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Mapping Invasive Giant Goldenrod (*Solidago gigantea*) with Multispectral Images Acquired by Unmanned Aerial Vehicle

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Abstract: Invasive alien species are one of the main threats to worldwide biodiversity loss. Unmanned aerial vehicles with multispectral sensors offer a cost-effective alternative to monitor invasive plant species at a centimetre scale. Giant Goldenrod (*Solidago gigantea*) is one of the most problematic invasive alien plant species in Switzerland and controlling this species – especially in nature protection areas – is a priority. In this study, a methodology is developed to detect the Giant Goldenrod coverage via unmanned aerial vehicle (UAV) equipped with multispectral sensors. Very high resolution maps (6.5 cm) are produced and high accuracy is achieved for the classification of the Giant Goldenrod coverage with a kappa coefficient of 0.902 and an overall accuracy of 92.12%. These results indicate that UAV equipped with multispectral sensors is a valuable tool in monitoring and combatting invasive alien species.

Keywords: Invasive Alien Species (IAS), invasive neophytes, Unmanned Aerial Vehicles (UAV), multispectral sensors, remote sensing

1 Introduction

Global biodiversity loss is alarming with current extinction rates likely to be 1000 times the background extinction rates (PIMM et al. 2014). The IPBES 2019 report states that around one million species are threatened with extinction with the underlying reasons for this biodiversity crisis being land-use changes, pollution, climate change, over-harvesting, and invasive alien species (IPBES 2019, DASGUPTA 2020). Invasive alien species (IAS) are defined as non-native species with dispersal potential extending their natural range to new ecosystems, survive and reproduce in these new ecosystems, and subsequently becoming a threat to native species (IUCN 2000). Hence, IAS are species that have been translocated beyond their natural biogeographical range by humans and that are causing economical, ecological, and human health damage or at least have the potential to cause harm (GIGON & WEBER 2005). IAS are found in every taxonomic group from viruses to mammals and their impacts are observed in every ecosystem type on Earth causing hundreds of extinctions in native species (IUCN 2000).

Since the arrival of Christopher Columbus in the Americas in October 1492, the pace of the world-wide translocation of non-native species has continuously increased with 37% of all first records on non-native species reported in the most recent decades (1970-2014; SEEBENS et al. 2017). Worldwide, 3.7% of the taxa in the global flora are now known to be naturalized (VAN KLEUNEN et al. 2020). Even though only a fraction of the naturalized species introduced by humans from other biogeographical regions becomes invasive (MACK et al. 2000), the collapse of biogeographical barriers due to global trade, new technologies, and transport is a

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major threat to biodiversity and ecosystem services (KUEFFER 2017), has implications for human health, and causes substantial economic damage (PIMENTEL et al. 2001, PIMENTEL et al. 2005). Hence, invasive alien species (IAS) are a global concern and explicitly treated in the Aichi Target 9 of the Convention on Biological Diversity (CBD 2011). Specific aims of the Aichi target 9 are the control and management as well as the prevention of introduction and establishment of priority invasive species (CBD 2011).

Introduced in the 18th century from its native North American habitats, the giant Goldenrod (*Solidago gigantea*) was first distributed among Botanical Gardens in Europe and from there escaped a century after its introduction to natural mesic habitats especially endangering species-rich wetlands (VOSER-HUBER 1983, WEBER & JAKOBS 2005, BOTTA-DUKÁT & DANCZA 2008). Based on herbarium specimens and literature data, the spread of this species was estimated to reach 910 km^2 per year (WEBER 1998).

There are ca. 500-600 neophytes in Switzerland and of these 58 are considered invasive or potentially invasive (Neophyten (infoflora.ch)). The Giant Goldenrod is one of the most common invasive neophytes in Switzerland and since 2008 nationwide legally listed as forbidden to plant. The success of invasive goldenrods in Europe can be attributed to their high competitive strength and adaptability (ECKERT et al. 2020). A single plant can produce up to 10,000 wind dispersed seeds per year and its rhizome (up to 300 sprouts/m^2) allows the plant, once established, to propagate a colonised site very efficiently. In contrast to their original area of distribution in America, the plants in Europe are hardly damaged by insects (JAKOBS et al. 2004).

