Supporting habitat conservation with automated change detection in Google Earth Engine

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Running head
Habitat-Change Detection

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Article impact statement
The use of satellite images to automatically detect habitat loss improves enforcement of conservation policy.
Abstract

A significant limitation in biodiversity conservation has been the effective implementation of laws and regulations that protect species’ habitats from degradation. Flexible, efficient, and effective monitoring and enforcement methods are needed to help conservation policies realize their full benefit. As remote sensing data become more numerous and accessible, they can be used to identify and quantify land-cover changes and habitat loss. However, these data remain underused for systematic conservation monitoring in part because of a lack of simple tools. We adapted 2 algorithms that automatically identify differences between pairs of images. We used free, publicly available satellite data to evaluate their ability to rapidly detect land-cover changes in a variety of land-cover types. We compared algorithm predictions with ground-truthed results at 100 sites of known change in the United States. We also compared algorithm predictions to manually created polygons delineating anthropogenic change in 4 case studies involving imperiled species’ habitat: oil and gas development in the range of the Greater Sage Grouse (Centrocercus urophasianus); sand mining operations in the range of the dunes sagebrush lizard (Sceloporus arenicolus); loss of Piping Plover (Charadrius melodus) coastal habitat after Hurricane Michael (2018); and residential development in St. Andrew beach mouse (Peromyscus polionotus peninsularis) habitat. Both algorithms effectively discriminated between pixels corresponding to land-cover change and unchanged pixels as indicated by area under a receiver operating characteristic curve >0.90. The algorithm that was most effective differed among the case-study habitat types, and both effectively delineated habitat loss as indicated by low omission (min. = 0.0) and commission (min. = 0.0) rates, and moderate polygon overlap (max. = 47%). Our results showed how these algorithms can be used to help close the implementation gap of monitoring and enforcement in biodiversity conservation. We provide a free online tool that can be used to run these analyses (https://conservationist.io/habitatpatrol).

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Introduction

To address the threat of habitat loss, biodiversity conservation often focuses on protecting species’ habitat through a variety of legal and policy mechanisms (UN Environment World Conservation Monitoring Centre & International Union for Conservation of Nature 2017). For example, the U.S. Endangered Species Act (ESA) requires the identification of “critical habitat” necessary for the conservation of listed species and prohibits destroying or adversely modifying these habitats (United States Congress 1978); Japan’s Nature Conservation Law designates “wilderness” and “nature conservation” areas (Japan National Diet 1972); the New Zealand Conservation Act created several specially protected areas (New Zealand Parliament 1987); and various international agreements include provisions to reduce habitat loss (e.g., Convention on Biological Diversity; UN Sustainable Development Goals). As written, these laws, policies, and treaties should be stopping or significantly slowing habitat loss and degradation, but this depends on the assumption that these laws are implemented as written. That assumption is often not independently tested, and the continued loss of species and their habitats indicate there is a substantial implementation gap (López-Bao et al. 2015; Chapron 2017).

If regulatory authorities lack the means to monitor and enforce habitat protections, conservation laws may be nothing more than paper tigers (Salomon et al. 2014), and there is little reason to think legal protections will change outcomes (Keane et al. 2008; Trouwborst et al. 2017). Currently, there is little research available on the extent of enforcement and compliance of habitat protection laws and policies (Malcom et al. 2017), but there are many reasons to believe they are lacking. Staff at U.S. federal agencies have acknowledged that they lack the resources to carry out even basic compliance monitoring and are unable to read monitoring reports submitted by permittees, much less carry out independent monitoring activities (Government Accountability Office 2009). Perennial funding shortages have left
These basic examples of a lack of monitoring and enforcement highlight a critical weakness in the implementation of conservation law and consequently the protection of biodiversity. Insufficient monitoring undermines imperiled species conservation in three ways. First, habitat protections may go unenforced. For example, satellite images revealed that under a habitat conservation plan for the eastern indigo snake (*Drymarchon couperi*) in Georgia (U.S.A.) over half of a forest parcel had been cleared despite the requirement that the permittee manage the parcel for the species until at least 2027 (Malcom 2017). Second and related, the lack of regular monitoring and enforcement sends a message to other actors that they can likely get away with habitat destruction without facing consequences. Third, inadequate monitoring leaves conservationists in the dark about the status of species’ habitats. If 60% of a species’ habitat is degraded, that knowledge should factor into decision making but cannot be.

