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Ground-level unmanned aerial system imagery coupled with spatially balanced sampling and route optimization to monitor rangeland vegetation

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TITLE:

Ground-level Unmanned Aerial System Imagery with Spatially Balanced Sampling and Route Optimization to Monitor Rangeland Vegetation

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KEYWORDS:
drone, GPS, rangeland management, route optimization, sample point, travelling salesperson problem, vegetation monitoring

SUMMARY:
The protocol presented in this paper utilizes route optimization, balanced acceptance sampling, and ground-level and unmanned aircraft system (UAS) imagery to efficiently monitor vegetation in rangeland ecosystems. Results from images obtained from ground-level and UAS methods are compared.

ABSTRACT:
Rangeland ecosystems cover 3.6 billion hectares globally with 239 million hectares located in the United States. These ecosystems are critical for maintaining global ecosystem services. Monitoring vegetation in these ecosystems is required to assess rangeland health, to gauge habitat suitability for wildlife and domestic livestock, to combat invasive weeds, and to elucidate temporal environmental changes. Although rangeland ecosystems cover vast areas, traditional monitoring techniques are often time-consuming and cost-inefficient, subject to high observer

bias, and often lack adequate spatial information. Image-based vegetation monitoring is faster, produces permanent records (i.e., images), may result in reduced observer bias, and inherently includes adequate spatial information. Spatially balanced sampling designs are beneficial in monitoring natural resources. A protocol is presented for implementing a spatially balanced sampling design known as balanced acceptance sampling (BAS), with imagery acquired from ground-level cameras and unmanned aerial systems (UAS). A route optimization algorithm is used in addition to solve the 'travelling salesperson problem' (TSP) to increase time and cost efficiency. While UAS images can be acquired 2–3x faster than handheld images, both types of images are similar to each other in terms of accuracy and precision. Lastly, the pros and cons of each method are discussed and examples of potential applications for these methods in other ecosystems are provided.

INTRODUCTION:

Rangeland ecosystems encompass vast areas, covering 239 million ha in the United States and 3.6 billion ha globally[1]. Rangelands provide a wide array of ecosystem services and management of rangelands involves multiple land uses. In the western US, rangelands provide wildlife habitat, water storage, carbon sequestration, and forage for domestic livestock[2]. Rangelands are subject to various disturbances, including invasive species, wildfires, infrastructure development, and natural resource extraction (e.g., oil, gas, and coal)[3]. Vegetation monitoring is critical to sustaining resource management within rangelands and other ecosystems throughout the world[4,5,6]. Vegetation monitoring in rangelands is often used to assess rangeland health, habitat suitability for wildlife species, and to catalogue changes in landscapes due to invasive species, wildfires, and natural resource extraction[7,8,9,10]. While the goals of specific monitoring programs may vary, monitoring programs that fit the needs of multiple stakeholders while being statistically reliable, repeatable, and economical are desired[5,7,11]. Although land managers recognize the importance of monitoring, it is often seen as unscientific, uneconomical, and burdensome[5].

Traditionally, rangeland monitoring has been conducted with a variety of methods including ocular or visual estimation[10], Daubenmire frames[12], plot charting[13], and line point intercept along vegetation transects[14]. While ocular or visual estimation is time-efficient, it is subject to high observer bias[15]. Other traditional methods, while also subject to high observer bias, are often inefficient due to their time and cost requirements[6,15,16,17]. The time required to implement many of these traditional methods is often too burdensome, making it difficult to obtain statistically valid sample sizes, resulting in unreliable population estimates. These methods are often applied based on convenience rather than stochastically, with observers choosing where they collect data. Additionally, reported and actual sample locations frequently differ, causing confusion for land managers and other stakeholders reliant upon vegetation monitoring data[18]. Recent research has demonstrated that image-based vegetation monitoring is time- and cost-effective[6,19,20]. Increasing the amount of data that can be sampled within a given area in a short amount of time should improve statistical reliability of the data compared to more time-consuming traditional techniques. Images are permanent records that can be analyzed by multiple observers after field data are collected[6]. Additionally, many cameras are equipped with global positioning systems (GPS), so images can be geotagged with a collection location[18,20]. Use of computer-generated sampling points, accurately located in the field, should reduce observer bias whether the image is acquired with a handheld camera or by an unmanned aerial system because it reduces an individual observer's inclination to use their opinion of where sample locations should be placed.

Aside from being time-consuming, costly, and subject to high observer bias, traditional natural resource monitoring frequently fails to adequately characterize heterogeneous rangeland due to low sample size and concentrated sampling locations[21]. Spatially balanced sampling designs distribute sample locations more evenly across an area of interest to better characterize natural resources[21,22,23,24]. These designs can reduce sampling costs, because smaller sample sizes are required to achieve statistical accuracy relative to simple random sampling[25].

In this method, a spatially balanced sampling design known as balanced acceptance sampling (BAS)[22,24] is combined with image-based monitoring to assess rangeland vegetation. BAS points are optimally spread over the area of interest[26]. However, this does not guarantee that points will be ordered in an optimal route for visitation[20]. Therefore, BAS points are arranged using a route optimization algorithm that solves the travelling salesperson problem (TSP)[27]. Visiting the points in this order determines an optimal path (i.e., least distance) connecting the points. BAS points are transferred into a geographic information system (GIS) software program and then into a handheld data collection unit equipped with GPS. After BAS points are located, images are taken with a GPS-equipped camera as well as an unmanned aerial system operated using flight software. Upon entering the field, a technician walks to each point to acquire 1 m^2 monopod-mounted camera images with 0.3 mm ground sample distance (GSD) at each BAS point while a UAS flies to the same points and acquires 2.4 mm-GSD images. Subsequently, vegetation cover data are generated using 'SamplePoint'[28] to manually classify 36 points/image. Vegetation cover data generated from the analysis of ground-level and UAS imagery is compared as well as reported acquisition times for each method. In the representative study, two adjacent, 10-acre rangeland plots were used. Finally, other applications of this method and how it may be modified for future projects or projects in other ecosystems is discussed.

PROTOCOL:

1. Defining area of study, generating sample points and travel path, and field preparation

1.1. Definition of the area of study

1.1.1. Use a GIS software program to draw a polygon graphic(s) around the area(s) of interest. This study was conducted on two 10-acre plots within a grazing allotment in Laramie County, WY, USA (**Figure 1**).

[Place **Figure 1** here]

1.1.2. Ensure that those areas that are not intended to be within the sample frame are excluded from the polygon (e.g., water bodies, building structures, roadways, etc.). This will ensure that images will not be taken of these areas later.

1.1.3. Convert the polygon graphic into a shapefile feature (.shp) in the GIS software program and ensure the shapefile is created in the desired coordinate system.

1.2. Generation of the BAS points and optimizing the travel path

NOTE: The code is attached as 'Supplemental_Code.docx'.

1.2.1. Use the R package 'rgdal'[29] to convert the GIS polygon into a Program R readable file.

1.2.2. Use the R package 'SDraw'[30] to generate the desired number of BAS points. This study used 30 BAS points per study area, though future research should be conducted to determine the optimal sampling intensity for areas of various size and vegetation composition.

1.2.3. Use the R Package 'TSP'[27] to order the BAS points. Visiting the points in this order minimizes the time required to obtain samples at the BAS points.

1.3. Preparation for handheld imagery acquisition

1.3.1. Use the R package 'rgdal' to transfer the points from step 1.2.1 back into the GIS program.

1.3.2. Edit the attribute table of the shapefile so the point ID field accurately reflects the optimized path order.

1.3.3. Transfer the GIS polygon and point file into the GIS software running on a handheld unit.

1.3.4. Ensure that the correct projected coordinate system for the area of interest is in place.

1.4. Preparation for UAS imagery acquisition

1.4.1. Use the R package 'rgdal' to transfer the points from step 1.2.1 back into the GIS software program.

1.4.2. In the GIS software program, use the **Add XY Coordinates** tool to create and populate latitude and longitude fields in the waypoint attribute table.

1.4.3. Export the waypoint attribute table containing Latitude, Longitude, and TSP columns to *.csv file format.

1.4.4. Open the *.csv file in an appropriate software package.

1.4.5. Sort waypoints by TSP identifier.

1.4.6. Open Mission Hub app.

1.4.7. Create arbitrary waypoint in Mission Hub.

1.4.8. Export arbitrary waypoint as *.csv file.

1.4.9. Open *.csv file in a spreadsheet program and delete arbitrary waypoint keeping column headings.

1.4.10. Copy TSP-sorted waypoint coordinate pairs from step 1.2.3 into relevant columns in *.csv file from step 1.4.8.

1.4.11. Import *.csv file from step 1.4.10 into Mission Hub as a new mission.

1.4.12. Define the settings.

1.4.12.1. Check the **Use Online Elevation** box.

1.4.12.2. Specify **Path Mode** as **Straight Lines**.

1.4.12.3. Specify **Finish Action** as **RTH** to enable the drone to **Return to Home** after the mission is complete.

1.4.13. Click on individual waypoints and **Add Actions** by specifying the following parameters: Stay: 2 s (to avoid image blur); Tilt camera: -90° (Nadir); Take Photo.

1.4.14. Save mission with an appropriate name.

1.4.15. Repeat process for additional sites.

2. Field data collection and postprocessing

2.1. Recording vegetation observed or expected in the study area

2.1.1. Prior to acquiring images, create a list of vegetation observed within the study area. This can be done on a handwritten sheet or on a digital form to aid in photo identification later. It may be beneficial to include species that are likely to be expected in the area in the inventory even if they are not observed in the field (e.g., species within reclamation seed mixes)[18].

2.2. Ground-based image acquisition

2.2.1. Attach a camera to a vertical monopod and point the camera down approximately 60°. The area of the image can be determined using the lens and resolution (megapixel) specifications of the camera and setting the monopod to a standard height. The height of the monopod coupled with the camera specifications will determine the ground sample distance (GSD). In this study, a 12.1-megapixel camera was used and the monopod was set at a constant 1.3 m above the ground to obtain Nadir images at ~0.3 mm GSD[18].

2.2.2. Tilt the monopod forward so the camera lens is in a Nadir position, and the angled monopod is not viewable in the image.

2.2.3. Adjust the height of the monopod or the zoom on the lens to achieve a 1 m^2 frameless plot size (or another desired plot size). For the most common 4:3 aspect ratio cameras, a plot width of 115 cm yields a 1 m^2 image field of view. There is no need to place a frame on the ground; the entire image is the plot. If adjusting the zoom on the lens to accomplish this, use painter's tape to prevent accidental changes in the zoom setting.

2.2.4. If possible, set the camera to shutter-priority mode and set the shutter speed to at least 1/125 s to avoid blur in the image; faster if it is windy.

2.2.5. Locate the first point in the optimized path order.

2.2.6. Place the monopod on the ground at point 1 and tilt the monopod until the camera is in Nadir orientation. Ensure the operator's shadow is not in the image. Hold the camera steady to prevent motion blur. Acquire the image.

NOTE: A remote trigger cable is useful for this step.

2.2.7. Check image quality to ensure successful data capture.

2.2.8. Navigate to the next point in the optimized path order and repeat the acquisition steps.

2.3. UAS image acquisition

2.3.1. Prior to launching the UAS, conduct a brief reconnoiter of the study area to ensure no physical obstacles are within the flight path. This reconnaissance exercise is also useful to locate a fairly flat area from which to launch the UAS.

2.3.2. Ensure weather conditions are suitable for flying the UAS: a dry, clear day (>4.8 km visibility) with adequate lighting, minimal wind (<17 knots), and temperatures between 0 °C–37 °C.

2.3.3. Follow legal protocols. For example, in the USA, Federal Aviation Administration policies should be followed.

2.3.4. Utilize Mission Hub software (**Figure 2**) and a mission execution application accessible via mobile devices (**Figure 3**).

[Place **Figure 2** here]

[Place **Figure 3** here]

2.3.5. Collect UAS imagery at each BAS point as described in step 1.4.

2.3.6. Verify that all images were acquired utilizing the mobile device prior to changing locations.

2.4. Ground-level image postprocessing.

NOTE: Directions are available at www.SamplePoint.org in the tutorial section; a supplemental .pdf file is attached.

2.4.1. Download images onto a computer with USB cable or SD card.

2.4.2. Ensure images were taken at correct locations. Various software exists to place images into the GIS software based on the metadata within the geotagged images.

2.4.3. If the images were acquired in multiple study areas, store them in separate folders for image analysis.

2.5. UAS image postprocessing

2.5.1. Transfer images saved on a removable microSD card from the UAS to the computer.

2.5.2. Repeat steps 2.4.2 and 2.4.3.

3. Image analysis

NOTE: All Steps can be found in the 'tutorial' section on www.SamplePoint.org; a supplemental 'tutorial.pdf' file is attached.

3.1. In SamplePoint, click **Options | Database Wizard | Create/Populate Database**.

3.2. Name the database based on the study area.

3.3. Navigate to the folder containing the desired study area samples and select those to be classified.

3.4. Click **Done**.

3.5. Click **Options | Select Database** and select the *.xls file that SamplePoint generates based on the image selection (this will be in the image).

3.6. Confirm the correct number of images were selected in the database when prompted by SamplePoint.

3.7. Select the desired number of pixels to be analyzed within each image. This can be done in a grid pattern or randomly. This study used a 6 x 6 grid to select a total of 36 pixels, though more or fewer pixels per image can be classified depending on the desired measurement precision for classification. A recent study found 20–30 pixels per image is adequate for sampling large areas[31]. The grid option assures pixels will be in the same position if the image is reanalyzed, whereas the random option will randomly generate pixels each time an image is reloaded.

3.8. Create a custom **Button** file for species classification. This list can be generated from the vegetation list recorded in the field prior to image acquisition, or it can be based on other information pertinent to the study area (e.g., seed mix list on reclaimed sites, or ecological site description information, etc.). Ensure a button is created for **Bare Ground** or **Soil** and other potential nonvegetation items that may be encountered, such as **Litter** or **Rock**. Creating an **Unknown** button is recommended to allow the analyst to classify species at a later date. The **Comment Box** in SamplePoint can be used to note the pixels that used this option. Additionally, if the image resolution is not high enough to classify to species levels, creating buttons for functional groups (e.g., **Grass**, **Forb**, **Shrub**) is beneficial.

3.9. Begin analyzing the images by clicking the classification button that describes the image pixel targeted by the red crosshair. Repeat this until SamplePoint prompts “That is all the points. Click next image.” Repeat this for all images within the database.

NOTE: The **Zoom** feature can be used to help with classification.

3.10. When all the images in the database are completely analyzed, SamplePoint will prompt “You have exhausted all the images.” At this point, select **OK** and then click **Options | Create Statistics Files**.

3.11. Go to the folder containing the database and open the *.csv file that was just created to ensure that the data for all images are stored.

4. Statistical analysis

4.1. Chi-square analyses to determine differences between sites

4.1.1. Because the same number of images (primary sampling units) and pixels (secondary sampling units) are collected and analyzed at both sites, the comparison between the two sites can be considered a product of multinomial design.

4.1.2. Using the *.csv file created in step 3.11, calculate the sum of points classified for each classification category.

4.1.3. Perform chi-square analysis on the point sums. If Site 1 and Site 2 are similar to each other, an approximately equal number of pixels classified as each cover type will be evident on both sites[18].

4.2. Regression to compare UAS versus ground-level images

4.2.1. Using the *.csv files created in step 3.11, copy and paste the average percent cover from each image and align the UAS image data with the ground-level image data.

4.2.2. Perform regression analysis in a database program.

RESULTS:
UAS image acquisition took less than half the time of ground-based image collection, while the analysis time was slightly less with ground-based images (**Table 1**). Ground-based images were higher resolution, which is likely the reason they were analyzed in less time. Differences in walking path times between sites were likely due to start and end points (launch site) being located closer to Site 1 than Site 2 (**Figure 1**). Differences in acquisition time between platforms was principally due to the UAS flying speed being 2–3x faster than the technician walking speed (**Figure 4**).

[Place **Table 1** here]

[Place **Figure 4** here]

Site 1 and Site 2 were significantly different ($p < 0.0001$) from each other in terms of vegetation cover, regardless of which image acquisition method was utilized (**Table 2**). Measured from both UAS and ground-level images, soil, fringed sage, and crested wheatgrass were different between sites (**Table 2**).

[Place **Table 2** here]

All correlation coefficients were strong (>0.5). Litter on both sites was the weakest correlation between UAS vs. ground-level images with a 0.52 correlation coefficient on Site 1 and a 0.58 correlation coefficient on Site 2. This could be due to GSD differences and it being more difficult to assess live or dead litter with coarser GSD. All other ground cover categories had correlation coefficients greater than 0.8 in Site 2 and greater than 0.9 in Site 1 (**Figure 5** and **Figure 6**). Site 1 had higher correlation coefficients than Site 2, likely due to Site 2 being more heterogeneous than Site 1.

[Place **Figure 5** here]

[Place **Figure 6** here]

FIGURE AND TABLE LEGENDS:

Figure 1: A depiction of the study areas of interest. This location is on a grazing allotment south of Cheyenne in Laramie County, WY, USA (Imagery Source: Wyoming NAIP Imagery 2017).

Figure 2: The user interface of Mission Hub. The map depicts the drone flight path along a series of 30 BAS points across one of the study sites while the popup window shows image acquisition parameters at each waypoint**. Figure 2** is specific to Site 1, though it is similar in appearance to Site 2.

Figure 3: The waypoint flight mission in Litchi's mission execution application running on an Android smartphone. Unique waypoint IDs are shown in purple and represent the relative order in which images were taken at various points in the study area. The numbers at each waypoint, such as 7(6), indicate the integer values of heights above the ground at which images were taken (first number) and heights above the home point or drone launch site (second number). Notice the distances between successive waypoints that are labeled on the map**. Figure 3** is specific to Site 1, though it is similar in appearance to Site 2.

Figure 4: Aside from waypoint 1, the UAS was able to reach all other waypoints accurately. The handheld imagery was far less accurate than the UAS at reaching waypoints, likely a combination of human error and a lower-quality GPS on the handheld equipment. **Figure 4** is specific to Site 1, though performance on Site 2 was similar.

Figure 5: Correlation plots for Site 1. The x- and y-axes represent percent total percent cover for each category.

Figure 6: Correlation plots for Site 2. The x- and y-axes represent percent total percent cover for each category.

Table 1. The amount of time taken for image acquisition and analysis. The start and end times for image acquisition were recorded when the technician and UAV left and returned to the launch point. Image analysis time was based on the start and end of image classification. Time to create flight paths and custom button files in SamplePoint were not recorded.

Table 2: W**hich categories drove significant differences between Site 1 and Site 2 when images were collected with the UAS and the handheld camera.** In both instances sites were significantly different ($p < 0.0001$). Individual categories with a * are those that were responsible for the differences. Numbers in parentheses indicate the proportion of the chi-square statistics that were accounted for by each category.

DISCUSSION:

The importance of natural resource monitoring has long been recognized[14]. With increased attention on global environmental issues, developing reliable monitoring techniques that are time- and cost-efficient is increasingly important. Several previous studies showed that image analysis compares favorably to traditional vegetation monitoring techniques in terms of time, cost, and providing valid and defensible statistical data[6,31]. Ground-level image acquisition can be conducted 7–10x faster than line point intercept[18,31]. This study and a recent study[20] demonstrate that UAS imagery can be collected in 2–3x less time than it takes to acquire handheld imagery. Aerial images obtained from unmanned aerial systems or vehicles are becoming increasingly popular to assess a wide variety of environmental issues[33], including habitat destruction and quality[34,35], and other forms of vegetation surveys[20,36]. However, direct comparison of vegetation monitoring from ground-based and UAS-acquired images is not well studied[20]. These results suggest UAS and ground-based image analysis accuracy and precision are similar. Accounting for both acquisition and analysis, the UAS platform was faster than ground-based by 10 min/site. Because travel costs are the most expensive part of large-scale vegetation monitoring programs[4], the ability to rapidly collect monitoring data is critical. The permanence of an image allows for analyses to be conducted long after it is collected[6], which suggests that the methods proposed here could allow for robust amounts of data to be collected in short periods of time with the ability to analyze field data at a later date and potentially by multiple individuals or interest groups. Rapid field data collection is important not only for time- and cost-savings, but to ensure monitoring can be completed during short periods where plant phenology renders them readily identifiable (e.g., during blooming)[18]. While repeat photography has been utilized to study phenological trends over time[37,38], the GPS capability of modern cameras and UAS systems can be used to further ensure image acquisition is occurring at the same location (or in very close proximity) over time, enhancing the ability to understand short- and long-term environmental changes.

Advantages of ground-level image collection compared to UAS image collection are: (1) higher resolution imagery, making species identification easier; (2) less concern about wind conditions with a handheld unit than with a UAS; (3) less preparation time needed for flight planning and field set up; (4) less concern about structure avoidance when walking than when flying; (5) less cost for equipment; and (6) less training required to operate the equipment. Advantages of the UAS include: (1) ability to fly at much higher speeds than bipedal locomotion, therefore reducing time to collect data; (2) higher spatial accuracy due to reduction of human error and increased GPS speed; (3) no sampling location bias (e.g., a technician may avoid an intended sample point if it is centered in a puddle, or may adjust the camera angle slightly to include more vegetation); (4) zero ground-disturbance sampling (e.g., obtaining quantitative data on an endangered plant species); (5) easier sampling in difficult terrain (e.g., steep, muddy, dense, or poisonous vegetation cover); (6) larger image size (i.e., images acquired from 7.6 m AGL capture more area than images acquired at 1.3 m AGL); and (7) consistent data collection speed and consistency over time. This study focused on two nearby locations on relatively unchallenging terrain, allowing the technician to avoid fatigue. However, if more walking or more difficult terrain was encountered, the technician’s speed would likely decrease.

Coupling spatially balanced sampling designs with rapid data collection devices like cameras should further increase time- and cost-savings associated with a variety of environmental monitoring programs. Although this study focused on rangelands, spatially balanced sampling designs are effective in other settings, such as clam bed monitoring[39], soil sampling[40], and reclamation monitoring[18,20]. The technique demonstrated within this manuscript is widely applicable to vegetation monitoring in other terrestrial ecosystems. It is, however, highly likely that modifications to the method will be required in other ecosystems (e.g., vegetation height, density, and diversity will require different image height and sampling intensities). Although only two dimensions were utilized, BAS is capable of operating in multiple dimensions[22] and has been used for underwater surveys[41]. While coupling TSP with BAS and image analysis may improve time efficiencies for these surveys, camera techniques are likely to change in underwater surveys compared to terrestrial studies, which rely on Nadir imagery.

The results reported here are based solely upon the comparison of the images obtained using software specific to this study (see **Supplemental Table**, 'SoftwareUsed.xlsx'). Given the wide-range of cost and capabilities available in the GPS and UAS marketplace, additional cost-benefit analyses to determine tradeoffs among different equipment and software will be useful. For the purposes of this study, images were also taken at predetermined heights based on a recent study[20]. Additionally, studies to determine optimal above-ground image heights for vegetation monitoring will likely benefit from future research and management. Finally, this study was limited to one timepoint in a fairly homogeneous vegetation community. Future studies in other ecosystems and long-term studies will increase universal understanding of advantages and limitations of UAS vegetation monitoring. Sample sizes in this study were consistent with a previous study[18], but more work is likely necessary to determine optimal sampling units in different sized areas as well as in different ecosystems.

DISCLOSURES:

The authors declare no conflict of interest. The software used in this study was available to authors either as open-source or through institutional permits. No authors are sponsored by any software used in this study and acknowledge that other software programs are available that are capable of doing similar research.

