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TITLE

Comparing Stability in Random Forest Models to Map Northern Great Plains Plant Communities
in Pastures Occupied by Prairie Dogs Using Pleiades Imagery

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ABSTRACT

Black tailed prairie dogs (*Cynomys ludovicianus*) have been described as a keystone species and important for grassland conservation, yet many concerns exist over the impact of prairie dogs on plant biomass production and consequently livestock production. The ability to map plant communities in pastures colonized by prairie dogs can provide land managers with an opportunity to optimize rangeland production while balancing conservation goals. The aim of this study was to test the ability of random forest (RF) to classify five plant communities located on and off prairie dog towns in mixed grass prairie landscapes of north central South Dakota, assess the stability of RF models among different years, and determine the utility of utilizing remote sensing techniques to identify prairie dog colony extent. During 2015 and 2016, Pleiades satellites were tasked to image the study site for a total of five monthly collections each summer (June-October). Training polygons were mapped in 2016 for the five plant communities and used to train RF models. Both the 2015 and 2016 RF models had low (1%) out of bag error rates. However, comparisons between the predicted plant community maps using the 2015 imagery and one created with the 2016 imagery indicate over 32.9% of pixels changed plant community class between 2015 and 2016. The results show that while RF models may predict with a high degree of accuracy, overlap of plant communities and inter-annual differences in rainfall may cause instability in fitted models. A final RF model combining both 2015 and 2016 data yielded the lowest error rates, and was also highly accurate in determining prairie dog colony boundaries.

Keywords

Remote sensing, random forest, rangelands, plant ecology, high resolution imagery

INTRODUCTION

51
52 Within the Northern Great Plains mixed grass prairie ecosystem, black tailed prairie dog
53 colonization is an issue of concern for livestock producers (Miller et al. 2007). Competition
54 between prairie dogs and livestock is a major concern for land managers looking to optimize
55 beef production while still conserving wildlife species (Augustine and Springer 2013). Prairie
56 dogs have been identified as a keystone species, and are often seen as ecosystem engineers
57 providing habitat to a number of other plant and wildlife species (Davidson et al. 2010; Kotliar et
58 al. 1999). Prairie dogs can also reduce availability of forage for livestock by directly reducing
59 the quantity of forage available (through direct consumption, clipping plants to increase predator
60 detection, and building soil mounds), and by changing species composition (Derner et al. 2006).
61 Within the mixed grass prairie, C3 mid-grasses tend to decrease and C4 short-grasses increase
62 along an increasing gradient of grazing intensity (Irisarri et al. 2016). Due to repeated
63 defoliation, older core areas of prairie dog towns often become characterized by extensive areas
64 of bare ground and low vegetation production, which is generally limited to annual forb and
65 dwarf shrub species. Pastures containing extensive areas of bare ground due to prairie dog
66 colonization may potentially depress livestock forage intake rates and ultimately beef production.
67 The ability to map the extent and monitor the impact of prairie dogs on the landscape can help
68 land managers looking to optimize livestock production on prairie dog occupied rangelands.

69 Remote sensing of rangelands greatly improves our ability to study and understand
70 complex ecological interactions across the landscape. As technology advances, monitoring of
71 rangelands via remote sensing platforms will facilitate research products freely available to land
72 managers (Browning et al. 2015). One of the main advantages of remote sensing data is its
73 capacity to cover wide areas, allowing assessment of plant communities at landscape level scales

74 as compared to traditional point-based assessments (Ramoelo et al. 2015; Yu et al. 2018).
75 Numerous studies have demonstrated the utility of remote sensing applications in monitoring
76 rangeland condition, including mapping of vegetation communities, plant species composition,
77 biomass estimation, and impact of grazing intensity on the landscape (Goodin and Henebry
78 1997; Blanco et al. 2008; Franke et al. 2012).

79 Many methods for accurately classifying plant communities using remote sensing
80 techniques have been used in ecological and natural resource studies. One method, random forest
81 classification (RF), has gained considerable traction in the remote sensing community for its
82 ability to produce accurate classifications, handle highly dimensional data, and provide efficient
83 computing times (Belgiu and Drăguț 2016). RF is seen as an improvement over simple
84 classification tree analysis by reducing noise and misclassification of outliers (Laliberte et al.
85 2007; Nitze et al. 2015). RF is an ensemble decision tree classifier which combines bootstrap
86 sampling to construct several individual decision trees from which a class probability is assigned
87 (Mellor et al. 2013). RF builds each tree using a deterministic algorithm selecting a random set
88 of variables and a random sample from the calibration data set (Ramoelo et al. 2015).

89 The utility of random forest algorithms has been demonstrated in remote sensing
90 applications across many plant communities at multiple scales (Mutanga et al. 2012; Lowe and
91 Kulkarni 2015; Ramoelo et al. 2015). Concerns exist, however, over the transferability of these
92 models to different sites, across seasons, or years. For example, RF models have shown to have
93 a high degree of classification accuracy for mapping fine scale coastal vegetation using digital
94 elevation maps and high resolution orthophoto imagery, but model accuracy decreased
95 significantly when applied to spatially separated sites (Juel et al. 2015). Selecting spatially
96 relevant training data or including species level cover data may help improve or explain

97 differences observed when transferring models between sites. Incorporating additional seasons
98 of data may also improve RF model accuracy; previous research has shown an improvement of
99 RF model accuracy in classifying wetlands in northern Minnesota with the inclusion Landsat 5
100 images across two years using full season data versus summer only, and fall only models
101 (Corcoran et al. 2013). Longer term studies have also demonstrated the utility of using RF
102 modeling with 30m Landsat data to monitor rangeland cover across the western United States
103 over a 33 year period (Jones et al. 2018). Results of these studies suggest the scale and
104 seasonality of the imagery may play an important role in the stability and accuracy of RF
105 models.

106 The stability in RF models to accurately map plant communities within prairie dog
107 occupied pastures may be particularly important for managers looking to monitor prairie dog
108 colony expansion or contraction over time. While classification rates are often reported in
109 studies, the potential overlap in plant community composition is rarely explored as a potential
110 source of error within the models. Many research studies focus solely on spectral differences in
111 plant communities and fail to analyze community differences on the ground at the species level
112 (de Colstoun et al. 2003; Geerken et al. 2005). This may be especially important within prairie
113 dog occupied rangelands, where shifts in plant community composition may be driven more by
114 the presence or absence of an herbivore species versus elevation, soils, or other landscape
115 features. These herbivory induced changes in plant community may facilitate or hamper
116 classification schemes. The ability to accurately map plant communities within prairie dog
117 occupied pastures can help improve management of rangelands colonized by prairie dogs, yet
118 little research has explored the possibility of utilizing remote sensing as a tool to do so.

