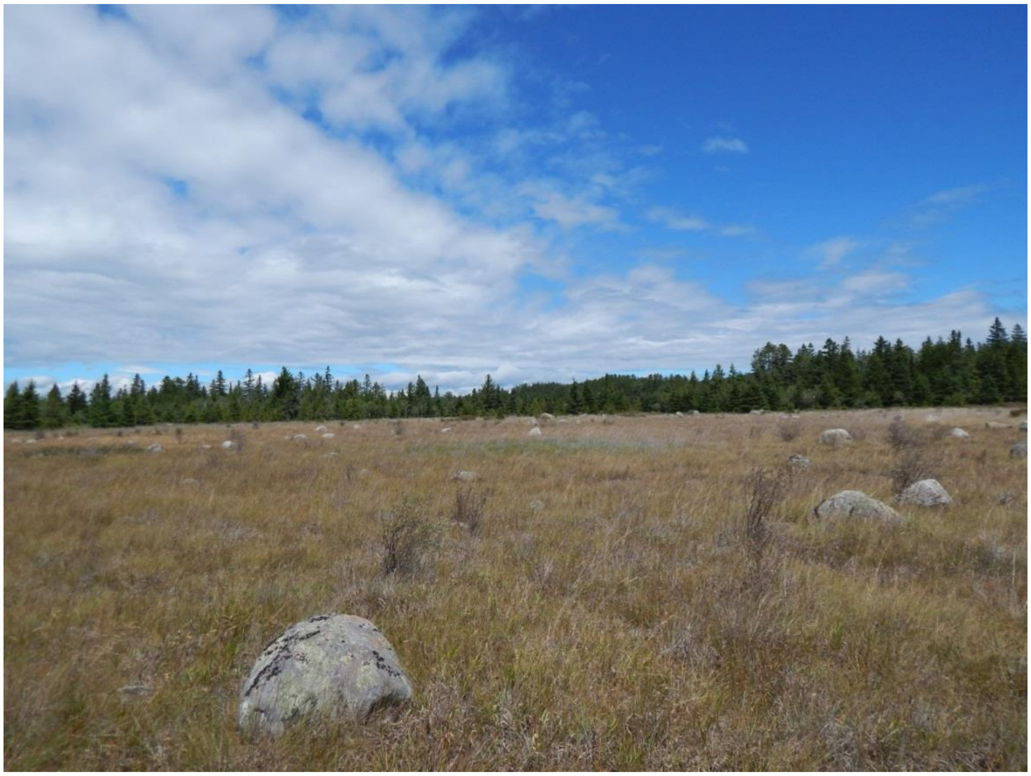
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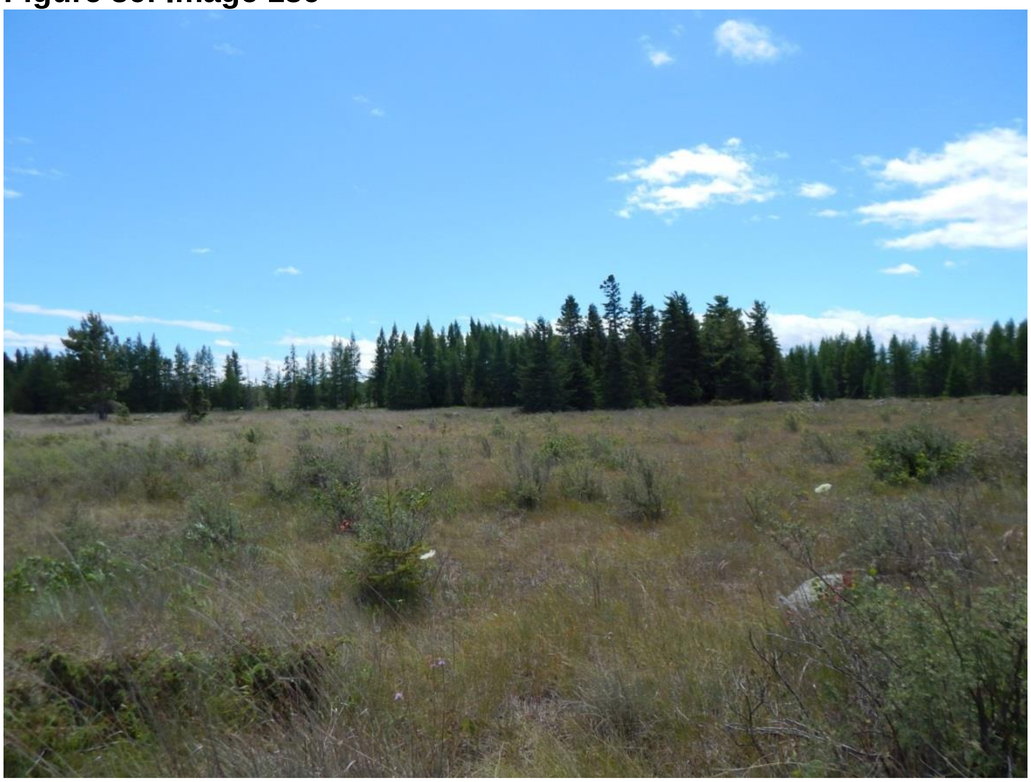
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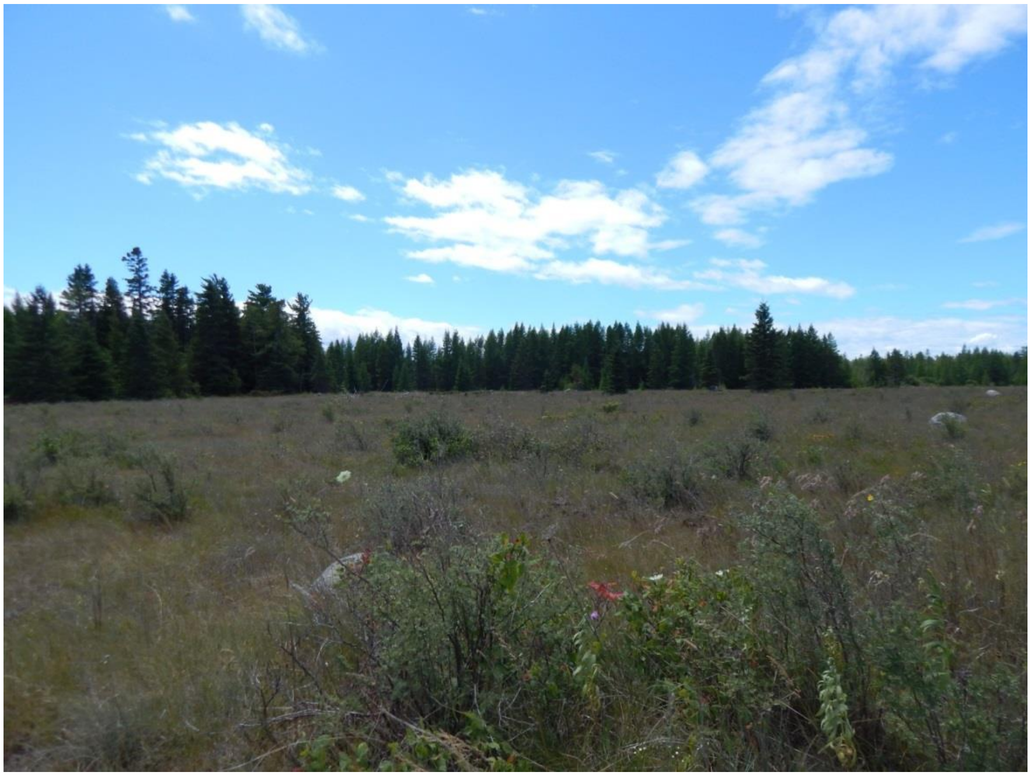
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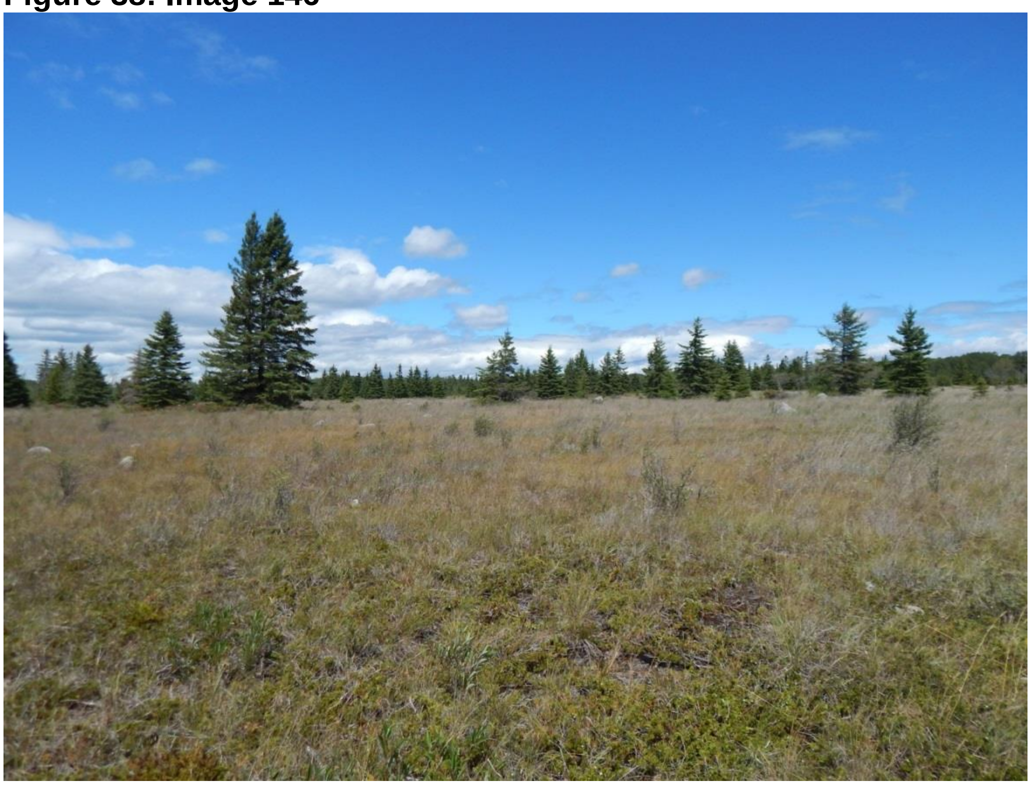
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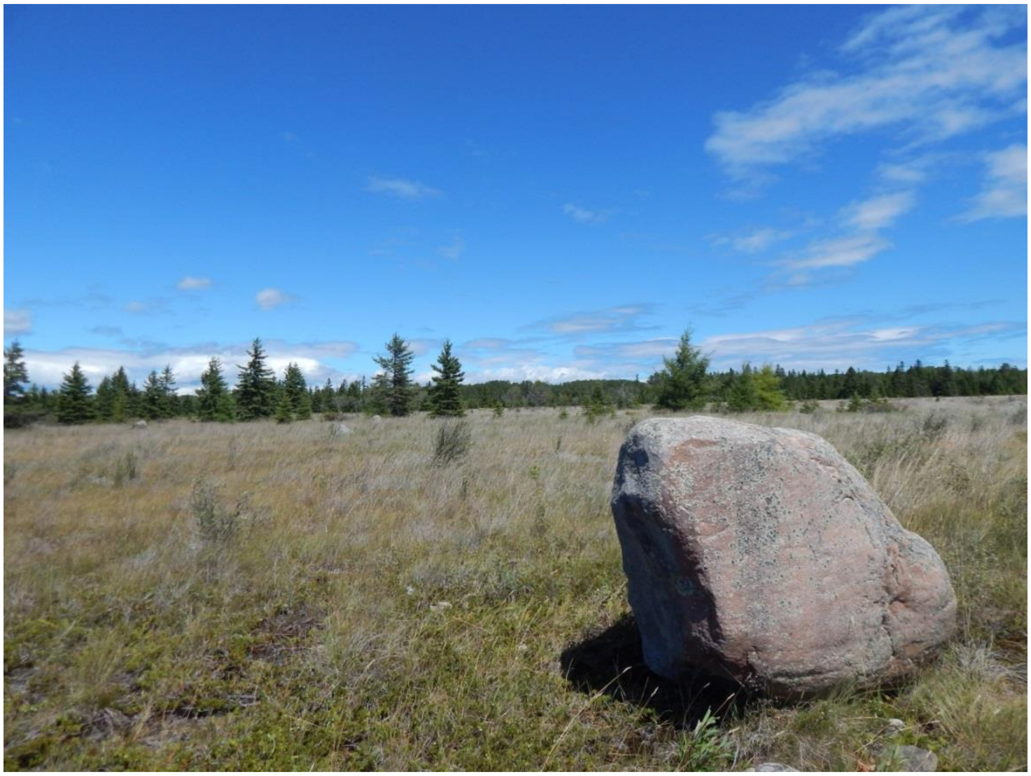