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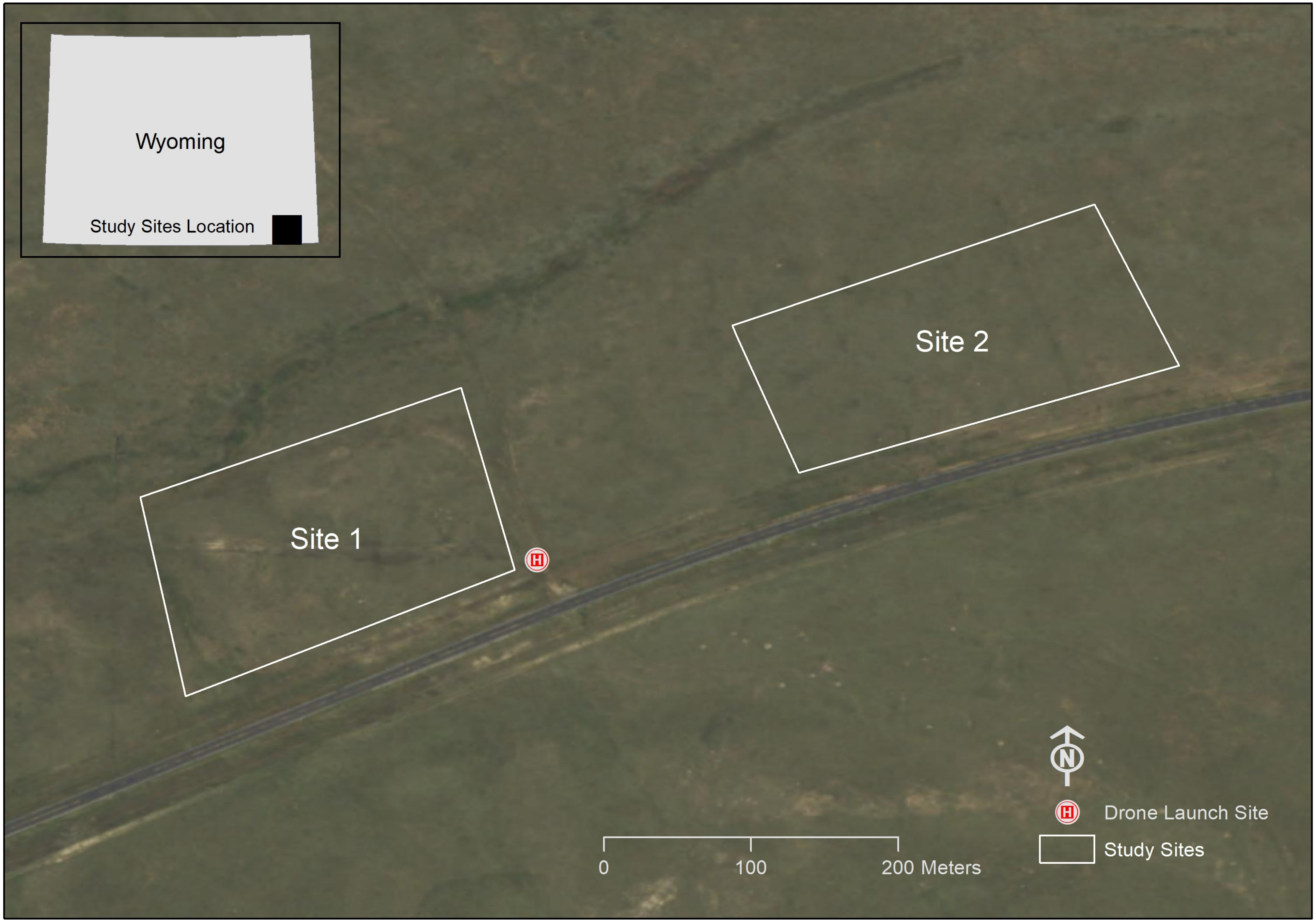
Wyoming
Study Sites Location
Site 1
Site 2
0
100
200 Meters
N
Drone Launch Site
Study Sites

Figure

Click here to access/download;Figure;Figure2.ai

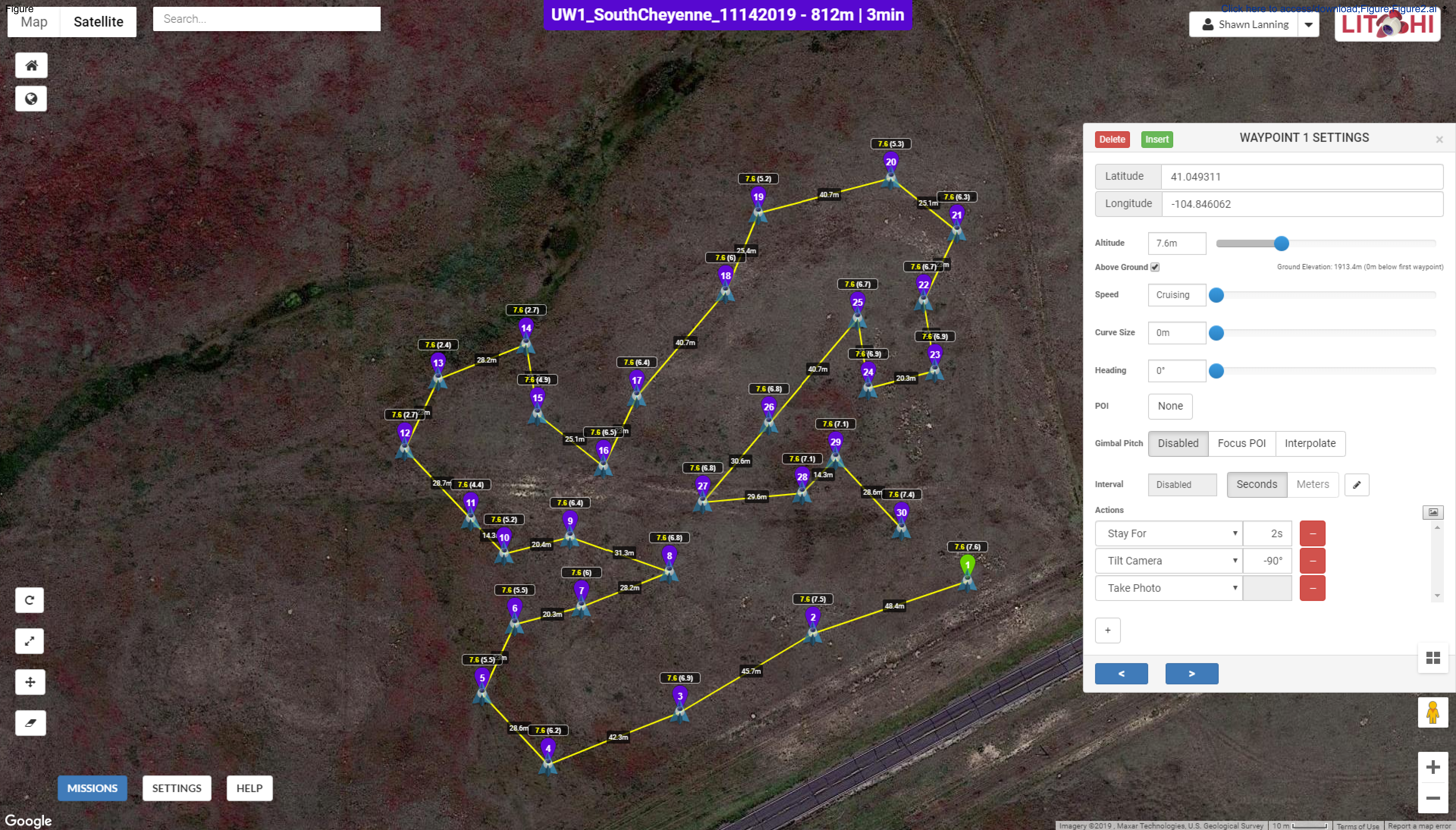

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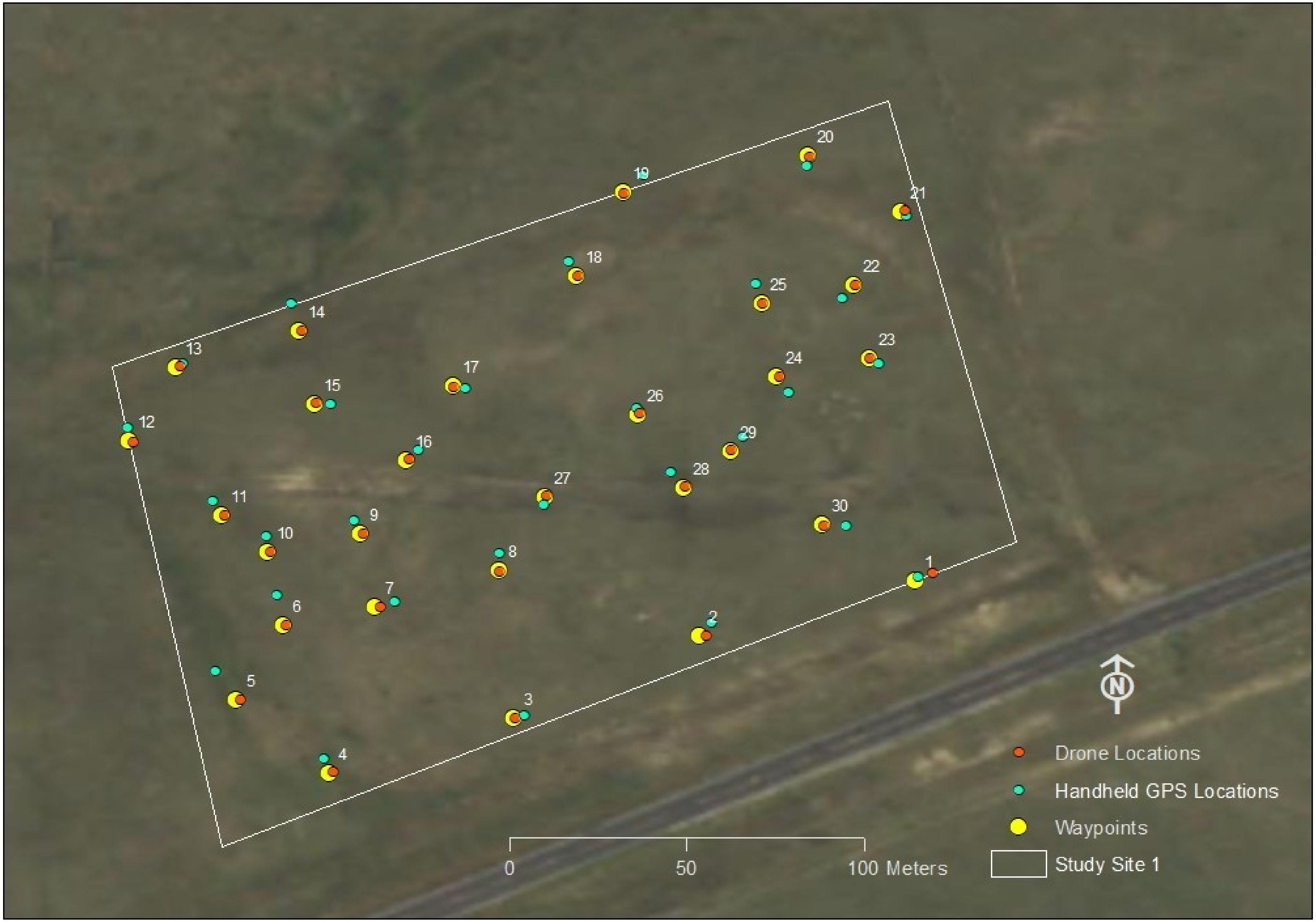
Figure

Click here to access/download;Figure;Figure4.ai



Figure

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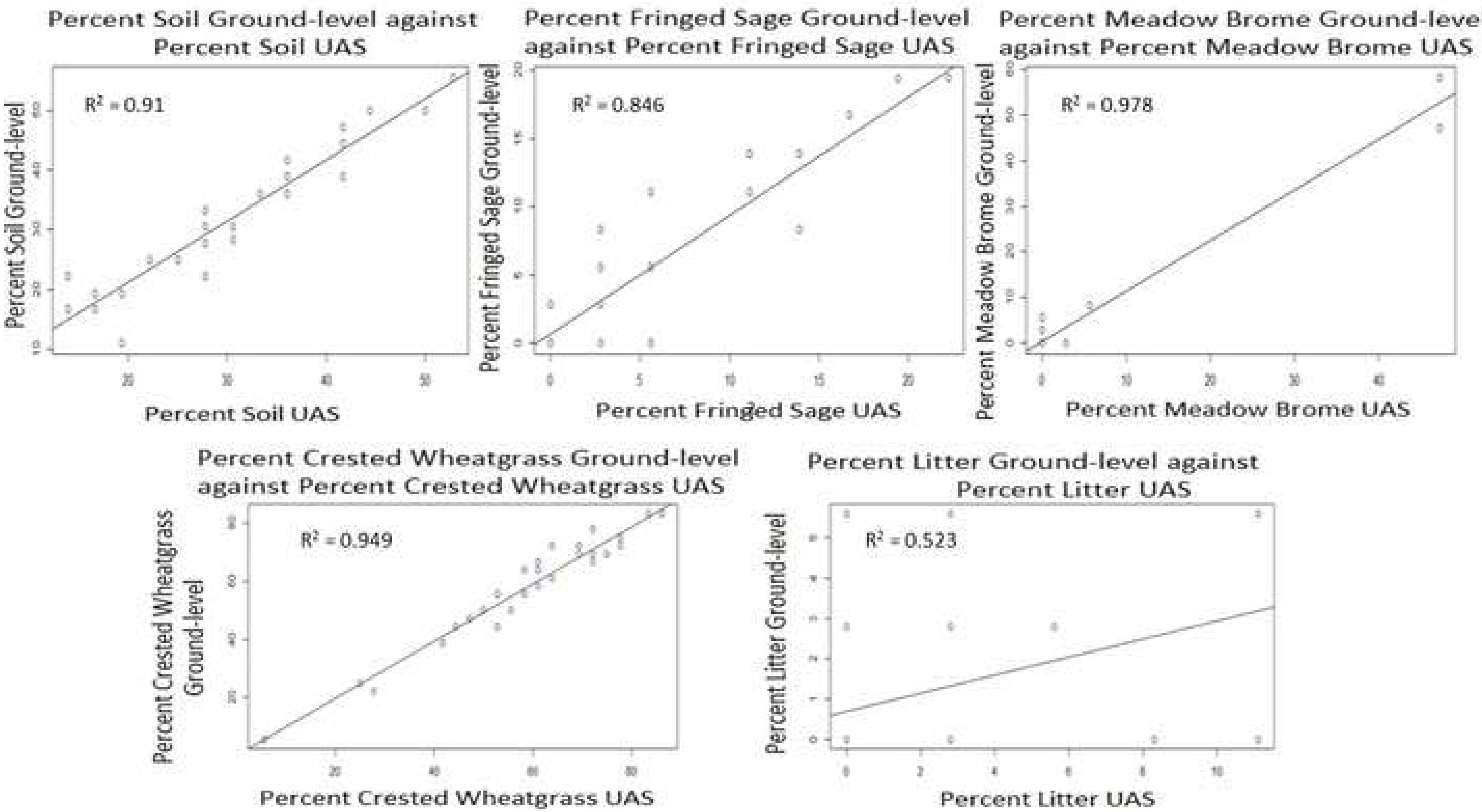

Figure

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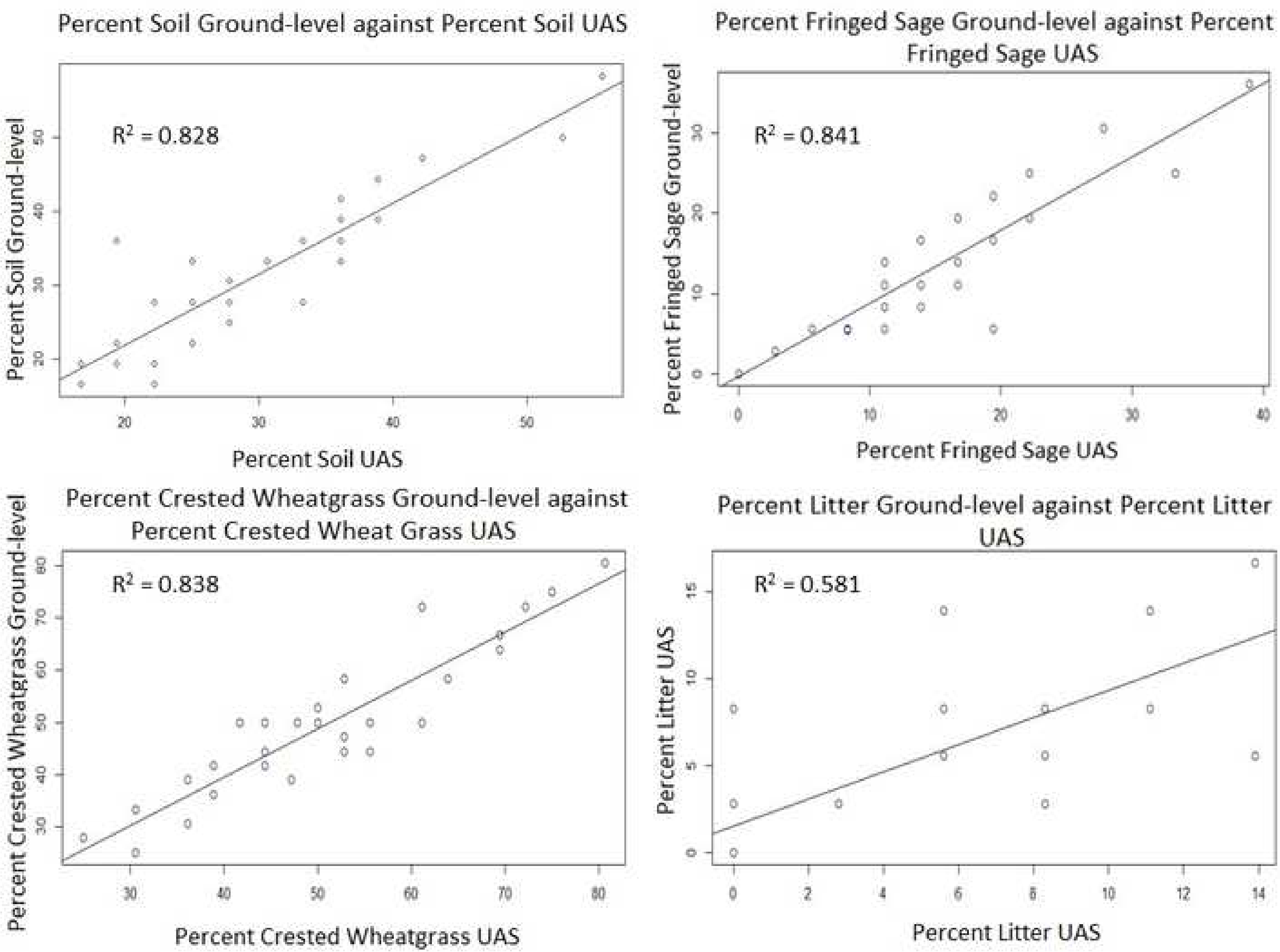


Table 1 Click here to access/download;Table;Table_1.xlsx

?	Acquisition Time (mm:ss)/Site		Analysis Time (mm:ss)/Site		Analysis Time (
	Ground-level	**UAS**	**Ground-level**	**UAS**	**Ground-level**
Site 1	18:24	8:14	45:14	47:28	1:31
Site 2	21:26	8:12	44:58	46:50	1:30
Mean	19:55	8:13	45:06	47:09	1:31

(mm:ss)/Image
UAS
1:35
1:34
1:35

Table 2

Method	Soil	Meadow Brome	Thistle	Fringed Sage	Crested Wheatgrass	Rock	Litter
UAS	(28.46)*	(1.71)	(0)	(9.92)*	(55.86)*	(0.18)	(3.69)
Handheld	(31.67)*	(1.85)	(0.09)	(8.84)*	(53.1)*	(0.09)	(4.35)*

Name of Material/ Equipment	Company	Comments/Description
ArcGIS	ESRI	GPS Software
DJI Phantom 4 Pro	DJI	UAS
G700SE	Ricoh	GPS-equipped camera
GeoJot+Core	Geospatial Experts	GPS Software
Juno 5	Trimble	Handheld GPS device
Litchi Mission Hub	Litchi	Mission Hub Software
Program R	R Project	Statistical analysis/programming software
SamplePoint	N/A	Image analysis software

Notes

Used to extract image metadata

We chose Litchi for its terrain awareness and its ability to plan robust waypoint missions

To JOVE Editorial Staff:

We appreciate your efforts in providing suggestions to our manuscript. We have done our best to address your comments and suggestions. We have got through edits of each reviewer thoroughly. We were concerned with reviewer 4's comments on committing to using the term 'drone' instead of Unmanned Aerial Systems. The FAA is the main authority on civil aviation in the United States and every civilian government agency in the United States refers to the type of technology we used as UAS. Drone is a more vague term; it can mean a flying bee, a talkative professor, a flying robot, a walking robot, etc. We are also concerned in general about overall comments on utilizing various software products. We have included in our conflict of interest statement that no author on this manuscript is endorsed or sponsored by of the non-open-sourced software used in our methodology. We have provided code snippets within the document and provided a supplemental table of the software we used. We did not know how to get out of saying the names of Program R and SamplePoint, two open-source softwares, in our manuscript, though we removed the names of commercial softwares. We appreciate reviewer 2's suggestion to use QGIS and open-access software, but the pilots implementing this study have access to ArcGIS through their institutions, which is common for academic, government and industry professionals. We were also surprised about Reviewer 4 calling rangelands a US-centric term. For 35 years, the International Rangeland Congress hosts researchers and land managers from around the world to discuss open spaces which are used by foraging animals. Additionally, Rangeland Ecology & Management is the primary journal for articles pertaining to these areas and accepts and publishes papers from throughout the world regarding them. Finally, we had some overall confusion as to what exactly to provide for film highlights. The SamplePoint process (e.g., button clicks) is freely accessible and very well explained in the 'tutorial' section on www.SamplePoint.com . We address other concerns directly to the editor and each reviewer below, though we did our best to take action on suggested comments. We added several citations based on the recommendation of Reviewer 4, though we were not under the impression that this manuscript was more to be methods based than very thorough in the literature review side .We used track changes in the document to allow editors and reviewers to see what we changed.

Specific to editor's comments:

We have provided snippets of code for running BAS and TSP. We utilized Program R, so our code may be specific to that program and the packages used within it. Therefore, we left those package and program R in the manuscript (it is open-source, so we were unsure if is against commercial policy – SamplePoint is also open-source). We removed other 'commercial' products from the manuscript and made a supplemental file for them. We added a statement to the conflict of interest section to let readers know we are not endorsing nor are we sponsored by any specific product, we used what we had available at our institutions.

We were unsure if we are supposed to provide screenshots for each bit of the software protocols. Also we are unsure if filming the SamplePoint process (e.g., button clicks, etc… this is all accessible in a tutorial for free through the SamplePoint website above) is the goal of this paper or if the goal is to do the route planning and image acquisition. We would be over the 2.5 suggested page limit of highlights if we choose both.   We are willing to provide these, but there are quite a bit of steps, which we felt may confuse the editor/reviewers and ultimately the readers if we listed all of them. I am happy to discuss further via telephone, screenshare or email communication. We would appreciate assistance from the editor and film team determining whether we selected the portions of the protocol which are most interesting to readers/watchers.

We are unsure how to address specific comments as to how to provide camera, lens and monopod specifications without mentioning the name of the equipment we used. Minimal standards to successfully operate SamplePoint are included on their website. We included this information.

We changed our numbering system as suggested for our protocol section.

We highlighted areas which we thought would be most important to film, though additional steps may be suggested by the editor (e.g., if the SamplePoint tutorial on the web is not sufficient enough, we should add that process into the highlights).

We expanded font size for visibility in Figure 5 and 6. We converted Figures 1-4 into .ai files and 5-6 into .tiff files.

We moved the tables into excel files.

Specific to Reviewer 1's comments:

We utilize the TSP to optimize the route to connect to BAS points. This is recently published and explained further in *Biodiversity* by Curran et al. (2020 – in press), which we have added to our citations. The code is included and should also address issues from other reviewers. We can work on addressing this visually through a second revision, though we believe Figures 2 and 3 demonstrate this and the code provided in the supplemental table ensures the start point is nearest to the starting area.

Time is a metric we discussed. Yes, the UAS is faster than a human and human time in this study was limited to one human (another human could potentially be faster or slower than the technician in this study). We felt it necessary to discuss factors which could increase human timing, as an advantage of the UAS is it (weather permitting) is likely to be more consistent in rough terrains.

The plots of interest we discussed here did not have cameras on them, and it is not likely a wide range of plots would be expected to have cameras on them. Plots with permanent cameras on them may nullify the value of either the UAS or ground-based approach.

We have edited our abstract to make it more specific.

We have edited paragraph 1.

It is necessary to exclude, when possible, sections which you do not wish to be in the study area. Without exclusion, the UAS (or human) may be directed to take photos in areas not of interest.

More direct specifications as to where bulleted/itemized points should be located would help the authors.

Specific to Reviewer 2's comments:

We suggested excluding areas which are not intended to be in the study/area of interest. This should be done to the best ability prior to the field, though certainly is not always avoidable. Not excluding these may result in sampling within the area.

The method we describe considers the study area and the survey area as the same thing.

QGISC could potentially substitute ArcGIS. However, ArcGIS is commonly available to professionals in academia, government and industry. We used what was available to us. We took advice from editor to remove specific product names and move them into a supplmental table.

The intent of this manuscript is to demonstrate how to use the method of creating BAS points, apply the TSP to them and to allow for a human with a GPS or an UAS to find those points in and optimal route. The number of BAS points can vary based on restrictions (e.g., time/cost/size of area). The size of the area we studied used 30 points because a similar sized area was studied with high confidence in Curran et al. 2019 (Restoration Ecology, cited in this manuscript). There is never a perfect solution to sample size, as various restrictions will dictate what can/can't be done. We added a bit to the discussion to address this.

We assume by excluding areas which are not of interest to the study should eliminate potential obstacles. The pilot, through FAA protocol, should take caution in the field to ensure potential obstacles not seen from pre-mapping are avoided. The human walking the camera around should also take caution of obstacles in the field, but trying to exclude them from the area by mapping likely helps reduce need to adjust in the field.

Again, we used what was available to us, and do not intend to redo the study with different technologies. In the discussion, we mention other technologies are available and in the conflict of interest statement we declare we are not promoting or endorsing one specific product.

The Bureau of Land Management recommends creating a list of vegetation species noticed in the field prior to collecting data. It should not necessarily matter how this list is created, as long as the species are recorded to help ID species when analyzing photos.

Directions on camera orientation are documented on www.SamplePoint.org and in several references found there. The are also listed in previous protocol steps.

We used GeoJot because it was available to us, a lot of software tools are available for similar purposes.

The images don't cover the exact same area. Likely, the images with higher resolution were analyzed faster due to clarity seeing pixels during SamplePoint process.

We reworded avoidance of structures to ensure that it is more likely for a human walking to be able to avoid an unintended structure than a UAS in flight, but it is important for the pilot to ensure the UAS flight path does not encounter structures.

We addressed potential issues with litter classification.

We indicated Figures 2,3,4 refer to site 1.

Specific to Reviewer #3's comments:

Line numbers were added.

In both regards, image-based monitoring is faster than traditional techniques, whether a person takes the images or an UAS takes them. We find the UAS to be faster than the human. While this study was conducted using one human taking the images, it is likely that multiple humans would vary in time due to things like fitness and familiarity with the study area.