119 A large collaborative study from 2012-2016 was conducted to evaluate livestock
120 production on mixed-grass prairie pastures with varying levels of prairie dog occupation. A
121 major goal of the larger study was to determine which plant communities on the pastures cattle
122 preferred to graze, and how those preferences shifted within and between years (Olson et al.
123 2016). Plant communities on the site were categorized based on location (on- or off-town) and
124 visually apparent dominant plant functional groups. Thus, plant community as defined for this
125 study was a collection of species within an area of a relatively uniform composition different
126 from neighboring patches. Differences in neighboring patches were evident by differences in
127 dominant functional group (forb vs grass) or differences in photosynthetic pathways (C3 vs C4
128 grasses). The overall goal of this paper, then, was to develop maps that accurately classify plant
129 communities based on satellite imagery collected between years. Specific objectives of this study
130 were to 1) determine differences in the five identified plant communities based on species
131 composition, 2) assess the utility of using a RF model with high resolution satellite imagery to
132 classify plant communities of interest within a mixed grass prairie ecosystem containing prairie
133 dogs, 3) determine the stability of the RF model when using subsequent years of satellite
134 imagery with identical training data, and 4) determine the ability of high resolution satellite
135 imagery to accurately map prairie dog towns. Our ability to map and understand these plant
136 communities' at large scales will give researchers insight into applying RF models across years
137 using high resolution imagery. Research from this study will allow us to better assess how
138 prairie dogs drive changes in plant communities, and provide a new tool to map the extent and
139 impact of prairie dog colonization on the landscape to better inform land management decisions.

140 **METHODS**

141 **Study site**

142 The study area (45.74N, 100.65W) was located near McLaughlin, South Dakota on a
143 northern mixed-grass prairie ecosystem. Native prairie pastures (810 ha total area) were leased
144 from 2012-2016; pastures were continuously stocked with yearling steers from June-October of
145 each year to achieve 50% utilization. Of the 810 ha, approximately 186 ha were occupied by
146 black-tailed prairie dogs (*Cynomys ludovicianus*). Predominant soils at the site were clays and
147 loams. Ecological sites, and the plant communities they support vary widely; Loamy and Clayey
148 were the predominant Ecological Sites at the site with inclusions of Dense Clay, Shallow Clay,
149 and Thin Claypan (Barth et al. 2014). Plant species dominating the site were largely native,
150 including western wheatgrass (*Pascopyrum smithii* Rydb.), green needlegrass (*Nassella viridula*
151 Trin.), and needle-and-thread (*Hesperostipa comata* Trin. & Rupr), intermixed with blue grama
152 (*Bouteloua gracilis* Willd. Ex Kunth), buffalograss (*Bouteloua dactyloides* Nutt.), and sedges
153 (*Carex* spp.). The most common non-native species on the site was Kentucky bluegrass (*Poa*
154 *pratensis* Boivin & Love). Woody draws occupied moist drainage areas; vegetation consists
155 primarily of bur oak (*Quercus macrocarpa* Nutt.), American plum (*Prunus americana* Marshall),
156 and chokecherry (*Prunus virginiana* L.). These draws were frequently flanked by snowberry-
157 dominated patches (*Symphoricarpos occidentalis* Hook.). Plant communities on areas occupied
158 by prairie dog towns on the site were largely dominated by western wheatgrass and shortgrasses
159 (buffalograss, blue grama, and sedges) intermixed with patches of bare ground and annual forb
160 dominated areas. Common annual forbs on prairie dog towns included prostrate knotweed
161 (*Polygonum aviculare* L.), fetid marigold (*Dyssodia papposa* Vent.), dwarf horseweed (*Conyza*
162 *ramosissima* Cronquist), and scarlet globemallow (*Sphaeralcea coccinea* Nutt.). A weather
163 station has been maintained on site from May 2013 operated by South Dakota Mesonet. Mean

164 annual rainfall at the site is 446 mm and average growing season (May through September)
165 temperature is 15.3°C (South Dakota Climate and Weather 2017).

166 Five plant communities of interest for our study site were identified: 1) Forb-dominated
167 sites on prairie dog towns (On-Forb), 2) Grass-dominated sites on prairie dog towns (On-Grass),
168 3) Snowberry-dominated sites off-town (Off-Snow), 4) Cool season grass-dominated sites off-
169 town (Off-Cool), and 5) Warm season-dominated sites off-town (Off-Warm). An additional
170 plant community labeled 'Draws' was delineated visually within ArcGIS software due to
171 difficulty in mapping these areas in the field. Areas delineated as Draws were removed from the
172 analysis area.

173 **Training sites**

174 To facilitate classification, training site polygons were mapped for On-Forb, On-Grass,
175 Off-Cool, Off-Warm, and Off-Snow plant communities using ArcPad for Trimble GPS units in
176 the summer of 2016. Twenty training sites were mapped for each of the plant communities
177 except Off-Warm, for which only 8 sites were mapped due to the difficulty of finding
178 homogenous stands of warm season grasses. Plant species in the Northern Great Plains are
179 dominated by cool season species; warm season species, where they occur, are typically
180 intermixed into stands of cool season species. Training sites for each plant community were
181 selected from across the entire study area to capture potential site differences across research
182 pastures. Sites were mapped in the field by walking the perimeter of the plant community patch
183 with a Trimble GPS unit. Training polygon perimeter boundaries were always at least 3 meters
184 interior of patch edge to minimize error introduced to the training data as a result of GPS signal
185 noise. Identified patches were then converted into a polygon shapefile within ArcGIS to be used
186 as training polygons for the RF classification algorithm. Within each training site polygon, three

187 0.25 m² plots were randomly located by tossing plot frames into the area of interest to determine
188 sampling area. Within each plot, percent cover by species was recorded in the summer of 2016
189 at the time of polygon mapping.

190 **Plant Community Analysis**

191 Plant community analysis was performed on vegetation data collected from the three
192 0.25m² plots measured in each training polygon. Differences between plant community
193 compositions were determined using a Multi-Response Permutation Procedure (MRPP) with the
194 Sorensen Bray-Curtis distance method. MRPP is a nonparametric procedure used for testing
195 hypotheses between two or more groups (Mitchell et al. 2015). Differences in community
196 compositions were analyzed for all plant communities, and pairwise comparisons generated. To
197 analyze trends in species composition between plant community plots, Non-metric
198 Multidimensional Scaling (NMS) ordination was used (Kruskal 1964). Only species that
199 occurred in 3 or more plots were included in the ordination analysis. NMS analysis was
200 conducted using the Sorensen Bray-Curtis distance method with 250 iterations and a stability
201 criterion of 0.00001. Analysis was repeated five times to confirm ordination pattern in the data.
202 Similarity index matrices were generated to compare plot differences between plant communities
203 and averaged by plant community. All ordination analyses (MRPP and NMS) were performed
204 using PC-ORD 6 software (McCune and Mefford 2002).