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

Fortunately, technological advances are expanding the options for cost-effective monitoring (e.g., aquatic telemetry [Hussey et al. 2015], remote cameras to detect poachers [Hossain et al. 2016]). The growing availability of free satellite images and other remote-sensing data...
provide an efficient and effective solution for many biodiversity monitoring challenges (Turner et al. 2003). When combined with information on species range and areas permitted for habitat disturbance or destruction, these data open a wealth of opportunities for compliance monitoring and enforcement. As remote sensing data has become more ubiquitous and accessible, so too have the number of approaches for change detection increased (Willis 2015). Often these analyses focus on one land-cover type, and most of the research has focused on forest loss (Potapov et al. 2008; Hansen et al. 2010; Song et al. 2018). A significant challenge now is to expand the generality of algorithms to automate change detection across land-cover types, which would enable and simplify monitoring at regional and continental scales. Given the central role that habitat conservation plays in conserving imperiled species, methods to automatically detect habitat loss in near real time could significantly enhance compliance monitoring and enforcement capabilities and substantially increase the effectiveness of conservation laws.

We used 2 previously developed, automated algorithms that detect land-cover change. We adapted them to aid conservation compliance monitoring across different land-cover types and at broad scales. We evaluated the utility of these methods with systematically collected validation data and four case studies. Both algorithms use data that are readily available online, meaning anyone, including government agencies, conservation organizations, and the public, can use them to advance conservation. We sought to determine whether these approaches are sufficiently effective, efficient, and flexible for use in large- and small-scale systematic conservation monitoring efforts. Adoption of automated change detection can help address one of the biggest shortcomings in biodiversity conservation, and we considered the potential for future technological and regulatory development to further leverage their potential.
Methods

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

The basic process for change detection (Fig. 1) involved the following steps: define an area of interest and collect satellite images; process images (mask clouds, correct for terrain, etc.); divide images into before and after collections of images; make composite images of before and after collections; calculate pixel-wise change metrics between composite images; identify thresholds that delineate changed and unchanged pixels; and use a threshold or thresholds to create a binary changed-unchanged image.

Image Processing

After defining an area of interest and collecting all the spatially overlapping Sentinel-2 images, we processed the images to remove clouds and cloud shadows, water, and terrain artifacts that hamper change detection, as detailed in Appendix S1. In brief, built-in cloud masking is limited for Sentinel-2 imagery because the system does not contain a thermal sensor measuring temperature, which is critical to common cloud-masking procedures (Zhu et al. 2015). Instead, we used the quality assurance bands included with all Sentinel-2 images and calculated cloud, water, and shadow probability metrics.

To identify cloudy pixels, we implemented an adaptation of the simpleCloudScore algorithm developed for Landsat provided in Google Earth Engine, which uses a combination of...
indices to assign a per-pixel cloud likelihood score from 0 to 1 and masked any pixels receiving a score of 0.15 or greater. We identified water pixels with a set of water indices including a normalized difference water index (Xu 2006) and masked any pixels over 0.25. We then calculated the RGB ratio shadow indices (Sarabandi et al. 2004) for each pixel and classified those with a score over 0.25 as shadow. These masking thresholds were determined empirically to balance omission and commission. Last, we applied per-pixel terrain correction with the C-correction equation (Teillet et al. 1982) and used the 30-m digital elevation model from the U.S. Geological Survey (Farr et al. 2007) to determine pixel slope and aspect.

To detect changes, we compared before and after composite images created using 2 collections of masked and corrected images – images collected 3 months before and images collected three months after a date of interest. This date of interest corresponded to a point in time after which we expected land-cover changes to occur. Following cloud, shadow, and water masking and terrain correction, we created a single-image composite for each period by selecting the median value of each pixel stack. These single before and after images were then clipped to the exact geometry of the study area and used as inputs to automated change-detection algorithms. Six bands corresponding to blue, green, red, near infrared, short-wave infrared 1, and short-wave infrared 2 were used in all calculations of change. All image processing was performed using Google Earth Engine (Appendix S1).

