

1 **Automated Change Detection Methods for Satellite Data that can Improve**
2 **Conservation Implementation**

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12 **Article impact statement**

13 Methods for automating the detection of habitat loss in satellite images that can be used to
14 monitor and enforce conservation policy.

15 **Running head**

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24

25 **Abstract**

26 A significant limitation in biodiversity conservation has been the effective
27 implementation of laws and regulations that protect species habitats from degradation. Flexible,
28 efficient, and effective monitoring and enforcement methods are needed to help conservation
29 policies realize their full benefit. As remote sensing data become more numerous and accessible,
30 they can be used to identify and quantify land cover changes and habitat loss. However, these
31 data remain underused for systematic conservation monitoring in part because of a lack of simple
32 tools. We adapted and developed two generalized methods that automatically detect land cover
33 changes in a variety of habitat types using free and publicly available data and tools. We
34 evaluated the performance of these algorithms in two ways. First, we tested the algorithms over
35 100 sites of known change in the United States, finding these approaches were effective (AUC >
36 0.90) at distinguishing between areas of land cover change and areas of no change. Second, we
37 evaluated algorithm effectiveness by comparing results to manually identified areas of change in
38 four case studies involving imperiled species habitat: oil and gas development in the range of the
39 Greater Sage Grouse; sand mining operations in the range of the dunes sagebrush lizard; loss of
40 Piping Plover coastal habitat in the wake of hurricane Michael (2018); and residential
41 development in beach mouse habitat. The relative performance of each algorithm differed in
42 each habitat type, but both provided effective means of detecting and delineating habitat loss.
43 Our results show how these algorithms can be used to help close the implementation gap of
44 monitoring and enforcement in biodiversity conservation and we provide a free online tool that
45 can be used to run these analyses.

46

47

48 **Introduction**

49 Biodiversity around the world is threatened with annihilation (Ceballos et al. 2017), and
50 direct habitat loss is the leading cause of the loss of individuals and species extinctions (Newbold
51 et al. 2015; Betts et al. 2017). To address this threat, biodiversity conservation is often focused
52 on protecting species' habitat through a variety of legal and policy mechanisms (UN
53 Environment World Conservation Monitoring Centre & International Union for Conservation of
54 Nature 2017). However, there is reason to believe entities with regulatory authority may lack the
55 means to monitor and enforce protections. Without regular monitoring and enforcement,
56 conservation laws may be nothing more than paper tigers (Salomon et al. 2014). Options for
57 monitoring and enforcing laws that protect habitat have historically required time intensive
58 efforts on the ground, and thus have been limited by funding and personnel availability.
59 However, technological advances are expanding the options for cost effective monitoring efforts
60 (e.g., aquatic telemetry; Hussey et al. 2015, remote cameras detecting poachers; Hossain et al.
61 2016). Given the central role that habitat conservation plays in conserving imperiled species,
62 methods to automatically detect habitat loss in near real-time could significantly enhance
63 compliance monitoring and enforcement capabilities, and substantially increase the effectiveness
64 of conservation laws.

65 Many conservation laws include provisions to protect habitat. For example, the U.S.
66 Endangered Species Act (ESA) is the primary tool for conserving imperiled species in the United
67 States. Among its strengths are the requirement for identification of 'critical habitat' that is
68 necessary for the conservation of listed species, and prohibitions against destroying or adversely
69 modifying these habitats (United States Congress 1978). Similarly, Japan's Nature Conservation

70 Law designates ‘Wilderness’ and ‘Nature Conservation’ areas (Japan National Diet 1972); the
71 New Zealand Conservation Act created several specially protected areas (New Zealand
72 Parliament 1987.); and various international agreements include provisions to reduce habitat loss
73 (e.g. Convention on Biological Diversity; UN Sustainable Development Goals). As written,
74 these laws, policies, and treaties should be stopping or significantly slowing habitat loss and
75 degradation. But this conclusion depends heavily on a critical assumption: that these laws are
76 implemented as written, including monitoring of conservation agreements and enforcement of
77 prohibitions. That assumption is often not independently tested, and the continued loss of
78 species and their habitats indicate there is a substantial implementation gap (López-Bao et al.
79 2015; Chapron 2017).

80 Enforcement is a critical component of any law. Without compliance monitoring and
81 punishment of infractions there is little reason to think legal protections will be effective at
82 changing outcomes (Keane et al. 2008; Trouwborst et al. 2017). For example, if drivers believe
83 there is little risk of punishment for exceeding a speed limit because there is no monitoring, there
84 is every reason to believe they will. Currently, there is little research available on the extent of
85 enforcement and compliance of habitat protection laws and policies (Malcom et al. 2017), but
86 there are many reasons to believe they are lacking. Staff at U.S. federal agencies have
87 acknowledged that they lack the resources to carry out even basic compliance monitoring and are
88 unable to read monitoring reports submitted by permittees, much less carry out independent
89 monitoring (Government Accountability Office 2009). Furthermore, the two federal agencies
90 responsible for implementing the ESA, the U.S. Fish and Wildlife Service and National Marine
91 Fisheries Service (hereafter ‘the Services’), have finalized over a thousand conservation
92 agreements, many of which authorize limited habitat destruction in exchange for mitigation to

93 offset some of those effects (Malcom & Li 2015). Perennial funding shortages, however, have
94 left the Services unable to monitor for compliance with many of those agreements; a
95 shortcoming that threatens to undermine the potential benefits of the ESA. These basic examples
96 of a lack of monitoring and enforcement highlight a critical weakness in the implementation of
97 conservation law and consequently the protection of biodiversity.