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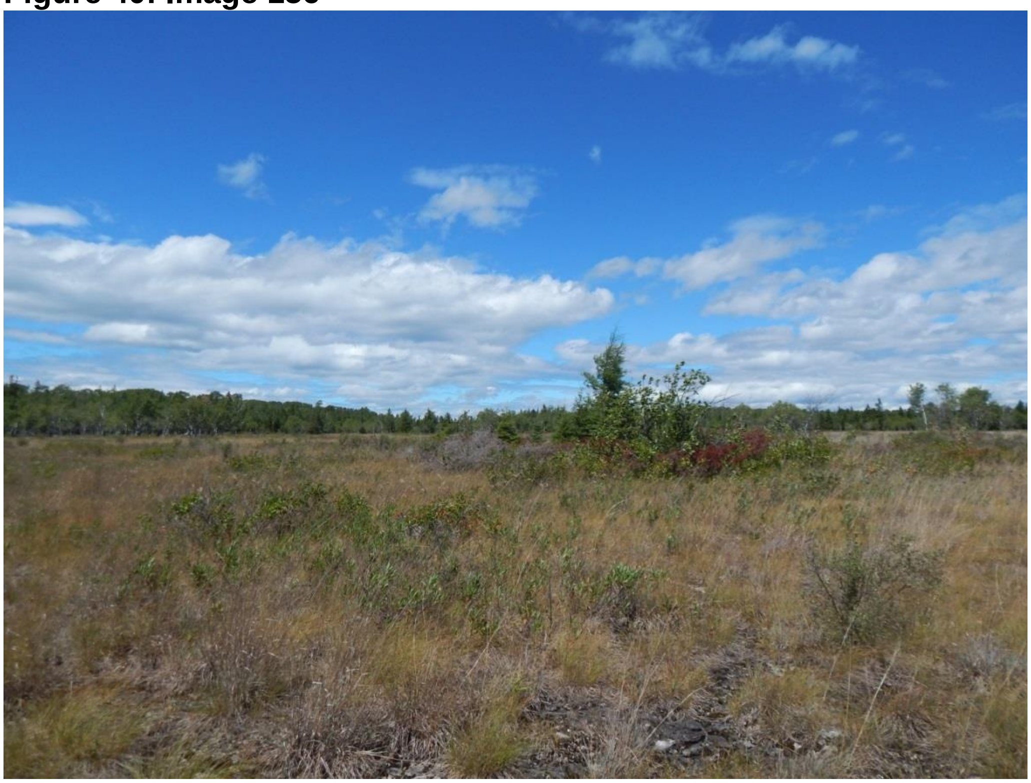

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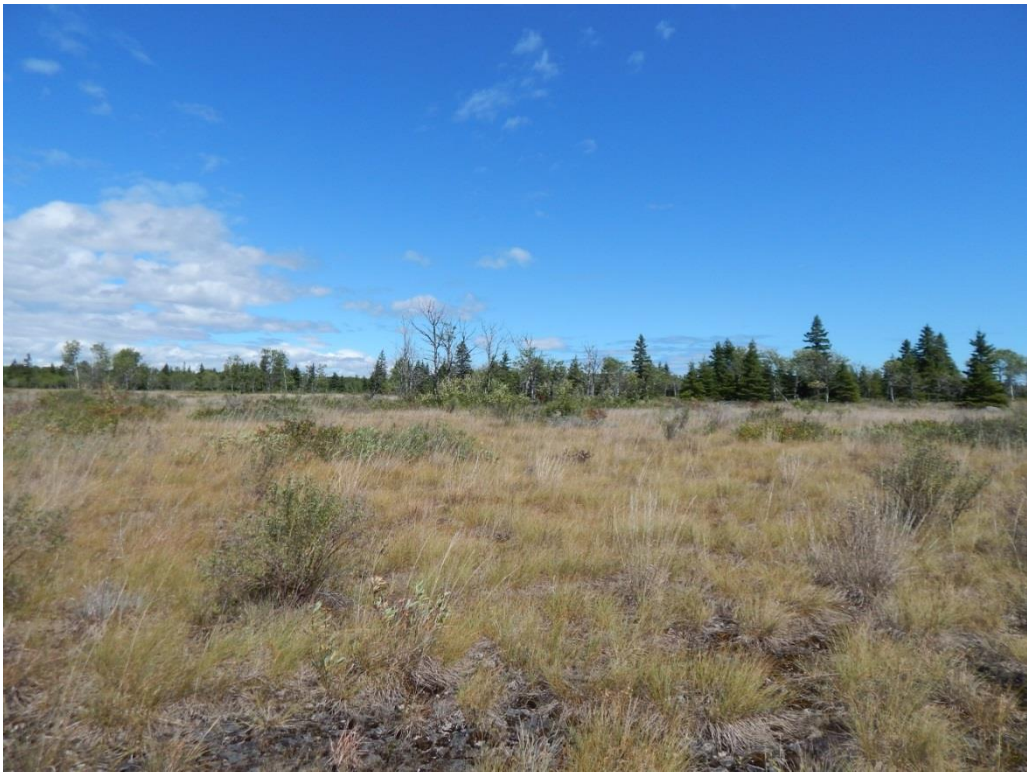

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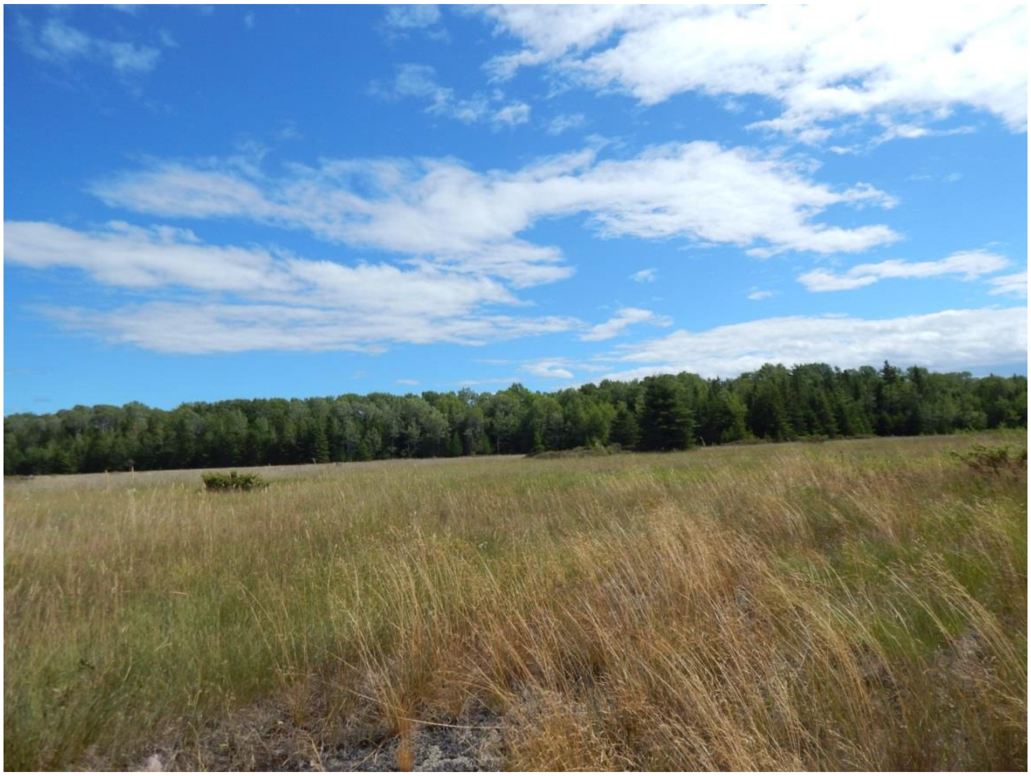