Our study was focused on western rangelands. We made a clarifying statement to suggest our method is not restricted to this area.

Correct, the UAS was intended to fly the same path as the person on the ground.

Numbering was corrected based on editor's comments.

36 pixels were analyzed in each image, though more or less pixels could be analyzed. .

Pixels are classified manually, as described on SamplePoint's tutorial.

We made a correction to suggest limitations of this type of monitoring include inability to assess certain vegetation characteristics.

Specific to Reviewer 4's comments:

We have added references to previous UAS literature for ecological purposes.

We have attempted to be consistent in our use of terms and abbreviations.

The code we provided shows how to get to the first point BAS point before optimizing path through TSP.

We added a sentence in discussion about time of pre-planning to suggest that it should be accounted for in future studies.

We addressed why we're sticking with UAS instead of drone above.

We corrected the typo, thank you for pointing it out.

We used R 3.5.3, which has since been updated to R version 3.6.2. We add this to the supplemental table of software used.

We renumbered our protocol and attempted to address differences.

We used ArcMapv10.3 and ArcGISv10.5.1 in this study, indicated in supplemental table.

Metadata from images can let the viewer know the size of the image. The largest problem with a reference frame is that it is cumbersome to carry to each site.

Wind speed can be measured in a variety of ways and can be checked on most any weather device.

Flight planning is extremely important. We have emphasized this in the text, though don't have a perfect solution to instances when the UAS cannot fly the complete path.

Legal protocols are FAA regulations in our instance. The pilots are licensed FAA pilots. This is the national standard in USA.

A single button for 'other' could be fine for certain studies, but can also be limiting if the analysis would be helpful by including things like rocks, vegetative litter, feces, lichens, etc.

We changed wording to suggest that data can be analyzed in a variety of software programs, we happened to analyze our data in those ways.

Regression was changed to correlation.

Citations were added to discussion paragraph 2.

Specific to Reviewer 5's comments:

Novelty is not a requirement for JoVE as suggested by the editor.

For 35 years, the International Rangeland Congress has hosted researchers from around the world to discuss issues surrounding grasslands, shrublands, and deserts used for foraging animals and ecosystem services. Rangeland Ecology and Management is the primary international journal for articles pertaining to these areas and publishes articles from authors all over the world. We do not believe rangelands is an ambiguous or US-centric term.

Best Regards,

Michael Curran, Paddington Hodza, Samuel Cox, Shawn Lanning, Blair Robertson, Tim Robinson, Peter Stahl

SamplePoint Tutorial

SamplePoint is a tool that facilitates point-sampling of digital images.

This presentation will demonstrate how to use SamplePoint 1.54 to collect cover data. Note that the program is updated more often than this tutorial, and thus some features may not be explicitly described here. Menu and interface may also change slightly with new versions. See the HELP menu for information about features not described in the tutorial.

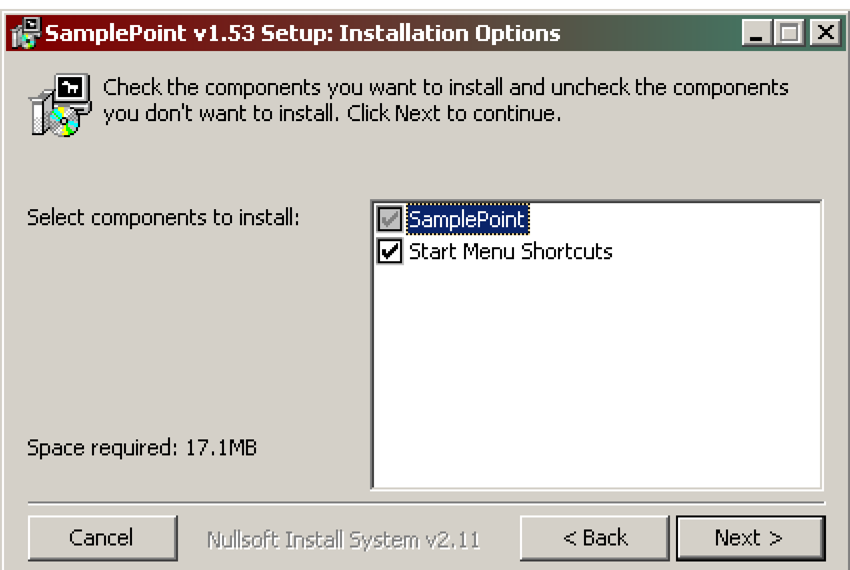
REQUIRED:
•SamplePoint Installation file
•18 MB free space on hard drive (performance increases with free space)
•Digital image files taken from a nadir perspective (looking straight down).
•Minimum 1024x768 monitor resolution (Control Panel>Display>Settings)
•Microsoft .NET Framework 2.0 installed (www.microsoft.com)
•Unfettered write access to the image directory

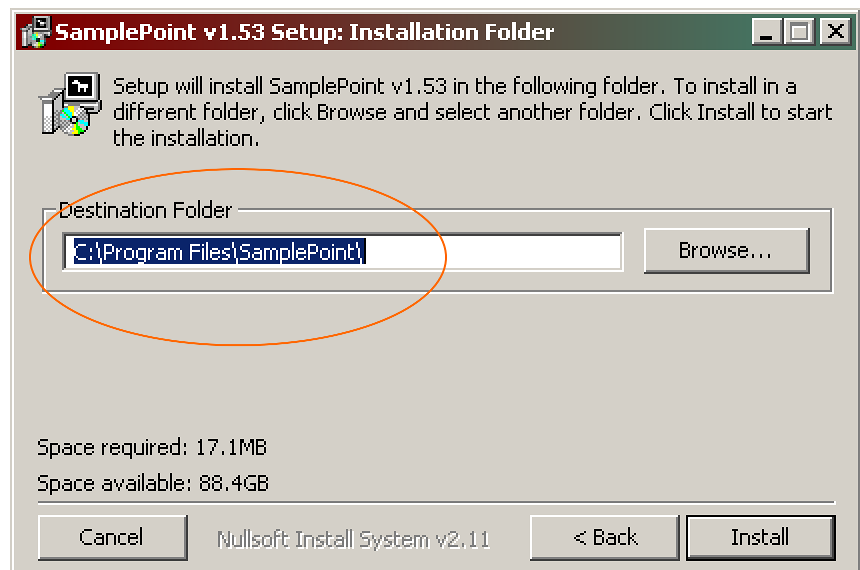
RECOMMENDED:
19” color display

Obtain the SamplePoint installation file and double-click to begin installation. Follow the on-screen directions. The following files will be loaded onto your PC into the specified directory:

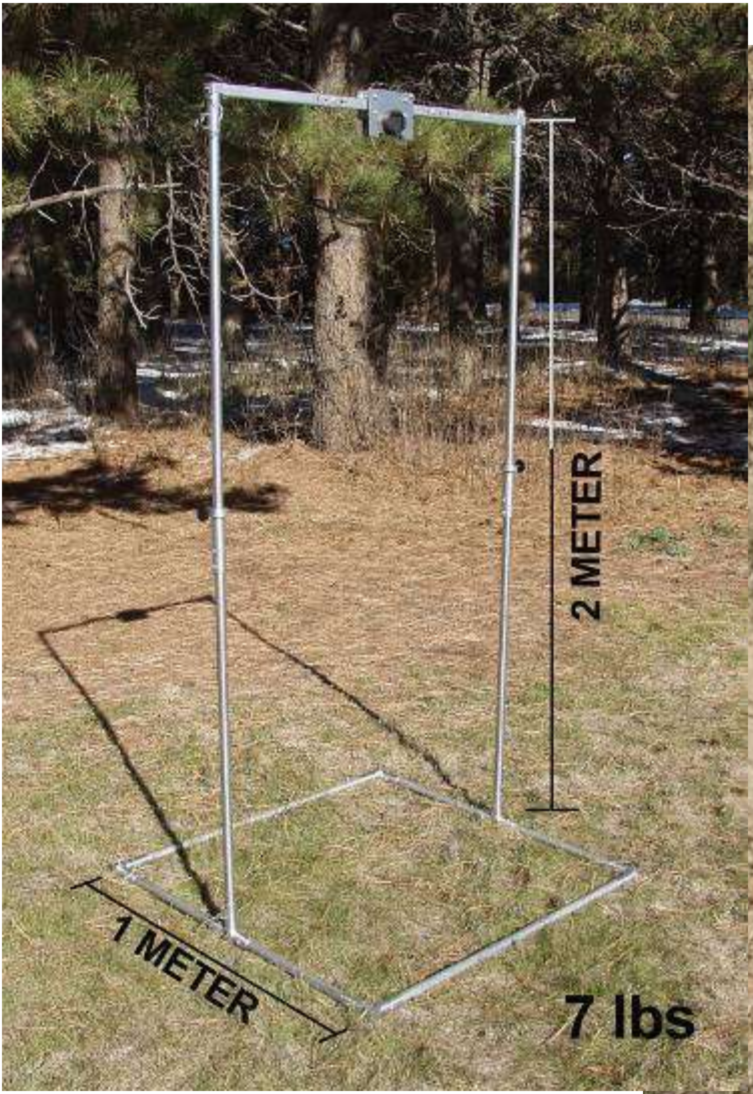
SamplePoint.exe
SamplePointTutorial.pdf
SamplePointHelp.pdf
SPDB.xls
Nadir Sample Image : dubois_41.bmp

The Nadir Sample Image is one of the images used in this tutorial. It was acquired from 2m above ground level using an aluminum camera stand and an Olympus E20 digital SLR camera, and covers approx. 1m x 1m with a ground sample distance of 0.9 mm.

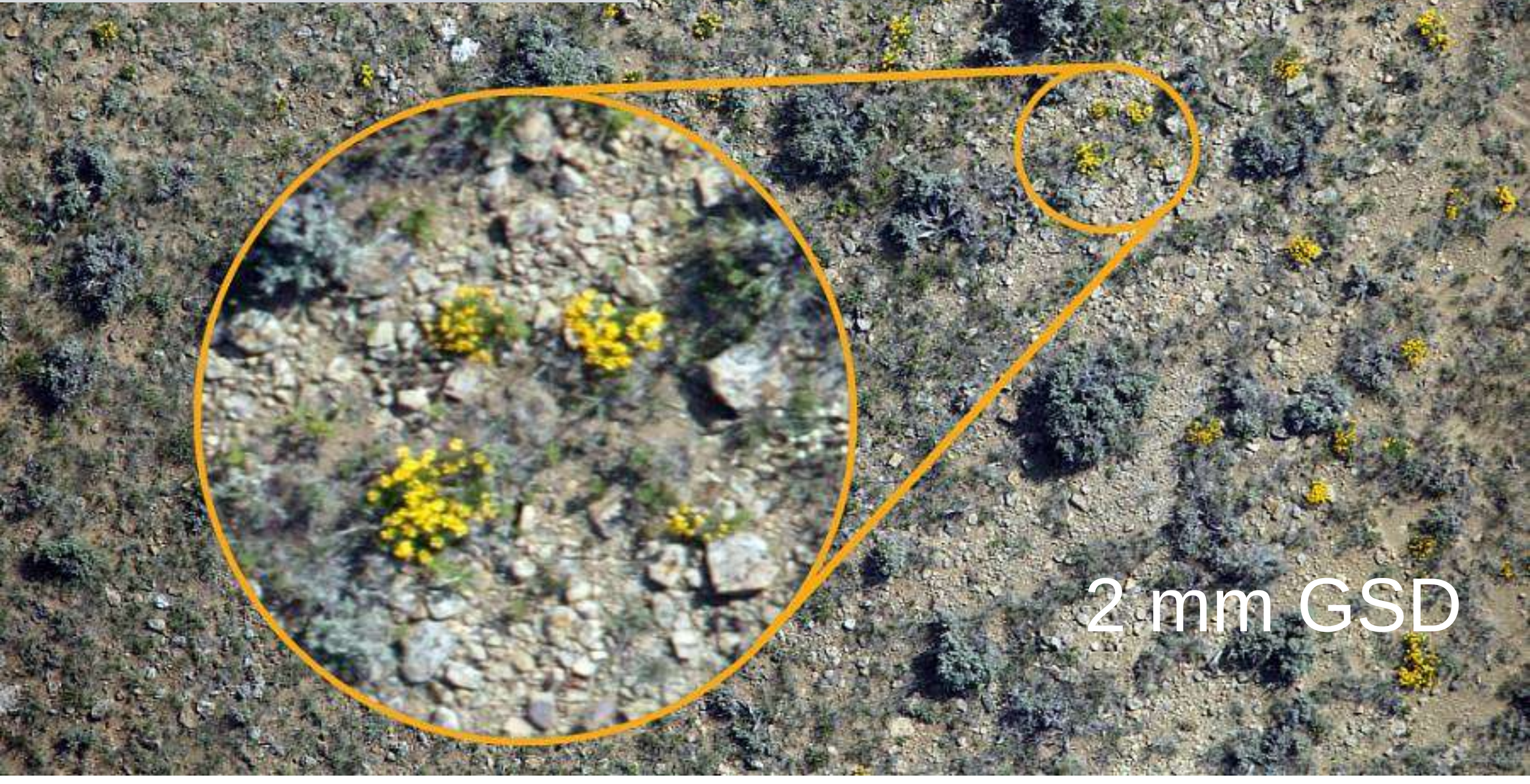




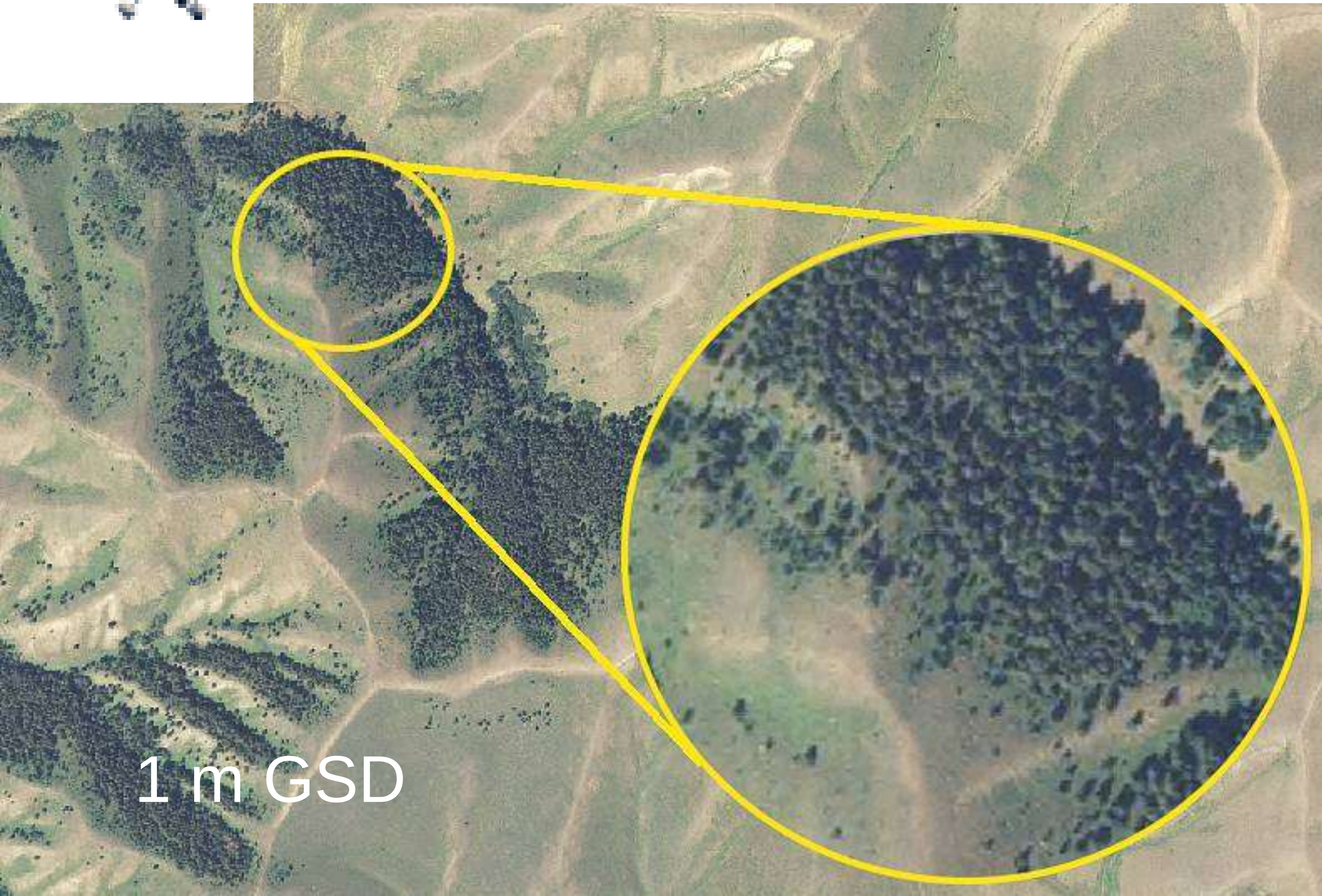
Use a camera stand to acquire nadir images using a digital camera.



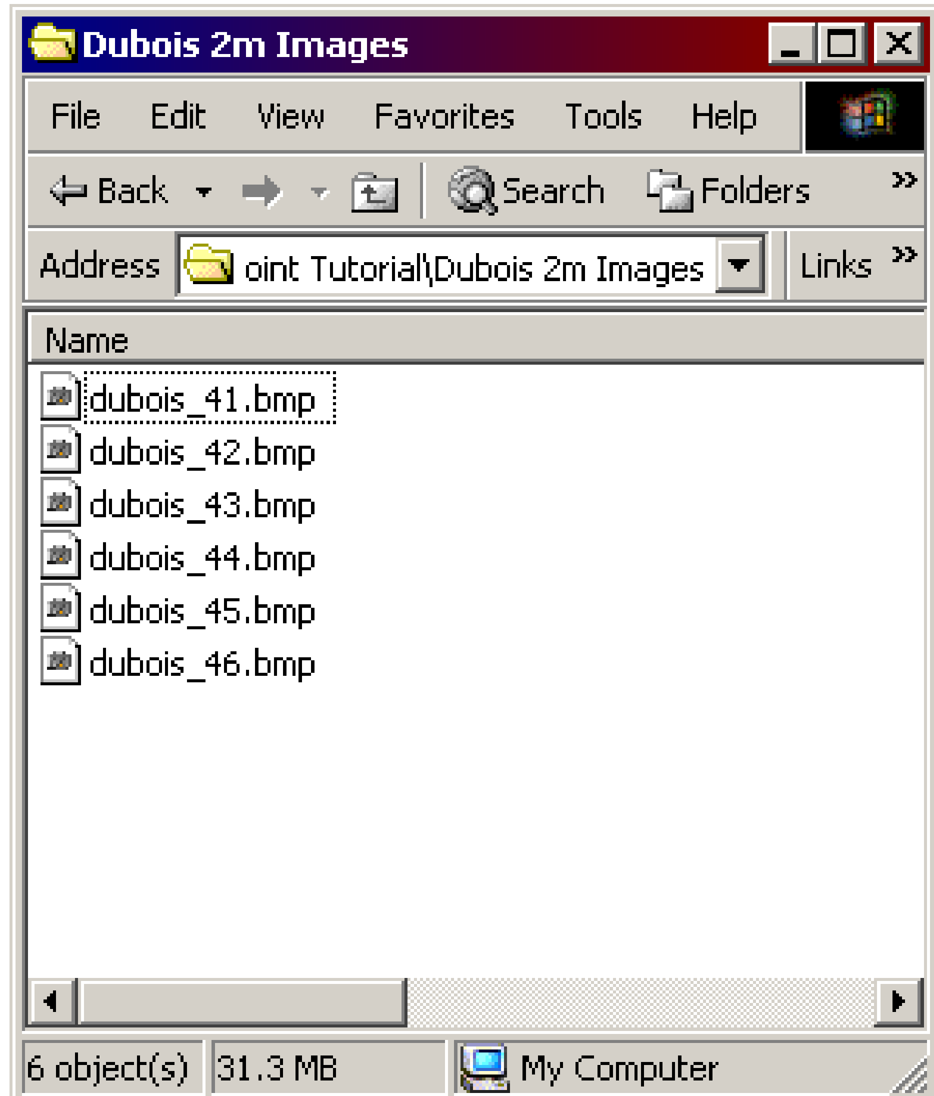
Use a light airplane to acquire large-scale nadir images



Use an airplane or helicopter to acquire small scale nadir images

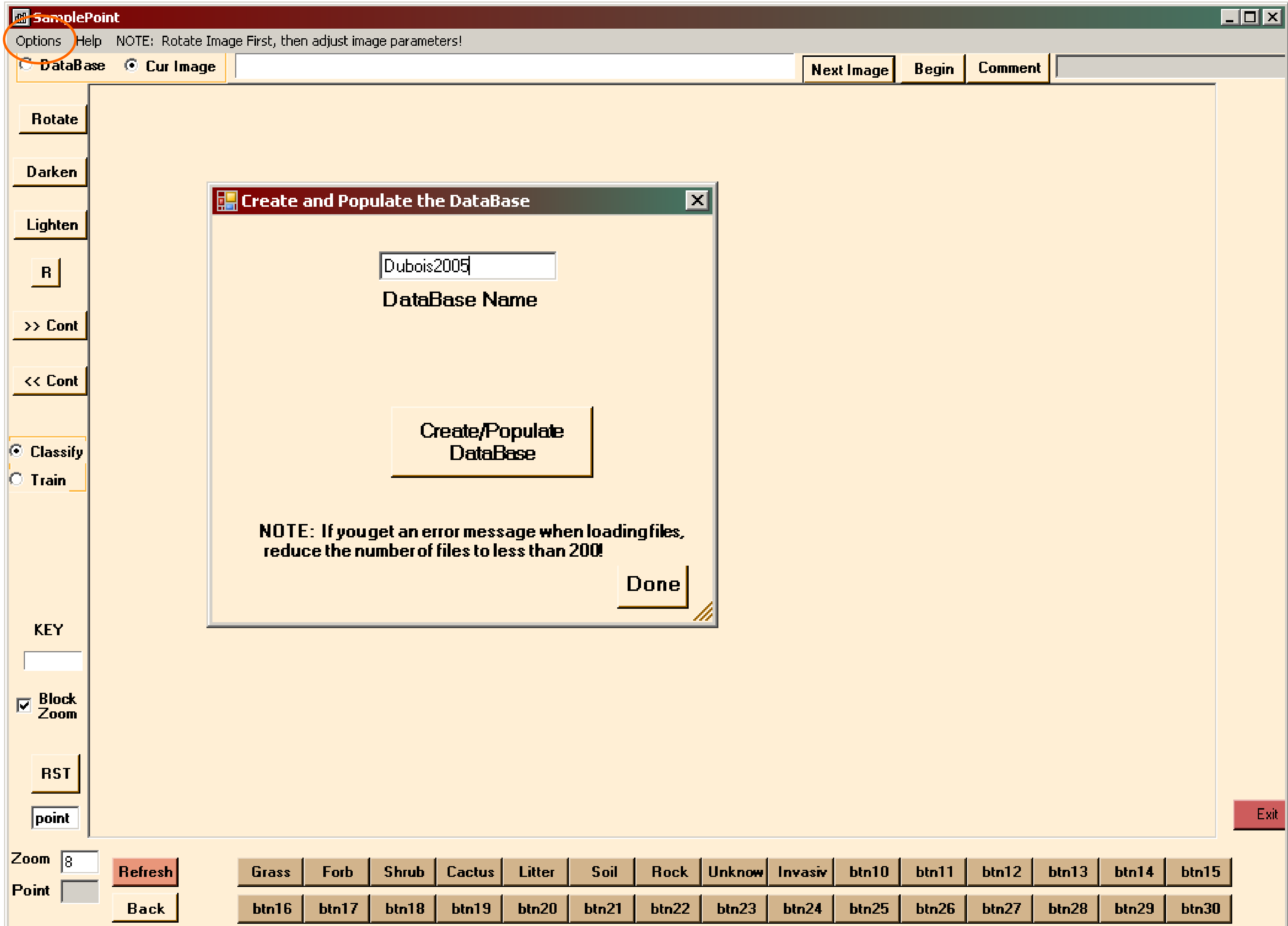


Save digital images to your hard drive in TIFF or BMP form. JPEG is a lossy-format but works as well as TIF at low compression ratios. Highly-compressed JPG files are not useful. Images MUST be nadir!