98 Insufficient monitoring undermines imperiled species conservation in two ways. First,
99 habitat protections may go unenforced. For example, satellite images revealed that under a
100 habitat conservation plan for the eastern indigo snake (*Drymarchon couperi*) in Georgia, USA,
101 over half of a forest parcel had been cleared despite the requirement that the permittee manage
102 the parcel for the species until at least 2027 (Malcom 2017). Situations like this are a double
103 blow for species: not only has authorized habitat loss occurred, but the conservation measures to
104 minimize or offset those losses were never fully realized. Second, inadequate monitoring leaves
105 conservationists in the dark about the status of species' habitat. If 60 percent of a species' habitat
106 has been degraded, that knowledge should factor into decision making. Left unresolved, a lack of
107 monitoring could negate the expensive and difficult work of securing legal protections for
108 species and their habitats and negotiating conservation agreements.

109 Although the challenge of inadequate enforcement is not new, solutions to date have
110 relied heavily on increased financial support for field work (Chandra & Idrisova 2011). This
111 strategy may be untenable at broad scales given inconsistent and decreasing political will and
112 concomitant funding declines (McCarthy et al. 2012; Waldron et al. 2013). Even when
113 government agencies monitor for compliance with certain projects, they may lack the ability to
114 do so regularly. Monitoring that occurs intermittently leaves ample opportunities for
115 noncompliance in the interim. By the time violations are identified, the environmental damage

116 may be irreversible. Large-scale monitoring programs to efficiently and automatically detect
117 disturbances to wildlife habitat are needed.

118 The growing availability of free satellite images and other remote-sensing data provide an
119 efficient and effective solution for many biodiversity monitoring challenges (Turner et al. 2003).
120 When combined with information on species range and areas permitted for habitat disturbance or
121 destruction, these data open a wealth of opportunities for compliance monitoring and
122 enforcement. As remote sensing data has become more ubiquitous and accessible, so too have
123 the number of approaches for change detection (Willis 2015). Often these analyses focus on one
124 land cover type, with most of the research focused on forest loss (Potapov et al. 2008; Hansen et
125 al. 2010; Song et al. 2018). A significant challenge now is to expand the generality of algorithms
126 to automate change detection across habitats, which would enable and simplify monitoring at
127 regional and continental scales.

128 Here we report on two automated land cover change-detection algorithms developed to
129 aid conservation compliance monitoring across different habitat types and at broad scale. We
130 evaluate the utility of these methods using systematically collected validation data and four case
131 studies. Both algorithms use data that is readily available online, meaning anyone, including
132 government agencies, conservation organizations, and the public, can use them to improve
133 conservation. We demonstrate that these approaches are sufficiently effective, efficient, and
134 flexible for use in large- and small-scale systematic conservation monitoring efforts. Adoption
135 of automated change detection can help close one of the biggest gaps in biodiversity
136 conservation, and we discuss the potential for future technological and regulatory development
137 to further leverage their potential.

138 **Methods**

139 We used the Google Earth Engine platform, which provides real-time access to terabytes
140 of remote sensing data and the cloud computing capabilities to analyze them (Gorelick et al.
141 2017), to create processes to automatically detect changes in land cover between satellite images
142 collected over two time periods. We analyzed images from the Sentinel-2 satellite system.
143 Sentinel-2 is deployed and maintained by the European Space Agency, providing global
144 coverage of 10-meter resolution imagery every 12 days. Sentinel-2 images contain 13 bands that
145 record reflectance values in the visible, near infrared, short-wave infrared, and near ultraviolet
146 spectra (Drusch et al. 2012).

147 The basic process (Fig. 1) involves the following steps:

- 148 1. Define an area of interest and collect satellite images.
- 149 2. Process images (mask clouds, correct for terrain, etc.)
- 150 3. Divide images into before and after collections
- 151 4. Composite before and after collections into single images.
- 152 5. Calculate pixel-wise change metrics between images.
- 153 6. Identify minimum values that correspond to the change to be detected.
- 154 7. Select pixels exceeding these minimum change thresholds.

155 **Image Processing**

156 After defining an area of interest and collecting all the spatially overlapping Sentinel-2 images,
157 we first removed cloud and cloud shadow pixels from each image in the collection. Built-in
158 cloud masking is limited for Sentinel-2 imagery, because this system does not contain a thermal
159 sensor measuring temperature, which is critical to common cloud masking procedures (Zhu et al.
160 2015). We used the quality assurance bands included with all S2 images, and additionally
161 calculated cloud and shadow probability metrics as follows.

162 To identify cloudy pixels, we implemented an adaptation of the simpleCloudScore
163 algorithm developed for Landsat provided in Google Earth Engine, which uses a combination of
164 indices to assign a per pixel cloud likelihood score from 0 to 1 (Supporting Information). We
165 identified any pixels receiving a score of 0.15 or greater as cloud. We then calculated a set of
166 likely cloud shadow locations by translating the location of cloud pixels in the x and y directions
167 according to

$$168 \quad x = \tan(\text{zen}) * h * \cos(\text{az})$$
$$169 \quad y = \tan(\text{zen}) * h * \sin(\text{az})$$

170
171 where h is the cloud height, zen and az are the sun zenith and azimuth at the time and
172 location of the image, as recorded by Sentinel-2. This translation is applied using a set of
173 possible cloud heights (h) to create a set of polygons encompassing possible cloud shadow
174 locations (Zhu & Woodcock 2012). We then calculated the RGB ratio shadow indices (Sarabandi
175 et al. 2004) for each pixel and classified those with a score over 0.25 as shadow (Supporting
176 Information). Any of these shadow pixels that fell within the translated cloud locations were
177 then labeled as cloud shadow. Finally, we identified water pixels using a set of water indices
178 including a normalized difference water index (Xu 2006), and darkness indices to obtain a 0 -1
179 water likelihood score (Supporting Information). We masked any pixels over 0.25. The set of
180 cloud, shadow, and water pixels were then removed from each image.

