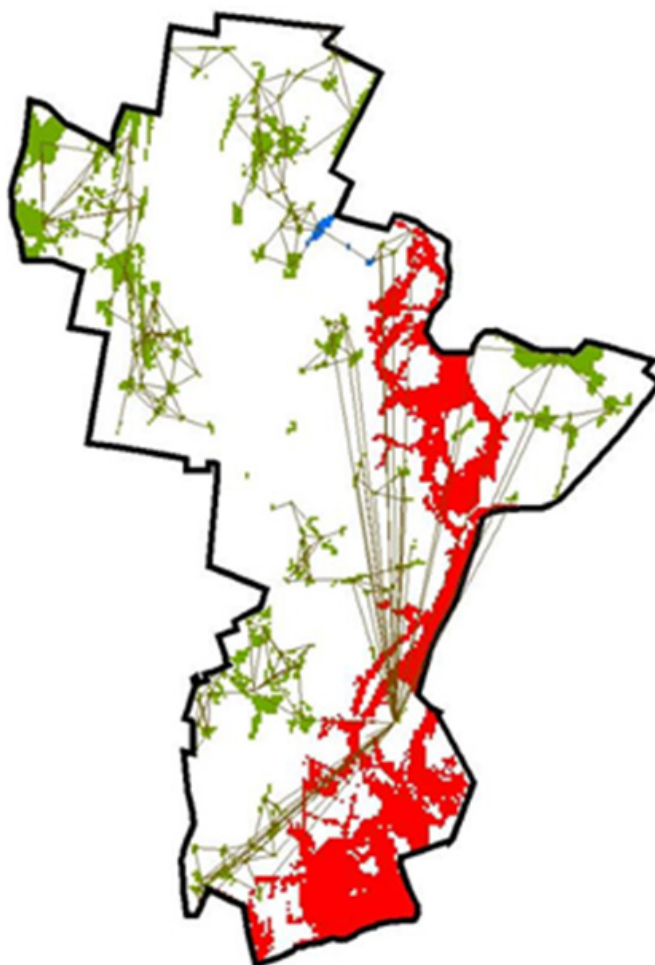




National Capital Region Network Remote Sensing and Landscape Pattern Protocol for Land-Cover Monitoring of Parks

Version 2.0

Natural Resource Report NPS/NCRN/NRR—2012/575



ON THE COVER

SENSINODE output for Antietam National Battlefield with Dcrit set to 210 m as determined from THINEDGE analysis as featured in SOP 6

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Natural Resource Report NPS/NCRN/NRR—2012/575

Phillip A. Townsend, Robert H. Gardner, Todd R. Lookingbill, Clayton C. Kingdon

University of Maryland Center for Environmental Science
Appalachian Laboratory
301 Braddock Road
Frostburg, MD 21532

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Executive Summary

These protocols describe the application of remote sensing imagery for monitoring spatially explicit ecological indicators (vital signs) of landscape pattern that have been identified for the National Capital Region Network (NCRN). The protocols employ land-cover data from multiple remote sensing platforms, including aerial photography, IKONOS satellite imagery, SPOT Imagery, and Landsat ETM+ imagery. The multi-scale approach facilitates the acquisition of fine-scale data suitable for detailed analyses of small areas (1-m resolution or smaller) and coarser data (e.g., up to 15 and 30m resolution) for repeat characterization of larger areas. For most applications, the coarser scale data are adequate for characterizing landscape pattern, although ultimately data from multiple sensors may be appropriate or necessary based on different objectives of landscape monitoring (e.g., mapping single trees vs. forest stands) and the scale at which a resource of interest interacts with the larger landscape (e.g., birds vs. herptiles). Eight Standard Operating Procedures are provided that document methods for the acquisition (SOP 1) and pre-processing of satellite imagery (SOP 2), the development of land cover maps from remotely sensed data (SOP 3), the processing of those maps in preparation for analyses of landscape patterns (SOP 4), calculation of landscape pattern metrics (SOP 5), graph analysis of landscape connectivity (SOP 6), stream buffer delineation (SOP 7), and image-to-image or map-to-map change detection (SOP 8). SOPs have been tested for 4 parks in the NCRN, Antietam National Battlefield (ANTI), Rock Creek Park (ROCR), Prince William Park (PRWI) and Catocin Mountain Park (CATO) and the results of these analyses are Townsend et al (2009).

List of Acronyms

ANTI	Antietam National Battlefield
CATO	Catoctin Mountain Park
CHOH	Chesapeake & Ohio Canal National Historical Park
GWMP	George Washington Memorial Parkway
HAFE	Harpers Ferry National Historical Park
MANA	Manassas National Battlefield Park
MONO	Monocacy National Battlefield
NACE	National Capital Parks - East
NCR	National Capital Region
NCRN	National Capital Region Network
NPS	National Park Service
PRWI	Prince William Forest Park
ROCR	Rock Creek Park
RSLP	Remote Sensing – Landscape Pattern
SOP	Standard Operating Procedure

Narrative

The long-term monitoring of key biological resources within National Park units is central to maintaining the biotic integrity and the historic and social value of those parks. Monitoring requires periodic data acquisition using well-documented and repeatable methods for consistent and comparable assessments. In addition, these methods must be flexible to allow for multiple objectives across broad spatial and temporal scales. Once such methods and protocols are developed and implemented, management decisions and comparisons among sites can be made based on internally consistent and rigorously evaluated data sources.

Changes in spatial patterns of land cover both within and adjacent to National Parks can greatly affect biological and physical processes within those parks. Specifically, landscape patterns related to disturbance, fragmentation, buffers, and land cover change have been shown to affect the abundance of rare and endangered species, levels of biodiversity, potential for invasion by exotic plants, habitat for birds, amphibians and other animals, water quality, and in-stream habitat for fish and other aquatic organisms. To address such concerns, aerial photography and satellite imagery (collectively, remote sensing) can be used to monitor the spatial extent of changes in land cover (i.e., conversion) or land condition. The benefit of remote sensing for monitoring is that it provides complete spatial coverage compared to point or plot samples. Remote sensing therefore complements survey data by providing information on the context of data sampled at points while also facilitating extrapolation of point measurements across landscapes. The results from remote sensing change detection analyses can also be used to identify areas of rapid change to target management efforts. Because remote sensing data and analysis methods are changing rapidly with evolving technologies, protocols are essential to ensure consistent data sources and analytical practices.

Although maps and mapping are inherently interesting for the purpose of developing comprehensive inventories, monitoring requires the derivation of meaningful information from those maps to interpret the nature and context of changes that occur between dates. Two approaches to landscape interpretation are provided: *pattern analysis*, which uses metrics of landscape pattern derived from categorical maps (represented by SOPs 5 and 6), and *descriptive change detection* via map-to-map or image-to-image comparisons (SOPs 7 and 8). Not all methods are necessary to address all questions. The specific method (SOP) will depend on the questions of interest, which can be grouped into the following general categories:

- What are the long-term trends in land cover distribution within and adjacent to the park, i.e., how has land cover changed? (SOP 8)
- What are the patterns of relevant land cover types within and adjacent to the park (e.g., what are average patch sizes, densities, edge/core areas, inter-patch distances, etc.)? (SOP 5, 6)
- What is the appropriate image resolution (grain size and map extent) for mapping and analyzing land cover in and adjacent to the parks? (all SOPs but addressed by SOP 4 in particular)
- What is the relative proportion of streams and/or upstream catchment area with riparian buffers and how wide are those buffers? (SOP 7)

- What is the condition of forests in the parks (e.g., have the forests undergone disturbance)? (SOP 8)

The narrative presented here is designed to address these questions, and with the collective SOPs forming the remote sensing – landscape pattern (RSLP) protocol for NCR parks. Although these parks are relatively small compared to their western counterparts, they cover over 30,000 ha spanning 4 physiographic regions: Atlantic Coastal Plain, Piedmont Plateau, Ridge and Valley, and Blue Ridge. They include long linear parkways, battlefield sites, and relatively large intact forest preserves. Nearly all of the park land in the NCRN lies within the Potomac River watershed in and around Washington, DC, one of the fastest growing regions of the country (Masek et al. 2000). As a consequence, many of the park management issues are related to anthropogenic stressors associated with land cover changes within the rapidly urbanizing landscape.

Justification/Rationale

Land cover distribution (i.e., maps) is a critical description of a park landscape, and may form the most obvious representation of the composition of resources within a park. Changes in land cover both within a park and adjacent to that park can dramatically influence a host of biological, physical and chemical resources within that park. Therefore, maps of land cover distribution and changes in those distributions are often a central component to assessing changes in other resources such as:

- Water quality. Variations in land cover and land use intensity within watersheds greatly influence sediment concentrations, water temperature and nutrient export into receiving waters (Swift and Messer 1971, Grant and Wolff 1991, Eshleman et al. 2000).
- Aquatic flora and fauna. Insofar as land use is a driver of water quality, land use within watersheds also affects habitat quality for aquatic plants as well as fish, benthos, and macroinvertebrates (Lenat 1994, Richards et al. 1996, Harding et al. 1998, Hawkins et al. 2000).
- Terrestrial vertebrates. Patterns of land cover (including patch size, shape, and distribution) within parks affect the availability of preferred or necessary habitat for species of interest (Andren 1994). Land cover adjacent to parks affects habitat quality (for species with ranges larger than park area), migration, and the maintenance of metapopulations (Fahrig 1997). The juxtaposition of habitat types (e.g., edge density) in particular may influence the quality of habitat for different types of bird species (Lynch and Whigham 1984, Robinson et al. 1995).
- Vegetation communities. Patterns of land cover in and adjacent to parks influence the development of natural vegetation communities (e.g., through seed dispersal) as well as susceptibility to invasive or undesirable species (Brothers and Spingarn 1992, Hobbs and Huenneke 1992).

The analysis of relationships between land cover distribution and these other resources of interest (which have their own monitoring protocols) requires the derivation of meaningful metrics of landscape composition and pattern from maps.

Measurable Objectives

The utility of remote sensing and landscape pattern protocols depends on the specific application for which a map or pattern analysis is used. In this respect, measurable objectives for RSLP protocols may vary depending on the other monitored resources with which RSLP outputs will be integrated. For example, the needs in an analysis of land cover patterns for examining stream water quality may differ substantially from the needs for an analysis of wildlife habitat.

Similarly, land cover parameters needed to analyze habitat quality for different organisms (e.g., salamanders, forest interior birds, and black bears) also vary substantially. It is beyond the scope of this protocol to present the appropriate scales and analytical approaches for all potential RSLP applications. However, a range of analytical concerns that can be used to guide personnel in the implementation and especially application of this protocol is presented. To this end, a series of pilot studies demonstrate the chief considerations for implementing the RSLP protocol for different applications (Townsend et al. 2009). The implementation of these specific studies entails decision-making regarding assessment of appropriate image resolution (grain and extent) and data sources, as well as reporting of map accuracy and other diagnostic statistics. The results of these pilot studies indicate that for most applications, coarser scale data (e.g., 30m Landsat) are adequate for characterizing landscape pattern, although ultimately data from multiple sensors may be appropriate or necessary based on different objectives of landscape monitoring (e.g., mapping single trees vs. forest stands) and the scale at which a resource of interest interacts with the larger landscape (e.g., birds vs. herptiles).

This protocol does not address in detail the practical issues associated with combining data sources from multiple satellite sensors for monitoring applications. A useful discussion about this issue along with a recommended approach for minimizing errors when comparing pattern statistics from image sources with differing resolutions can be found elsewhere (Gardner et al. 2008).

Overview Of Protocol Components

The RSLP protocol does not consist of SOPs regarding sampling design and field methods that are comparable to other resources. Field sampling of forest vegetation, water chemistry, insect pests, landbirds, white-tailed deer, etc. is explicitly addressed through other NCRN monitoring protocols (see NCRN Monitoring Plan). By definition, RSLP protocols are implemented remotely, and require a unique decision-making process. Field sampling and methods in support of the RSLP protocol are imbedded into the protocol, but are a small component of the overall process of mapping and analysis. Figure 1 provides a flow chart as an overview of the process that might be undertaken to fully implement a landscape pattern protocol. It provides a list of the statistics, tables and maps that should be generated at each interval in the monitoring cycle. Multiple combinations of imagery, analytic window and land cover classification are possible as part of a full implementation, each of which would result in a new set of output products. At a minimum, we recommend the analysis of forest land cover (i.e., the dominant natural land cover for the NCR) using Landsat imagery for all of the parks and “5x buffers” (see SOP 4) at a five-year return interval.

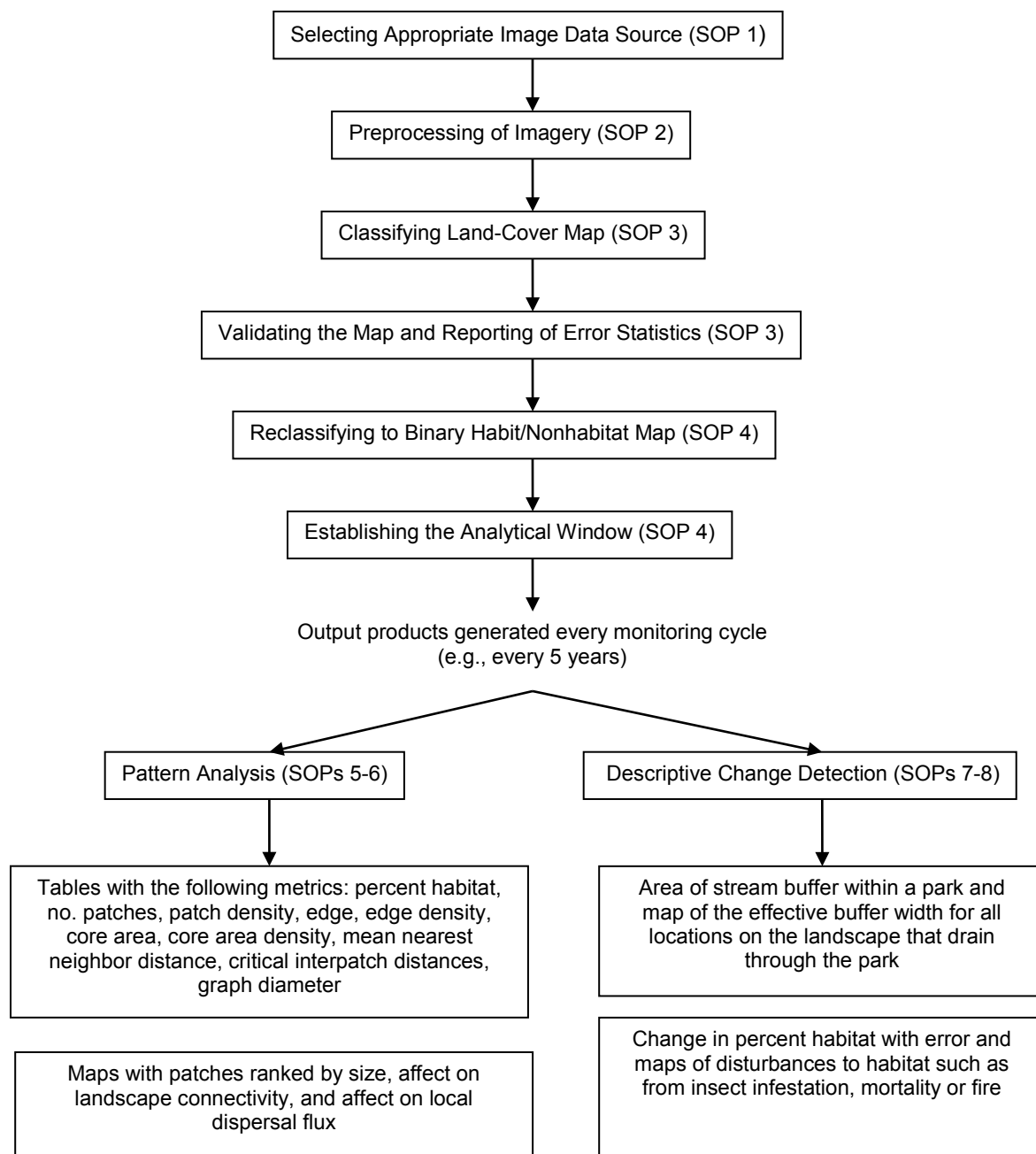


Figure 1. Sample flowchart for implementing Remote Sensing and Landscape Pattern Protocol (See text and SOPs for full explanation of terms).

Mapping (SOP 1, 2 and 3)

Maps form the basis for all components of the RSLP protocol. Therefore, the protocol outlines the process involved in the acquisition of image data and creation of land cover maps from the imagery. The mapping process follows the following four steps.

- 1) Selection of the appropriate image data source (SOP 1) based on:
 - Appropriate data type (e.g., multispectral/color infrared, panchromatic, radar, etc.) and availability
 - Appropriate image resolution – pixel size – matched to the particular application of interest
 - Appropriate image extent to cover the park of interest and critical adjacent areas
- 2) Preprocessing of imagery for analysis (SOP 2), including:
 - Geometric correction of imagery
 - Derivation of important image measurements, such as the Normalized Difference Vegetation Index (NDVI), if necessary
 - Radiometric correction or normalization of imagery, if necessary
- 3) Mapping appropriate land cover types (SOP 3):
 - Selection of the appropriate land cover mapping scheme
 - Development of training data
 - Selection of a mapping algorithm
- 4) Map assessment (SOP 3):
 - Collection of validation data
 - Implementation of the appropriate map validation strategy

There are literally hundreds of methods to develop maps from digital imagery, and there are dozens of software packages capable of generating credible maps. It is expected that a remote sensing analyst with training and experience in digital image processing will have responsibility for these tasks. Therefore, the protocol does not provide specific software-dependent instructions, but rather general instructions for the development of maps that should be consistent among image processing software packages. Common tasks such as these are detailed in most general image processing textbooks and include: geometric and radiometric correction, image enhancement, and map validation.

The selection of a specific image resolution and land cover scheme is a critical component of the RSLP protocol as these factors dictate the ultimate utility of the resulting maps to NPS monitoring needs. Pilot studies therefore were done using land cover maps from imagery at 4 different grain sizes (4, 10, 15 and 30 m) to illustrate the differences in landscape patterns that result from the selection of specific data types. A detailed description of the pilot study is provided in the Townsend et al. (2009). The study quantifies the impacts of changing image resolution for four parks of the NCRN.

The desired map classes also influence interpretation. The use of the Anderson Level II classification (Anderson et al. 1976) is recommended because of its wide use and hierarchical design that facilitates aggregation (or further disaggregation) based on NPS needs. Because of its strict definition of land cover classes, maximum compatibility with archival and potential future map products is ensured. Thus, a slight refinement of the Anderson Level II classification is

presented that is completely compatible with aggregation to Anderson Level II classes, but also cross-walks to the National Land Cover Classification (NLCD, Vogelmann et al. 2001) being used for NPS I&M landscape monitoring at the national level.

Establishing the Analytical Window (SOP 4)

Depending on the specific application of the RSLP protocol, decisions must also be made on map extent for a particular analysis. For example, it makes sense that the use of maps to evaluate water quality within a park would employ watershed boundaries to quantify land cover. Similarly, the use of park boundaries to quantify land cover may not be appropriate for monitoring species with ranges or habitat/dispersal needs that require connectivity to adjacent landscapes. Some parks may have important differences in land cover composition within and adjacent to the park. More specifically, habitat patches outside of some parks may represent critical source habitat to the park (e.g., Antietam). These issues are especially important for small urban parks such as those included in the NCRN. The protocol therefore derives and applies four types of analytical windows:

1. *Park boundaries.* This is the simple case of using the park boundary to determine analytical extent. This might be appropriate for the evaluation of habitat or resources contained entirely within park boundaries and requiring no connectivity to exterior lands. All area within the park is considered habitat or nonhabitat for analysis, while all land outside the boundary is considered background or “no data”.
2. *Uniform buffers around parks.* This is the case of developing uniform buffer width around a park to delineate the analytical extent. An arbitrary buffer width (e.g., 1 km) may be employed so that lands immediately adjacent to a park can be considered for their importance to within-park resources. This is an inelegant solution. The protocol therefore provides a method to determine a uniform buffer width based on an increase in analysis area (above the area of the park alone) referred to as the ‘effective’ landscape size. For example, based on the question of interest, an effective landscape may require a 2X buffer (e.g., the width of the buffer defines an analysis window double the area of the park), or a 5X buffer, and so on.
3. *Watersheds.* Watershed boundaries are used to delineate map extent. GIS coverages of watershed boundaries have already been developed for all NCRN parks. However, watershed boundaries can be generated using a digital elevation model (DEM) and simple routines within the ARC software. Note that the delineation of only low-order watersheds draining into the park is recommended. Some parks (e.g., Antietam Creek in ANTI) may include streams with very large drainage areas outside the park boundary that may affect park resources but are well outside the effective domain of park management.
4. *“Intersecting patches” buffers.* The analytical extent is defined by all unique patches that intersect the park boundary or alternatively all patches of an important habitat type (e.g., forest) that intersect the park boundary. This will yield different analytical extents for different parks and different types of landscapes. However, this approach is probably necessary in landscapes of highly mixed land cover or extensive fragmentation. This approach reflects the reality that species moving within patches rarely respect boundary lines that are not demarked by fences, roads or other potential obstacles.

The decision on the maximum approximate map extent that will be needed should be made prior to the actual acquisition of imagery for mapping. This ensures that the resulting maps will have a sufficient extent to address different types of analyses. Maps made from images (SOP 2) should completely cover an areal extent that will meet the needs of multiple buffer types. With the exception of the “intersecting patches” buffer, this extent can be determined in advance (watersheds and uniform buffers are based on simple GIS analyses requiring only maps of the park boundary and a DEM). Even area to be delineated by the “intersecting patches” buffer can be approximated using existing land cover maps such as NLCD. The pilot study (Townsend et al. 2009) demonstrates the importance of analytical window definition to the derivation of important landscape metrics (SOPs 5 and 6).

Pattern Analysis (SOP 5 and 6)

Once land cover maps are generated, objective measures of landscape pattern are required to assess changes in the amount and distribution of landscape resources in and around the parks (and/or their surrounding landscapes). For this, we offer a protocol (SOP 5) to calculate the key landscape metrics that have been identified in the landscape ecology literature as representative of landscape heterogeneity (Riitters et al. 1995; Turner et al. 2001). Critical categories of metrics include p (proportion of area in different cover types), patch metrics (number and density of patches, mean patch size), perimeter and core area metrics, and measures of landscape connectivity including nearest neighbor metrics. These metrics provide measures of the distribution and fragmentation of patches and land cover on the landscape. The quantitative representation of fragmentation through time facilitates the assessment of the park as habitat for different species, and permits the tracking of trends in improving or declining habitat suitability.

Small urban parks can play a vital role as biological refugia, migration rest stops, and dispersal corridors, all of which have been shown to greatly enhance regional biodiversity. The value of these parks is likely to increase in the context of increasing levels of disturbance, fragmentation, and land cover change in the surrounding landscape. Graph theory is a well-developed analytic technique for evaluating landscape connectivity under conditions of habitat modification and change (Urban and Keitt 2001, Calabrese and Fagan 2004). We therefore offer a protocol (SOP 6) to employ graph theory to identify critical habitat patches on park landscapes. The definition of what constitutes a critical patch will depend on the relevant cover types as well as assumptions about minimum patch size and species dispersal distances.

In the pilot study, a complete suite of landscape metrics were computed (SOPs 5 and 6) at 4 levels of resolution and using all buffer scenarios to determine the influence of grain size and map extent on measurements (Townsend et al. 2009). Based on these analyses, discussions with park managers in the NCRN, and the recent availability of the Landsat archive free-of-charge, the use of 30m Landsat imagery is recommended for most general monitoring activities. Ultimately decisions about these important variables must be made through the consultation of NPS experts with remote sensing and landscape ecology specialists.

SOPs 5 and 6 employ specialized or custom software packages that are freely available, including FRAGSTATS (version 3.3, McGarigal et al. 2002, see SOP 5 and LANDGRAPH (version 1.0, Urban 2003, see SOP 6). Whereas most SOPs are generally written without regard to software packages, detailed and specific instructions for application of these tools are provided in the respective SOPs.

The original SOP 5 (generation of random or “neutral” maps) has been removed from the protocol at the recommendation of the National Park Service.

Stream Buffers (SOP 7)

Forest buffers along streams represent a subset of a specific land cover type (Forest at Anderson Level I) that are important to the maintenance of water quality (through the filtration of nutrients, e.g., Peterjohn and Corell 1984), the reduction of erosion and sediment transport to streams (Roy et al. 2006), and the protection of cool water fish habitat (through shading, e.g., Leblanc et al. 1997). SOP 7 therefore uses a land cover map, DEM, stream coverage, and watershed boundaries to determine the area of stream buffer within a park and to determine the effective buffer width for all locations on the landscape that drain through the park.

Map or Image Comparison (Change Detection) (SOP 8)

The simplest map and image-based analyses involve the direct comparison of two maps from two time periods. Comparison of two categorical maps that have been derived from remotely sensed data is termed “post-classification change detection” (PCCD, Jensen 1996) and at the most basic level yields measures of changes in p (SOP 5) between time periods. Maps generated from PCCD are highly sensitive to differences in map accuracy between dates, differences in classification strategies (classification used, algorithms used) and especially differences in base imagery used to make the maps. All errors are multiplicative, meaning that a PCCD of two maps with 80% accuracy would be at best 64% reliable. Although this level of accuracy is still better than no information at all, the resulting pixel-by-pixel change map must be used with caution. Analysis of tabular data of changes (e.g., in SOP 5) limit misinterpretations from this concern, but also do not provide mapped representation of where changes have occurred.

An alternative approach to the categorical change detection approach is the analysis of changes based on changing spectral responses within the original image data. This provides a continuous measure of change that can be related to the intensity of change, especially if the land cover class has not changed (e.g., a disturbed forest). This approach depends on having compatible imagery from two time periods, usually images from the same sensor (e.g., Landsat 7) or with nearly identical properties (Landsat 5 and Landsat 7). All images to be compared must be normalized (Collins and Woodcock 1996) to facilitate comparison, after which algebraic or trigonometric (e.g., change vector analysis, CVA, Townsend et al. 2004) can be applied to quantify differences. This approach is suitable for mapping disturbances to forests such as from insect infestation, mortality or fire. A classification map is usually used to stratify the landscape into comparable cover types (e.g., forest) so that dramatic changes within cover type (e.g., agriculture) do not mask more subtle but more important changes in another (e.g., disturbed forests).

Finally, if only one image is available for analysis in conjunction with a land cover map from an earlier time frame, simple statistics can be used on a class-by-class basis to determine pixels that deviate substantially from the mean reflectance of a specific land cover classification and may therefore be undergoing change. This approach is not suitable for agricultural lands, which may have high within-class spectral variance due to different crop types and rotation schedules.

SOP 8 outlines the basic implementation of PCCD and spectral change detection.

Data Handling

SOP 2 addresses data handling and processing issues. Standardized metadata are an integral component of any remote sensing project. All geospatial data and products must be maintained to FGDC data standards (<http://www.fgdc.gov/standards/standards.html>) with associated documentation. Database design cannot be strictly hierarchical, as some images cover multiple parks. We recommend that image data be stored by data type (i.e., sensor type: Landsat, SPOT, IKONOS, aerial), with separate directories for raw imagery, georectified imagery, normalized imagery, and map output. Analyses and map subsets for individual parks should be stored in a separate section of the database by analytical unit (presumably park units). Documentation of analyses and modifications to datasets should be provided as readme files within the relevant directory structure. All data should be archived permanently once analyses are completed, and all work should be backed up onto a separate system regularly (at least weekly) while processing is ongoing.