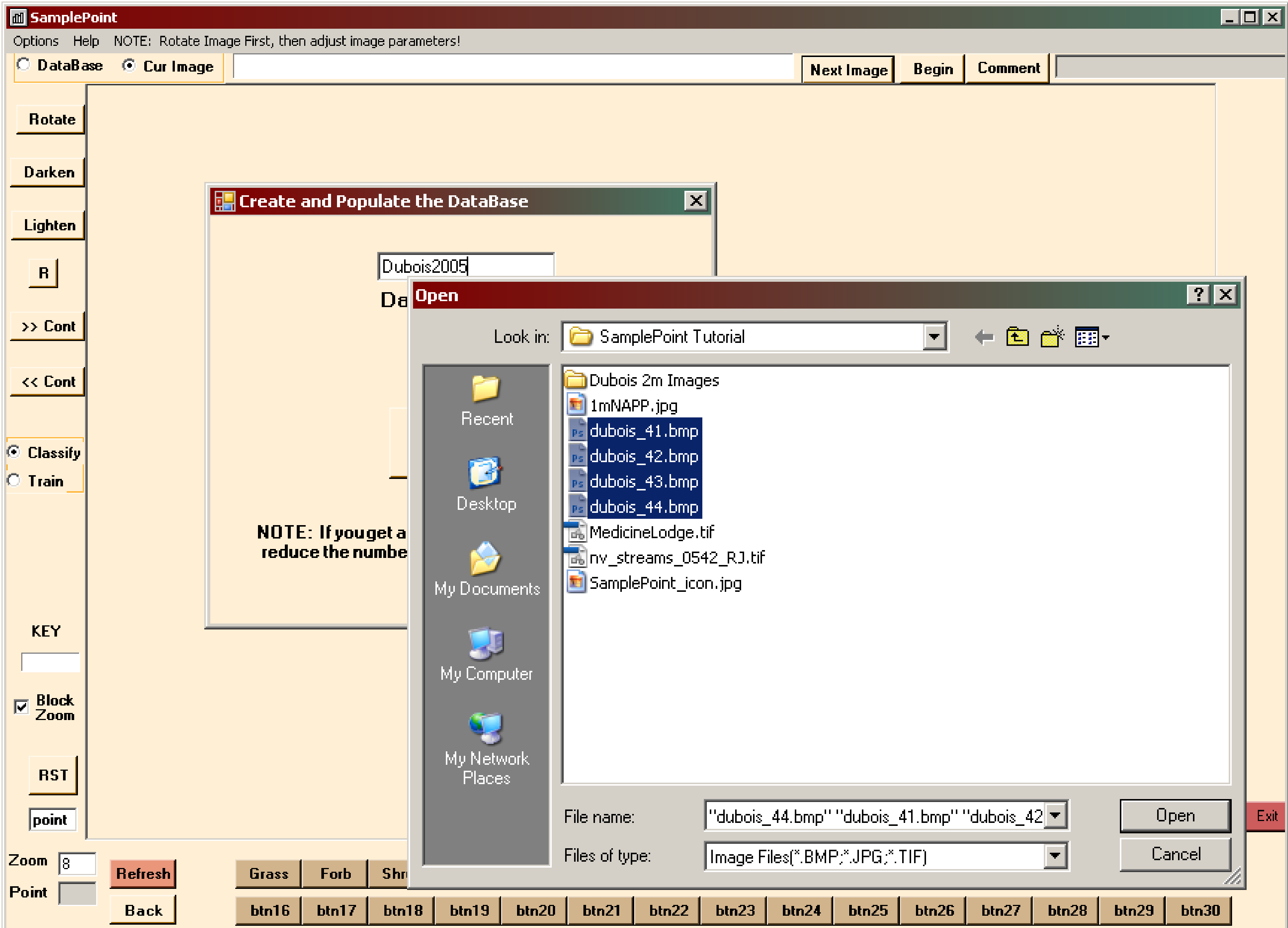


Open SamplePoint by clicking Start>Programs>SamplePoint>SamplePoint.exe.
If you encounter trouble, please reference “SamplePointHelp.PDF” in the program directory.

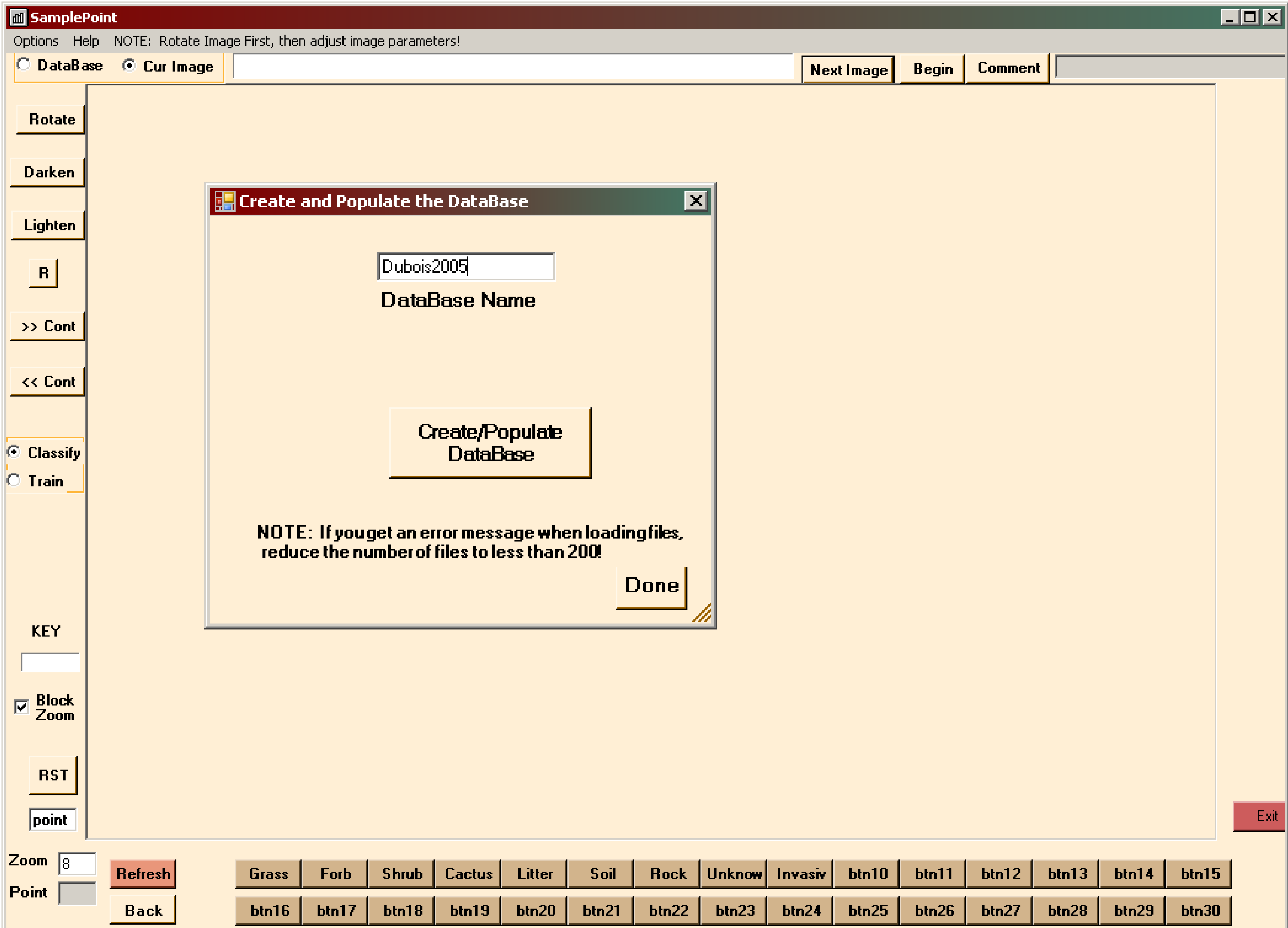
Click Options>Database Wizard.
Provide a name for the database, then click Create/Populate Database.



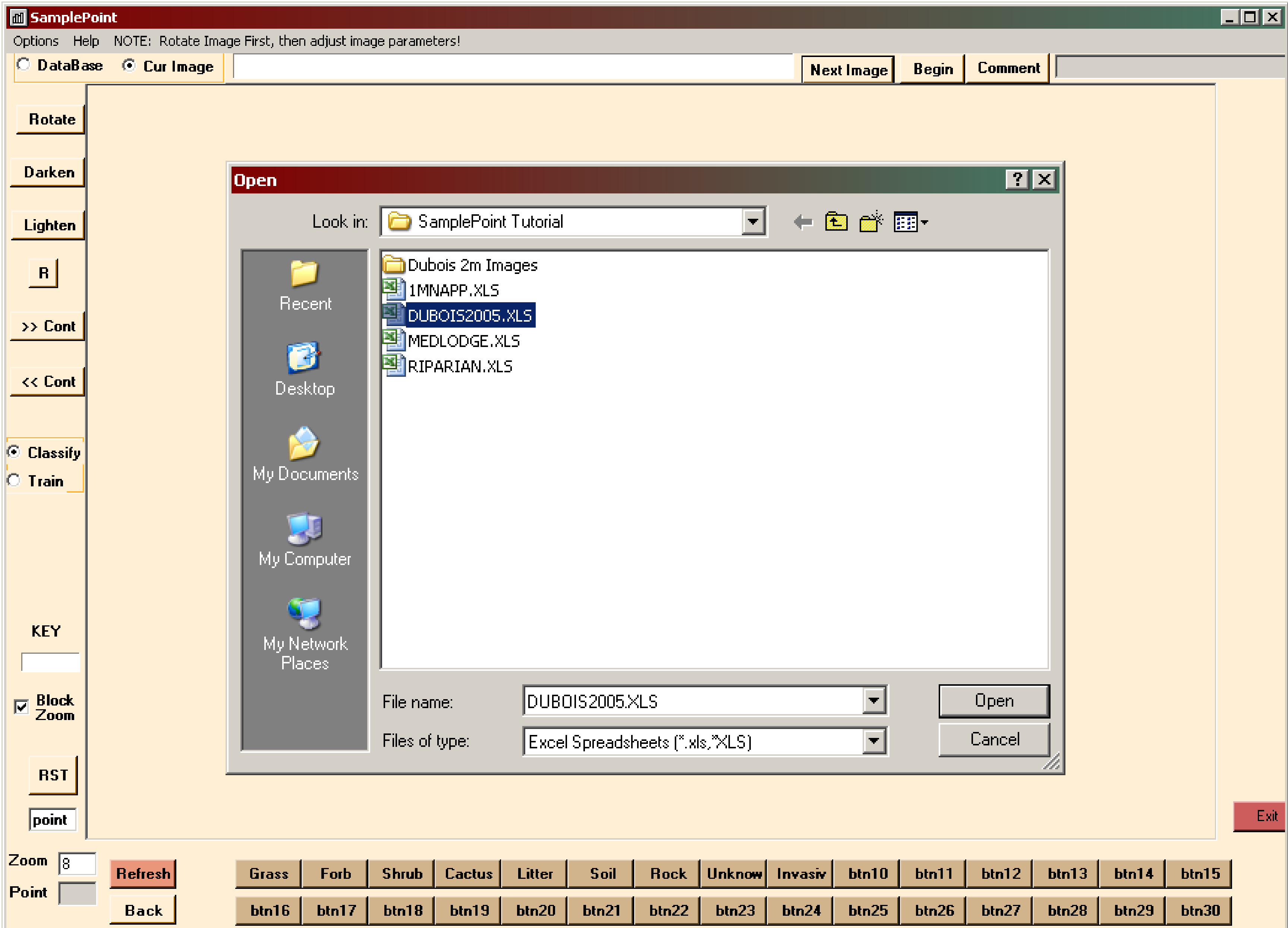
Navigate to the folder containing the images you wish to classify. Select the images you want to classify. Click Open.



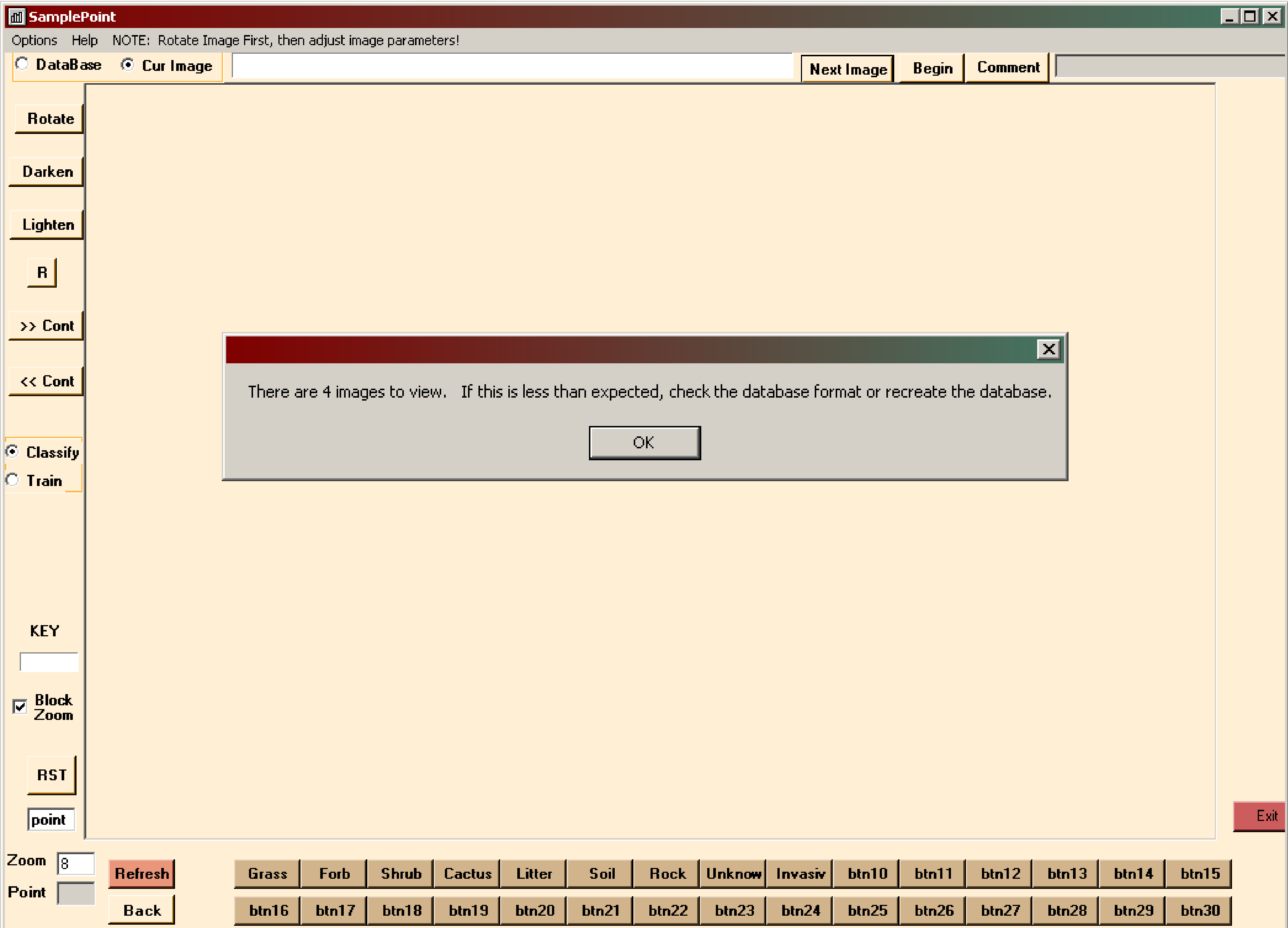
Images may only be selected from one folder. All images must be selected at once (you cannot populate the database twice using the wizard). After images have been selected, click Done. The database is saved to, and must remain in, the folder containing the analysis images.



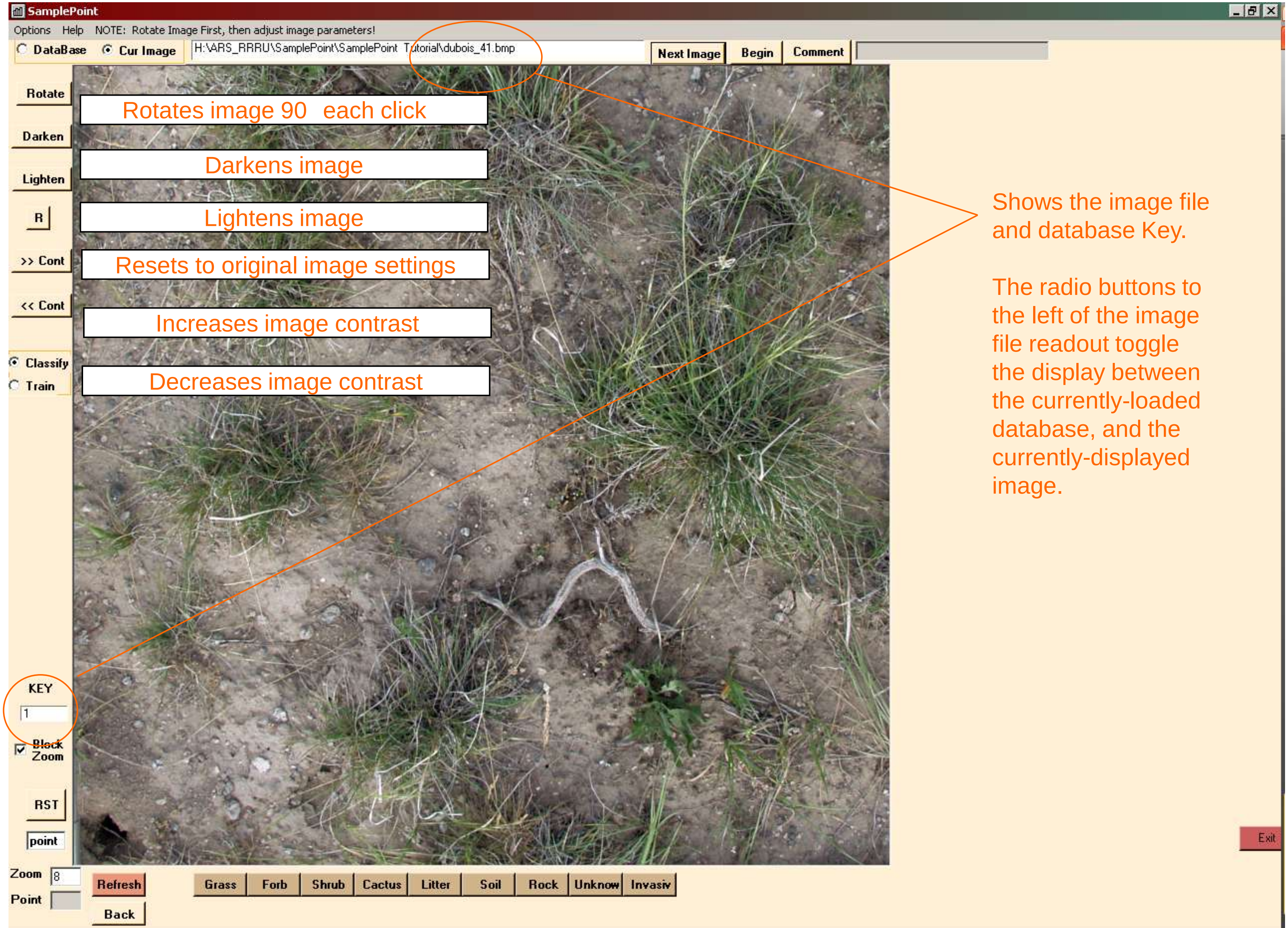
Click Options>Select Database and navigate to the image folder and select the *.xls file. Click Open.



A Pop-up box will confirm the number of images in the database. Click OK if this is correct.

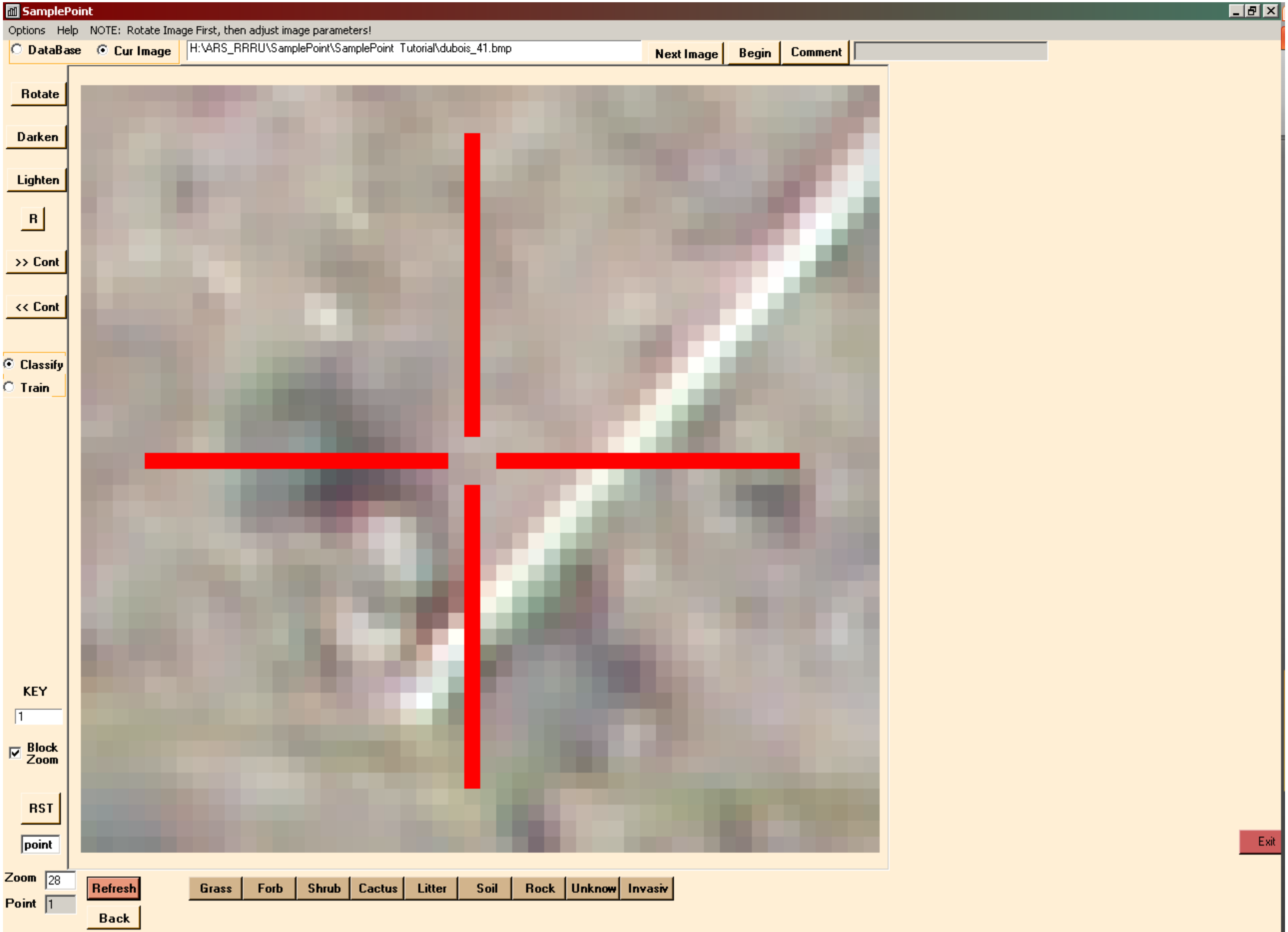


The first image listed in the database (Image Key 1) will appear in the screen at full-view. To begin classification using default settings of 100 systematic points and 8 default classes, click Begin.

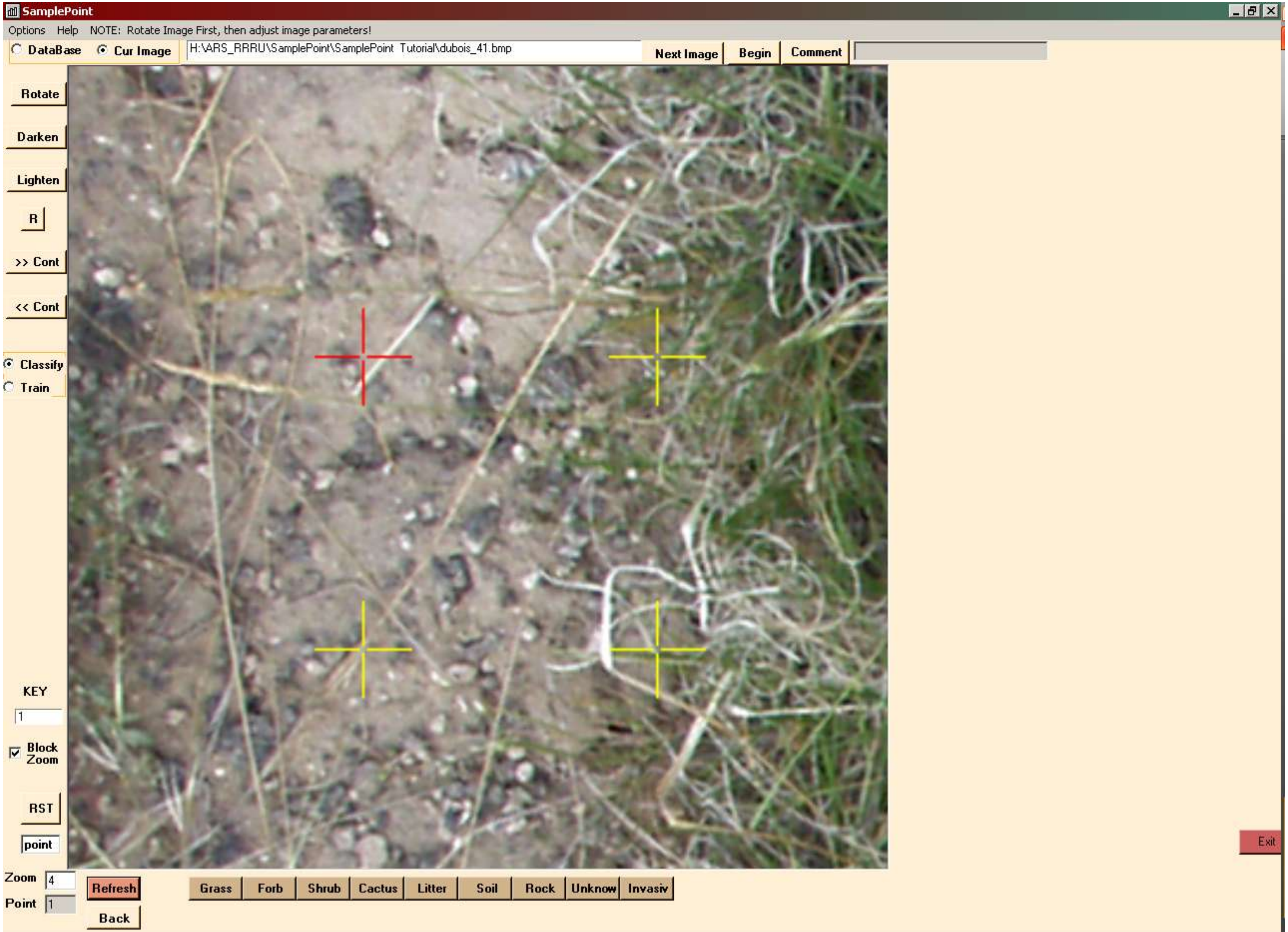


You are taken to point 1 in the upper left corner of the grid. Zoom in by pressing the ↑ key on your keyboard, zoom out by pressing ↓ key, zoom by typing a value in the Zoom box and pressing Refresh, or zoom by using a scroll wheel mouse.