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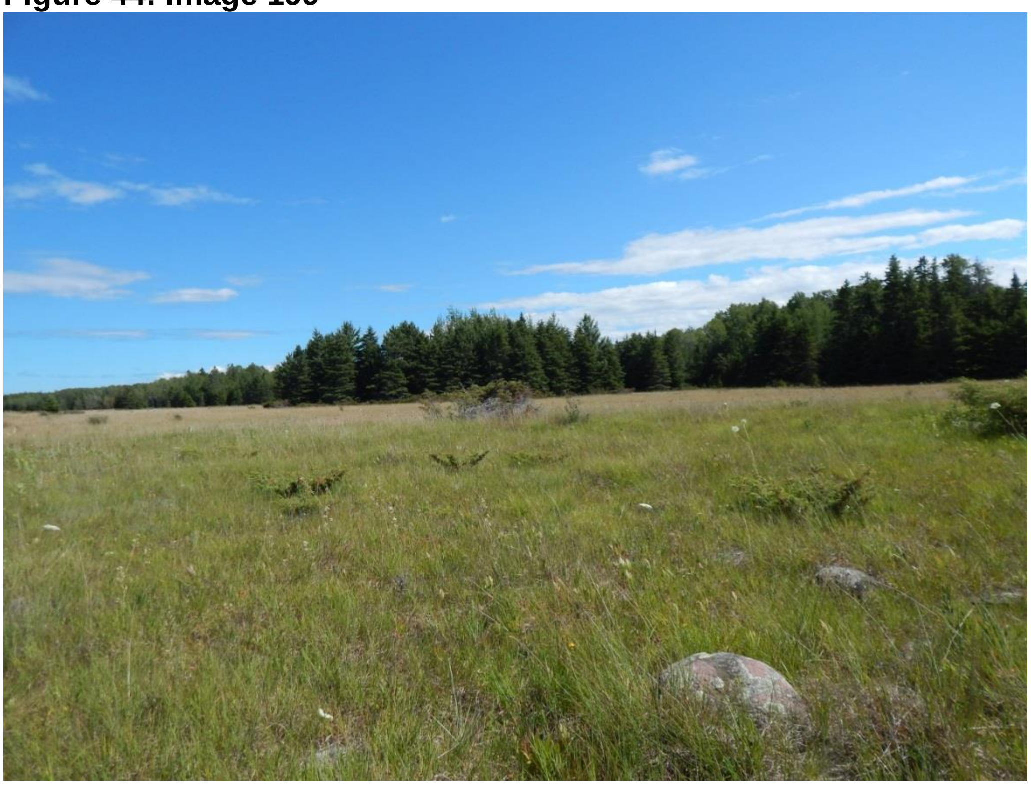