In Switzerland, especially in fens, the original vegetation is under pressure from the invasive *Solidago gigantea*. Therefore, monitoring of *S. gigantea* is crucial to protect the vulnerable local species. Combatting and monitoring the *S. gigantea* in Europe is, however, expensive and mostly ineffective. Remote sensing with Unmanned Aerial Vehicles (UAVs) offers expanded cost-effective opportunities to detect and monitor invasive species on a high spatial resolution up to a centimetre scale. The aim of this study was to identify Giant Goldenrod stands by creating high resolution multispectral maps acquired via drone images, monitoring remnant nature conservation areas of once extensive pre-Alpine wetlands.

1.1 Study Area

The areal coverage of wetlands in Switzerland dramatically decreased from 1850-2010, between 92 to 94% (STUBER & BÜRGI 2018). The study area – Entensee Pond – belongs to one of those wetland ecosystems that were at the brink of loss at the beginning of the 20th century. ProNatura Switzerland bought the area in 1938 and saved it from drainage. Today, in winter and spring, parts of the wet meadows are flooded by ditches fed by a nearby creek.

The Entensee Pond is located in the Northeastern part of Switzerland in the Canton of St. Gallen at 407 m a.s.l. (Figure 1a). It is part of the Kaltbrunner Riet, which is listed in the Swiss Federal Inventory of water and migratory bird reserves of international and national importance (Ramsar site). It is one of the last remainders of once an extensive wetland, breeding and resting ground for birds, spawning areas for amphibians, and ecologically significant for rare plants such as rice cut grass (*Leersia oryzoides)* and yellow flat sedge (*Cyperus flavescens*) (Naturschutzgebiet Kaltbrunner Riet (SG) | Pro Natura). However, especially in species-rich purple moor-grass fen meadows (Molinion) with local and vulnerable species and often dominated by Reed (*Phragmites australis* (Cav.) Steud), a heavy giant goldenrod cover is observed (Figure 1e).

Combatting of the giant goldenrod in the area is continuing since 2013, but without major success. Although only in 2016, 1.4 tons of goldenrod have been removed from the nearby Kaltbrunner Riet, *Solidago gigantea* expansion is still a major threat to local species in the fragile ecosystem (PRONATURA 2016).

2 Materials & Methods

2.1 Data Acquisition & Materials

Due to the protected area status of the Entensee Pond, a limited time frame in August 2020, peak flowering time of the Giant Goldenrod and least disturbing time for birds, was granted to conduct field research and data acquisition. Data acquisition was planned in three different stages. In the first stage, field observations were conducted to document the dominant vegetation types in the area. Planning and simulating flights were the next stage of acquiring drone data, requiring careful preparation to achieve targeted coverage of different areas. Two flights were performed on August 17, 2020 by using an eBee SenseFly X drone together with eMotion3 ground station flight management software, which is used for planning, simulating, and monitoring the flights. Red Green and Blue (RGB) images were acquired with a S.O.D.A 3D camera and multispectral images were acquired using a MicaSense RedEdge-MX Sensor (Wavelengths: Blue= 475 nm, Green= 560 nm, Red= 668 nm, Red Edge= 717 nm, and Near InfraRed= 840 nm). To perform the drone flights, a day with full cloud cover was chosen to reduce the effects of shading from trees on the ground. Full cloud cover also reduced the correction needs for different bands, especially for the blue band, compared to sunny conditions (AKANDIL 2020). In the third stage, ground truth points were acquired with a GPS device (Leica iCON 70, Leica Geosystems, Heerbrugg, Switzerland) on August 30, 2020.

2.2 Methods

The data collected in the field research were first pre-processed to create the necessary orthomosaics, then classified, and finally validated by using the ground truth points (Table 1).

Before each flight, weather conditions were documented and a MicaSense Calibrated Reflectance Panel was utilized to capture the information about position of the sun and the sensor, and the irradiance data from the panel, indicating the light conditions of the flight and working as a control to adjust the rest of the pixels (MicaSense). Through radiometric calibration, digital numbers of the pixels in multispectral data were converted first to sensor reflectance and then to surface reflectance. Without robust calibration, the data acquired cannot be used for comparisons of images from different dates. Therefore, correct calibration is one of the crucial steps before the analysis, especially for future monitoring purposes.