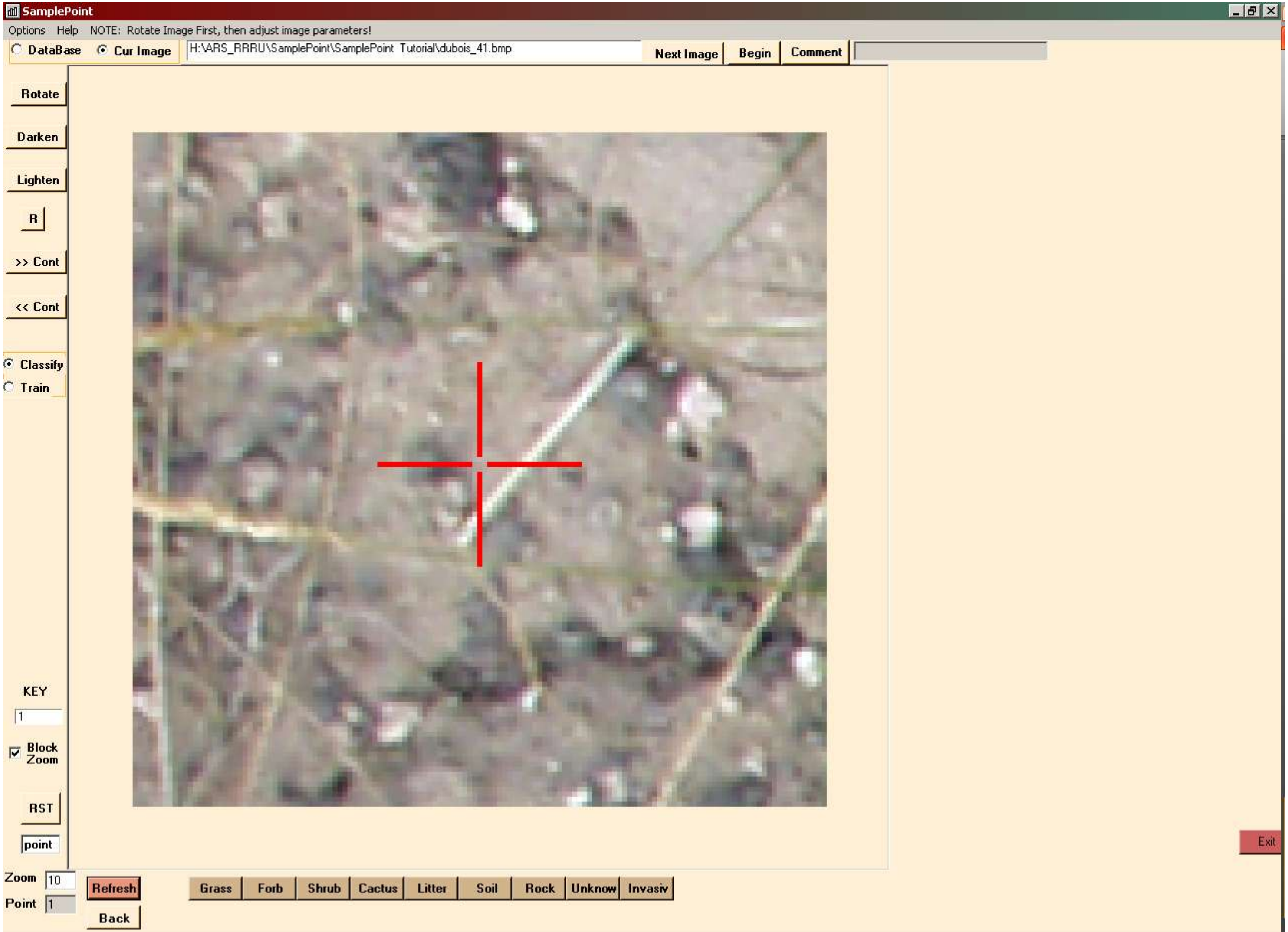
Zoomed in to 28X.



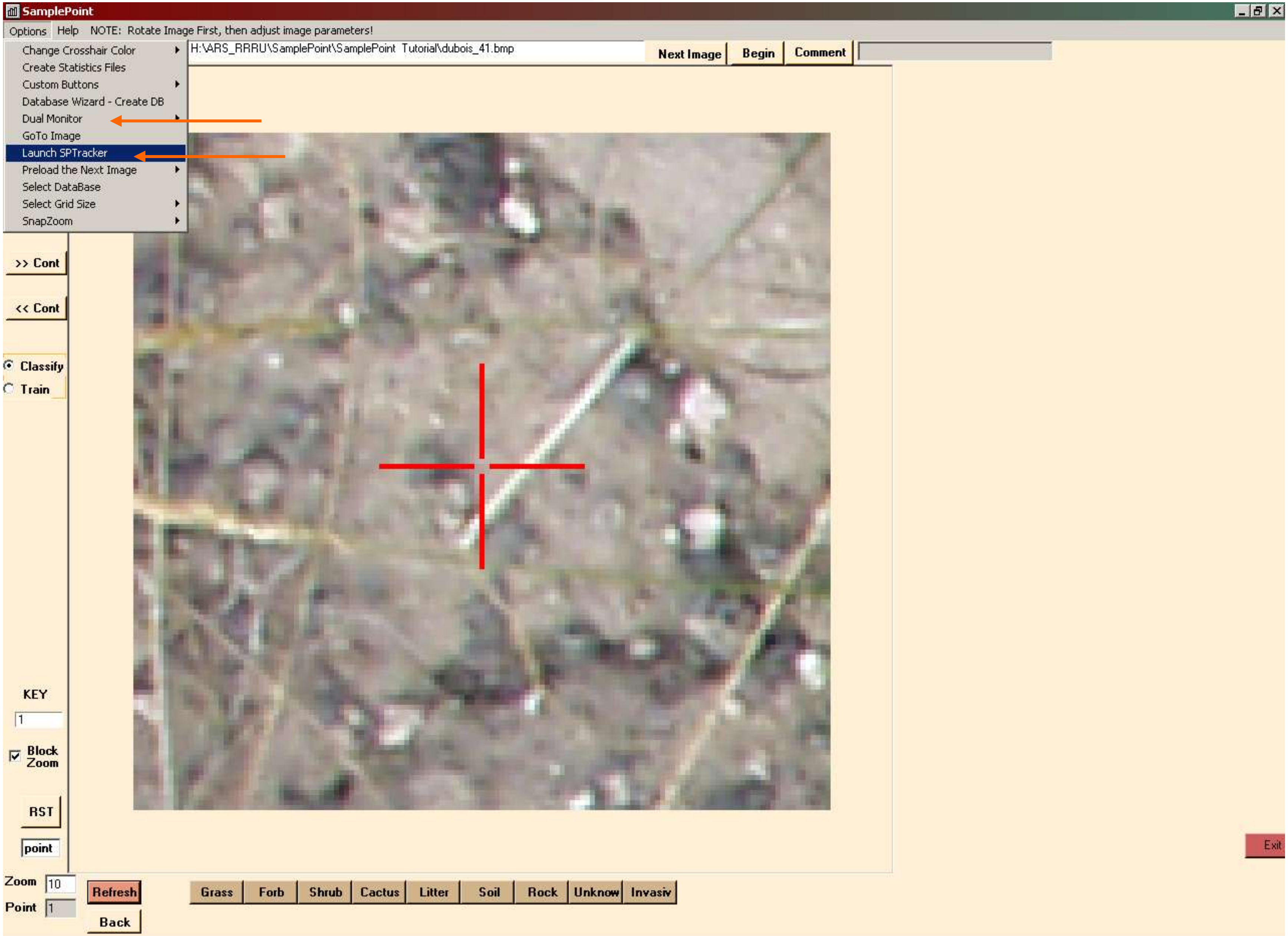
Zoomed out to 4X. Note that the point is no longer centered as you zoom further out and are on the edge of the image. Current point is red, all others are yellow.



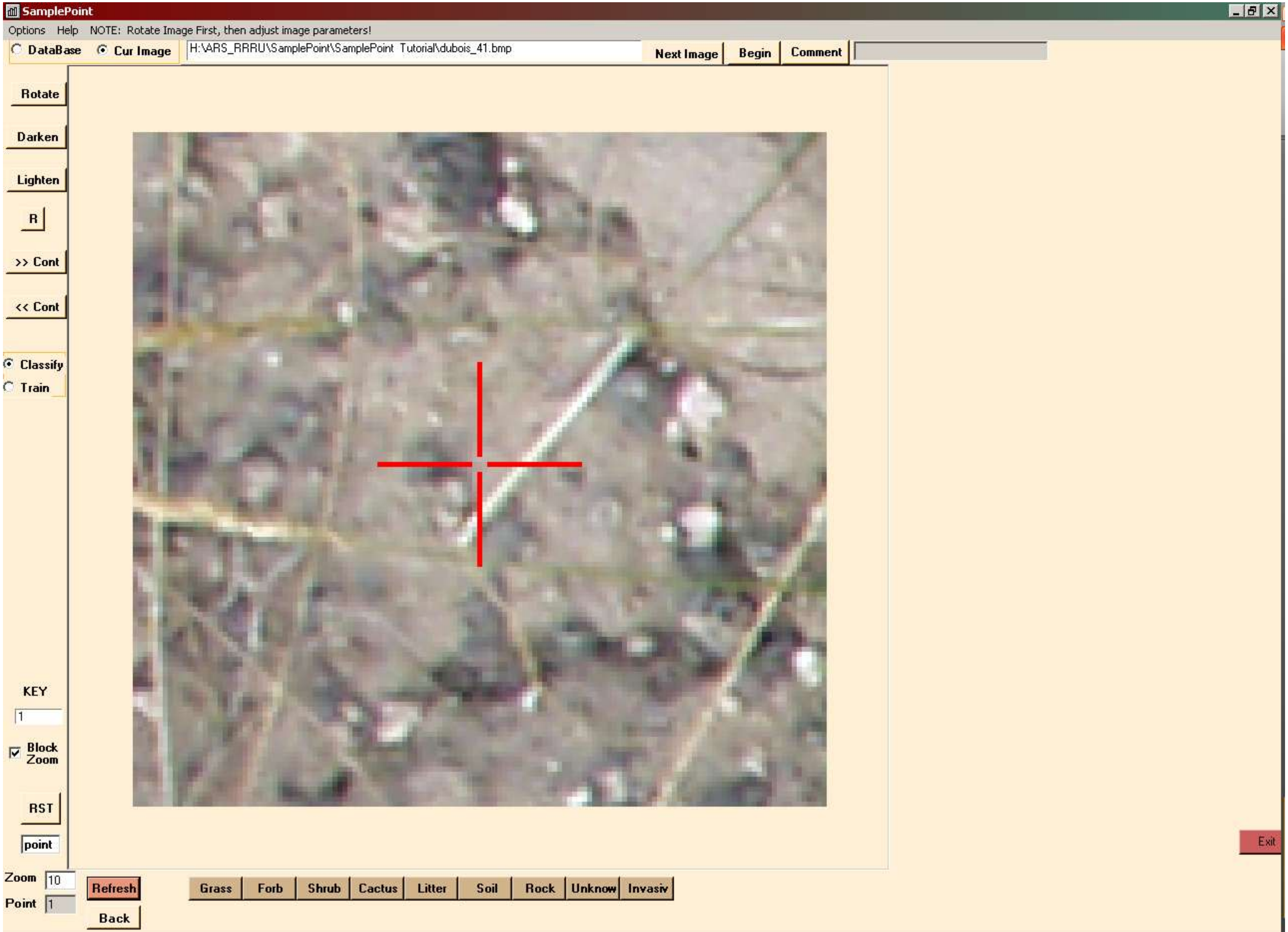
You should be able to distinguish individual pixels. The goal is to classify the single pixel in the center of the crosshairs. Zoom out if needed to gain perspective.



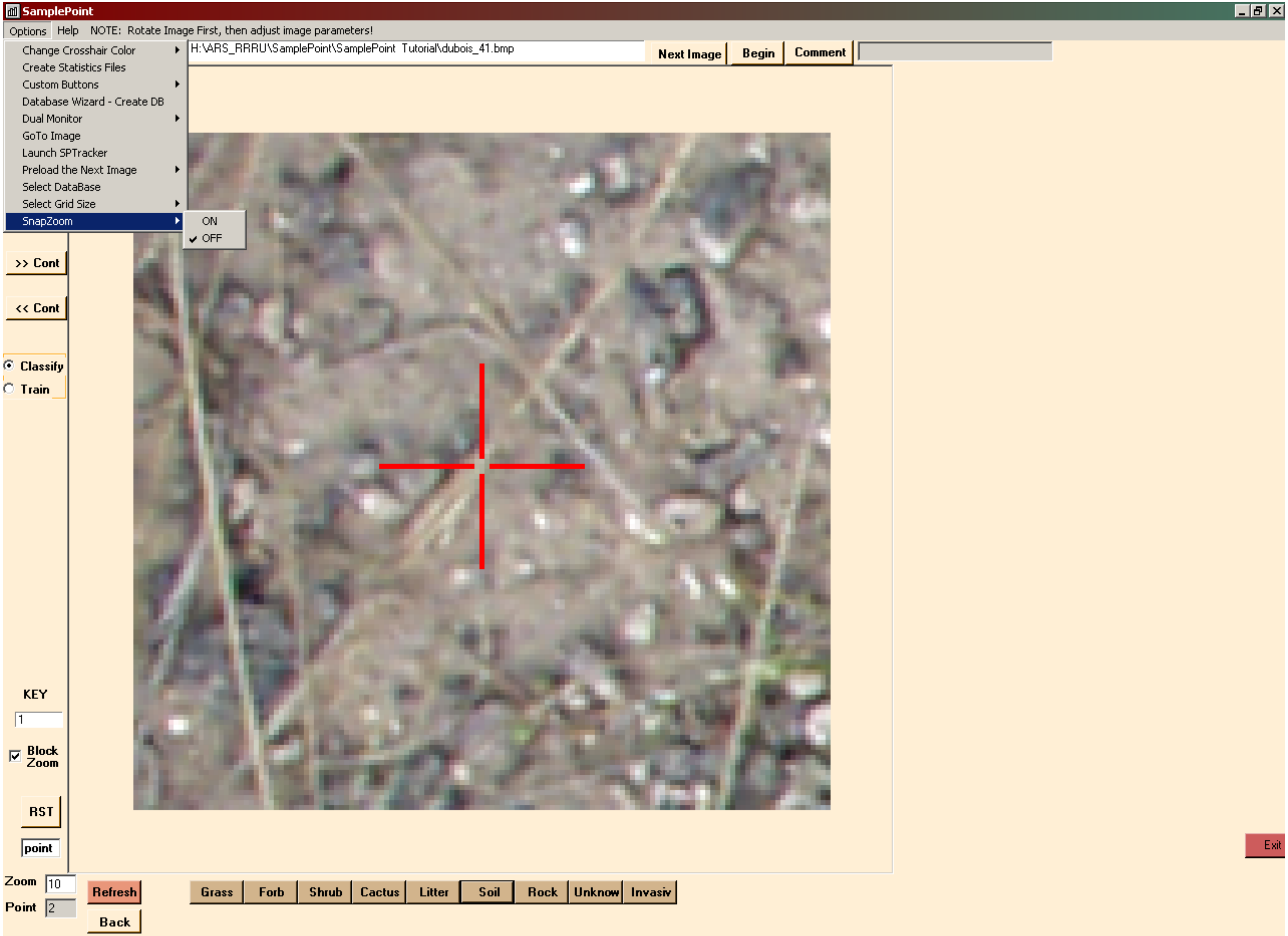
If you have a 2- or 3-monitor array, you can view multiple zoom levels on different screens by launching SP Tracker, and/or selecting Dual Monitor mode. This saves the time required to zoom in and out.



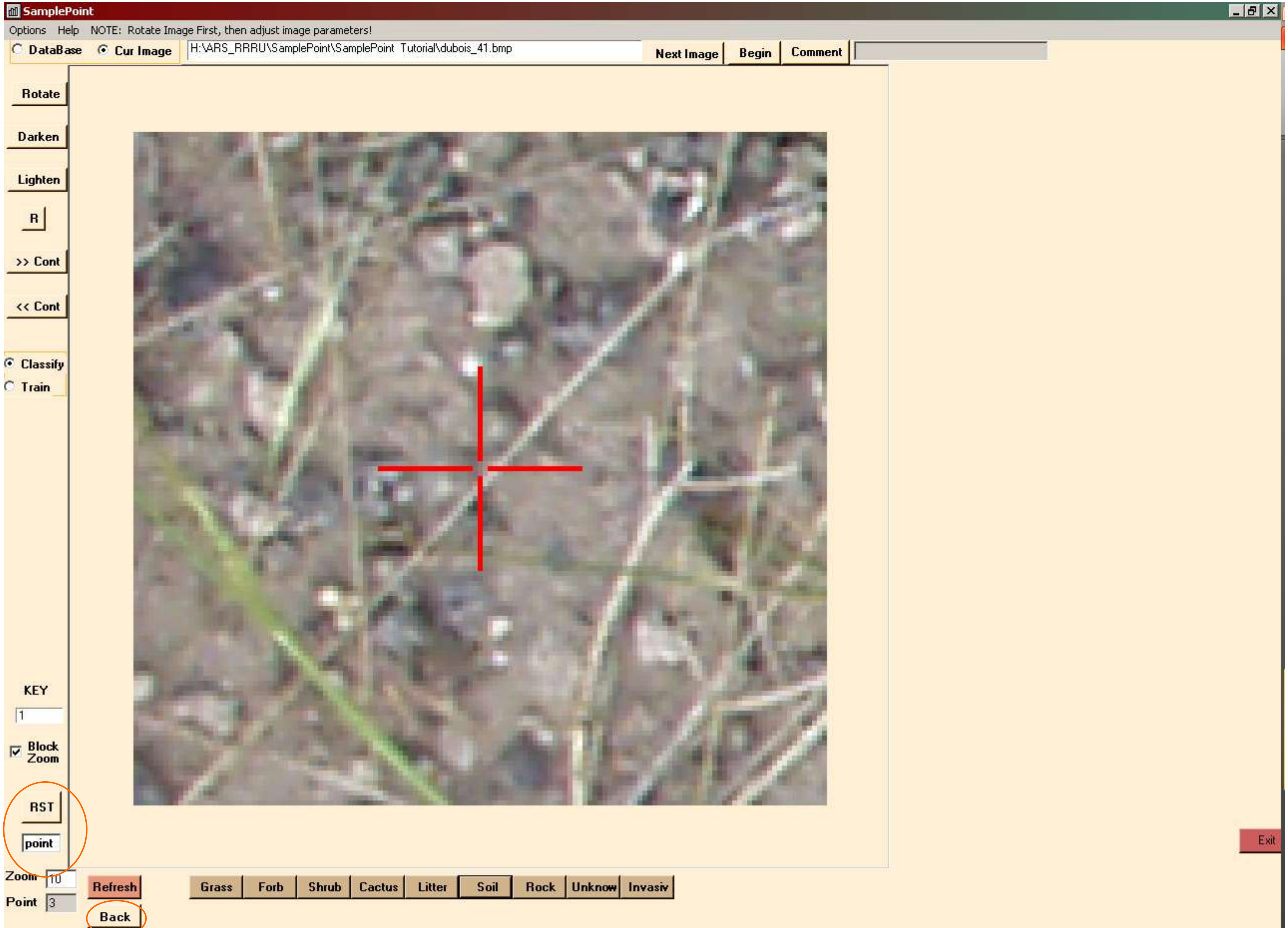
Classify by clicking on the button below the image which describes the point. In this case, Soil. The button will flash red, then you will be taken to point 2. The classification is automatically saved to the database.



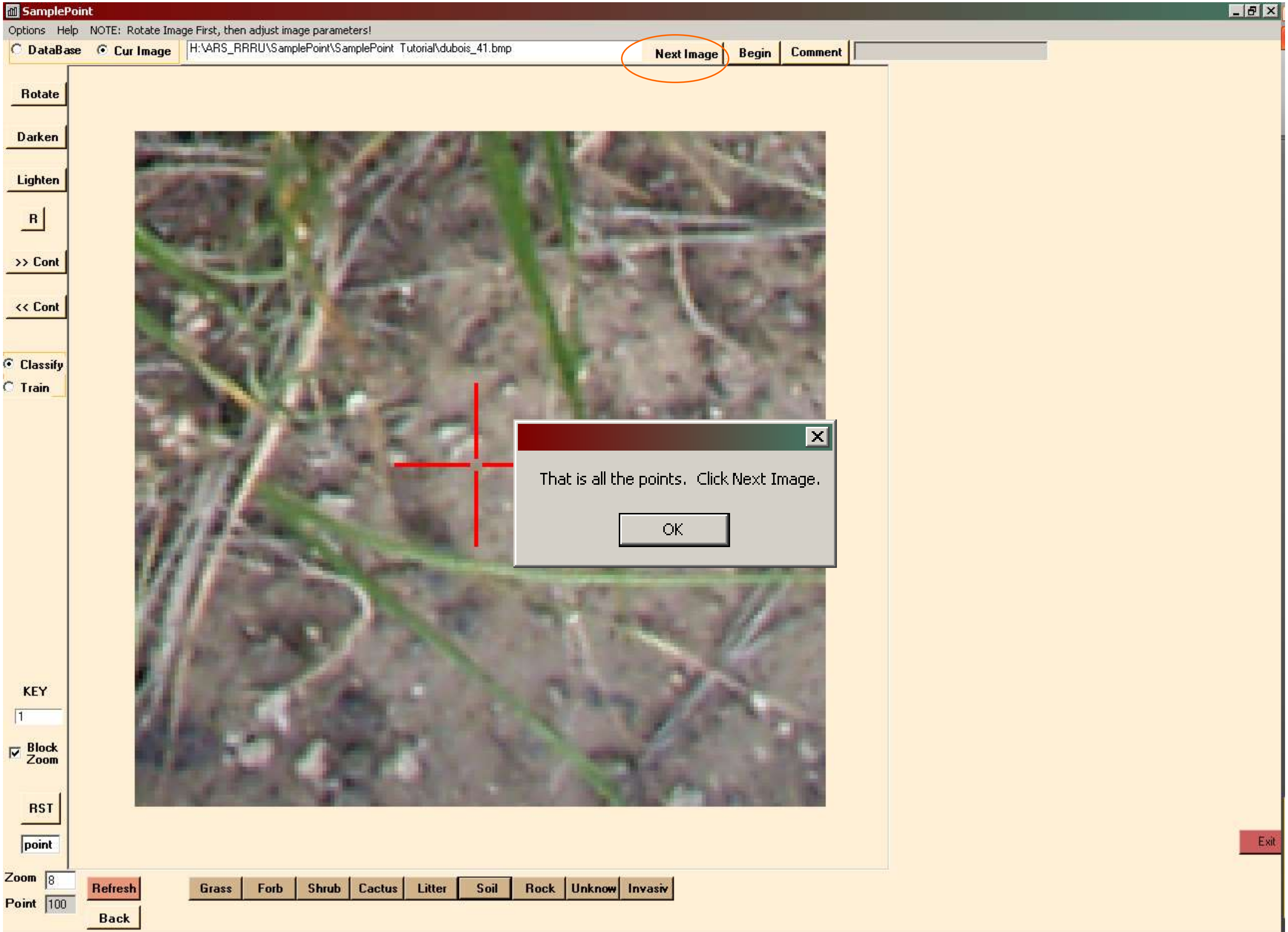
Note that the point number is displayed in the lower left corner. The zoom setting stays the same from point to point unless you change it. If you want the zoom to always return to a certain level, click Options>Snap Zoom>On and specify zoom level. Classify point 2: It is close to a piece of litter, but the center pixel is in fact soil. Zoom in if you are unsure.