181 After all images in the spatially filtered collection were masked for clouds, shadows, and
182 water, we applied per-pixel terrain correction using the *c-correction* equation (Teillet et al.
183 1982). This method standardizes the reflectance of sloped surfaces using the illuminance of each
184 pixel as determined by a digital elevation model and the solar zenith and azimuth at the time and
185 location of the image. We used the 30m resolution digital elevation model from the U.S.
186 Geological Survey (Farr et al. 2007) to determine slope and aspect.

187 Change detection was ultimately run between single before and after images. However,
188 clouds, shadows and other artefacts can make detection difficult between any two images.
189 Therefore, we compared two composites of all the masked and corrected images in before and
190 after time periods. By default, the before period contained a year of images preceding the date
191 after which we wanted to check for changes, and a three-month period following this date
192 comprised the after period. Following cloud/shadow/water masking and terrain correction, we
193 created a single-image composite for each time period by selecting the median value of each
194 pixel stack. These single before and after images were then clipped to the exact geometry of the
195 study area and used as inputs to automated change detection algorithms. Six bands
196 corresponding to blue, green, red, near infrared, short-wave infrared 1, and short-wave infrared 2
197 were used in all calculations of change.

198 **Change Detection Algorithms**

199 While a variety of algorithms have been developed to detect changes between satellite images
200 (Willis 2015) we started from two fundamentally different approaches. The first builds on the
201 method used by the U.S Geological Survey to produce the National Land Cover Dataset land
202 cover change (LCC) data (Jin et al. 2013) and uses features that relate to real phenomena. We
203 refer to this as the LCC algorithm. First, six spectral change metrics are calculated between
204 before and after imagery on a per-pixel basis:

- 205 1. The Change Vector (*CV*) measures the total change in reflectance values between two
206 images across the visible and infrared spectrum.
- 207 2. Relative CV Maximum (RCV_{MAX}) measures the total change in each band scaled to their
208 global maxima.

- 209 3. Differences in Normalized Difference Vegetation Index (*dNDVI*) uses ratios between
210 near infrared and red reflectance to indicate changes in the concentration of vegetation.
- 211 4. Ratio Normalized Difference Soil Index (*dRNDSI*) uses ratios between short-wave
212 infrared and green reflectance to indicate changes in the concentration of bare ground.
- 213 5. Normalized Burn Ratio (*dNBR*) is the normalized difference between the green and short-
214 wave infrared bands, indicating the severity of burned areas of vegetation.
- 215 6. Normalized Difference Water Index (*dNDWI*) is the normalized difference between the
216 near- and short-wave-infrared bands, indicating moisture.

217 Calculating all six metrics at each pixel produces an unscaled change image with six
218 bands (one band per metric). We then convert pixel values for each band to z-scores using the
219 mean or minimum value and standard deviation of values across the image. We use global means
220 for normalized indices (*dNDVI*, *dRNDSI*, *dNBR*, *dNDWI*), and global minimums for scaled
221 indices (*CV* and *RCV_{MAX}*) as in Jin et al. (2013). The output is a six-band image consisting of the
222 standardized z-scores for each change metric. This transformation on the change image centers
223 and scales per pixel changes relative to baseline changes in reflectance, brightness, etc. between
224 the before and after images.

225 The output image is then iteratively re-weighted using the probability that a pixel
226 represents no-change. We approximate this probability with *p-values* from the relevant
227 distributions for each band. For normalized indices (*dNBR*, *dRNDSI*, *dNDVI*, *dNDWI*) we use the
228 cumulative distribution function of a standard normal distribution $\sim N(0, 1)$. The *CV* statistic is
229 calculated as the sum of squared deviations for each image band, and therefore is approximately
230 chi-square distributed (Lancaster & Seneta 2005). We calculated *p-values* using the cumulative

231 distribution function of a chi-square distribution with degrees of freedom equal to the number of
232 image bands minus one.

233 The second algorithm is the multivariate alteration detection (MAD) algorithm (Nielsen
234 2007). This approach uses canonical correspondence analysis to identify linear transformations
235 that maximize correlation between two sets of variables, in this case, the bands of two images.
236 Extreme deviations are identified by calculating the sum of squared deviations from the mean of
237 each canonical variate, relative to its variance. We implement the MAD algorithm by
238 performing singular value decomposition on a correlation matrix of the bands of two images.
239 Singular value decomposition produces two orthogonal vectors, U and V which equate to the
240 coefficients for the CCA linear transformation. Singular value decomposition also produces a
241 diagonal vector S , equivalent to the correlation coefficients (ρ_i) of canonical correlation.
242 Canonical variates are then obtained as the difference between the bands of the first image
243 transformed by U and the bands of the second image transformed by V .

244 The output of a single iteration of the MAD algorithm is an image with $\min(m, n)$ bands
245 corresponding to the canonical variates V , a band containing the chi-square summary statistic at
246 each pixel (χ^2), and a band containing the corresponding p -value from a chi-square distribution
247 with $\min(m, n)$ degrees of freedom. As with the LCC algorithm, we then recalculate the MAD
248 variates using these p -values to weight the calculation of means and variances as in Nielsen
249 (2007). This procedure is performed iteratively until the output image has stabilized, or a
250 maximum of $k = 30$ iterations has been reached (Nielsen 2007). We use changes in the
251 correlation coefficients between iterations, $c_k = \text{abs}|\max(S_k) - \max(S_{k-1})|$ to evaluate convergence
252 of the reweighting algorithm by inferring stability when $c_k < 0.001$. All image processing,

253 calculations and transformations are performed in Google Earth Engine (Supporting
254 Information).