205 **Imagery**

206 During the summers of 2015 and 2016, Pleiades satellites were tasked to image the study
207 site. Pleiades satellites, which are members of the SPOT family of satellites, are operated by
208 AIRBUS Defense and Space. This platform was chosen due to its high spatial resolution (0.5 m
209 pan chromatic, 2 m multispectral) and four band spectral resolution: pan chromatic (480-830

210 nm), red (600-720nm), green (490-610 nm), blue (430-550 nm), and near infrared (750-950 nm).
211 Pleiades satellites were designed for commercial tasking and monitoring, allowing multiple
212 revisits to a project site. A total of ten image collections were acquired in the summer of 2015
213 and 2016 (five each year) from June through October during the 1st-15th of each month (Table 1).
214 Image collection times were chosen to correspond to the time periods when cattle were actively
215 grazing on the site. Multispectral images were pan-sharpened and orthorectified by the image
216 provider (Apollo Imaging Corp). Each monthly image collection was converted into an NDVI
217 image. In addition, boundaries of the prairie dog town were mapped using a handheld Trimble
218 GPS unit to compare predicted colony location with ground truth location.

219 **Random Forest model**

220 For the RF model, the Random Forest package of the Comprehensive R Archive Network
221 (CRAN) implemented by Liaw and Wiener (2002) was utilized. Training data were constructed
222 by stacking all satellite imagery spectral bands (Red, Blue, Green, and NIR) and NDVI bands for
223 each month of each year (25 total dimensions per year) to create a raster stack for each year's
224 imagery (2015 and 2016). To train the model, pixel values were extracted from the satellite
225 imagery raster stack for each training polygon mapped in the field. The random forest models
226 were built using 200 decision trees and default number of nodes at each split (\sqrt{n}), with plant
227 community data as the response category (On-Grass, On-Forb, Off-Cool, Off-Warm, and Off-
228 Snow) and spectral band values as the predictor. Models were checked for error stabilization, for
229 all models error rates stabilized around 50 trees. Yearly models (2015 and 2016) were built for
230 output comparison. A combined years model was also constructed using all available spectral
231 data from 2015 and 2016 (50 dimensions).

232 Within the random forest package, Out of Bag (OOB) error rates were calculated by
233 reserving one-third of the training data to test the accuracy of the predictions. Models were then
234 used to predict class belonging for 2015 and 2016 raster stacks and the combined 2015 and 2016
235 stack using the ‘predict’ function within program R. To assess the stability of the RF models
236 from year to year, the “crosstab” function in the raster package in program R was used to
237 calculate the number of pixels that changed class from 2015 to 2016. The output was used to
238 calculate percent of pixels that were unchanged from 2015 to 2016 model predictions and
239 percent of pixel change that occurred between years for plant community predictions.

240 **Results and Discussion**

241 **Plant Community**

242 MRPP pairwise comparisons results showed a significant difference between all plant
243 communities ($P < 0.001$). Differences are evident between plant communities in the 2-D plot of
244 the NMS ordination (final stress = 20.01, instability < 0.00001 after 66 iterations), with some
245 overlap occurring between communities (Figure 1). Plant communities on-town and off-town
246 are clustered at opposite ends of the ordination plot, with the greatest distance being between On-
247 Forb and Off-Snow. Detrended correspondence analysis of plant communities ranging from
248 uncolonized, 2 years post colonization, and 4-6 years post colonization showed that uncolonized
249 sites were clustered at one extreme and the 4-6 year sites at the other extreme (Archer et al.
250 1987). Interestingly, Off-Warm and On-Grass communities are clustered closer in ordination
251 space. Plant communities shifts on-town towards those dominated by shortgrass species have
252 been documented (Agnew et al. 1986; Koford 1958), and is probably attributable to the high
253 grazing resistance of the C4 species blue grama and buffalograss (Derner et al. 2006).

254 Similarity index differences between plant communities were generated from a Sorensen
255 (Bray-Curtis) distance matrix, and can be seen in Table 2. While there is some overlap between
256 plant communities, in general similarities are low (< 29%), with the greatest distance occurring
257 between the On-Forb communities and the off-town communities (Table 2). Based on how plant
258 communities were selected in this study, we expected plant community composition to be
259 distinct between groups. Though plant communities are defined by dominant functional group in
260 this study, the amount of overlap occurring demonstrates that other functional groups and species
261 exist within these distinct patches, which may be a potential source of instability in classification
262 models.

263 **Random Forest Model Results**

264 Results from the RF models show low OOB misclassification error rates for each
265 individual plant community (Table 3) indicating a high degree of accuracy in the model. Overall
266 the OOB model error rates were 0.9% and 1.12% for the 2015 and 2016 model respectively.
267 OOB accuracy is an unbiased estimate of the overall classification accuracy eliminating the need
268 for cross-validation (Breiman 2001). OOB error rates have been shown to be reliable estimates
269 of class accuracy for identifying invasive species (Lawrence et al. 2006), and mapping corn and
270 soybean fields across multiple years (Zhong et al. 2014). Belgiu and Drăguț (2016) in their
271 review of RF applications in remote sensing acknowledge that the reliability of OOB error
272 measurements needs to be further tested using a variety of datasets in different scenarios
273 Consistency in error rates for plant communities appears to indicate stability in the 2015 and
274 2016 RF models which used identical training sites on consecutive yearly satellite imagery.
275 However, when comparing yearly predicted plant community maps, differences between

276 community classifications are slightly more pronounced, indicating the models may not be as
277 stable as predicted based solely on the OOB error rates.

278 Overall a total of 67.04% pixels remained unchanged in their plant community
279 classification from 2015 to 2016 (Table 4). Of the pixels that changed classification between
280 years, 15.13 were on-town to off-town transitions, 2.26 were on-town to on-town transitions, and
281 15.57 were off-town to off-town plant community transitions. It is unlikely in this northern
282 mixed-grass prairie ecosystem that all the changes in plant communities indicated by
283 classification of pixels were real changes from one plant community type to another over one
284 year. In the absence of a major disturbance event, such major shifts in species composition
285 typically occur much more slowly (Vermeire et al. 2018). The results from the plant community
286 analysis indicate training sites were chosen appropriately to account for differences in species
287 composition on the ground, therefore apparent changes are much more likely due to factors that
288 affect the spectral signature of the vegetation. Factors that may potentially affect spectral
289 signatures could include changes resulting from prairie dog herbivory, changes in precipitation
290 regimes, or changes occurring along plant community transition zones.

291 The pixels changing from On-Grass to Off-Cool represented the highest percentage of
292 pixels that changed plant community classification at 7.28%; these are likely occurring along
293 transition zones at the prairie dog colony edge. Both On-Grass and Off-Cool plant communities
294 have western wheatgrass as a dominant species. Similarity in species dominance may explain
295 some of the challenges to distinguishing between some on and off colony plant communities.
296 Difficulty in classifying Off-Cool and On-PDG may also be due to subtle vegetation changes
297 likely induced by the level of herbivory. Research on a South Dakota mixed grass prairie
298 showed that prairie dogs remove over four times more biomass than cattle grazing on-town

299 (Gabrielson 2009). Up to 7 times more standing dead forage and 60% less standing crop
300 biomass has been reported on uncolonized sites compared to colonized areas, mainly attributed
301 to prairie dogs clipping vegetation which greatly reduced the amount of grasses that reached
302 maturity (Johnson-Nistler et al. 2004). Areas either less maintained on-town by prairie dogs or
303 grazed by cattle repeatable off-town may show similar spectral signatures.