Each photo taken by the drone during the flight was assigned to its correct geographic coordinates by a process called geotagging, which is another critical step for the accuracy of the maps and the Digital Surface Model (DSM). These geotagged photos are utilized to create orthomosaics for RGB and multispectral images in the Pix4D software. Very high resolution orthomosaics, 3.5 cm for RGB & DSM and 6.5 cm for multi spectral data, were generated (Figure 1c, Figure 1d). RGB and DSM were further resized to 6.5 cm resolution by using nearest neighbour method in ENVI 5.4.1 image analysis software. False colour composites (FCC) were also created by using multispectral images (Figure 1b). Compared to medium resolution data in meters scale, very high resolution drone data at a centimetre scale extends the analysis opportunities profoundly.

Table 1: Summary of the workflow performed in this research

Preprocessing	Classification	Validation
– Calibration	– Defining the Classes	– Cohen's Kappa
– Geotagging	– Classifying Surface Water	– Confusion Matrix
– Orthomosaics (RGB & Multispectral)	– Classifying Trees	– Producer & User Accuracies
– Digital Surface Model (DSM)	– Performing Jeffries Matusita & Transformed Divergence Test	
	– Creating Control and Training ROIs	
	– Maximum Likelihood Classification	

Spectral indices are produced by using two or more spectral bands to create new information related to biophysical parameters of interest (JONES & VAUGHAN 2010). To identify and mask the water surface area, the Blue Chromatic Coordinate (BCC) index was utilized, which is the ratio of Blue band to an aggregate of the Red, Green and Blue bands (MOORE et al. 2017). Illumination conditions play a significant role for the digital numbers of the blue band, which are sometimes inflated up to 50% under sunny conditions (AKANDIL 2020). To avoid this problem, the drone flights were performed under full cloud cover, therefore no atmospheric correction were needed to be able to separate surface water reliably via BCC. To isolate water bodies, the index value was set as above or equal to 0.334, indicating the blue band is dominant in that pixel (Figure 1f).

The DSM model was utilized to isolate the tree cover around the Entensee Pond. Along with the field research, the trees and observation tower nearby were classified and masked by setting the threshold in DSM model at 410 m a.s.l. and classified everything above as trees (Figure 1g).

RICHARDS (1986) defines five stages in a supervised classification: 1) defining the ground cover types to classify, 2) choosing the training data representative of each class, 3) using this training data to calculate the band statistics going to be used in the classification algorithm, 4) assigning each pixel to the possible classes based on the statistics, 5) producing the classification maps.

Based on the field observations and orthomosaics, five different ground cover types to classify the area were defined: Giant Goldenrod (*Solidago gigantea*), Reed (*Phragmites australis*) – a plant species that is morphologically similar to Giant Goldenrod, Surface Water, Trees, and Mown & Other Vegetation. As the clonal goldenrods have two different phenotypic stages, the class was further divided to vegetative and flowering goldenrod before the analysis. After the classification, they were combined under the class "Giant Goldenrod". A similar approach was taken for reed because the spectral footprint of reed plants growing in water or on land, was different.

Training samples through region of interests (ROIs) were chosen for different classes according to field observations with GPS data. CONGALTON (1991) recommends using at least 50 samples for each class. Therefore, 198 pixels for each class were determined in the analysis. Jeffries-Matusita and Transformed Divergence (RICHARDS 1999) tests were implemented in ENVI to assess the separability of the different classes in RGB and FCC for different band combinations (Table 2). We achieved the best result in FCC by combining Near Infrared (NIR), Red Edge (RE), and Green bands. Jeffries-Matusita and Transformed Divergence test result in values between 0 and 2. Any value above 1.9 indicates the classes are separable and any value between 1.7 – 1.9 is considered fairly good (JENSEN 1996).

Table 2: ROIs Separability test based on Jeffries-Matusita and Transformed Divergence. Bold numbers indicate in which band combination higher separability results were achieved.

