M.L. 2015 Project Abstract
For the Period Ending June 30, 2018

PROJECT TITLE: A Foundational dataset characterizing historic forest disturbance patterns
PROJECT MANAGER: Michael Falkowski
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FUNDING SOURCE: Environment and Natural Resources Trust Fund
LEGAL CITATION: M.L. 2015, Chp. 76, Sec. 2, Subd. 03q

APPROPRIATION AMOUNT: $ 200,000
AMOUNT SPENT: $ 200,000
AMOUNT REMAINING: $ 0.00

Overall Project Outcome and Results
Forest disturbance (arising from harvesting, fire, land conversion, etc.) has a fundamental impact on the health and resilience of multiple forest resources including water quality, wildlife habitat, and wood resources, among others. Recently the United States Geological Survey made a revolutionary decision by allowing open access to a historic archive of Landsat satellite data dating back to 1972, providing a new opportunity to assess historic forest disturbance (type, timing, and patterns). The objective of this project was to utilize the historical satellite images to characterize >40 years of Minnesota forest trends and disturbance patterns, and provide spatial mapping resources for a variety of local forest management and research applications. After the necessary processing to compile the Landsat imagery in a way that would allow the data to be comparable through time, we created models to produce annual (1973-2015) state-wide maps of canopy cover. These maps allow for the characterization of forest resources at a given point in time, as well as the monitoring of forest change and recovery trends, providing a valuable and versatile dataset for a variety of Minnesota users. For the second part of this project, we focused on the Laurentian Mixed Forest Province, which contains much of the public and forested lands of Minnesota, where we utilized additional Landsat data to map the most recent abrupt disturbance events over time. We further enhanced the disturbance map by classifying the disturbance agent (harvest, land conversion, fire, wind, flooding), as well as providing information about the year, duration, and magnitude of each event. Currently we are working with several collaborators to input our mapping products to address a variety of forest management, wildlife habitat, and water quality assessment applications.

Project Results Use and Dissemination
Our initial publication from this project, entitled "Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973–2015)" was published in Remote Sensing and Environment in March 2018, and is already providing a valuable resource for fellow researchers through our approach for incorporating rarely integrated early Landsat MSS imagery to time series analyses for the creation of >40 years of annual forest attribute mapping. While only recently published, the paper has already received 4 citations in peer reviewed publications and boasts 423 reads on research focused social media platform. We were invited to present this work through a webinar for the USDA Forest Service's Forest Inventory and Analyses National Research Techniques Band (recording

available at: https://usfs.adobeconnect.com/prjhzov1f5fi/), and continue to utilize the valuable state-wide data set presented in this publication for our disturbance mapping efforts and various forest, wildlife, and water resources applications.

We have worked with, and continue to work with, several collaborators to provide our canopy cover and disturbance mapping products for a variety of forest management, wildlife habitat, and water quality assessment applications. In addition to providing mapping resources to UMN moose biologists to assess habitat use and movement, we are also currently working with wildlife researchers from UMN-Duluth to incorporate our canopy cover and disturbance mapping products in a project assessing the impacts of harvest intensities and the quantity and spatial arrangement of retained tree canopy on avian and small mammal communities across a chrono-sequence of harvest ages. We have also provided initial harvest maps to contractors working with the MN PCA, to incorporate into a watershed planning tool for assessing forestry best management practices and impacts on water quality.

We have presented our work to a variety of research groups, local managers, and state and federal agencies throughout the project time period, and we continue to disseminate our results and mapping products to a variety of audiences to ensure that our products can provide vital additions to existing projects and management planning needs. We also continue to explore additional applications of the data and are working to compile manuscripts related to utilizing the disturbance products to assess various forest ecology and resource management questions and issues.

Date of Report: 8-17-2018

Final Report

Date of Work Plan Approval: 06-11-2015

Project Completion Date: 06-30-2018

PROJECT TITLE: **A foundational dataset characterizing historic forest disturbance patterns**

Project Manager: Michael Falkowski

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Location: Carlton, Lake, and St. Louis Counties

Total ENRTF Project Budget:		
	ENRTF Appropriation:	**$200,000**
	Amount Spent:	**$200,000**
	Balance:	**$0**

Legal Citation: M.L. 2015, Chp. 76, Sec. 2, Subd. 03q

Appropriation Language:
$200,000 the first year is from the trust fund to the Board of Regents of the University of Minnesota to quantify forest disturbance impacts over the past forty years on water quality, wildlife demographics, and wood fiber supply to identify management strategies that better respond to disturbance impacts and improve and sustain forest resources. This appropriation is available until June 30, 2018, by which time the project must be completed and final products delivered.

I. PROJECT TITLE:
A foundational dataset characterizing historic forest disturbance patterns

II. PROJECT STATEMENT:

Forest disturbance dynamics (arising from harvesting, fire, land conversion, etc.) have a fundamental control on the health and resilience of multiple forest resources including water quality, wildlife habitat, and wood resources, among others. Disturbance impacts on forest resources can persist across a landscape for decades and ultimately impact the sustainability of resources, positively or negatively. Understanding disturbance dynamics and associated impacts is readily recognized as being critically important to developing forest management responses that improve and sustain forest resources. Despite this recognition, until recently it has been nearly impossible to quantify and interpret disturbance configurations (type, timing, and pattern) that have persistent impacts on forest resources. Recently the United States Geological Survey made a revolutionary decision by allowing open access to a 40-year historic archive of Landsat satellite data, providing a new opportunity to assess historic forest disturbance dynamics. These satellite-derived disturbance observations can be used to (i) determine the fundamental drivers of past disturbance and (ii) assess the impacts of disturbances on current forest resources.

The overarching objective of this project is to leverage historical satellite images in the archive to develop a foundational dataset that characterizes trends and patterns in historic forest disturbances Across Minnesota's arrowhead region. As a secondary objective we will demonstrate the utility of foundational disturbance dataset to sustainable resource management in two key areas: wildlife habitat and wood resource management.

We will develop the foundational dataset characterizing trends and patterns in forest disturbance by processing and analyzing Landsat satellite images (1974-present) from the aforementioned archive. This step will involve: (i) acquiring cloud free imagery across each growing season from 1974-present, (ii) preprocessing the imagery to ensure intra-seasonal and inter-annual comparability of the images, and (iii) running semi-automated image classification procedures that characterize disturbance type (e.g., fire, insect outbreak, blow-down, etc.) and duration of impacts and ecosystem recovery (e.g., how long did the disturbance last and how long did it take the ecosystem to return to its pre-disturbance state). The utility of this dataset to resource management will be demonstrated in specific applied examples. For the case of wildlife habitat we will integrate disturbance data with historic demographic data characterizing moose populations across Minnesota's Arrowhead region to understand how disturbance can enhance or degrade moose habitat quality and ultimately population sustainability. For the wood resource example we will link information from the disturbance dataset with repeated forest inventory data (e.g., data from the US forest service FIA (Forest Inventory and Analysis) program) to understand the impacts of different disturbance types on wood resources across Minnesota's Arrowhead region. In this example we will specifically develop an understanding how disturbances impact the amount (e.g., biomass, volume, etc.) and quality (e.g., species composition, age, etc.) of the forest resource landscape, which ultimately impact long term resource sustainability.

The foundational dataset will be a powerful tool for identifying threshold disturbance patterns that positively or negatively impact multiple forest resources across Minnesota. This foundational dataset will allow end users to evaluate how the type, timing, duration, and configuration of disturbances influence forest resources over the last forty years, and will ultimately help in the identification of management responses that improve and sustain forest resources into the future.

III. OVERALL PROJECT STATUS UPDATES:

Project Status as of ***February 2016*****:**

The project is moving forward successfully. All appropriate Landsat growing season images have been selected, requested, and downloaded for the time period of 1972-2015 and much of the pre-processing completed. Methods were developed and implemented for the initial pre-processing steps, and the next steps have been outlined and in some cases tested with small subsets of data (including the next immediate step of calibrating the disturbance trend algorithm, LandTrendr). Pre-processing work is well underway for all scenes including the unpacking of data and initial quality assessments of images, geo-referencing of images where needed, calculation of spectral indices, calibration between Landsat sensors (MSS, TM, and OLI), and compositing of images into annual composites of growing season spectral indices used for later disturbance/recovery algorithms and classification. Initial contact has been made with potential Minnesota wildlife research collaborators (including Jerry Niemi's lab group and MN DNR Wildlife Habitat team), to solicit input on their specific needs for disturbance products and initiate collaborative project planning.

Project Status as of *September 2016***:**

After substantial work in the pre-processing of Landsat images to produce corrected, calibrated, and comparable annual stacks of spectral information, we now have usable annual growing season composites for the entire Arrowhead region from 1972-2015. We have continued forward with these image stacks, completing the first step of the change detection algorithm, LandTrendr, which segments the spectral trends through time and assigns smoothed values important in identifying disturbance and recovery patches and providing information on the timing, duration, and magnitude of change. To provide initial insight into historic forest cover and change and to provide information about an important wildlife habitat component through time, we are currently creating models for canopy cover which will be mapped across the 44 year image stack. Forest Inventory and Analysis data and plot locations along with two years of NAIP imagery has been obtained for the study area in preparation for building training and validation data sets of known disturbance agents vital to the future steps of the project where we will classify and map disturbance agent and characteristics of recovery trends.

Project Status as of *February 2017***:**

As initial products important to a variety of applications including wildlife habitat modeling, forest monitoring, and to aid in the next steps of identifying and interpreting forest change and recovery, we have finish the creation of forest mask and continuous canopy cover models for the Arrowhead region. This involved NAIP photo interpretation of canopy cover at >1000 FIA plot locations for consistent estimates of cover across all land cover types, and exploration into several statistical modeling approaches in order to determine the most appropriate method for minimizing canopy cover prediction error. In addition to the model for continuous canopy cover, we also developed a forest mask model which can differentiate forest from all other land cover types, a vital tool for next steps of the project, as well as for monitoring trends of forest area change over the last 4 decades. This forest mask and canopy cover models are in the final stage of creating predictive maps using the 44 years of Landsat imagery, which will result in stacks of annual forest masks and continuous canopy cover maps for the entire Arrowhead Region across all land cover types from 1972-2015. We plan on submitting the manuscript pertaining to this work for peer review in the coming months. We are also actively planning for immediate incorporation of these products in a variety of applications once complete.

Project Status as of *September 2017***:**

Following completion of the annual canopy cover and forest mask maps (1973-2015) described above, we have prepared the associated manuscript and submitted to Remote Sensing of Environment. The manuscript also includes many of the preprocessing steps for our larger change detections work, including the compiling of the Landsat stacks into annual harmonized composites of the spectral indices utilizing a new R package called LandsatLinkr which we beta-tested in this project. Initial reviews of the manuscript were favorable and we are currently addressing revisions. Successful publication of this work will serve as an important introduction of methods for our subsequent change detection manuscripts as well as providing insight into Minnesota forest trends across the last four decades. In addition to our canopy cover mapping manuscript work, we have completed initial runs of LandTrendr change detection although we continue to tweak parameters to best match the disturbance patterns in the Arrowhead Regions and are working to compile the agent classification training data base. Preliminary exploration into post-processing of the change products for the mapping of true change polygons of fast and slow disturbances and classifications of agent of change are currently underway. We have also conducted field visits to various locations around the Arrowhead region which included meetings with foresters within the Chippewa National Forest, Superior National Forest, and the UMN Cloquet Forestry Center to discuss local disturbance patterns, future applications of mapping products, and the needs of the on-the-ground forest managers.

Project Status as of *February 2018***:**

Our manuscript presenting our initial methods for producing harmonized spectral indices for the Landsat Time Series, and the application of the data for the creation of annual canopy cover and forest mask maps from 1973-2015 for the state of Minnesota, has been accepted for publication within Remote Sensing of Environment. On the disturbance mapping front, we continue to do quality assessments of the initial change detection products to finalize the parameters utilized in the identification of disturbance patches across the Arrowhead Region. Change mapping is a multi-iterative process, where we model and map change patches and create classification of agents using training data, assess the maps, and evaluate where additional training data, predictive metrics, and/or calibration of parameters may be needed for the next iteration of the process. With initial models and maps complete, we are currently working to improve the quality of the data sets to work towards finalized disturbance products and validation assessments. We were able to present our initial findings and our overall project methods and products at multiple meetings within the twin cities and Cloquet in January 2018. These meetings included presenting an invited webinar to members of MN DNR, forest service, and UMN affiliates; participating in, and presenting at the 2018 SFEC Forestry and Wildlife Research Review meeting at the Cloquet Forestry Center; and multiple smaller meetings with various forest service, MN DNR, and UMN researchers to discuss potential collaborations and applications of our data products. All of these meetings displayed a wide breadth of interest from a variety of research and management agencies in the use of our forest attribute and change detection products for a range of forest, wildlife, water quality, and monitoring applications.