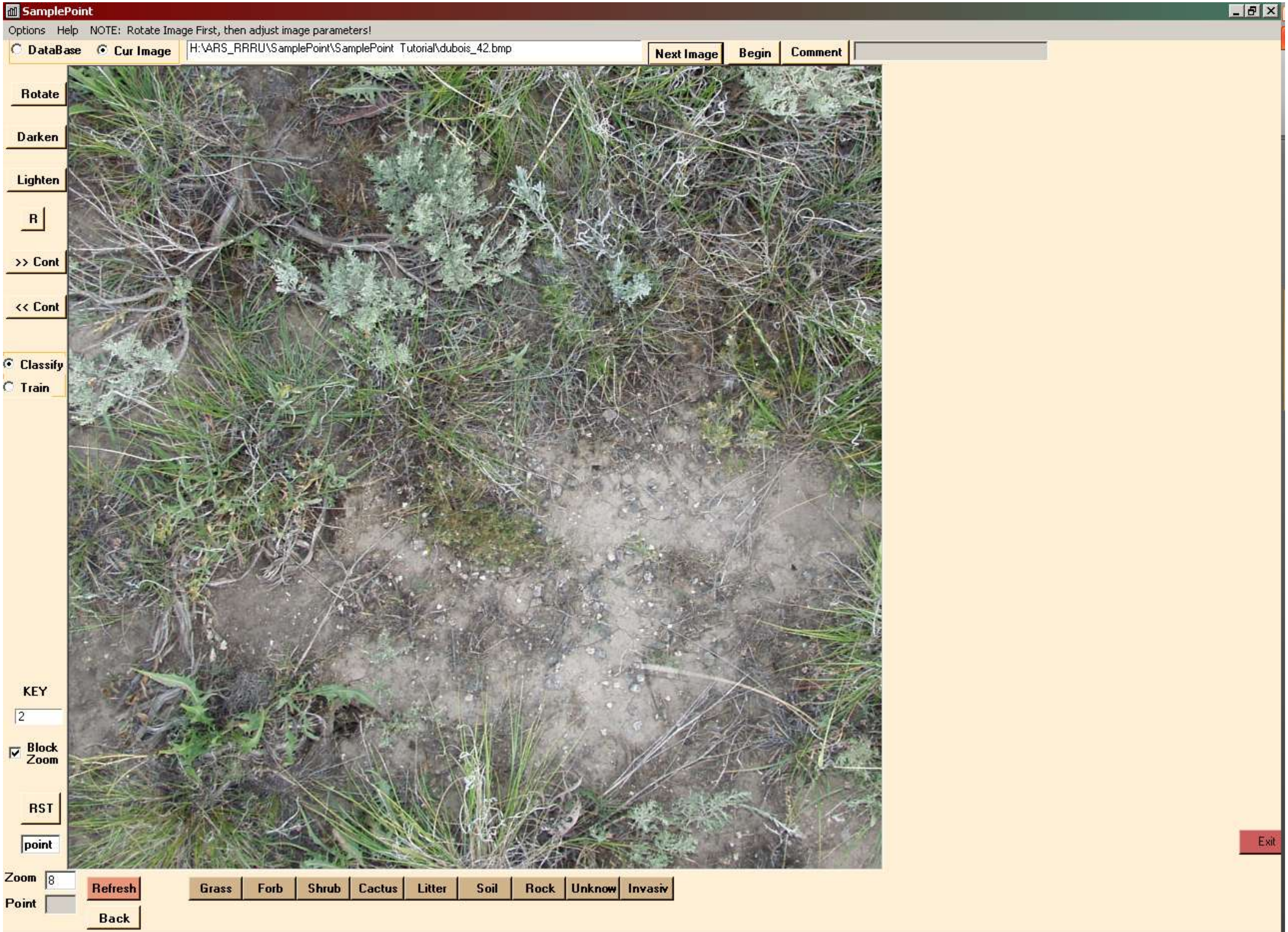
Now you're on point 3. If you feel you made a mistake on point 2, you can click the Back button to go back and reclassify point 2. If you want to start over at point 1 or go back 10 points at once, type in the target point number in the lower left corner "point" box, then click the RST (reset) button. Point location is constant for each image unless you alter the grid size.



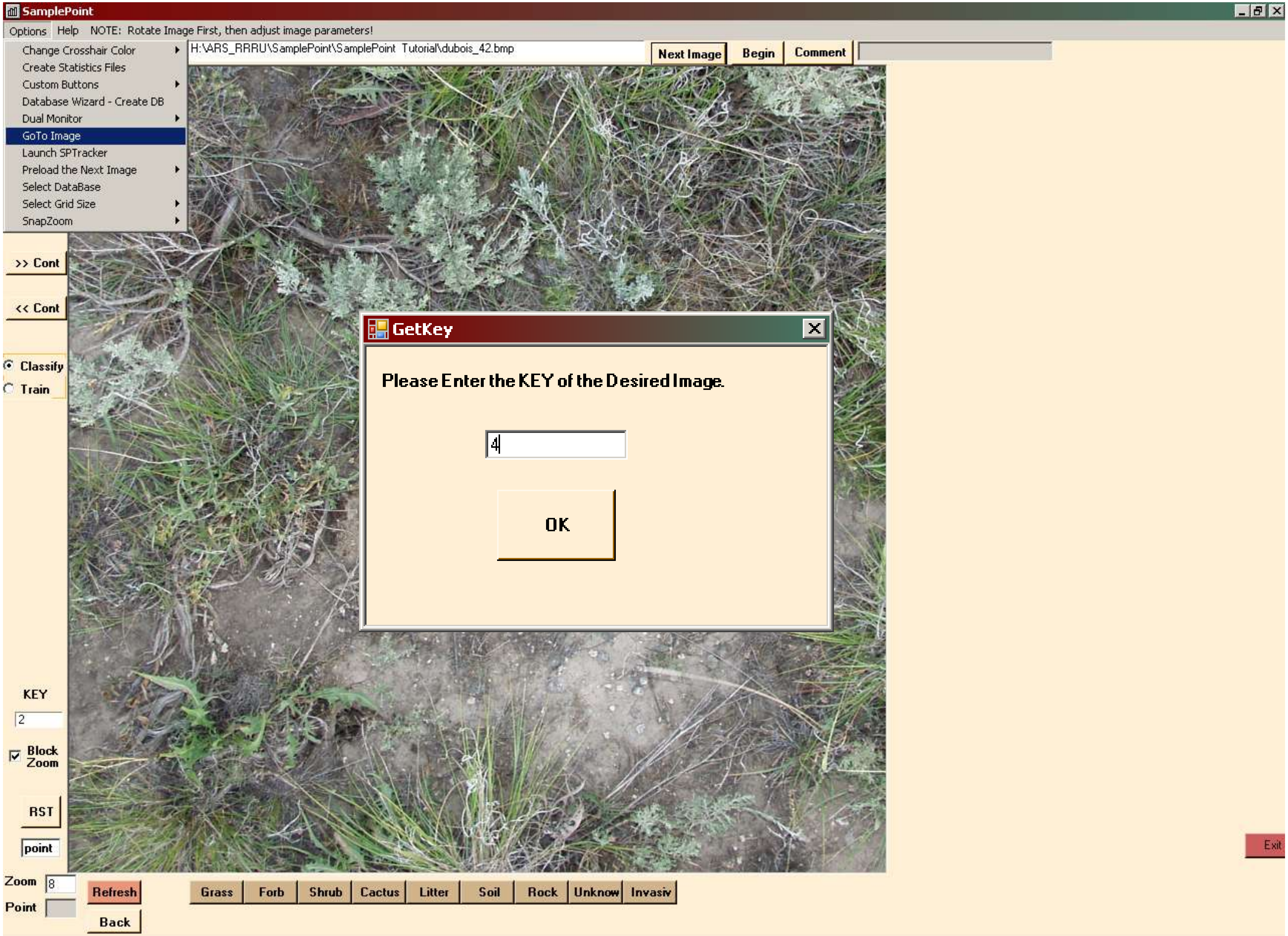
A notification pop-up appears when the final point for each image is classified.
Click OK, then click the Next Image button to continue to the Image Key 2.



The next image will appear at full size. Note the Key now reads 2. Click Begin to start classification.

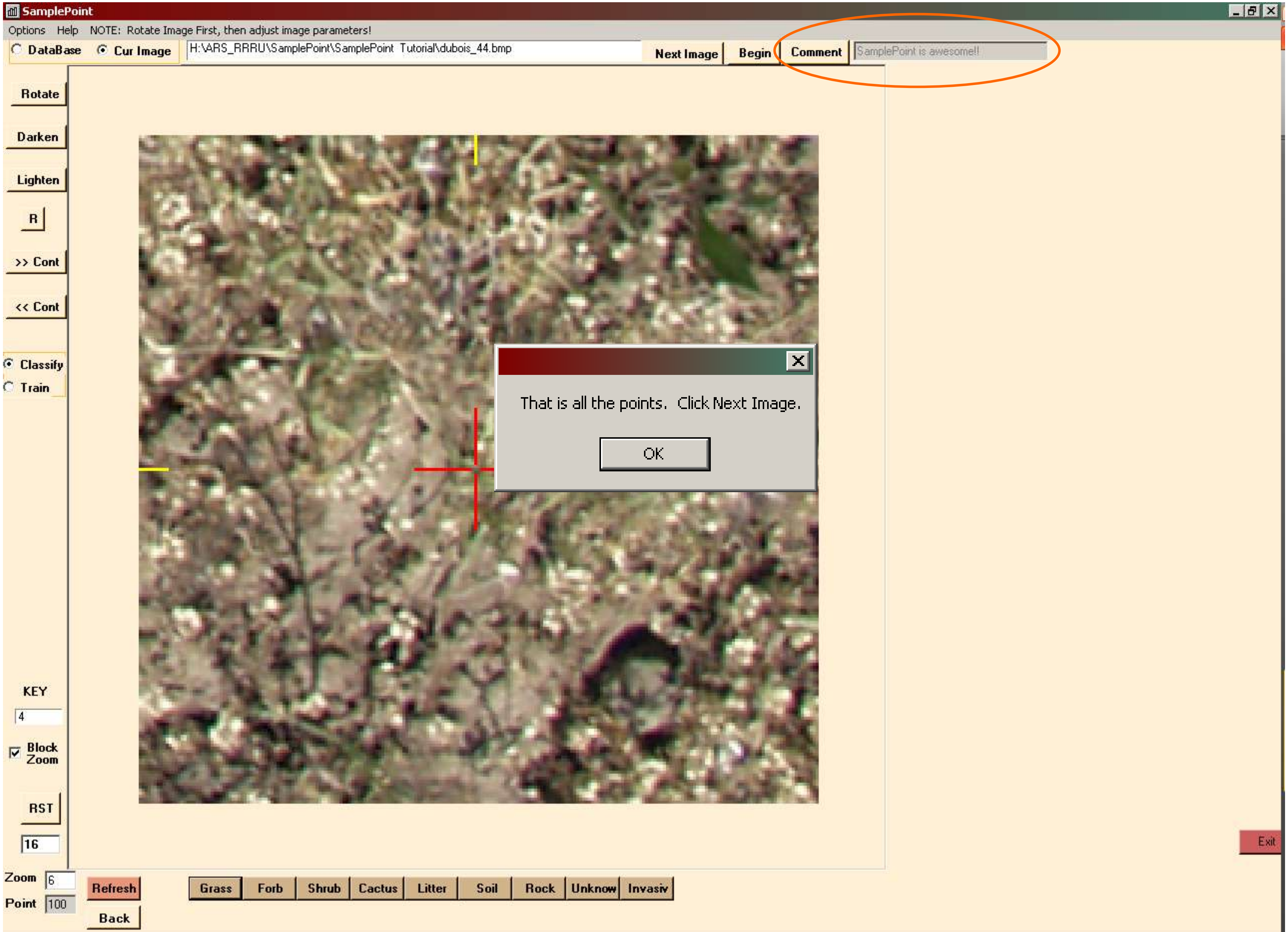


At no point do you need to save anything. All classification is saved automatically and instantly by SamplePoint. You can Exit at any time, even in the middle of an image, without losing any data. To restart at a different time on a particular image, select the database, then click Options>Go To Image, and type in the KEY of the image you want to start with. Click OK and the image will load.

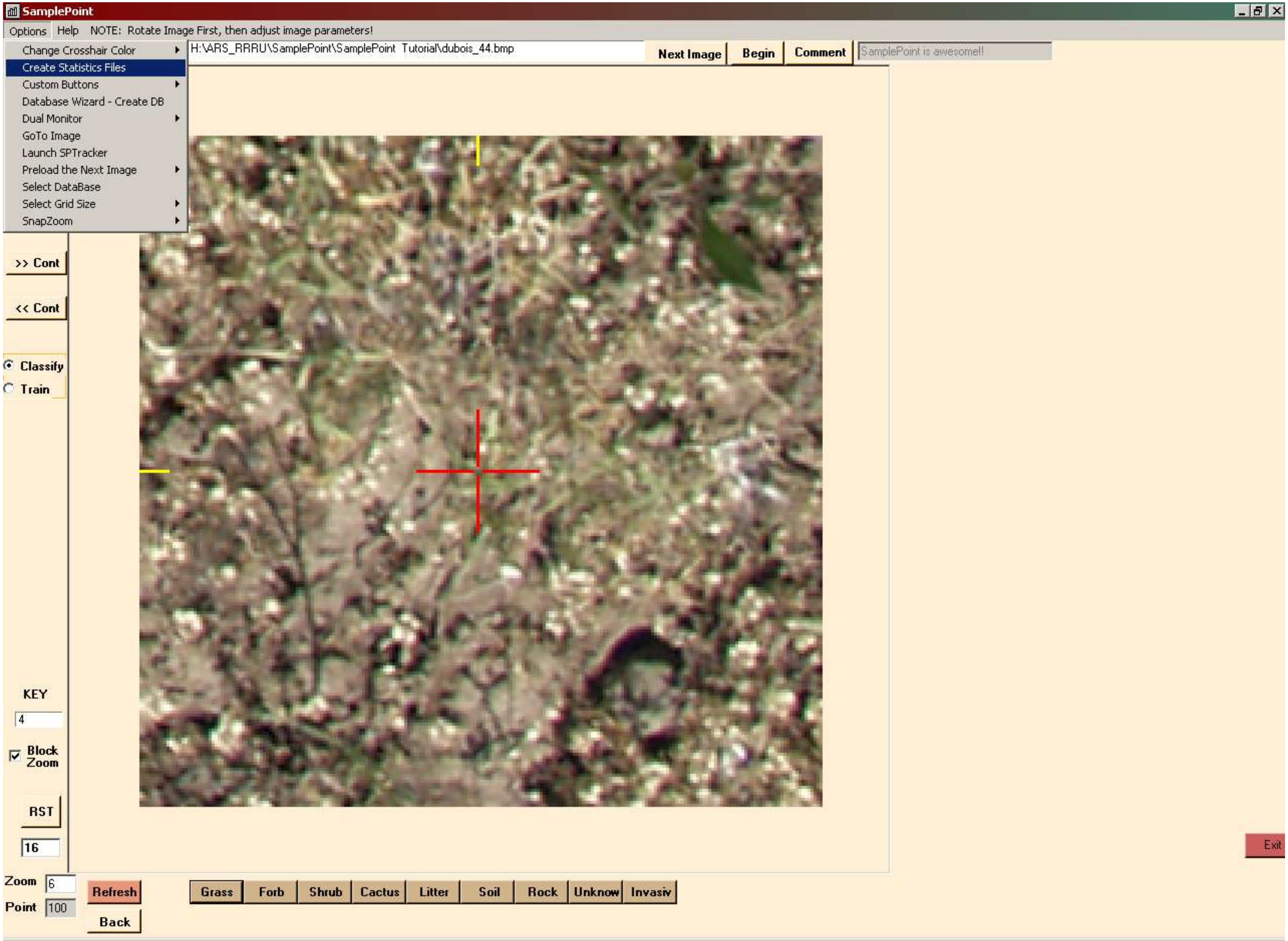


The Unknown button is useful for places like shadow, where the actual groundcover cannot be discerned.
Toggling between pixelated and interpolated view is accomplished with the Block Zoom check box. Default is for block zoom.

Comments typed into the Comment field are also saved to the Excel database. When you've completed the last image, a notification pops up to tell you so. Click OK.



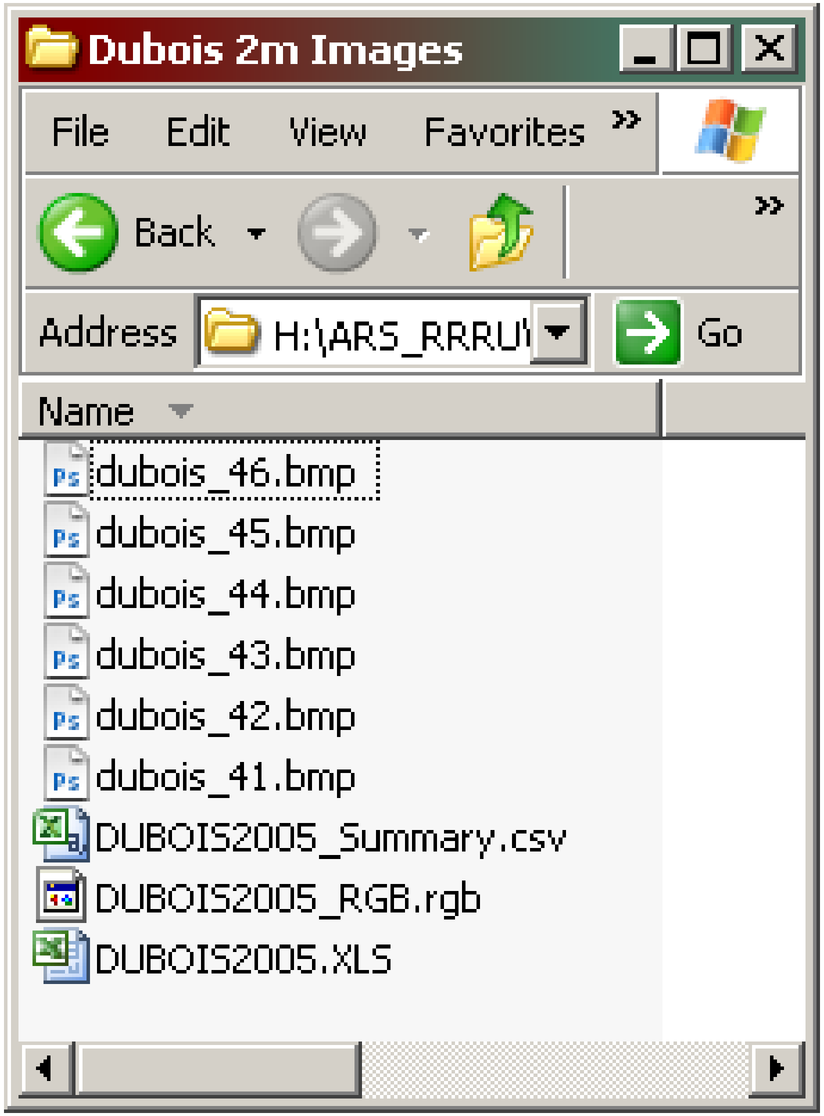
Click Options>Create Statistics Files. This generates two comma-delimited text files with a summary of the results. You can create these files at any time during the classification process, instead of waiting until all images are classified. These files are saved to the image folder.



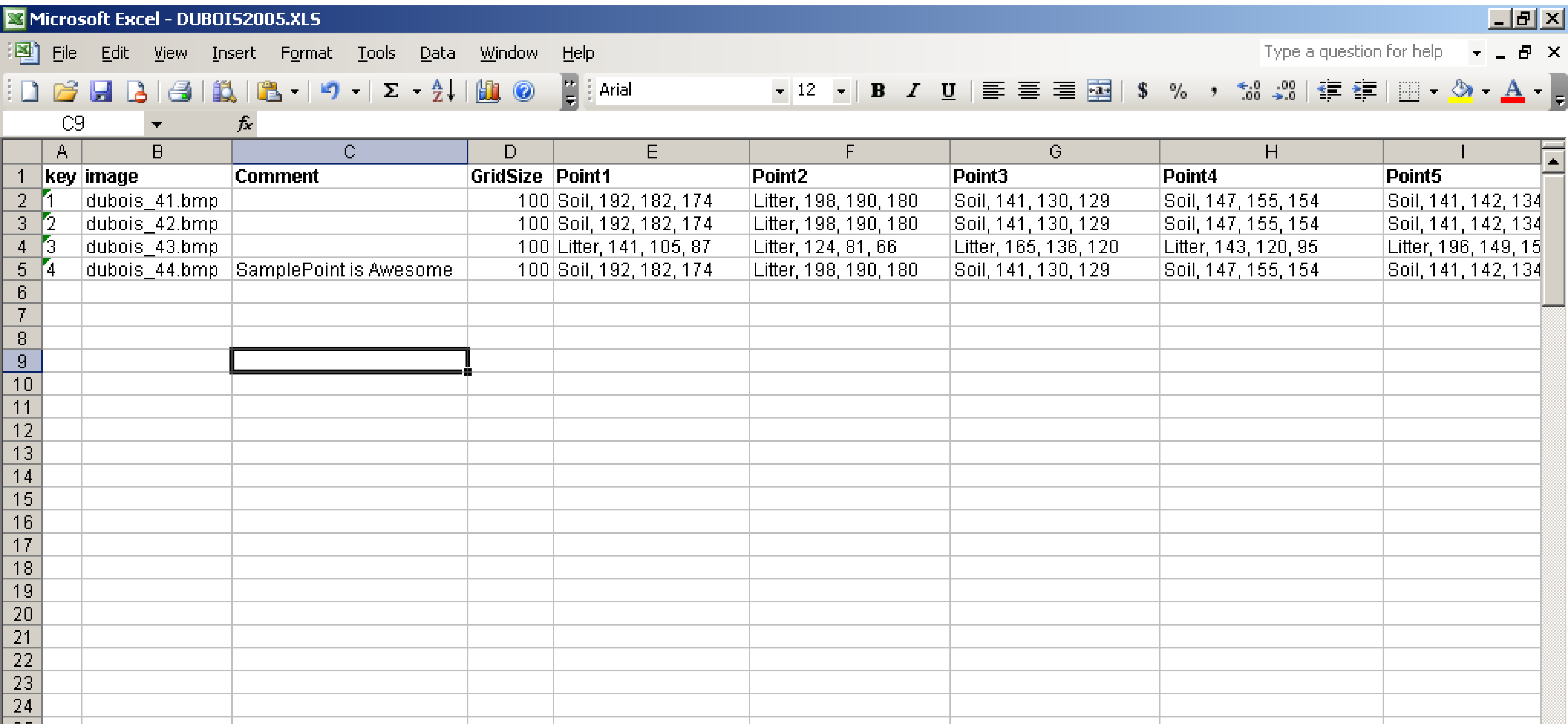
After the Statistics Files are created, look in the image folder. You'll see the database Excel file (DUBOIS2005.XLS), the data summary file (DUBOIS2005_Summary.csv) and a text file listing the red green blue values of every classified pixel (DUBSOI2005_RGB.rgb).

The .csv file is the summary that can be opened in Excel. It simply calculates % cover for each class for all images and is the starting point for statistical comparisons.

The .rgb file is simply a comma-delimited list of each classification with respective red, green and blue pixel values. This is sometimes useful to compare pixel color distribution among different classes. It can be opened in either Notepad or Excel.

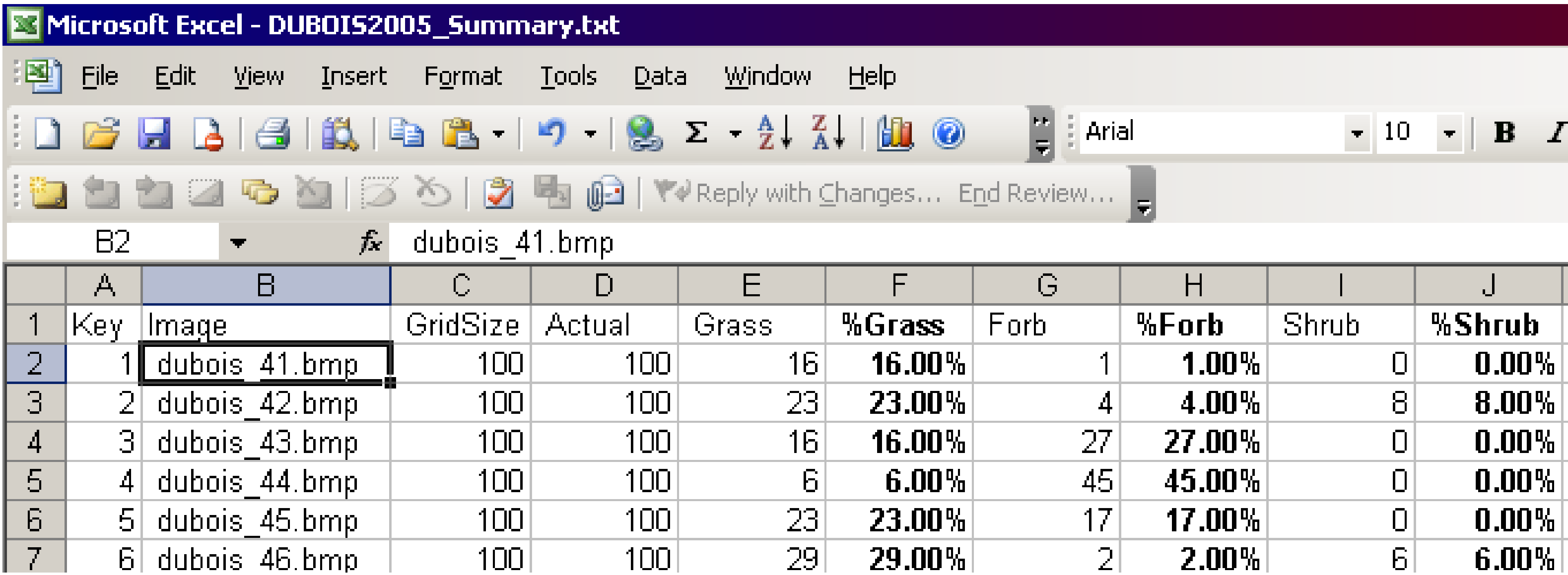


If you Exit SamplePoint, you can examine the database using Excel. It shows the Key, Image file, Gridsize and classification of each point. The numbers beside the classification are the RGB values for the classified pixel. Custom button information is also stored in the database in columns HV-HX. You cannot open the database in SamplePoint if it is open in Excel on your PC, and vice-versa. You can add image files to the database manually using Excel by typing in additional keys and filenames or pasting them from a list. Filenames are case sensitive.