255 **Algorithm Validation**

256 We collected algorithm output at 100 study sites across the continental United States that
257 had been manually identified as undergoing habitat loss due to anthropogenic landscape
258 modification since 2016 (Supporting Information). The predominant land cover undergoing
259 change at each site was broadly categorized according to National Land Cover Dataset classes
260 (Fry et al. 2011) as either desert ($n = 12$), forest ($n = 40$), grassland ($n = 14$), shrub/scrub ($n =$
261 10), or wetland ($n = 14$). Sites were chosen opportunistically while systematically balancing
262 sample sizes among non-forested land cover types. At each study site, we manually delineated
263 polygons in all areas of real change, and categorized observed changes as either bare ground,
264 building (residential and commercial development), paved (roads, parking lots, etc.), or solar
265 development. We then sampled the algorithm output values at all pixels within change area(s),
266 and the maximum of either an equal number of random pixels or 1,000 random pixels within the
267 study area not falling within areas of change and split these data into 70% training and 30%
268 validation sets.

269 We used a combination of linear discriminant analysis and receiver operating
270 characteristics to create sets of thresholds delineating changed and unchanged pixels based on
271 algorithm outputs. First, we estimate the coefficients for a linear transformation of algorithm
272 outputs (CV , $dNDVI$, etc. for LCC; $V1$, $V2$, ..., X^2 for MAD) into a single discriminant score that
273 maximized the differentiation between algorithm outputs in changed and unchanged pixels.
274 Coefficients were estimated from training data for changes occurring in all habitats, and specific
275 to major habitat types. We then used receiver operating characteristic curves to identify the

276 discriminant score providing greatest separation between true and false positives among
277 validation data and assessed the performance of each algorithm in terms of the area under the
278 curve. We identified the discriminant score that maximized the ratio between true and false
279 positive rates as a threshold for automatically identifying changes. Linear discriminant and
280 receiver operating characteristic analyses were conducted in R (Team 2014) using the *pscl*
281 (Jackman 2017) and *pROC* (Robin et al. 2011) packages (Supporting Information).

282 **Case Studies**

283 To demonstrate how these methods might be applied in situ, we evaluated the outputs
284 from both change detection algorithms in each of four case studies (Table 1). These case studies
285 were chosen as a sample of ongoing threats to imperiled species in a diversity of non-forested
286 habitats. We focused outside of forested areas due to the extensive work and tools available for
287 detecting deforestation (e.g., Global Forest Watch). Additionally, each case study represents a
288 different potential use case for automated change detection; large-scale retrospective detection
289 (dune sagebrush lizard); small-scale retrospective detection (beach mouse); rapid inventory after
290 a natural disaster (Piping Plover); and active small-scale monitoring (Greater Sage Grouse).

291 To evaluate algorithm effectiveness in these case studies, we compared algorithm outputs
292 to changes identified by visual inspection of before and after images. Within each study area, an
293 independent reviewer manually delineated all anthropogenic changes in the habitat type of
294 interest. We refer to these polygons as ‘ground truth’ polygons. We then ran both the LCC and
295 MAD algorithms within each study area, and delineated pixels representing change using the
296 thresholds identified during LDA analysis. These areas representing change were then converted
297 to polygons.

298 We use two complementary metrics to assess the algorithms' performance. First, the
299 Jaccard index measures the area of overlap between two geometries as the intersection divided
300 by the union; $J(A, B) = A \cap B / A \cup B$. Second, we calculate the omission and commission
301 error rates as the proportion of ground truth polygons that did not overlap algorithm output and
302 the proportion of algorithm output that did not overlap any ground truth polygons, respectively.

303 In practice, we would apply a majority filter to these binary results to eliminate single,
304 isolated pixels and create more contiguous areas of change or no change before conversion to
305 polygons. However, to identify potential scale dependencies in algorithm performance, we
306 converted to polygons all pixels identified as change. We then considered only sets of polygons
307 greater than a sequence of minimum size {0 ac, 0.1 ac, 0.5 ac, 1 ac}, and calculate performance
308 metrics within each of these subsets.

309 **Results**

310 **Algorithm Validation**

311 We collected algorithm output data from areas of real and no change at 100 locations
312 (Supporting Information). Bare ground was the most common form of disturbance (86/100).
313 Because bare ground preceded residential development and pavement, we did not detect these
314 disturbance forms at any location. In 12 instances, solar fields were built directly over existing
315 desert and grassland areas within the three-months comprising the 'after' image, and therefore
316 appeared as a direct change from habitat to solar development.

317 Overall, both algorithms effectively discriminated change from no-change among
318 validation data, as indicated by AUC scores > 0.90 for all habitat types (Fig. 2). Generally, the
319 MAD algorithm performed slightly better than the LCC algorithm, as indicated by higher AUC
320 scores. This was especially true in detecting 'generic' change, when thresholds were not

321 optimized to a specific habitat type (Fig. 2). The LCC algorithm was least successful at
322 identifying changes in grassland habitats ($AUC = 0.95$), and most successful in forested areas
323 ($AUC = 0.99$). The MAD algorithm was most successful in wetland habitats ($AUC = 1$), and the
324 least successful in forests ($AUC = 0.98$).

325 **Case Studies**

326 We found these change detection methods were effective for detecting habitat loss in important
327 conservation areas in all four case studies. We detected 8.5 km² of dune sagebrush lizard habitat
328 removed by either sand mining or oil and gas well construction within the Permian Basin, TX
329 case study area (797.8 km²) between January 2017 and January 2018. The rapid appearance and
330 expansion of large sand mines, in conjunction with ongoing oil and gas development identified
331 by both algorithms (Fig. 3) indicated current protections for the imperiled lizard were insufficient
332 to conserve the species.