Personnel Requirements

Image analyses should be conducted by specialists trained in remote sensing data analysis and image processing. Pattern analyses should be conducted by personnel with exposure to the theory of landscape ecology (e.g., Turner et al. 2001). Pattern analysis yields a very large quantity of data that can be misused without proper understanding of the intent of the metric and its interpretation (Li and Wu 2004). Decisions on image data types, map extent, scale of analysis, and specific landscape metric of interest should be made based on consultation between experts on a resource of interest (e.g., hydrologists, wildlife ecologists, etc.) and the RSLP specialist. Linkages between RSLP results and other resources should be based on a solid theoretical or question-driven foundation that facilitates hypothesis-testing (Gardner and Urban 2007). These linkages are described in detail in the NCRN monitoring plan (see also Lookingbill et al. 2007).

Operational Requirements

This protocol requires significant computing facilities, including high-end computer workstations for image processing and landscape analysis, with ample disk space for data storage. In addition, disk space or other media must be available for data backup to calculate data storage needs on an image-by-image basis. Software needs include a fully functional image-processing package (e.g., ERDAS Imagine), a GIS package for overall data analysis and storage (ArcMap), as well as pattern analysis packages (FRAGSTATS, LANDGRAPH). A spreadsheet program should be used to store tabular results.

Personnel time will depend on the number of images being processed and the experience level of the analyst. Because of the small size of the NCRN parks, the time frame for image acquisition, processing and mapping is short relative to larger areas, but will still require at least two weeks per park for a moderately experienced analyst. Map validation may require fieldwork consisting of several days to more than a week per landscape, depending upon the effective landscape size that is used. Image processing and pattern analysis may take weeks to months depending on the specific monitoring questions of interest.

A 5-year interval for mapping is recommended, with more frequent mapping implemented for dynamic landscapes or to capture periodic changes such as due to insect infestations.

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Standard Operating Procedures (SOPs)

SOP 1: Designing a Remote Sensing Change Detection Study for Landscape Monitoring

Introduction

This Standard Operating Procedure (SOP) contains checklists and questions that will aid in the selection of remotely sensed imagery to complete the land cover mapping and landscape pattern analyses described in later SOPs.

Identification of suitable data (image and ancillary reference data) for any application of remotely sensed imagery is important. Resource monitoring and inventorying requires, “at a minimum, (1) clear definition of the problem at hand, (2) evaluation of the potential for addressing the problem with remote sensing techniques, (3) identification of the remote sensing data acquisition procedures appropriate to the task, (4) determination of the data interpretation procedures to be employed and the reference data needed, and (5) identification of the criteria by which the quality of information collected can be judged” (Lillesand and Kiefer 1994).

Preparation of remotely sensed imagery for the development and interpretation of land cover maps are addressed by SOP 2 and SOP 3 respectively. SOP 2 presents steps for the preparation of imagery for land cover classification. The outputs of SOP 3 are maps of Anderson Level II (Anderson et al. 1976) land cover classes. In SOP 4 these maps will be reclassified into habitat and non-habitat classes and cropped to various buffer sizes around each park. This will facilitate the completion of the analyses described in SOPs 5 through 8.

Imagery is available from many data sources at multiple spatial resolutions for the purpose of land cover mapping. The RSLP SOPs were created based upon pilot studies that addressed land cover mapping at four spatial scales to compare image resolutions (i.e., pixel size) for drawing inferences about landscape pattern:

- 4-m IKONOS satellite imagery
- 10-m SPOT imagery,
- 15-m panchromatic sharpened Landsat ETM+ imagery
- 30-m Landsat ETM+ imagery

It is reasonable to expect that the most appropriate spatial resolution will vary among parks, vital signs, and monitoring objectives. As a rule of thumb, 15-m resolution Landsat imagery or 10-m SPOT data provide a good balance between cost-effectiveness and high spatial accuracy for repeated characterizations of landscape pattern in NCRN parks.

The selection of appropriate image data for a particular application depends on interaction between Park resource experts and the RSLP specialist. The selection process for appropriate image types and resolution should follow a standard set of questions designed to determine the appropriate data source.

Procedures

Step 1: Identify Management Needs and Appropriateness of Remote Sensing

1. What is the organism or resource of interest? _____

Complete a separate checklist for each organism or resource (attribute) of interest. To determine whether multiple organisms/resources can be addressed using the same data type, compare the answers to STEP 6 for each attribute to identify those that can be monitored coincidentally.

2. Can this attribute be identified directly using remote sensing? YES / NO

If YES, go to 4. If NO go to 3.

3. Can something directly or indirectly related to this attribute be measured or characterized using remote sensing? YES / NO

If YES go to 4. If NO, remote sensing change detection is inappropriate for the monitoring objective and ground-based monitoring approaches should be considered.

4. What category of remote sensing technology is useful for monitoring the attribute of interest?

- Optical remote sensing (including aerial photography, color infrared and panchromatic imagery, thermal, multispectral and hyperspectral imagery)
- Synthetic aperture radar (SAR)
- LIDAR

For each category selected in question 4 above (and for each organism/resource selected in question 1), answer the questions in Steps 2 - 6.

Step 2: Grain Size of Interest

5. What is the grain size (e.g., spatial resolution, pixel size) at which the attribute of interest is detectable? (Alternatively, what is the grain size of the process to which the attribute responds?)

6. What remote sensing data sets (i.e., specific sensors) meet this requirement?

7. Can these data sets be obtained for the study area? YES / NO

8. What is the target accuracy of the analysis both in terms of spatial error and attribute error?

9. Based on the literature, what are the best potential accuracy levels of the likely input data sets?

10. Are the error levels of the potential input data sets sufficient to attain the desired accuracy level? YES / NO

If the answers to questions 7 or 10 are NO, then remote sensing change detection is inappropriate for the monitoring objective and alternative monitoring approaches should be considered.

Step 3: Temporal Frequency

11. What are the base date(s) and/or time frame(s) from which changes will be detected?

12. Does the monitoring require within-year monitoring (high temporal frequency) or between-year monitoring?

If the answer to 12 is “within-year,” go to 13. Else, go to 15.

13. If within-year monitoring is required, is the monitoring required every year?

14. If within-year monitoring is required and considering the answer to Question 13, do suitable data sets (identified in Step 2) exist for within-year monitoring?

If the answer to this question is NO, then remote sensing change detection is likely unsuitable for the monitoring objective. If the answer is YES, then proceed to Step 4.

15. What is the required temporal frequency of future monitoring for annual or multi-year (e.g., 5-year, 10-year) monitoring?

16. Considering the answer to question 15, what data sets exist (identified in Step 2) for monitoring?

If NO data sets exist, then remote sensing change detection is likely unsuitable for the monitoring objective. If data sets exist, then proceed to question 17.

17. Are retrospective analyses required? If the answer is NO, then go to Step 4.

18. Are the data sets required for retrospective analyses compatible with the current data sets?

If the answer to 18 is NO, then go to question 19. Otherwise, retrospective analyses are possible and proceed to Step 4.

19. If the answer to Question 18 is NO, do metadata exist to facilitate cross-walking between data sets?

If the answer to 19 is NO, then the monitoring can only be implemented from the base year forward into the future. Otherwise, limited retrospective analyses are possible and proceed to Step 4.

Step 4: Type of Change

20. Are the changes to be detected (a) between-class changes (conversion from one land-use/land-cover type to another) or (b) within-class changes (transformation in condition of a type)?

If the answer to 20 is (a), then a post-classification change detection will be used (go to 22). If the answer is (b), then a spectral (continuous) change detection will be employed (go to 21).

21. For spectral change detections, do the selected data types facilitate quantitative analysis of either the spectral data or some derivative of the spectral data? The answer is YES if the data have well characterized radiometric values or values can be derived that relate to specific

physical quantities (e.g., reflectance, leaf area index, fractional cover). The answer is NO if such quantities cannot be derived, and post-classification change detection is the only suitable option for the data type.

22. Will ground/field data or other ancillary information be available to both interpret the initial analyses and validate the final change detection (these two data sets must be either independent or split from the same data set)? Ground data may include field samples or plot information, whereas ancillary data may include photographs, alternative imagery, or other documentation that can be georeferenced and archived. If the answer is yes, then the change detection can proceed to STEP 5. If the answer is NO, then validation of the results is not possible and the change detection study will be of little formal utility (although it still may be informative in identifying potential areas of change for further study). Note that some ancillary or ground information must be available for both the “from” and “to” dates.

Step 5: Assessing Likely Sources of Error

23. Will different image data sources likely be used for the monitoring through time? YES / NO

If the answer is YES, then go to 24. Else go to Step 6.

24. Do the grain sizes of the imagery vary across monitoring dates? YES / NO

If the grain sizes match (answer NO), then go to 25. If YES, then go to 24.

25. If the grain sizes are mismatched, do methods exist to aggregate the finer resolution data to the grain size of the coarse resolution data? If YES, then go to 26. Otherwise, the data sources are fundamentally mismatched, and the change detection study may need to be redesigned to make use of more compatible data.

26. Are the spectral characteristics of the images comparable/consistent through time? YES / NO

For spectral change classifications, ask the following to determine the answer:

- Are the radiometric values of the imagery on an equivalent scale?
- Do the radiometric values measure the same quantity?
- Were the derived indices or continuous values computed similarly or from similar base data?
- Is the signal-to-noise ratio of both the “from” and “to” data sets sufficient to detect actual changes rather than changes due noise inherent in the data?

For post-classification change detections, ask the following to determine the answer :

- Were the class maps generated consistently and with the same classes?
- If not, can the classes be aggregated hierarchically to produce consistent classifications?
- If not, can the classes be cross-walked to produce consistent classifications?
- If not, are ancillary data available to re-construct one of the input classifications to match the second?

If the answers to these questions result in a final answer of NO for Question 26, then a remote sensing change detection will not provide results of sufficient confidence for a landscape monitoring program.

Step 6: Assessing Extent, Cost and Utility

27. What is the spatial extent of the study?

28. Are the selected data sources available to cover the necessary extent?

If the answer to this NO, then the study must be abandoned or re-designed so that the appropriate spatial extent can be characterized.

29. Are the data suitably complete to conduct the study? (For example, is there significant striping or other anomalies in the data that are problematic? Does topographic shading or clouds obscure areas of interest?)

30. Are necessary ancillary data sets available for the processing and interpretation of the imagery (e.g., digital elevation models for orthorectification or topographic normalization)?

31. What is the cost of data to cover the desired extent?

32. What is the cost of software, hardware and personnel to implement the change detection?

33. Are the costs in 31 and 32 within the budget of monitoring program?

If the answer to this question is NO, then the study must be abandoned or re-designed to be less ambitious in its scope.

34. Whether the cost is reasonable or unreasonable, do alternative existing data sets or interpretations exist to substitute for the proposed monitoring (i.e., has the study, a portion of it, or something like it already been conducted)?

If the answer to this is YES, then the landscape manager must consider whether using existing monitoring or change detection studies will be sufficient and reduce the analytical load associated with implementing a new change detection program using remote sensing.

35. List the characteristics of potential remote sensing data sets that still remain for conducting a change detection monitoring study.

Step 7: Comparing All Potential Data Sets

The answers from Steps 2–6 for all attributes of interest and from all potential data types should be collected. For many organisms or resources, remote sensing change detection may have been identified as inappropriate or too expensive to implement. For those that have reached Question 35 with acceptable data sets still available, compare the answer to 35 to determine whether multiple organisms/resources can be monitored coincidentally. At this point, the resource manager must determine which monitoring objectives are most critical to their needs, and whether intensive or extensive analyses are required.

Step 8: Final Image Selection Considerations

It is assumed that imagery at one of four resolutions (4, 10, 15 or 30m pixel sizes) will be most appropriate for monitoring NCRN parks. At the finest resolution, data from two sensors are available, IKONOS and Quickbird. Multispectral data (i.e., image bands in blue, green, red and near infrared) are available at 4.0 and 3.6 m resolutions respectively. Each of these sensors also provide panchromatic data at 1 or 0.6 m resolutions respectively, but panchromatic data are generally inferior to multispectral data for land cover mapping. 10m multispectral data are available from SPOT, whereas 15m panchromatic and 30 m multispectral data are available from Landsat. The 15m dataset used for the pilot studies involved “pan-sharpened” multispectral data from Landsat, in which the 30 m and 15m data were merged to take advantage of the spatial resolution of the 15m data and the spectral quality of the 30m data. Generally, Landsat imagery has the best spectral quality of the data sets listed, but because of the failure of the scan-line corrector on Landsat 7 in May of 2003, complete coverage within a Landsat 7 scene is no longer reliable. Until a replacement for Landsat 7 is launched, SPOT data represent the most reliable imagery available for mapping at moderate to fine scales. Note that very high-resolution satellite data (such as from Quickbird or Ikonos) are expensive, cover relatively small areas, and are more susceptible to effects of geometry (localized shadows and spatial distortion). For parks with significant geographic extent, such data are both impractical and expensive to use. If high-resolution data are needed for a particular application for a large area (see checklist above), then it is recommended that digital aerial photography be acquired. This protocol does not address the processing of digital aerial photography acquired on a one-time basis.

Land cover mapping is best accomplished using multi-seasonal image data sets to maximize cover discrimination based on phenological attributes (Townsend and Walsh 2001). Ideally, data from four images would be merged for mapping, including some combination of the following conditions:

- Full leaf-on (late spring or summer): June/July in the NCR
- Leaf-off (winter or very early spring): March in the NCR
- Green-up (early- to mid-spring): April or early May in NCR
- Senescence (late summer or early fall): October in NCR

The top priority should be one leaf-on and one leaf-off image. However, with more expensive data (IKONOS, Quickbird, SPOT), often only one image is available or affordable, in which case the available image(s) should be previewed to determine their appropriateness for mapping.

Reference Documents

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SOP 2: Preparation of Remotely Sensed Imagery for Land Cover Mapping and Landscape Analysis

Introduction

This Standard Operating Procedure (SOP) describes steps that can be taken to process raw remote sensing imagery to a format that can be used for land cover mapping and later, landscape pattern analysis. An image processing software package is used to perform the processing.

Procedures for deriving and interpreting land cover maps are provided in SOP 3. The outputs of that protocol are maps of Anderson Level II (Anderson et al. 1976) land cover classes. This classification scheme is consistent with the I&M NPScape landscape monitoring being conducted at the national level. For pattern analysis in later SOPs, the derived maps will be reclassified into binary habitat and non-habitat classes and clipped to different buffering widths around the parks (SOP 4).

The assessment of landscape pattern is affected by the map extent (area) used for mapping. This concern is addressed explicitly in SOP 4 and is also discussed in SOP 1. It is important that imagery be acquired that encompass the entire study area of concern, which may be just the park, or may be the park plus some surrounding area that is hypothesized to be important to resources within the park (see SOP 4). It may be the case that the area of interest is considerably larger than the area of the imagery that is available for mapping. In that case, the analysis may have to acquire multiple images to map land cover changes for the park. This is certainly the case for parks such as the C&O Canal National Historical Park, which extends 184.5 miles from Georgetown to Cumberland, MD. When this occurs, it is usually best to map land cover for each individual image, *unless* those images were acquired on the same date and under the same general environmental conditions, in which case image merges are appropriate.

An alternative approach is to merge data sets. An accurate classification can be developed for the park and its immediate environs, and existing classifications can be used to characterize the larger area around the park. Such an approach could use the National Land Cover Data maps (NLCD, <http://landcover.usgs.gov/prodescription.asp>), which are produced from 30m Landsat data using a modified Anderson classification (see SOP 3). Because of the broad scale of its development, the NLCD is designed to be accurate regionally, although its accuracy in a single locality may be low. For this reason, the NLCD is not appropriate for intensive local analyses. A new NLCD will be developed at approximately 10-year intervals. The 1992 and 2001 NLCD classification are now widely available (Vogelman et al. 2001; Homer et al. 2004).

Any analyses that use the NLCD classifications will have to assure class compatibility.

Procedures

Image Pre-processing Recommendations

Image pre-processing is accomplished in a digital image processing (IP) software package that will be dependent on the preferences of the person or organization conducting the work. Common packages include ERDAS Imagine, ENVI, and PCIWorks. The following instructions are provided independent of software package, as the operations listed below can be completed in most IP software packages.

Read Imagery from Native Format

The remotely sensed data will be provided on some media, (e.g., CD, DVD, internet file transfer, tape) and likely in a format that is not native to the available IP software. Use the IP software's import utilities to convert the data provider's format to one that is usable by your IP software.

Radiometric Calibration

This step is not necessary if the only task is the development of a land cover classification, but is necessary if image-to-image comparisons will be applied.

The numeric range of pixel values in imagery from the data provider is normally scaled to reduce the image file size. The intensity of each pixel is represented by a digital number (DN) in a range that will allow the data to fit more easily onto media for delivery to the end-user. Using vendor-supplied scaling coefficients the DN image can be scaled to at-sensor radiance and/or at-sensor reflectance. An example of this is provided in Appendix A.

Image Rectification

Satellite data vendors provide images at various levels of spatial accuracy. If an image does not have high spatial accuracy or is not registered to a coordinate system you will need to follow the guidelines below to spatially register and rectify your image. *Orthorectification* (i.e., a model that takes into account the shape of the Earth's surface and the sensor's geometry relative to it) is the preferred method for georeferencing all images in this study.

For the spatial extent of NCRN parks, the recommended projection is Universal Transverse Mercator (UTM) projection (Zone 18), with the WGS 84 spheroid and datum, in units of meters. All imagery for an individual park should be rectified to a common base data set that has high reported levels of spatial accuracy. For this work, we have used as a standard the Global Land Cover Facility's Landsat GeoCover product (<http://glcf.umiacs.umd.edu/portal/geocover/>). This base image should be supplemented with roads coverages (such as from USGS digital line graphs, USGS digital raster graphics of 7.5 minute topographic maps, or TIGER coverages) to identify fine features not apparent in the base Landsat data. Additional data sources, such as rectified finer resolution imagery from IKONOS or USGS digital orthophoto quadrangles may be used, but the spatial accuracy of these coverages may not always be well documented. Before using any data set to aid in georeferencing, the lineage of that data set must be evaluated. In addition, a digital elevation model (DEM) that completely covers the image being rectified must also be specified. As a default, the 30m National Elevation Dataset (NED) should be used, as it has high published standards of accuracy. For many parks, a 10m or finer DEM may be available and can be used for higher resolution data only. The following should be reported for all orthorectification activities:

- Number of ground control points (GCPs, recommended: 25 per image, well distributed throughout the image extent)
- Model formulation (sensor specific ortho model, if possible)
- Root mean square error (RMSE) of orthorectification (should be less than 0.5 pixel total, less than 0.5 pixel in both X and Y dimensions; should target overall error of less than 0.3 pixels in each dimension)

- Resampling method (nearest neighbor is recommended as this preserves image spectral fidelity: see He et al. 2002 for a general discussion of resampling methods and Gardner et al. 2008 for an application comparing methods for NCR parks)
- Base image and target image GCPs should be saved in separate ASCII text files so that the rectification model can be reconstructed at a later date if needed.

For more information on image rectification see the Erdas Field Guide (Leica Geosystems 2002) or the Erdas Technical Support Article titled Image Rectification found in Appendix B.

Spatial Accuracy Assessment

The spatial accuracy of the georeferenced (i.e., orthorectified) image should be assessed. The image should be assessed at a minimum of 25 points that are well distributed throughout the newly corrected image. This is often done through visual inspection, but can be accomplished formally by measuring the offset between the corrected image and the base image at known points (e.g., road intersections). The results of this assessment should be documented in a narrative if performed visually or a table if done quantitatively. The offset between images should be less than one-third the pixel size if image-to-image or map-to-map comparisons are to be implemented.

Image-to-Image Normalization

If direct image-to-image comparisons are to be implemented (either Landsat or SPOT), then the images must be normalized to each other to account for differences in atmospheric conditions between dates.

A host of physically-based methods have been developed to do this, but Collins and Woodcock (1995) indicated that for most applications, the simplest correction is usually the best. The method suggested is called pseudo-invariant reflector normalization, and involves selecting invariant bright and dark areas in the overlapping images. For this purpose, one image is established as the base image, the other becomes the target. Pixel intensity values from these coincident areas in both the base and target images are extracted and regressed against one-another on a band-by-band basis. The regression coefficients are then used to recalculate reflectance from the target image into the data range of the base image.

Specifically, five areas each of bright and dark stable reflectors should be co-located on each image (minimum 100 pixels total). Typical bright areas include quarries, gravel or sand. Agricultural areas should not be used. Water bodies (lakes and reservoirs, not rivers) are used for dark objects. Image reflectance data for these areas are exported into a statistical software. For each image band a regression relationship is developed such that $R_b[\text{target}] = f(R_b[\text{base}])$, where R = reflectance and b = band number. The slope and intercept coefficients are then applied uniformly to the target image to normalize it to the base image. The coefficient of determination (R^2) for normalization usually well exceeds 0.9, but an $R^2 > 0.8$ is considered sufficient.

Topographic Normalization

In areas of high relief, topographic normalization is sometimes required to correct for differential terrain shadowing and illumination. This differential illumination is caused by low incident sun angle at the time of image acquisition (e.g., November to March in the northern hemisphere) and/or high terrain features (e.g., in mountainous areas). The result is that sunward slopes are

artificially brightened, and slopes facing away from the sun are shaded. This can affect map classification, making forested pixels darker, for example, and leading to confusion between evergreen and deciduous forests, or between deeply shaded forests and water.

Topographic normalization adds an additional level of complexity to the processing and is covered in more detail in Appendix C. Generally, for the NCR parks topographic normalization should not be necessary. Topographic illumination may only be an issue in Catoctin Mountain Park and the C&O Canal National Historical Park. Topographic illumination can be normalized using the routines provided by the IP software, or by following the methods of Meyer et al. (1993).

Derivative Image Products

Combinations of image bands yield derivative images that can add information and enhance the ability to discriminate among land cover classes. These band combinations can also result in data reduction that may be needed for some of the change detection methods described in SOP 8. These methods are very well developed in the literature, and are generally referred to under the category of data enhancement. Not all data enhancements will necessarily be used, but they can all be evaluated during the process of classification. We recommend the following three enhancements:

Vegetation Index

The most widely used vegetation index is the Normalized Difference Vegetation Index (NDVI) and is computed as:

$$\text{NDVI} = (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED}), \text{ where}$$

NIR = near infrared band reflectance and RED = red band reflectance. High values of NDVI indicate high vegetation greenness based on the principal that healthy vegetation reflects strongly in the near infrared and absorbs strongly in the red. Because NDVI is very sensitive to soil brightness, we instead recommend use of the Soil-Adjusted Vegetation Index (SAVI), calculated as:

$$\text{SAVI} = (1 + L) (\text{NIR} - \text{RED}) / (\text{NIR} + \text{RED} + L)$$

SAVI includes a correction factor (L, usually set to 0.5 based on empirical studies) that reduced background influence on vegetation greenness measures.

Tasseled Cap Transformation

For Landsat imagery, the calculation of the Tasseled Cap index (Crist and Kauth 1986) is automated in most image processing packages. This data transformation is based on empirical relationships among Landsat bands that yield three output layers, Brightness (surface brightness), Greenness (vegetation greenness) and Wetness (surface darkness). These derivative bands have been found to convey much of the meaningful information content in the six Landsat multispectral bands. Coefficients for computing Brightness, Greenness and Wetness for Landsat 7 ETM+ images are published by Huang et al. (2000). Appendix D contains coefficients for some types of multispectral imagery. Others may be found in the literature.

Principal Components Analysis (PCA)

PCA on image data sets (e.g., six bands) has been demonstrated to reduce noise and distill image data into fewer bands (e.g., from 6 to 3) that convey the majority of the covariation among bands within image datasets. PCA should be implemented on the multispectral image, with the output data scaled to the range of the original layers (e.g., for Landsat, 8-bit, 0–255). PCA layers that cumulatively contain up to 95% of the variation in the original multispectral image data should be retained.

Once appropriate derivative image layers have been created they should be combined into a single data stack. The functions and algorithms described in the classification protocol (SOP 3) will be completed using this data stack. Any combination of layers can be used during classification, including original image bands. The selection of these layers should be left to the discretion of the RSLP specialist.

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SOP 3: Classification of Remotely Sensed Imagery into Land Cover Maps

Introduction

This Standard Operating Procedures (SOP) describes the steps to be followed to classify remote sensing imagery into land cover maps that can be used for landscape pattern analysis. An image processing (IP) software package is used to perform the work.

Once image data are prepared for analysis (SOP 2), classification of imagery is conducted within the IP software. Numerous software packages and classification algorithms exist that may be used to accurately classify satellite imagery into land cover maps. No single method is necessarily more correct than any other, and RSLP (remote sensing – landscape pattern) specialists should have the freedom to select the method that is most appropriate to a particular application. It is important that a single method not be set in stone because classification methods are constantly being revised. Below, a two-step method for classification is outlined based on the two most commonly used algorithms (ISODATA and Maximum Likelihood) that have long histories of providing robust results. More advanced methods such as Decision Tree and Support Vector machine classifiers (Friedl and Broder 1997; Brown de Colstoun et al. 2003) may also be explored at the discretion of the RSLP specialist. This SOP also includes information on map validation. The SOP provides information on fuzzy accuracy assessment (Townsend 2000), though these procedures are not required for this protocol.

Procedures

Data Preparation

A data stack of the corrected imagery and derivative image layers should be prepared for use in the classification scheme. This stack might include data from all bands of the imagery (and all dates if multi-date imagery is used), as well as derivatives described in SOP 2, such as the soil-adjusted vegetation index (SAVI, Huete 1988), the Tasseled Cap Index of Brightness, Greenness, and Wetness (Crist and Kauth 1986), and PCA layers. It may not be necessary to use all layers in the final image classification, but most software packages allow the user to specify the bands to be used during the classification processing.

Step 1: Establish Classification Scheme

The recommended classification scheme for NCR parks is Anderson Level II (Anderson et al. 1976). This classification scheme is presented in modified form below (Table 3-1), although it is recommended that the final classification conform to Anderson Level II classes. The additional classes are offered because they are included in the National Land Cover Database (NLCD, Vogelmann et al. 2001), which is being used nationally with the NPScape landscape monitoring program. It is recommended that all training/evaluation data be collected using the additional classes, which can be aggregated to the Anderson Level II during mapping.

Table 3-1. Anderson Level I (single digit) and Level II (double digit) classes. Classes with letters are supplemented from NLCD.