304 Differences in year to year classification could also be attributed to the interannual
305 variability of rainfall between 2015 and 2016 (Figure 2). Yearly rainfall patterns can result in
306 large differences in NDVI and biomass measurements across years (Wehlage et al. 2016). While
307 overall total rainfall between years was similar, differences in timing of precipitation that
308 occurred likely affected timing of green up and dormancy for many of the cool and warm season
309 species on the site. This, then, would create different NDVI patterns between years (Figure 3).
310 Goward and Prince (1995) suggested that the relationship between NDVI and annual rainfall in
311 any given year also depends on the previous year history of rainfall at the site. Previous research
312 has shown that annual above ground primary production of shortgrass communities is related to
313 current as well as previous two years precipitation (Oesterheld et al. 2001). The above average
314 rainfall at the study site in 2015 could have added to the increase in average NDVI in 2016 when
315 compared to 2015 through an increase in cumulative biomass or production at the site. Increased
316 cumulative biomass in 2016 may cause higher NDVI values for example in On-PDG plant
317 communities resulting in classification shifts to Off-Cool; similarly, greater NDVI values in Off-
318 cool in 2016 may result in some of those pixels being classified as Off-Snow.

319 Another possible cause for changes in plant community classifications between years is
320 overlap of species where two communities share a boundary. One issue with using categorically
321 classified vegetation maps is that plant communities in space are rarely mutually exclusive, and

322 tend to change along a continuum with environmental gradients (Equihua 1990). Plant
323 communities in the region, which are predominantly comprised of cool season grasses, often
324 include varying levels of warm season species; and snowberry thickets often have an understory
325 of grasses, especially near the perimeter. The challenge of accurately classifying plant
326 communities along an ecological continuum may be further exacerbated by changes induced by
327 prairie dogs, where transition zones are less defined by environmental gradients and more
328 defined by the level of herbivory. Thus, within and between on-town and off-town plant
329 communities, transition zones are likely to account for a portion of the classification change
330 between plant communities between years (Figure 4). Alternative approaches to mapping plant
331 communities can be the recognition of fuzzy properties enabling a single point in space to exhibit
332 characteristics of a number of plant communities (Duff et al. 2014; Fisher 2010). While fuzzy
333 classification maps are more likely to give a better picture of plant community composition on a
334 per pixel basis, they are also more difficult to use to draw inferences of species dominance,
335 livestock use patterns, and extent of prairie dog colonization.

336 A final RF model combining all available bands and NDVI values for 2015 and 2016
337 reduced error rates for all plant communities below 1% (Table 3). While we have shown that
338 lower error rates may not result in more stable predictions, using all available data for a model
339 will likely improve accuracy and result in a more accurate thematic map. Other studies have
340 reported increases in classification accuracy in RF models with the addition of combined
341 seasonal images, hyperspectral data, LiDAR images, radar (SAR) images, and ancillary
342 geographical data such as elevation and soil types (Corcoran et al. 2013; Pu et al. 2018; Shi et al.
343 2018; Xia et al. 2018; Yu et al. 2018; Zhou et al. 2018). RF models have the ability to handle
344 highly dimensional correlated data, and data combined from multiple different data sources

345 across different temporal scales; however, one disadvantage to using non-parametric classifiers
346 such as RF and decision trees is that they require a large number of observations to accurately
347 estimate the mapping function (James et al. 2014). Thus the incorporation of additional predictor
348 variables as well as additional training data will likely result in higher accuracy rates.

349 The variable importance graph of the combined model indicates that NDVI variables
350 contribute the most to the model over individual bands (Figure 5). In classifying vegetation
351 morphology in a savanna grassland, Mishra and Crews 2014 found spectral classification
352 features (mean NDVI or ratio NDVI) were the most significant. The variable importance plot
353 from the combined data model also indicates that different months between years contribute
354 highly to the classification accuracy. Of the ten most important variables in the model, 6 were
355 from 2015 and 4 from 2016, suggesting additional years' data in the model is likely to yield
356 greater classification accuracy. The internal information provided by the model, such as variable
357 importance, can be a useful tool for researchers to select features of greatest importance to
358 reduce computation times in the instance of large datasets. At the size of our study area (810 ha)
359 and a maximum of 50 variables, the combined 2015-16 data model only slightly added to
360 computation time, but not enough to warrant feature trimming from the dataset. Land managers
361 looking to classify prairie dog colonies on more extensive grasslands may look to including only
362 NDVI variables into training datasets to increase computational efficiency.

363 **Remote Sensing Prairie Dog Colonies**

364 Visual comparison of the predicted on-town plant communities versus off-town plant
365 communities show a clearly defined boundary between areas colonized by prairie dogs and areas
366 not colonized (Figure 6). Results from mapping colony boundaries with a hand held GPS device
367 estimated the colony to be 276 ha in 2012 to 186 ha in 2015. Total colony acreage estimated

368 from summing the pixel area occupied by the On-Grass and On-Forb community pixels from the
369 combined 2015-2016 RF model was 246 ha. Previous research has demonstrated that
370 colonization by prairie dogs and subsequent increases in grazing pressure can result in significant
371 differences between on- and off-town plant community composition and production (Coppock et
372 al., 1983; Winter et al. 2002; Johnson-Nistler et al. 2004; Geaumont et al. 2019). The results of
373 our study demonstrate that these differences are significant enough to be identified using remote
374 sensing techniques. Interestingly, a considerable portion of the area misclassified as on-town is
375 from a previously colonized area that had been poisoned in 2013, suggesting that, at least
376 spectrally, these areas still resemble plant communities similar to those actively colonized. The
377 higher area estimate from the RF model is likely the result of transition areas controlled two
378 years prior. Additionally, most other pixels misclassified as on-town are likely drainage areas
379 with high bare ground off-town, whose variability was not captured in the dataset. One prior
380 study had sought identify prairie dog colonies using 30m Landsat imagery, however concluded
381 that the scale was too coarse for accurately measuring prairie dog towns (Wolbrink et al. 2002).
382 High resolution satellite imagery used in this study appears capable at capturing fine scale
383 transitions that occur between plant communities along the on-town off-town gradient.

384 The RF model was also able to accurately predict older core areas of prairie dog towns
385 (On-forb) often characterized by a high percentage bare ground, low vegetation production, and
386 dominance by annual forb and dwarf shrub species (Coppock et al., 1983). Area estimates of
387 On-Forb were 33 ha and 32 ha in 2015 and 2016 respectively. State and transition models for
388 prairie dog towns developed within Custer State Park South Dakota, found older core areas were
389 considered undesirable for management due to losses of native grasses, increased bare ground,
390 potential for erosion, extensive presence of exotic species, and increased inputs to restore to a

391 more desirable state (Hendrix 2018). The ability to monitor these older core areas of prairie dog
392 towns remotely may help land managers limit sites from becoming highly degraded, and serve as
393 a useful tool for land managers concerned over balancing wildlife conservation with losses in
394 livestock production.