Land-Cover Change Algorithm

Although a variety of algorithms have been developed to detect changes between satellite images (Willis 2015), we started from two fundamentally different approaches, described in greater detail in Appendix S2. The first builds on the method used by the U.S. Geological Survey to produce the National Land Cover Dataset land-cover change (LCC) data (Jin et al. 2013) and uses features that relate to real phenomena. In brief, the LCC algorithm involves
calculating six spectral change metrics between before and after images per pixel, normalizing the metrics given the distribution of values across the image, and then approximating the probability that no change occurred for each pixel. This transformation centers and scales per pixel changes relative to baseline changes in reflectance, brightness, phenology, etc., between the before and after images. The output is an image with 12 bands. For each of the six metrics one band contained the normalized value, and one band contained the probability of change.

Multivariate Alteration Detection Algorithm
The second algorithm is the multivariate alteration detection (MAD) algorithm (Nielsen 2007). It uses canonical correspondence analysis to first identify linear transformations that maximize correlation between two sets of variables, in this case, the bands of two images. Then, extreme deviations are identified per pixel by calculating the sum of squared deviations from the mean of each canonical variate, relative to its variance across the image. These extreme deviations represent changes in pixel values relative to background shifts between images (e.g., phenology). The output is an image with number of bands equal to the minimum of the number of bands in the before and after images, plus two. These bands contain the values of the canonical variates, the value of the chi-square summary statistic ($\chi^2$), and the corresponding $p$ value per pixel. Calculations and image transformations were performed using Google Earth Engine (Appendix S2).

Change Delineation
Next, we determined thresholds that effectively delineated changed and unchanged pixels based on multiband algorithm outputs. We sampled pixel values from each band of algorithm output images – the change metrics for LCC and the canonical variates and $\chi^2$ for MAD - at 100 study sites across the continental United States that had been manually identified as undergoing habitat loss due to anthropogenic landscape modification since 2016 (Fig. 2).

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The predominant land-cover undergoing change at each site was broadly categorized according to National Land Cover Dataset classes (Fry et al. 2011) as either desert \((n = 12)\), forest \((n = 43)\), grassland \((n = 15)\), shrub or scrub \((n = 12)\), or wetland \((n = 17)\). Sites were chosen opportunistically while balancing sample sizes among nonforested land-cover types and including dates from all 12 months of the year (Appendix S1). We manually delineated polygons in all areas of anthropogenic change as determined by visual inspection of the imagery and categorized observed changes as either bare ground, building (residential and commercial development), paved (roads, parking lots, etc.), or solar development. We then extracted the algorithm output values at all pixels within change areas, and the maximum of either an equal number of random pixels or 1,000 random pixels within the study area not falling within areas of change. These data were divided into 70% training and 30% validation sets.

We used these data in linear discriminant analysis (LDA) to transform algorithm outputs into a single discriminant score maximizing the difference between values from changed and unchanged pixels in training data. We then used receiver operating characteristic curves to select the score that minimized true and false positives among validation data when used as a threshold for delineating changed and unchanged pixels. The area under a receiver operating characteristic curve (AUC) was used to assess the performance of each algorithm because the metric indicates the accuracy of binary class predictions (i.e., changed and unchanged pixels). We selected the discriminant score that maximized the ratio between true and false positive rates as a threshold to automatically identify changed pixels. The LDA coefficients and subsequent thresholds were estimated for each land-cover type with subsets of training data collected from study sites occurring in each cover type. The LDA and receiver operating characteristic analyses were conducted in R (Team 2014) with the pscl (Jackman 2017) and pROC (Robin et al. 2011) packages (Supporting Information). The final output of each
algorithm was a binary image created by using LDA coefficients to transform algorithm output at each pixel to a discriminant score and labeling all pixels above the relevant threshold as changed.