333 We detected 0.85 km² of Piping Plover habitat within 26.2 km² of designated critical
334 habitat lost in the wake of Hurricane Michael (between August and October 2018), illustrating
335 the threat posed by natural disasters to already imperiled species. In the Gulf County, FL case
336 study area (4.7 km²), 0.03 km² of potential beach mouse habitat were lost to residential
337 development between January 2017 and January 2018. These areas of loss identified by
338 automated change detection must be considered by the U.S. Fish and Wildlife Service when
339 permitting future development in the species range. In the Wright, WY case study area (215.7
340 km²) we detected 0.17 km² of grassland habitat loss between June and September 2017. This
341 loss was due to oil and gas drilling pad and road construction.

342 The MAD algorithm was more sensitive to landscape changes, but less specific than the
343 LCC algorithm, as indicated by higher commission rates and lower omission rates (Table 2).

344 Both algorithms had relatively high commission rates, indicating detection of changes not
345 identified by manual inspection of before and after images. A post-hoc analysis of commission
346 indicated ~60% of these polygons represented real changes missed by manual inspection.
347 Jaccard indices indicated low to moderate agreement in the area of overlap between change
348 polygons delineated manually and those produced by both automated change detection
349 algorithms (Table 2). Commission rates decreased substantially when the minimum polygon size
350 considered as change was increased from zero.

351 Finally, algorithms detected changes between before and after images faster than human
352 review. Both the LCC and MAD algorithms took < 40 min to produce change polygons in each
353 study area. The time required for manual delineation of changes ranged from 6 hours in the
354 Wright, WY case study area to several days in the Permian Basin, TX study area.

355 **Discussion**

356 The conservation of biodiversity has been limited, in part, by an inability to monitor and
357 enforce conservation laws, regulations, and agreements. While remote sensing data have long
358 held the promise of transforming environmental monitoring efforts, publicly accessible tools
359 leveraging this data to achieve actionable insights have been lacking (Willis 2015). In addition
360 to cost, ease of use is critical if these tools are to be widely adopted for conservation monitoring
361 and enforcement, as many land managers and regulators will not have expertise in ecology,
362 policy, and remote sensing (Wiens et al. 2009). In this paper we adapt and present two
363 algorithms for automated habitat change detection using satellite imagery, and demonstrate their
364 efficacy, efficiency, and flexibility in a variety of test areas and case studies. Built on publicly
365 available data and technology, these tools can be used by anyone - from local property managers

366 to government agencies charged with national monitoring programs - to automatically detect
367 habitat loss (Supporting Information).

368 Both the MAD (Nielsen 2007) and LCC (Jin et al. 2013) algorithms exhibited excellent
369 performance discriminating habitat loss from background changes between images in test cases
370 (Fig. 1). Beyond performing well in forested landscapes, where many algorithms have been
371 developed (Hansen et al. 2010), both algorithms were effective in a variety of non-forest areas
372 (Fig. 1). This flexibility is in part attributable to the use of land cover specific thresholds
373 obtained from simple linear discriminant analysis using subsets of algorithm output data. We
374 observed slightly lower AUC scores when receiver operating characteristic curves were
375 produced using thresholds estimated from all data across land cover types. Specific thresholds
376 were also important in detecting changes other than bare ground (e.g., solar energy
377 development). The availability of a flexible tool that can be applied in a variety of contexts,
378 rather than requiring a different tool for different ecosystems, should make automated change
379 detection more readily adopted by entities with regulatory authority.

380 The ability of each algorithm to detect meaningful change was confirmed in case studies,
381 where both methods identified nearly all instances of anthropogenic habitat loss that were
382 manually delineated (i.e., low omission rates; Table 2). The MAD algorithm appeared more
383 sensitive and less specific than LCC as illustrated by outputs from case studies. Generally higher
384 commission rates among MAD outputs reflect the tendency of this algorithm to detect all types
385 of change - even those occurring naturally due to phenology and seasonality. The change
386 metrics included in the LCC algorithm that related to real-world phenomena (e.g., *dNDVI*, *dNBR*,
387 etc.) likely enabled better discrimination between generic and habitat-specific change.
388 Commission occurred from one of two outcomes: instances of habitat loss missed by manual

389 review, or natural changes to the landscape that were not of interest. Object oriented, or
390 computer vision-based approaches may be helpful for distinguishing among these (Malof et al.
391 2016; Ghorbanzadeh et al. 2019). Here, we present algorithms that are ready to be applied to a
392 variety of habitats using only a Google Earth Engine account. Future work that integrates
393 dynamically updated machine learning classification approaches, rather than a predefined set of
394 thresholds, may also improve discrimination.

395 However, most instances of commission were not errors, illustrating a key advantage of
396 automated change detection methods for conservation monitoring and enforcement: Both
397 algorithms may be more effective than human review, particularly over large areas. The finding
398 that ~60% of instances of commission by both algorithms were in fact true cases of habitat loss
399 demonstrates the potential for an automated change detection system to produce more complete
400 result, especially over large areas, than manual inspection of before and after images.
401 Furthermore, both algorithms were more efficient than manual inspection of satellite imagery.
402 Human delineation of changes required several orders of magnitude more time to complete than
403 automated algorithms and scaled with the size of the area of interest. Thus, automated change
404 detection methods are vastly more time efficient, making them applicable and preferable in
405 situations that require repeated or continuous monitoring. For entities wanting to use satellite
406 imagery to implement a comprehensive conservation monitoring and enforcement program, this
407 kind of efficiency is critical.