395 **Conclusions**

396 Stability of models is important when applying similar techniques across different sites,
397 plant communities, and in this case years. Differences in year-to-year NDVI values may alter
398 classification results, and the addition of two years' worth of data likely resulted in improved
399 model performance. One of the main benefits to RF classification in remote sensing is the
400 relatively fast computing time (Belgiu and Drăguț 2016), and, given the availability of free
401 satellite imagery, researchers would be prudent to include multiple images across years and
402 seasons in their model to improve accuracy. Furthermore, while the desired outcome is often to
403 produce thematic maps, recognizing that plant communities rarely exist in discrete communities
404 is important when selecting community types to map. Combining plant community ordination
405 results with remote sensing results can aid in understanding sources of model error and
406 limitations of classification algorithms. This is likely to be magnified as pixel size decreases,
407 resulting in fine scale predictions which may be more susceptible to plant community transitions
408 zones. Results from this study indicate that plant community changes induced by prairie dogs
409 are significant enough to be detected via remote sensing techniques. Land managers looking to
410 optimize rangeland health on pastures occupied by prairie dogs may potentially utilize high
411 resolution imagery to monitor colony size and make recommendations of appropriate stocking
412 rates based on extent of colonization.

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622 **Tables and Figures**

Table 1. Acquisition dates of Pleiades satellite imagery tasked for each month (June – October) in 2015 and 2016.

2015 Dates of Acquisition	2016 Dates of Acquisition
6/1/2015	6/5/2016
7/9/2015	7/2/2016
8/4/2015	8/2/2016
9/1/2015	9/11/2016
10/8/2015	10/1/2016

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625 Table 2. Similarity index (Sorensen (Bray-Curtis) distance method) values averaged by plot
 626 across plant communities.

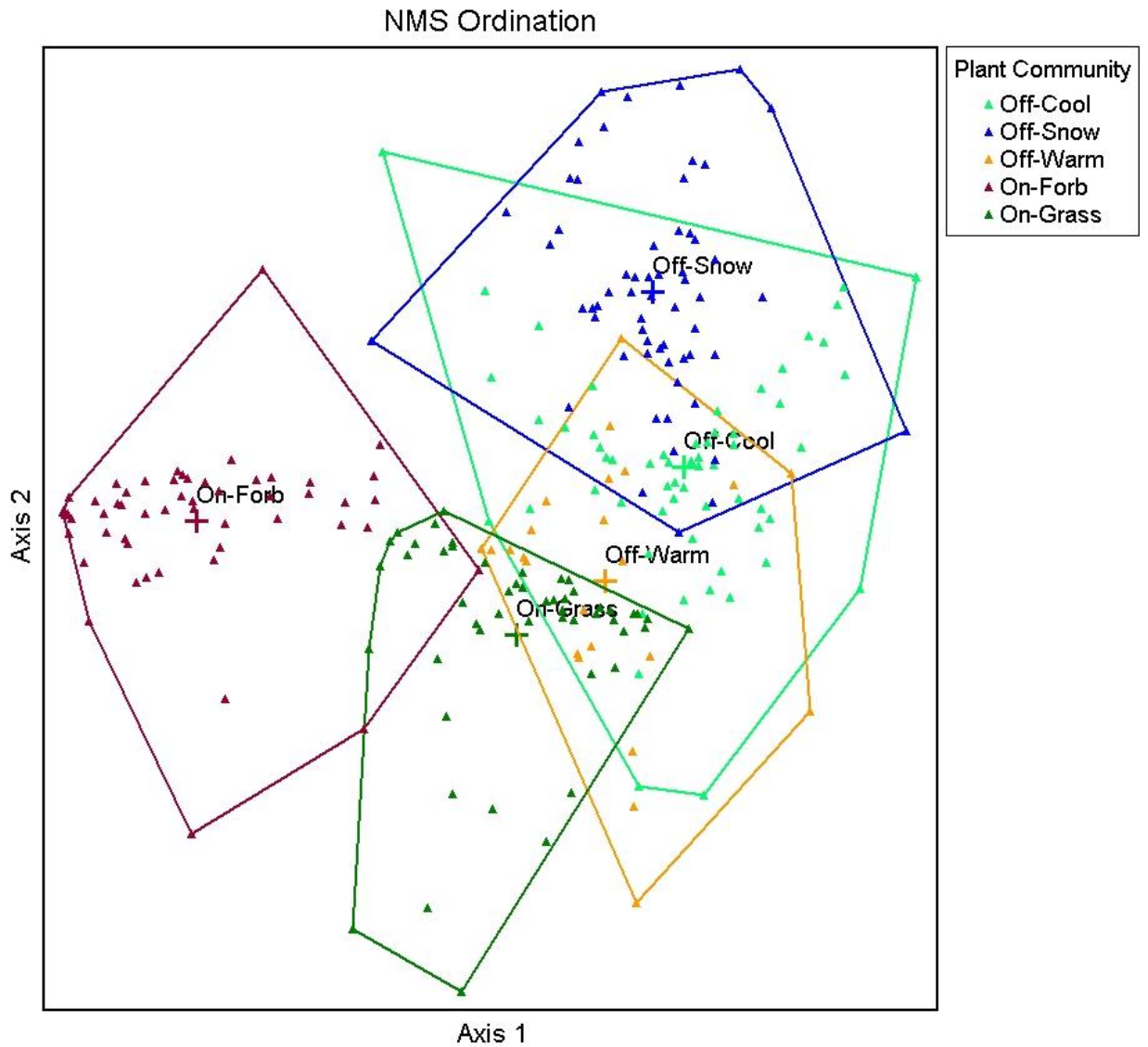
Community Comparison ¹	Similarity Index (%)
Off-Cool vs. Off-Snow	28.2
Off-Cool vs. Off-Warm	27.8
Off-Cool vs. On-PDG	27.7
Off-Snow vs. Off-Warm	21.6
On-PDG vs. On-PDF	17.8
Off-Snow vs. On-PDG	17.3
Off-Warm vs. On-PDG	17.3
Off-Cool vs. On-PDF	7.9
Off-Snow vs. On-PDF	6.2
Off-Warm vs. On-PDF	6.2

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 628 ¹Plant communities on prairie dog towns are grass-dominated (On-Grass) and forb-dominated
 629 (On-Forb); plant communities in off-town areas are cool season grass-dominated (Off-Cool),
 630 warm season grass-dominated (Off-Warm), and snowberry-dominated (Off-Snow).

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636 Figure 1. NMS ordination plots for plant communities located on and off of prairie dog towns,
 637 based on plant cover by species data collected in 2016 on the study site in north central South
 638 Dakota. The '+' symbol followed by the community name represent the weighted mean
 639 (centroid) of the multivariate dataset. Plant communities on prairie dog towns are grass-
 640 dominated (On-Grass) and forb-dominated (On-Forb); plant communities in off-town areas are
 641 cool season grass-dominated (Off-Cool), warm season grass-dominated (Off-Warm), and
 642 snowberry-dominated (Off-Snow).