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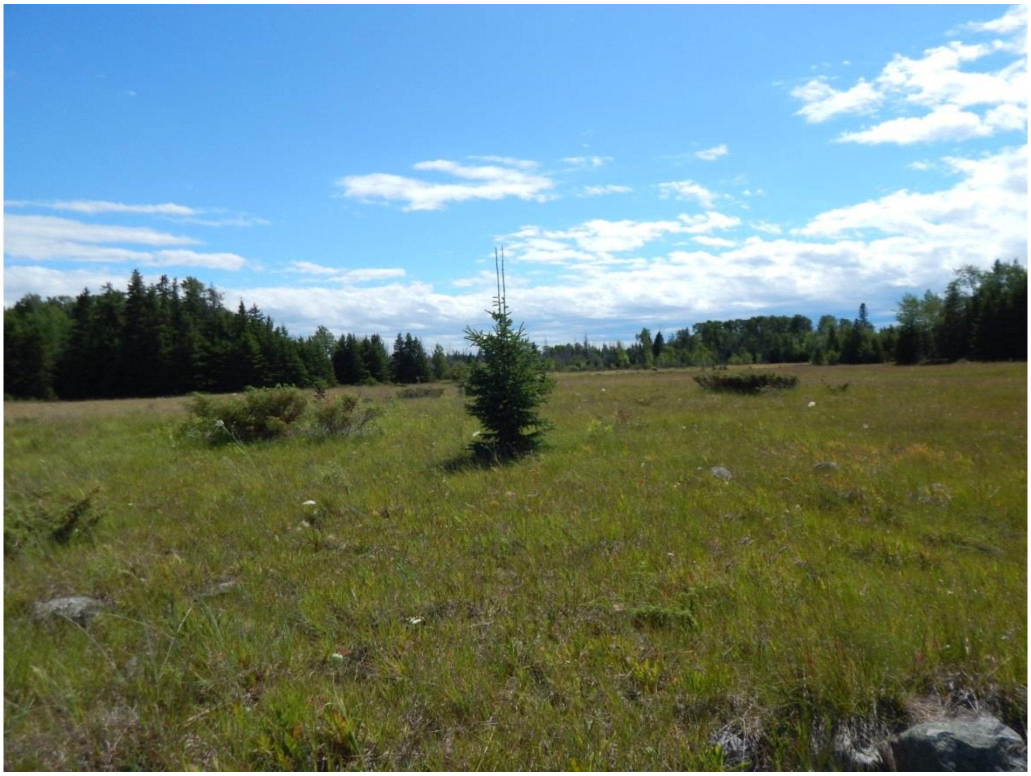
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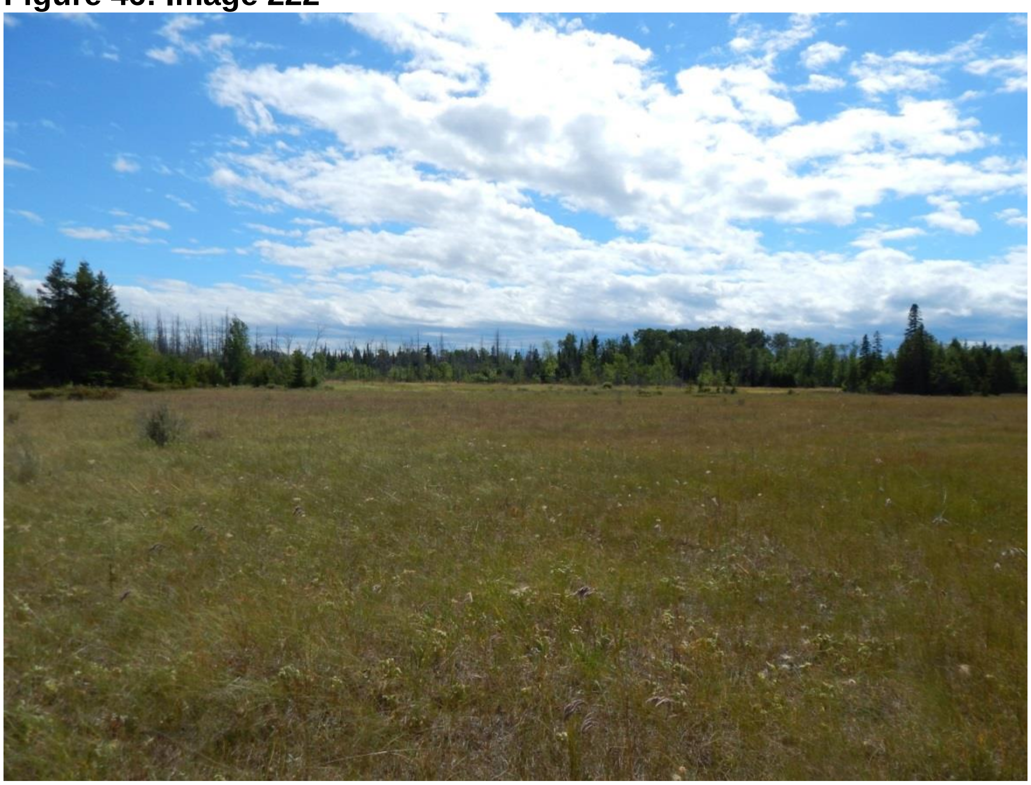
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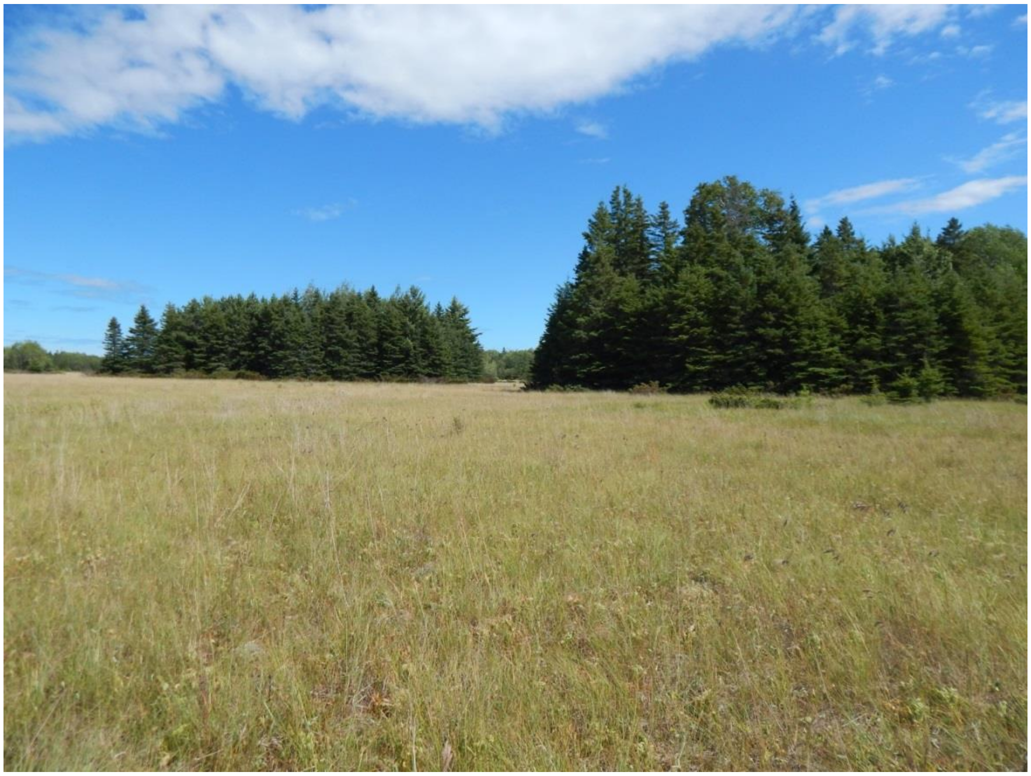
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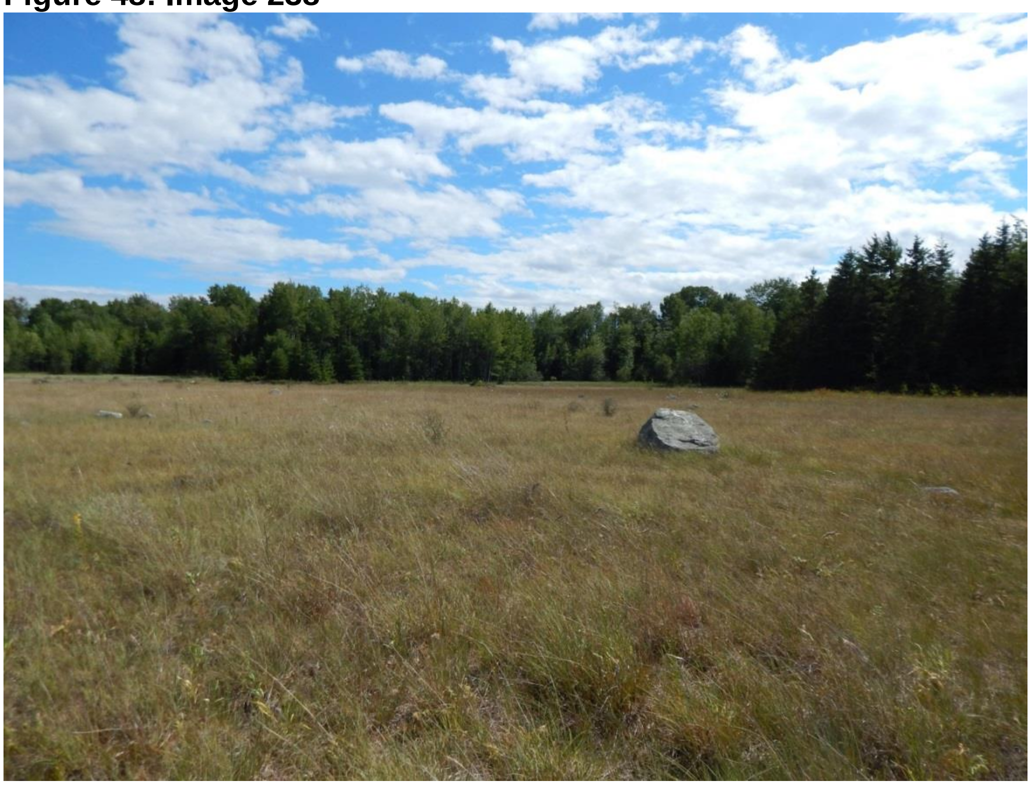
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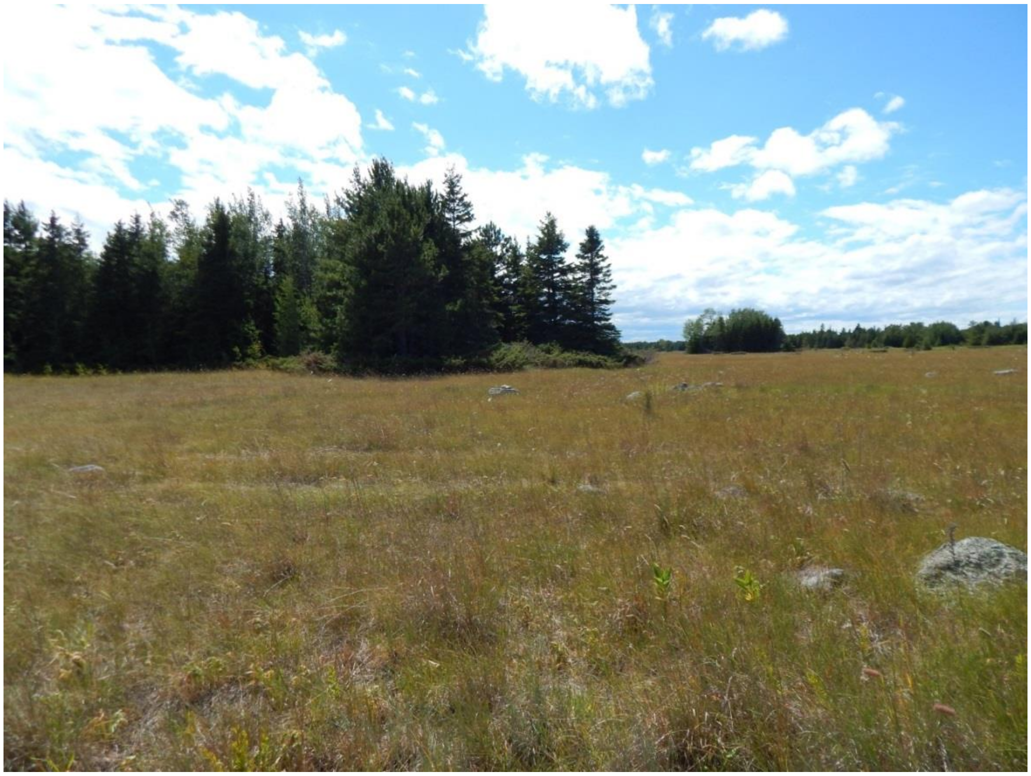
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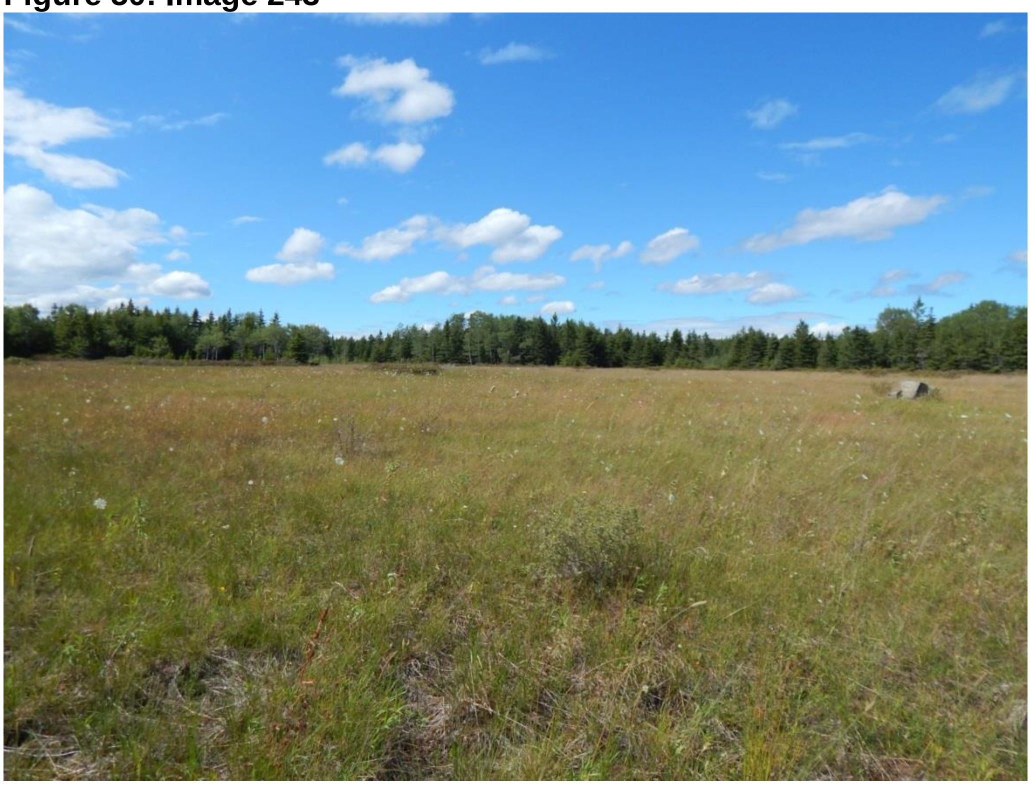
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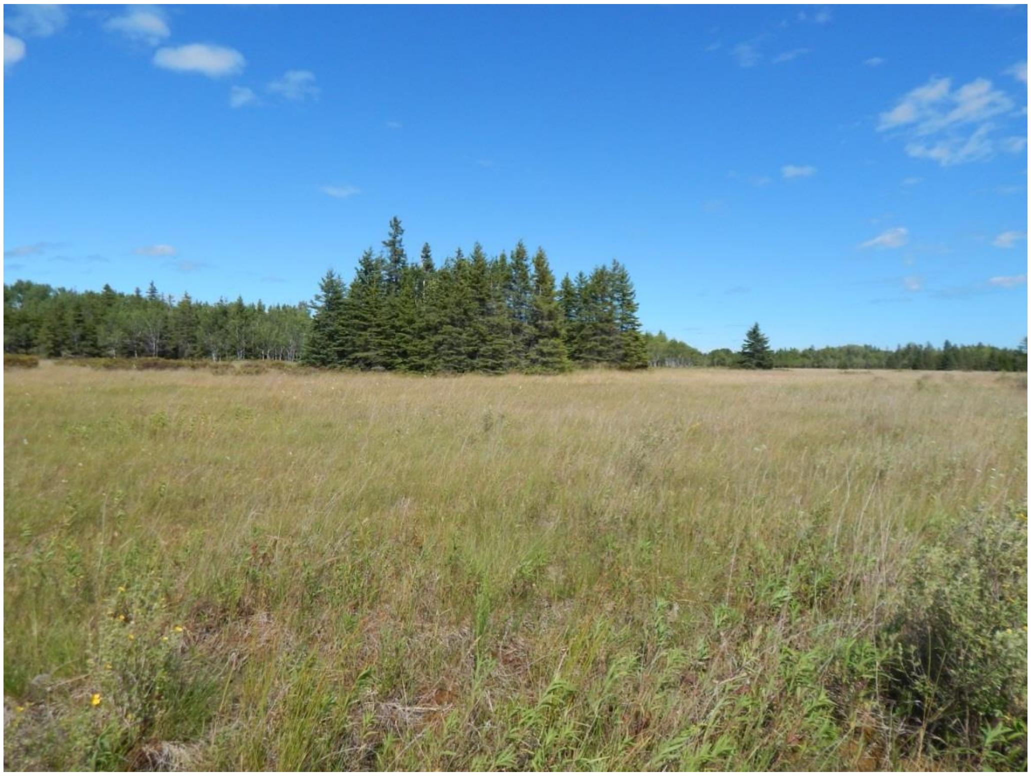