408 In the context of environmental laws that protect habitat, these automated change
409 detection approaches could be used by regulatory agencies to enforce prohibitions on habitat
410 destruction. In the United States, federal agencies responsible for implementing the Endangered
411 species Act might use tools like this to monitor and enforce compliance with the terms and

412 conditions of federal consultations under section 7 of the ESA, or habitat management plans
413 associated with conservation agreements under section 10. These potential applications are
414 illustrated by our case studies. For example, Gulf County, Florida has been developing a Habitat
415 Conservation Plan to offset harm to endangered St. Andrew beach mice due to residential
416 construction. These algorithms can be used to measure past and ongoing development and
417 inform the plan as it is developed, as well as to monitor for compliance in the future.
418 Additionally, the extent of historic habitat loss must be considered in future permitting decisions.
419 Similarly, the ability to identify and track the expansion of sand mines within the range of the
420 dune sagebrush lizard provided evidence that a state-run voluntary conservation agreement was
421 insufficient to minimize threats faced by the species, and informed a petition to list the species
422 under the ESA (<https://ecos.fws.gov/docs/petitions/92210//1040.pdf>). Finally, conservation
423 agreements may often involve specifications of where development can and cannot occur within
424 an area. The Wright, Wyoming case study provides a hypothetical example of how a small area
425 could be monitored with relatively short (~3 month) frequency to detect habitat destruction.
426 Here, the changes detected here were legal, but in other instances might alert an enforcement
427 agency to unauthorized activities.

428 Our results demonstrate the capability of both the MAD and LCC algorithms to
429 automatically detect habitat loss, but those hoping to use these approaches should be aware of
430 several caveats. First, both algorithms were more effective at identifying the occurrence of
431 change than accurately delineating the extent of those changes. This was reflected by relatively
432 low (< 0.5) Jaccard index scores. Change thresholds designed for specificity rather than
433 sensitivity will invariably exclude some real changes, meaning the area of detected change will
434 underestimate area changed. Additionally, the commission rates of both algorithms decreased as

435 the minimum size of changes considered increased. This pattern suggests a minimum size of
436 disturbance that can be regularly detected by these algorithms using Sentinel-2 data. If
437 disturbances $< 500 \text{ m}^2$ need to be detected, users may experience a higher number of false
438 positives.

439 While the algorithms presented here were run using Sentinel-2 data, they were written
440 generically and can be applied to other passive remote sensing systems with the requisite bands
441 and rigorous orthorectification and co-registration. For instance, Landsat 8, which provides
442 global coverage of 30-meter resolution imagery every 16 days, contains analogous bands to
443 Sentinel-2 as well as a thermal band measuring surface temperature allowing for more robust
444 detection of clouds (Zhu et al. 2015). Our cloud detection and masking approaches are imperfect
445 with Sentinel-2 imagery and may not perform as well in very cloudy areas. While habitat
446 specific parameters help, clouds may still occasionally be flagged as change. Using these
447 algorithms with Landsat data may be useful in cases where some resolution can be sacrificed for
448 more robust cloud removal. Generic change detection algorithms using SAR data, which is
449 invariant to cloud cover, may also prove useful in future development (Nielsen et al. 2017;
450 Rüetschi et al. 2019).

451 By adapting two change detection algorithms and validating their efficacy across a
452 variety of habitats, we have developed tools to help enforce conservation laws and agreements
453 with remote sensing data (Supporting Information). The approaches described here do not
454 require remote sensing expertise and can be used by local land managers, as well as federal
455 agencies responsible for administering national and international laws. In addition, they are
456 flexible, run much more quickly than manual delineation, and can be run repeatedly in many
457 different contexts and at large spatial scales, making them suitable for the monitoring and

458 enforcement of environmental laws. Most importantly, they are built using publicly available
459 data and computing platforms. Many previous tools have been limited in their use in regulatory
460 capacities because they are only available for a fee under pay-for-service structures. For remote
461 sensing data to be used to improve conservation, it is critical that platforms like Google Earth
462 Engine continue to provide open access. The continued improvement of automated change
463 detection methods and adoption by regulatory authorities holds the potential to close a significant
464 gap in the protection of biodiversity.

465 **Supporting Information**

466 A public app running change detection is available at
467 <https://defendersofwildlifegis.users.earthengine.app/view/dowacd>. All code used for image
468 processing and change detection in Google Earth Engine, R code used to perform statistical
469 analyses, and algorithm output data used for validation are available in an Open Science
470 Framework repository (DOI: 10.17605/OSF.IO/5QAD8). The authors are solely responsible for
471 the content and functionality of these materials. Queries (other than absence of the material)
472 should be directed to the corresponding author.

473 **Literature Cited**

- 474 Betts MG, Wolf C, Ripple WJ, Phalan B, Millers KA, Duarte A, Butchart SHM, Taal L. 2017.
475 Global forest loss disproportionately erodes biodiversity in intact landscapes. *Nature*
476 **547**:441–444.
- 477 Ceballos G, Ehrlich PR, Dirzo R. 2017. Biological annihilation via the ongoing sixth mass
478 extinction signaled by vertebrate population losses and declines. *Proceedings of the*
479 *National Academy of Sciences* **114**:6089–6096.
- 480 Chandra A, Idrisova A. 2011. Convention on Biological Diversity: a review of national
481 challenges and opportunities for implementation. *Biodiversity and Conservation* **20**:3295–
482 3316.
- 483 Chapron G. 2017. The environment needs cryptogovernance. *Nature* **545**:403–405.
- 484 Drusch M et al. 2012. Sentinel-2: ESA’s Optical High-Resolution Mission for GMES
485 Operational Services. *Remote Sensing of Environment* **120**:25–36.