1. Urban or Built Up Land	4. Forest
11. Residential	41. Deciduous Forest
11A. High Intensity Residential	42. Evergreen Forest
11B. Low Intensity Residential	43. Mixed Forest
12. Commercial	5. Water
13. Industrial	51. Streams/canals
14. Transportation, Comm, Util	52. Lakes
15. Indust/Commercial Complexes	53. Reservoirs
16. Mixed Urban or Built-up Land	54. Bays/estuaries
17. Other Urban or Built-up Land	6. Wetland
17A. Urban/Recr'l Grasses	61. Forested (woody) wetland
2. Agricultural Land	62. Nonforest (herbaceous) wetland
21. Cropland & Pasture	7. Barren Land
21A. Crops	72. Beaches
21B. Pasture	73. Other sand
21C. Fallow	74. Bare exposed rock
22. Orchards, Vineyards, etc.	75. Strip mines/quarries/gravel pits
23. Confined Feeding Operations	76. Transitional areas
24. Other Agriculture	77. Mixed barren lands
3. Rangeland	
31. Herbaceous Rangeland	
32. Shrub/Brush	
33. Mixed Rangeland	

Step 2: ISODATA

ISODATA is an unsupervised classification scheme (no *a priori* information on land cover type is used) that groups image information into classes (called clusters) that are spectrally uniform and unique. In application, more ISODATA clusters must be specified than Anderson Level II classes to be mapped. Thus, most Anderson classes will be represented by several ISODATA clusters, which can be aggregated at a later stage. This approach is necessary to correctly classify agricultural areas that may include multiple spectrally unique clusters representing different crop types. ISODATA should be run specifying 70 classes with a 98% convergence threshold and a maximum of 25 iterations. If ISODATA cannot conclude the clustering, the convergence threshold can be lowered to 95%. If the 70-class ISODATA is later determined to be inadequate, it can be run with more classes. However, for small study areas, larger numbers of clusters will create small, uninterpretable classes.

Step 3: Interpreting ISODATA Clusters

Ancillary information is required to identify most land cover classes associated with each ISODATA cluster. Some classes are obvious (e.g. water) and can be interpreted from the base imagery. However, identification of other classes will likely require the use of ancillary information such as aerial photographs, additional satellite images, or field observations. The necessity for a field visit will depend on the quality of the available ancillary data and the specialist's familiarity with the field site. Each of the 70 clusters should be displayed on screen

within the IP software in a unique color to label that cluster. Only those classes that can be labeled unambiguously should be labeled.

Step 4: Assessing Class Separability

Once the ISODATA classes have been labeled, the class information should be input into the IP software package's signature editor, and spectral signatures should be developed for all of the labeled (not aggregated classes) using the base image stack. If any classes known to occur on the ground have not been mapped adequately, areas of interest (AOIs) for those classes should be delineated on the image stack and also entered into the signature editor as additional training areas. The transformed divergence separability statistic should be calculated on the signatures for the ISODATA clusters and additional training areas. All signatures/clusters that have been labeled as the same class and are statistically inseparable should be merged. Signatures for the same class that are spectrally separable should be retained (and then aggregated after the classification has been completed). Confused classes (different classes that are spectrally inseparable) should be eliminated if other spectral signatures are available for those classes. Otherwise, those signatures can be enhanced with additional training signatures (from AOIs) or retained with the knowledge that those classes may have higher errors due to spectral confusion.

Once a final set of signatures has been derived, the feature set (number of input bands) may be reduced by computing separability statistics and specifying that the software package identify the best 4, 5, 6 and up to 8 bands for distinguishing those classes. A fewer number of bands leads to more efficient mapping and lower noise levels in the output maps. A feature subset should be selected that still retains separability among the Anderson Level II classes.

Step 5: Supervised Classification

We recommend a hybrid approach called "guided clustering" which uses the unsupervised classification (ISODATA) to identify satellite data that can distinguish the cover classes of interest, and then uses a supervised classifier (Maximum Likelihood) to map the classes based on signatures derived from the unsupervised step (Bauer et al. 1994). The spectral signatures from the unsupervised classification can be used directly as *a priori* probabilities in a Maximum Likelihood Classification (MLC) to derive maps from the image data stack. Alternatively, a non-parametric Parallelepiped approach can be implemented, using MLC to classify ties or those pixels outside the spectral space identified by the parallelepiped algorithm. The nonparametric parallelepiped method is recommended because of its fast computation and flexible definition of spectral feature space.

Step 6: Class Aggregation

The map produced from Step 5 will still have multiple clusters per land cover class. These should be aggregated to one class per cover type using a class merge function within the IP software. All intermediate data sets and signature files should be retained and archived.

Step 7: Map Validation

A stratified random sample of validation points should be derived for the final aggregated classification. The rule-of-thumb in image processing is that a validation requires approximately 50 validation points per land cover class (Congalton 1991), so a classification with 10 classes should have on the order of 500 validation points, distributed proportionally among the classes. Large maps or maps with more than 12 classes should have larger validation data sets (perhaps

75–100 samples per class), with fewer samples needed in classes exhibiting low variability (e.g., water) (Jensen 1996). The total number of validation points can be lowered if a significant number of classes are very limited in spatial extent. For parks in the NCRN (which are small), it may be reasonable to have as few as 25–30 validation points for many classes. If accessibility to validation points is an issue, a larger number of points than is needed can be generated, with those in inaccessible areas deleted from the analysis.

Table 3-2. Classes used in fuzzy sets evaluation of land cover maps (after Gopal and Woodcock 1994)
Fuzzy

Set	Answer	Description
1	Absolutely Wrong	The answer is unambiguously unacceptable; very wrong
2	Understandable but Wrong	Not a good answer. There is something about the site that makes the answer understandable, but there is clearly a better answer; this answer would pose a problem for the user of the map; not right.
3	Reasonable or Acceptable Answer	Maybe not the best possible answer but it is acceptable; this answer does not pose a problem to the user if it is seen on the map; right.
4	Good Answer	Would be happy to find this answer given on the map; this happens often when two classes are equally right; very right.
5	Absolutely Right	No doubt about the match; perfect

Map validation can be accomplished using ancillary data, such as a secondary map, image or aerial photograph, or using field data. High resolution imagery such as digital orthophotoquads from Google Earth can be valuable in minimizing the expenses of field validation. An example of how to extract map classes for accuracy assessment in Erdas Imagine 8.7 is included in Appendix A. All validation points should be evaluated as follows.

During the evaluation process, the analyst should note both the appropriate Anderson Level II class as well as the supplementary class (Table 3-1). Evaluation to Anderson Level II is required, but the supplemental data should be retained in case it is needed later.

The analyst will record the map class (produced from the image classification) and the reference class (actual land cover type on the ground). The analyst will then evaluate all possible Anderson Level II classes for the reference location and record the “fuzzy membership” for the reference point to each class (Table 3-2). Fuzzy membership recognizes that many locations on the ground may reasonably be classified to multiple land cover classes, with none of the classes being strictly wrong, but some more correct than others (Gopal and Woodcock 1994). For example, an evergreen forest stand mapped as water is clearly wrong (accuracy level 1 on Table 3-2), but a forest stand that is 75% deciduous and 25% evergreen may reasonably be mapped as either deciduous or mixed, with mixed being more correct (accuracy level 4) than deciduous (accuracy level 3) or evergreen (accuracy level 2). Accuracy levels should also be assessed at Anderson Level I.

A sample validation data sheet is provided in Figure 3-1. This sample sheet is filled out for the two forest examples provided above. Townsend et al. (2009) provide example map accuracy statistics for different types of imagery covering four of the NCR parks.

Details on the fuzzy set evaluation can be found in Gopal and Woodcock (1994). Accuracy data should be presented in the form of a confusion matrix (Table 3-3) and accuracy assessment tables (Table 3-4). The validation data should be used to compute the following validation metrics.

Class Accuracy is computed on a class-by-class basis as:

- Producer's accuracy: percent of the reference data mapped to a specific class that match the correct cover type on the map (a measure of errors of omission)
- User's accuracy: percent of the map observations on the map that match the correct reference observations (a measure of errors of commission)

Traditional map accuracy is computed as:

- Map producer's accuracy (all classes)
- Map user's accuracy (all classes)
- Map accuracy (percent of all observations that are mapped accurately)
- Kappa statistic (improvement in accuracy of the map taking into consideration the probability of chance agreement). Calculation of the Kappa statistic is covered in most general image processing textbooks, with brief details below.

Table 3-3. Example confusion matrix for a simplified classification. Diagonal indicates correct observations. In this case overall map accuracy is 70/96 (70 = sum of diagonals; 96 = total number of validation points) or 72.9%.

Image Map Class	Reference Class					Total
	Ag	DF	EF	MF	W	
Agriculture	23	0	0	0	0	23
Deciduous Forest	0	12	2	5	0	19
Evergreen Forest	0	1	18	1	0	20
Mixed Forest	0	10	5	6	0	21
Water	0	0	2	0	11	13
Total	23	23	27	12	11	96

Table 3-4. Producer's (errors of omission) and User's accuracy for the confusion matrix shown in Table 3-3. Producer's accuracy represents the proportion of reference data (i.e. validation points assessed using ancillary data) where the map class matched the reference class. It is a measure of how well the mapmaker matched reality. User's accuracy indicates the proportion of map locations that match the correct reference type, i.e., the percentage of the time that a user of the map would find him or herself located in the cover type indicated on the map.

Level I Class	Correct	Reference Total	Map Total	Producer's Accuracy	User's Accuracy
Agriculture	23	23	23	100.0%	100.0%
Deciduous Forest	12	23	19	52.2%	63.2%

Evergreen Forest	18	27	20	66.7%	90.0%
Mixed Forest	6	12	21	50.0%	28.6%
Water	11	11	13	100.0%	84.6%
Total	70	96	96		

For pattern analyses and other applications, aggregations of the Anderson Level II classification may be used. Accuracy should be recomputed for each aggregated classification. For example, if a particular application requires the mapping of forest (but not deciduous, evergreen or mixed), the Producer's and User's accuracies shown in Table 3-4 would improve, as is shown in Table 3-5.

Table 3-5. Revised accuracy levels for Table 3-4 when forest classes are aggregated. This map has a total accuracy of 94/96, or 97.9%.

Aggregated Class	Correct	Reference	Map	Producer's	User's
Agriculture	23	23	23	100.00%	100.00%
Forest	60	62	60	96.77%	100.00%
Water	11	11	13	100.00%	84.62%
Total	94	96	96		

The Kappa statistic is calculated from the confusion matrix (Table 3-3) as:

$$kappa = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \times x_{+i})}$$

Where N = number of validation observations, $\sum x_{ii}$ = the number of correct observations for all r classes (i.e., the sum of the diagonals), and $\sum (x_{i+} \times x_{+i})$ = the number of chance correct observations for all r classes (i.e., the row total times the column total per class).

For Table 3-3, Kappa (called K-hat) = 0.659, which indicates that the map has an accuracy level that significantly improves upon a random map by 65.9%. For Table 3-5, K-hat = 0.96.

Fuzzy accuracy is computed on a class-by-class basis by several metrics. The most useful is the difference operator, computed for each validation point as the difference in fuzzy class assessment for the reference class minus that of the best (or next best) class. This is then averaged by class. Higher positive values indicate distinct classes, low positive values indicate significant fuzziness among classes (but an accurate classification nevertheless), whereas negative values indicate a confused class. Detailed examples of the computation of fuzzy accuracy are provided in Gopal and Woodcock (1994), Townsend (2000) and Townsend and Walsh (2001). Fuzzy accuracy assessment is not required for this protocol. However, to maintain complete compatibility with classifications that are generated and evaluated using fuzzy class assessment, it is strongly recommended that validation data be collected that is consistent with fuzzy evaluation practices (Table 3-2).

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SOP 4: Creation of Maps for Pattern Analysis

Introduction

This section describes the steps to be followed to subset (clip) land cover maps (developed in Standard Operating Procedure [SOP] #2) to the appropriate extent for use in pattern analyses. A Geographic Information System (GIS) software package is used to perform the processing. Appendix A provides an example analysis for Antietam National Battlefield (ANTI) using Arc/Info commands.

Map extent significantly impacts the derivation of landscape metrics from land cover maps (Saura and Martinez-Millan 2001). For example, *p* (proportion of the landscape in a particular land cover class) of forest for Rock Creek Park may be very high for areas within the park itself, but considerably lower for an area defined by a rectangular box around the park. However, land cover adjacent to the park may be important to habitat considerations within the park (Lookingbill et al. 2007). Landscape monitoring must anticipate considerations of spatial context (i.e., map extent) or risk not capturing landscape dynamics outside the boundaries of a preserve that may be drivers of processes within the park (e.g. exogenous fragmentation reducing habitat for interior birds). The establishment of map extent is not standardized in the protocol but should be assessed based on the question being asked of the land cover map (SOP 1). The results of a pilot study examining the affect of varying buffer shape and size for four NCR parks are provided in Townsend et al. (2009).

Procedures

A variety of approaches exist to define map extent, ranging from the extent of the image purchased from the vendor to the administrative boundaries of a managed area, to the boundaries plus some buffer. It is generally recognized that the unit of study for monitoring parks should include a greater ecosystem representing a more ecologically relevant delineation of the park and its surroundings (Hansen and Defries 2007). We recommend considering at least four methods for delineating map extent: (1) Park boundaries, (2) watershed boundaries, (3) uniform buffers, and (4) intersecting patches.

Preliminary data concerns

All coverages, shapefiles and grids must be in a common coordinate system. For the NCR project, we use UTM, zone 18, units meters, datum WGS84, spheroid WGS84. The process will work using any projection, but all coverages or grids must be in the same projection. If needed, convert shapefiles to built and cleaned polygon coverages.

Required data

In areas like the NCR, fragmentation of forest habitat for interior birds and other species that are dependent on contiguous forests is of primary concern to resource managers. Therefore, the pattern analysis methods (SOPs 5-8) described in this protocol are for binary maps of habitat (forest land) and nonhabitat (everything else). The Anderson Level II land cover classification produced from SOP 2 was subsequently merged to two classes (nonhabitat = 1, habitat = 2). Background areas are classified as nodata.

Other inventory and monitoring efforts in the parks address forest vegetation at a finer level of classification (e.g., NPS Vegetation Mapping Program and NCR Forest Vegetation Monitoring).

It is also reasonable to expect that not all landscape monitoring objectives identified in SOP 1 will relate to forest resources (e.g., it may be desirable to map grasslands as “habitat”). The methods and procedures outlined in this protocol for forest habitat will work for other classification schemes as well.

Additional GIS data required for SOP:

- Watershed boundaries (polygon) WSHED
- Park boundary (polygon) PARKBND

Buffers

The first is to use the park boundary, in which only resources within that protected area are evaluated. This approach is not useful for monitoring the effects of fragmentation adjacent to that area, but is worthwhile for evaluating habitat within the park.

4. The second analysis extent is that of watershed boundaries, which are increasingly being used to identify the landscape areas that affect aquatic resources within protected areas (Pringle 2000). Watershed boundaries can be readily delineated from digital elevation models. For this SOP, we use boundaries for watersheds draining into the park, but not for larger watersheds whose streams pass entirely through the parks

The third approach uses a uniform area buffer around each park, whereby the width of the buffer is calculated individually for each park as the distance at which a park’s area is increased by a certain expansion factor. For example, a “5X buffer” is defined as map extent which increased the effective area of the park by five times. This method varies buffer distances as a function of park size, with larger parks having wider buffers and smaller areas having narrower buffers. The expansion factor could be varied depending on the resource of interest (based on SOP 1), but the basic principal is to establish a buffer area that is related to the amount of habitat outside a park that might be available for use by biota within the park (e.g., foraging, feeding, migration, nesting and reproduction). For NCR parks, the “5X buffer” approach yielded buffer widths of 2088 m for Antietam, 2761 m for Catoctin, 415 m for Rock Creek and 3942 m for Prince William (Townsend et al. 2009).

Arbitrary buffer widths have the potential to split habitat patches that intersect the buffer boundary. The truncation of patches will affect associated fragmentation metrics by reducing the importance of habitat patches that cross administrative or buffer boundaries. Therefore, the fourth map extent definition is the “intersecting habitat patches” (IHP) buffer, in which the pattern metrics are calculated for an extent defined by all habitat patches that intersect the a given boundary (e.g., 5X buffer). This IHP method yields different analytical extents for different parks and different types of landscapes (see Townsend et al. 2009). However, the IHP approach is probably necessary in landscapes of highly mixed land cover or extensive fragmentation and reflects the reality that species moving within patches rarely respect boundary lines not demarked by fences, roads or other potential obstacles. For example, the importance of map extent is critical for Antietam, where the 5X buffer adds an extensive area of forest to the analysis window, and IHP connects the Antietam landscape to a much larger forested area along a nearby ridge.

Important considerations

A primary theme of this protocol is the determination of the area (or extent) for which an analysis will be undertaken. We ask the question, *what constitutes the boundary of interest?* The simplest case is that we analyze only habitat within park boundaries. However, there are many cases, especially for parks in NCRN, in which even the determination of the relevant park boundary may not be straightforward. A case in point is Rock Creek Park, which has both in-holdings (non-park areas completely within park boundaries) and out-holdings (small patches of park not connected directly to the park).

For this protocol, we have addressed the issues of in-holdings and out-holdings as follows. Unless otherwise stated, in-holdings are considered in effect part of the park. If needed, these areas can be excluded from analyses by use of a simple mask. However, because in-holdings are completely surrounded by park, we considered their inclusion as park a more realistic representation of the effective park landscape. Out-holdings are also considered part of the park. When delineating buffers around parks, the importance of these out-holdings may be enhanced relative to the main body of the park because the buffer area-to-parcel area ratio is considerably higher for an out-holding than the primary park area. Small out-holding may therefore disproportionately impact connectivity between the park and the larger surrounding landscape.

A key issue when generating a land cover map from remotely sensed data is the selection of the minimum mapping unit to be employed, which determines the extent of detail contained in the map (Loveland et al. 1999; Saura 2002). Although we do not explicitly address filtering in the protocols (other than in SOP 6), any parcels whose area is less than the size of one pixel (grain resolution) will be dropped in the conversion from vector covers to raster grids.

As presented here, the habitat boundaries in the maps are only those that are depicted from the image analyses (SOPs 1 and 2). For instance, where roads are not depicted (e.g., because trees overhang those roads), no boundary or barrier to movement is shown. This may be important in urban areas such as the landscape adjacent to Rock Creek Park, where large urban trees overhanging roads may in fact yield maps that show connectivity that while realistic for some species (squirrels) is not for others (box turtles). There are potential solutions to this: (1) One may use road covers to “burn” in such non-habitat barriers. The limitation to this occurs when the road size is smaller than the pixel dimension. (2) Use of coarse resolution imagery. At the grain size of 10m or 4m, single pixels may be entirely filled by trees and therefore mapped as forest. In contrast, a 30m pixel within an urban area will usually be a mix of forest and urban cover, and will therefore be mapped as such. (3) Similarly, a filter can be used to reclassify salt-and-pepper forest-urban areas to the appropriate non-habitat class. (4) The image classification (SOP 2) can be revisited. The use of multi-seasonal imagery (leaf-on and leaf-off) may facilitate the improved discrimination of forested urban areas from forest. This incurs concerns about added cost or availability of imagery from SPOT or IKONOS. Ultimately, these are decisions that should be made in conjunction with the appropriate landscape manager, and with specific hypotheses in mind about what constitutes habitat and non-habitat. As it stands, this protocol is presented in the default case, i.e. where no such modifications are required.

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SOP 5: Calculation of Landscape Pattern Metrics

Introduction

This section describes the computation of statistics and metrics used to assess land cover patterns and measure the degree of fragmentation of critical habitat(s) within the landscape.

Spatial patterns produced from the loss and fragmentation of natural habitat may adversely affect the sustainability and viability of diverse biota (Turner et al. 2001). Satellite images provide a synoptic view of spatial patterns of land cover, and have become an important tool for conservation and management. Landscape statistics and pattern metrics, which summarize changes in the amount and distribution of landscape resources provided by remote imagery, provide an early-warning of potential threats to the sustainability of these landscapes.

A diverse set of tools are now available for tracking changes in the statistics and metrics of landscape change. Fragstats (version 3.3 was available at the time this protocol was written) is recommended as a primary tool because Fragstats is widely available as a freeware product, runs under the Windows operating system, and provides a comprehensive set of methods for spatial pattern analysis (McGarigal et al. 2002). Use of Fragstats requires the user to import a landscape map, define the cover types to be analyzed (covered in earlier SOPs) and specify the metrics of interest.

Fragstats metrics include measures of the attributes of patches (defined as adjacent map units), land cover types/classes (e.g., wetland, deciduous forest, pasture, etc.), and the entire landscape. For most applications patch and/or class level statistics are most appropriate. Class-level statistics are useful for assessing overall map trends for a given cover type (e.g., forest habitat). Patch-level statistics can be used to identify specific patches on the landscape that meet desired criteria (e.g., >10 ha in area). Both types of metrics can be used to respond to specific monitoring questions as outlined in SOP1.

Some Caveats

The value of any single metric will be directly dependent on the resolution and extent (scale) of the data and the classification scheme used to define landscape cover types from remote images (Turner et al. 2001). In addition, pattern metrics are often correlated with one another (Riitters et al. 1995), therefore a parsimonious set of useful metrics should be selected to provide the most useful information for management and conservation needs and avoid Type II errors (Riitters et al. 1995; Zar 1996). We have attempted to select such metrics (Table 5-1) from the long list of those available within Fragstats.

Table 5-1. Description of recommended landscape pattern metrics.

Metric	Symbol	Units	Tab	Definition
Number of Patches	NP	<i>Unitless</i>	Area	The number of patches, defined as adjacent sites of land cover (nearest-neighbor rule).
Percent of Landscape	PLAND or %P	%	Area	The percent of area occupied by a particular land cover estimated by taking the sum of the areas (m ²) of all patches divided by the total landscape area (m ²), multiplied by 100.
Total Class Area	CA	Ha	Area	The sum of the areas (m ²) of all patches of a single land cover (class) type, divided by

Metric	Symbol	Units	Tab	Definition
				10,000 (converts to hectares). This parameter is always calculated by Fragstats.
Total Edge	TE	M	Area	The sum of all the lengths (m) of all edge segments for each class type (sum of all patch edges).
Edge Density	ED	ha	Area	The amount of edge per m ² . Estimated by dividing TE by the total landscape area (m ²), multiplied by 10,000 to convert to hectares.
Total Core Area	TCA	ha	Core area	The sum of all the core areas of each patch (m ²) of type divided by 10,000 (converts to hectares). Note: this metric requires the user to input a fixed edge depth or, alternatively, use an edge depth file (see Fragstats documentation). An edge depth of 1.0 treats all area within each patch as core area.
Largest Patch Index	LPI	%	Area	The area (m ²) of the largest patch in the landscape divided by total landscape area (m ²), multiplied by 100 (to convert to a percentage). Note, total landscape area (A) includes any internal background present.
Patch Area Mean	Area_MN	ha	Area	The mean patch size is the sum of the patch areas (m ²) divided by the number of patches.
Patch Area Area-weighted Mean	Area_AM	ha	Area	The area-weighted mean patch size is the sum of the patch areas (m ²) divided by the total patch area.
Mean nearest neighbor distance	ENN_MN	m	Isolation	Mean euclidean nearest neighbor distance.
Proximity Index	Prox_MN	unitless	Isolation	The sum, across all patches, of the patch area divided by the squared distance to the nearest neighbor. This is a unitless index increasing in value as proximity increases.

The Recommended Metrics

The number of patches (NP), the total area (CA) and percent area within a particular class (PLAND, or more simply 'p' (Gardner et al. 1987)) were selected to provide a general summary of the amount of habitat present; total edge (TE), edge density (ED), and total core area (TCA) measure habitat availability for both edge and interior species; the largest patch index (LPI) and mean patch area (Area_MN) provide an estimate of the amount of habitat present in a single contiguous patch; and the nearest neighbor distance (ENN_MN) and proximity index (Prox_MN) measure the relative degree of isolation of habitat patches. Because the frequency distribution of patch sizes are usually skewed, a weighted mean patch size (Area_AM) was also selected to produce an unbiased estimate of the characteristic patch size (Stauffer and Aharony 1992). Although these metrics provide a variety of perspectives on landscape pattern, other indices may be selected and substituted as the problem may require (Gardner and Urban 2007) and the interpretation of results should always depend upon the biota or resource of interest. The recommended metrics may still be correlated and may require additional parsing depending the specific monitoring objectives and landscapes being monitored. At an absolute minimum, PLAND, Area_AM and a measure of habitat connectivity (e.g., ENN_MN or graph-theory based metric from SOP6) should be recorded for all applications.

Procedures

Pre-processing for Fragstats

Map files input to Fragstats may be formatted as either Arc Grid format or ASCII file format. Conversion of Arc Grid files to an ASCII format can be accomplished using the ARC command GRIDASCII:

GRIDASCII <map.samp>.

Before running Fragstats a “class properties file” also should be created. An easy way to do this is to use Notepad to create a file describing the different cover types of the map that will be analyzed (Table 5-2). The FRAGSTATS convention is to use the file extension .fdc for this class properties file. Although the .fdc extension is not mandatory, it is good practice to follow this convention. The example file in Table 5-2 is comma delimited with 4 variables:

Table 5-2. Example class properties file.

0,nonhabitat,false,true
1,nonhabitat,false,false
2,habitat,true, false
3,nonhabitat,false,false

Each record of the class properties file contains four fields: ClassID, ClassName, Status, isBackground. The ClassID is a unique integer value assigned to each cover type (i.e., pasture, forest, wetlands, etc.). The ClassName is a text description of the corresponding class. These names can be any length and contain any characters, including spaces, but cannot include a comma. The Status variable is Boolean (true, false) and can be specified by the full word or single character (e.g., true, or t; false, or f.). A “true” or “t” indicates that the class is ‘enabled’ and should be output in the patch and class output files. A “false” or “f” indicates that the class is ‘disabled’ and should not be included in the output. The class status affects only the output, but not the computation of landscape metrics. Disabled classes are still analyzed but are not included in the output. The isBackground is also Boolean (true, or t; false, or f) and determines whether the corresponding class will be reclassified as background (i.e., not included in the analysis of landscape pattern). A single record should be present for each land cover type with all arguments separated by a comma or space(s) (Table 5-2).

In summary, the class properties file allows you to do three things: (1) specify character descriptors for each class in order to facilitate interpretation of the output files, (2) limit the output files to only the classes of interest, and (3) reclassify classes to background.

Fragstats Analysis

A few simple steps are required to run Fragstats. These steps are:

Select map to analyze: The latest version of Fragstats (3.3) may be downloaded from http://www.umass.edu/landeco/research/fragstats/downloads/fragstats_downloads.html. Follow instructions to download, unzip and install. Then open Fragstats 3.3 and select the “Fragstats” drop-down menu. From this menu select “Set Run Parameters”. The window shown in Figure 5-1 appears. The following options are recommended (illustrated choices in brackets):

- “Grid name” {file location and name}
- “Output File” {file location and name}
- “Input File Type” {Landscape}
- “Automatically save results” {Check}
- “Input Data Type” {Arc Grid}
- “Analysis Type” {Standard}
- “Unique Patch ID’s” {Do Not Output ID Image}
- “Class properties file ...” {file location and name of .fdc file created earlier}
- “Patch Neighbors” {8 Cell Rule}
- “Output Statistics” {Class Metrics}

Then click “OK” to continue. Other selections may be required for different data types and grid attributes. See the Fragstats documentation for details and for a more detailed discussion of the implications of choosing alternative option settings.