Pairs to Separate	**In RGB Bands**	**In False Colour Composites Based on NIR/RE/Green bands**
Reed on Water vs. Mown & Other Vegetation	**1.46040**	1.31715
Flowering Goldenrod vs. Mown & Other Vegetation	**1.60247**	0.25575
Vegetative Goldenrod vs. Mown & Other Vegetation	1.71213	**1.96521**
Vegetative Goldenrod vs. Reed on Land	1.77214	**1.78316**
Reed on Water vs. Reed on Land	**1.77287**	1.51057
Reed on Land vs. Mown & Other Vegetation	**1.83301**	1.83144
Vegetative Goldenrod vs. Reed on Water	**1.99823**	1.99355
Vegetative Goldenrod vs. Flowering Goldenrod	**1.99884**	1.97353
Flowering Goldenrod vs. Reed on Water	**1.99890**	1.04508
Flowering Goldenrod vs. Reed on Land	**1.99999**	1.64385

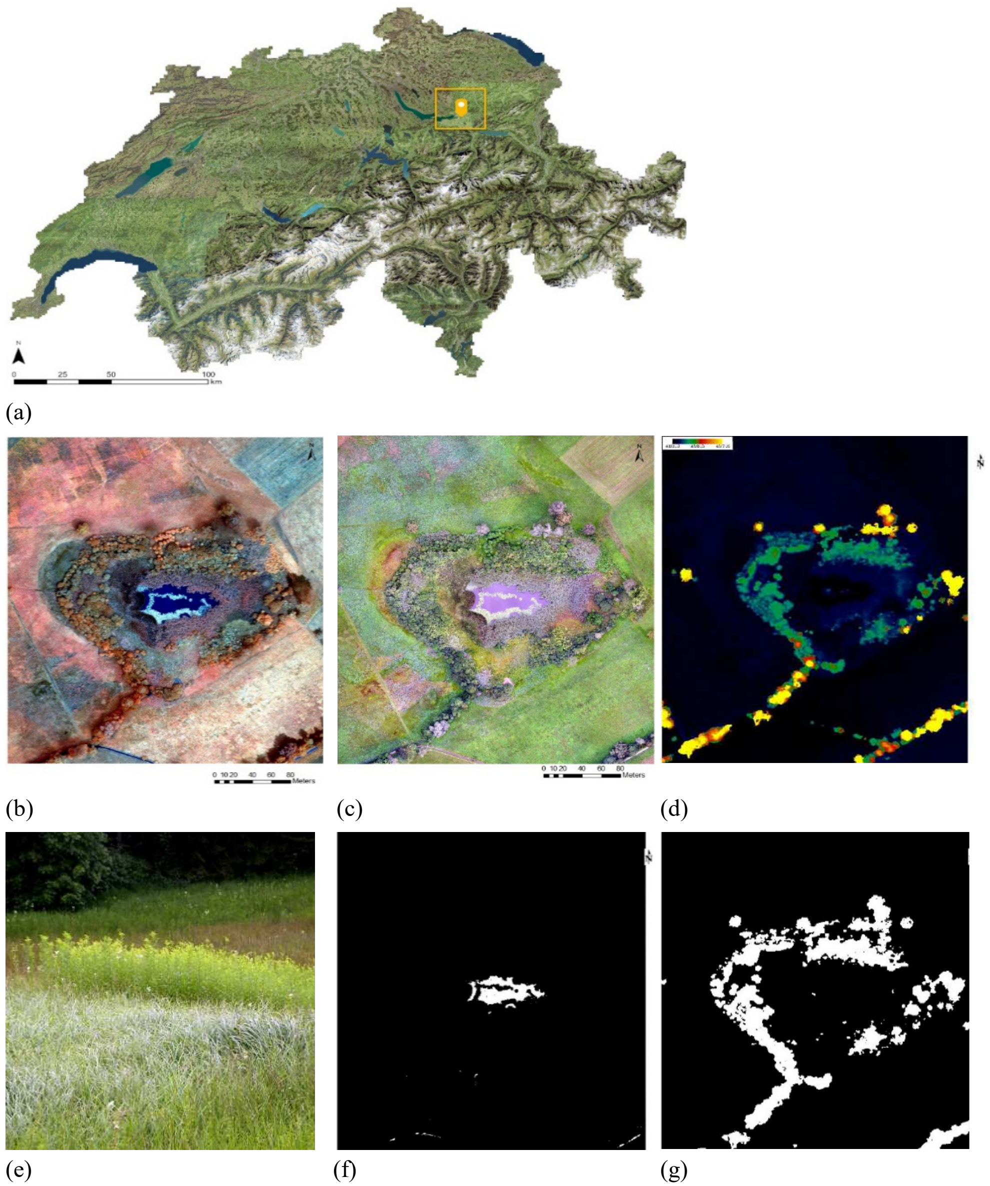

Fig. 1: (a) swissimage Level 3 (Geodata © swisstopo) with reference point on the Entensee Pond, (b) False Color Composite (FCC) of the Entensee Pond with 6.5 cm resolution acquired by a drone on August 17, 2020, (c) Red Green Blue (RGB) image of the Entensee Pond with 6.5 cm resolution acquired by a drone on August 17, 2020, (d) Digital Surface Model (DSM) of the Entensee Pond (colour ramp is meter above sea level), (e) Heavy goldenrod coverage in a wet meadow, (f) Mask created by using BCC index for isolating surface water, (g) Mask created by using DSM for isolating trees.