- 486 Farr TG et al. 2007. The Shuttle Radar Topography Mission. *Reviews of Geophysics*
487 **45**:RG2004.
- 488 Fry JA, Xian G, Jin S, Dewitz JA, Homer CG, Limin Y, Barnes CA, Herold ND, Wickham JD.
489 2011. Completion of the 2006 national land cover database for the conterminous United
490 States. *Photogrammetric Engineering and Remote Sensing* **77**:858–864.
- 491 Ghorbanzadeh O et al. 2019. Evaluation of Different Machine Learning Methods and Deep-
492 Learning Convolutional Neural Networks for Landslide Detection. *Remote Sensing* **11**:196.
- 493 Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. 2017. Google Earth
494 Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*
495 **202**:18–27.
- 496 Government Accountability Office. 2009. Endangered Species Act: The U.S. Fish and Wildlife
497 Service has incomplete information about effects on listed species from section 7
498 consultations. Washington, DC.
- 499 Hansen MC, Stehman S V, Potapov P V. 2010. Quantification of global gross forest cover loss.
500 *Proceedings of the National Academy of Sciences of the United States of America*
501 **107**:8650–5.
- 502 Hossain ANM, Barlow A, Barlow CG, Lynam AJ, Chakma S, Savini T. 2016. Assessing the
503 efficacy of camera trapping as a tool for increasing detection rates of wildlife crime in
504 tropical protected areas. *Biological Conservation* **201**:314–319.
- 505 Hussey NE et al. 2015. Aquatic animal telemetry: A panoramic window into the underwater
506 world. *Science* **348**:1255642.
- 507 Jackman S. 2017. *pscl: Classes and methods for R developed in the Political Science*
508 *Computational laboratory*. United States Studies Centre, University of Sydney, Sydney,
509 New South Wales, AUstralia.
- 510 Japan Naitonal Diet. 1972. Nature Conservation Law.
- 511 Jin S, Yang L, Danielson P, Homer C, Fry J, Xian G. 2013. A comprehensive change detection
512 method for updating the National Land Cover Database to circa 2011. *Remote Sensing of*
513 *Environment* **132**:159–175.
- 514 Keane A, Jones JPG, Edwards-Jones G, Milner-Gulland EJ. 2008. The sleeping policeman:
515 Understanding issues of enforcement and compliance in conservation. *Animal Conservation*
516 **11**:75–82.
- 517 Lancaster HO, Seneta E. 2005. Chi-Square Distribution. *Page Encyclopedia of Biostatistics*. John
518 Wiley & Sons, Ltd, Chichester, UK.
- 519 López-Bao JV et al. 2015. Toothless wildlife protection laws. *Biodiversity and Conservation*
520 **24**:2105–2108.
- 521 Malcom J. 2017. *ESA Compliance Monitoring and the Langboard HCP*. Washington, DC.
522 https://defenders-cci.org/working_papers/Langboard_HCP/
- 523 Malcom J, Kim T, Li Y-W. 2017. Free Aerial Imagery as a Resource to Monitor Compliance

- 524 with the Endangered Species Act. bioRxiv:204750.
- 525 Malcom JW, Li YW. 2015. Data contradict common perceptions about a controversial provision
526 of the US Endangered Species Act. *Proceedings of the National Academy of Sciences of the*
527 *United States of America* **112**:15844–15849.
- 528 Malof JM, Bradbury K, Collins LM, Newell RG. 2016. Automatic detection of solar
529 photovoltaic arrays in high resolution aerial imagery. *Applied Energy* **183**:229–240.
- 530 McCarthy DP et al. 2012. Financial costs of meeting global biodiversity conservation targets:
531 current spending and unmet needs. *Science* **338**:946–949.
- 532 New Zealand Parliament. 1987. Conservation Act 1987.
- 533 Newbold T et al. 2015. Global effects of land use on local terrestrial biodiversity. *Nature*
534 **520**:45–50.
- 535 Nielsen AA. 2007. The regularized iteratively reweighted MAD method for change detection in
536 multi- and hyperspectral data. *IEEE Transactions on Image Processing* **16**:463–477.
- 537 Nielsen AA, Canty MJ, Skriver H, Conradsen K. 2017. Change detection in multi-temporal dual
538 polarization Sentinel-1 data. Pages 3901–3904 *IEEE International Geoscience and Remote*
539 *Sensing Symposium*. Fort Worth, TX.
- 540 Potapov P et al. 2008. Mapping the World's Intact Forest Landscapes by Remote Sensing.
541 *Ecology and Society* **13**.
- 542 Robin X, Turck N, Hainard A, Tiberti N, Lisacek F, Sanchez J-C, Muller M. 2011. pROC: an
543 open-source package for R and S+ to analyze and compare ROC curves. *BMC*
544 *Bioinformatics* **12**:77.
- 545 Rüetschi M, Small D, Waser L, Rüetschi M, Small D, Waser LT. 2019. Rapid Detection of
546 Windthrows Using Sentinel-1 C-Band SAR Data. *Remote Sensing* **11**:115.
- 547 Salomon M, Markus T, Dross M. 2014. Masterstroke or paper tiger – The reform of the EU's
548 Common Fisheries Policy. *Marine Policy* **47**:76–84.
- 549 Sarabandi P, Yamazaki F, Matsuoka M, Kiremidjian A. 2004. Shadow detection and radiometric
550 restoration in satellite high resolution images. Pages 3744–3747 *International Geoscience*
551 *and Remote Sensing Symposium (IGARSS)*.
- 552 Song X-P, Hansen MC, Stehman S V., Potapov P V., Tyukavina A, Vermote EF, Townshend JR.
553 2018. Global land change from 1982 to 2016. *Nature* **560**:639–643.
- 554 R Core Development Team. 2019. R: a language and environment for statistical computing.
555 Version 3.5.1. R Foundation for Statistical Computing, Vienna, Austria.
- 556 Teillet PM, Guindon B, Goodenough DG. 1982. On the Slope-Aspect Correction of
557 Multispectral Scanner Data. *Canadian Journal of Remote Sensing* **8**:84–106.
- 558 Trouwborst A et al. 2017. International Wildlife Law: Understanding and Enhancing Its Role in
559 Conservation. *BioScience* **67**:784–790.
- 560 Turner W, Spector S, Gardiner N, Fladeland M, Sterling E, Steininger M. 2003. Remote sensing