Overall Project Outcomes and Results:

Forest disturbance (arising from harvesting, fire, land conversion, etc.) has a fundamental impact on the health and resilience of multiple forest resources including water quality, wildlife habitat, and wood resources, among others. Recently the United States Geological Survey made a revolutionary decision by allowing open access to a historic archive of Landsat satellite data dating back to 1972, providing a new opportunity to assess historic forest disturbance (type, timing, and patterns). The objective of this project was to utilize the historical satellite images to characterize >40 years of Minnesota forest trends and disturbance patterns, and provide spatial mapping resources for a variety of local forest management and research applications. After the necessary processing to compile the Landsat imagery in a way that would allow the data to be comparable through time, we created models to produce annual (1973-2015) state-wide maps of canopy cover. These maps allow for the characterization of forest resources at a given point in time, as well as the monitoring of forest change and recovery trends, providing a valuable and versatile dataset for a variety of Minnesota users. For the second part of this project, we focused on the Laurentian Mixed Forest Province, which contains much of the public and forested lands of Minnesota, where we utilized additional Landsat data to map the most recent abrupt disturbance events over time. We further enhanced the disturbance map by classifying the disturbance agent (harvest, land conversion, fire, wind, flooding), as well as providing information about the year, duration, and magnitude of each event. Currently we are working with several collaborators to input our mapping products to address a variety of forest management, wildlife habitat, and water quality assessment applications.

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Our initial publication from this project, entitled "Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973–2015)" was published in Remote Sensing and Environment in March 2018, and is already providing a valuable resource for fellow researchers through our approach for incorporating rarely integrated early Landsat MSS imagery to time series analyses for the creation of >40 years of annual forest attribute mapping. While only recently published, the paper has already received 4 citations in peer reviewed publications and boasts 423 reads on research focused social media platform. We were invited to present this work through a webinar for the USDA Forest Service's Forest Inventory and Analyses National Research Techniques Band (recording available at: https://usfs.adobeconnect.com/prjhzov1f5fi/), and continue to utilize the valuable state-wide data set presented in this publication for our disturbance mapping efforts and various forest, wildlife, and water resources applications.

We have worked with, and continue to work with, several collaborators to provide our canopy cover and disturbance mapping products for a variety of forest management, wildlife habitat, and water quality assessment applications. In addition to providing mapping resources to UMN moose biologists to assess habitat use and movement, we are also currently working with wildlife researchers from UMN-Duluth to incorporate our canopy cover and disturbance mapping products in a project assessing the impacts of harvest intensities and the quantity and spatial arrangement of retained tree canopy on avian and small mammal communities across a chrono-sequence of harvest ages. We have also provided initial harvest maps to contractors working with the MN PCA, to incorporate into a watershed planning tool for assessing forestry best management practices and impacts on water quality.

We have presented our work to a variety of research groups, local managers, and state and federal agencies throughout the project time period, and we continue to disseminate our results and mapping products to a variety of audiences to ensure that our products can provide vital additions to existing projects and management planning needs. We also continue to explore additional applications of the data and are working to compile manuscripts related to utilizing the disturbance products to assess various forest ecology and resource management questions and issues.

IV. PROJECT ACTIVITIES AND OUTCOMES:

ACTIVITY 1: Process Landsat satellite imagery into a useable format

Description:

Although Landsat satellite data are now available free of charge from the USGS archive, processing is required to convert them into a useable format. We will acquire and process archived Landsat imagery that encompasses the Arrowhead region of Minnesota (~4.5 million acres). Specifically, this imagery will be obtained on a bi-monthly basis during all growing seasons over the last 40 years (1974-Present). The raw imagery will be processed to correct for atmospheric and geometric related errors to ensure image comparability. In total we will acquire and process approximately 500 images across the Arrowhead region. The total number of images acquired and processed will depend upon availability of suitable, cloud-free imagery. Our original plan was to process and analyze imagery for the entire forested region of Minnesota. However, due to the reduced level of funding recommended for this project we have decided to constrain the total area considered in this project. The reduction in acres processed is not directly proportional to the reduction in funding due to economies of scale. Specifically, the cost per acre of processing imagery decreases with an increase in total area. This is due to the fact that a baseline processing capacity (e.g., creating processing protocols and computer programming of processing algorithms) needs to be built regardless of the total area processed, and the cost associated with developing this baseline capacity is the same regardless of the total area of imagery processed.

Summary Budget Information for Activity 1: **ENRTF Budget: $ 43,817**
Amount Spent: $ 43,817
Balance: $ 0

Outcome	**Completion Date**
1. *Complete Acquisition and Local Storage of Landsat Imagery*	October 2015
2. *Complete Pre-processing of Landsat Imagery*	January 2016

Project Status as of *February 2016***:**

After determining the appropriate time windows for growing season images using averaged NDVI curves (indicative of vegetation productivity) for each Landsat scene and assessing the quality of images for cloud cover and other initial sensor/data issues, we compiled lists of the large number of images within the required Landsat scenes needed to cover our study area and submitted the requested image lists to USGS. All images were downloaded, organized, and processed through an initial unpacking and quality assessment step. Although we attempted to choose images with low amounts of cloud cover, conditions in the Arrowhead region required us to include some images with clouds which had to be masked from the images during the atmospheric correction phase of pre-processing. Varying amounts of atmospheric correction were required depending on the Landsat sensor and the product available from USGS (data from more recent sensors are sometimes available as surface reflectance products processed by USGS, although this is not the case for earlier sensors which require additional pre-processing steps). Images from earlier sensors (the MSS series) also required additional geo-referencing efforts to ensure all images were properly aligned and resampled to match the spatial resolution of the TM and OLI images (30m x 30m pixels). We then calculated tasseled cap (brightness, greenness, and wetness) spectral indices for all images. As the Landsat sensors have some variation in the spectral bands and sensitivity through time, we calibrated the indices between sensors so that they are comparable through time and space, an important step in the pre-processing. Our final step will now be to create annual composites of the study area by averaging the inter-annual growing season indices for all scenes (thus producing annual stacks for the area representing the spectral trends though time to use in our next step of identifying disturbance/recovery trends using change algorithms, such as LandTrendr).

There has been a slight delay in the final composite step due to some additional work needed to complete the annual coverage of all areas. During initial processing, we discovered gaps in our yearly coverage of some areas during the early Landsat MSS sensors years (1972-1984). Adding these additional 12 years of historical information for our disturbance/recovery mapping efforts is extremely valuable for multiple applications. The problem is that some of the images we requested were only available from USGS in a less georeferenced form (L1G products), which makes them more difficult to directly include in the mostly automated steps appropriate for the other MSS images (L1T products). We have developed a solution for this issue using a semi-automated approach in which we first go through an initial geo-referencing step using manually detected tie points with a reference image in ArcGIS which does an initial correction on the image. The image is then ready to be entered back into the automated approach for final geo-referencing, tasseled cap calculations, calibrations, and ultimately, annual composites. The addition of this manual step has increased the expected processing time, but we expect to be finished with all pre-processing by the end of March.

Project Status as of *September 2016***:**

After completing the pre-processing steps and exploring several available methods for compositing the image stacks into annual growing season spectral values, we created annual tasseled cap maps using the median of the input images per year. This compositing method further minimized undesirable noise and the appearance of seamlines between scenes within the annual maps. Activity 1 is now complete for the Arrowhead region for the years of 1972-2015.

Project Status as of *February 2017***:**

Activity 1 is complete.

Project Status as of *September 2017***:**

Activity 1 is complete.

Project Status as of *February 2018***:**

Activity 1 is complete.

Final Report Summary:

The acquisition, pre-processing of all Landsat imagery, and ultimately the creation of harmonized annual composites of spectral indices, were the critical first products of our project which were integrated into all forest attribute modeling, disturbance mapping efforts, and assessments of forest trends. Our methodology for the harmonization of imagery from the different Landsat sensors, and the creation of our fitted annual composites, are published in our manuscript entitled "Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973–2015)" (Vogeler et al. 2018). Our current goal is to secure future support to update these products beyond 2015 and develop semi-automated methods to facilitate annual additions to all mapping products in the future, leveraging recent developments in Google Earth Engine, a cloud computing platform. Our project is extremely unique in our inclusion of the more difficult to process MSS imagery, allowing for an additional decade of forest attribute and disturbance information to our time series analyses. This is significant for policy and management applications as we are now able to conduct more in-depth analyses of historic forest cover and its implications for future decision making. Any semi-automated methods developed through Google Earth Engine will be unable to replicate the inclusion of MSS data (which is still unavailable through that platform), but we hope to be able to add future years to our valuable dataset to ensure up to date forest maps so that the immense value of the products from this project can continue to stay current and relevant.

ACTIVITY 2: Disturbance database development and classification
Description:

We will employ a Landsat time series image analysis algorithm to detect forest disturbances from 1974-present. The basic approach involves using change detection to identify where disturbances occurred on the landscape as well as their severity and duration. In addition to detecting the disturbance, we will use semi-automated procedures to classify the type (i.e., cause) of each disturbance identified. At a minimum, disturbance type will be classified into the following categories (and subcategories): Harvesting (clear-cut, partial harvest, land use conversion) and Natural Disturbance (Insect Outbreak, Fire, and Blow Down). The semi-automated disturbance classification procedure attributes disturbance type to areas where disturbance has occurred based upon spatial and temporal patterns in the satellite image time series. An abrupt disturbance (e.g., clear-cut or high severity fire), for example, would likely be characterized by a sharp decline in the time series that is also spatially contiguous. Conversely, a more gradual or subtle disturbance (e.g., defoliating insect or low severity fire) will likely be characterized by a gradual decline in in the time series that is spatially variable (i.e., not spatially contiguous). Forest recovery rates, which are indicative of disturbance severity, will also be readily available for the time-series. Following disturbance identification and classification, historical information (e.g., FIA data, aerial photography, forest health surveys) and field data collected specifically for this project will be used to validate and assess the accuracy of the disturbance products.

Summary Budget Information for Activity 2: **ENRTF Budget: $ 73,994**
Amount Spent: $ 73,994
Balance: $ 0

Outcome	**Completion Date**
1. *Disturbance patterns from 1974-2015 Identified*	June 2016
2. *Disturbances classified into primary categories*	October 2016
3. *Database with validated disturbance patterns over time completed*	January 2017

Project Status as of *February 2016***:**

No progress has been made on this Activity at this time due to the delay in image processing described above. We anticipate that outcome 1 will be completed on schedule or shortly thereafter, and all other outcomes will occur on schedule.

Project Status as of *September 2016***:**

Although the initial calibration and other pre-processing steps of the project took longer than expected, we are close to being back on track for other scheduled outcomes. We have completed the first steps of the change algorithm, LandTrendr, which fits the annual composites with trend lines summarizing the spectral trajectories of each 30m x 30m image pixel. The process is called "segmentation" and the outputs are new annual spectral indices maps with the values smoothed to fit onto these trajectory lines. These new smoothed maps help to further reduce annual noise and serve as the input for the next tier of LandTrendr. The next step, referred to as "change labeling", uses these fitted images to: 1) identify segments of disturbance/recovery and vertices between different segments; 2) group patches of pixels that may have experienced the same disturbance event; and 3) characterizes the disturbance/recovery events by their timing, magnitude of change (i.e. high severity vs. low severity), and duration (i.e. abrupt vs. slow). Characteristics of the disturbance and recovery events within patches aid in the classification of disturbance agent (i.e. harvest vs. insect infestation). We have begun to test the change labeling LandTrendr algorithm on a subset of the Arrowhead region, although there is much calibration of parameters still needed before we are able to apply the algorithm to the whole region.

In addition to serving as inputs to the change labeling portion of LandTrendr, we also incorporated the smoothed annual spectral images from the segmentation procedure into historical canopy cover mapping efforts. We estimated canopy cover at a subset of FIA plots locations using 4-band NAIP imagery, then extracted tasseled cap predictors from the corresponding year of segmentation images to create statistical models of forest cover. We are currently working on selecting the best model and preparing the other years of imagery, for which we will then apply the model to create maps of annual estimated canopy cover from 1972-2015. These historical canopy cover maps may help identify conversion of land to/from forest cover types through time, estimate trends of canopy cover change due to disturbance/recovery, and characterize an important habitat component for wildlife habitat monitoring efforts through time.

Project Status as of *February 2017***:**

After creating an extensive training canopy cover dataset from NAIP imagery across all land cover types, testing multiple statistical modeling approaches and Landsat time series along with static predictors to find the best model for minimizing prediction error, we have selected our final models for delineating forest vs non-forest and for predicting continuous canopy cover across the entire Arrowhead region. We are currently applying these models to the stacks of smoothed/fitted tasseled cap outputs from LandTrendr time series stacks to create annual forest mask and canopy cover models across all land cover types from 1972-2015. Predictive mapping across large spatial areas as well as across 44 years of imagery is computer intensive and thus takes a significant amount of time, although these products should be complete by the end of February. Immediate applications of the products are already being outlined in addition to their use as valuable inputs for the identification and interpretation of change and recovery within our forest disturbance mapping and classifications.

As we finish these forest attribute maps which will also aid in the disturbance mapping and classification, we continue to test the LandTrendr change algorithm across the Arrowhead region. There are multiple parameters within LandTrendr which must be calibrated for specific study areas as well as setting thresholds within the outputs for designating patches as true change. While we are behind in the timeline for Activity 2, we feel strongly that these additional products and calibration steps will be vital in creating quality change detection products as well as providing important canopy cover information for wildlife habitat modeling, forest stand characterization, and monitoring trends in overall forest area across the last 44 years. Incorporating the early Landsat sensors into time series stacks to add an additional 12 years of forest information, such as we are doing here, is rarely done and thus timelines for spectral and spatial calibrations throughout the process were difficult to predict.