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Table 3: Out of Bag misclassification error rates (%) for each plant community for 2015, 2016, and combined year random forest models.

Plant Community ¹	2015 Model	2016 Model	2015-2016 Combined Model
Off-Cool	0.20%	0.40%	0.04%
Off-Snow	2.2%	1.9%	0.69%
Off-Warm	3.2%	5.3%	0.73%
On-Grass	0.40%	0.60%	0.09%
On-Forb	0.60%	0.70%	0.19%

648 ¹ Plant communities on prairie dog towns are grass-dominated (On-Grass) and forb-dominated
649 (On-Forb); plant communities in off-town areas are cool season grass-dominated (Off-Cool),
650 warm season grass-dominated (Off-Warm), and snowberry-dominated (Off-Snow).
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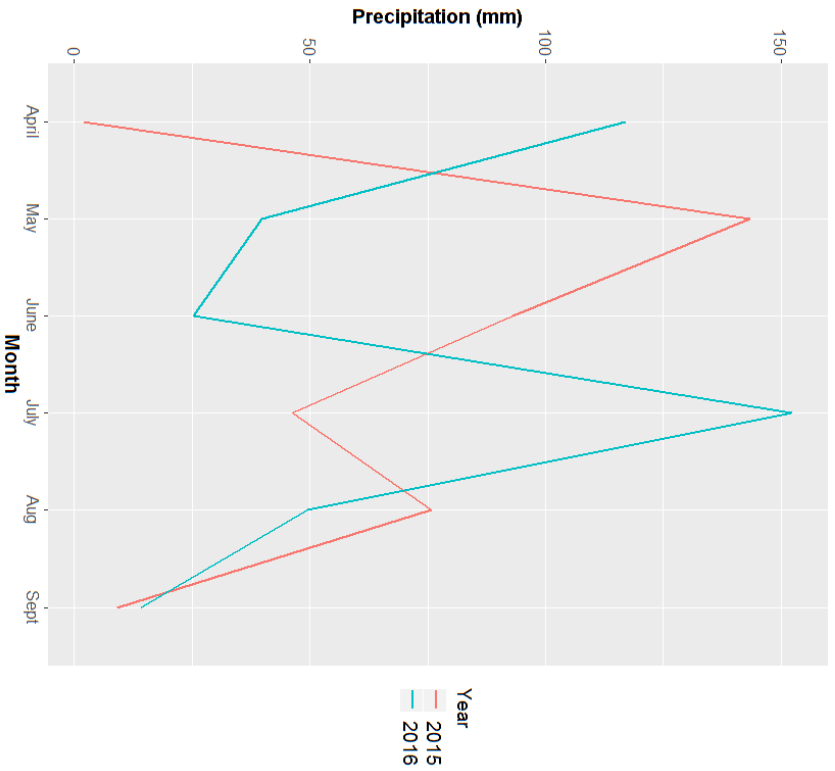
Table 4: Percent of pixels within each plant community that remain unchanged and that changed class belonging between 2015 and 2016 models.

Transition	2015 PC ¹	2016 PC	Total Pixels	Percent of Total Pixels
Unchanged Pixels	Off-Cool	Off-Cool	9712857	31.03
	On-Grass	On-Grass	6427817	20.54
	Off-Snow	Off-Snow	3401264	10.87
	On-Forb	On-Forb	887151	2.83
	Off-Warm	Off-Warm	555635	1.78
Changed Pixels	On-Grass	Off-Cool	2278390	7.28
	Off-Cool	Off-Snow	1468042	4.69
	Off-Cool	On-Grass	1262373	4.03
	Off-Snow	Off-Cool	1174565	3.75
	Off-Warm	Off-Cool	729511	2.33
	Off-Cool	Off-Warm	716503	2.29
	Off-Warm	Off-Snow	629212	2.01
	On-Grass	Off-Snow	626695	2.00
	On-Grass	On-Forb	362417	1.16
	On-Forb	On-Grass	343774	1.10
	Off-Snow	On-Grass	281061	0.90
	Off-Snow	Off-Warm	155213	0.50
	On-Grass	Off-Warm	82450	0.26
	On-Forb	Off-Cool	72758	0.23
	Off-Cool	On-Forb	69188	0.22
	Off-Warm	On-Grass	43132	0.14
	On-Forb	Off-Snow	19575	0.06
Off-Warm	On-Forb	573	0.00	
On-Forb	Off-Warm	314	0.00	
Off-Snow	On-Forb	17	0.00	

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¹Plant communities (PC) on prairie dog towns are grass-dominated (On-Grass) and forb-dominated (On-Forb); plant communities in off-town areas are cool season grass-dominated (Off-Cool), warm season grass-dominated (Off-Warm), and snowberry-dominated (Off-Snow).

Monthly Growing Season Precipitation for 2015 and 2016



Cumulative Growing Season Precipitation for 2015 and 2016

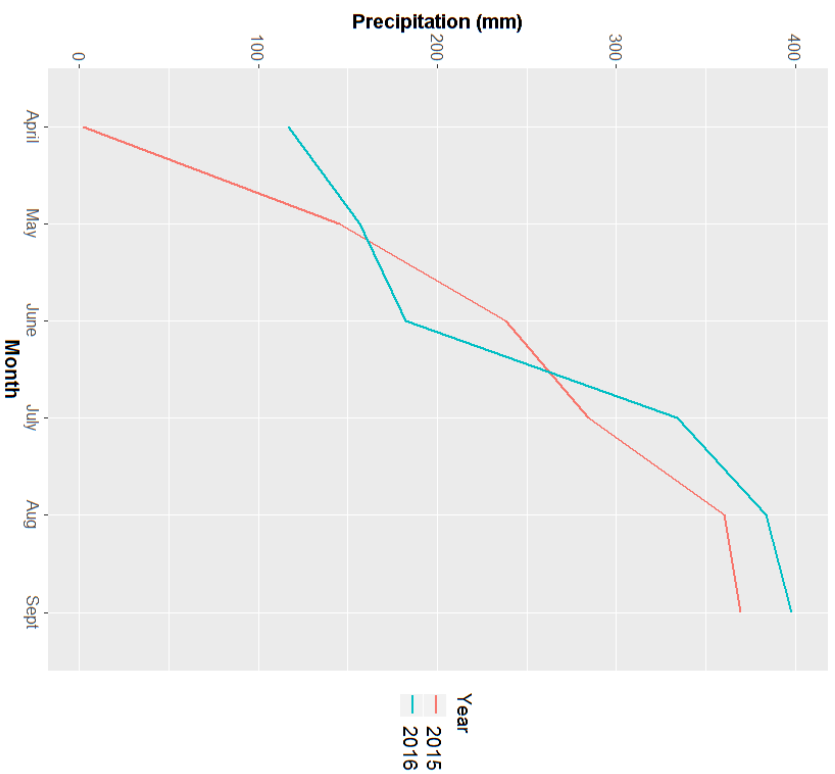


Figure 2: Monthly and cumulative growing season precipitation patterns for 2015 and 2016 recorded at a weather station located on the study area in north central SD (45.737296 N, -100.657540 W)(South Dakota Mesonet 2018).