Case Studies
To demonstrate how these methods might be applied in situ, we evaluated the outputs from both change-detection algorithms in each of four case studies (Table 1). These case studies were chosen as a sample of ongoing threats to imperiled species in a diversity of nonforested habitats due to the extensive work and tools available for detecting deforestation (e.g., Global Forest Watch). Additionally, each case study represented a different potential-use case for automated change detection: large-scale retrospective detection (dunes sagebrush lizard \textit{[Sceloporus arenicolus]}; small-scale retrospective detection (beach mouse \textit{[Peromyscus polionotus ssp.]}; rapid inventory after a natural disaster (Piping Plover \textit{[Charadrius melodus]}; and active small-scale monitoring (Greater Sage Grouse \textit{[Centrocercus urophasianus]}).

To evaluate algorithm effectiveness in these case studies, we compared binary change-unchanged images produced by transforming algorithm outputs to areas of change identified by visual inspection of before and after images. Within each study area, an independent reviewer manually delineated all anthropogenic changes in the cover type of interest. We referred to these polygons as ground truth polygons. We then ran both the LCC and MAD algorithms within each study area and delineated pixels representing change with the thresholds identified during LDA analysis. These areas representing change were then converted to polygons.

We used three complementary metrics to assess the algorithms’ performance. First, we calculated the Jaccard index (a measure of the area of overlap between two geometries as the intersection divided by the union \(J(A, B) = A \cap B / A \cup B\)) between ground truth polygons

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and change polygons predicted by each algorithm. We also calculated the omission and commission error rates as the proportion of ground truth polygons that did not overlap predicted change polygons and the proportion of predicted change polygons that did not overlap any ground truth polygons, respectively.

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

**Results**

**Algorithm Validation**
We collected algorithm output data from areas of real and no change at 100 locations (Fig. 2).

Transition to bare ground was the most common form of disturbance (86 of 100). Because bare ground preceded residential development and pavement, we did not detect these disturbance forms at any location. In 12 instances, solar fields were built directly over existing desert and grassland areas within the 3 months comprising the after image and therefore appeared as a direct change from habitat to solar development.

Both algorithms effectively discriminated changed from unchanged pixels among validation data, as indicated by AUC scores > 0.90 for all cover types (Fig. 3). The MAD algorithm performed slightly better than the LCC algorithm, as indicated by higher AUC scores. This was especially true in detecting generic change, when thresholds were not optimized to a specific habitat type (Fig. 3). The LCC algorithm was least successful at identifying changes in grassland (AUC = 0.95) and most successful in forested areas (AUC = 0.99). The MAD
algorithm was most successful in wetland habitats (AUC = 1) and least successful in forests (AUC = 0.98).

Case Studies
Change-detection methods effectively detected habitat loss in important conservation areas in all four case studies and were faster than human review. Both the LCC and MAD algorithms took < 40 minutes to produce change polygons in each study area. The time required for manual delineation of changes ranged from 6 hours in the Wright, Wyoming, case study to several days in the Permian Basin, Texas, study area.

We were able to detect and measure habitat loss in a variety of environments due to both natural and anthropogenic causes. These included losses of desert sand dunes due to sand mining, coastal grassland due to hurricane, grassland due to oil and gas drilling, and wetland due to residential development (Table 1). The MAD algorithm was more sensitive to landscape changes, but less specific than the LCC algorithm, as indicated by higher commission rates and lower omission rates (Table 2). Both algorithms had relatively high commission rates, indicating detection of changes not identified by manual inspection of before and after images. A post hoc analysis of commission indicated approximately 60% of these polygons represented real changes missed by manual inspection. Jaccard indices indicated low to moderate overlap between change polygons delineated manually and those produced by both automated change-detection algorithms (Table 2). Commission rates decreased substantially when the minimum polygon size considered as change was increased from 0.