We have begun to turn our attention to creating our forest disturbance agent database for training and validation of change agent classifications. We have developed methods for delineating harvest boundaries within Google Earth historic imagery, we have compiled the FIA plot data for our study region and are exploring attributes which may be extracted from this extensive data base, and we continue to explore new avenues for acquiring accurate spatial information for forest disturbance agents and recovery characteristics.

Project Status as of *September 2017***:**

We have completed the annual forest mask and canopy cover maps including analyzing forest cover trends across the >40 year study period, and the associated manuscript has been prepared and submitted to Remote Sensing of Environment. Initial reviews were favorable and we are currently addressing manuscript revisions. We are now exploring the change detection products from initial runs of the second step of the LandTrendr algorithm. We have focused our efforts on the "fast" disturbance patches to begin with, which are disturbances that have durations of 4 years or less (i.e. harvest, fire, and wind blow). Change patch predictors have been extracted for these initial patches including LandTrendr derived pre- and post- disturbance spectral values, magnitudes of change, along with additional spatial predictors. We are working to compile the "fast" agent training data base and have begun to explore classification modeling using preliminary training data, although we continue to explore additional predictors and training data sources. We have identified preliminary versions of "slow" disturbance patch maps (i.e. those resulting from insects and other agents of forest decline), although change parameters for defining the final patches are still being calibrated for the Arrowhead region's disturbance patterns and agents. We are primarily utilizing historic photos in google earth and the annual forest health aerial surveys for the extraction of fast and slow agent classification training data. In August, we conducted field visits to various forest and disturbance types in the study region as well as meeting with foresters from the Chippewa National Forest, Superior National Forest, and UMN Cloquet Forestry Center to discuss local disturbance patterns, future applications of mapping products, and the needs of the on-the-ground forest managers.

Project Status as of *February 2018***:**

While initial change detection products and models classifying the agents of change for fast disturbances (i.e. harvest, fire, wind, and land conversions) have been created, we continue to work to improve the quality of these products through a multi-iterative approach common for Landsat time series studies. In this multi-iterative approach, initial change patches are identified, agent training data is collected, predictive metrics from the time series spectral indices as well as other ancillary data are created, classification models are selected, and classified change maps are produced. Within Landsat time series analysis methodologies, after such a "run" is finished, the products are thoroughly assessed for quality and accuracy, potential areas for improvement are identified, and steps are taken to either add needed training data or expand predictors to then proceed with a new "run" of the data and mapping process. These steps are repeated until a level of quality is achieved that meets projects goals, at which time finalized change maps undergo independent validation efforts which are presented with the mapping products and within publications so that the strengths and limitations of the data are well understood by all future users. We have currently undergone several of these "runs" of our classified change maps, and we are working towards finalizing our models and maps of fast disturbances to proceed with validation efforts. Coding and workflows have also been created for analyzing the trends from the classified change maps so that when finalized products are created, the framework is in place to conduct further trends analyses to include in planned publications.

Final Report Summary:

Among the foundational mapping products created through this project were 43 years of annual forest mask and percent canopy cover maps for the entire state of Minnesota. The canopy cover products have been integrated into several application projects as well as serving as the basis for assessing forest trends in Minnesota across 4 decades within the publication in Remote Sensing of Environment (Vogeler et al. 2018). The canopy cover maps have also played an important role as model inputs for classifying the agent of change in our disturbance mapping efforts.

We have now also completed the mapping of the most recent fast disturbances dating back to 1974 across the Laurentian Mixed Forest Province, classified by the agent of change, also an unprecedented temporal and spatial data set for Minnesota. We expanded beyond the Arrowhead region to better match the focal region of many of the proposed application collaborations. After exploring several mapping approaches, we decided to focus on fast disturbance events (durations of 4 years or less) in our change mapping methods. We believe that these abrupt change events include the majority of the natural and anthropogenic disturbance agents in this region, and are able to be identified through aerial photos and existing spatial data for the creation of training and validation data sets. We used a minimum mapping size of 11 pixels, as the focus of this project was on events that impact at least a large portion of a forest stand. This size limit also increased our confidence in our change detection by excluding smaller events that may have been captured in error as a product of spectral noise. Out of the spectral indices created in this project, tasseled cap wetness (TCW) has been identified as the most indicative of forest canopy structure by previous studies. Therefore, we utilized thresholds of TCW change representative of moderate- to high- intensity changes to identify our disturbance patches. We converted initial raster based change information to polygons for the next steps in map creation and disturbance agent classifications.

Agents included in the classification represent the common moderate- to high-intensity natural and anthropogenic disturbance agents characteristic of the study region, including: harvest, land conversion, fire, wind/weather, flooding, and an “other natural” category for rare natural events not represented by the other classes. Training data of known disturbance events for a sample of the change polygons was opportunistically compiled using a combination of google earth historic imagery, the national Monitoring Trends in Burn Severity fire perimeter maps, online historical records of large natural disturbance events often reported by county which could be used in conjunction with photos for identifying change areas, and personal communications with local land managers for more recent large-scale natural events. Using a sample of known events as our training data set, we employed a random forest classification approach to predict the agent for all disturbance polygons across the study area. We mapped these classified agents to create a map of the most recent fast disturbances across the study area dating back to 1974.

To validate the accuracies of the initial change/no-change maps, we created a random sample of points within forests across the study area with buffers of 3x3 pixels. We assessed if changes had occurred within the validation buffers, and whether those events were captured by our change detection methodologies. This also allowed us to evaluate potential limitations and/or biases in our maps to later relay to map users. Within the validation efforts, we utilized historical imagery within google earth and the Minnesota Historical Aerial Photos Online database (https://www.lib.umn.edu/apps/mhapo/), as well as any additional spatial information we had compiled for the disturbance agent modeling work. We choose to focus on stand replacing events that we could validate with some confidence and which were the major focus of our project. We therefore excluded flooding (which was often the result of change in moisture in overlapping forest and riparian non-forest areas and did not always result in stand mortality), and the “other natural” polygons (which were associated with more rare within stand natural events such as tent caterpillar outbreaks, which did not always result in large changes in canopy and which were difficult to confidently validate in older black and while historic photos). While we were able to identify polygons for training purposes within the flooding and “other natural” categories, we did so opportunistically for areas with known events. Identifying these events with confidence across larger areas and back in time within black and white historical photos proved to be more difficult. Our validation efforts thus focused on a reduced map of change polygons classified as harvest, land conversion, fire, or wind/weather. Within the reduced map, if we were not able to confidently assign a change or no-change classification (for instance, historical photos were not available for a given point), we excluded this validation plot from our data.

Our final maps of the most recent fast disturbances had an overall change/no-change classification accuracy of 92%, with a TPR (sensitivity) of 0.859, and a TNR (specificity) of 0.960 for moderate- to high-intensity stand replacing events. Our final random forest classification model for the agent of change also had an overall classification accuracy of 92% (as calculated from out-of-bag error rates), with class accuracies ranging from 78% to 96%, where the harvest class had the highest accuracies and fire had the lowest classification success.

ACTIVITY 3: Development of spatial descriptors and application of findings
Description:
Statistical descriptors of the disturbance patterns will be derived from the disturbance database. These statistical descriptors will be integrated into models assessing disturbance impacts on the current status of two critical resources: wildlife habitat (specifically moose) and wood resources (specifically the amount, type, and quality). In these example applications, we will compare existing moose population demography data and forest inventory data with disturbance descriptors in a modeling framework. This modeling framework will provide a quantitative assessment of how the temporal and spatial configurations of specific disturbance types can either enhance or degrade the sustainability of the resources (Figure 1). Through this process we will identify management responses that will sustain and or improve forest resources under future disturbances. Results quantifying the impacts of disturbance dynamics on the health and resilience of forest resources will be summarized in public project reports and conveyed to forest managers through outreach activities.

Summary Budget Information for Activity 3:	**ENRTF Budget:**	**$ 82,189**
	Amount Spent:	**$ 82,189**
	Balance:	**$ 0**

Outcome	Completion Date
1. *Develop statistical descriptors of disturbance patterns*	August 2017
2. *Model impacts of disturbance dynamics on forest resources*	January 2018
3. *Publish project summaries and conduct outreach activities*	June 2018

Project Status as of *February 2016***:**

Work on this activity will commence after completion of Activity 2.

Project Status as of *September 2016***:**

Work on this activity will commence after completion of Activity 2.

Project Status as of *February 2017***:**

Work on this activity will commence after completion of Activity 2.

Project Status as of *September 2017***:**

Work on this activity will commence after completion of Activity 2.

Project Status as of *February 2018***:**

Our first manuscript from this project, titled “Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973-2015)”, has been accepted for publication within Remote Sensing of Environment. This manuscript presents many of the initial methods of our project for the harmonization of the Landsat time series stacks, creation of spectral indices, and the modeling and mapping of annual statewide canopy cover and trends through time. As we work to finalize our change detection products classified by agent and associated validation efforts, we are outlining additional forest trend analyses and associated manuscripts to publish findings of this project.

In January 2018, we presented our project methods, forest attribute products, and initial forest disturbance trend results at several MN meetings, including an invited webinar to members of MN DNR, forest service, and UMN affiliates, and presenting at the 2018 SFEC Forestry and Wildlife Research Review meeting at the Cloquet Forestry Center. We also conducted smaller meetings with members of MN DNR, forest service, and UMN, to discuss potential collaborations and applications of our mapping products and project results. All of these meetings displayed a wide breadth of interest from a variety of research and management agencies in the use of our forest attribute and change detection products for a range of forest, wildlife, water quality, and monitoring applications. Several collaborations are also now underway for the use of these products in the assessment of wildlife habitat and the impacts of management and other drivers of landscape changes through time.

Final Report Summary:

Through our annual mapping of forest/non-forest masks and percent canopy cover, we were able to evaluate forest trends across the state of Minnesota dating back to 1973. These trends were presented in our Remote Sensing of Environment publication (Vogeler et al. 2018). Generally, we observed a significant, although slight, positive trend in forest area across the state throughout the time period of the study (1973-2015). It should be noted that this trend does not account for changes in forest types or stages of structural development, and may include some areas not commonly classified as forests (e.g., shrub-scrub wetlands). Trends were also evaluated within specific Minnesota ecological provinces, where the significant positive trend in forest area was maintained across all provinces. We also assessed temporal trends of forest area within five canopy cover classes estimated using our percent canopy cover maps. Across the 43 years of the study, all provinces experienced significant growth in the land area within the two highest cover classes (50-74% and 75-100%), with the exception of a non-significant trend for the 50-74% class within the Tallgrass Aspen Parkland. The greatest growth in the two highest cover classes occurred within the Laurentian Mixed Forest province.

The base spectral composites utilized within all mapping products within this project, as well as the forest attribute and disturbance mapping products themselves, have been (or are currently being) incorporated into several wildlife, forest resources, and water quality assessment application projects, although we continue to establish additional collaborations and explore new applications for the data. Some notable examples include:

- Early in the project, we utilized our fitted Landsat-derived spectral indices to create bi-annual land cover maps for the Arrowhead region (1999-2015) as requested by University of Minnesota moose biologist, James Forester, to facilitate the assessment of moose habitat use and movements as impacted by land cover types and changes through time. This data is being used to develop predictive models of moose population dynamics to address ongoing questions related to long-term moose viability in Minnesota.
- We are also collaborating with wildlife researchers at the University of Minnesota-Duluth and the Natural Resources Research Institute to assess the impacts of harvest characteristics (e.g. quantity and spatial arrangement of retained canopy during harvest activities) on avian and small mammal communities through the incorporation of our canopy cover products and disturbance map. The study includes an array of aspen dominated stands across the Arrowhead region representing a chrono-sequence of harvest years. We are utilizing our disturbance products to assign the initial year of harvest

activity, as well as assessing change intensities. Our annual canopy cover products are facilitating the characterization of stands prior to harvest, changes in canopy after timber removal, and the recovery of canopy at the time of wildlife surveys. Ultimately, this data is being used to determine the suitability of Minnesota's forest management guidelines at maintaining wildlife populations following forest harvesting.

- Recently, we provided initial harvest disturbance maps to the Minnesota consulting firm, RESPEC, for incorporation into a tool for assessing best management practices and impacts on water quality. Below is a write-up pertaining to the utilization of our disturbance mapping products provided by our RESPEC liaison, Paul Marston:

  "RESPEC Consulting was hired by the Minnesota Pollution Control Agency (MPCA) to add forestry best management practices (BMPs) to the existing Scenario Application Manager (SAM) user interface for the Hydrologic Simulation Program-Fortran (HSPF) models. The MPCA has invested in HSPF to model the entire state of Minnesota at the HUC-8 watershed level. SAM was developed to allow watershed professionals a tool to access the data from the HSPF models as well as run scenarios using the model information. SAM allows users to apply BMPs to certain land use classes and rerun the model to determine the water quality implications. To incorporate forestry BMPs into SAM, a key data need was quantifying the area of harvest on a year to year basis. The harvest area data was the foundation for determining what areas within the model framework could have forestry BMPs applied. The disturbance product provided by Dr. Falkowski and his team was critical as it was the only data available that identified specific agents of forest canopy disturbance. Using Dr. Falkowski et al.'s work gave the project team strong confidence that a critical data requirement for our methodology was met. Other forest disturbance data available grouped all agents of forest canopy change together, providing a dataset with areas not specific to harvesting areas. This data was used in areas of the state that Dr. Falkowski et al.'s data did not cover. Our hope in the future, would be to have statewide versions of Dr. Falkowski et al.'s disturbance products to quantify the harvest area for the entire state of Minnesota, which would ensure we are using the most accurate data available for a critical component of our project."