Comparison of Yearly Plant Community NDVI by Month

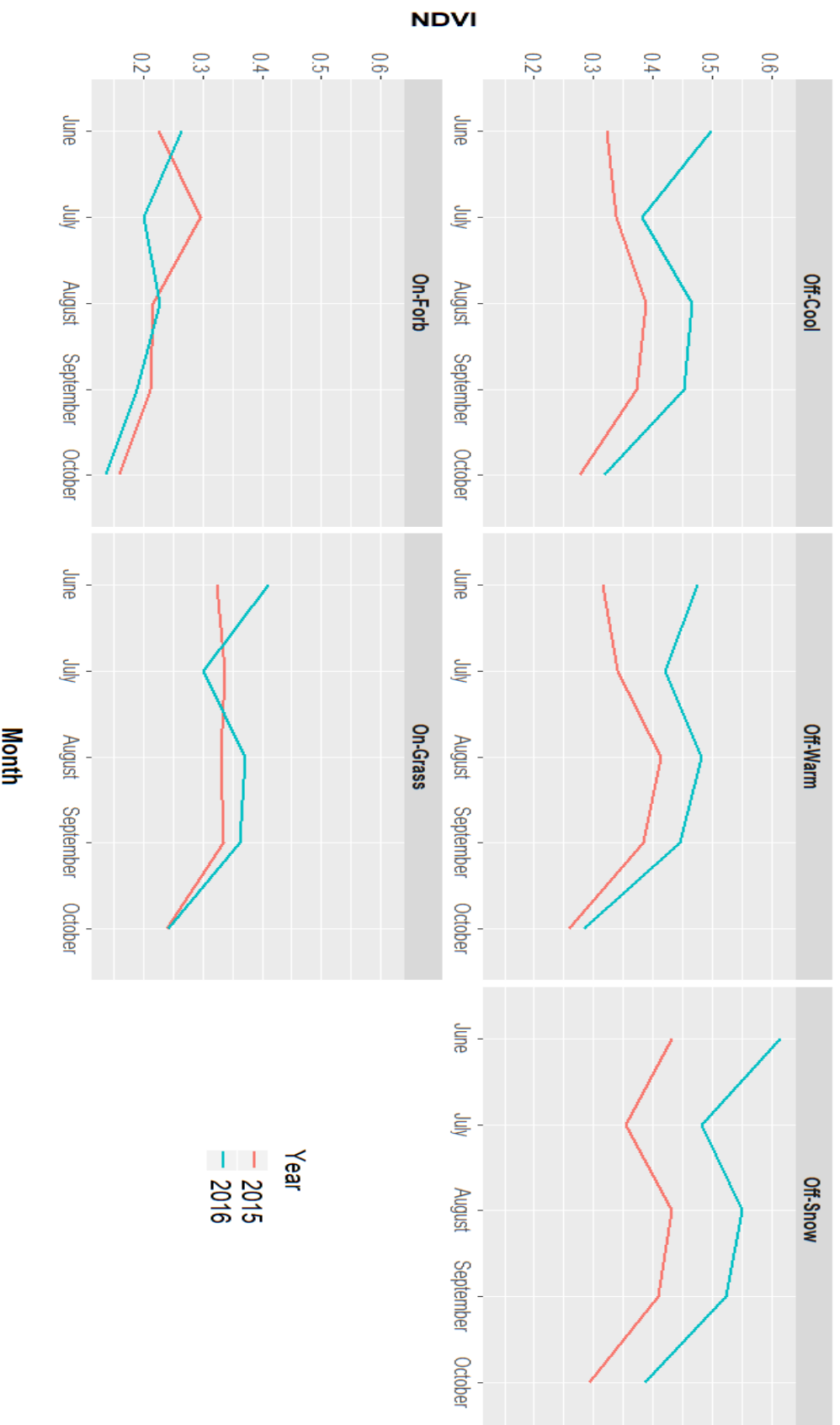
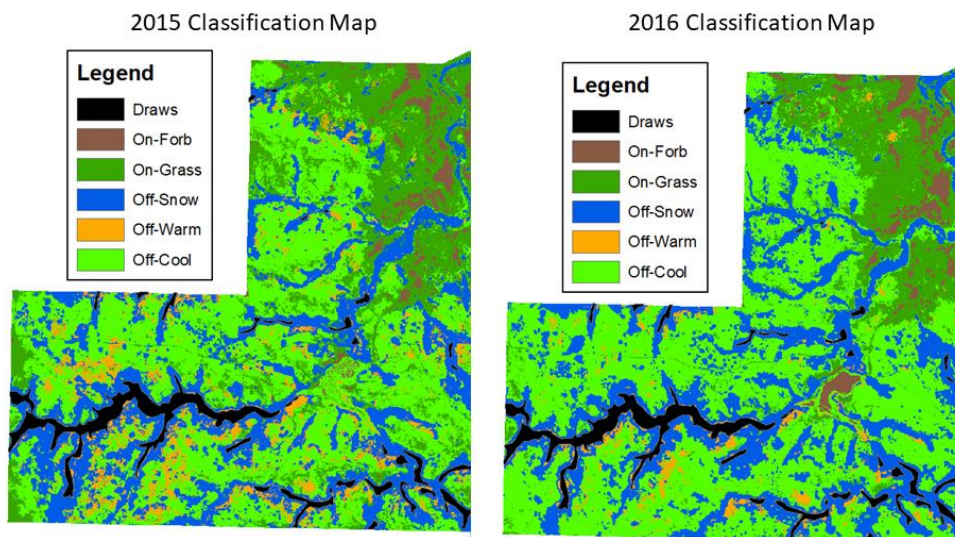