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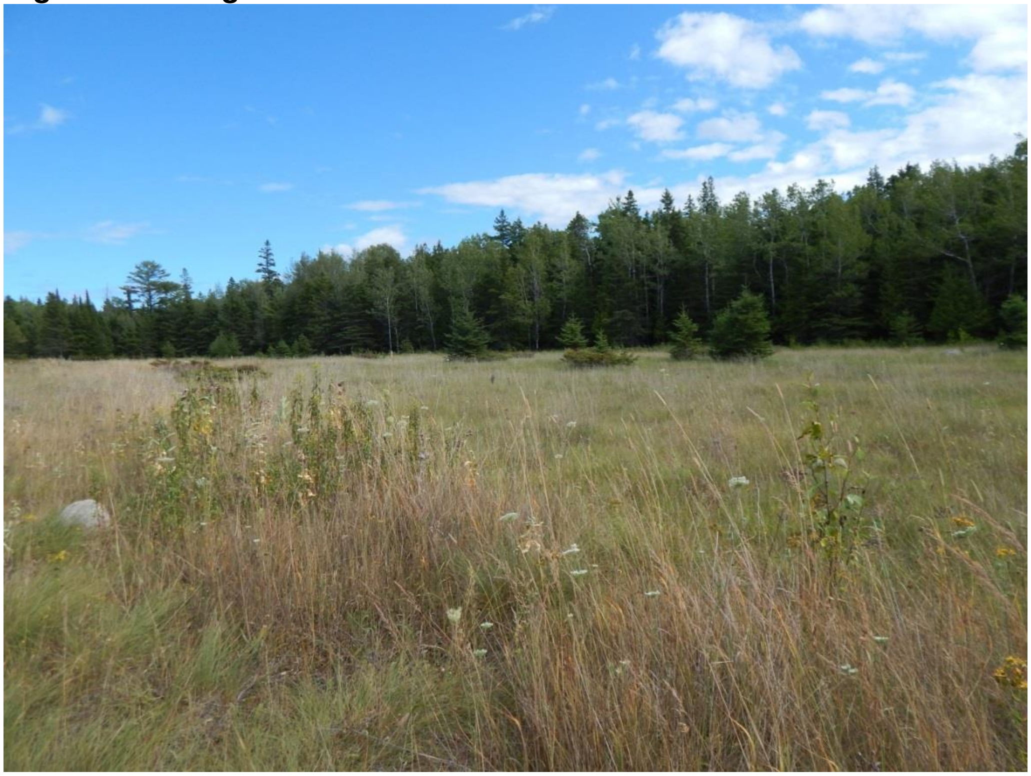

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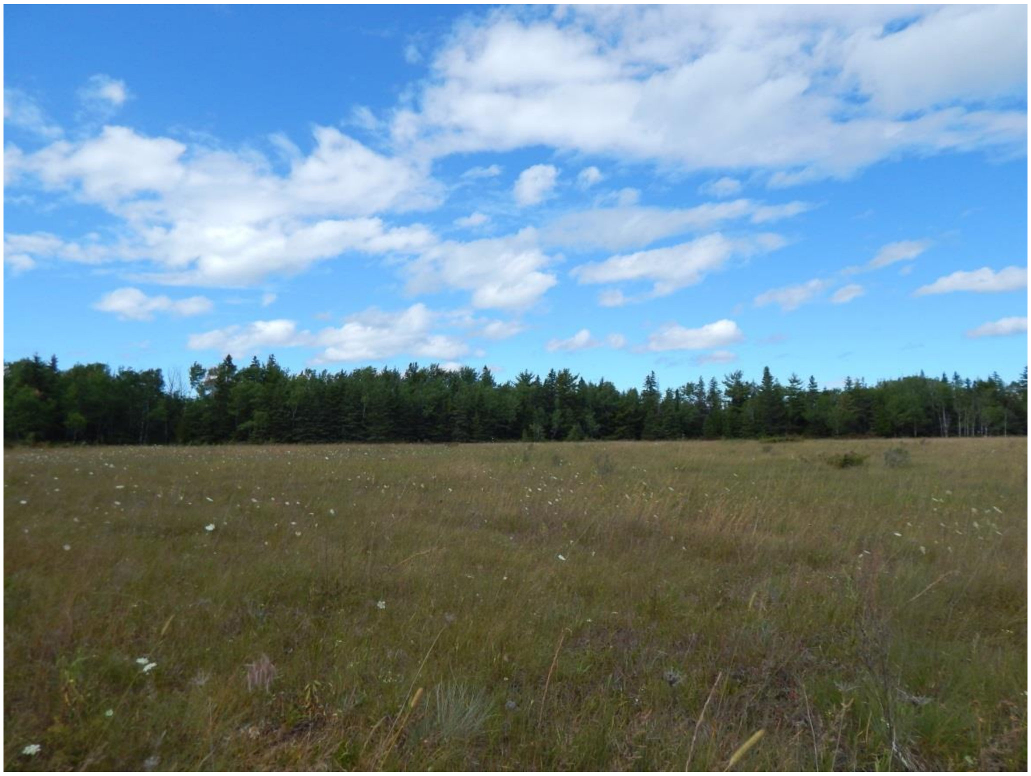

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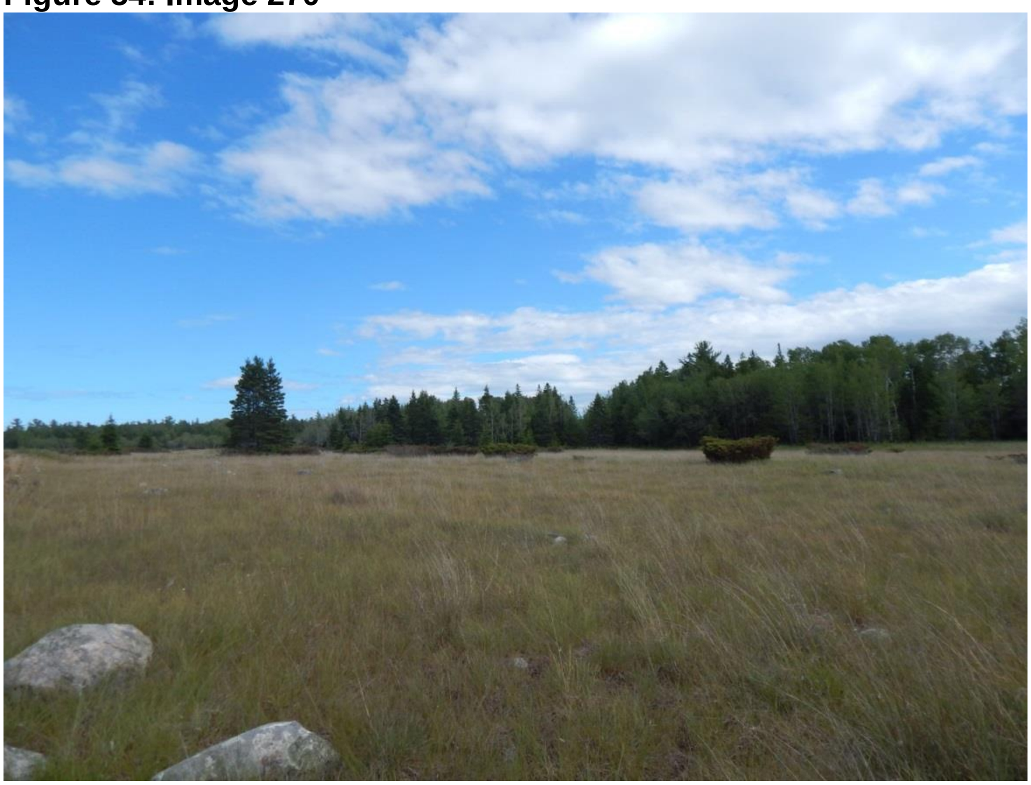