Paul Marston
Watershed Scientist
RESPEC
Paul.Marston@respec.com
651-305-2278

Among the proposed outcomes of Activity 3, was the publishing of project summaries and conducting outreach activities. In addition to the already published manuscript entitled "Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973–2015)" (Vogeler et al. 2018), we are currently working towards the submission of a manuscript summarizing our most recent fast disturbance mapping work and associated applications. We hope to continue to publish work related to the data products from this project as existing collaborations pertaining to the applications of the mapping products move forward.

Project team members have also been active in the presentation of project methods and preliminary results to a variety of audiences and potential users of the data over the last few years. These included two invited webinars, one to the MN Department of Natural Resources and UMN affiliates, the other to the USDA Forest Service's Forest Inventory and Analysis (FIA) Research and Techniques Band (recording available at: https://usfs.adobeconnect.com/prjhzov1f5fi/), as well as a department seminar within the Department of

Ecosystem Science and Sustainability at Colorado State University in Fort Collins, CO. We also participated in the 2018 Annual Forestry and Wildlife Research Review at the Cloquet Forestry Center, with our presentation titled "A foundational data set characterizing historic forest attributes and disturbance patterns". Our work has even reached the international forest remote sensing community through our presentation of early project methodologies at the bi-annual ForestSAT conference in Santiago, Chile in 2016 (attended using non-ENRTF funds). We will once again present to this international community at this year's ForestSAT held in College Park, MD in October 2018. In addition to the many official presentations, our team has also met with countless researchers and managers around Minnesota, representative of a number of state and federal agencies as well as UMN affiliates, including site visits with local managers at the Chippewa National Forest, Superior National Forest, and the Cloquet Forestry Center.

PROJECT PUBLICATIONS:

Vogeler, J.C., J.D. Braaten, R.A. Slesak, M.J. Falkowski. 2018. Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973 -2015). Remote Sensing of Environment, 209, 363-374.

PROJECT PRESENTATIONS:

Vogeler, J. C., R. A. Slesak, and M. J. Falkowski. 2018. Characterizing forest change dynamics in Minnesota for forest and wildlife science applications (1975-2015). USDA Forest Service Forest Inventory and Analysis Research Techniques Band, Invited Webinar, 26 April 2018. Recording available at: https://usfs.adobeconnect.com/prjhzov1f5fi/

Vogeler, J. C., R. A. Slesak, and M. J. Falkowski. 2018. Characterizing Forty Years of Forest Change: Applications in Forest and Wildlife Science. Department of Ecosystem Science and Sustainability Seminar, Colorado State University, Fort Collins, CO, 18 April 2018.

Vogeler, J. C., J. Braaten, R. A. Slesak, and M. J. Falkowski. 2018. A foundational data set for >40 years of forest characterization and change detection. Minnesota Department of Natural Resources Webinar, St. Paul, MN, 9 January 2018.

Vogeler, J. C., J. Braaten, R. A. Slesak, and M. J. Falkowski. 2018. A foundational data set characterizing historic forest attributes and disturbance patterns. Forestry and Wildlife Research Review, Cloquet, MN, 11 January 2018.

Vogeler, J. C., J. Braaten, R. A. Slesak, and M. J. Falkowski. 2016. Mapping historical canopy cover change and recovery using Landsat time series imagery (1972-2015). ForestSAT, Santiago, Chile, 16 November 2016.

V. DISSEMINATION:

Description:

The final product of this project will be a digital geospatial database characterizing disturbance trends and types across the forested regions of Minnesota. In addition we will prepare an interpretative report detailing case studies that demonstrate how the geospatial disturbance database can be used to assess the impacts of historic disturbances on the resilience of three key forest resources: water quality, wildlife habitat, and wood fiber
We will work in conjunction with the Minnesota Department of Natural Resources to make the geospatial database publically available for download from the GIS Data Deli website (http://deli.dnr.state.mn.us). The interpretative report will be made available on the Internet as a Department of Forest Resources Staff Paper Report. In addition, several manuscripts will be written based on this research and submitted for publication in peer-reviewed journals. A fact sheet summarizing principal findings of this project will be distributed to LCCMR members and legislators at the state and federal level. Results will be presented at state and national forest

management and forest health conferences, and notably to agency and individual participants in the Sustainable Forests Education Cooperative. All reports and publications from this project will be made available via the Department of Forest Resources web site (www.forestry.umn.edu).

Project Status as of *February 2016*:

Work on this activity will commence after completion of Activity 3

Project Status as of *September 2016*:

Work on this activity will commence after completion of Activity 3.

Project Status as of *February 2017*:

Work on this activity will commence after completion of Activity 3.

Project Status as of *September 2017*:

Work on this activity will commence after completion of Activity 3.

Project Status as of *February 2018*:

Work on this activity will commence after completion of Activity 3 (although see above section for current publication work and recent presentations/meetings).

Final Report Summary:

As we finish packaging our mapping products, we are compiling the necessary metadata for posting our annual canopy cover and most recent fast disturbance maps to the MN DNR GIS Data Deli website, which we anticipate will be completed in the next few months. We will also work to post all publications and project reports to UMN Department of Forest Resources web site as they become available. A fact sheet summarizing principal findings of this project is included in the supplementary materials, along with several visuals related to our work and results, and our publication. In addition to the publication and presentations listed above, we are working on an additional manuscript summarizing the most recent fast disturbance mapping work and associated applications and continue to present our project results and mapping products to various research and management audiences and other potential future users of the data. In addition, project partner Dr. Robert Slesak is actively exploring additional applications of this dataset through his work at the MN Forest Resources Council and related activities.

VI. PROJECT BUDGET SUMMARY:

A. ENRTF Budget Overview:

Budget Category	$ Amount	Overview Explanation
Personnel:	$ 193,500	-Salary and fringe (0.336) for three years for Falkowski - PI; 0.083 FTE each year (0.25 FTE over entire project) -Salary and fringe (0.336) for a post-doctoral researcher; 1.0 FTE for 2.5 project years (2.5 FTE over entire project) -Salary and fringe (0.336) for a technician; 0.083 FTE for 2 years (0.16 FTE over entire project).

Equipment/Tools/Supplies:	$ 1,500	Equipment and supplies include $1,500 for data hard drives for storing the satellite data and archiving the final geospatial disturbance database.
Travel Expenses in MN:	$ 5,000	This money will be used to pay for mileage ($3,750) and lodging ($1,250) for researchers when performing validation of the disturbance dataset.
TOTAL ENRTF BUDGET:	**$ 200,000**	

Explanation of Use of Classified Staff: N/A

Explanation of Capital Expenditures Greater Than $5,000: N/A

Number of Full-time Equivalents (FTE) Directly Funded with this ENRTF Appropriation: 2.91

Number of Full-time Equivalents (FTE) Estimated to Be Funded through Contracts with this ENRTF Appropriation: N/A

B. Other Funds: N/A

VII. PROJECT STRATEGY:
A. Project Partners:

In addition to the project leader, Michael Falkowski other project partners are included below.

Dr. Alan Ek, Department of Forest Resources – University of Minnesota (not receiving funding). Role: Dr. Ek will serve as a liaison to several county forestry departments in the State of Minnesota who will be able to assist with database validation by providing disturbance datasets, and will ultimately be end users of the final disturbance database.

Dr. Joe Knight, Department of Forest Resources – University of Minnesota (not receiving funding). Role: Dr. Knight will assist with some remote sensing aspects of this project primarily by providing feedback to the post-doctoral researcher.

Dr. Matthew Russell, Department of Forest Resources & and Extension– University of Minnesota (not receiving funding). Role: Dr. Russell will assist with characterizing insect and disease related disturbances in the final database. In addition he will assist in project dissemination via his role in the University Extension program.

Dr. Linda Nagel, Department of Forest Resources – University of Minnesota (not receiving funding). Role: Dr. Nagel will assist with characterizing harvest related disturbances in the final database

Dr. Robert Slesak, Minnesota Forest Resources Council. Role: Dr. Slesak will assist with the water quality related applications of the disturbance database. Dr. Slesak will also serve as a liaison to Forest Resource Council members who will ultimately be end users of the final disturbance database. In addition he will integrate efforts of this project with other projects he’s currently working on in conjunction with the Minnesota Department of Natural Resources Resource Assessment and Wildlife groups.

Collaborators will include the Minnesota Department of Natural Resources Resource Wildlife and Assessment groups, the Superior National Forest, University of Minnesota Extension, and several counties in northern Minnesota.

B. Project Impact and Long-term Strategy:

Due to the multiple disturbance threats (e.g., insect outbreaks, fire, conversion to agriculture, and climate related stress) facing Minnesota's forest resources, as well as the fact the these threats will only increase under projected climate change, there is a critical need for datasets that can be used to assess the impacts of disturbance on the long term sustainability of Minnesota's forest resources. In addition, understanding how past disturbances have influenced current forest resources is essential to improving and sustaining future resource conditions under existing and eminent threats. This 3 year project will develop a foundational dataset characterizing historic forest disturbance dynamics -and related resource impacts- which will be a powerful tool for identifying threshold disturbance patterns that impact multiple forest resources across Minnesota**.** This foundational dataset will allow us to evaluate how disturbance and landuse configuration over the past 40 years have influenced the current status of forest resources and help to identify management responses that improve and sustain forest resources into the future, and will ultimately guide forest management response aimed at avoiding or mitigating persistent detrimental impacts of forest disturbance on forest resources. For example, forest managers will be better equipped to strategically plan disturbance mitigation practices where risks to forest resources are high, or manipulate disturbed areas to enhance forest response in a manner beneficial to multiple resources. Given the long-term nature of forest disturbance dynamics and associated management, we will link our work with on-going work in the MNDNR resource assessment office that is focused on using similar technology to understand future disturbance impacts. We also plan to explore additional funding opportunities from federal sources such as NASA, the National Science Foundation, and the US Forest Service to build upon and extend this work into the future.

C. Funding History: N/A

VIII. FEE TITLE ACQUISITION/CONSERVATION EASEMENT/RESTORATION REQUIREMENTS: N/A

IX. VISUAL COMPONENT or MAP(S):

See attached Figure 1

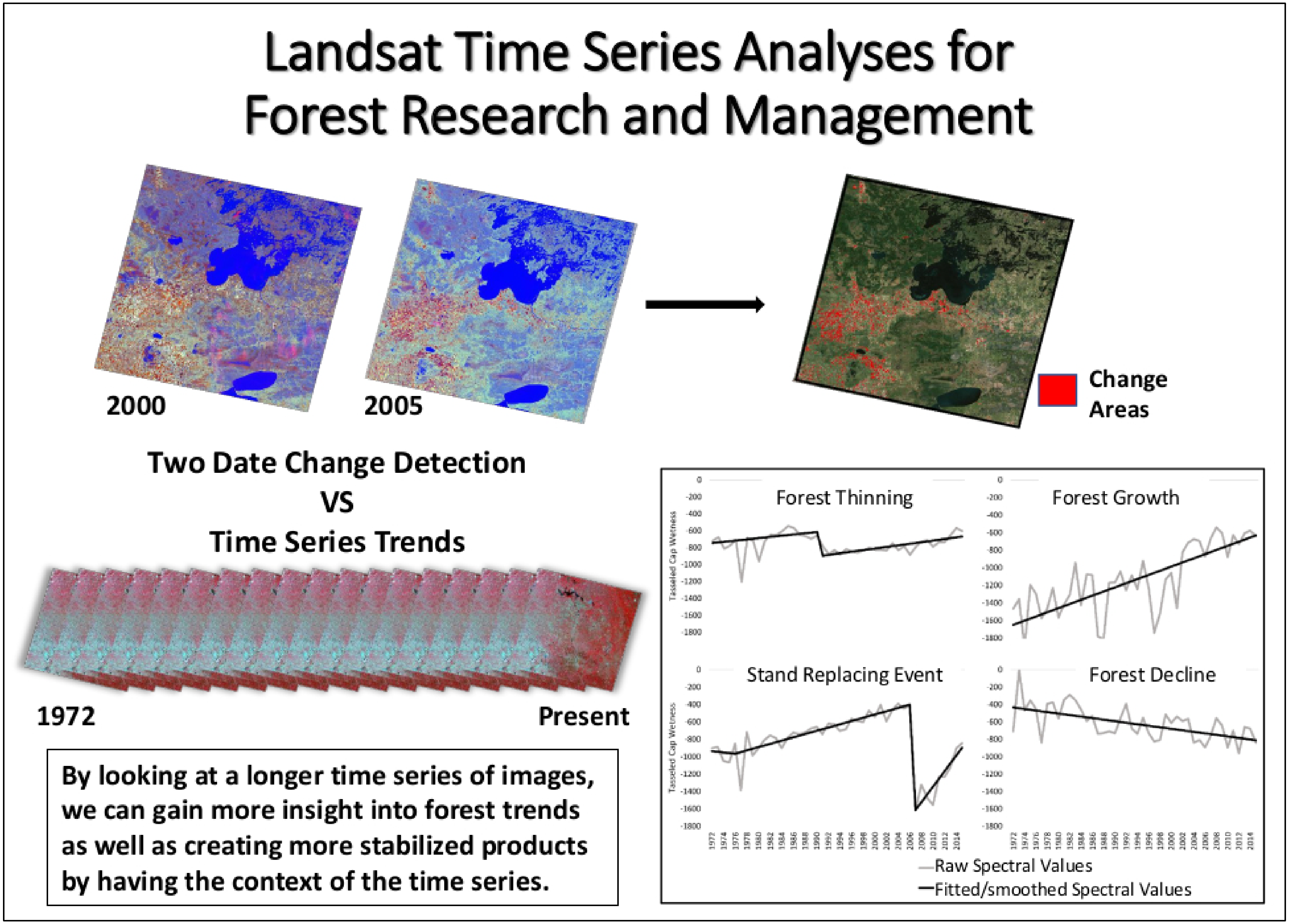
X. RESEARCH ADDENDUM: N/A

XI. REPORTING REQUIREMENTS:
Periodic work plan status update reports will be submitted no later than September 2015, February 2016, September 2016, February 2017, September 2017, February 2018. A final report and associated products will be submitted between June 30 and August 15, 2018.