- 561 for biodiversity science and conservation. *TRENDS in Ecology and Evolution* **18**:306–314.
- 562 UN Environment World Conservation Monitoring Centre, International Union for Conservation
563 of Nature. 2017. World Database on Protected Areas. Available from
564 www.protectedplanet.net
- 565 United States Congress. 1978. The Endangered Species Act Amendments of 1978.
- 566 Waldron A, Mooers AO, Miller DC, Nibbelink N, Redding D, Kuhn TS, Timmons Roberts J,
567 Gittleman JL. 2013. Targeting global conservation funding to limit immediate biodiversity
568 declines. *Proceedings of the National Academy of Science* **110**:12144–12148.
- 569 Wiens JA, Stralberg D, Jongsomjit D, Howell CA, Snyder MA. 2009. Niches, models, and
570 climate change: assessing the assumptions and uncertainties. *Proceedings of the National*
571 *Academy of Sciences of the United States of America* **106**:19729–36.
- 572 Willis KS. 2015. Remote sensing change detection for ecological monitoring in United States
573 protected areas. *Biological Conservation* **182**. 233-244.
- 574 Xu H. 2006. Modification of normalised difference water index (NDWI) to enhance open water
575 features in remotely sensed imagery. *International Journal of Remote Sensing* **27**:3025–
576 3033.
- 577 Zhu Z, Wang S, Woodcock CE. 2015. Improvement and expansion of the Fmask algorithm:
578 Cloud, cloud shadow, and snow detection for Landsats 4-7, 8, and Sentinel 2 images.
579 *Remote Sensing of Environment* **159**:266–277.
- 580 Zhu Z, Woodcock CE. 2012. Object-based cloud and cloud shadow detection in Landsat
581 imagery. *Remote Sensing of Environment*:83–94.
- 582

583 **Tables**

584 Table 1. Study areas used in algorithm case studies covered a range of non-forested habitats and
585 disturbances affecting imperiled species in the United States.

<i>Species</i>	<i>Location</i>	<i>Habitat</i>	<i>Disturbance</i>	<i>Dates*</i>
Greater Sage Grouse (<i>Centrocercus urophasianus</i>)	Wright, WY	Grassland	Oil & gas	Jun., 2017 - Sept., 2017
Dune sagebrush lizard (<i>Sceloporus arenicolus</i>)	Permian Basin, NM & TX	Shrub/Scrub	Sand mining	Jan., 2017 - Jan., 2018
Beach mouse ssp. (<i>Peromyscus polionotus</i>)	Gulf County, FL	Wetland/ Grassland	Residential construction	Jan., 2017 - Jan., 2018
Piping Plover (<i>Charadrius melodus</i>)	Panama City, FL	Grassland	Hurricane Michael	Aug., 2018 - Oct., 2018

586 *Dates indicate the 'after' period during which changes were detected. A one-year interval preceding the earlier
587 date was used as the 'before' period.

588

589

590 Table 2. Metrics of agreement between areas of change delineated by human review and
 591 automated change detection algorithms, using different minimum size thresholds for change
 592 polygons.

Study Area	Min. Size (ac.)	MAD algorithm			LCC algorithm		
		<i>Jaccard</i> ^a	<i>Commission</i> ^b	<i>Omission</i> ^b	<i>Jaccard</i>	<i>Commission</i>	<i>Omission</i>
Wright, WY	0.0	0.17	0.40	0.00	0.22	0.15	0.00
	0.1	0.16	0.30	0.10	0.21	0.12	0.00
	0.5	0.13	0.23	0.27	0.17	0.00	0.36
Gulf County, FL	0.0	0.41	0.67	0.04	0.46	0.40	0.14
	0.1	0.44	0.32	0.28	0.47	0.10	0.23
	0.5	0.31	0.00	0.80	0.33	0.00	0.80
Panama City, FL	0.0	0.23	0.41	0.11	0.26	0.33	0.15
	0.1	0.25	0.27	0.19	0.26	0.17	0.22
	0.5	0.22	0.13	0.28	0.24	0.05	0.31
Permian Basin, TX	0.0	0.36	0.89	0.04	0.37	0.79	0.08
	0.1	0.37	0.72	0.11	0.37	0.58	0.15
	0.5	0.39	0.39	0.34	0.37	0.29	0.43
	1	0.39	0.17	0.42	0.36	0.13	0.60

593 ^a*Jaccard index measures the degree of overlap between two sets of polygons on a zero (no overlap) to one (perfect*
 594 *overlap) scale*

595 ^b*Commission and omission rates were measured in terms of the number of polygons exclusive to either the ground*
 596 *truth (omission) or algorithm output (commission) sets.*

597

598 **Figure Legends**

599 Figure 1. Conceptual model showing steps for processing and automatically detecting changes
600 between two sets of satellite images used in this paper. Numbers correspond to the steps for
601 selecting and preprocessing image collections and performing change detection between two
602 time periods described in the text.

603 Figure 2. Receiver operating characteristic curves are used to identify thresholds for change
604 detection. Curves plot the true and false positive rates for change detection among validation
605 data as the linear discriminant analysis scores used as a delineating threshold increases. Curves
606 constructed from the MAD algorithm outputs are shown in blue, and LCC algorithm outputs in
607 orange. The values at which the rate of increase in detection rate relative to false positive rate
608 decreases most rapidly are selected as threshold values. Curves are displayed for algorithm
609 output data collected in different habitat types, and for all habitat types combined.

610 Figure 3. Habitat changes around a large dune complex in West Texas used by the dunes
611 sagebrush lizard (*Sceloporus arenicolus*) were quickly identified by the LCC (red) and MAD
612 (black) algorithms and align with those found by time-consuming manual delineation (blue).
613 Changes were identified between pre-processed median composites from January 2018 as the
614 before image, and January 2019 as the after image.