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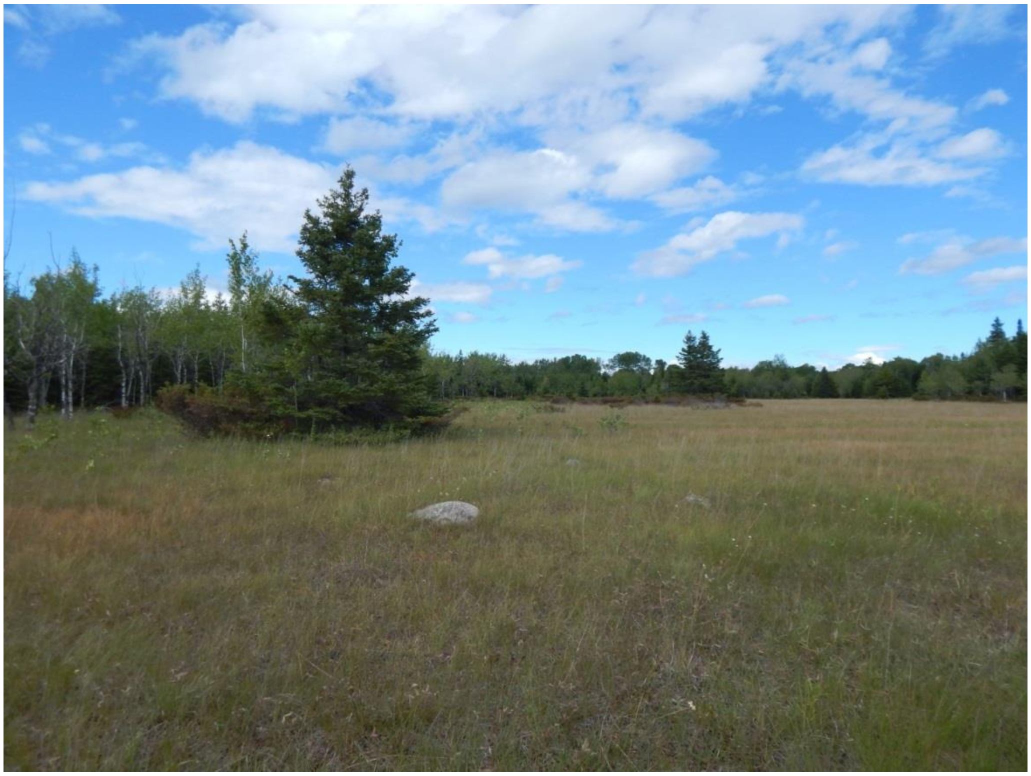

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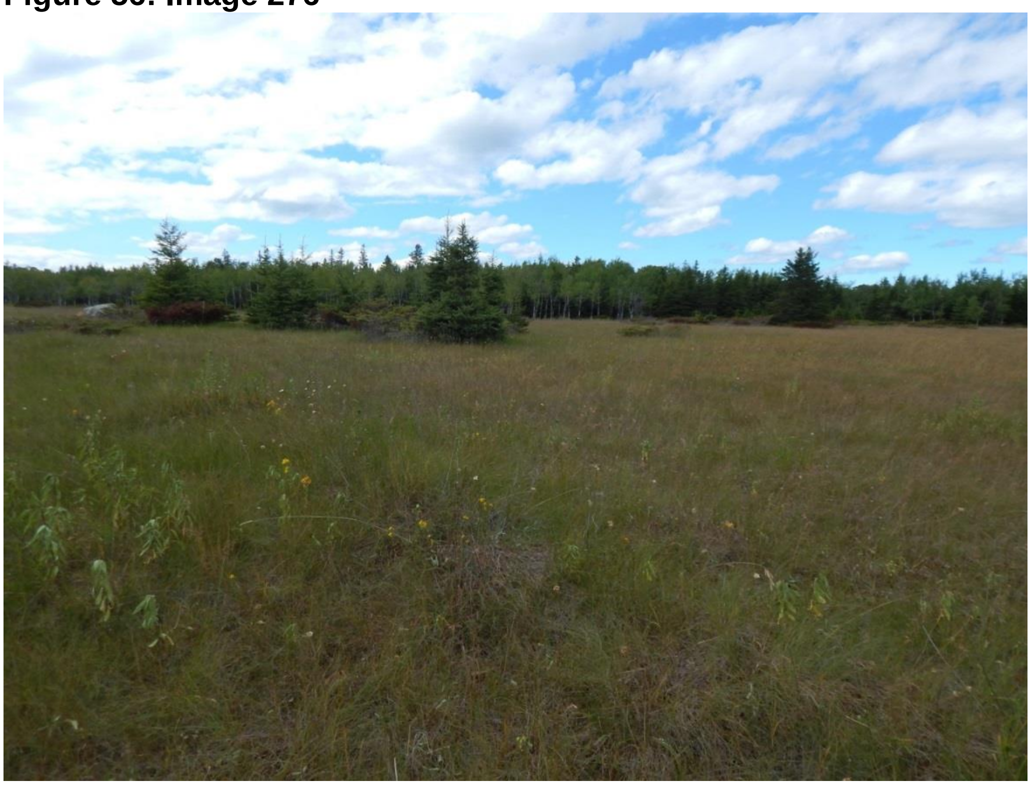

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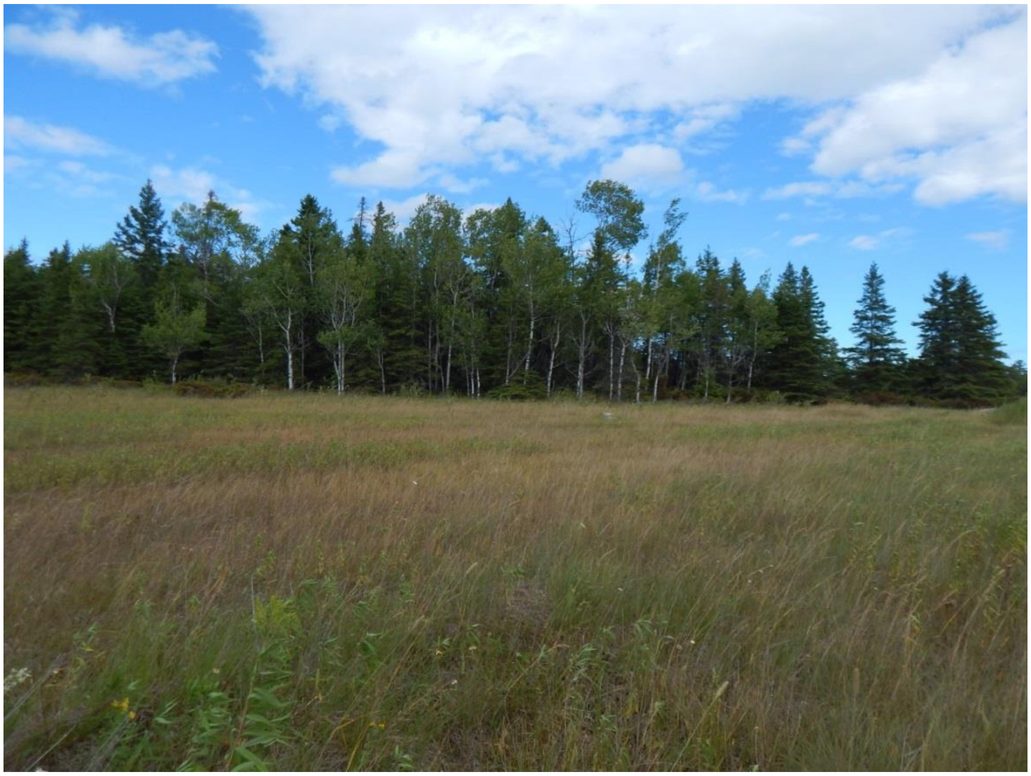