Before the classification, the ROIs were randomly separated into two groups as training and control. Training ROIs are used to classify the image and control ROIs are used to calculate the accuracy tables.

Classification of the Entensee Pond was performed based on a maximum likelihood algorithm, which runs a statistical analysis based on the covariances and means of the training data to assign probabilities to each pixel falling into a different class category (JONES & VAUGHAN 2010).

The ROIs separability test showed that Flowering Goldenrod and Reed on Water classes were better separable on the RGB bands; therefore, those classes were first classified (Table 2). Subsequently, the rest of the classes were classified in FCC as they were better or almost as well separable as RGB in the combination of NIR, RE, and Green bands. Therefore, RGB bands were used to classify the Flowering Goldenrod and Reed on Water, and FCC bands to classify Reed on Land, Vegetative Goldenrod, and Mown & Other Vegetation classes.

To validate the results of the classification, the Kappa coefficient, producer accuracies, and user accuracies were calculated and a confusion matrix was created by using the control ROIs.

3 Results

The dimensions of the area analysed were 331.7 x 398.4 m corresponding to 132,149 m^2. The areal coverage of Giant Goldenrod was determined to be 13,677 m^2 corresponding to 10.35% of the total area analysed according to classification run by a maximum likelihood algorithm (Table 3). Goldenrod cover was concentrated around the pond as well as the northern, and western portion of the area, which was similar to ground observations made by ProNatura (Figure 2).

Table 3: Areal coverage of different classes in the Entensee Pond

Class	Percentage (%)	Total Area (m^2)
Goldenrod	10.35%	13,677
Reed	20.31%	26,839
Surface Water	1.12%	1,480
Trees	11.57%	15,289
Mown & Other Vegetation	56.64%	74,849
Unclassified	0.05%	66

Producer's accuracy was calculated by dividing accurately classified pixels in a class to the total number of pixels of reference, indicating how well the area is classified including error of omissions. User's accuracy, on the other hand, shows how reliable the map is by dividing accurately classified pixels to the total number of pixels in that class, including error of commission (BANKO 1998). For every class analysed, above 80% producer's and user's accuracy were achieved in the classification of the Entensee Pond (Table 4).