The screenshot shows the 'Run Parameters' dialog box for Fragstats. The settings are as follows:

- Grid name...**: D:\jb_NPS\Antietam\outputs\ls30m_park
- Output File**: D:\jb_NPS\Output\ls30m_park (Base Name Only)
- Input File Type**: ☒ Landscape, ☐ Batch File
- Automatically save results**: ☒
- Input Data Type**: ☒ Arc Grid, ☐ ASCII, ☐ 8 Bit Binary, ☐ 16 Bit Binary, ☐ 32 Bit Binary, ☐ ERDAS, ☐ IDRISI
- Grid Attributes**:
 - Cellsize (in meters): 30.000
 - Background Value (Enter Positive Value): 999
 - Number of Rows (y): 217
 - Number of Columns (x): 149
- Analysis Type**: ☒ Standard, ☐ Moving window
 - ☒ Round, ☐ Square
 - Radius (meters): 0.000
- Unique Patch ID's**: ☒ Do Not Output ID Image, ☐ Create and Output ID Image, ☐ Input ID Image
 - ID File: [Empty field]
- Class properties file ...**: D:\jb_NPS\Input\class_prop_mod.fdc
- Patch Neighbors**: ☐ 4 Cell Rule, ☒ 8 Cell Rule
- Output Statistics**: ☐ Patch Metrics, ☒ Class Metrics, ☐ Landscape Metrics
- Buttons**: OK, Cancel

Figure 5-1. Fragstats Run Parameters

Select class metrics

As noted, a variety of metrics may be selected in Fragstats. To recreate the example described in Appendix A:

Open the drop-down menu “Fragstats”

Then select “Class metrics” and the window illustrated in Figure 5-2 will appear. This window is activated by the “Area / Density/Edge” tab and the following recommended metrics have been selected:

- Total Area
- Percentage of Landscape
- Number of Patches
- Largest Patch Index
- Total Edge
- Edge Density
- Mean Patch Area
- Area-Weighted Mean Patch Area

Class Metrics

Area/Density/Edge | Shape | Core Area | Isolation/Proximity | Contrast | Contagion/Interspersion | Connectivity

Select All

☒ Total Area (CA/TA) ☐ Landscape Shape Index (LSI)
☒ Percentage of Landscape (PLAND) ☐ Normalized LSI (NLSI)
☒ Number of Patches (NP)
☐ Patch Density (PD)
☒ Largest Patch Index (LPI)

☒ Total Edge (TE)
☒ Edge Density (ED)

Background / Boundary

☒ Do not count any as edge
☐ Count all as edge
☐ Specify the proportion to treat as edge
Proportion =

Distribution Statistics

	Mean (MN)	Area-Weighted Mean (AM)	Median (MD)	Range (RA)	Standard Deviation (SD)	Coefficient of Variation (CV)
Patch Area (AREA_?)	☒	☒	☐	☐	☐	☐
Radius of Gyration (GYRATE_?)	☐	☐	☐	☐	☐	☐

Select All

Select All

NOTE: Radius of Gyration Area-Weighted Mean (GYRATE_AM) is equivalent to Correlation Length (CL) as used in the literature.

OK Cancel Help

Figure 5-2. Fragstat Class Metrics (Area/Density/Edge)

Open the “Core Area” tab (Figure 5-3), select Total Core Area and “Use fixed edge depth”. Edge depth is application specific, but should be in multiples of cell sizes, as they are rounded to entire cells in any case (e.g., 30 m).

Class Metrics

Area/Density/Edge | Shape | **Core Area** | Isolation/Proximity | Contrast | Contagion/Interspersion | Connectivity

☒ Total Core Area (TCA)

☐ Core Area Percent of Landscape (CPLAND) ☒ Use fixed edge depth

☐ Number of Disjunct Core Areas (NDCA)

☐ Disjunct Core Area Density (DCAD)

Distribution Statistics

	Mean (MN)	Area-Weighted Mean (AM)	Median (MD)	Range (RA)	Standard Deviation (SD)	Coefficient of Variation (CV)
Core Area (CORE_?)	☐	☐	☐	☐	☐	☐
Disjunct Core Area (DCORE_?)	☐	☐	☐	☐	☐	☐
Core Area Index (CAI_?)	☐	☐	☐	☐	☐	☐
Average Depth Index (ADEPTH_?)	☐	☐	☐	☐	☐	☐
Maximum Depth Index (MDEPTH_?)	☐	☐	☐	☐	☐	☐

NOTES: Core Area Index Area-Weighted Mean (CAI_AM) is the same as Total Core Area Index (TCAI) as reported in Fragstats2.0.

Figure 5-3 Fragstat Class Metrics (Core Area)

Open the “Isolation/Proximity” tab (Figure 5-4) and select Mean Proximity Index and Mean Euclidean Nearest Neighbor Distance. Set search radius for indices (e.g., 100 m).

Then click “OK” to continue. Other selections may be required for different data types and grid attributes. See the Fragstats documentation for details.

Select patch metrics

To recreate the example described in Appendix B:

Open the drop-down menu “Fragstats”

Select “patch metrics” under the run parameters. The following recommended patch metrics may then be selected:

- Patch Area
- Core Area
- Proximity Index or Nearest Neighbor Index

Class Metrics

Area/Density/Edge | Shape | Core Area | **Isolation/Proximity** | Contrast | Contagion/Interspersion | Connectivity

Select All

Search Radius: 100.000

Distribution Statistics

	Mean (MN)	Area-Weighted Mean (AM)	Median (MD)	Range (RA)	Standard Deviation (SD)	Coefficient of Variation (CV)	
Proximity Index (PROX_?)	☒	☐	☐	☐	☐	☐	Select All
Similarity Index (SIMI_?)	☐	☐	☐	☐	☐	☐	Select All
	Sim. Wgt. File						
Euclidean Nearest Neighbor Distance (ENN_?)	☒	☐	☐	☐	☐	☐	Select All
Functional Nearest Neighbor Distance (FNN_?)	☐	☐	☐	☐	☐	☐	Select All
	Resist File						
	Select All	Select All	Select All	Select All	Select All	Select All	

OK Cancel Help

Figure 5-4 Fragstat Class Metrics (Isolation/Proximity)

Execute analysis

Using the “Fragstats” drop-down menu, select “Execute.” Results are written to an ASCII output file as specified in step 1 (Output file).

Export results

The output file containing the results of the Class Level analysis (e.g., summary of all habitat patches) can be exported to Excel for inspection, summarization and graphical analysis (Appendix A). The output file containing the results of the Patch Level analysis can be joined to the Arc habitat patch coverage for graphical display (see the post-processing step of SOP #6).

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SOP 6: Analysis of Landscape Connectivity using Graph Theory

Introduction

This section describes the analysis of landscape connectivity using graph theory. The Standard Operating Procedure (SOP) includes methods for extracting patch-level data from binary habitat grids, implementing LANDGRAPH software (version 1.0, Urban 2003) analyses to calculate graph metrics, and importing patch-level indices into a geographic information system (GIS) for visualization. A general approach is first presented that does not require any species-level information for identifying: (1) potential source patches, (2) stepping-stone patches, (3) the maximum distance an organism can travel across the landscape (i.e., the graph diameter or backbone), and (4) the minimum distance an organism would need to be able to disperse through non-habitat in order to traverse the entire graph diameter. The analysis is then applied to a hypothetical organism with a maximum potential dispersal distance of 700 m and a minimum habitat patch size requirement of 1 ha.

Small urban parks can play a vital role as biological refugia, migration rest stops, and dispersal corridors, all of which have been shown to greatly enhance regional biodiversity (Falkner & Stohlgren 1997). Graph theory is a well-developed analytic technique for evaluating landscape connectivity under conditions of habitat modification and change (Urban & Keitt 2001, Calabrese & Fagan 2004). A landscape graph is composed of a set of nodes representing the centroid (average X and Y) of each habitat patch and a corresponding set of edges that represent some type of ecological connection between patches (Figure 6-1). Patches are considered connected if an edge can be drawn between them. A landscape is considered fully connected if every patch can be reached from every other patch via some pathway of connected patches. This SOP applies graph analysis to remote sensing imagery of the parks to evaluate overall landscape connectivity of forest habitat and to identify which forest patches are most important to preserving long-distance dispersal potential and which patches are most influential to local dispersal. Example outputs from the application of the protocol to four NCR parks are provided in Townsend et al. (2009). Related applications of graph theory in Antietam (Minor et al. 2009) and Manassas (Lookingbill et al. 2008) also illustrate the approach.

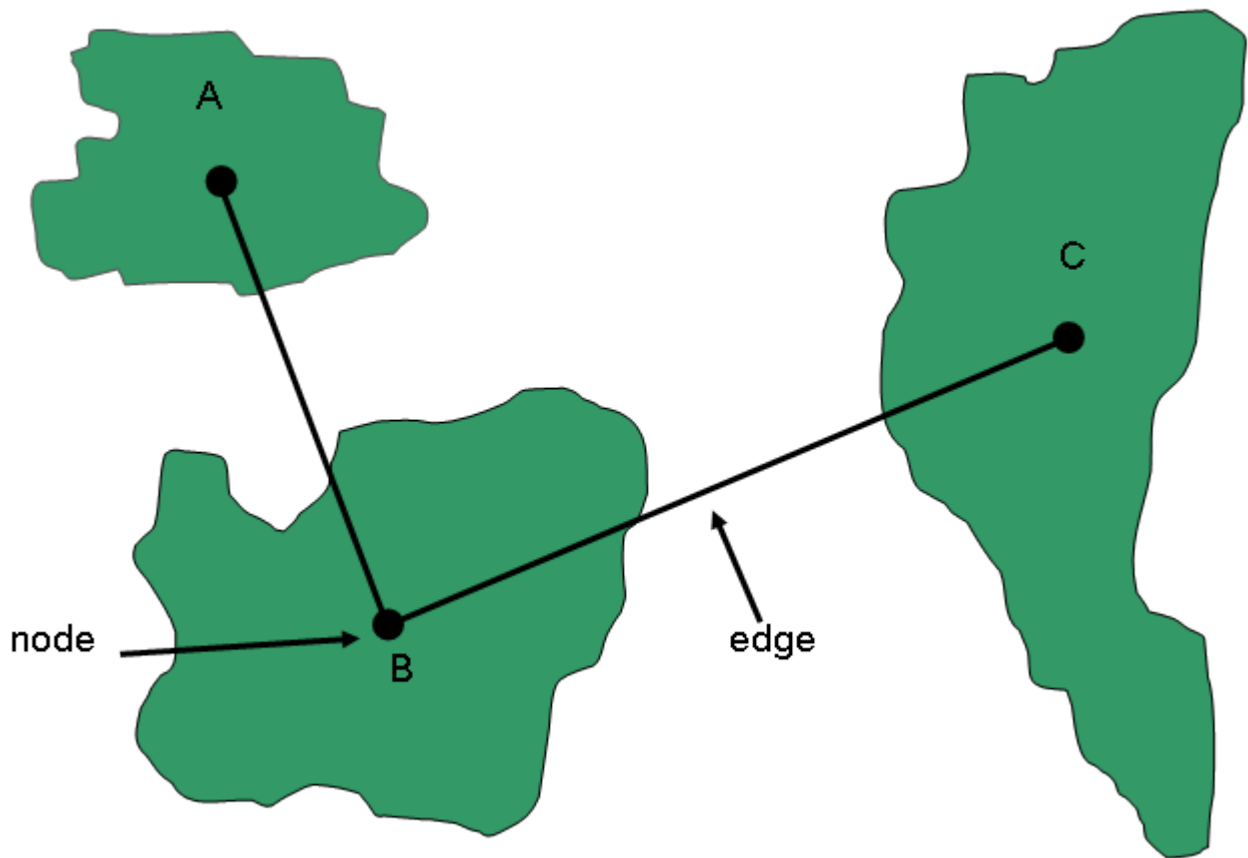


Figure 6-1. A connected graph component illustrating graph patches, nodes, and edges. Patch A is directly connected to B and indirectly connected to C.

Procedures

Pre-processing

Input maps for the connectivity analyses are binary habitat maps as described in SOP 4. For most applications, habitat will consist of forest land cover, but assessment of connectivity of other land cover types (e.g., wetlands) may also be desirable depending on the monitoring objective. Each grid of land use/land cover types must be: 1) reclassified to habitat/nodata, 2) delineated into discrete clusters of habitat cells, 3) filter small patches and 4) converted to an ASCII data format compatible with the LANDGRAPH program requirements. This can be accomplished using a series of GIS commands (see Appendix A).

The Anderson Level II land cover classification produced from SOP 2 can be merged to two classes (nonhabitat = 1, habitat = 2) using a simple conditional statement.

Discrete patches can be delineated in the resulting map using a REGIONGROUP command. An 8-neighbor rule (includes diagonal connections) is recommended, but a 4-neighbor rule (connections made in only the 4 cardinal directions) can also be used to identify clusters of habitat cells.

Patches that do not meet a minimum area requirement (MAR) can be removed at this step of the processing. The MAR sets the smallest patch size to be considered viable habitat. It is a function

of both the imagery resolution (size of cells) and the number of contiguous cells considered to comprise a patch.

When conducting graph-based connectivity studies for specific organisms, it is recommended that a MAR be set relative to the biological requirements of that organism. For example, large mammals may only recognize patches of habitat that are larger than the mapping resolution of the input imagery (e.g., 30-m cells for Landsat imagery). Information on setting a minimum area requirement is contained in the MAR section.

It may also be necessary to set an MAR that is different from the resolution of the input imagery if too many patches are present in the imagery. Setting the MAR to resolution of the input imagery can result in a substantial number of single-cell patches (e.g., roughly 40% of the patches delineated for Antietam National Battlefield contained only a single grid cell regardless of the resolution of the imagery). These small patches are much more likely to be the product of random error introduced by classification errors than are large patches (Keitt et al. 1997). Also, the analysis software can take several days to run when many thousands of patches are present.

The final pre-processing step is to write the habitat patches to an input file for the graph analysis. The graph programs provide an option to weight each habitat node by an index of habitat quality. The definition of habitat quality is specific to the application (e.g., could be based on a separate habitat suitability model developed for a target species) and is set to 1 for all habitat cells in the current protocol. Alternative applications may choose to assign each cell a quality index scaled from 0 (worst quality) to 1 (best quality).

The landscape graph - GENGRAPH

Four separate Fortran programs are included as the LANDGRAPH software suite. The first (GENGRAPH) converts the ASCII file constructed above into node and distance files used for all subsequent graph analyses. The second (THINEDGE) analyzes the graph in the absence of species-specific dispersal information in terms of its landscape-scale connectivity. The third (SENSINODE) assesses the importance of individual nodes (or patches) to long-distance traversability of the graph and to local dispersal flux. The final program (EDGES) generates a graphic file in ARC format for visualization of the results.

GENGRAPH first computes the centroid, area, and average quality of all patches. Next, a patch-to-patch distance matrix is calculated using one of three alternative methods. Centroid-to-centroid (C) distance is the quickest to calculate, but relies upon the assumption that organisms are equally likely to disperse from and to all cells within the patches under consideration; thus, an average distance between the patches is a sufficient measure. Edge-to-edge (E) distance assumes organisms leave from the closest edge of the donor patch and arrive at the closest edge of the target patch. Finding this minimum distance requires the calculation of interpatch cell-to-cell distances for all pairs of habitat cells, which can be computationally prohibitive for large data sets. A third alternative is to adjust the centroid-to-centroid distance by each patch's radius of gyration (R), the average distance from the centroid to each cell in the patch. This approach is computationally fast and adjusts the inter-node distances to account for patch size. It is recommended for coarse analyses when computational time is limited; however, final assessments should be based on edge-to-edge distances. Example GENGRAPH inputs are provided in Appendix B.

A general assessment of landscape connectivity - THINEDGE

THINEDGE provides landscape-scale graph metrics over a range of sequential threshold distances. Each threshold distance is used to compute an edge adjacency matrix coded as 1 if two nodes are connected (i.e., they are separated by less than the given threshold distance) and 0 if they are not. As an alternative to straight Euclidean distance, edges can be defined in terms of dispersal probabilities computed as a negative-exponential decay function of the distance between nodes. A third alternative is to adjust the dispersal probabilities based on the area of the two patches being considered. In the example given below, raw Euclidean distance is used to compute edges and none of the adjacency matrices that are computed are saved for later use.

The THINEDGE program is useful for landscape analyses that are not species specific (see Lookingbill et al. 2008 for an example in the NCR). The result can be used to show the extent to which the landscape is connected for organisms with different dispersal capabilities. Most landscapes show strongly nonlinear responses in connectivity (Gardner et al. 1987), and this type of edge-thinning exercise can be used to identify the threshold distance at which the landscape may be perceived as disconnected (Dcrit). Organisms with dispersal capabilities greater than this threshold distance have the potential to move more freely from patch to patch than organisms with lower dispersal capabilities, which have a greater likelihood of becoming isolated on the landscape. This analysis provides an overview of landscape connectivity for multiple species and can be used to identify species that are particularly sensitive to change in the landscape given the current configuration of habitat. If the monitoring question identified in SOP1 relates to a specific species with known dispersal capabilities, this step may be skipped. Example THINEDGE inputs are provided in Appendix C.

Output consists of the following graph indices calculated at each increment of the edge-thinning process (Table 6-1):

- Maximum allowable lag distance (D; Dist). The potential dispersal distance or lag distance between nodes used to generate the edge adjacency matrix for that record.
- Number of edges (nedge). Each edge represents a 1 in the adjacency matrix or a pair of connected nodes. This value increases with increasing D.
- Number of components (nc). A component is defined as a set of connected nodes (or patches). This value is 1 when the landscape is completely connected and equal to the number of nodes when there are no connections.
- Number of nodes in the largest component (nnlc). Also referred to as the order of the largest component. Ranges from 1 in a completely unconnected graph to the total number of nodes in a completely connected graph.
- Number of edges in largest component (nelc). Ranges from 0 in a completely unconnected graph to a maximum value of $N(N-1)$, where N is the number of nodes in the landscape and $N(N-1)$ represents a maximally connected landscape with every node directly connected to every other node.

- Graph diameter (gdiam). The shortest distance (i.e., summed edges) between the two nodes in the largest component that are the farthest apart. This index tends to increase with increasing D up to an asymptote at full connectivity.

Table 6-1. Example of landscape-scale connectivity metrics available from THINEDGE for three D settings.

10-m SPOT imagery for ANTI	D	D	D
Lag distance (m)	210	230	320
Graph diameter (m)	3,522	4,286	4,961*
Change in graph diameter (m)	2,230	763	917
Number of patches connected	277	545	578
Percent of patches connected	47.9%	94.3%	100%
Change in number of connected patches	13	268	30

* Maximum distance an organism can travel across the landscape given the configuration of habitat patches.

The indices can be plotted against D in EXCEL or some other graphing software package to determine critical lag distances for landscape connectivity (Dcrit) (Figure 6-2). These distances are informative of the minimum distance an organism would need to be able to disperse through non-habitat in order to traverse the landscape. Three alternative options are recommended for assigning Dcrit:

- distance where there is the maximum change in diameter of the largest component,
- distance at which 75% of the nodes are connected, and
- distance at which 100% of the nodes are connected (full connectivity).

In addition to providing basic information about the connectivity of the landscape, the Dcrit values can be used to help identify individual habitat nodes of special importance using the node-removal program SENSINODE.

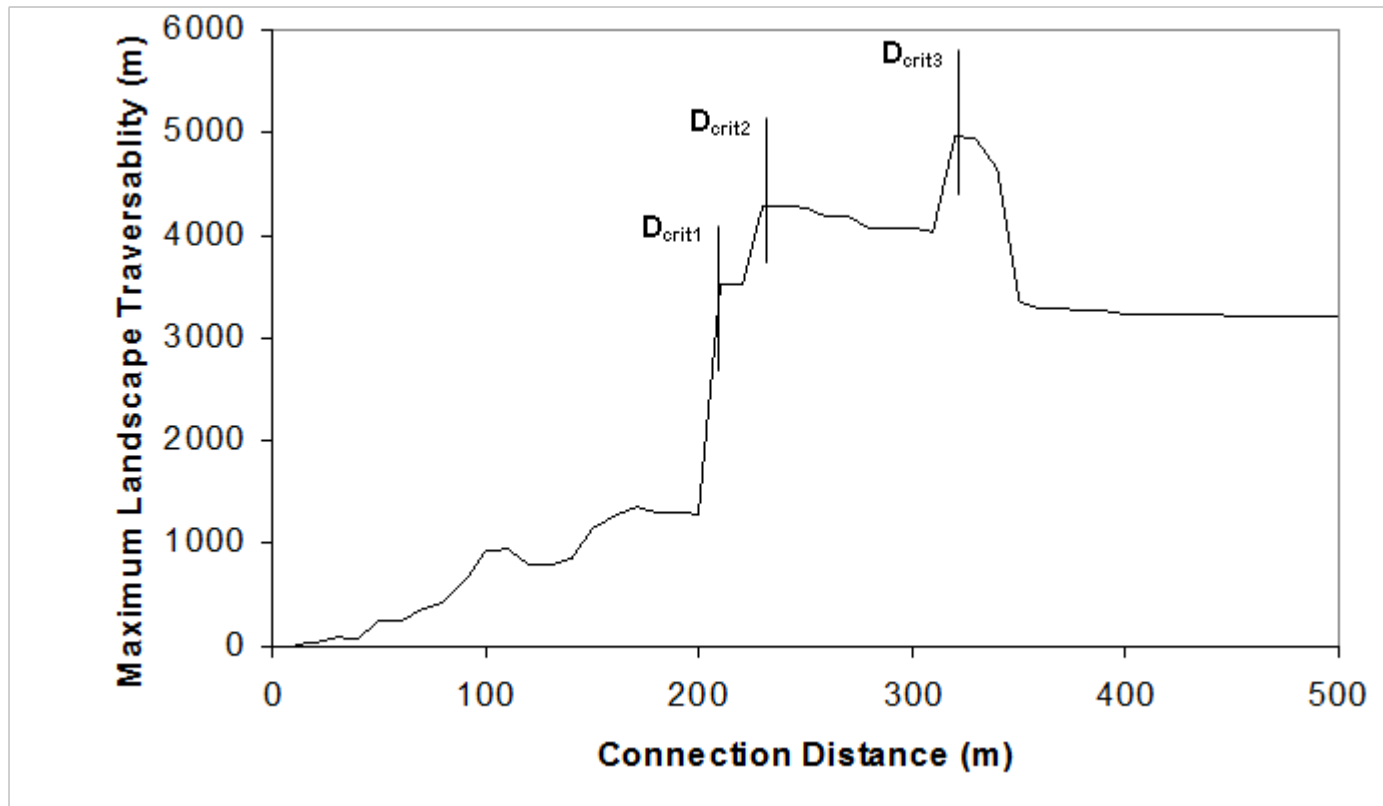


Figure 6-2. Example calculation of Dcrit values.

Identification of critical patches - SENSINODE

Graph theory can also be used to identify specific patches that are especially important to connectivity. This information could be used to inform the location of samples for other monitoring protocols, to guide management or restoration, or simply to document how the critical patches for landscape connectivity may change over time. SENSINODE evaluates the importance of individual patches by computing the change in connectivity statistics accompanying the potential removal of each patch from the landscape. Methods follow those of Urban and Keitt (2001). The following statistics are considered in the analysis:

- Landscape traversability (T): represents critical pinchpoints for long-distance movement potential. These would be patches that if lost/damaged/modified would greatly reduce the diameter of the graph (i.e., traversability of the landscape).
- Dispersal flux (F): represents potential local movement of individuals away from natal patches (e.g, the ability of a patch to act as a local source in a metapopulation framework). This measure incorporates information on patch size, probability of dispersing a given distance, and, if available, patch quality.

The patches identified might be different for each metric, or some patches might be important for both metrics. By targeting specific patches for further study, the analysis provides a powerful tool for resource monitoring. Flexibility built into the sample design of complementary monitoring protocols (e.g., forest vegetation monitoring) will allow the distribution of future

sample plots to be at least partially guided by the graph analysis results. In addition to informing the allocation of future field efforts, the identification of critically important patches within a landscape context can be used to assess the potential impact of spatially explicit changes in habitat through time (see Lookingbill et al. 2008).

Because the same set of nodes may yield different graphs for species with shorter or longer dispersal capabilities, the definition of a landscape graph is clearly organism-specific. In instances where the dispersal characteristics (e.g., dispersal probability function, maximum dispersal distance) of an organism of concern are known, those attributes may be used to define node adjacencies in the SENSINODE analysis (Bunn et al. 2000 and see Species-specific analysis section below). Otherwise, the Dcrit distances described above should be used to generate landscape representations that are more-or-less connected under current conditions, but which are highly sensitive to any loss or degradation of habitat. Use of these threshold distances has been shown to be highly informative for prioritizing site acquisition, protection, and monitoring (Keitt et al. 1997, Urban & Keitt 2001).

Post-processing

The output of the graph analyses is designed for ready display in a GIS. First, EDGES can be used to create ARC graphic files with edges defined for a single threshold distance (Appendix E). The threshold distance may be set to one of the Dcrit values from the THINEDGE analysis described above or it may be set to match the known dispersal capabilities of a target species described below.

The edge graphic files along with the node graphic files created by GENGRAPH can be built into ARC coverages for visualization.

The output from SENSINODE can be joined to the nodes coverage to map important patches for landscape traversability (T), dispersal flux (F), or other metrics, including those computed in the FRAGSTATS pattern metric analysis (SOP5). Once imported into EXCEL, the FRAGSTATS patch metric output can be added to the SENSINODE output file (common field = patch ID or node) and saved as a comma delimited (*.txt) file <MAPSENSI.TXT>. The resulting table can be joined to the GIS node attribute table from GENGRAPH for viewing in ARC. The attribute table can be sorted on any field to identify the most important node for a given attribute, or the joined coverage can be shaded to show node prioritization for an attribute using a visually appropriate number of graduated colors. Alternatively, the landscape pattern metric table <MAPSENSI.TXT> can be joined to the regiongrouped patch attribute table to display rankings for the entire patches rather than their centroid nodes (Figure 6-3).

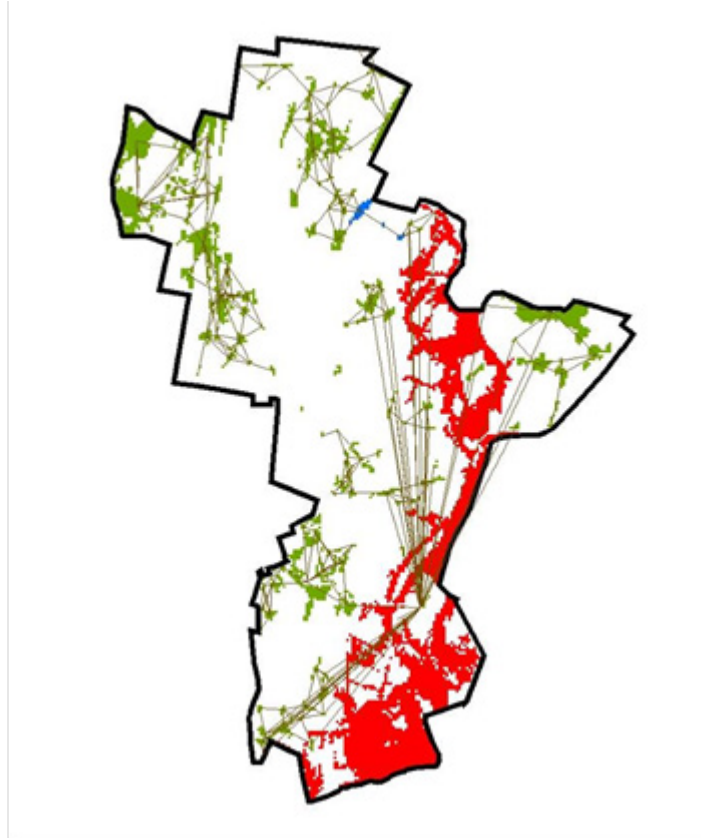


Figure 6-3. SENSINODE output for Antietam National Battlefield with Dcrit set to 210 m as determined from THINEDGE analysis. Green shading indicates different forest patches. Lines represent potential connections among patches. The blue patches are most important to long-distance traversability of the landscape (potential pinchpoints). The red patch is highlighted as most important to local dispersal flux (potential source habitat).