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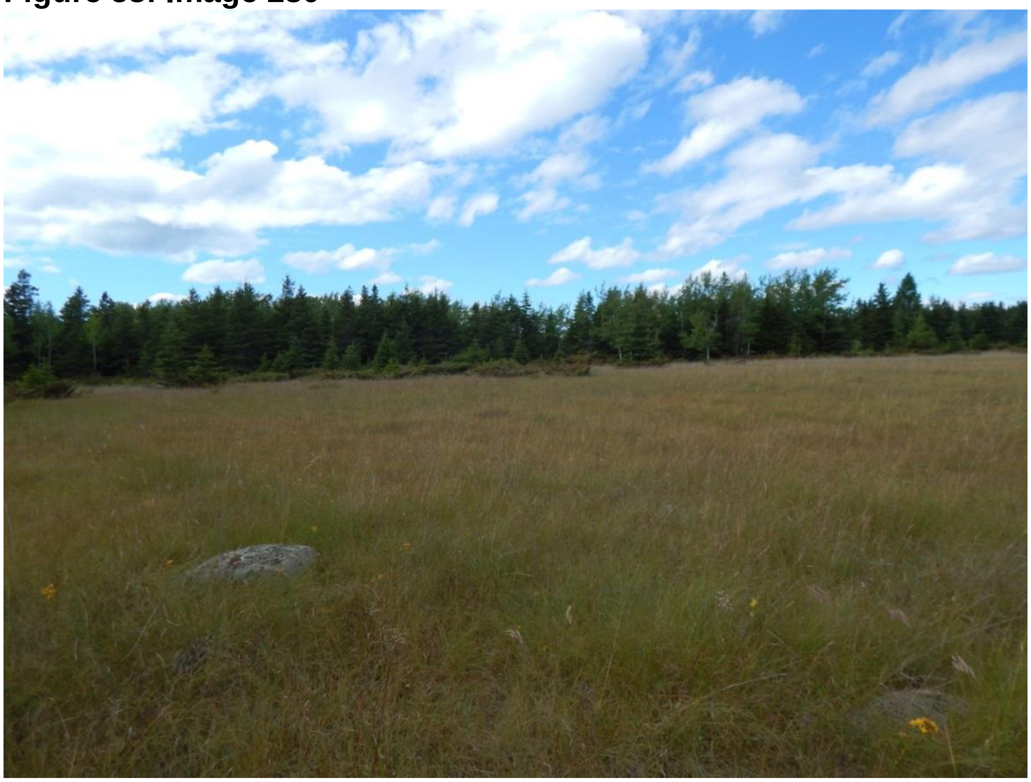

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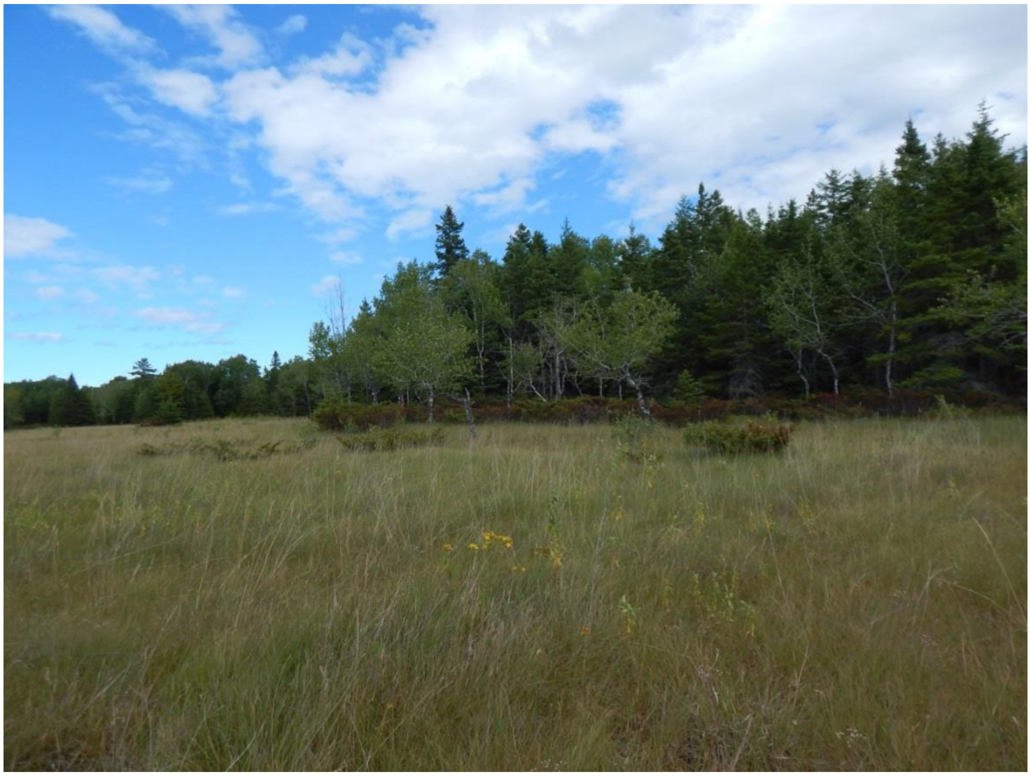

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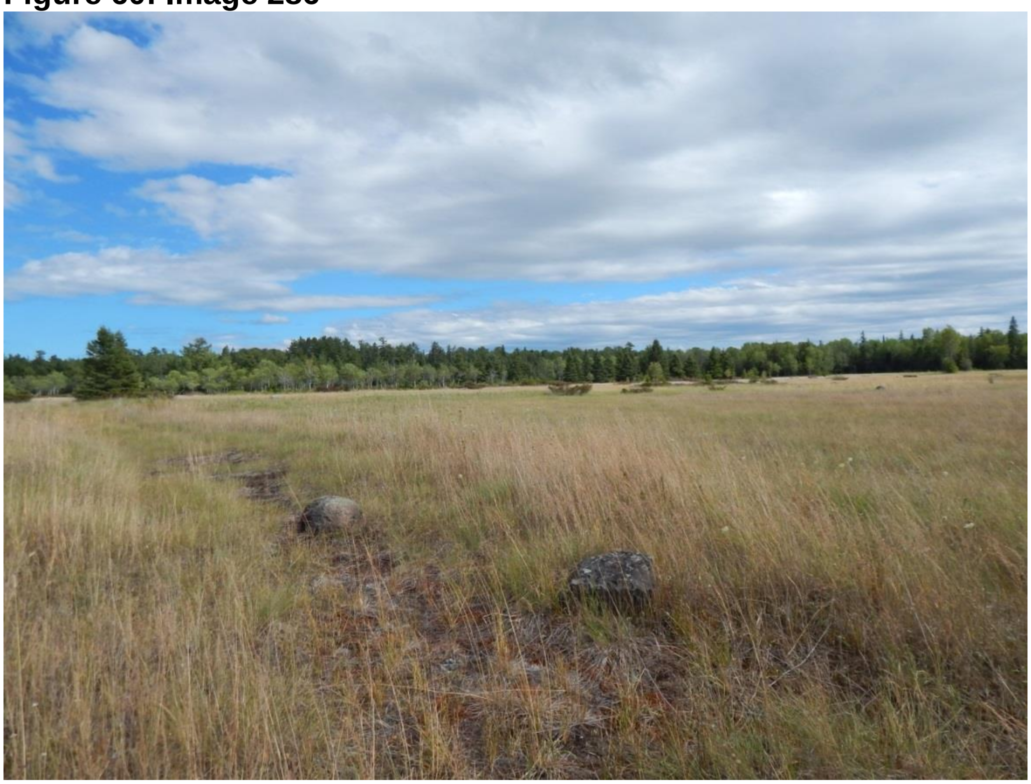