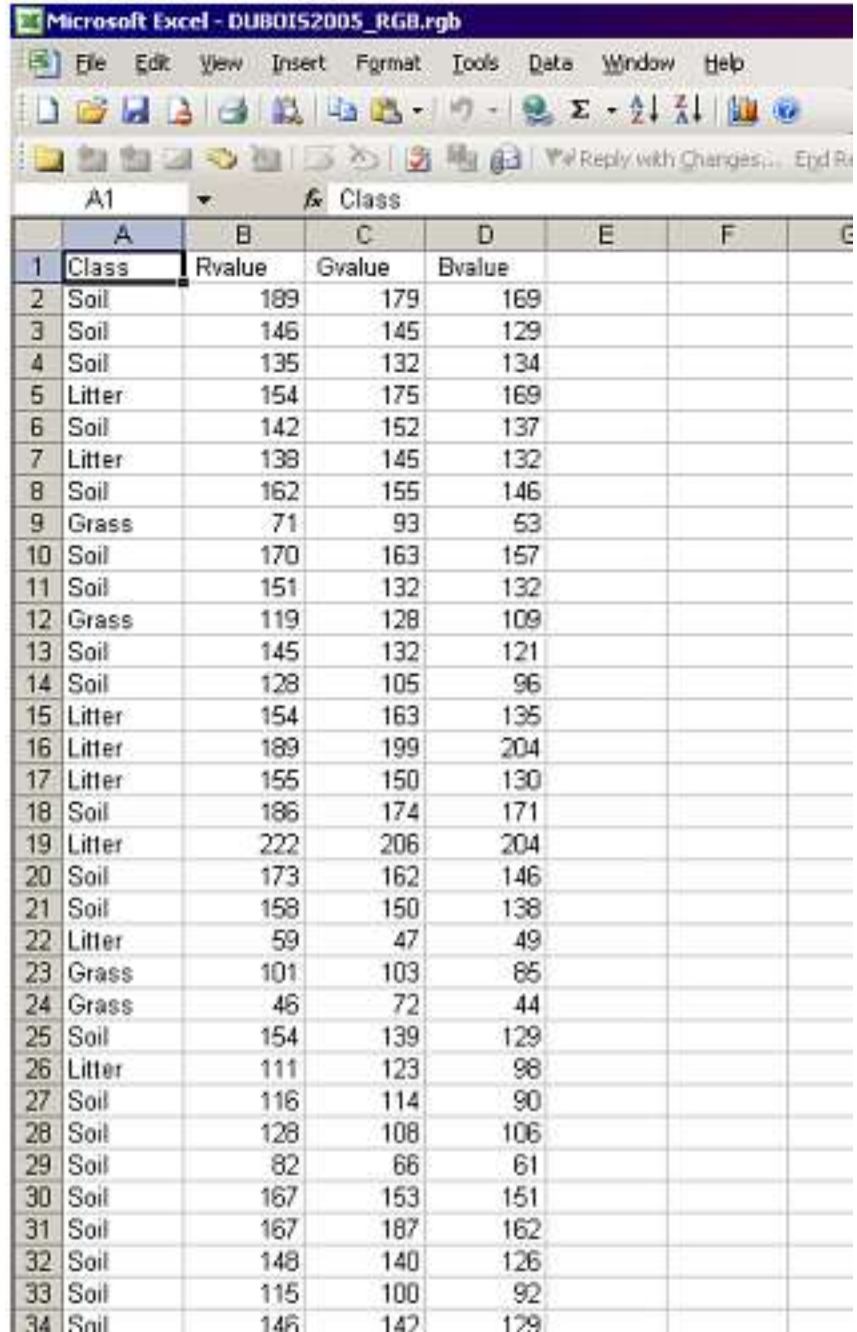
key	image	Comment	GridSize	Point1	Point2	Point3	Point4	Point5
1	dubois_41.bmp		100	Soil, 192, 182, 174	Litter, 198, 190, 180	Soil, 141, 130, 129	Soil, 147, 155, 154	Soil, 141, 142, 134
2	dubois_42.bmp		100	Soil, 192, 182, 174	Litter, 198, 190, 180	Soil, 141, 130, 129	Soil, 147, 155, 154	Soil, 141, 142, 134
3	dubois_43.bmp		100	Litter, 141, 105, 87	Litter, 124, 81, 66	Litter, 165, 136, 120	Litter, 143, 120, 95	Litter, 196, 149, 15
4	dubois_44.bmp	SamplePoint is Awesome	100	Soil, 192, 182, 174	Litter, 198, 190, 180	Soil, 141, 130, 129	Soil, 147, 155, 154	Soil, 141, 142, 134

This is the Summary file displayed in Excel. It shows the % cover for each image by cover type. For each cover class, the first column shows the actual number of hits, and the second column shows the percent of hits in the image.



	A	B	C	D	E	F	G	H	I	J
1	Key	Image	GridSize	Actual	Grass	**%Grass**	Forb	**%Forb**	Shrub	**%Shrub**
2	1	dubois_41.bmp	100	100	16	**16.00%**	1	**1.00%**	0	**0.00%**
3	2	dubois_42.bmp	100	100	23	**23.00%**	4	**4.00%**	8	**8.00%**
4	3	dubois_43.bmp	100	100	16	**16.00%**	27	**27.00%**	0	**0.00%**
5	4	dubois_44.bmp	100	100	6	**6.00%**	45	**45.00%**	0	**0.00%**
6	5	dubois_45.bmp	100	100	23	**23.00%**	17	**17.00%**	0	**0.00%**
7	6	dubois_46.bmp	100	100	29	**29.00%**	2	**2.00%**	6	**6.00%**

This is the RGB file in Excel. This file allows easy mathematical summary and analysis of the class color characteristics.

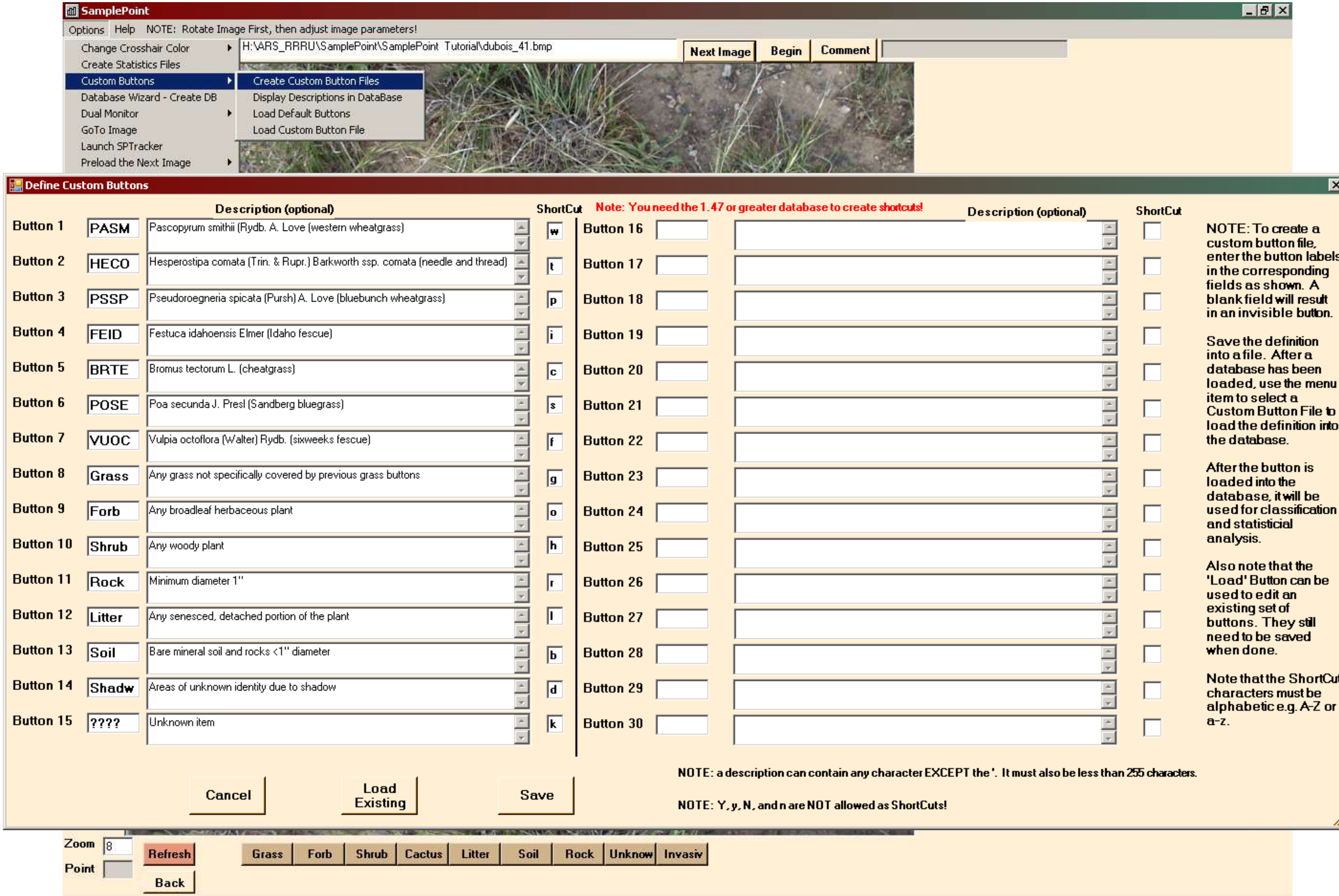


	A	B	C	D
1	Class	Rvalue	Gvalue	Bvalue
2	Soil	189	179	169
3	Soil	146	145	129
4	Soil	135	132	134
5	Litter	154	175	169
6	Soil	142	152	137
7	Litter	138	145	132
8	Soil	162	155	146
9	Grass	71	93	53
10	Soil	170	163	157
11	Soil	151	132	132
12	Grass	119	128	109
13	Soil	145	132	121
14	Soil	128	105	96
15	Litter	154	163	135
16	Litter	189	199	204
17	Litter	155	150	130
18	Soil	186	174	171
19	Litter	222	206	204
20	Soil	173	162	146
21	Soil	158	150	138
22	Litter	59	47	49
23	Grass	101	103	85
24	Grass	46	72	44
25	Soil	154	139	129
26	Litter	111	123	98
27	Soil	116	114	90
28	Soil	128	108	106
29	Soil	82	66	61
30	Soil	167	153	151
31	Soil	167	187	162
32	Soil	148	140	126
33	Soil	115	100	92
34	Soil	146	142	129

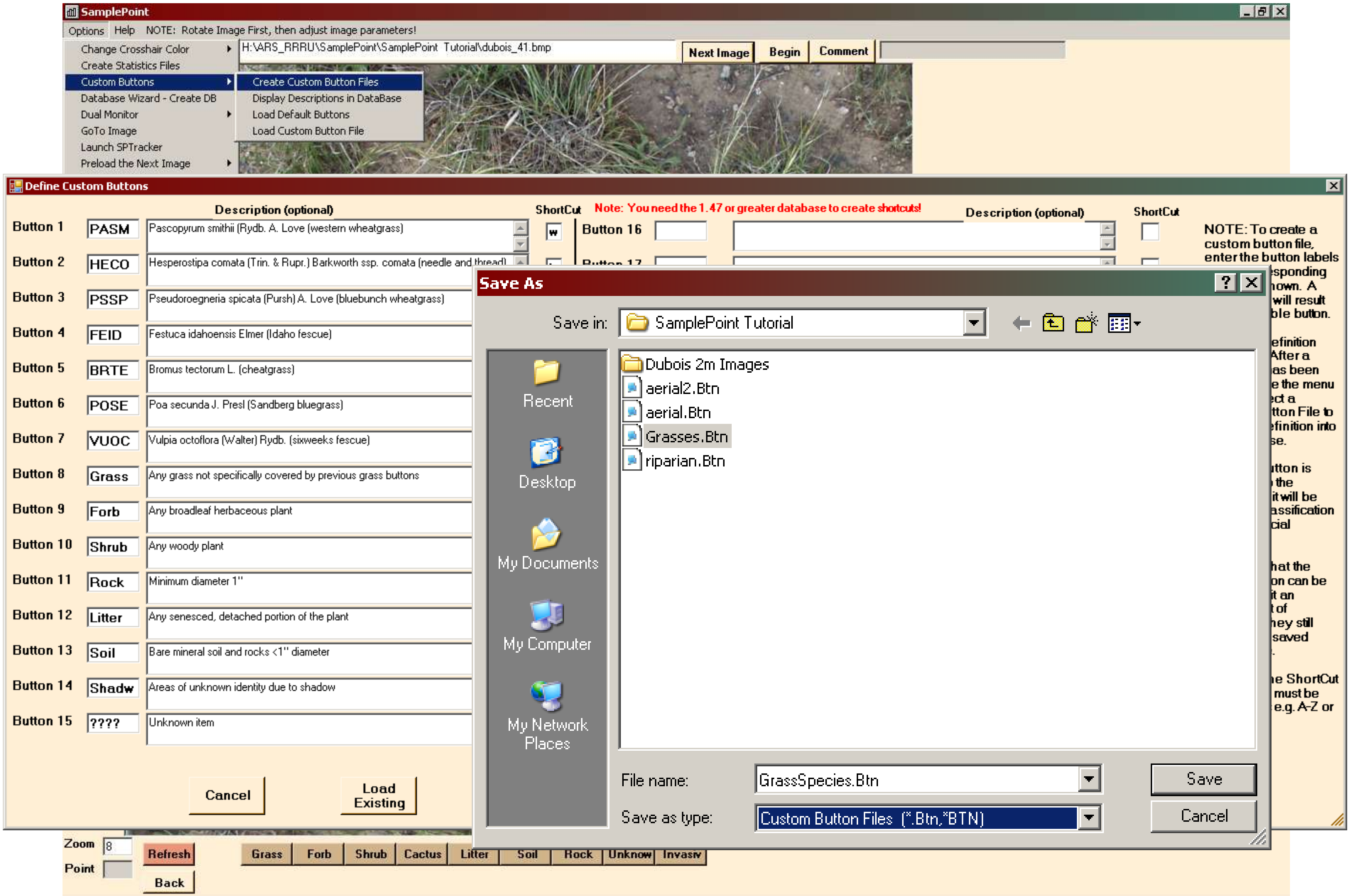
OPTIONS

- Defining custom buttons
- Changing the number of classification points
- Random classification points

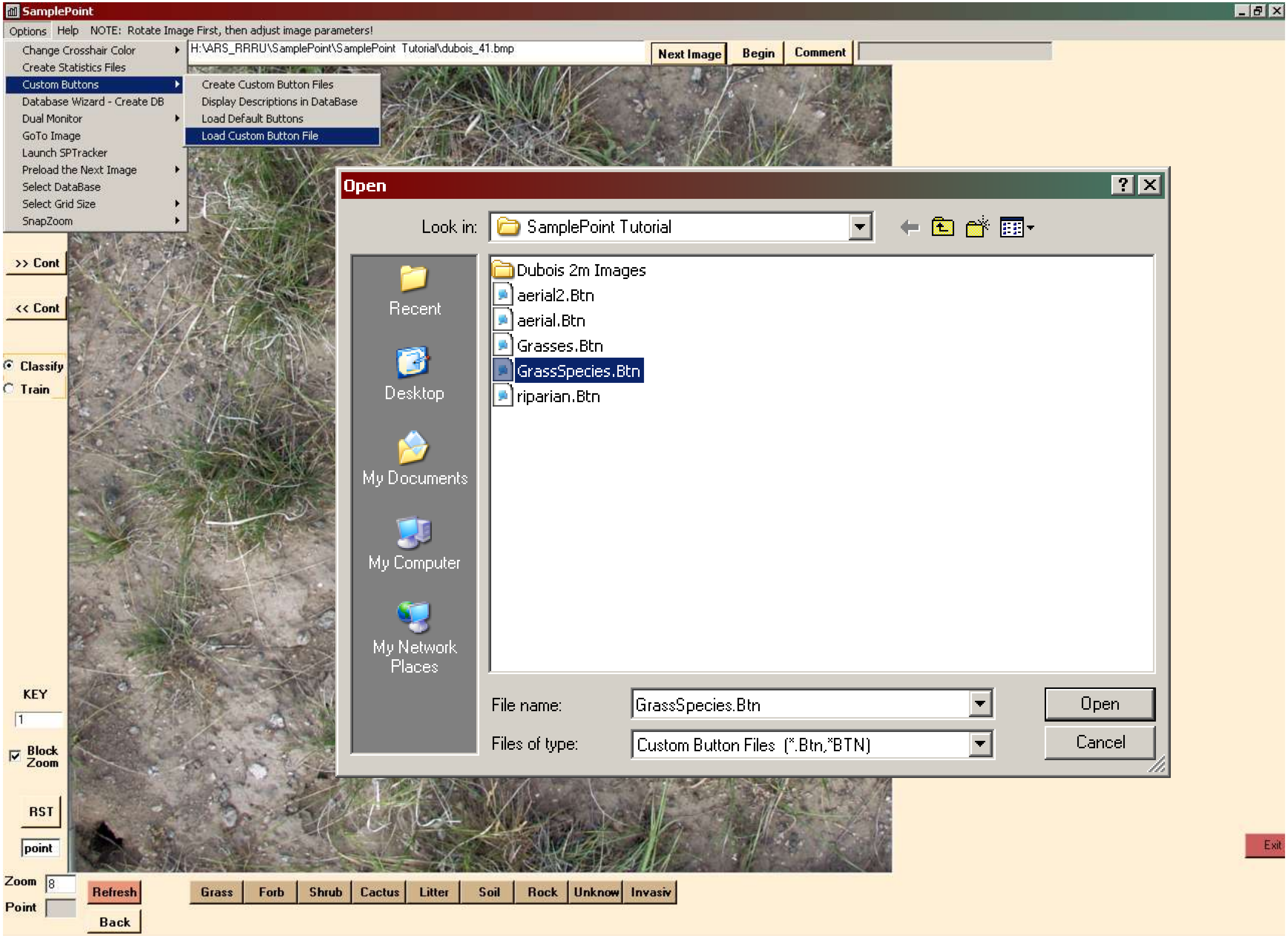
The classification buttons can be defined by the user. To create up to 30 custom classes, click Options>Custom Buttons>Create Custom Button Files. Define the button labels with titles of 6-7 characters each, perhaps using NRCS species codes as button titles and including species and common names in the description field. Create one letter shortcuts for keyboard classification. Click Save when complete and name the button file.



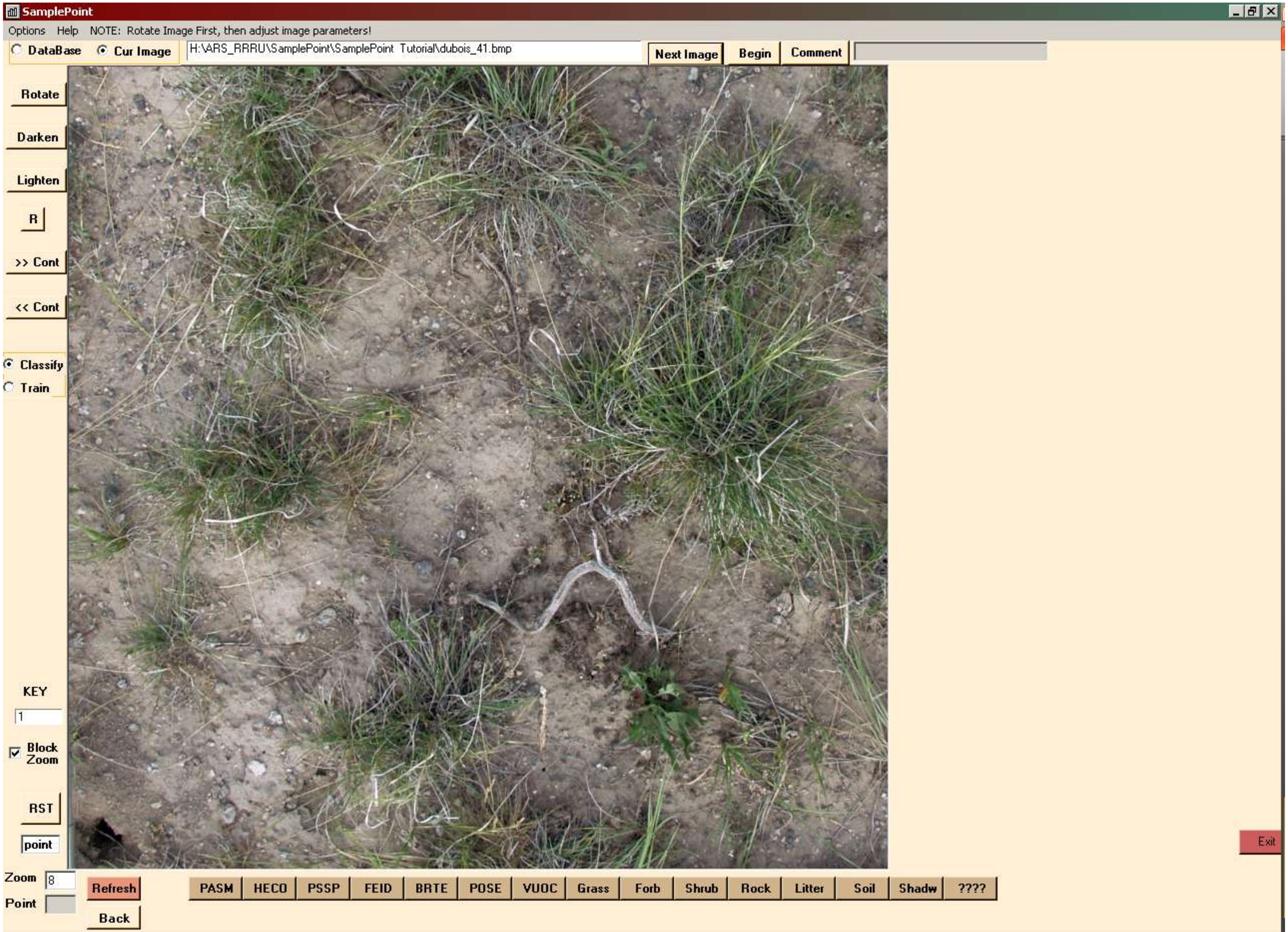
Navigate to the Image folder, name the button class file, then click Save.



To activate the custom buttons, click Options>Custom Buttons>Load Custom Button File. Select the file you just created, or some other *.btn file. Click Open. **You must have a database loaded before you can load a custom button file.**



The custom classes are now ready to use. The data saved to the database will be saved using these classes. The custom buttons must be in place prior to classification, with one exception: A class can be added to the end of a custom button file at any time with no adverse effect. Just follow the same steps as above and overwrite the old button file.

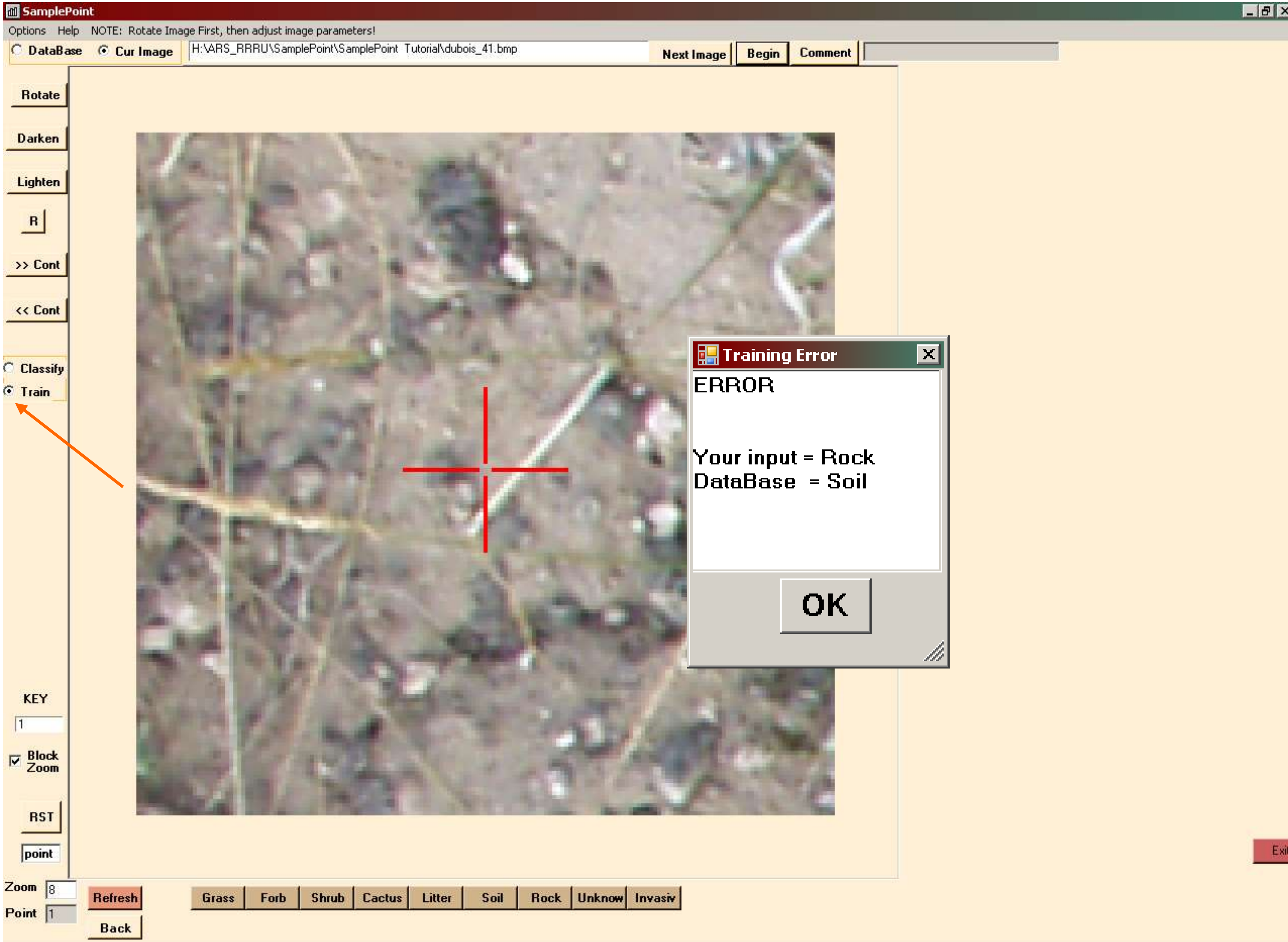


To change the number of classification points from the default of 100, click Options>Select Grid Size> and select the desired number of points. All points are systematically placed with equal points in rows and columns. The selected grid is used for all subsequent images unless you change it, or exit the software. Random point placement is also available for 25 to 200 points.