Species-specific assessments of connectivity

If a specific organism of interest is identified, then the analysis can be tailored to that organism's life history characteristics. For example, forest patches within Antietam National Battlefield of importance to the connectivity of a hypothetical organism with a maximum interpatch dispersal distance of 700 m and an MAR of 1 ha can be highlighted (Figure 6-4). These traits are representative of small vertebrates of the NCRN such as chipmunks, squirrels, and shrews (MD DNR 2005). To generate this figure, the park habitat-nonhabitat map was preprocessed in ARC using the MAR extension steps to eliminate patches less than 1 ha in size. Graph analyses were then conducted using GENGRAPH and SENSINODE (THINEDGE is not necessary for this type of monitoring objective). Finally, output graph products were generated using EDGES and imported back into ARC where important pinchpoint (change in T) and source patches (changes in F) can be visualized.

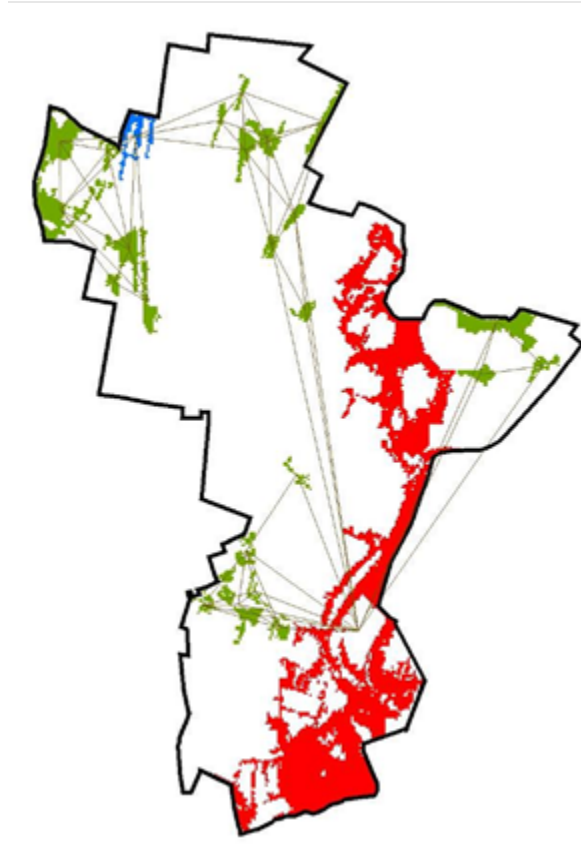


Figure 6-4. Graph analysis of Antietam National Battlefield for hypothetical organism with maximum dispersal distance = 700 m and MAR = 1 ha (10-m SPOT imagery with no buffer). Green shading indicates different forest patches. Lines represent connections among patches given the organism's dispersal limitations. The blue patch is most important to long-distance traversability for the organism (T). The red patch is highlighted as most important to local dispersal flux (F).

Important Considerations

Buffering Schemes: Parks do not exist in isolation, and analyses of connectivity should consider the surrounding landscape matrix (see SOP4). In addition to the park boundaries themselves, input imagery can be clipped to the following extents for analysis: watersheds, fixed-width buffer, or variable-width buffer. The choice of buffering scheme greatly affects connectivity metrics (see Townsend et al. 2009). Buffers should be matched with ecological and monitoring objectives. For example, watershed boundaries are frequently used as management units. This buffering scheme is particularly appropriate for issues related to water-dispersed and riparian species.

Image Resolution: Imagery may be analyzed at multiple resolutions (i.e., pixel size) to identify the appropriate spatial scales for drawing inferences about landscape pattern. Townsend et al. (2009) also addresses the importance of image resolution for connectivity analysis for four parks of the NCR with varied landscape compositions and configurations (Antietam, Catoclin, Prince William, and Rock Creek). The choice of image resolution was found to have less of an impact than the choice of analysis buffer on the graph metrics.

It is reasonable to expect that the most appropriate spatial resolution for connectivity analyses will vary among parks and monitoring objectives. As a rule of thumb, 30-m resolution Landsat imagery provides a good balance between cost-effectiveness (free) and high spatial accuracy for repeated characterizations of landscape pattern in NCR parks.

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SOP 7: Delineation of Stream Buffers and Stream Buffer Width

Introduction

This section describes the steps to be followed to monitor changes in stream buffering capacity on a landscape. It utilizes the ArcGIS software. The approach provides an alternative to mapping land cover only in fixed-width riparian corridors.

The land cover in riparian buffer regions has an increased importance on water quality and biotic condition in NCR streams relative to broader, landscape-level land cover patterns (Roth et al. 1996, Utz et al. 2009). The conversion of riparian forests and agriculture to urban and suburban development affects aquatic condition not only through direct inputs, but the loss of vegetation also influences the terrestrial processing of water that flows from upland areas. New and creative ways of quantifying riparian buffers have shown that substantial nutrient interception may be occurring on land at considerable distance from the water's edge (Baker et al. 2006, Roy et al. 2007). These findings suggest that narrow, fixed-width riparian buffer strips may be a useful but not a sufficient condition for protecting park waters in urbanizing environments.

This Standard Operating Procedure (SOP) provides a method to identify stream buffers and to associate the width of buffer available to all non-buffer (upslope of stream) locations. The method is based on identifying land cover classes associated with buffers (forest, wetlands) along topographically-constrained flowpaths. This provides advantages to the traditional delineation of buffers according to fixed distance methods by indicating the effective buffer width in relation to upland contributing areas. It allows identification of those upland areas with little downslope buffer area that may contribute disproportionately to poor water quality. The method provided here follows an approach outlined by Baker et al. (2006).

Procedures

Data Preparation

This SOP requires a line stream coverage (ponds and lakes that are not part of a stream network should be removed), a digital elevation model (DEM), a land cover map in which land cover has been coded into non-buffer (type = 0) and buffer (type = 1) cover types. Anderson Level I Forest (class 4) and Wetlands (class 6) are employed as buffer cover types. The digital elevation model and land cover classification should match in resolution (grid cell size). The pilot example used a 10m DEM provided by NPS with a SPOT-derived land cover classification also at 10m. All geographic data layers should be clipped to a common extent. Because the method suggested employs topographic information to identify flowpaths, the map extent should include the watershed boundaries identified in SOP #4. Otherwise, map extent should be limited to reduce computer processing time. All data should be projected into a common coordinate system.

DEM Preparation

Digital elevation models generally include a number of inconsistencies that require processing prior to topographic analysis. First, vector stream coverages often do not align with topographic flowpaths in the DEM. To align the DEM with mapped stream coverages, the DEM must be reconditioned to adjust the surface elevation of the DEM to be consistent with a vector coverage

(e.g. stream or ridge lines). The Arc macro (AML) agree.aml (Hellweger 1997) is provided to perform the reconditioning (Appendix O).

Inputs for the analysis are as follows (from Hellweger 1997):

- Elevation Grid. The original elevation grid (DEM) of the area. The DEM does not have to be 'filled' in advance (see below for a description of DEM filling).
- Vector Coverage. The stream or ridgeline coverage of the area.
- Buffer Distance. The buffer distance controls the spatial extent of the surface reconditioning. This distance should be set roughly equal to or slightly larger than the approximate spatial scale of error among the elevation grid and vector coverage. The spatial scale of the error can be determined by delineating streams or sub-basins from the original DEM and comparing those streams to the lines in the vector coverage. If, for example, the two lines are found to vary at most by about 400 meters, the buffer distance might be set to 600 meters. A reconditioning of 100m was used for the pilot example and should be adequate for 10m DEMs. A larger distance (500m) is recommended for 30m DEMs.
- Smooth Drop/Raise Distance. The smooth drop/raise distance controls how much the cells corresponding to the vectors are dropped/raised. DEM cells adjacent to the stream boundaries must be dropped or raised to force DEM topography to align with streams. In order to develop some guidelines for the smooth drop/raise distance a formula was developed which normalizes the distance based on the average surface slope inside the buffer and the buffer distance: $(\text{smooth drop/raise distance}) = (\text{mean surface slope inside buffer}) * (\text{buffer distance}) * (\text{forcing factor})$. The forcing factor controls the magnitude of the alteration. Note that positive smoothing is up and negative is down (negative values are used with streams and positive values are used with ridgelines). If it is set to 0.00 the vector cells will remain at the original elevation and the slope inside the buffer will be fairly close to the original one. A factor of 0.50 will result in a rough doubling of the slope inside the buffer. A factor of -10 was found to work well for Antietam pilot study. It is important to realize that this calculation should be used only to get a rough idea of the order of magnitude for the smooth drop/raise distance. Sometimes trial and error is required to select the optimal parameters.
- Sharp Drop/Raise Distance. The sharp drop/raise distance controls how much the cells corresponding to the vectors are dropped/raised after the smooth modified elevation grid is computed. This is essentially digging a trench/raising a wall. If vector elevation for the subsequent hydrologic analysis is not essential the sharp drop/raise distance should be large (i.e. 1000). This is effectively a 'burning in the streams' after the original AGREE procedure. The reason for this is as follows: most of the sinks in a DEM are located on the streams. This means that filling after the original AGREE procedure could wipe out the smoothed channel upstream of the sink. This can be eliminated by dropping the stream a large distance. That way any filling done to remove sinks in the stream remains in the trench of the stream. A factor of -10 was found to be adequate for Antietam.

The output elevation grid (elevgrid) must then be “filled” in GRID to remove sinks. All hydrologic or topographic flow calculations require filled DEMs. A flowdirection grid should be output while filling the sinks as this is used in the buffer delineation process.

GRID: fill elevgrid elevfill sink # elevdir

Buffer Quantification

The stream coverage should be rasterized to an identical resolution as the DEM and land cover map. All arcs in the stream coverage should have an attribute code with the same value (1).

Set analysis window to the clipped common area.

The cells immediately adjacent to streams should be recoded as to whether they contain a buffer class (class 1 in the recoded land cover map) or not (class 0). The resulting grid should have 0 for cells adjacent to streams that are not a buffer class and 1 for all other cells (including non-adjacent pixels).

Following Baker et al. (2006), this provides a measure of whether a cell adjacent to the stream is a buffer or not. A weighted surface can then be used to identify flow paths that include stream buffers. The weighted surface is computed as the product of the binary land cover map and the adjacency grid created above.

Preliminary flowpaths are then computed for all cells on the grid. Unconstrained flowpaths are computed to determine the flowlength along a topographic drainage pathway. Weighted flowlengths (using the weighting surface above) are computed to determine the length of flow that contains buffer. An equivalent value in both flowpath surfaces indicates a contiguous, downstream buffered pathway to the stream (Baker et al. 2006). Comparing these two outputs results in a binary representation of buffer (e.g., forest & wetland classes adjacent to stream).

A final flowpath is calculated using the binary comparison above map to weight flow distances. This indicates the width of buffer available to each non-buffer (upland) location. This flowpath grid is used to identify the width of buffer associated with each upland cell. The final buffer width grid has buffer areas coded to nodata.

The two final output grids are buffermap (presence and absence of a buffer, Figure 7-1) and bufwidth (width of buffers associated with all locations on upland landscape, Figure 7-2).

Example ArcInfo commands for this procedure provided in Appendix P

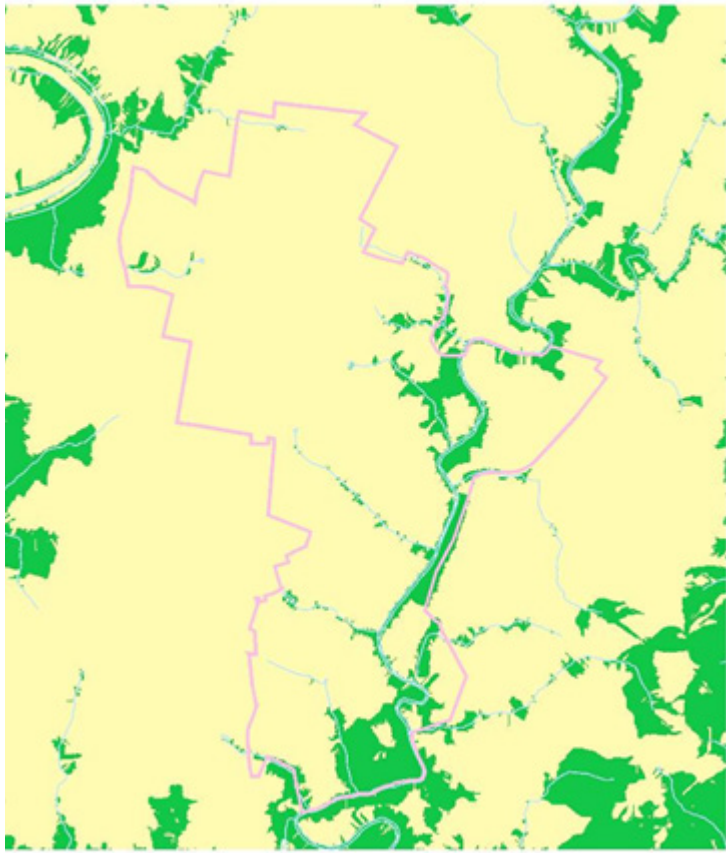


Figure 7-1. Buffers in Antietam National Battlefield (indicated in green). Non-buffers are tan. Streams are indicated in blue and park boundary in pink.



Figure 7-2. Buffer width for non-buffer areas in Antietam National Battlefield. Buffers are indicated in green and buffer width is scaled in gray tones. Black areas have no buffers. The four gray classes (in decreasing darkness) indicate upland areas with buffers 0–10m, 10–25m, 25–50m and 50–100m. White areas have buffers > 100m. Streams are indicated in blue and park boundary in pink.

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SOP 8: Remote Sensing Change Detection

Introduction

This section describes the steps to be followed conduct a change detection analysis using digital imagery or classified land cover maps derived from digital images.

This Standard Operating Procedure (SOP) provides guidelines on conducting image-based change detection analysis. Change detection has a long history in remote sensing and consists of hundreds of methods that have been outlined in the scientific literature. Most image processing textbooks as well as Lunetta and Elvidge (1998) provide a good overview of standard change detection methods. A change detection product is also now available from the National Land Cover Data (NLCD, <http://www.mrlc.gov>) for the 1992 and 2001 products (Fry et al. 2009). Continental scale processing of Landsat data for disturbance mapping has been further demonstrated by the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS; Masek et al. 2008).

Change detection can involve the detection of changes in cover type (land cover conversion) or changes in cover condition. Three general methods are suggested:

- 1) Using two classifications, e.g. from time period 1 (T1) and time period 2 (T2). This is suitable only for detecting changes in cover type.
- 2) Using a classification from T1 and an image from T2. With interpretation, this is suitable for detecting changes in cover type and condition.
- 3) Using images from T1 and T2. This is suitable for determining changes in cover condition.

Methods 2 and 3 are suitable for the detection of forest disturbance (e.g., gypsy moth defoliation) within a forest class. This SOP requires access to a GIS program (e.g., ArcMAP) and an image processing software (e.g., Imagine).

Procedures

Data Preparation

This SOP requires classified images (e.g., SOP 3) and/or processed, corrected and normalized digital images (SOP 2). It is assumed that all pre-processing and data evaluation have been completed following SOPs 1, 2 and 3.

Change-Detection using Two Classifications (Post-Classification Change Detection)

Post-classification change detection involves the simple overlay of maps from two time periods to determine the locations of changes in cover types between times T1 and T2. Analytically, the approach is simple: two maps are intersected, creating a transition map with unique codes for each combination of T1 and T2 classes. The two maps must have identical class types, and – in the raster environment – should have the same cell (pixel) resolution.

This is probably the least reliable form of change detection because errors at each step of the analysis (i.e., creation of the original maps for T1 and T2) are propagated multiplicatively to the

final analysis. However, when used cautiously, this approach can yield very useful maps. The following example illustrates the issues with post-classification change detection.

Consider a landscape for which two land cover maps are available from T1 and T2. T1 and T2 might be ten years apart, during which some agricultural and forest land may have been converted to urban/suburban land uses, and some agricultural land may have been abandoned to forest regrowth. For the sake of simplicity, this example will include only three classes (forest, agriculture and urban). Table 8-1 shows the proportion (p) of each class at T1 and T2.

Table 8-1. Proportion of three classes at T1 and T2.

Class	T1	T2
Forest	0.6	0.55
Agriculture	0.3	0.25
Urban	0.1	0.2

Each map (T1 and T2) have confusion matrices and user's/producer's error levels (Tables 8-2, 8-3).

Table 8-2. Error matrix (top) and accuracy levels (bottom) for T1.

TIME 1 Map	Reference Forest	Agriculture	Urban	Total
Forest	90	5	5	100
Agriculture	0	80	20	100
Urban	0	20	80	100
Total	90	105	105	300

TIME 1	Correct	Reference	Map	Producer's	User's
Forest	90	100	90	90.0%	100.0%
Agriculture	80	100	105	80.0%	76.2%
Urban	80	100	105	80.0%	76.2%
Total	250/300	83.3%			

Table 8-3. Error matrix (top) and accuracy levels (bottom) for T2.

TIME 2 Map	Reference Forest	Agriculture	Urban	Total
Forest	95	2	3	100
Agriculture	1	85	14	100
Urban	5	15	80	100
Total	101	102	90	300

TIME 2	Correct	Reference	Map	Producer's	User's
Forest	95	100	101	95.0%	94.1%
Agriculture	85	100	102	85.0%	83.3%
Urban	80	100	97	80.0%	82.5%
Total	260/300	86.7%			

Note that the overall accuracy for T1 is 83.3% and T2 is 86.7%. The maximum composite accuracy level for a change detection computed on the cross-tabulation of the two maps is 72.2%. However, the accuracy levels for the per-class transitions may be lower (or higher) depending on the accuracy levels of those classes (Table 8-4).

Table 8-4. Per-class accuracies for transitions between T1 and T2 for the example. P indicates proportion of the landscape.

From Class	To Class	P	T1 Users	T2 Users	Change - Users	T1 Prod	T2 Prod	Change - Producers
Forest	Forest	0.5	100.0%	94.1%	94.1%	90.0%	95.0%	85.5%
Agriculture	Agriculture	0.24	76.2%	83.3%	63.5%	80.0%	85.0%	68.0%
Urban	Urban	0.1	76.2%	82.5%	62.9%	80.0%	80.0%	64.0%
Forest	Agriculture	0.01	100.0%	83.3%	83.3%	90.0%	85.0%	76.5%
Forest	Urban	0.03	100.0%	82.5%	82.5%	90.0%	80.0%	72.0%
Agriculture	Forest	0.05	76.2%	94.1%	71.7%	80.0%	95.0%	76.0%
Agriculture	Urban	0.07	76.2%	82.5%	62.9%	80.0%	80.0%	64.0%
Urban	Forest	0	76.2%	94.1%	71.7%	80.0%	95.0%	76.0%
Urban	Agriculture	0	76.2%	83.3%	63.5%	80.0%	85.0%	68.0%

Note that because of low class accuracy of urban and agricultural classes at T1 the accuracy of some transition classes (e.g., agriculture to urban at 62.9% user's accuracy and 64% producer's accuracy) is quite low compared to the overall accuracy of the change detection. This is where careful consideration of the question being asked is important. If, for example, the question only revolves around changes or conversions in the forest class, and not specific transitions (i.e., to/from either agriculture or urban), then the agriculture and urban classes can be aggregated and a more robust analysis presented (Table 8-5).

Table 8-5. Analysis of changes derived from aggregating urban and agricultural classes from Tables 8-1 - 8-4.

Class	T1	T2
Forest	0.6	0.55
Nonforest	0.4	0.45

From Class	To Class	P	T1 Users	T2 Users	Change - Users	T1 Prod	T2 Prod	Change - Producers
Forest	Forest	0.5	100.0%	94.1%	94.1%	90.0%	95.0%	85.5%
Nonforest	Nonforest	0.41	95.2%	97.5%	92.8%	100.0%	97.0%	97.0%
Forest	Nonforest	0.04	100.0%	97.5%	97.5%	90.0%	97.0%	87.3%
Nonforest	Forest	0.05	95.2%	94.1%	89.6%	97.0%	95.0%	92.2%

This example is provided to demonstrate that post-classification change detection can be used with confidence if driven by questions about specific classes.

Change Detection using one Classification (from T1) and Digital Imagery (T2)

The second change detection approach uses a classified map to stratify areas for analysis of a more recent digital image. The digital imagery may consist of image bands, but more frequently, derivatives such as NDVI, SAVI, the Tasseled Cap Index, or Principal Components are used. This approach focuses specifically on identifying areas that have changed within a given land cover class. Ground observations are used to interpret the changes within each class, e.g., whether the change is due to a change in condition or due to cover type conversion. This approach assumes that cover classes are relatively homogenous in terms of spectral characteristics, which means that this approach is not appropriate for spectrally dynamic cover types (e.g., agriculture). This approach is best suited for the identification of differences within forest or wetland cover types that may be the result of disturbance or other degradation. The limitation to this approach is that the assumption of homogenous spectral characteristics within a cover type is often violated, especially at broad spatial scales.

The imagery should be subset by cover type, e.g. deciduous forest is analyzed by itself. Then, for each pixel of the desired cover type, a Z-score is calculated, where $Z = (x - \mu) / \sigma$, where x = the reflectance value at a pixel, μ = mean value for reflectance for the class, and σ = standard deviation of reflectance in the class. The Z-score can be computed from multiple bands or image derivatives, indicating the overall deviance of a pixel from the class mean. Z scores simply tell how many standard deviations away from the mean reflectance of a class a certain pixel resides. Depending on which band(s) or derivative(s) are used, the Z-score indicates whether a pixel exhibits higher or lower values relative to the rest of the class. For example, an NDVI value much lower (-2 standard deviations) than the class mean for a deciduous forest pixel may indicate a significant disturbance. The exact interpretation of changes should be accomplished using ancillary field data.

Change Detection using Two Sets of Digital Imagery (Image Algebra, Change Vector Analysis)

The change detection approach that involves the fewest number of assumptions about the quality of the input data is an approach that uses two (rectified, normalized) digital images. The two images should closely match in spatial resolution, image noise levels, and spectral characteristics. This analysis is further enhanced by the use of an existing classification, preferably tied to the T1 time period. This allows the stratification of the analysis by known cover types. If transitions among cover types are of interest, stratification should not be used. This approach involves the application of simple image algebra or trigonometry. Image algebra may involve simple differencing between two dates, however the use of a normalized difference index normalizes the changes to facilitate easier interpretation. For example, the Tasseled Cap Greenness and Wetness indices are often used as robust measures of vegetation condition. The normalized difference greenness index (NDGI) and normalized difference wetness (NDWI) indices are calculated as:

$$\text{NDGI} = (G_{T2} - G_{T1}) / (G_{T2} + G_{T1})$$

$$\text{NDWI} = (W_{T2} - W_{T1}) / (W_{T2} + W_{T1}), \text{ where}$$

G and W indicate greenness and wetness at times 2 (T2) and 1 (T1) respectively. These analyses work best if the imagery have been normalized, e.g., following Collins and Woodcock (1996, see SOP #2).

A widely used approach to change detection is change vector analysis (CVA), which is based on the principles of spherical data analysis to identify the overall trajectory in image spectra between dates. This approach is usually employed using 3 orthogonal bands of data, e.g., Brightness, Greenness and Wetness from the Tasseled Cap Index. In its most basic application, CVA yields a change direction index as well as a change magnitude index. Following Townsend et al. (2004), The equations to compute change vector statistics using Tasselled Cap brightness (B), greenness (G), and wetness (W) for images from two dates are:

(1) Magnitude change, $M = \sqrt{\Delta B^2 + \Delta G^2 + \Delta W^2}$, where ΔB , ΔG , and ΔW refer to the changes in image

BGW between the two dates.

The differences in raw B, G and W can be used to identify 8 classes of image change (Table 8-6).

Table 8-6. Change vector classes.

Class	Brightness	Greenness	Wetness
1	increases	Increases	increases
2	increases	Increases	decreases
3	increases	Decreases	increases
4	increases	Decreases	decreases
5	decreases	Increases	increases
6	decreases	Increases	decreases
7	decreases	Decreases	increases
8	decreases	Decreases	decreases

These classes can subsequently be interpreted to identify the nature of changes occurring on the landscape. For example, for forest classes, decreases in G and W accompanied by increases in B (class 4) usually indicate forest disturbance. The magnitude value (M above) can be interpreted using field observations to identify the level of change in forest condition.

Most analyses stop at the identification of change magnitude and change direction (Allen and Kupfer 2000). However, the information of the angles of change between two dates may also be useful (Figure 8-1).

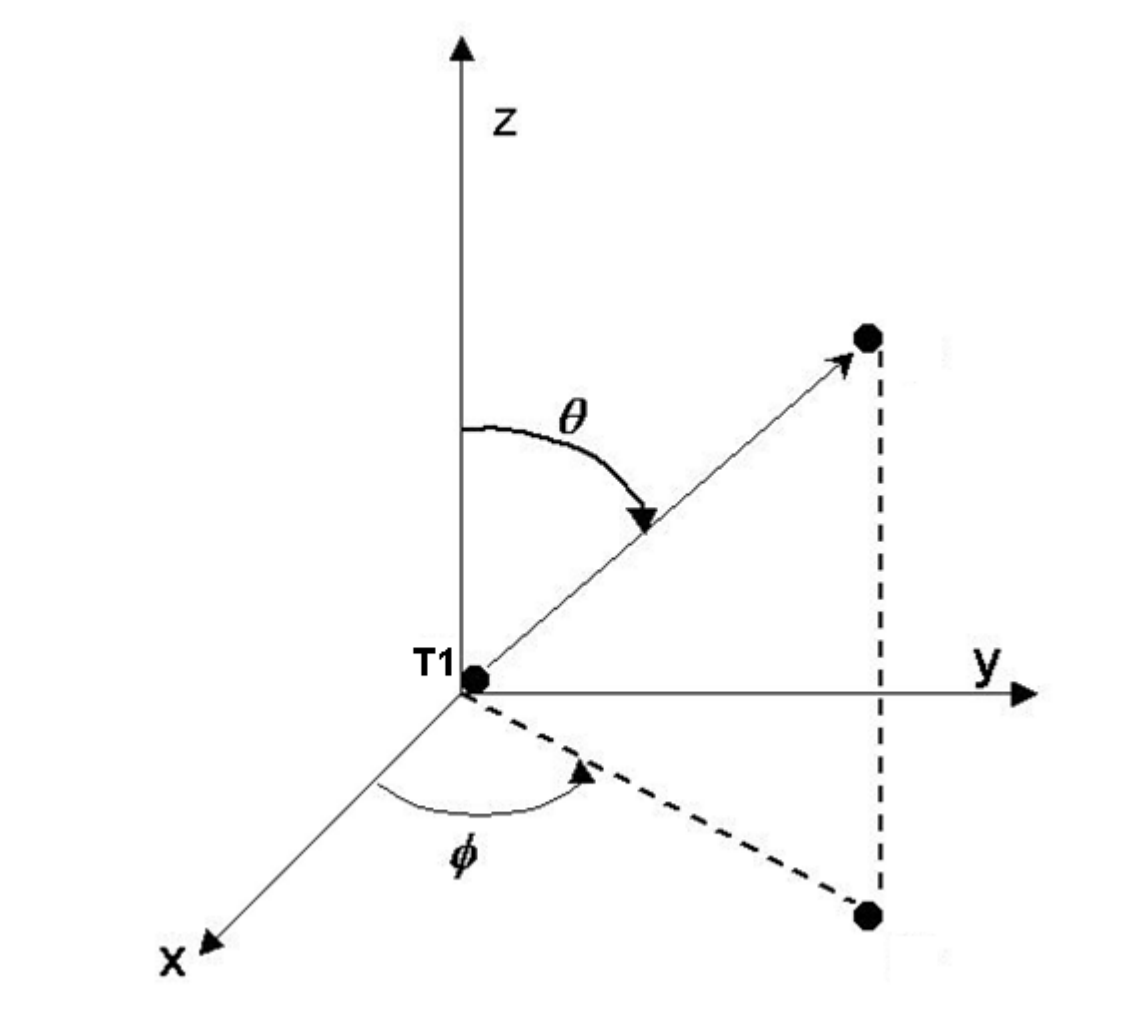


Figure 8-1. Graphical representation of change vector analysis. In three-dimensional space (e.g. X, Y and Z dimensions refer to the Tasseled Cap Brightness (B), Greenness (G) and Wetness (W) bands), the length of the vector from T1 at the origin to T2 at a different date represents the overall magnitude (M) of change between dates. M is calculated from the Pythagorean theorem. The angles of change, θ and ϕ , between the two planes (designated as the X, Y plane and Y, Z plane) quantify the overall direction of change in contrast to simple classes of change (Table 8-6).