Discussion

The conservation of biodiversity has been limited, in part, by an inability to monitor and enforce conservation laws, regulations, and agreements. While remote sensing data have
long held the promise of transforming environmental monitoring efforts, publicly accessible tools leveraging these data to achieve actionable insights have been lacking (Willis 2015). In addition to cost, ease of use is critical if this technology is to be widely adopted for conservation monitoring and enforcement because many land managers and regulators will not have expertise in ecology, policy, and remote sensing (Wiens et al. 2009). We adapted 2 algorithms for automated detection of habitat change with satellite imagery and demonstrated their efficacy, efficiency, and flexibility in a variety of test areas and case studies. Built on publicly available data and technology, these tools can be used by anyone—from local property managers to government agencies charged with national monitoring programs—to automatically detect habitat loss in near real time (Appendix S1).

Both the MAD (Nielsen 2007) and LCC (Jin et al. 2013) algorithms performed excellently, discriminating habitat loss from background changes between images in test cases (Fig. 3). Beyond performing well in forested landscapes, where many algorithms have been developed (Hansen et al. 2010), both algorithms were effective in a variety of nonforest areas (Fig. 4). This flexibility is in part attributable to the use of land-cover-specific thresholds obtained from simple LDA from subsets of algorithm output data. We observed slightly lower AUC scores when receiver operating characteristic curves were produced using thresholds estimated from all data across land-cover types. Specific thresholds were also important in detecting changes other than bare ground (e.g., solar energy development). The availability of a flexible tool that can be applied in a variety of contexts, rather than requiring a different tool for different ecosystems, should make automated change detection more readily adopted by entities with regulatory authority.

The ability of each algorithm to detect meaningful change was confirmed in case studies, where both methods identified nearly all instances of anthropogenic habitat loss that were manually delineated (i.e., low omission rates) (Table 2). The MAD algorithm appeared more
sensitive and less specific than LCC, as illustrated by outputs from case studies. Generally higher commission rates among MAD outputs reflected the tendency of this algorithm to detect all types of change - even those occurring naturally due to phenology and seasonality. The change metrics included in the LCC algorithm that related to real-world phenomena (e.g., dNDVI, dNBR, etc.) likely enabled better discrimination between generic and cover-specific change. Commission occurred from one of two outcomes: instances of habitat loss missed by manual review or natural changes to the landscape that were not of interest. Object oriented or computer-vision-based approaches may be helpful for distinguishing among these (Malof et al. 2016; Ghorbanzadeh et al. 2019). Future work that integrates dynamically updated machine learning classification approaches, rather than a predefined set of thresholds, may also improve discrimination. Most instances of commission were not errors, illustrating a key advantage of automated methods of change detection. Both algorithms may be more effective than human review, particularly over large areas. The finding that approximately 60% of instances of commission by both algorithms were in fact true cases of habitat loss shows that automated change-detection systems may produce more complete results, especially over large areas, than manual inspection of imagery. Furthermore, both algorithms were more efficient than manual inspection of satellite imagery. Human delineation of changes required several orders of magnitude more time to complete than automated algorithms and scaled with the size of the area of interest. This efficiency makes automated methods preferable in situations that require repeated or continuous monitoring – a critical attribute if satellite imagery is used to implement a comprehensive conservation monitoring and enforcement program. Detecting land-cover changes rapidly is particularly important in conservation monitoring and enforcement. The LCC and MAD algorithms may be especially advantageous in these situations because, fundamentally, they detect changes between pairs of images. In our study,
composite images were necessary only to account for imperfect cloud masking in Sentinel-2 data. Clear images or improved cloud masking would alleviate this need. Although we used three months of imagery each to form our before and after composite images, any before and after period could be defined, including successive single images or comparison of composites from the same period in different years (e.g. June – August 2019 vs. 2020). This flexibility makes the LCC and MAD algorithms complimentary to other well-known change-detection approaches, such as LandTrendr (Kennedy et al. 2010) and Continuous Change Detection (Zhu & Woodcock 2014), that use dense time series of images to identify temporal trend breakpoints in spectral indices per pixel. By directly detecting changes between pairs of images, the LCC and MAD algorithms can potentially detect habitat loss as soon as imagery is available and in circumstances where a long history of images may not exist.