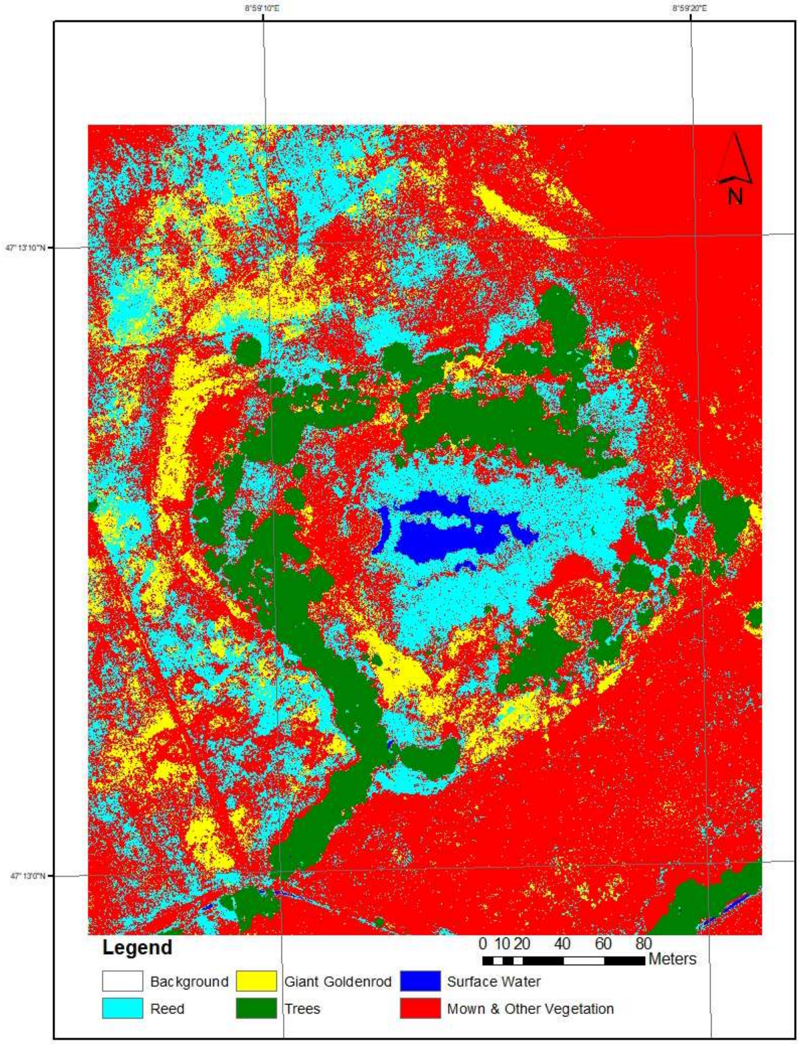

Fig. 2: Final classification of Entensee Pond based on RGB and multispectral data

The Kappa coefficient developed by COHEN (1960) shows how much of the error is reduced by the classification algorithm if the classification was performed randomly (JENSEN 1996). We achieved a Kappa coefficient of 0.902 indicating the classification process avoids 90% of the errors that a random classification generates. Overall accuracy of the classification was 92.12% (Table 4).

Table 4: Accuracy table of the classification of the Entensee Pond, including producer, user, overall accuracies, and Kappa coefficient

		Control Data						User Accuracies
Classified Data	**Class**	**Vegetative Goldenrod**	**Flowering Goldenrod**	**Mown & Other Veg.**	**Reed on Water**	**Reed on Land**	**Total**	
	Vegetative Goldenrod	94	0	0	0	2	96	94/96 97.92%
	Flowering Goldenrod	0	95	0	0	0	95	95/95 100%
	Mown & Other Veg.	0	4	91	8	8	111	91/111 81.98%
	Reed on Water	0	0	8	89	2	99	89/99 89.90%
	Reed on Land	5	0	0	2	87	94	87/94 92.55%
	Total	99	99	99	99	99	495	
Producer Accuracies		94/99 94.95%	95/99 95.96%	91/99 91.92%	89/99 89.90%	87/99 87.88%		
Overall Accuracy: (456/495) 92.12%								
Kappa Coefficient: 0.902								

4 Discussion

Our results demonstrate that remote sensing techniques with UAV are a powerful tool for monitoring and combatting invasive alien plant species by rapidly providing high accuracy maps with high resolution. Multispectral sensors beyond the 700 nm spectrum offer alternatives to differentiate structures with similar spectral characteristics in the RGB bands. In this study, Red Edge and Near Infrared bands were exploited to classify vegetative goldenrod (*Solidago altissima*) from reed (*Phragmites australis*) on land and mown & other vegetation classes which had similar spectral characteristics in the RGB bands.

Phenological phase and plant-community composition are important factors to differentiate the Giant Goldenrod from the other plant species in the community. Therefore, the peak flowering period of Giant Goldenrod was chosen to acquire the images. The methodology developed in this study might have been different, if the drone images were acquired at a different time of the year than peak flowering season of our target species. The absence of other bright yellow flowering plants in the plant community might have increased the accuracy of this study.

The Maximum Likelihood algorithm led to very high classification results in this study; however, the use of other machine learning algorithms such as random forest and minimum distance or convolutional neural networks are alternatives that might result in even higher classification results. It has been demonstrated that convolutional neural networks are extremely efficient to identify invasive species in the wild with very high accuracy (LEE et al. 2016, KATTENBORN et al. 2019, QIAN et al. 2020, QIAO et al. 2020). Convolutional neural networks might also be utilized to develop a methodology for upscaling the identification results to larger spatial extents.

Mapping Giant Goldenrod was the first step of a long-term monitoring study, which will extend to multi-year analysis with the aim of creating change-detection maps to quantify how the Giant Goldenrod stand responds to current available control techniques. Change detection maps will be critical to assess opportunistic growth patterns of the Giant Goldenrod to develop novel techniques to control its expansion.

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