The change vector angles, can be computed as:

(2) Colatitude, $\theta = \arccos\left(\frac{\Delta W}{M}\right)$, and

(3) Longitude, $\phi = \arctan\left(\frac{\Delta G}{\Delta B}\right)$.

To compute the summary spherical statistics (such as the mean θ or ϕ for all for all forested pixels in a park), the direction cosines x, y and z are computed for the B, G, and W dimensions for every pixel:

(4) $x = \frac{\Delta B}{M}$, $y = \frac{\Delta G}{M}$ and $z = \frac{\Delta W}{M}$.

These values are summed for all forested image pixels i in a sub-basin such that mean direction cosines are calculated as:

$$(5) \quad \hat{x} = \frac{\sum_{i=1}^n x_i}{\sqrt{\left(\sum_{i=1}^n x_i\right)^2 + \left(\sum_{i=1}^n y_i\right)^2 + \left(\sum_{i=1}^n z_i\right)^2}}, \text{ with } \sum_{i=1}^n y_i \text{ in the numerator of } \hat{y} \text{ and } \sum_{i=1}^n z_i \text{ in the numerator of } \hat{z}.$$

4.3.7 Finally, the mean direction angles are:

$$(6) \quad \hat{\theta} = \arccos(\hat{z}), \text{ and}$$

$$(7) \quad \hat{\phi} = \arctan\left(\frac{\hat{y}}{\hat{x}}\right).$$

Equations 1-4 follow standard trigonometry and were derived from *CRC Standard Tables and Formulae* (Zwillinger 1995). Equations 5 – 7 are from Fisher et al. (1987).

The output data can be viewed in an image processing software and interpreted with respect to changes that are hypothesized to have occurred. The angular data have been shown to aid greatly in interpreting changes of similar magnitude and direction, but with different causation, e.g., gypsy moth defoliation vs. selective logging (Townsend et al. 2004) and Fraser fir mortality (Allen and Kupfer 2000).

The file CVA.gmd is provided for implementation of change vector analysis. This graphical model runs using two three-band images in Erdas Imagine.

Reference Documents

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- Lunetta, R.S., and C.D. Elvidge, editors. 1998. Remote Sensing Change Detection: Environmental Monitoring Methods and Applications. Ann Arbor Press, Chelsea, Mich.
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Appendices

Appendix A : Radiometric Calibration of Landsat ETM+ Image Data

Calculating At-Sensor Reflectance

Each image pixel can be converted to radiance, and later to at-sensor reflectance, using the appropriate calibration coefficients for its band.

Scaling DN to Radiance:

$$\text{rad} = \text{gain} * \text{pixelDN} + \text{bias}$$

where:

rad = spectral radiance at the sensor's aperture in watts/(meter squared * ster * μm)

gain = NLAPS or LPGS (two processing systems used to scale radiance values) Gain, depending on ground-station processing stream

bias = in watts/(meter squared * ster * μm)

pixelDN = the pixel value as an 8-bit digital number

Conversion of Radiance to At-sensor Reflectance:

$$\text{refl} = (\text{pi} * \text{rad} * \text{d}^2) / (\text{ESUN} * \cos\theta_s)$$

where:

refl = unitless at-sensor reflectance (not corrected for atmospheric effects)

pi = mathematical constant 3.14159

rad = spectral radiance at the sensor's aperture in watts/(meter squared * ster * μm)

d = Earth-Sun distance in astronomical units for day of image acquisition

ESUN = mean solar exoatmospheric irradiance

θ_s = solar zenith angle in degrees

Calibration Coefficients

Table A-1. Radiometric Calibration Parameters for Landsat ETM+ for NLAPS and LPGS processing streams processed on or before July 1st, 2000.

Band	Lmax	Lmin (Bias)	NLAPS Gain	LPGS Gain	ESUN
1	194.3	-6.2	0.7862745	0.789370	1969
2	202.4	-6.0	0.8172549	0.820472	1840
3	158.6	-4.5	0.6396078	0.642126	1551
4	157.5	-4.5	0.6352941	0.637795	1044
5	31.76	-1.0	0.1284706	0.128976	225.7
7	10.932	-0.35	0.0442431	0.044417	82.07

Table A-2. Radiometric Calibration Parameters for Landsat ETM+ for NLAPS and LPGS processing streams processed after July 1st, 2000.

Band	Lmax	Lmin (Bias)	NLAPS Gain	LPGS Gain	ESUN
1	191.6	-6.2	0.775686	0.778740	1969
2	196.5	-6.0	0.795686	0.798819	1840
3	152.9	-4.5	0.619216	0.621654	1551
4	157.4	-4.5	0.637255	0.639764	1044
5	31.06	-1.0	0.125725	0.126220	225.7
7	10.80	-0.35	0.043725	0.043898	82.07

NLAPS – National Landsat Archive Production System

LPGS – Level 1 Generation System

ESUN – Exoatmospheric Spectral Irradiance

source: Landsat 7 Science Data Users Handbook,

http://ftpwww.gsfc.nasa.gov/las/handbook/handbook_htmls/chapter11/chapter11.html

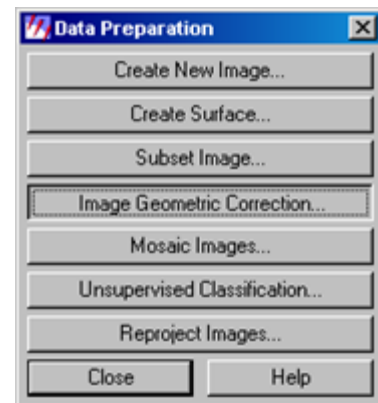
Appendix B : Image Rectification

Reproduced from: Leica Geosystems 2006. Technical Support Article: Image Rectification. [gis.leica-geosystems.com](http://www.gis.leica-geosystems.com/Support/Procedures/Procedure_detail.aspx?article_ID=31), viewed: 11 November 2005, http://www.gis.leica-geosystems.com/Support/Procedures/Procedure_detail.aspx?article_ID=31

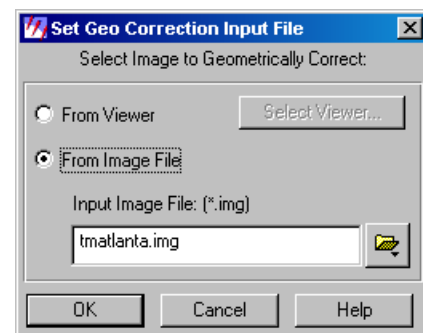
Image rectification is the process of making image data conform to a map projection system. Most often the image is also oriented in such a manner that the north direction corresponds with the top of the image. Images can be converted to real-world ground coordinates by referencing the image to another source that is in the desired map projection. Source information may be obtained from another image, vector coverages, or map coordinates. In order to accomplish this task, ground control points (GCPs) need to be selected from both the input source and the reference source. GCPs are points that are used to depict the same location on the Earth's surface.

1. From the ERDAS IMAGINE main icon panel, select Data Prep | Image Geometric Correction....

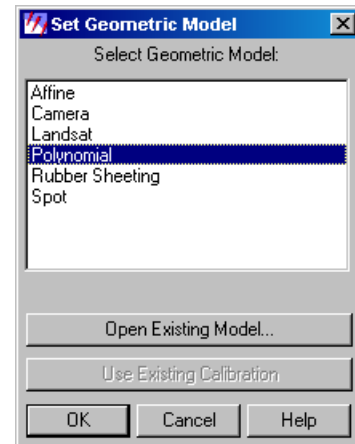
1. From the ERDAS IMAGINE main icon panel, select **Data Prep | Image Geometric Correction....**



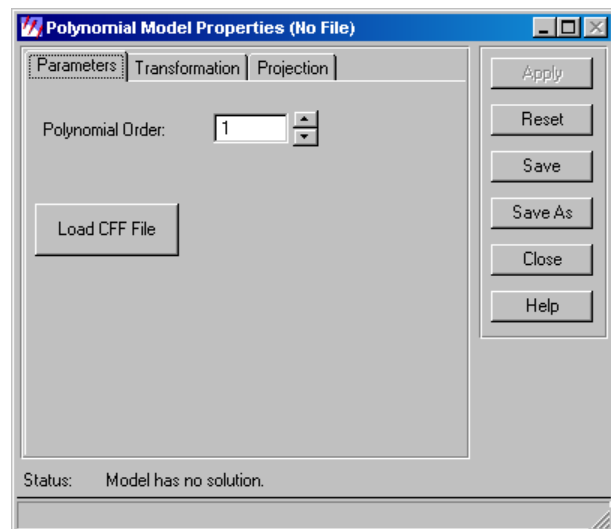
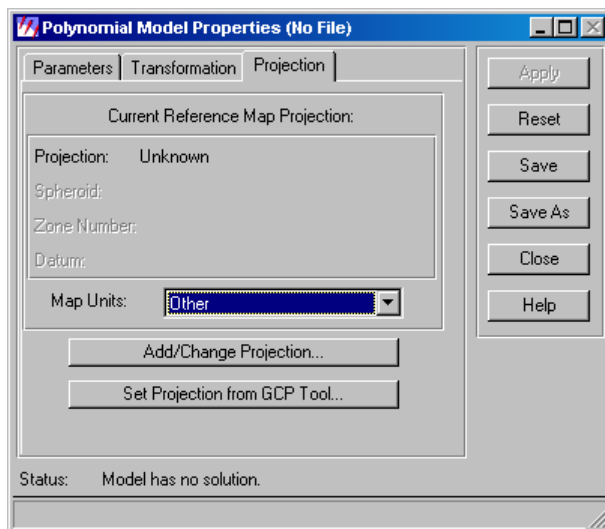
2. Select the file that you wish to geometrically correct. If the file you wish to correct is already in a Viewer, ensure that the **From Viewer** option is selected and then select **Select Viewer...** and subsequently select the appropriate Viewer. If the image you wish to use is not currently displayed, select the **From Image File** option. Use the **File Open** symbol to locate the file in your workspace. When the desired file has been selected, select **OK**.



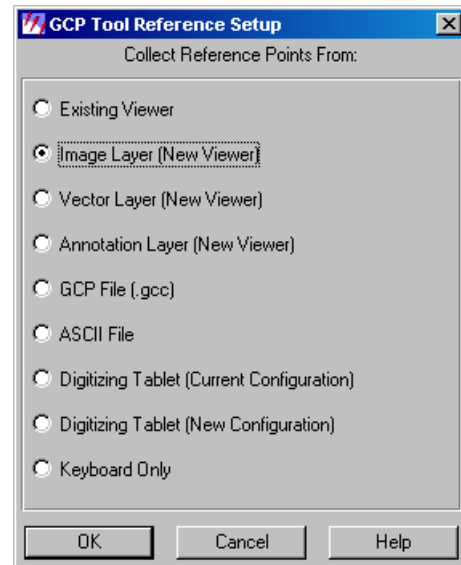
3. In the Set Geometric Model dialog, select the geometric model that you wish to use. For this example we will be using **polynomial**. Select **OK**.



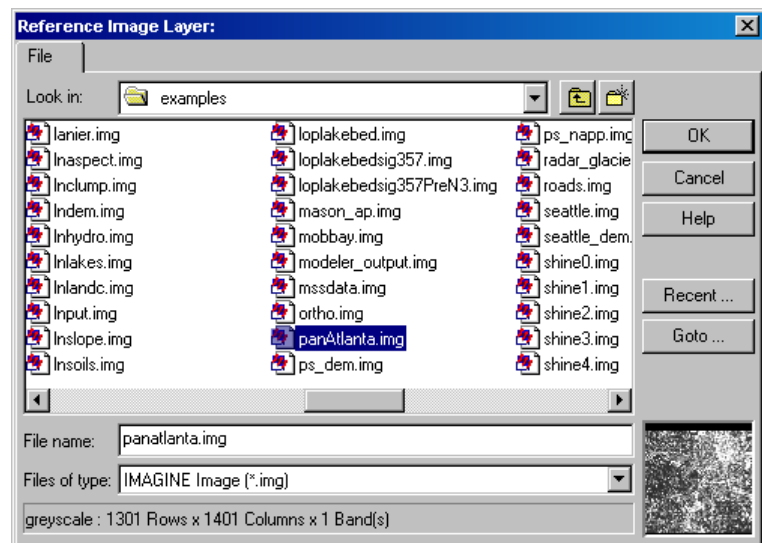
4. Select the order of the polynomial that you wish to use. See the ERDAS Field Guide for detailed information on this subject. Select the **Projection Tab**. Since the projection has not yet been defined, no projection will appear. Select the **Set Projection from GCP Tool** button.



5. This will open the GCP Tool Reference Setup dialog. Define what type of reference input you will be using. For this example, we will be using image-to-image rectification and thus will be selecting the **Image Layer (New Viewer)** option. Select **OK**.

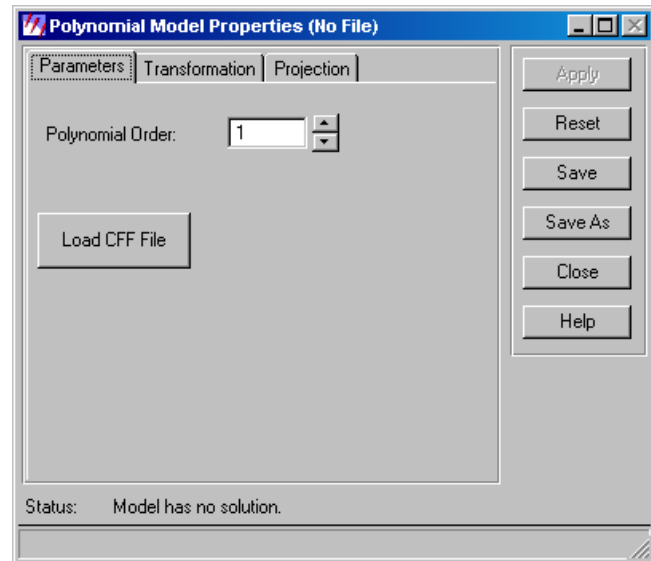


6. This prompts the user to select the reference image that is to be used for the geometric correction. Select the image you wish to use as the reference image, then select **OK**.



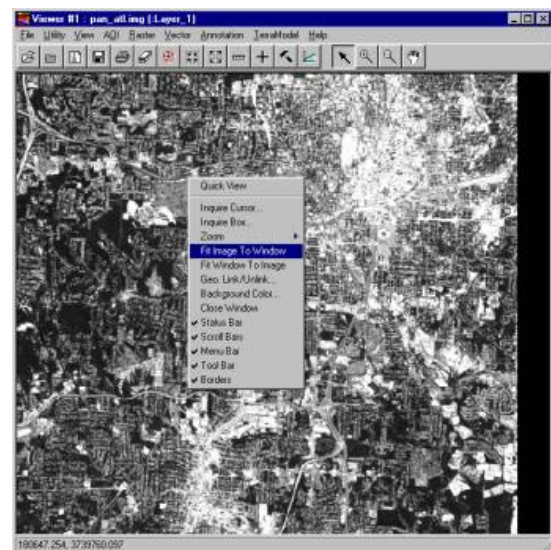
7. Click **Apply** and **Close** in the **Polynomial Model Properties** dialog.

Tip: To aid in determining the same general geographic location on each image right-click in both images and select *Fit Image to Window*.



Tip: To aid in determining a more defined geographic location within each image enlarge the chip viewers and reduce the size of the link box in the Image Viewer such that a larger zoom factor is possible. This can be accomplished by “grabbing” a corner of the Viewer or the link box and resizing the window.

Adjust the size of the link boxes to either zoom in or zoom out to obtain the level of detail that is needed to select the most accurate GCP. This is accomplished through “grabbing” a corner and resizing the link box



8. Move both link boxes (outlines of what is displayed in the chip viewers) so that they cover a common identifiable point feature. This feature should now be seen in both chip viewers. From the GCP Editor tool bar, select the **Keep Current Tool** icon (looks like an open padlock). Then click the **Create GCP** icon (looks like a circle with a cross through it). Now digitize the common point in each of the chip viewers (select a location within each chip viewer that is the same geographic location). Once this is done, you will need to click on the **Select GCP** icon (looks like an arrow) to either move a GCP or to click and drag the link boxes to other identifiable features.



Tip: To change colors of your GCPs more visible, simply click in the **Color** Column and select your color of choice to be used to represent the GCP.



9. Repeat step 5 until at least eight ground control points have been selected. Remember to distribute your GCPs as evenly as possible over the entire image.



10. To remove any unwanted GCPs, select the point (the entire row) by selecting the **Point #**. This will highlight the unwanted point. Ensure that the cursor is located in the farthest left-hand column and right-click to reveal the hidden functions. Select **Delete Selection**.

Point #	Point ID	Color	X Input	Y Input	X Ref	Y Ref	Type	X Residual	Y Residual	RMS Error	Contrib	Match
1	GCP #1		30.375	-104.625	176398.009	3741402.574	Control	0.123	0.834	0.843	1.442	
2	GCP #2		31.974	-157.523	176098.829	3739865.703	Control	-0.295	-1.027	1.069	1.828	
3	GCP #3		127.147	-129.173	178913.812	3740172.181	Check					
4	GCP #4		166.631	-432.245	178824.578	3731317.906	Control	0.278	-0.102	0.296	0.506	
5	GCP #5		302.396	-203.759	183404.964	3737035.548	Control	0.323	0.034	0.325	0.555	
6	GCP #6		377.523	-360.806	184960.593	3732224.842	Control	-0.422	0.309	0.523	0.895	

11. In order to evaluate your transformation matrix, you will now convert some of the GCPs from control points to check points. The check points are an independent means of evaluating the rectification. These points will not be used in the calculations of the transformation matrix. To make a control point into a check point, you will need to select the desired points from the CellArray (select the row that the point occupies). While the selected points are highlighted, select **Edit/Set Point Type/Check**. The type column will update.

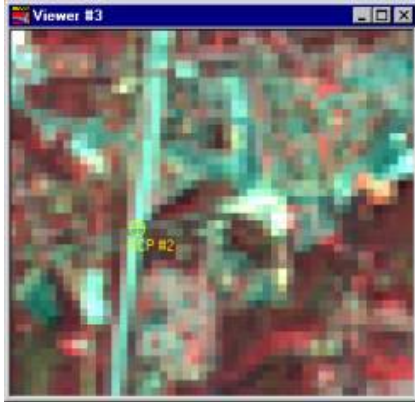
Point #	Point ID	Color	X Input	Y Input	X Ref	Y Ref	Type	X Residual	Y Residual	RMS Error	Contrib	Match
1	GCP #1		30.375	-104.625	176398.009	3741402.574	Control	0.123	0.834	0.843	1.442	
2	GCP #2		31.974	-157.523	176098.829	3739865.703	Control	-0.295	-1.027	1.069	1.828	
3	GCP #3		127.147	-129.173	178913.812	3740172.181	Check					
4	GCP #4		166.631	-432.245	178824.578	3731317.906	Control	0.278	-0.102	0.296	0.506	
5	GCP #5		302.396	-203.759	183404.964	3737035.548	Control	0.323	0.034	0.325	0.555	
6	GCP #6		377.523	-360.806	184960.593	3732224.842	Control	-0.422	0.309	0.523	0.895	

12. To calculate RMS (root mean square) error for the check points, select the **Compute Error For Check Points** icon (little box with a check mark in it). The Control Point Error will now change to be the Check Point Error. In order to see the error for the control points again, select the **Solve Geometric Model with Control Points** icon (the summation character) and the RMS will change.

Point #	Point ID	Color	X Input	Y Input	X Ref	Y Ref	Type	X Residual	Y Residual	RMS Error	Contrib	Match
1	GCP #1		30.375	-104.625	176398.009	3741402.574	Control	0.123	0.834	0.843	1.442	
2	GCP #2		31.974	-157.523	176098.829	3739865.703	Control	-0.295	-1.027	1.069	1.828	
3	GCP #3		127.147	-129.173	178913.812	3740172.181	Check					
4	GCP #4		166.631	-432.245	178824.578	3731317.906	Control	0.278	-0.102	0.296	0.506	
5	GCP #5		302.396	-203.759	183404.964	3737035.548	Control	0.323	0.034	0.325	0.555	
6	GCP #6		377.523	-360.806	184960.593	3732224.842	Control	-0.422	0.309	0.523	0.895	

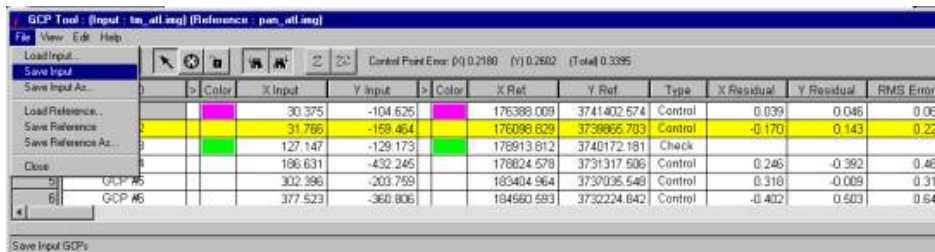
13. If you have an RMS error greater than 1, then select the point(s) with the highest **Contribution Value** and make them check points and recalculate the RMS error without those points.

14. An alternative to the above, examine the points with the highest contribution values and assess them visually to determine whether or not the points represent the same geographic location in both images. This is accomplished through the use of adjusting and resizing of the link boxes and the chip viewers. If the GCP in question is not located in the same geographic location, use the GCP selection tool (icon looks like an arrow) to first select the point and then slightly adjust the geographical location of the improperly placed point.

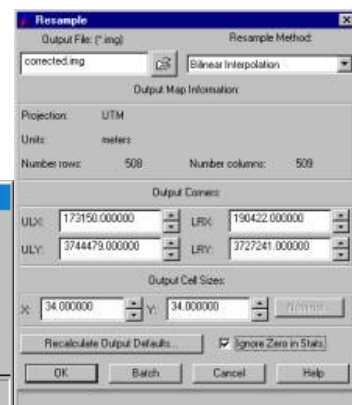
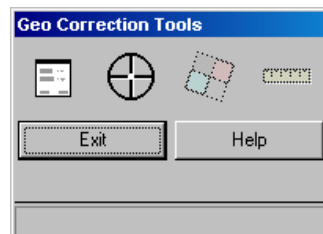


Another option is to delete a control point as described in step 7.

15. When the RMS error is at an acceptable value, you may save your GCPs. Select **File/ Save Input**, and then select **File/Save Reference** in the GCP Tool Window.



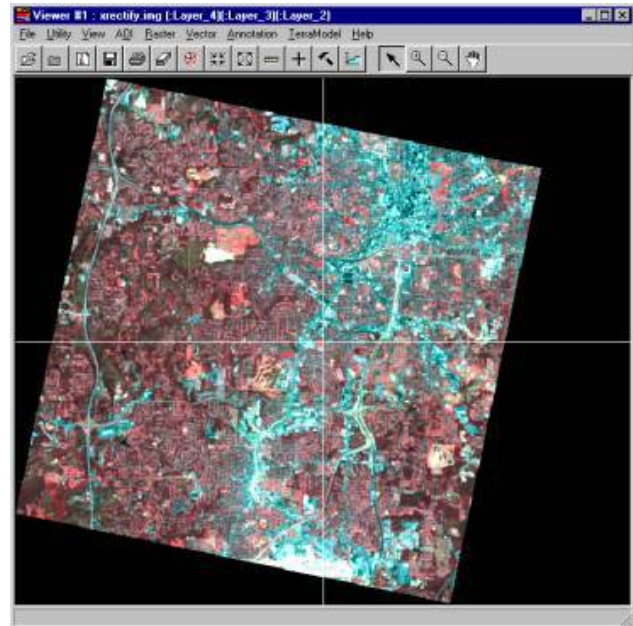
16. From the Geo Correction Tools dialog, select the **Display Resample Image Dialog** icon. In the Resample dialog, enter the name of the output file. The resample method used will change with different data types. In this instance, **Bilinear Interpolation** is selected. Click on the Ignore Zero Stats checkbox. Ensure that the projection information is displayed at the top of the dialog. Select OK to start the rectification.



17. When the progress meter indicates that the process is complete, select **OK** in the status box. Close all the Geo Correction dialogs. If changes have been made since the last save to the GCP

Editor, then you will be prompted to save the edits. Select **Yes** to save the current geometric model.

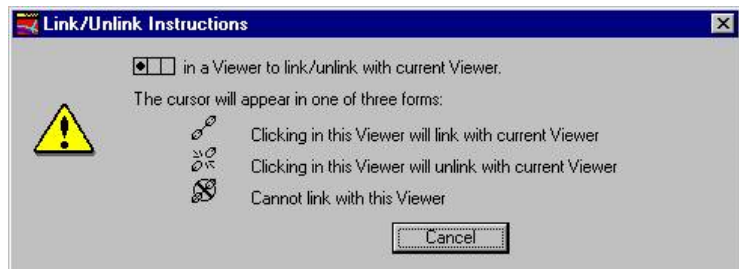
18. To verify the rectification process, first load the corrected image into the Viewer where the uncorrected image was (leave the reference image where it is) and click on the **Inquire Cursor** icon from the menu bar (the plus sign).