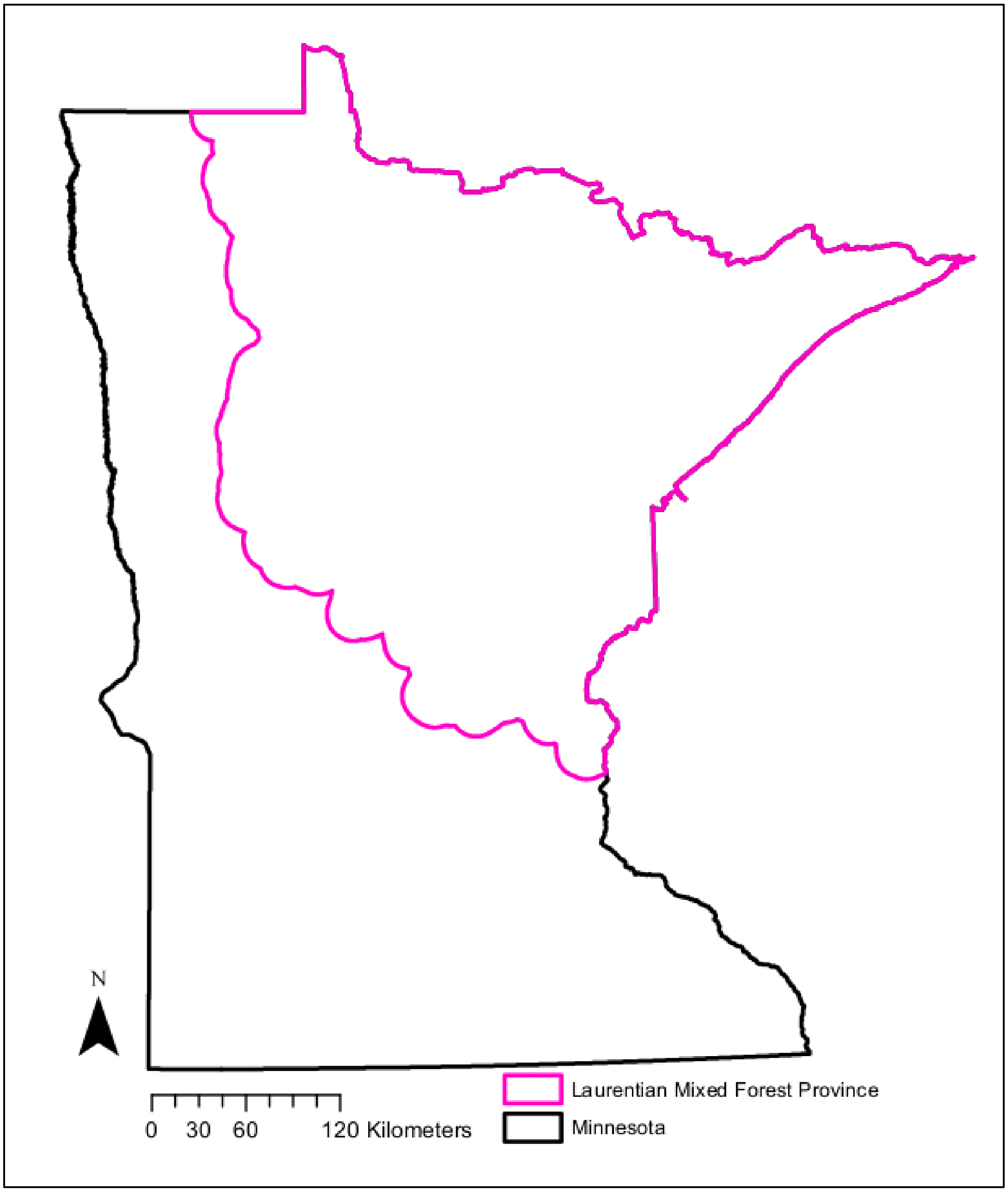
Supplementary Material 1. Project Summary Fact Sheet

- We were able to combine data from all Landsat sensors, allowing for the mapping of >40 years of forest attributes and forest change detection in Minnesota.
- Use of smoothed time series composites highlighted the value of using a time series context (as opposed to 2 date methodologies) and a segmentation fitting approach for more stabilized land cover and forest attribute mapping through time, as well as improved change detection.
- Our annual forest mask and canopy cover mapping products provided the opportunity to observe forest area and cover trends across the state from 1973-2015. We observed a significant, although slight, positive trend in forest area across the state throughout the time period of the study, although we should note that this trend does not account for changes in forest types or stages of structural development, and may include some areas not commonly classified as forests (e.g., shrub-scrub wetlands).
- All ecological provinces experienced significant growth in land area within the two highest cover classes (50-74% and 75-100%), with the exception of a non-significant trend for the 50-74% class within the Tallgrass Aspen Parkland. The greatest growth in the two highest cover classes occurred within the Laurentian Mixed Forest province.
- Our change detection approach captured moderate- to high-intensity stand events with overall accuracy of 92% for differentiating areas of change vs. no-change across Laurentian Mixed Forest Province.
- We were able to further classify the most recent fast disturbance patches into 6 change classes representative of the fast anthropogenic and natural disturbance agents common to the study area (e.g., forest harvest, fire, wind disturbance, etc.), with class accuracies ranging from 78-96% with an overall accuracy of 92%.
- Forest attribute and disturbance products from this project provide unprecedented spatial and temporal information for a variety of Minnesota forest resources applications.
- We utilized our fitted Landsat-derived spectral indices to create bi-annual land cover maps for the Arrowhead region (1999-2015) as requested by University of Minnesota moose biologists to facilitate the assessment of moose habitat use and movements as impacted by land cover types and changes through time. This data is being used to develop predictive models of moose population dynamics to address ongoing questions related to long-term moose viability in Minnesota.
- We are currently collaborating with wildlife researchers at the University of Minnesota-Duluth and Natural Resources Research Institute to assess the impacts of harvest characteristics (e.g. quantity and spatial arrangement of retained canopy during harvest activities) on avian and small mammal communities through the incorporation of our canopy cover products and disturbance map.
- We have provided harvest disturbance maps to the Minnesota consulting firm RESPEC, under contract to the MN PCA, for incorporation into a watershed planning tool for assessing best management practices and impacts on water quality.

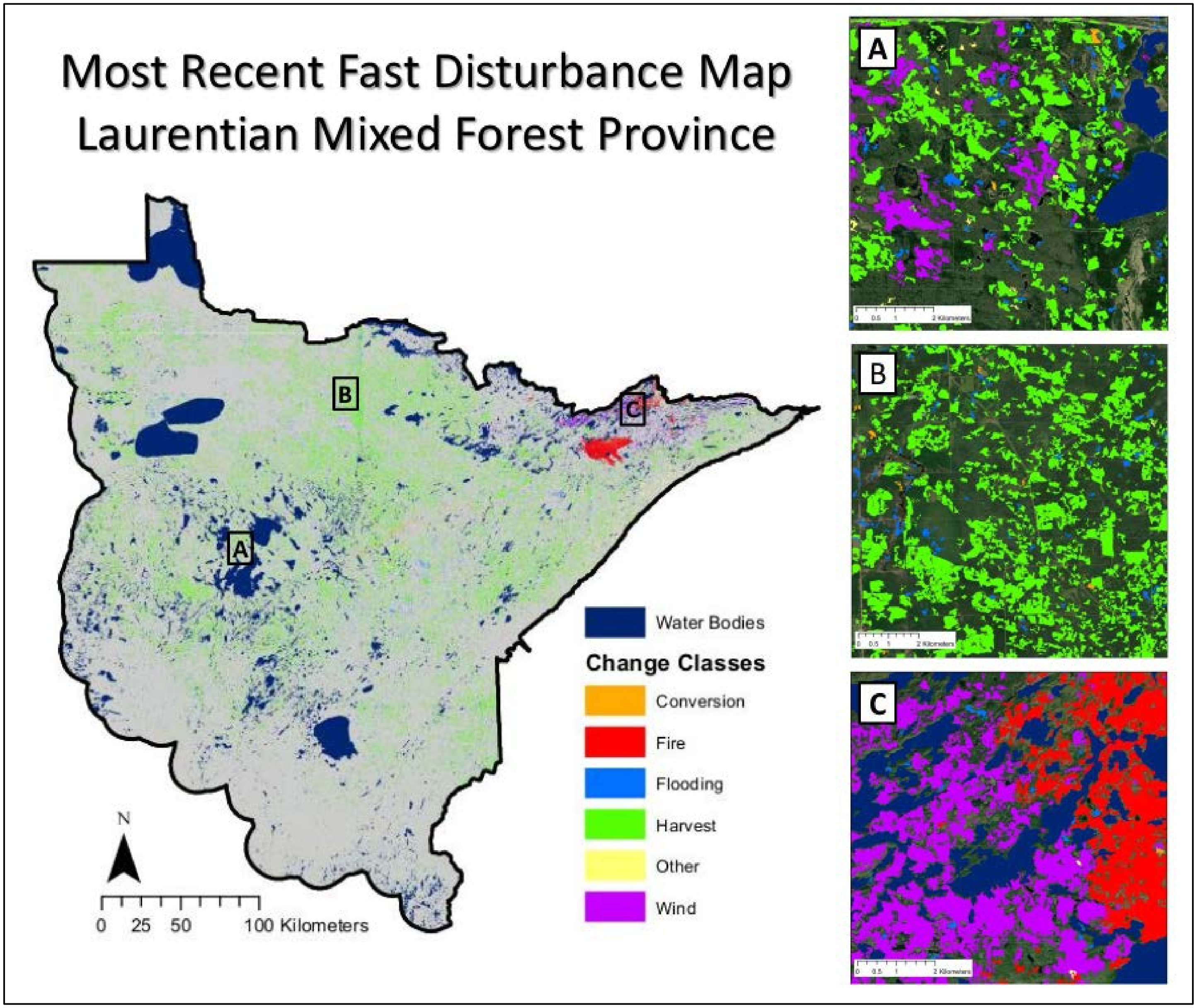
Supplementary Material 2. Visual comparing two date change detection with our Landsat time series approach for forest mapping and change detection.