Grid points will always be in the same XY position on the image, even if you load it a year from now. All point classifications are thus **repeatable**.

Random points will have different XY positions on the image every time the image is loaded, so they are **not repeatable.**

To ensure classification consistency across users, you can train users with a completed database. When any completed database is loaded, click the Train radio button. In Train mode, data is not written to the database, but is instead simply compared to the database and the user is given feedback on their classification. This is a good step to take when someone takes over SamplePoint classification duties from someone else.

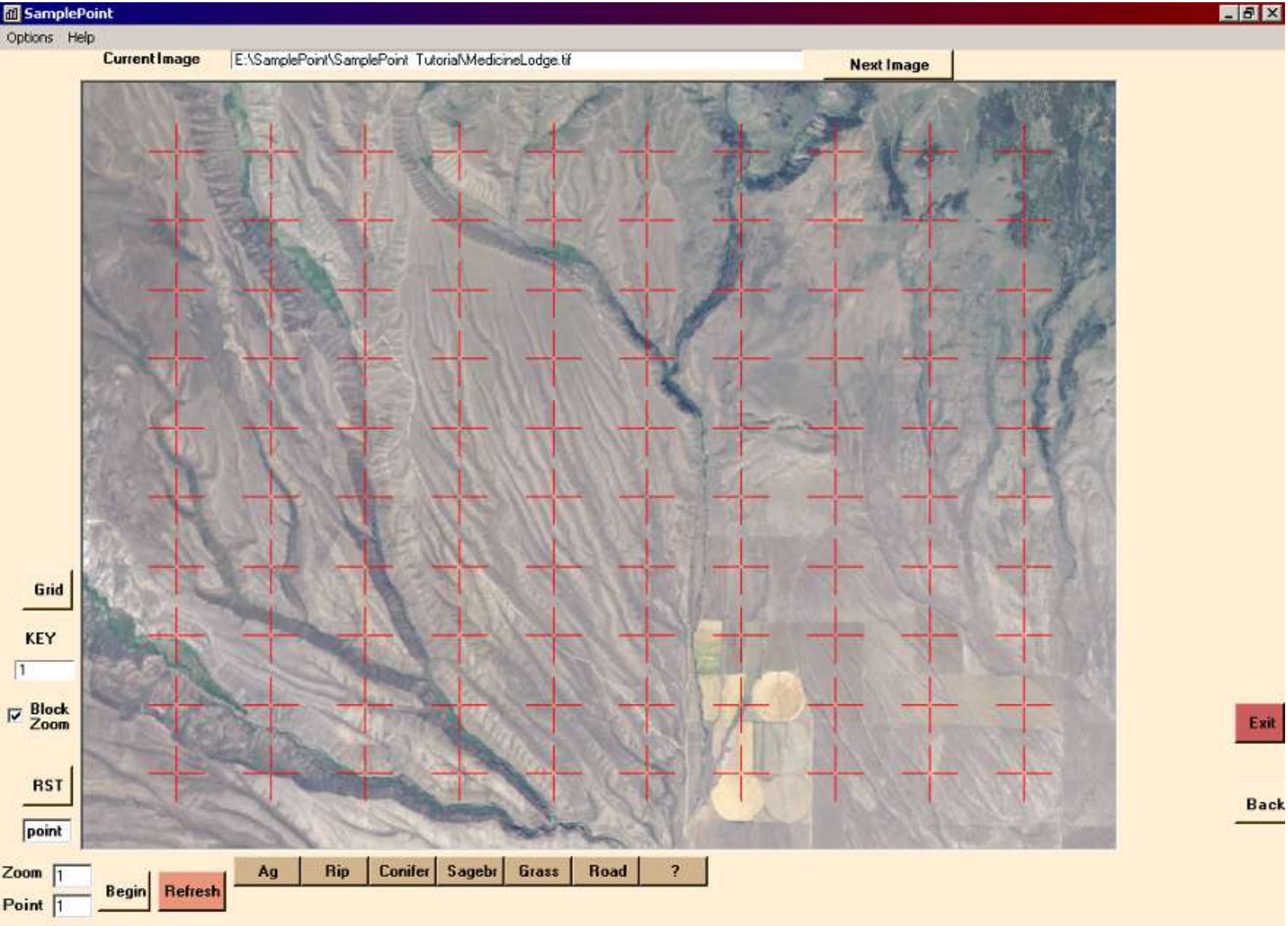


APPLICATIONS

The previous example utilized images taken with the camera positioned 2m above ground level (AGL) using a camera stand. Aerial images are also easily analyzed using SamplePoint.

This aerial image was acquired 100m AGL from a light airplane. SamplePoint operates in the same way regardless of the image type. Note the new custom buttons specific to this project.

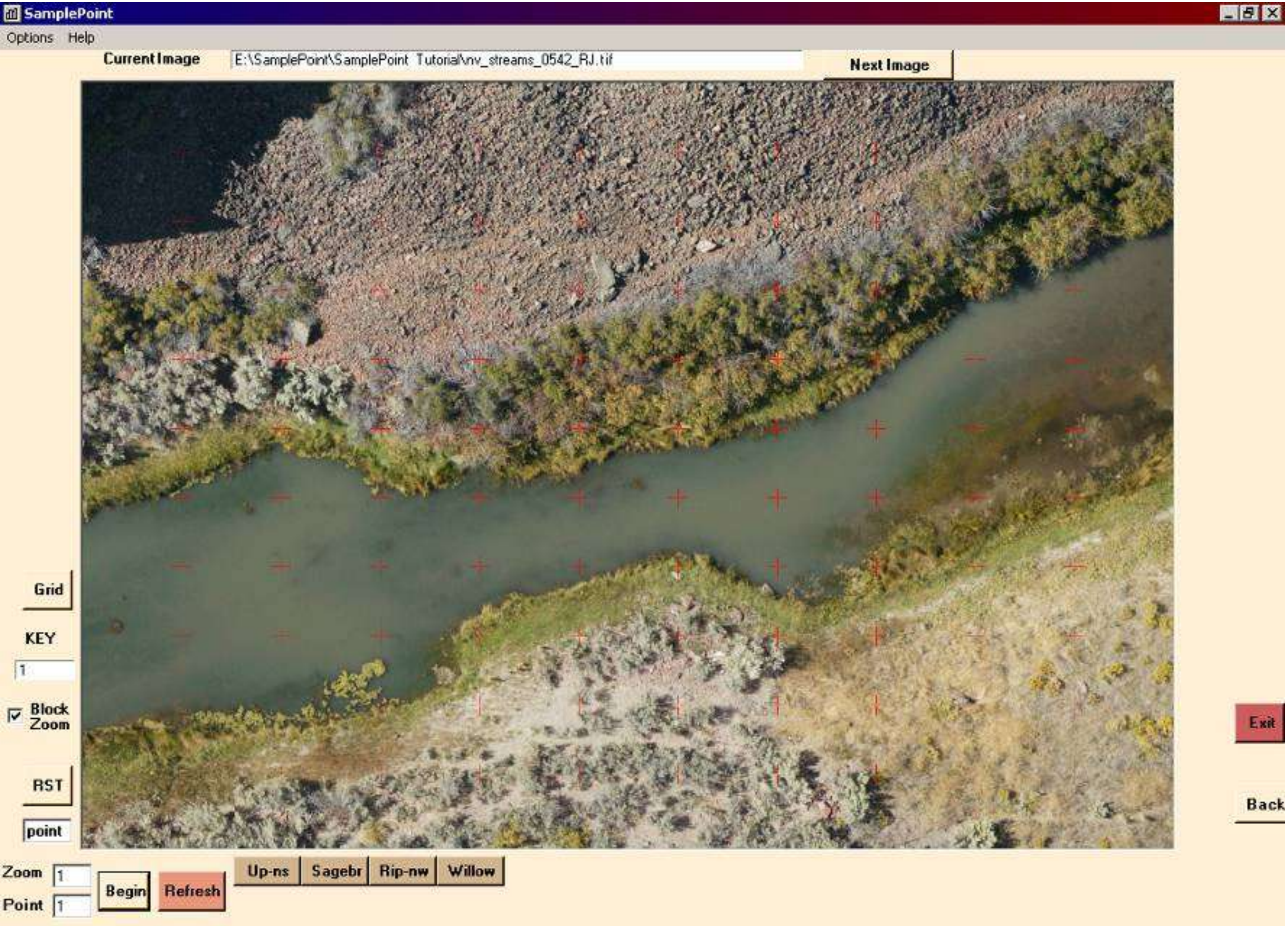
This image was acquired from 3000m AGL. Landscape-scale cover types, such as riparian zone, conifer forest, sagebrush steppe, etc., can be obtained using SamplePoint.



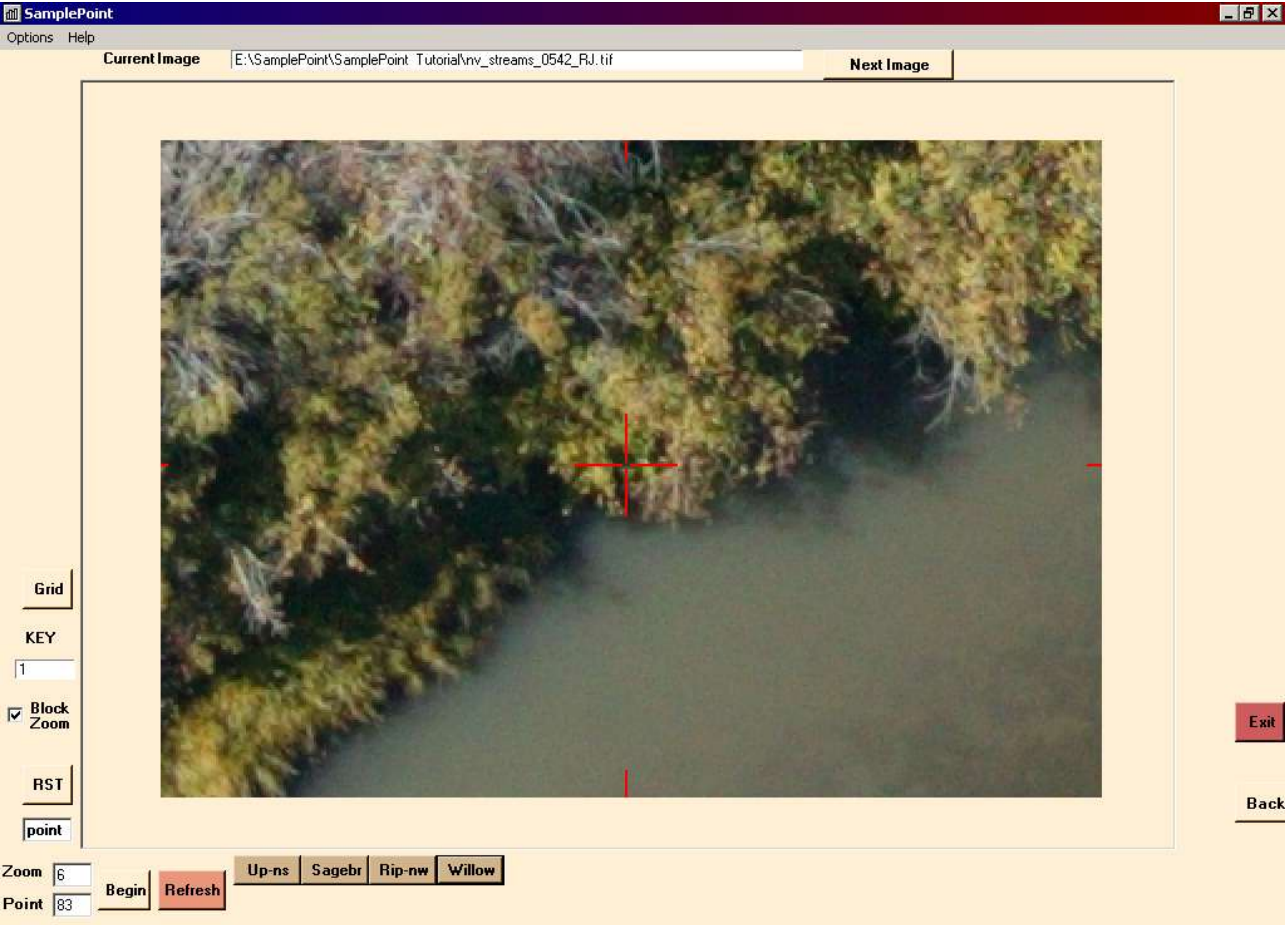
APPLICATIONS

Previous examples demonstrate how to obtain cover measurements over an entire image, but cover measurements can also be made within a specific area of the image. For example, a user wants to measure the % willow cover within the riparian area, and the % sagebrush cover in the surrounding upland area. This can be done using 4 customized buttons: Willow, Sagebrush, Riparian-not willow (Rip-nw) and Upland-not Sagebrush (Up-ns). Demonstration made with SamplePoint v1.25.

The custom buttons are created and loaded,and a database is created with a single aerial image (≈ 2cm GSD).



Points falling in water are here classified as “Riparian-not willow” but it would be a simple change to add a separate water class for those points.



Classification results:
Sagebrush = 6%
Upland Non-sagebrush = 39%
Willow = 15%
Riparian Non-willow = 40%

An implicit assumption is that sagebrush are found only in upland areas, and willows are found only in riparian areas. If this assumption is true, then any point classified as willow is inherently classified as riparian. Thus, willow cover in the riparian area is calculated as:

Willow / (Willow + Riparian Non-Willow) = 15 / (15 + 40) = 27%

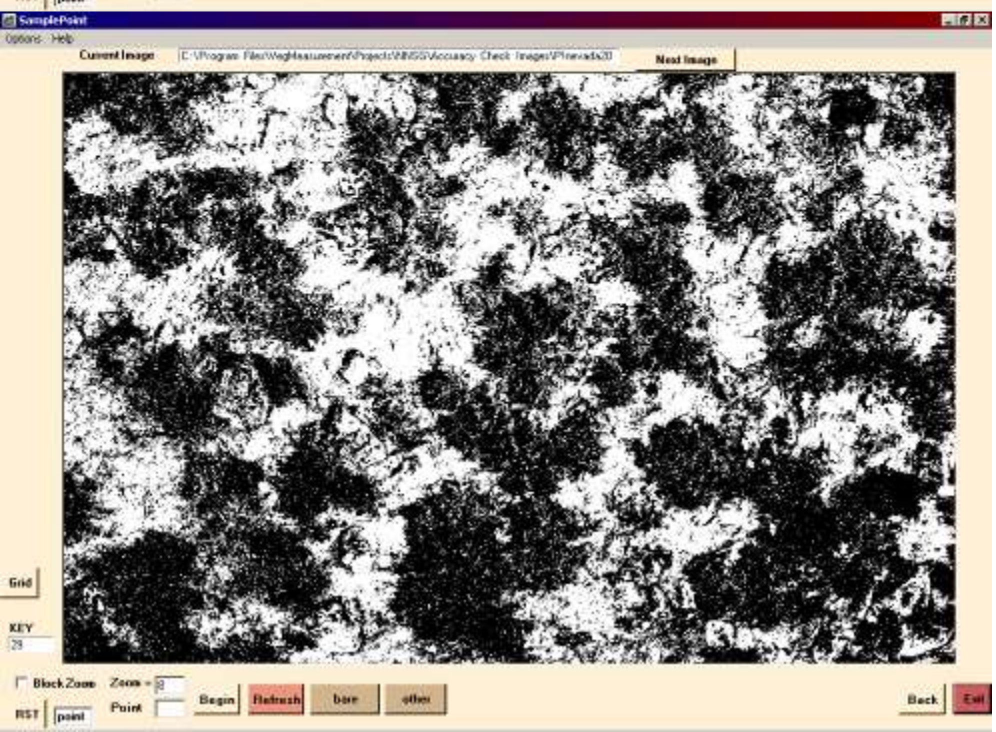
And, sagebrush cover in surrounding upland area is calculated as:

Sagebrush / (Sagebrush + Upland Non-sagebrush) = 6 / (6 + 39) = 13%

Conclusion of this classification:
Willow cover in the riparian area is 27%, and Sagebrush cover in the surrounding upland area is 13%.

APPLICATIONS

Because systematic classification points are assigned based on image size, and are always located in the same X,Y position for images of equal size, SamplePoint provides a simple way to perform accuracy assessments on image classification by software like Erdas Imagine or VegMeasurement.

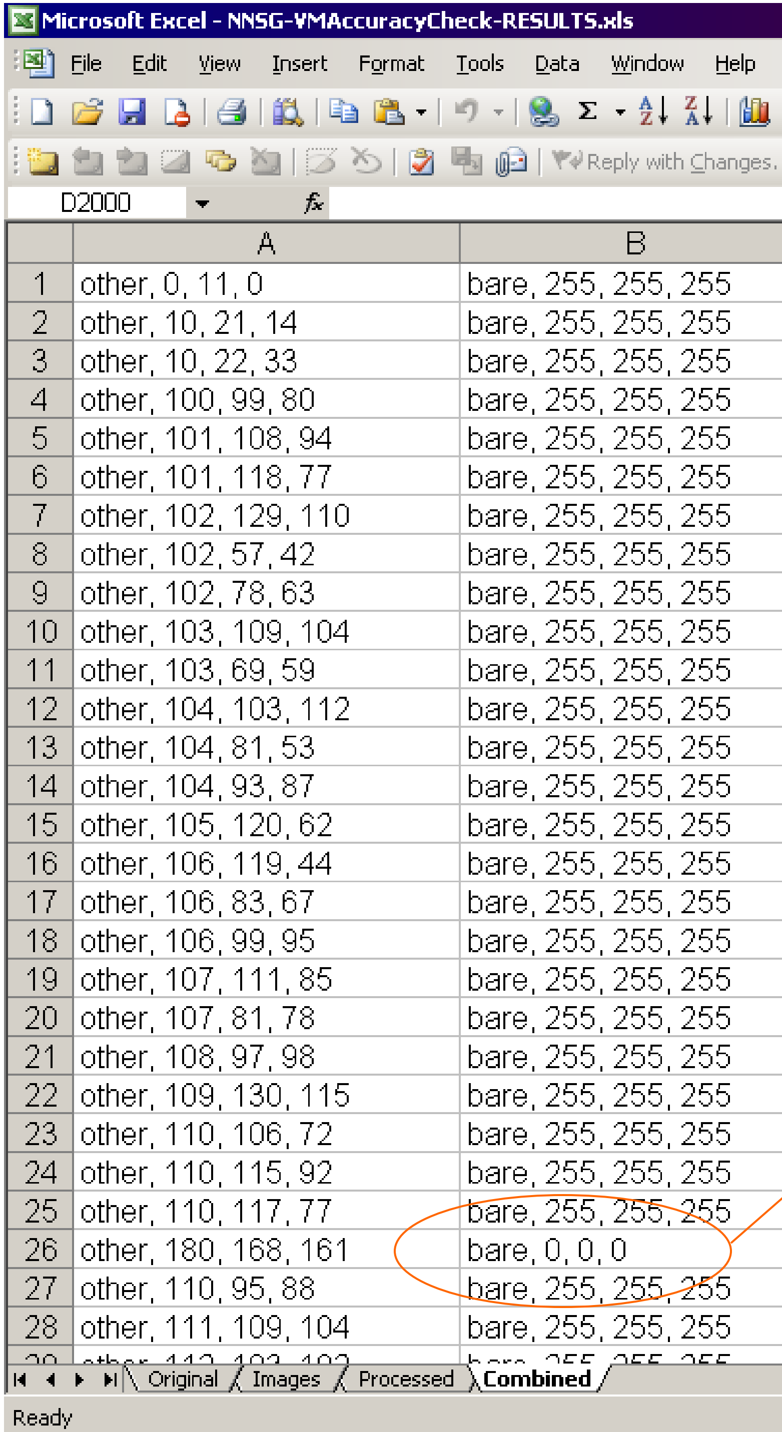


Export the processed image from VegMeasure or Imagine as a TIF or BMP, and run both the original and processed images through SamplePoint. In this example, a processed image from VegMeasurement was used. Since point 1 will occupy the same X,Y location on both images, classification accuracy can be determined by comparing the known to classified for a number of points over a number of images.

For example, point 1 in the original image is classified as bare ground. Point 1 in the classified image is white, so point 1 was correctly classified.

To perform the assessment, the first step is to classify all points into the classes of interest, though you cannot change buttons mid-assessment. In this example, white color is classified as bare ground, black is classified as other.

REMEMBER: You must use systematic point distribution for this operation.



	A	B
1	other, 0, 11, 0	bare, 255, 255, 255
2	other, 10, 21, 14	bare, 255, 255, 255
3	other, 10, 22, 33	bare, 255, 255, 255
4	other, 100, 99, 80	bare, 255, 255, 255
5	other, 101, 108, 94	bare, 255, 255, 255
6	other, 101, 118, 77	bare, 255, 255, 255
7	other, 102, 129, 110	bare, 255, 255, 255
8	other, 102, 57, 42	bare, 255, 255, 255
9	other, 102, 78, 63	bare, 255, 255, 255
10	other, 103, 109, 104	bare, 255, 255, 255
11	other, 103, 69, 59	bare, 255, 255, 255
12	other, 104, 103, 112	bare, 255, 255, 255
13	other, 104, 81, 53	bare, 255, 255, 255
14	other, 104, 93, 87	bare, 255, 255, 255
15	other, 105, 120, 62	bare, 255, 255, 255
16	other, 106, 119, 44	bare, 255, 255, 255
17	other, 106, 83, 67	bare, 255, 255, 255
18	other, 106, 99, 95	bare, 255, 255, 255
19	other, 107, 111, 85	bare, 255, 255, 255
20	other, 107, 81, 78	bare, 255, 255, 255
21	other, 108, 97, 98	bare, 255, 255, 255
22	other, 109, 130, 115	bare, 255, 255, 255
23	other, 110, 106, 72	bare, 255, 255, 255
24	other, 110, 115, 92	bare, 255, 255, 255
25	other, 110, 117, 77	bare, 255, 255, 255
26	other, 180, 168, 161	bare, 0, 0, 0
27	other, 110, 95, 88	bare, 255, 255, 255
28	other, 111, 109, 104	bare, 255, 255, 255
29	[illegible]	[illegible]

The second step takes place in Excel. Sort the data from the database into two columns, where original images line up with processed images precisely. For example, point 56 of original image 28 lines up with point 56 of processed image 28. Sort both columns in ascending order. For a binary classification, this will lump the data into 4 groups:

Other – Other (Correct classification)
Bare – Bare (Correct classificaiton)
Other - Bare (Omission error)
Bare – Other (Commission error)

Overall accuracy is calculated as:

Correct / (Correct + Incorrect)

The use of an error matrix will facilitate the calculation of user's and producer's accuracy rates (Congalton 1991).

This technique allows, by default, an assessment of user classification accuracy. If bare ground is always white in the processed image, then any point with black RGB values that is classified as bare ground is an error, and vice versa. This yields the user error rate, as opposed to the software error rate.

Congalton, RG. 1991. A review of assessing the accuracy of classification of remotely sensed data. Remote Sens. Environ. 37:35-46.

		Original Images (Reference Data)		
		Bare Ground	Other	Total
Processed	Bare Ground	60	134	194
Images	Other	434	1372	1806
	Total	494	1506	2000

A simple error matrix set up with original image classification data in columns, and processed-image classification data in rows. For example, a total of 494 points were classified as Bare Ground in the original images, but only 194 points were so classified by the automated analysis.

Overall Accuracy = (60 + 1372)/2000 = 71.6%
This is often a misleading statistic if what you're really interested in is a small class, such as bare ground. Measures of accuracy that ignore other classes are more useful.

Bare Ground:
Producer's Accuracy: Probability that a point of known cover type is correctly classified by the software.

60/494 = 12.1%

User's Accuracy: Probability that a point classification made by the software is correct.

60/194 = 30.9%

The SamplePoint concept was developed by the USDA Agricultural Research Service, Rangeland Resources Research Unit in Cheyenne, Wyoming, and the USDI Bureau of Land Management Wyoming State Office, Cheyenne, WY. Software code was written by Robert Berryman of Boulder, CO. Installation file was generated using Nullsoft Install System v 2.11. SamplePoint is free software available at www.SamplePoint.org

For user information not covered in this tutorial, click Help>Contents to open the PDF Help File. For publications on SamplePoint, go to www.SamplePoint.org.

This Tutorial is current as of February 1, 2012.

For technical assistance, email support@samplepoint.org