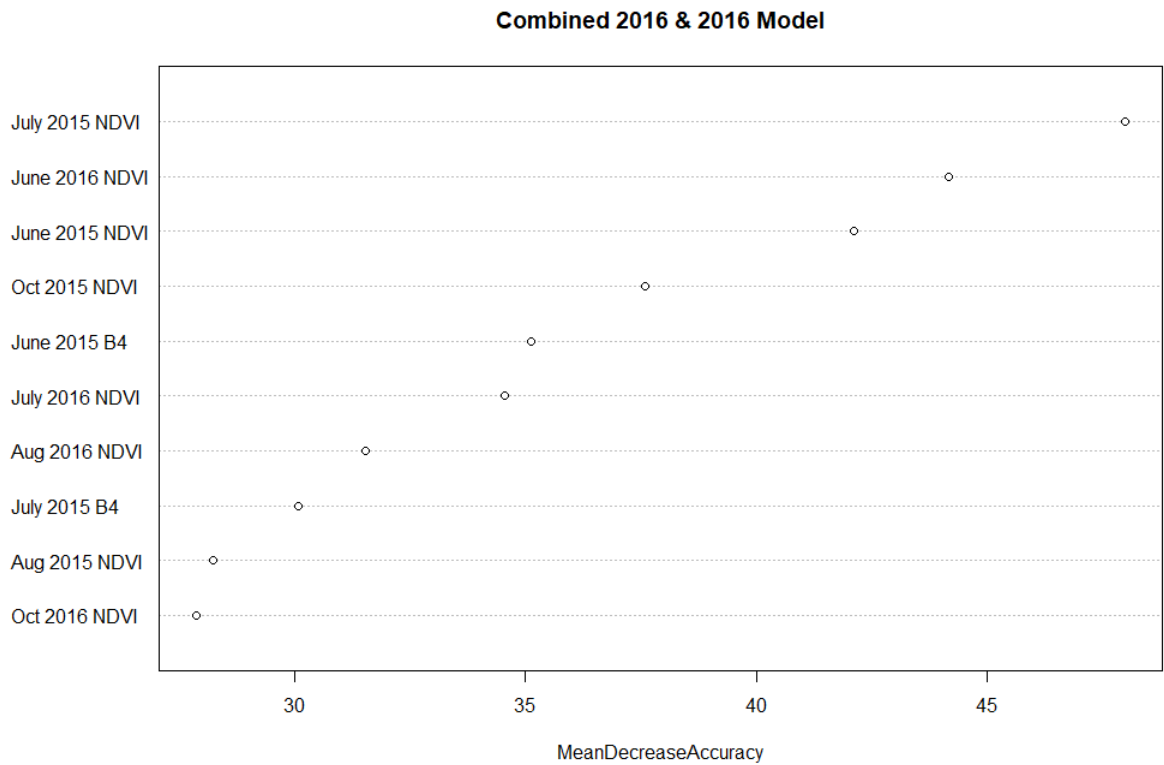
Figure 3: Comparison of mean monthly NDVI for training polygons in five plant communities on the study site in north central SD. Plant communities on prairie dog towns are grass-dominated (On-PDG) and forb-dominated (On-PDF); plant communities in off-town areas are cool season grass-dominated (Off-Cool), warm season grass-dominated (Off-Warm), and snowberry-dominated (Off-Snow).

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Figure 4: Random forest classification maps from 2015 and 2016 of one pasture in the study area in north central South Dakota. Plant communities on prairie dog towns are grass-dominated (On-Grass) and forb-dominated (On-Forb); plant communities in off-town areas are cool season grass-dominated (Off-Cool), warm season grass-dominated (Off-Warm), and snowberry-dominated (Off-Snow).



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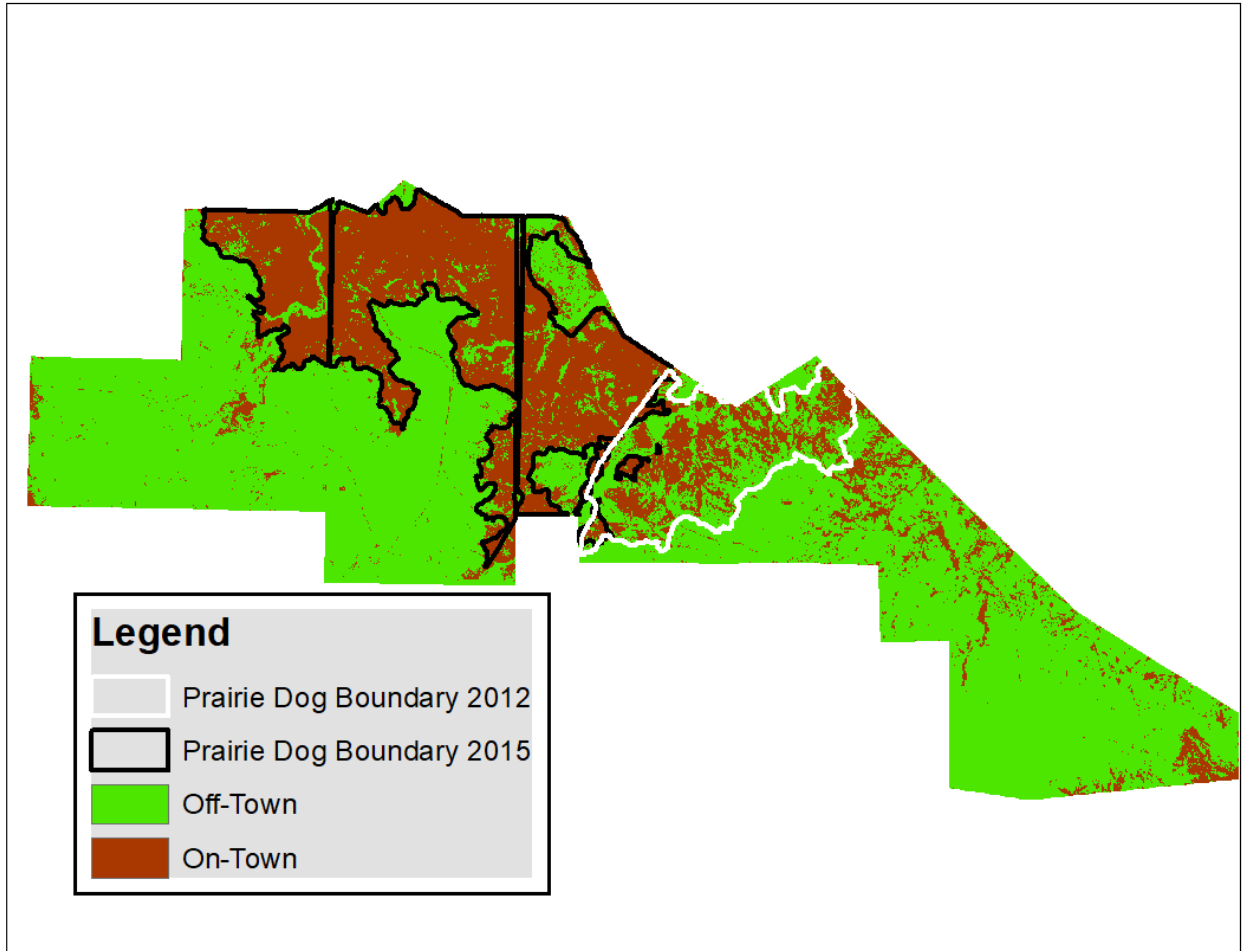
711 Figure 5: Variable importance reported as mean decrease in accuracy. Ten most important
 712 variables are shown, with B1 and B4 corresponding to spectral bands 1 and 4 respectively from
 713 Pleiades image. Variable importance is determined by the model output as the decrease in
 714 accuracy due to the exclusion of that variable during the out of bag error calculation process.
 715 Higher mean decrease in accuracy variables are more important in classifying the data.

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Figure 6: Random forest classification map created from predictions from the combined 2015 and 2016 models. Off-town areas were created by combining the predicted off-town plant communities (Off-Cool, Off-Warm, and Off-Snow) and on-town plant communities (On-Grass and On-Forb). The prairie dog boundary was mapped using a handheld GPS unit, the outlined 2012 prairie dog boundary was former prairie dog colony poisoned in 2013.