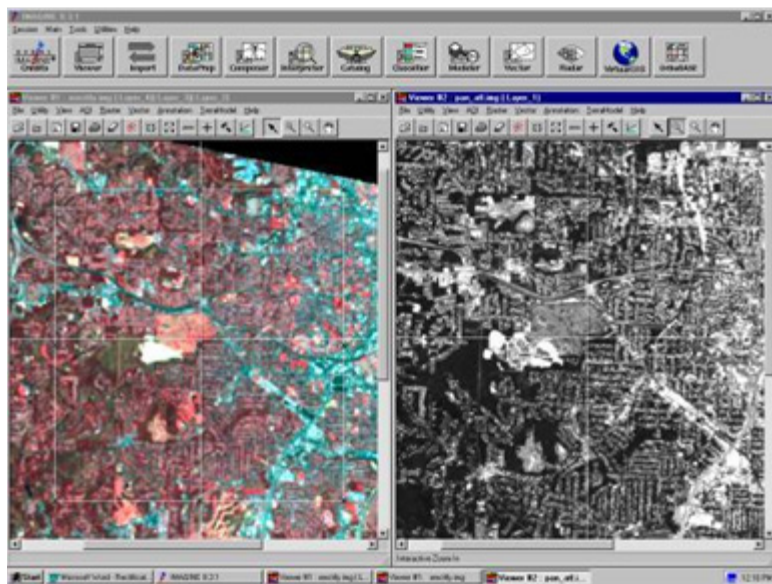


19. Now use the hidden functions within the image (right-click) and select **Quickview / GeoLink-Unlink**. Follow the prompt to click in the other Viewer.



20. Use the **Select**, **Zoom** and **Roam** tools to move the cursor around to verify the correspondence of identifiable features (other than the control points that were used).





Appendix C : Topographic Normalization

Topographic normalization corrects for differential terrain shadowing and illumination caused by low incident sun angle at the time of image acquisition. For one cover type (deciduous forests are recommended), reflectance values are extracted for a range of topographic positions, including both illuminated (usually east-facing) and shaded (west-facing) slopes. A digital elevation model (DEM) is used to compute the solar incidence angle to the normal of all pixels, as:

$$i(\theta, \alpha) = \arccos[\cos(\theta) * \cos(Gz) + \sin(\theta) * \sin(Gz) * \cos(\theta - Ga)], \text{ where}$$

i = incidence angle between the surface normal and the solar beam

θ = solar zenith angle

α = solar azimuth angle

Gz = surface normal zenith angle (terrain slope calculated from DEM)

Ga = surface azimuth angle (surface aspect of the slope, calculated from DEM)

The solar elevation (zenith) and angle (azimuth) may be found in the image metadata from the image provider, or can be derived by entering the image center coordinates and acquisition date and time into a solar position calculator such as the one found at <http://www.srrb.noaa.gov/highlights/sunrise/azel.html>. A regression relationship is developed on a band-by-band basis:

$$R_b(x, y) = f(i(x, y)), \text{ where}$$

R_b = reflectance for band b at the pixel with coordinates x, y and i = the incidence angle at coordinate x, y

Data from a minimum of ten areas each on illuminated and shaded slopes should be extracted, with a minimum of 200 total pixels. R^2 values should exceed 0.8 for all bands except the near infrared band, which should exceed 0.6. Note that R^2 values are generally low closer to the summer solstice (June 21), when the sun is at its highest elevation in the northern hemisphere and illumination effects are minimized. Normalization should not be applied when illumination effects are minimal or regression relationships yield weak coefficients of determination. Normalized images are computed across the entire image on a pixel-by-pixel and band-by-band basis as:

$$R_{b\text{-corrected}} = R_{b\text{-raw}} - \cos(i)m - b + R_{b\text{-average}}, \text{ where}$$

$R_{b\text{-corrected}}$ = terrain-corrected reflectance for band b , $R_{b\text{-raw}}$ = original reflectance on sloped terrain, $R_{b\text{-average}}$ = average reflectance for training data used to build the statistical model, i = solar incidence angle to the normal of the pixel, m = the slope of the regression relationship determined above, and b = y-intercept of the regression relationship.

Appendix D : Tasseled Cap Coefficients

Table D-1. Coefficients for Landsat 7 ETM+ at-Satellite Reflectance

Index	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Brightness	0.3561	0.3972	0.3904	0.6966	0.2286	0.1596
Greenness	-0.3344	-0.3544	-0.4556	0.6966	-0.0242	-0.2630
Wetness	0.2626	0.2141	0.0926	0.0656	-0.7629	-0.5388
Fourth	0.0805	-0.0498	0.1950	-0.1327	0.5752	-0.7775
Fifth	-0.7252	-0.0202	0.6683	0.0631	-0.1494	-0.0274
Sixth	0.4000	-0.8172	0.3832	0.0602	-0.1095	0.0985

Source: Huang, C., B. Wiley, L. M. Yang, C. Homer, and G. Zylstra. 2000. Derivation of a tasseled cap transformation based on Landsat-7 at-satellite reflectance. <http://landcover.usgs.gov/pdf/tasseled.pdf>)

Table D-2. Coefficients for Landsat 5 TM at-Satellite Reflectance

Feature	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Brightness	0.2043	0.4158	0.5524	0.5741	0.3124	0.2303
Greenness	-0.1603	-0.2819	-0.4934	0.7940	-0.0002	-0.1446
Wetness	0.0315	0.2021	0.3102	0.1594	-0.6806	-0.6109
Fourth	-0.2117	-0.0284	0.1302	-0.1007	0.6529	-0.7078
Fifth	-0.8669	-0.1835	0.3856	0.0408	-0.1132	0.2272
Sixth	0.3677	-0.8200	0.4354	0.0518	-0.0066	-0.0104

Source: Crist, E. P. 1985. A TM Tasseled Cap Equivalent Transformation for Reflectance Data. Remote Sensing of Environment 17:301-306.)

Table D-3. Coefficients for Landsat 5 TM Pixel DN

Feature	Band 1	Band 2	Band 3	Band 4	Band 5	Band 7
Brightness	0.2909	0.2493	0.4806	0.5568	0.4438	0.1706
Greenness	-0.2728	-0.2174	-0.5508	0.7221	0.0733	-0.1648
Wetness	0.1446	0.1761	0.3322	0.3396	-0.6210	-0.4186
Haze	0.8461	-0.0731	-0.4640	-0.0032	-0.0492	0.0119
Fifth	0.0549	-0.0232	0.0339	-0.1937	0.4162	-0.7823
Sixth	0.1186	-0.8069	0.4094	0.0571	-0.0228	0.0220

Source: Crist, E. P., R. Laurin, and R. C. Ciccone. 1986. Vegetation and soils information contained in transformed Thematic Mapper data. In Proceedings of IGARSS' 86 Symposium, 1465-70. Ref. ESA SP-254. Paris: European Space Agency. <http://www.ciesin.org/docs/005-419/005-419.html>

Table D-4. Coefficients for Ikonos Multispectral Imagery

Component	Band 1	Band 2	Band 3	Band 4
First	0.326	0.509	0.560	0.567
Second	-0.311	-0.356	-0.325	0.819
Third	-0.612	-0.312	0.722	-0.081
Fourth	-0.650	0.719	-0.243	-0.031

source: Horne, J.H. 2003. A Tasseled Cap Transformation for Ikonos Images. In ASPRS 2003 Annual Conference Proceedings. Anchorage, Alaska.

Sample calculation of Brightness (B), Greenness (G), and Wetness (W) components for a Landsat 5 TM DN pixel intensity.

$$B = (0.2043)*\text{band1} + (0.4158)*\text{band2} + (0.5524)*\text{band3} + (0.5741)*\text{band4} + (0.3124)*\text{band5} + (0.2303)*\text{band7}$$

$$G = (-0.1603)*\text{band1} + (-0.2819)*\text{band2} + (-0.4934)*\text{band3} + (0.7940)*\text{band4} + (-0.0002)*\text{band5} + (-0.1446)*\text{band7}$$

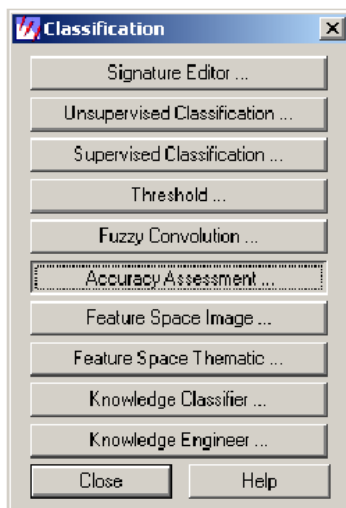
$$W = (0.0315)*\text{band1} + (0.2021)*\text{band2} + (0.3102)*\text{band3} + (0.1594)*\text{band4} + (-0.6806)*\text{band5} + (-0.6109)*\text{band7}$$

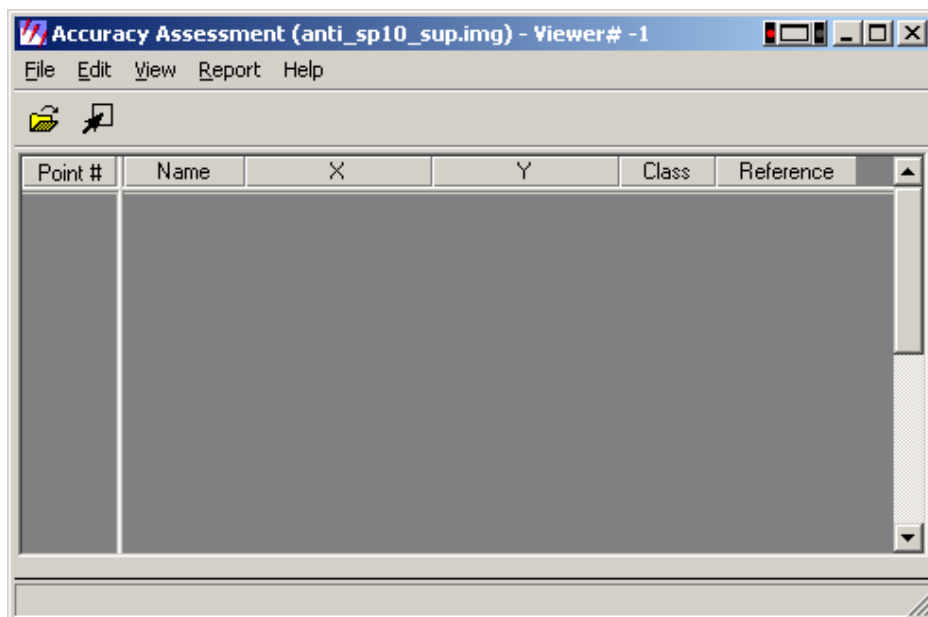
Appendix E : Extracting Map Data for Accuracy Assessment

Following are instructions for creating random points for image map classification accuracy assessment using Erdas Imagine 8.7.

From the main **Classifier** menu, select **Accuracy Assessment**.

Main → Image Classification... → Accuracy Assessment



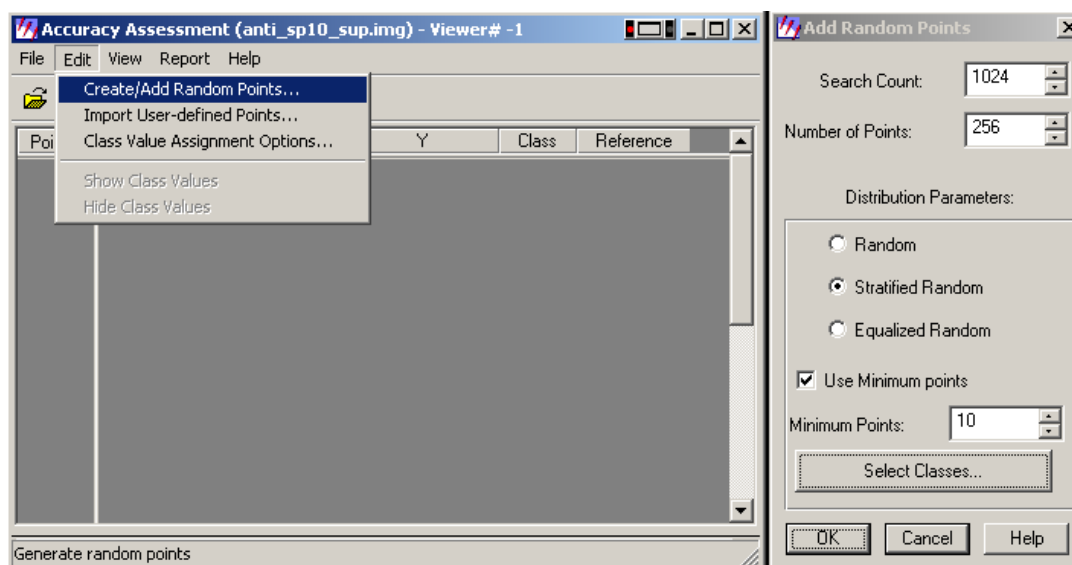


Open a classified image map file.

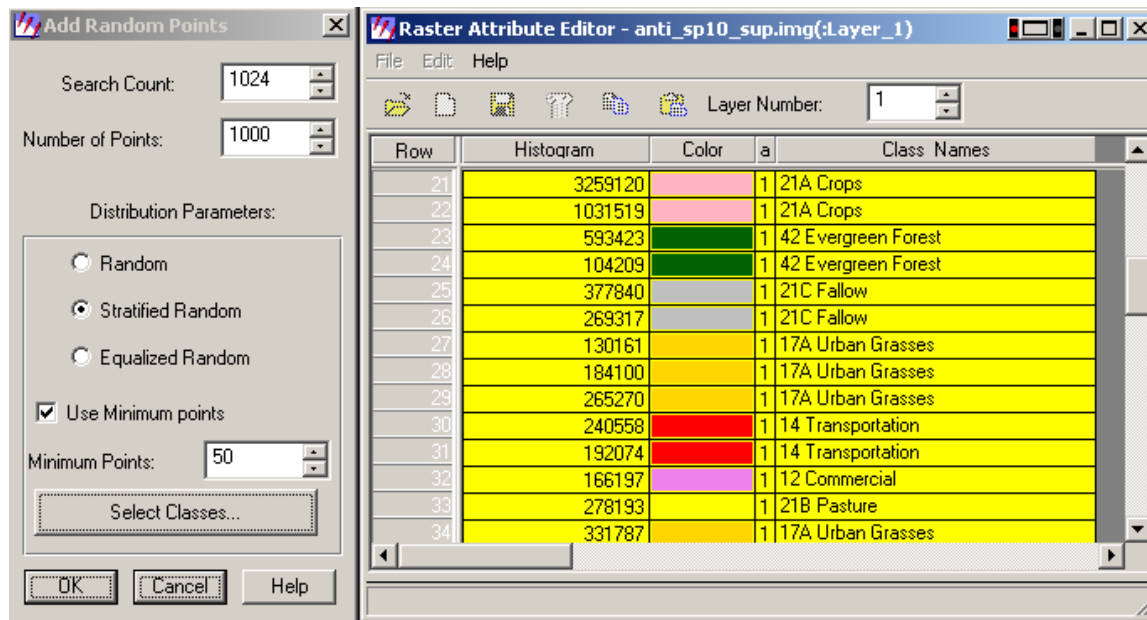
File → Open.... 

Create stratified random points for assessment classes.

Edit → Create/Add Random Points...

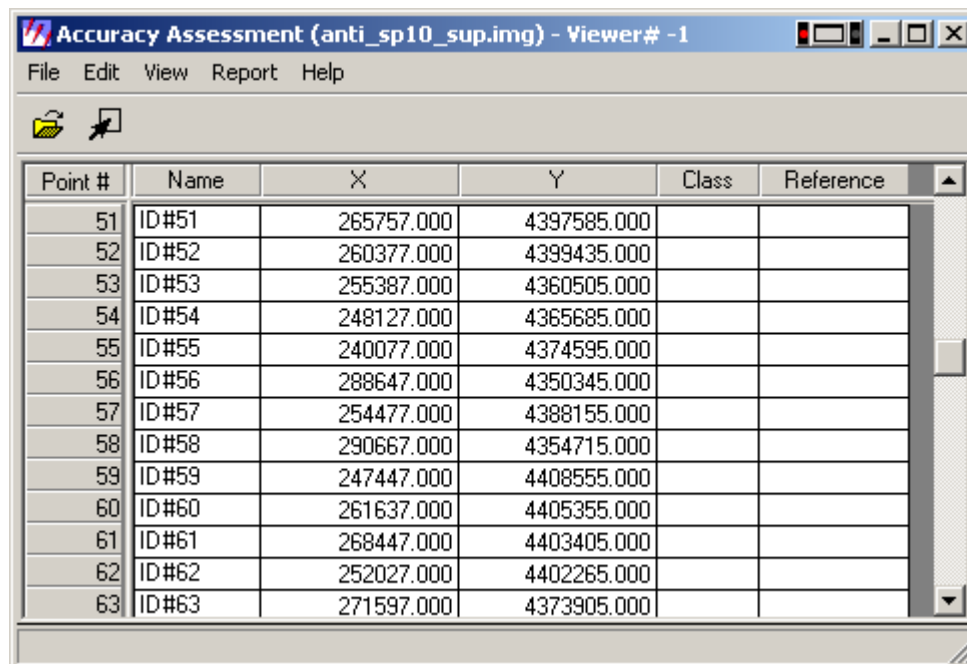


Set the total **Number of Points**, select **Stratified Random** as the point distribution method, and set the **Minimum Points** per class. Then click **Select Classes** and select the classes you would like to generate check points for from the **Raster Attribute Editor**.



Click **OK**.

Random points will now be generated.



To see the class that each point falls into on the classified image, pick **Edit → Show Class Value**

		Y	Class	Reference
		4355755.000	33	
		4401055.000	25	
		4396515.000	45	
4	ID#4	290347.000	4365185.000	34
5	ID#5	287897.000	4393105.000	47
6	ID#6	288807.000	4378455.000	45
7	ID#7	291777.000	4406545.000	45
8	ID#8	247577.000	4364315.000	48
9	ID#9	277467.000	4390845.000	31
10	ID#10	277667.000	4400735.000	48
11	ID#11	239787.000	4389395.000	46
12	ID#12	262077.000	4364105.000	26
13	ID#13	265697.000	4388805.000	28
14	ID#14	273267.000	4382575.000	33
15	ID#15	291337.000	4399115.000	33
16	ID#16	268457.000	4393625.000	31
17	ID#17	237807.000	4383915.000	46
18	ID#18	246447.000	4362195.000	25
19	ID#19	284887.000	4366635.000	28
20	ID#20	260027.000	4369395.000	45
21	ID#21	298717.000	4382225.000	30
22	ID#22	293687.000	4390735.000	45
23	ID#23	266867.000	4389885.000	32
24	ID#24	257557.000	4414935.000	29
25	ID#25	275497.000	4397285.000	28
26	ID#26	270417.000	4374435.000	29
27	ID#27	291237.000	4377735.000	45
28	ID#28	280697.000	4360175.000	26

Show the actual classes

Reference values for each point, based on data collected by the analyst in the field or through the use of ancillary data, now need to be added manually. Now image map accuracy can be assessed using several methods.

Appendix F : Arc/Info Commands for Buffer Creation

Park Area Only

GRID: gridclip HABITAT HABITAT_PRK cover PARKBND

Figure F-1 shows a habitat map for the region surrounding Antietam National Battlefield (ANTI), where forest (in green) is habitat and all other classes (tan) are non-habitat. The park boundary is indicated in red. Figure F-2 indicates the area of analysis using a park-only buffer.

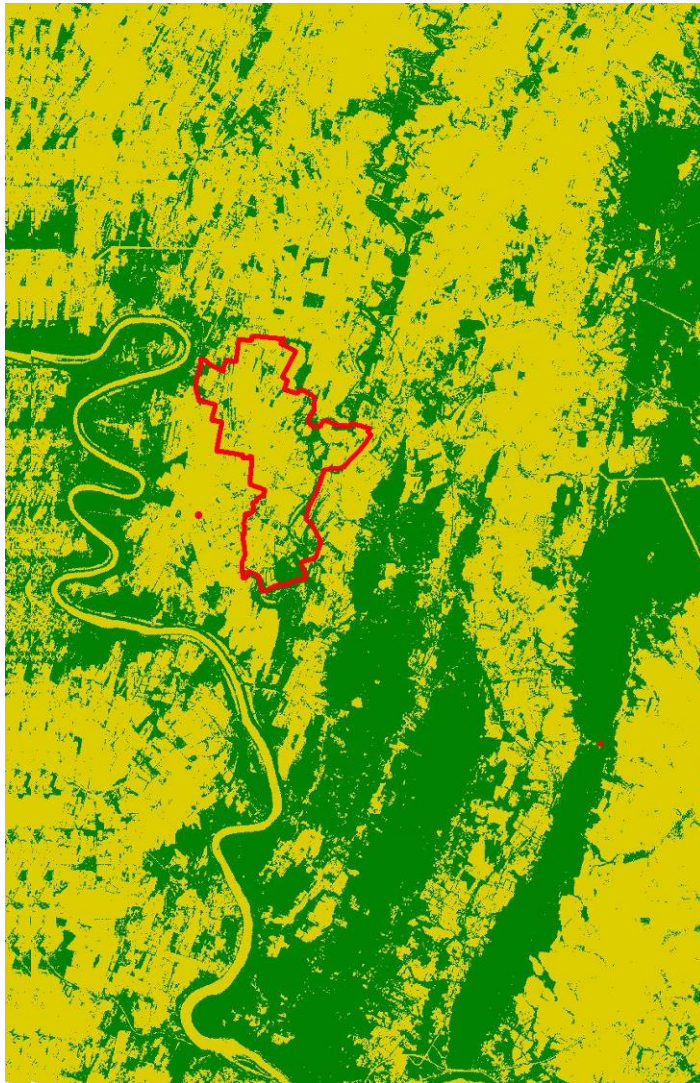


Figure F-1. Habitat (forest in green) and non-habitat (non-forest in tan) for the region surrounding ANTI.

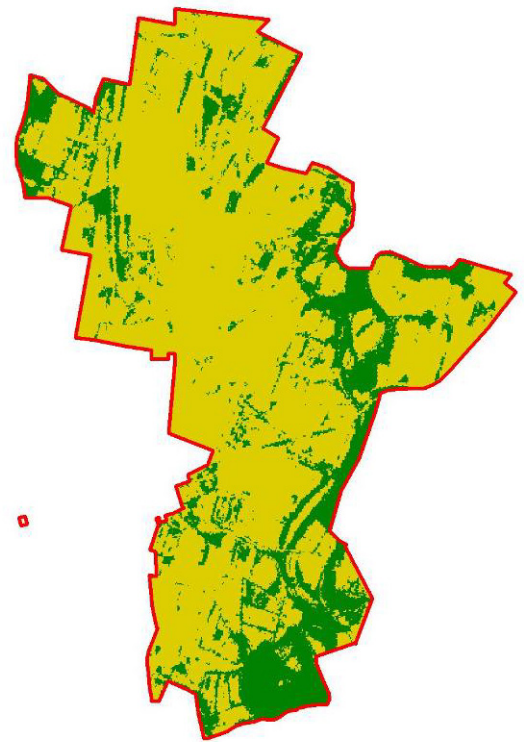


Figure F-2. Habitat and non-habitat for ANTI alone.

Watersheds

GRID: gridclip HABITAT HABITAT_WS cover WSHED

Figure F-3 illustrates the area covered using the watershed buffer for ANTI.

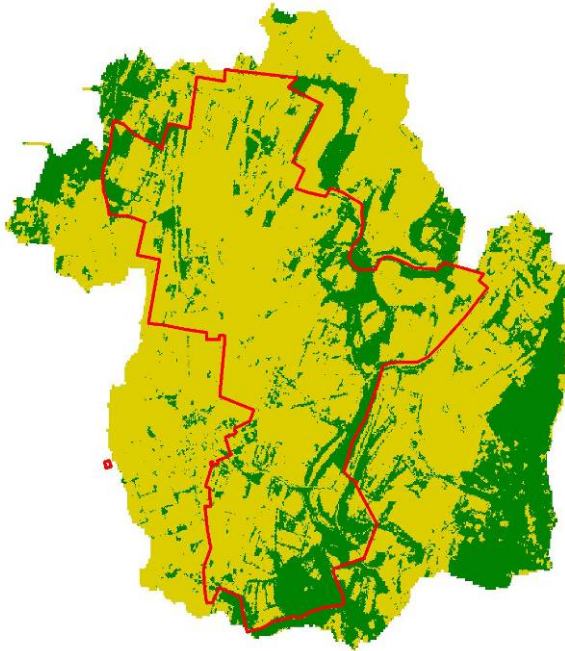


Figure F-3. ANTI habitat/non-habitat map clipped to watershed boundaries.

Uniform around Park

Make sure that the polygon(s) in the boundary coverage have an item with a unique value to identify the park boundary.

ARC: additem PARKBND.PAT PARKBND.PAT code 3 3 1

Tables: Sel parkbnd.pat

Tables: Calc code = 1

Tables: quit

Convert the park boundary to a grid of the same cell size as the land cover grid.

GRID: PARKBNDGRID = polygrid(PARKBND, code, #, #, 10) [this is for a 10m grid]

Use eucdistance in GRID to create buffer boundaries. You can set some arbitrary maximum distance

GRID: BNDEUC = eucdistance(PARKBNDGRID, #, #, 4000) [this one goes out 4000m]

GRID: BNDEUC1 = int(BNDEUC + .5)

GRID: kill BNDEUC

Go into tables to dump the data to a text file.

TABLES: sel BNDEUC1.VAT

TABLES: unload buffer.txt

Open the file “buffer.txt” in excel. Save it as an excel spreadsheet “bndeuc1.xls”

The first column is the buffer distance. The second column is the number of pixels found in that buffer distance.

Note that the first entry has a buffer distance of zero. This is the park itself. It will have a large number of pixels compared to the subsequent buffer zones (e.g., 10m, 14m, 20m, and so on up to 4000m in this case)

Compute a running sum of each consecutively further buffer (third column in excel spreadsheet). Divide this by the first entry in the second column (i.e., the number of cells in the park itself, buffer distance 0) to get the size of the park+buffer relative to the park alone (the 4th column in excel spreadsheet). For ANTI, for example, the park+buffer is 2.00182x the size of the park alone at a buffer distance of 590m, Thus, 590m is the 2X buffer size. Likewise, 2080m is the 5X park buffer. The 2X buffer for Rock Creek was 100m, while the 5X buffer was 420m.

The formula in cell C1 should be: =B1

The formula in cell D1 should be =C1/\$B\$1

The formula in cell C2 should be =B2 + C1

The formula in cell D2 should be = C2/\$B\$1

Click and drag cells C2 and D2 to populate the rest of the cells in columns C and D with these formula

Column D indicates the % of park size represented by the buffer distance shown in corresponding Column A.

Create a grid that shows the different buffer sizes. This is done using reclass and a remap table in GRID. The contents of the remap table “reclass.txt” for the ANTI example would be a plain text file that would look something like this:

0 0 : 1
1 589 : 2
590 1137 : 3
1138 1630 : 4
1631 2079 : 5

Arc remap tables are read as follows: the first two numbers on a line represent the range of values to be reclassified (0 to 0 on the first line, 1 to 589 on the second line and so on). The colon indicates that the next number is the reclassified value for that range (all values 0 to 0 are reclassified as “1”; all values 1 to 589 are reclassified to “2” and so on).