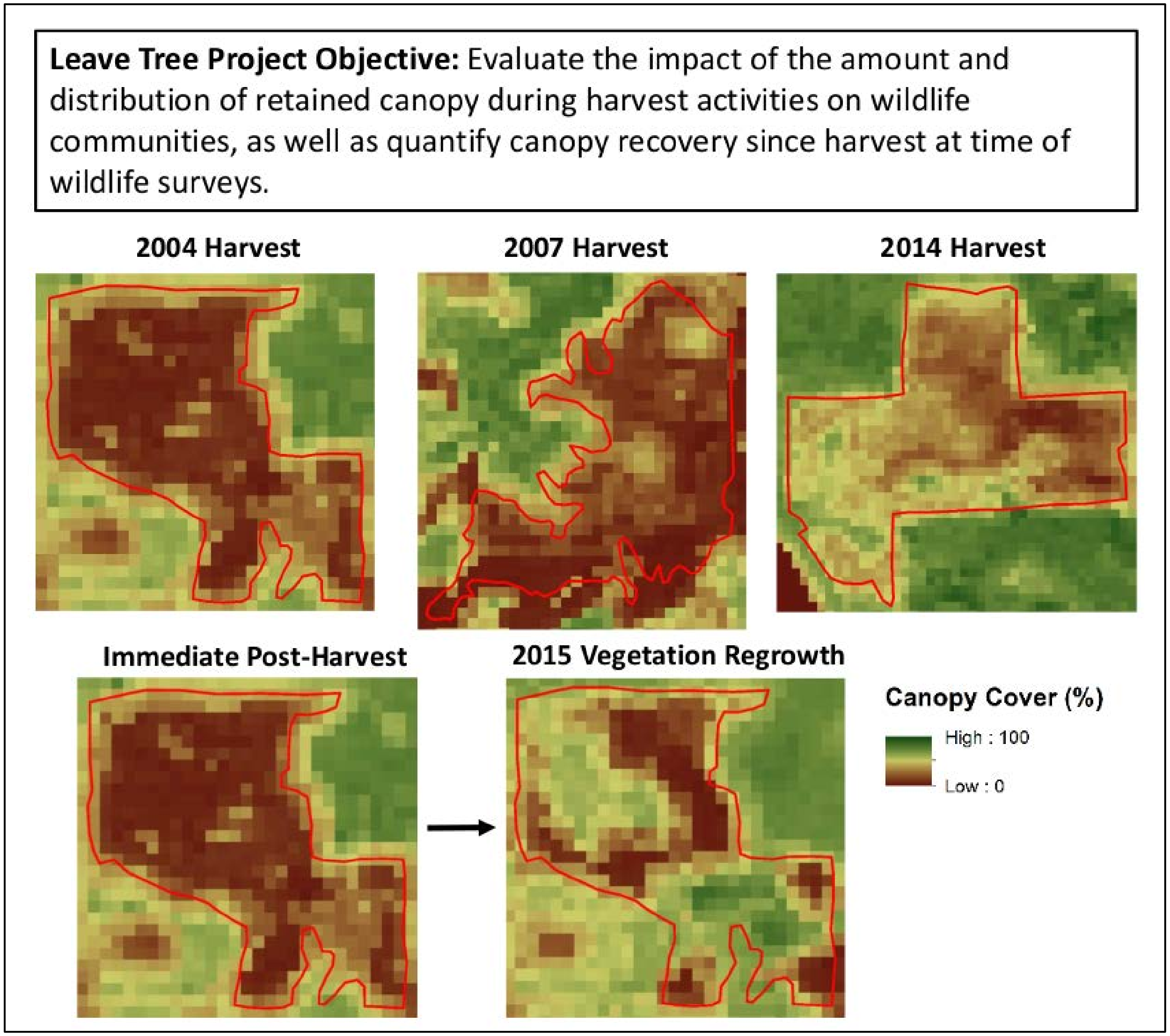
Supplementary Material 3. Project mapping product extents. Annual maps of canopy cover were created at the Minnesota state extent (1973-2015), while disturbance mapping and change agent classification efforts were focused on the Laurentian Mixed Forest Province (with an additional 15km buffer).



Supplementary Material 4. Most Recent Fast Disturbance Map for the Laurentian Mixed Forest Province with 3 example inset areas. Inset A is part of the Chippewa National Forest, inset B represents a mixed ownership landscape, and inset 3 falls within the Boundary Waters Canoe Wilderness Area.



Supplementary Material 5. Visual example of a wildlife application of our data products where we utilized our disturbance map toidentify- the initial year of harvest activities for study stands and characterized the amount and spatial arrangement of retained canopy and vegetation regrowth following harvest from our canopy cover data sets. This project is a collaboration with wildlife researchers from UMN-Duluth and Natural Resources Research Institute.



Supplementary Material 6. Publication entitled "Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973–2015)". Published in Remote Sensing of Environment (Vogeler et al. 2018). Delivered as pdf with this report.

Environment and Natural Resources Trust Fund
M.L. 2015 Project Budget

Project Title: *Foundational Dataset Characterizing Historic Forest Disturbance Impacts*
Legal Citation: *M.L. 2015, Chp. 76, Sec. 2, Subd. 03q*
Project Manager: *Michael J. Falkowski*
Organization: *University of Minnesota*
M.L. 2015 ENRTF Appropriation: $ *200,000*
Project Length and Completion Date: 3 *Years, June 30, 2018*
Date of Report: 08/17/2018

ENVIRONMENT AND NATURAL RESOURCES TRUST FUND BUDGET	Activity 1 Budget	Amount Spent	Activity 1 Balance	Activity 2 Budget	Amount Spent	Activity 2 Balance	Activity 3 Budget	Amount Spent	Activity 3 Balance	TOTAL BUDGET	TOTAL BALANCE
BUDGET ITEM	**Process Landsat satellite imagery into a**			**Disturbance database development and**			**Development of spatial descriptors and**				
Personnel (Wages and Benefits)	$42,317		$42,317	$71,494	$0	$70,494	$79,689	$0	$79,689	$193,500	$0
Michael Falkowski, Project Manager: $8,684 (66.4% Salary, 33.6% benefits); 0.083 FTE each year (0.25 FTE over entire project).		$1,430			$2,576			$24,746			
Jody Vodeler, Postdoctoral Researcher: $167,000 (66.4% Salary, 33.6% benefits); 1.0 FTE each year for 2.5 years (2.5 FTE over entire project).		$41,403			$69,494			$49,120			
Reinhardt, Jason, Technician: $6,948 (66.4% Salary, 33.6% benefits); 0.083 FTE for 2 years (0.16 FTE over entire project)								$6,702			
Equipment/Tools/Supplies											
Equipment and supplies include $1,500 for data hard drives for storing the satellite data and archiving the final geospatial disturbance database.	$1,500	$984								$1,500	$0
Travel expenses in Minnesota											
This money will be used to pay for mileage (3,750) and lodging (1,250) for researchers when performing validation of the disturbance dataset.				$2,500	$1,924	$2,500	$2,500	$1,621	$2,500	$5,000	$0
COLUMN TOTAL	**$43,817**	**$43,817**	**$0**	**$73,994**	**$73,994**	**$0**	**$82,189**	**$82,189**	**$0**	**$200,000**	**$0**

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Extracting the full value of the Landsat archive: Inter-sensor harmonization for the mapping of Minnesota forest canopy cover (1973–2015)

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ARTICLE INFO

Keywords:
Canopy cover
Landsat time series
LandsatLinkr
LandTrendr
Minnesota

ABSTRACT

Remote sensing estimates of forest canopy cover have frequently been used to support a variety of applications including wildlife habitat modeling, monitoring of watershed health, change detection, and are also correlated to various aspects of forest structure and ecosystem function. Although data from the long running Landsat earth observation program (1972–present) have been previously utilized to characterize forest canopy cover, the variability in spatial and spectral resolutions between the Landsat sensors has generally limited analyses to readily comparable imagery from the TM and ETM+ sensors, which omits large portions of the full temporal record. In this study, we present an R package, LandsatLinkr, which automates the processes for harmonizing Landsat MSS and OLI imagery to the spatial and spectral qualities of TM and ETM+ imagery, allowing for the generation of annual cloud-free composites of tasseled cap spectral indices across the entire Landsat archive. We demonstrate the utility of LandsatLinkr products, further enhanced through the LandTrendr segmentation algorithm, for characterizing forest attributes through time by developing annual forest masks and maps of estimated canopy cover for the state of Minnesota from 1973 to 2015. The forest mask model had an overall accuracy of 87%, with omission and commission errors for the forest class of 17% and 10%, respectively, and 9% and 16% for non-forest classification. Our resulting maps depicted a significant positive trend in forest cover across all ecological provinces of Minnesota during the study period. A random forest model used to predict continuous canopy cover had a pseudo R^2 of 0.75, with a cross validation RMSE of 5%. Our results are comparable to previous Landsat-based canopy cover mapping efforts, but expand the evaluation time period as we were able to utilize the entire Landsat archive for assessment.

1. Introduction

Remote sensing of forest attributes continues to advance the field of forest ecology and management by expanding our spatial and temporal records, ultimately leading to a deeper understanding of forest ecosystem pattern and processes. High (< 10 m) and medium spatial resolution remote sensing data (10–100 m) provide detailed depictions of within-stand forest characteristics, while also providing synoptic views of the complex dynamics and interactions of patches across large spatial extents (Cohen and Goward, 2004). Long running satellite programs, such as Landsat, are expanding opportunities to monitor forest trends through time (Huang et al., 2010; Kennedy et al., 2010), improving our understanding of forest disturbance and recovery patterns (Masek et al., 2013; Kennedy et al., 2015).

Remote sensing estimates of within-stand forest structural attributes, such as canopy cover, have frequently been used to support a variety of applications related to research and management (Hansen et al., 2013; Koy et al., 2005). When viewing the forest from above, canopy cover is defined as the proportion of the forest floor in a given unit of space that is obscured by the vertical projection of tree canopies (Jennings et al., 1999). Canopy cover often correlates with additional forest structural attributes, such as stand basal area and volume (Jennings et al., 1999), and serves as an important input into fire behavior models (Pierce et al., 2012). Further, as an identified driver of wildlife habitat use, canopy cover may directly provide hiding cover (Schwab and Pitt, 1991) and nesting substrates (Swanson et al., 2008) for certain species, and also governs the amount of available light for understory growth and associated nesting and foraging resources for wildlife (Jennings et al., 1999). The health and functioning of watersheds may also be correlated with canopy cover through thermal

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regulation of streams (Moore et al., 2005), the introduction of woody debris (Crook and Robertson, 1999), buffering of nutrient loading (Jones et al., 2001), and erosion control (Hartanto et al., 2003).

Annual maps of historic canopy cover allow for the characterization of forest resources at a given point in time, as well as the monitoring of forest change and recovery trends which aid in the prediction of biotic and abiotic stressors on forest systems into the future. Indeed, the patterns of insects and pathogens are of great interest to many forest managers, which can be identified through slow declines in canopy cover (often represented by vegetation indices) that result from mortality or defoliation through time (Neigh et al., 2014). In addition to monitoring a variety of slow or abrupt forest disturbances, annual maps of canopy cover may aid in the tracking of recovery following disturbance events (Pickell et al., 2016). A variety of methods have been devised by foresters to measure canopy cover (Jennings et al., 1999), although variations in data collection efforts across space and time can make it difficult to assemble a contiguous data set. One useful alternative is leveraging Landsat data, which provide a consistent data source with a temporally rich archive of imagery at spatial resolutions appropriate for characterizing forest canopy cover (Ahmed et al., 2015; Pierce et al., 2012) and is available free to the public as of 2008 (Woodcock et al., 2008). Until recently, however, utilizing Landsat for estimates of canopy cover through time has been constrained by the different spatial, spectral, and/or radiometric properties of the varying Landsat sensors.

New approaches for the harmonization of multi-sensor imagery and creation of comparable vegetation indices are expanding the utility of the Landsat archive for historic forest mapping purposes (Braaten et al., 2017; Pflugmacher et al., 2012; Roy et al., 2016). Although many algorithms for analyzing Landsat time series image stacks have emerged in recent years (Brooks et al., 2014; Huang et al., 2010; Hughes et al., 2017; Jin et al., 2013; Kennedy et al., 2010; Vogelmann et al., 2012; Zhu et al., 2015; Zhu and Woodcock, 2014), most of the applications have been limited to leveraging data from the Thematic Mapper (TM) (1984–2012) and the Enhanced Thematic Mapper Plus (ETM+) (1999–present) sensors. Exclusion of data from the earliest sensor, the Multispectral Scanner (MSS) (1972–1999), and the latest sensor, the Operational Land Imager (OLI) (2013–present), are likely due to differences in the spatial, spectral, and/or radiometric resolutions of these sensors, which require much additional processing to incorporate them harmoniously into a time series with TM and ETM+ data. However, the additional twelve years (1972–1984) of imagery available through MSS sensors may improve the value of the Landsat record for characterizing forest ecosystems dynamics, as the cumulative time series approaches a more ecologically significant amount of time (Pflugmacher et al., 2012), and inclusion of OLI ensures continuation past ETM+.

In addition to harmonization between sensors, pixel level characterizations of forest attributes through time may benefit from the removal of year-to-year noise inherent to spectral imagery to better depict realistic patterns of forest recovery and change. Although Landsat time series change detection often utilizes such a segmentation or fitting procedure as an initial step in the identification of disturbance patches, such as that used in the LandTrendr algorithm (Kennedy et al., 2010), few studies have focused on the value of such fitted and smoothed annual products for the mapping of more specific forest attributes (Moisen et al., 2016).

In this study, we present an automated system for normalizing Landsat MSS and OLI imagery to the spatial and spectral qualities of TM and ETM+ imagery, allowing for the generation of annual cloud-free composites of spectral indices across the Landsat archive. This system, termed LandsatLinkr, is implemented as a code library for the R programming environment (R Development Core Team, 2016). We demonstrate the utility of LandsatLinkr and subsequent LandTrendr (Kennedy et al., 2010) fitted products for characterizing forest attributes through time by developing annual forest masks and maps of estimated canopy cover for the state of Minnesota from 1973 to 2015.

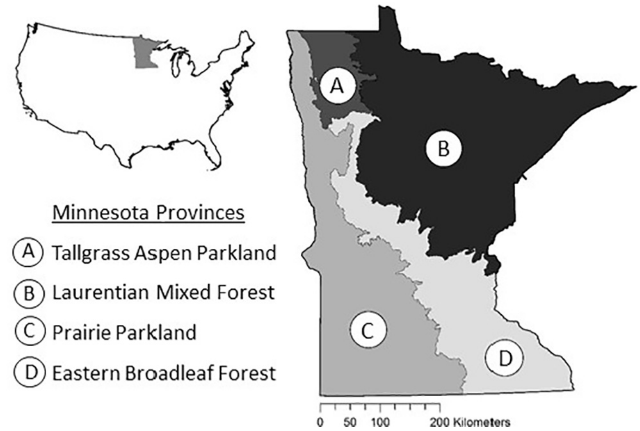

Fig. 1. The Minnesota, USA, study area divided by ecological provinces.