The use of automated change-detection approaches can directly improve the conservation prospects of imperiled species because the results can be used by regulatory agencies and the public to enforce prohibitions on habitat destruction. In the United States, conservation agreements like those developed under sections 7 and 10 of the Endangered Species Act (ESA) often involve specifications of where development can and cannot occur within an area. The Wright, Wyoming, case study provides a hypothetical example of how federal agencies with the authority to enforce these agreements, such as the U.S. Fish and Wildlife Service (FWS) can use tools like those described here to monitor a small area undergoing oil and gas infrastructure development with relatively short (approximately 3 month) frequency to detect habitat destruction in unauthorized areas. The changes detected here were legal, but in other instances they might alert an enforcement agency to unauthorized activities. Under the ESA, FWS must also account for habitat loss due to anthropogenic factors or natural disasters, such as losses that occurred in the Panama City, Florida, case study, in species status assessments and 5-year reviews. These assessments inform future permitting decisions.
and species recovery under the ESA. Citizens and organizations can also use this information in reports and public comments to affect agency actions. For example, Gulf County in Florida has been developing a habitat conservation plan with the FWS to offset harm to endangered St. Andrew beach mice (*Peromyscus polionotus peninsularis*) caused by residential construction. Any plan will be subject to a comment period when the public can comment on historic loss and likely effects of the plan - data that can be generated and provided as demonstrated here. Finally, the case of the dune sagebrush lizard illustrates how the rapid detection and delineation of habitat loss can be used to garner increased protections for imperiled species. In this case, the LCC and MAD algorithms identified losses to lizard habitat due to sand mines, which served as evidence that the species is inadequately protected and informed a petition to list the species under the ESA (https://ecos.fws.gov/docs/petitions/92210//1040.pdf).

Our results demonstrate the capability of both the MAD and LCC algorithms to automatically detect habitat loss, but those hoping to use these approaches should be aware of several caveats. First, both algorithms were more effective at identifying the occurrence of change than accurately delineating the extent of those changes. This was reflected by relatively low (< 0.5) Jaccard index scores. Recent advances in computer vision-based change detection may improve the spatial precision of predicted changes (Peng et al. 2019). Change thresholds designed for specificity rather than sensitivity will invariably exclude some real changes, meaning the area of detected change will underestimate area changed. Additionally, the commission rates of both algorithms decreased as the minimum size of changes considered increased. This pattern suggests a minimum size of disturbance that can be regularly detected by these algorithms with Sentinel-2 data. If disturbances < 500 m² need to be detected, users may experience a higher number of false positives.
While the algorithms presented here were run with Sentinel-2 data, they were written generically and can be applied to other passive remote sensing systems with the requisite bands and rigorous orthorectification and coregistration. For instance, Landsat 8, which provides global coverage of 30-m resolution imagery every 16 days, contains analogous bands to Sentinel-2 and a thermal band that measures surface temperature, which allows for more robust detection of clouds (Zhu et al. 2015). Our cloud detection and masking approaches are imperfect with Sentinel-2 imagery and may not perform as well in very cloudy areas. Although habitat-specific parameters help, clouds may still occasionally be flagged as change. Using these algorithms with Landsat data may be useful in cases where some resolution can be sacrificed for more robust cloud removal. Generic change-detection algorithms based on SAR data, which is invariant to cloud cover, may also prove useful (Nielsen et al. 2017; Rüetschi et al. 2019).

By adapting 2 change-detection algorithms and validating their efficacy across a variety of habitats, we have developed tools to help enforce conservation laws and agreements with remote sensing data (Appendix S2). These tools do not require remote sensing expertise and can be used by the public, conservation organizations, and federal agencies responsible for administering conservation laws. In addition, they are flexible, run much more quickly than manual delineation, and can be run repeatedly in many different contexts and at large spatial scales, making them suitable for the monitoring and enforcement of conservation laws. Most importantly, they are built with publicly available data and computing platforms. Many previous tools have been limited in their use in regulatory capacities because they are only available for a fee under pay-for-service structures. For remote sensing data to be used to improve conservation, it is critical that platforms like Google Earth Engine continue to provide open access. The continued improvement of automated change-detection methods
and adoption by regulatory authorities holds the potential to close a significant gap in the protection of biodiversity.

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Tables

Table 1. Loss of habitat detected by automated algorithms in a range of nonforested environments and due to a variety of disturbances affecting 4 imperiled species in the United States.