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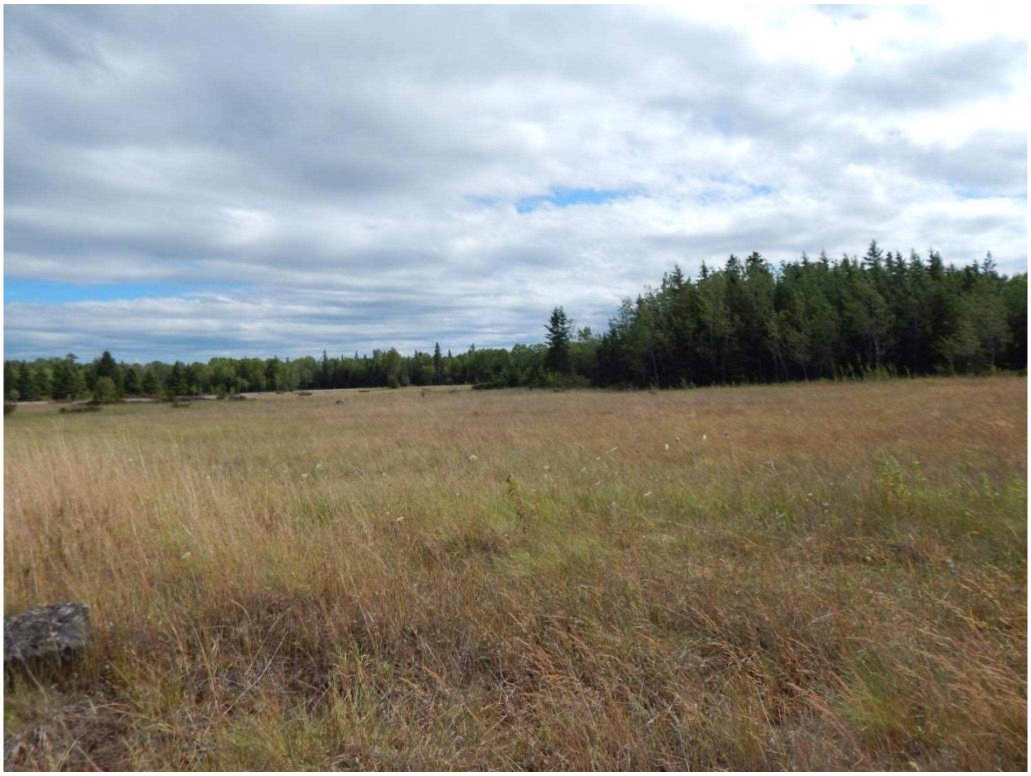
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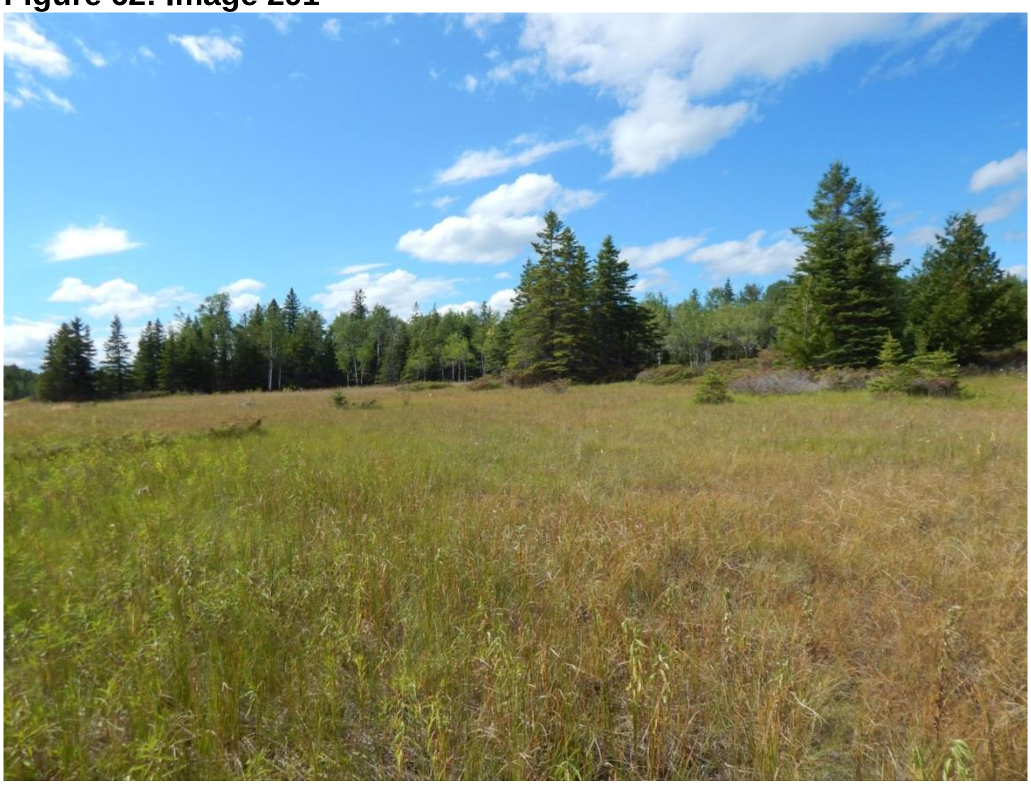
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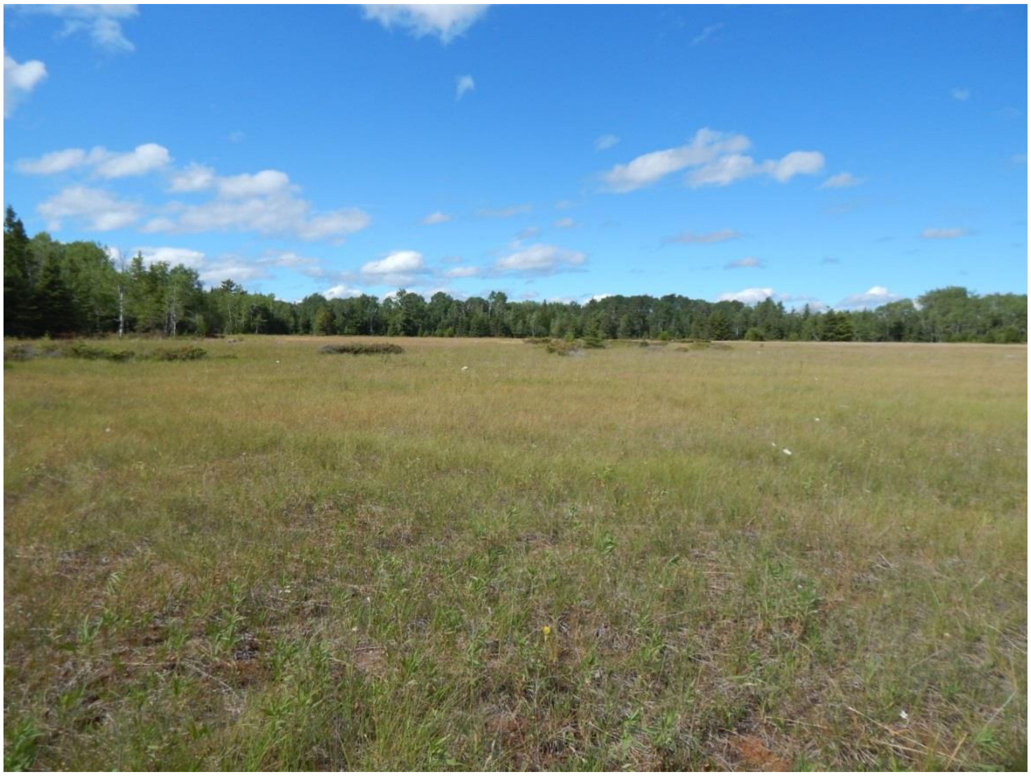

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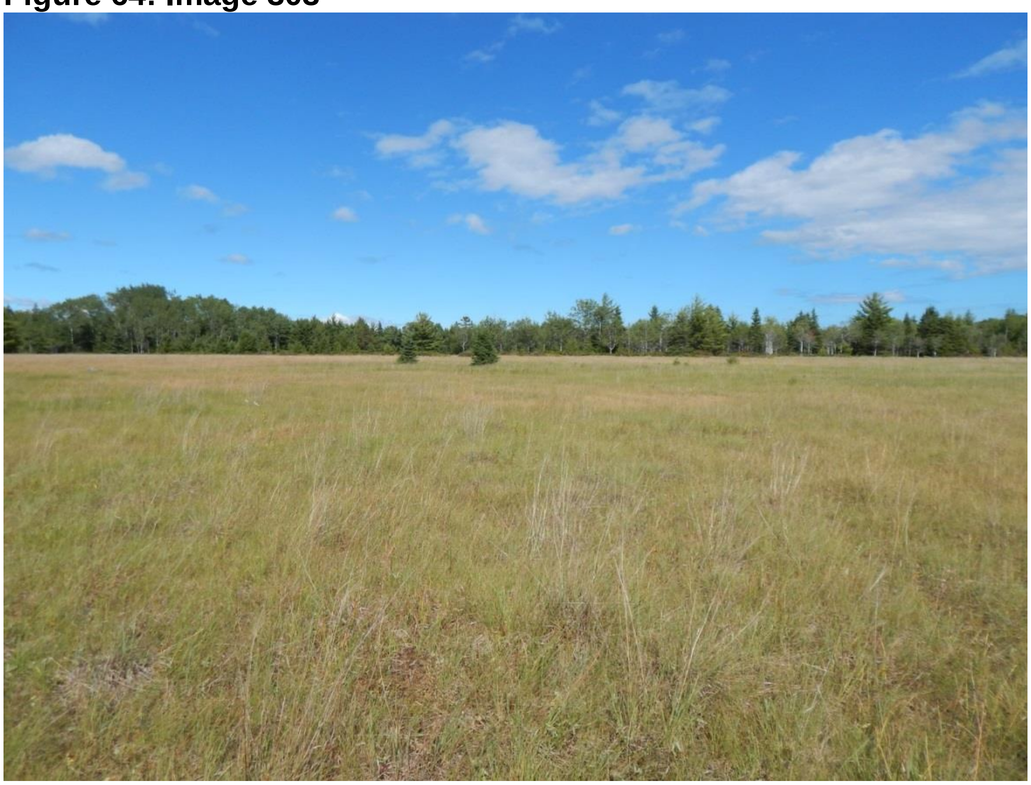

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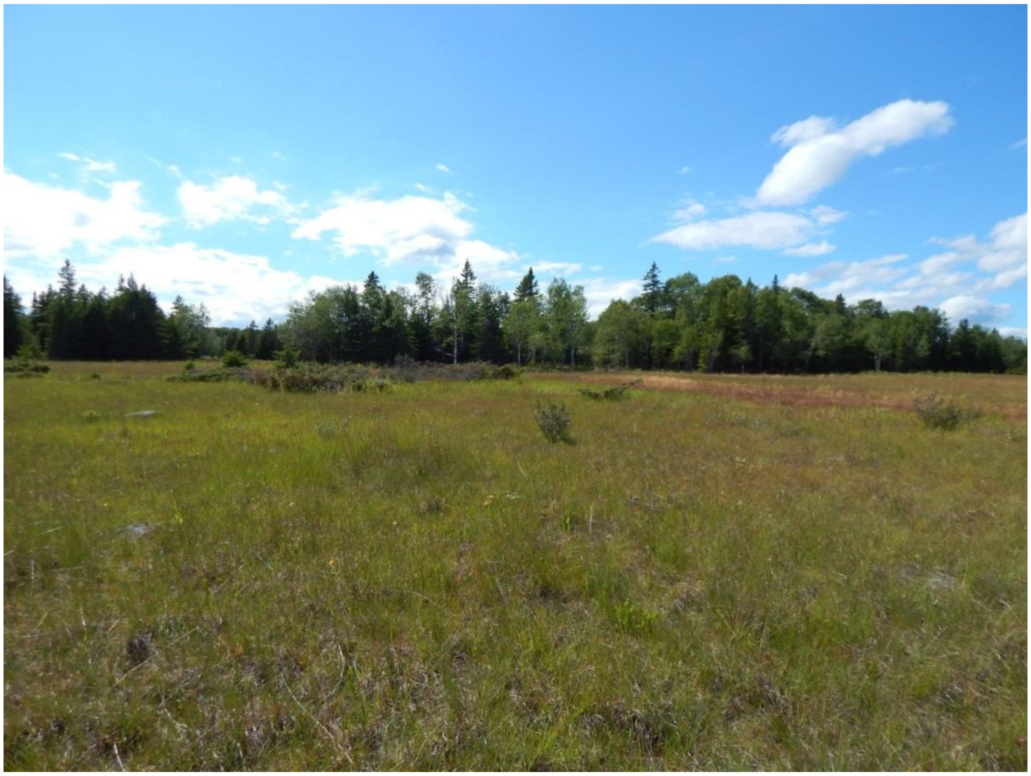
Figure 66: Image 310

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