In the ANTI example, class 1 is the park itself. Class 2 is the 2X buffer, determined as the area up to a 590m buffer and so on. The numbers for the reclass are determined from the excel spreadsheet. The third line is the 3X park boundary (590-1137m). If you were only interested in the park area, and the 2X and 5X buffers, then the remap file could look like this:

```
0 0 : 1
1 589 : 2
590 2079 : 5
```

GRID: BUFFERCLASS1 = reclass(BNDEUC1,reclass.txt)

GRID: BUFFERCLASS2 = con(BUFFERCLASS1 le 5,bufferclass1) [this example just includes buffers up to 5X park size]

GRID: kill BUFFERCLASS1

Create new buffers of habitat areas in GRID. Figure F-4 shows the 2X and 5X buffers for ANTI

GRID: habitat_2x = con(bufferclass2 < 3,habitat)

GRID: habitat_5x = con(bufferclass2 < 6,habitat)

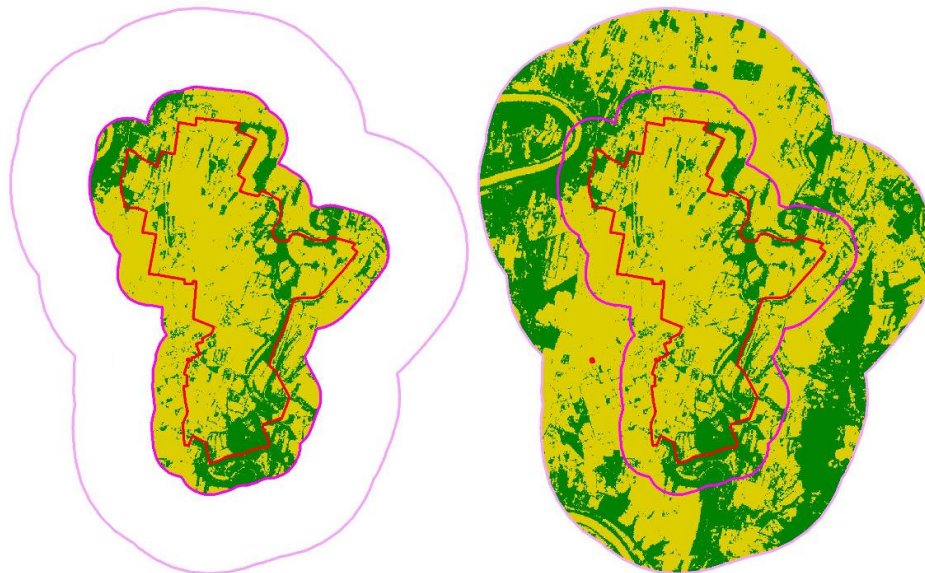


Figure F-4. Habitat/non-habitat maps for ANTI (red boundary) with a 2X buffer (left, magenta boundary) and a 5X buffer (right, light pink boundary).

Intersecting Habitat Patches (IHP) Buffer

The objective of this buffer is to include habitat that intersects with the park boundary (or alternatively one of the buffers identified above). For the “intersecting patches” buffer, there are a variety of important issues, the two critical ones being:

- 1) Are we only interested in patches that intersect the park boundary, or are we interested in patches that intersect the 2X or 5X boundary?
- 2) Whichever intersection we chose, these buffers yield map extents (assuming a rectangular map with max/min X and Y coordinates) that include areas of habitat that do not meet the intersection rule. Are these areas considered non-habitat? The approach outlined below generates output that can be treated either way.

Use regiongroup at the GRID prompt to identify unique habitat/nonhabitat patches.

GRID: HABITAT_RG = regiongroup(HABITAT,#,eight) [this uses the “queen’s case,” allowing diagonals to be connected]

GRID: HABITAT_RG2 = con(HABITAT > 0, HABITAT_RG) [this makes sure that if any areas of the habitat are mapped as 0 (background), they are excluded]

*** This second step is not necessary if the background has always been set to nodata. In that case, *HABITAT_RG2 = HABITAT_RG*.

Intersect the map of patches created above with the buffers grid to determine which buffers (or the park itself) that each patch intersects. Of course, many patches intersect many buffers, so we are only interested in identifying the closest buffer (or the park itself) that the patch intersects.

GRID: HAB_RGMIN = zonalmin(HABITAT_RG2, BUFFERCLASS2)

Remember that HABITAT should have 2 classes, 1 = nonhabitat and 2 = habitat. HAB_RGMIN has 5 classes based on the five buffer zones defined in section 4.8.6: 1 = park itself, 2 = 2X buffer, 3 = 3X buffer, 4 = 4X buffer and 5 = 5X buffer.

Create a new grid where each patch is identified by its cover class and the buffer it intersects.

*GRID: HAB_RGMIN2 = 10 * HABITAT + HAB_RGMIN*

Therefore HAB_RGMIN2 has nonhabitat patches identified as 11, 12, 13, 14 and 15 (we are not so interested in these), while habitat is coded 21 (patch intersects park), 22 (patch intersects 2X buffer), 23, 24 and 25 (patch intersects 5X buffer).

In order to use this information, we now need to know how to subset (clip) the habitat grid to the appropriate area (map extent) defined by patch buffers. This is an important step because map extent significantly impacts the calculation of fragmentation statistics within the gridded map file. This step is included to prevent bias based on using an arbitrarily established map extent. This allows maps of different parks to be compared because a common method for identifying map extent has been employed.

Determine the maximum and minimum extents (X and Y coordinate systems) of habitat patches intersecting the desired boundaries.

GRID: HAB_RGMIN1X = con(HAB_RGMIN2 == 21, HAB_RGMIN2) [saves only habitat patches 21, touches park boundary]

GRID: HAB_RGMIN2X = con(HAB_RGMIN2 == 21, HAB_RGMIN2, con(HAB_RGMIN2 == 22, HAB_RGMIN2)) [saves only habitat patches 21-22, i.e. the park and the 2X buffer]

GRID: HAB_RGMIN5X = con(HAB_RGMIN2 > 20, HAB_RGMIN2) [saves only habitat patches 21-25, any buffer up to 5X... note that in the Antietam example 2x-5x are same]

Convert to a polygon coverage.

GRID: POLYBUF1X = gridpoly(HAB_RGMIN1X)

GRID: POLYBUF2X = gridpoly(HAB_RGMIN2X)

GRID: POLYBUF5X = gridpoly(HAB_RGMIN5X)

Use describe at the arc prompt to get the map extents.

ARC: describe polybuf1x

ARC: describe polybuf2x

ARC: describe polybuf5x

Write down the map extents (Xmax, Xmin, Ymax, Ymin). Then use *arccedit* to create arc polygon coverages for clipping the grids.

Copy base covers from the original park boundaries.

ARC: copy PARKBND PATCHBND1X

ARC: copy PARKBND PATCHBND2X

ARC: copy PARKBND PATCHBND5X

For each coverage, open up *arccedit*. Select the existing arcs and delete. Add new arcs that represent the desired map boundaries. This is done manually. In the example below, you will need the map extent coordinates for POLYBUF2X obtained using *describe* above.

Arcedit: disp 9999

Arcedit: ec PATCHBND2X

Arcedit: de arc lab

Arcedit: draw

Arcedit: ef arc

Arcedit: sel all

Arcedit: delete

Arcedit: snapping closest 100 [enter a snapping distance so that the corners of the bounding box snap into a closed polygon]

Arcedit: coord keyboard

Arcedit: add

Enter Key,X,Y: 2,Xmin,Ymin [first node, these coordinates were obtained using describe]

Enter Key,X,Y: 1,Xmin,Ymax [add a vertex]

Enter Key,X,Y: 1,Xmax,Ymax [add a vertex]

Enter Key,X,Y: 1,Xmax,Ymin [add a vertex]

Enter Key,X,Y: 2,Xmin,Ymin [last node, snaps to the first]

Enter Key,X,Y: 9

Arcedit: save

Arcedit: q

ARC: build PATCHBND2X poly

Follow the same instructions for PATCHBND1X and PATCHBND5X, except use the coordinates gleaned from describe on POLYBUF1X and POLYBUF5X, respectively.

Identify patches within map extent as whether they are habitat-intersecting or habitat-nonintersecting.

GRID: HABITAT2 = con(HABITAT > 0, HABITAT + 2) [this creates a new habitat coverage which is used to identify 3 = nonintersecting non-habitat and 4 = nonintersecting habitat]

Intersect with park only:

GRID: HAB_P1A = con(HAB_RGMIN le 1, HABITAT)

GRID: HAB_P1B = merge(HAB_P1A, HABITAT2)

GRID: gridclip HAB_P1B HABITAT_P1 cover PATCHBND1X

This grid HABITAT_P1 represents the map for patches intersecting the park boundary. The classes are:

- 1 = nonhabitat, patch intersects the park
- 2 = habitat, patch intersects the park
- 3 = nonhabitat within map extent, does not intersect park
- 4 = habitat within map extent, but does not intersect park

Class 3 is of no concern: it can be recoded to 1 (nonhabitat). Class 4 is of concern. If you want to consider it habitat, recode it to 2; otherwise it too should be recoded to nonhabitat (1).

Intersect with park + 2X buffer:

GRID: HAB_P2A = con(HAB_RGMIN le 2, HABITAT)
GRID: HAB_P2B = merge(HAB_P2A,HABITAT2)
GRID: gridclip HAB_P2B HABITAT_P2 cover PATCHBND2X

Intersect with park + 5X buffer:

GRID: HAB_P5A = con(HAB_RGMIN le 5, HABITAT)
GRID: HAB_P5B = merge(HAB_P5A,HABITAT2)
GRID: gridclip HAB_P5B HABITAT_P5 cover PATCHBND2X

*****Note:** for Antietam, the 2X and 5X map extents are identical; thus, PATCHBND2X can be used for the 5X intersection. This will not be the case for all parks.

HAB_P1A, HAB_P2A, HAB_P5A, HAB_P1B, HAB_P2B and HAB_P5B can be deleted.

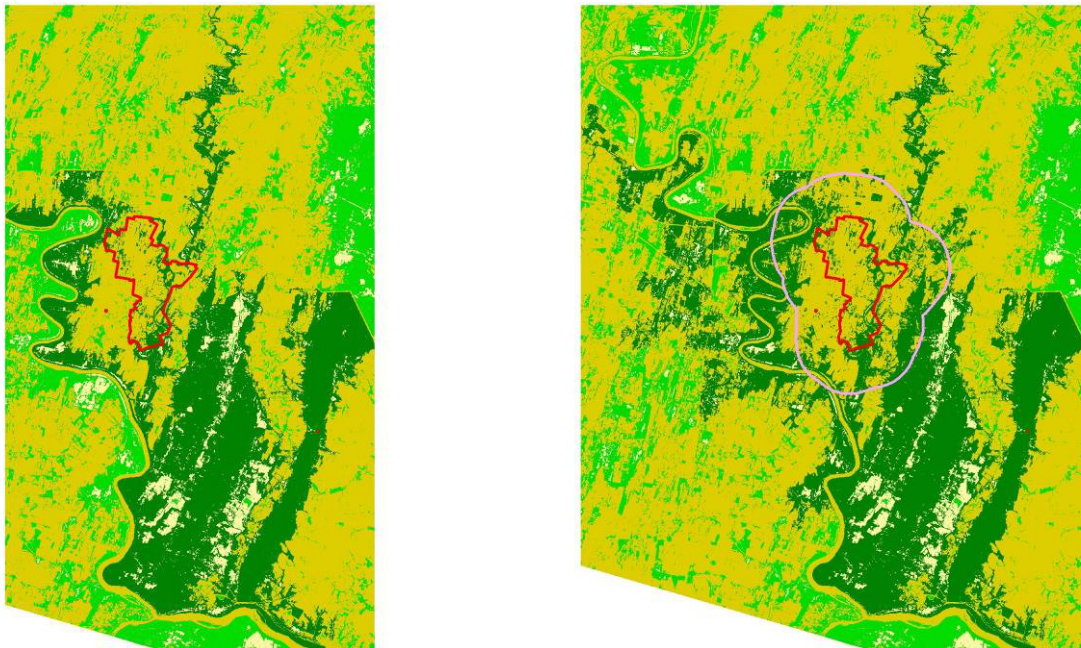


Figure F-5. Patch intersection boundary for ANTI. Left: patches that intersect with the park boundary. Right: patches that intersect with the 5X park buffer. Dark green indicates all habitat patches that intersect with the ANTI park boundary. Light green indicates habitat patches within the map extent but that do not intersect with the park boundary. Dark tan patches are non-habitat patches that intersect with the park boundary while light tan are within the map extent, but do not intersect.

Appendix G : Fragstats Analysis of Example Landscapes (Class-Level Output)

This example provides landscape pattern metrics summarized for all forest habitat patches in maps of Antietam National Battlefield. The binary habitat/nonhabitat input maps are generated from SOP4. Townsend et al. (2009) provide additional examples for Catoctin Mountain Park, Prince William Forest Park and Rock Creek Park. An interpretation of the findings across parks, resolution and buffer extent is also provided in Townsend et al. (2009).

Table G-1. Landscape pattern metrics summarized for Antietam National Battlefield

Landscape ^a	Resolution ^b (m)	Buffer ^c	Landscape Metric ^d										
			CA	PLAND	NP	LPI	TE	ED	AREA_MN	AREA_AM	TCA	PROX_MN	ENN_MN
ANTI	4	None	273.3328	20.7473	4757	5.9474	642016	487.3215	0.0575	29.2533	1.0352	1151.4486	11.3561
ANTI	10	None	319.74	24.2685	578	14.2488	197950	150.2455	0.5532	111.7485	87.23	518.4172	32.8604
ANTI	15	None	231.1054	17.5413	534	4.8828	160198.5	121.5937	0.4328	25.1494	54.8472	67.1405	38.698
ANTI	30	None	462.8201	35.0949	157	24.5196	158374.5	120.0927	2.9479	228.7939	188.7669	242.9392	71.9372
ANTI	10	2X	702.25	26.5651	1090	14.1426	400730	151.5901	0.6443	215.9698	188.7669	1018.5911	71.9372
ANTI	10	5X	2338.57	35.4838	2322	8.7363	999130	151.6011	1.0071	215.9698	1026.83	1708.6453	32.4868

1. Landscape name: ANTI – Antietam National Battlefield
2. Resolution refers to the pixel size of the original imagery (in meters).
3. Buffer width of the park follows the convention described in SOP4.
4. Metrics, and associated units, are defined in Table 5-1.

Appendix H : Fragstats Analysis of Example Landscapes (Patch-Level Output)

The images below provide examples of patch-level metrics of pattern projected graphically for a 30-m map of the forest habitat of Antietam National Battlefield. The binary habitat/nonhabitat input map was generated from SOP4. (H-1) Patches are shaded according to patch size (larger patches have darker shading). (H-2) Patches are shaded according to proximity to nearest neighbor (isolated patches have darker shading). Brown shading indicates nonhabitat.

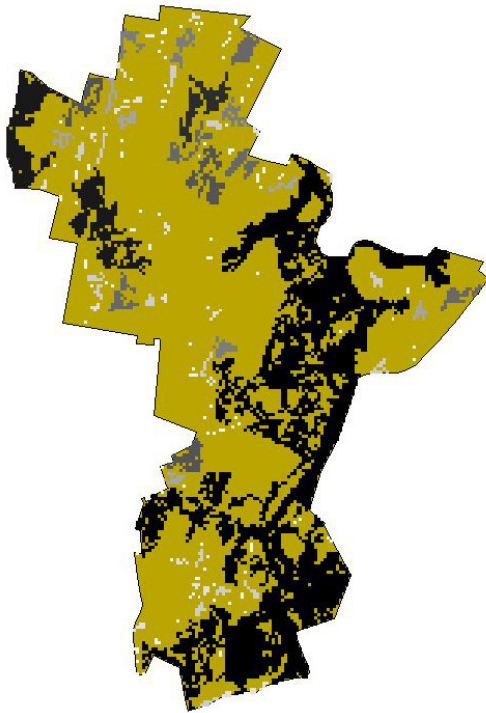


Figure H-1. Patches shaded according to patch size

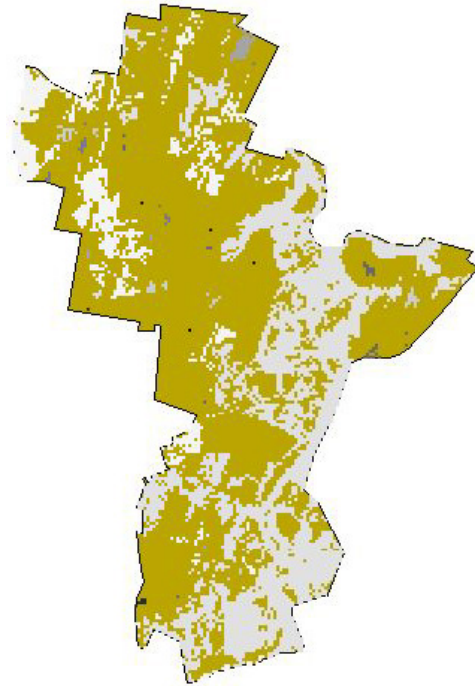


Figure H-2. Patches shaded according to proximity to nearest neighbor

Appendix I : Pre-processing example

The following Arc/Info commands return an ASCII data file <MAP.SAMP> with each record containing the geographic coordinates of a cell, its patch ID, and its habitat quality index. This file format (including habitat quality values) is required by the LANDGRAPH software.

1. Reclassify land cover map to habitat/nodata. For example, a simple conditional statement can be used in GRID to create a temporary file <TEMP> from a map <MAP> with forest habitat coded as 2:

GRID: TEMP = CON(MAP == 2, 1)

2. Delineate patches from binary habitat map. The cell values in the resulting file <MAP_PAT> contain a patch ID from 1 to however many discrete patches exist.

GRID: MAP_PAT = REGIONGROUP (TEMP, #, eight)

3. Filter small patches. Patch filtering can be done as part of the GENGRAPH program, but is computational more efficient to do in ARC before running the SAMPLE command. An example of the GRID commands required to set an MAR of 1 ha in size for a 30-m resolution grid follows:

GRID: TEMP2 = MAP_PAT.count > 11

GRID: TEMP3 = SETNULL(TEMP2 == 0, TEMP2)

GRID: KILL MAP_PAT

GRID: MAP_PAT = REGIONGROUP (TEMP3, #, eight)

GRID: KILL TEMP2

GRID: KILL TEMP3

4. Convert to an ASCII data format compatible with the LANDGRAPH program. The <TEMP> grid described above with all values coded to 1 can be sampled if variable habitat quality is not a consideration (recommended for this protocol).

GRID: MAP.SAMP = SAMPLE (MAP_PAT, TEMP)

GRID: KILL TEMP

Appendix J : GENGRAPH Example

To begin, the <MAP.SAMP> file should be placed in the same folder as the graph analysis software. The programs can then be run by typing the program name (e.g., GENGRAPH) at a DOS prompt within this directory.

Example GENGRAPH input is provided below:

MAP.SAMP	COMMENT: name input data
1	COMMENT: minimum patch size (can increase to limit number of patches)
10	COMMENT: resolution of input imagery (change to match input imagery)
MAP.NODE	COMMENT: name for output habitat mosaic (node) file
R	COMMENT: radius corrected centroid distances (choose E for final analysis)
MAP.DIS	COMMENT: output distance matrix file
MAP.RAD	COMMENT: output cluster radii file (not required if choose E distance type)
Y	COMMENT: write node file for use in ARC
MAP.PTS	COMMENT: graph node (ARC) output file

Appendix K : THINEDGE Example

Example THINEDGE input is provided below.

MAP.THIN.LOG	COMMENT: output log file name
MAP.NODE	COMMENT: name of file with node data
N	COMMENT: node file contains habitat quality?
Y	COMMENT: read raw distance matrix as input?
MAP.DIS	COMMENT: name of distance matrix
N	COMMENT: read dispersal probability to define connectivity?
N	COMMENT: generate dispersal probability matrix?
N	COMMENT: read adjacency matrix?
N	COMMENT: generate adjacency matrix? (Y if want to save a specific matrix)
N	COMMENT: use area-weighted flux?
MAP.THIN	COMMENT: output data file name
T	COMMENT: M to thin by max edge length, T by increments
20	COMMENT: starting distance*
300	COMMENT: ending distance
20	COMMENT: distance increment

*To minimize run-time of the program, start with a relatively large range between starting and ending distances and a large distance increment. Graph the output to get an idea of where D_{crit} falls (see below) and then rerun THINEDGE with a shorter distance increment over this reduced range. Make sure that the ending distance is large enough to yield a single connected component.

Appendix L : SENSINODE Example

Example SENSINODE input is provided below:

MAP.SENSI.LOG	COMMENT: log file
MAP.SENSI	COMMENT: output
MAP.NODE	COMMENT: name of file with node data
N	COMMENT: does file have habitat quality?
Y	COMMENT: read raw distance matrix as input?
MAP.DIS	COMMENT: name distance file
N	COMMENT: read dispersal probability as input?
Y	COMMENT: generate dispersal probability? (calculates local flux)
210	COMMENT: distance corresponding to $P=0.05$ (use D_{crit})
N	COMMENT: write matrix output
N	COMMENT: read adjacency matrix as input
Y	COMMENT: generate adjacency matrix (calculates graph diameter)
D	COMMENT: D to define based on distance, P to use probabilities
210	COMMENT: tail distance to define adjacencies (use D_{crit})
N	COMMENT: write adjacency
N	COMMENT: redefine adjacency on area-weighted fluxes (for graph diameter calculation)

Note: These calculations can be time consuming and it is recommended that the combination of MAR and map extent be defined such that the total number of patches is less than 5000.

Output consists of changes in the following indices accompanying the removal of a node:

Area weighted dispersal flux (dAWF or F): preferred measure of dispersal flux that does account for differences in patch areas.

Graph diameter (dGDiam or T): computed only for largest component, so may contain large numbers of zero values for graph input that is not fully connected.

Additional output provided by SENSINODE but not used in this protocol:

Habitat area (dA_q): an index of recruitment potential that assumes larger patches contribute more to recruitment. Optionally, habitat quality may also be considered.

Dispersal flux (dFlux): measure of local dispersal flux that does not account for differences in patch areas.

Appendix M : EDGES Example

Example EDGES input is provided below:

map.edge.log	COMMENT: output log file name
map.node	COMMENT: name of file with node data
N	COMMENT: does file have habitat quality?
Y	COMMENT: read raw distance matrix as input?
map.dis	COMMENT: name of distance file
N	COMMENT: read dispersal probability to define connectivity?
N	COMMENT: generate dispersal probability matrix?
N	COMMENT: read adjacency matrix?
Y	COMMENT: generate adjacency?
D	COMMENT: D to define on distance, P to use probabilities
210	COMMENT: distance to define edges (e.g., D_{crit} value from THINEDGE)
N	COMMENT: write adjacency matrix?
N	COMMENT: redefine based upon flux?
Y	COMMENT: write edge data to graphic file?
Y	COMMENT: write edge ARC format?
map.210	COMMENT: name graphic edge line (ARC) output file

The edge graphic files along with the node graphic files created by GENGRAPH can be built into ARC coverages <MAP_NODE> and <MAP_210> for visualization:

```
ARC:  Generate MAP_node
Generate: Input MAP.pts
Generate: points
Generate: quit
ARC:  Build MAP_node points
ARC:  Generate MAP_210
Generate: Input MAP.210
Generate: lines
Generate: quit
ARC:  Build MAP_210 lines
```


Appendix N : File Naming Convention

Examples and descriptions of the different files created and used in a typical analysis. A standardized naming convention is strongly recommended.

FILE	EXAMPLE	DESCRIPTION
MAP	ls30_pk	original map grid
EXTENSIONS		
_PAT	ls30_pk_pat	grid with patches delineated
.SAMP	ls30_pk.samp	input for GENGRAPH
.NODE	ls30_pk.node	node location output from GENGRAPH
.DIS	ls30_pk.dis	distance matrix output from GENGRAPH
.RAD	ls30_pk.rad	radius of gyration output from GENGRAPH (optional)
.LOG	ls30_pk.thin.log	log files from graph programs
.THIN	ls30_pk.thin	output from THINEDGE
.SENSI	ls30_pk.sensi	output from SENSINODE
.PTS	ls30_pk.pts	ARC node file output from GENGRAPH
_NOD	ls30_pk_nod	Generated point coverage in ARC
.###	ls30_pk.130	ARC edge file output from EDGES for given distance
_###	ls30_pk_130	Generated line coverage in ARC
.CSV	ls30_pk.csv	SENSINODE & FRAGSTAT tables to be joined to _NOD or _PAT in ARC

Appendix O : DEM Reconditioning Example

The following text provides details on AGREE reconditioning of digital elevation models and is modified from <http://www.ce.utexas.edu/prof/maidment/gishydro/ferdi/research/agree/agree.html>

The AGREE aml is run from the GRID prompt and requires several user inputs.

Grid: &run agree.aml

AGREE:

AGREE: INPUT REQUIRED

AGREE:

AGREE: Elevation Grid: elev (*enter DEM name here*)

AGREE:

AGREE: Vector Coverage: stream (*enter stream vector coverage name here*)

AGREE:

AGREE: Buffer Distance: 100 (*see main text*)

AGREE:

AGREE: Note that for the upcoming smooth and sharp drop/raise

AGREE: distance positive is up and negative is down.

AGREE:

AGREE: Smooth Drop/Raise Distance: -10 (*see main text*)

AGREE:

AGREE: Sharp Drop/Raise Distance: -10 (*see main text*)

AGREE:

AGREE: Starting...

AGREE:

AGREE:

Appendix P : Stream Buffer Quantification Example

1. All arcs in the stream coverage should have an attribute code with the same value (1).

Arc: additem hyline.aat hyline.aat code 3 3 1

Tables: sel hyline.aat

Tables: cal code = 1

Tables: quit

2. Set analysis window to the clipped common area.

GRID: setwindow elevfill

GRID: hygrid = linegrid(hyline,code,#,#,10) [nodata in non-stream cells]

GRID: hygrid2 = linegrid(hyline,code,#,#,10,zero) [zero in non-stream cells]

[code = attribute with value 1, 10 is the DEM cell size]

GRID: elevdir2 = con(isnull(hygrid),elevdir) [this removes the streams from the direction grid and is used later]

3. Identify and recode grid cells adjacent to (i.e., upslope of) stream boundaries.

GRID: hyeuc = eucallocation(hygrid,#,#,15) [15 is 1.5x the cell size of the input]

GRID: hyeuc2 = con(hygrid2 == 1,0,hyeuc)

GRID: hyeuc3 = con(isnull(hyeuc2),0,hyeuc2)

GRID: buffer1 = con(hyeuc3 == 1,landcover,1)

4. Compute weighted surface to identify flow paths that includes stream buffers.

*GRID: buffer2 = buffer1 * landcover*

5. Compute preliminary weighted flowpaths for all cells on the grid.

GRID: flowlen1 = flowlength(elevdir2,#,downstream)

GRID: flowlen2 = flowlength(elevdir2,buffer2,downstream)

GRID: compare12 = con(flowlen1 == flowlen2,1,0)

6. Compute final flowpath indicating the width of buffer available to each non-buffer (upland) location.

GRID: buffer0 = con(compare12 == 1,landcover,compare12)

GRID: buffermap = merge(buffer0,landcover)

GRID: flowlen3 = flowlength(elevdir2,buffer0,downstream)

GRID: bufwidth = con(buffermap == 0,flowlen3)

The Department of the Interior protects and manages the nation's natural resources and cultural heritage; provides scientific and other information about those resources; and honors its special responsibilities to American Indians, Alaska Natives, and affiliated Island Communities.

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Natural Resource Stewardship and Science

1201 Oakridge Drive, Suite 150
Fort Collins, CO 80525

www.nature.nps.gov

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