We focus on Minnesota where forests are not only vital for sustaining one of the largest state industries, timber, but are also important components of wetland systems that cover a large portion of the state, and as critical habitat for many wildlife species of conservation interest. Therefore, maps of canopy cover across the state and through time may provide valuable resources to a variety of Minnesota land management, monitoring, and research efforts.

2. Methods

2.1. Study area

The area of study is the entire state of Minnesota, USA, which encompasses the Laurentian Mixed Forest, Eastern Broadleaf Forest, Prairie Parkland, and Tallgrass Aspen Parklands ecological provinces (MN DNR, 1999; Fig. 1). Statewide, agricultural and forest land comprise approximately 50% and 30%, respectively, of total area. Surface waters cover approximately 10% of the total area, with the remaining 10% including managed grasslands, developed urban, and mining land uses (Rampi et al., 2016). There is a strong agricultural to forest land cover gradient extending from the southwest to northeast portions of the state. The regional climate is continental, with mean annual precipitation ranging from 500 to 800 mm and a mean growing season (May-Oct.) temperature of 11–16 °C. Annual precipitation is roughly comprised of about one-third snow and two-thirds rainfall. A variety of forest types occur in the region, but dominant forest types include the aspen-birch and spruce-fir types, and to a lesser extent oak-hickory and pine (Miles and VanderSchaaf, 2015). Wetlands, including forested bogs, peatlands, and swamps, are found extensively throughout the state (MPCA, 2015).

2.2. Landsat imagery

The Landsat earth observation program has been collecting satellite image data from 1972 to present. This archive represents the longest global earth observation record from remote sensing. Landsat sensors include MSS, TM, ETM+, and OLI, which have been deployed on eight different satellites (only seven of which attained orbit). Satellites 1–3 only carried the MSS sensor, 4–5 carried both MSS and TM sensors (coincident image pairs), 6 carried the ETM sensor (was lost on launch), 7 carries the ETM+ sensor, and 8 carries the OLI and Thermal Infrared (TIRS) sensors. Satellites 1–3 had a higher altitude orbit as compared to satellites 4–8, so image data exists according to two different World Reference System (WRS) grids, the former being in WRS-1 and the latter being WRS-2. To fully include the area of the state of Minnesota in our analysis, we utilized Landsat imagery from 28 WRS-1 (MSS) and 28 WRS-2 (MSS, TM, ETM+, and OLI) scenes to create annual growing season composites of tasseled cap spectral indices (Crist and Cicone, 1984). We viewed mean NDVI curves by day-of-year for all scenes to determine an ideal range of peak growing season dates from which to select our imagery (early July–early September). A total of 5945 images across all scenes and years were downloaded from the USGS Earth Explorer website (http://earthexplorer.usgs.gov/) and incorporated into our inter-sensor harmonization and creation of annual composites. After initial assessments, we found that there was insufficient image coverage of our study area during the first year of Landsat MSS, 1972, thus we removed this year from our study. We requested and downloaded the Surface Reflectance High Level Data Product available for TM and ETM+ (LEDAPS algorithm; Masek et al., 2006), and OLI (L8SR algorithm; Vermote et al., 2016) images, and Level 1 Product Generation System (LPGS) images for MSS. TM and ETM+ surface reflectance images were considered the spatial and spectral standard for the time series and remained unaltered. MSS and OLI data, however, went through a normalization process to harmonize them with the TM/ETM+ data.

The work flow for harmonizing the MSS and OLI data to TM/ETM+ and generating annual cloud-free composites was handled by the LandsatLinkr (LLR) system (Braaten et al., 2017). LLR is an R package designed to automate much of the pre-processing and harmonization required to create annual cloud-free composites of tasseled cap indices across a user-defined study area throughout the Landsat archive. Using previously established methodologies, LLR spectrally and spatially aligns images from multiple sensors through additional georegistration, resampling of coarser resolution MSS images, and the modeling and harmonization of tasseled cap indices. The six LLR steps include: 1) MSS unpacking; 2) TM/ETM+ unpacking; 3) OLI unpacking; 4) MSS to TM harmonization; 5) OLI to ETM+ harmonization; and 6) annual composite creation (Fig. 2). Steps 1–5 are completed at the scene level and step 6 incorporates all scenes required to cover a user-defined study area.

In the first step, MSS images are unpacked (decompressed, stacked, re-projected) and georegistration accuracy is assessed. For those images with an a total positional RMSE ≥0.5, the georegistration is enhanced using an image-to-image tie point search and warp procedure (MSSwarper), which is based on the methods presented in Kennedy and Cohen (2003). Unfortunately, in our case there were a large number of MSS images for some of our scenes that were not available as desired USGS L1T products (i.e., orthorectified) for which LLR is set up to handle. They were instead only available as L1G products (systematic geocorrection based on spacecraft ephemeris data) which left gaps in our time series stacks. To improve the initial georegistration of L1G images, we did a shift and rotation procedure in ArcGIS by manually selecting three tie points from an additional 96 images. Following this step, we then continued with MSSwarper on the manually corrected L1G images, further fine-tuning the georegistration and filling in the gaps in our annual stacks. LLR then further radiometrically corrects the MSS images to top-of-atmosphere and surface reflectance. Surface reflectance is calculated using the COST method (Chavez, 1996), with the *Lhaze* parameter or “dark object value” estimated from an automated implementation of the histogram method (Chavez, 1988). Finally, cloud masks are created following the MSScvm procedure (Braaten et al., 2015), which along with surface reflectance are resampled to 30 m to match the spatial resolution of the later Landsat sensors.

In the next LLR steps TM, ETM+, and OLI image data are automatically decompressed, stacked, re-projected, and a cloud mask is derived from the product-included Fmask (Zhu and Woodcock, 2012) cloud and cloud shadow mask. Fmask reclassification is performed to match the MSS cloud mask classes produced above to allow efficient mask application during the compositing process. For the TM and ETM+ data, tasseled cap spectral transformations brightness, greenness, and wetness (Crist, 1985) are produced, as well as a derivation of greenness and brightness called the tasseled cap angle (Powell et al., 2010).

LLR steps 4 and 5 involve the inter-sensor harmonization of MSS to TM and OLI to ETM+ indices. MSS images are normalized to the TM images through the modeling of TM tasseled cap indices from the 4 MSS bands using samples from offsets of coincident images and multiple linear regression; a similar approach presented by Roy et al. (2016) is utilized to transform OLI data to TM. This is done separately for each tasseled capped index to create index specific models. Since the models incorporate variance introduced by multiple individual MSS/TM relationships from the samples within the sets of coincident images (which occurred during the period of overlap between MSS and TM with Landsat 4 and 5), the final models represent mean or aggregate models which are then applied to all MSS images from a given scene. Since aggregate models were created using MSS Landsat 4 and 5 which are on the WRS-2 grid, and MSS Landsat 1–3 are WRS-1, the model from the WRS-2 scene that most overlaps each WRS-1 scene is used for harmonization. OLI images are harmonized to ETM+ images in the same way as MSS to TM, except that only 6 of the 7 OLI reflectance bands are included as predictors (band 1 – ultra blue is excluded), and near-date images are used since there are not coincident image pairs available for ETM+/OLI. We evaluated the performance of the LLR harmonization between sensors by calculating the difference between annual summer image composites produced for each sensor for the same year during sensor overlaps, which are intermediate products available from LLR.

The final step of LLR is to create annual composites of the tasseled cap indices. All of the previous LLR steps are completed on an individual scene basis, while the compositing step is applied to a user defined area which can encompass multiple WRS-1 and WRS-2 scenes. Images from a given year are compiled using one of several summary metric options within the compositing function, ignoring clouds, shadows, or no data pixels such as those from the ETM+ SLC-off lines. We chose to utilize the median summary statistic as we found this method best removed any remaining pixel noise from the composites and was the most suited for our purposes.

After creating annual composite stacks using LLR, we then applied the LandTrendr temporal segmentation algorithm presented in Kennedy et al. (2010). While LandTrendr is mostly used as a change detection algorithm, the first step involves a segmentation procedure that fits vertices to the spectral trends for each pixel. Among the outputs are revised annual pixel values interpolated from lines between the vertices. We used this approach to smooth the annual trends to minimize year to year noise, providing a better representation of true forest dynamics, which do not usually exhibit abnormal growth spikes or dips for a single year (Fig. 3). In addition to the annual spectral indices from Landsat, we also included topographic variables in our modeling efforts. We downloaded the Minnesota 30 m Digital Elevation Model (DEM; MDNR, 2004) to represent elevation and to create maps of slope, aspect, and several aspect transformations in ArcGIS 10.3 (Table 1).

2.3. Canopy cover estimates

To generate canopy cover estimates to use in model training and validation, we randomly identified 1340 sample locations across the state which we first evaluated to ensure that all forest and non-forest classes in the 2011 National Land Cover Dataset were represented (NLCD; Homer et al., 2015). Following similar methodologies as Coulston et al. (2012), we created 3 × 3 Landsat pixel windows (90 m × 90 m) surrounding each sample location. Within each 90 m × 90 m sample plot, we generated a 100 point dot grid using the fishnet tool in ArcGIS 10.3. These dot grids were overlaid onto false color composites from 2008 4-band National Agriculture Imagery Program (NAIP) aerial imagery, and the proportion of dots within each sample window that intersected tree crowns was used to estimate canopy cover for that plot. The observer used surrounding landscape in addition to the plot view within the NAIP imagery to aid in differentiating between forest and non-forest vegetation prior to designating

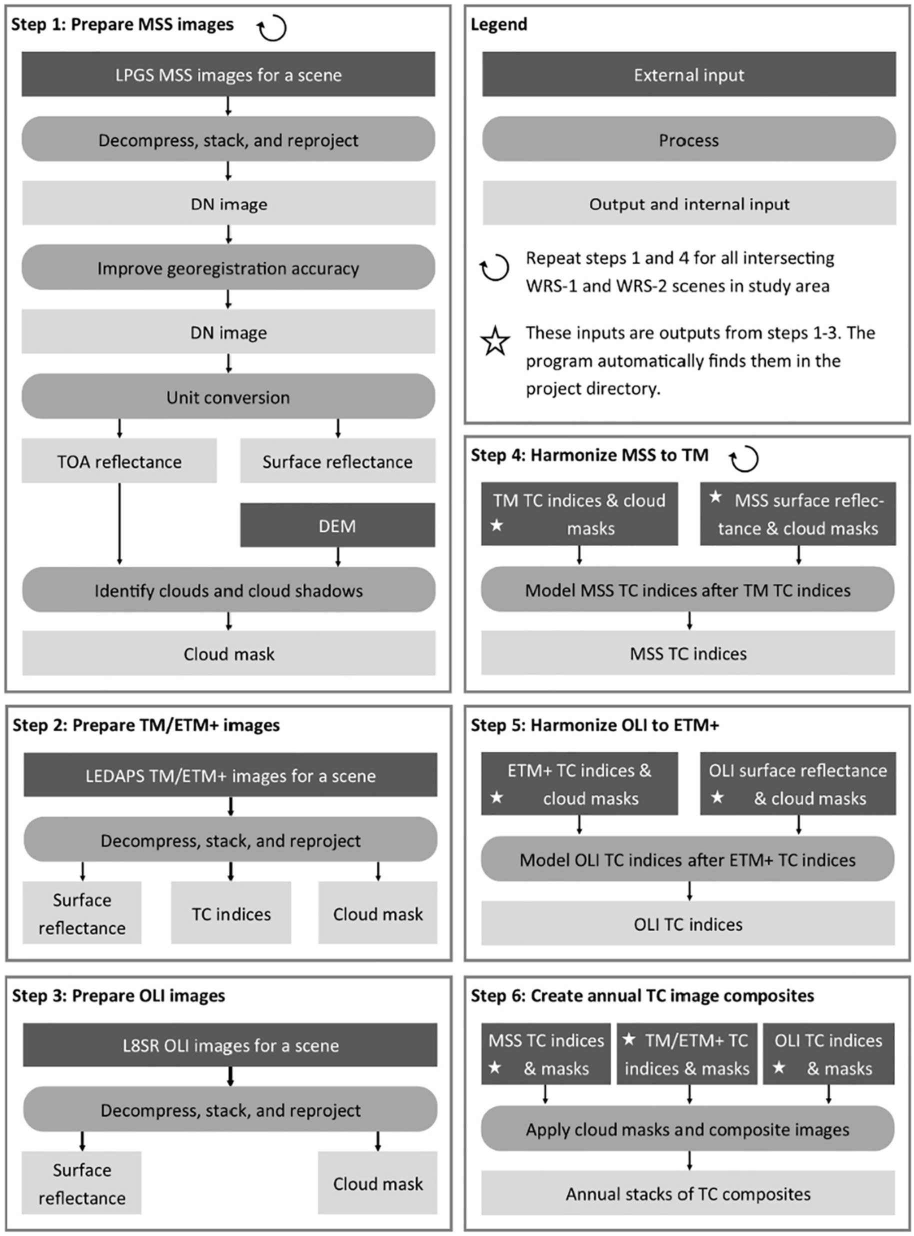

Fig. 2. Work flow for LandsatLinkr, an R package which automates the pre-processing, harmonization, and compositing of imagery from all sensors throughout the Landsat archive (1972–present).

canopy vs. non-canopy within the sample plots. When using aerial imagery for estimating canopy cover, observers must decide how to classify shadows within forest stands. In our study, we choose to classify dark shadows within a forest stand as non-canopy cover. A single observer conducted the photo interpretation to minimize any potential bias between different observers (Frescino and Moisen, 2012).