<table>
<thead>
<tr>
<th>Species</th>
<th>Location</th>
<th>Habitat</th>
<th>Disturbance</th>
<th>Dates*</th>
<th>Area (km²)</th>
<th>Loss (km²)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Greater Sage Grouse</td>
<td>Wright, Wyoming</td>
<td>grassland</td>
<td>oil &amp; gas</td>
<td>Jun 2017-Sep. 2017</td>
<td>215.7</td>
<td>0.17</td>
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<tr>
<td>Dunes sagebrush lizard</td>
<td>Permian Basin, TX</td>
<td>shrub or scrub</td>
<td>sand mining</td>
<td>Jan 2017-Jan 2018</td>
<td>797.8</td>
<td>8.5</td>
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<tr>
<td>St. Andrew beach mouse</td>
<td>Gulf County, FL</td>
<td>wetland or grassland</td>
<td>residential construction</td>
<td>Jan 2017-Jan 2018</td>
<td>4.7</td>
<td>0.3</td>
</tr>
<tr>
<td>Piping Plover</td>
<td>Panama City, FL</td>
<td>grassland</td>
<td>Hurricane Michael</td>
<td>Aug 2018-Oct 2018</td>
<td>26.2</td>
<td>0.85</td>
</tr>
</tbody>
</table>

*The after period during which changes were detected. A 1-year interval preceding the earlier date is the before period.
Table 2. Metrics of agreement between all polygons delineating areas of land-cover change between before and after images created by human review and automated change-detection algorithms for different minimum polygon size thresholds.

<table>
<thead>
<tr>
<th>Study area (habitat)</th>
<th>Min. size (ha)</th>
<th>MAD\textsuperscript{a} algorithm</th>
<th>LCC\textsuperscript{b} algorithm</th>
</tr>
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<tr>
<td></td>
<td></td>
<td>Jaccard\textsuperscript{c}</td>
<td>Commission\textsuperscript{d}</td>
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<td>Wright, Wyoming (grassland)</td>
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<td>Gulf County, Florida (wetland)</td>
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<td>0.04</td>
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<td>0.31</td>
<td>0.00</td>
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<td>0.0</td>
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<td></td>
<td>0.04</td>
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<td></td>
<td>0.2</td>
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<tr>
<td>Permian</td>
<td>0.0</td>
<td>0.36</td>
<td>0.89</td>
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<tr>
<td>Basin, Texas (shrub &amp; desert)</td>
<td>0.04</td>
<td>0.37</td>
<td>0.72</td>
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</table>

*a* Multivariate alteration detection.

*b* Land-cover change.

*c* Jaccard index measures degree of overlap between 2 sets of polygons on a 0 (no overlap) to 1 (perfect overlap) scale.

*d* Commission and omission rates measured in terms of the number of polygons exclusive to either the ground truth (omission) or algorithm output (commission) sets.
Figure Legends

Figure 1. Conceptual model of the steps in processing and automatically detecting land-cover changes between 2 sets of satellite images used (numbers, steps for selecting and preprocessing image collections and performing change detection between the 2 periods described in the text; LDA, linear discriminant analysis).
Figure 2. Study sites at which the output data from algorithms for detection of land-cover change was sampled for use in developing thresholds used to automatically delineate changed and unchanged pixels (symbols, predominant land-cover type at each site, as identified by the National Land Cover Dataset).
Figure 3. True and false positive rates of land-cover change detection among validation data shown as the linear discriminant analysis scores used as a delineating threshold increases (MAD, multivariate alteration detection algorithm outputs; LCC, land-cover change algorithm outputs). Values at which the rate of increase in detection rate relative to false-positive rate decreases most rapidly are the threshold values. Curves are displayed for algorithm output data collected in different land-cover types and for all land-cover types combined.
Figure 4. Habitat changes in the four case studies of different land-cover types identified by the land-cover change (LCC) (red) and multivariate alteration detection (MAD) (black) algorithms. The change polygons predicted by each algorithm align closely with those found by time-consuming, manual ground truthing (blue).