2.4. Forest cover models

Landsat tasseled cap and topography predictors corresponding to 2008, the year of NAIP imagery acquisition, were extracted for each 90 m square plot using zonal statistics in ArcGIS 10.3 (Table 1). We first created a statistical model to differentiate between forest and non-forest where plots with < 10% canopy cover were considered as non-forest. To create this forest mask model, we employed the random forest (RF) statistical modeling approach (Breiman, 2001). The RF algorithm is a classification and regression tree technique that has achieved excellent results in the generation of classifications or continuous predictions from remotely sensed data (e.g., Falkowski et al., 2009; Hudak et al., 2008; Lawrence et al., 2006). Indeed, RF has rapidly been adopted by the ecological modeling community as an attractive alternative to traditional statistical approaches because of its flexibility in handling data with non-normal distributions, a large number of predictor variables, and the use of averaged bootstrap training samples for improved predictions (Cutler et al., 2007). In the case of classification, the RF algorithm develops classifications by growing numerous (100s to 1000s) classification trees from a random subset of training data (approximately 63% random subset), while randomly permuting predictor variables at each node. The RF algorithm then determines the final classification by selecting the most common classification outcome at each node within the group of multiple trees (Breiman, 2001; Lawrence et al., 2006; Prasad et al., 2006). Bootstrap error estimates are calculated for each tree in the forest by classifying the response variable(s) from each observation in the portion of training data not selected for model development (approximately 37% of the training data). After all the trees in the forest are grown, overall classification error is

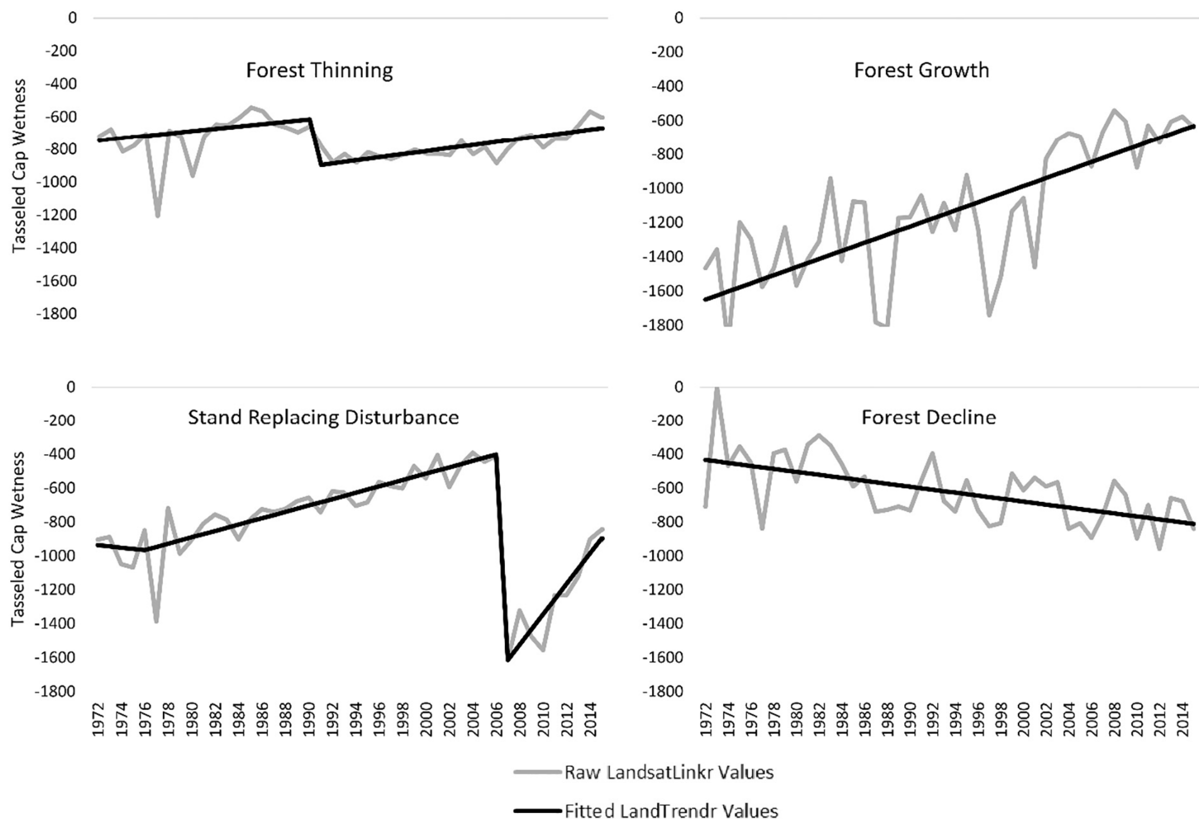

Fig. 3. Comparison of raw annual Landsat composite values from LandsatLinkr and fitted vertices from LandTrendr segmentation algorithm. Examples include tasseled cap wetness values for four pixels in Minnesota.

calculated by averaging errors across all trees in the forest; this is analogous to cross-validated estimate of error and accuracy (Cutler et al., 2007). The algorithm also calculates the influence each predictor variable has upon model accuracy based on the ratio of improvement in the mean squared error across bootstrap replicates, which can be used to determine the relative importance of each variable used in the classification. For this study, the RF algorithm was implemented as the RandomForest package (Liaw and Wiener, 2002) in the R statistical program (R Development Core Team, 2016).

Although collinearity between predictors has been reported as less

Table 1
Descriptions and abbreviations for Landsat-derived tasseled cap predictors and DEM extracted topographic metrics included in the forest mask and canopy cover models. Model metrics were summarized for the 90 m × 90 m canopy cover training plots and the models were later mapped using 3 × 3 focal grids of the predictors. “X” indicates the inclusion of a predictor in the final random forest mask (RF Mask) and canopy cover (RF Cover) models.

Predictor	Abbrev.	Description	Included in final models	
Landsat			RF Mask	RF Cover
Tasseled cap brightness		Soil reflectance[a,b]		
Mean	TCB_mn		X	X
Standard deviation	TCB_sd		X	
Tasseled cap greenness		Variations in green vegetation[a,b]		
Mean	TCG_mn		X	X
Standard deviation	TCG_sd			
Tasseled cap wetness		Correlated with forest structure[a,c]		
Mean	TCW_mn		X	X
Standard deviation	TCW_sd		X	X
Tasseled cap angle		TCA = arctan(TCG/TCB)[d]		
Mean	TCA_mn		X	X
Standard deviation	TCA_sd		X	
Topography				
Elevation	ELEV	Elevation (meters)		
Slope	SLOPE	Degree topographic slope	X	
Aspect transformed	ASPECT	ASPECT = COS * [45 − (aspect in degrees)] + 1		
ssina	SSINA	SSINA = percent slope * SIN * (aspect in degrees)		
scosa	SCOSA	SCOSA = percent slope * COS * (aspect in degrees)		
Prediction maps				
Forest mask prediction	MASK	Forest vs. non-forest prediction included as a factor	NA	X

[a] Presented in Crist (1985).
[b] Crist and Cicone (1984).
[c] Cohen et al. (1995).
[d] Presented in Powell et al. (2010).

Table 2
Estimated non-forest and forest classification error matrix with cells representative of the error-adjusted proportions of area. Observed classes are the columns, while predicted classes are the rows. Reported users', producer's, and overall accuracy measures include 95% confidence intervals.

Class	Non-forest	Forest	Total	User's	Producer's	Overall
Non-forest	0.46	0.09	0.55	0.85 ± 0.02	0.91 ± 0.02	0.87 ± 0.02
Forest	0.05	0.41	0.45	0.90 ± 0.02	0.83 ± 0.02	
Total	0.51	0.49	1			

of a concern with a RF approach, recent research has suggested otherwise (Murphy et al., 2010). Thus, we employ a model selection procedure to determine the optimal suite of predictor variables to use in the classification of forest presence and absence. The model selection procedure was implemented via the rfUtilities package in R (Evans and Murphy, 2017) to develop the most parsimonious classification model, while retaining the highest possible classification accuracy. In order to reduce data redundancy and improve overall model interpretability, multi-collinear predictor variables were identified and removed via a multivariate variable screening process based upon Gram–Schmidt QR-Decomposition (Evans and Murphy, 2017; Falkowski et al., 2009). The final classification model is arrived at based on the criteria of smallest total and within class errors, and fewest numbers of predictor variables. In order to stabilize classification error, each RF model was run with 500 bootstrap replicates (i.e., individual classification trees), and then evaluated for the point of MSE stabilization which occurred at 400 trees for this model. After constructing our error matrix for the final forest mask model, we followed the methods presented in Olofsson et al. (2013) to calculate a poststratified estimator to translate the matrix into terms of unbiased proportions of area in the forest and non-forest classes. These sample-based estimates of area were incorporated into classification accuracy measures and associated confidence intervals (Olofsson et al., 2013).

We used a similar RF model selection procedure for canopy cover as with our forest mask models with the exception of designating a regression tree approach rather than a classification tree approach. In addition to the spectral and topographic variables, we included predictions from our forest mask classification as a factor in the models to aid in the continuous prediction of forest canopy cover across all land cover types within one model. To avoid overfitting the model, we chose the appropriate number of decision trees from our initial model run which incorporated all predictors by determining the number of trees at which the MSE had stabilized from the RF tree plot (300 trees). To assess bootstrap prediction errors, we averaged 100 iterations where 70% of the data was used to train each model and 30% was retained for validation. We calculated pseudo R^2 values using the model mean square error (MSE) and variance in the response variable (y) with the equation:

$$R^2 = 1 - \frac{MSE}{var(y)} \tag{1}$$

Relative importance of model predictors were assessed using variable importance values reported by RF which represent the percent increase in model MSE if a predictor was randomized.

2.5. Annual prediction mapping

To match the scale of the model variables, we created focal grids of the annual Landsat tasseled cap indices and static topographic predictors in ArcGIS at the 30 m Landsat resolution, where the center pixel within a moving focal window is assigned a summary statistic for the larger 3×3 pixel window. We applied the selected forest mask and canopy cover models to the Landsat time series stacks for the state of Minnesota using the focal grids within R to create annual maps of forest masks and canopy cover from 1973 to 2015. While cover was modeled as a proportion (0–1), during predictive mapping we multiplied by 100 to produce percent canopy cover products.

We used the stacks of predictive maps for a general assessment of change in forest area and cover across the state through time. All trends presented for the forest/non-forest classification maps reflect error-adjusted estimations of area (Olofsson et al., 2013), although the unbiased estimator was calculated from the single year (2008) utilized in model creation and validation. While the ultimate objective of this study was to create maps of continuous cover through time, we derived five classes from our continuous cover products to aid in the visualization of temporal trends: (1) < 10% (from here on referred to as non-forest); (2) 10–24%; (3) 25–49%; (4) 50–74%; (5) ≥75%. We also divided the maps by ecological provinces (Fig. 1) to evaluate differences in trends across Minnesota ecoregions. The summaries of forest cover and cover classes through time were fit with linear coefficients and evaluated for significance of general trends across the full span of the time series using *t*-tests.

3. Results

3.1. Forest cover models

Through the use of Landsat-derived spectral indices and topographic information, we were able to create models of forest cover for the state of Minnesota. After the model selection procedure, our final random forest classification model of forest vs. non-forest included TCB_mn, TCB_sd, TCG_mn, TCW_mn, TCW_sd, TCA_mn, TCA_sd and SLOPE predictor variables (Table 1). After incorporating the error-adjusted estimator of area, the forest mask model had an overall accuracy of 87% (Table 2), with omission and commission errors for the forest class of 17% and 10%, respectively, and 9% and 16% for non-forest classification. The selected random forest model for canopy cover had a pseudo R^2 of 0.75 while minimizing prediction errors with a cross validation RMSE of 5%. The importance of predictors was ranked as follows according to the RF algorithm (with values of relative importance): forest mask prediction (37.24); TCW_mn (26.76); TCA_mn (26.04); TCB_mn (20.01); TCW_sd (9.94); and TCG_mn (9.61).

3.2. Landsat time series stacks

Landsat spectral indices harmonized across sensors and fitted to temporal trend lines facilitated the annual mapping of the forest mask and continuous canopy cover models across the state of Minnesota from 1973 to 2015 (Fig. 4). The R package presented here, LandsatLinkr (LLR), efficiently executed all necessary steps for the creation of the spatially and spectrally comparable annual tasseled cap composites (Fig. 5). These composites spanned the entire Landsat archive and successfully minimized seam lines between scenes, maximized data coverage on an annual basis, and adequately removed clouds and cloud shadows from the images. Evaluation of the distribution of differences between image data from two different sensors from the same annual composite period for a sample of points (n = 5964 for each year, distributed randomly throughout MN) show medians near zero and tight variance (Fig. 5), providing support for the successful inter-sensor harmonization by LLR.

3.3. Forest cover mapping and time series trends

Annual values of forest area (> 10% forest cover) from the mask maps depict a significant, although slight, positive trend across the state throughout the time period of the study (1973–2015; Fig. 5). Note that this estimate does not account for changes in forest types or stages of structural development, and may include some areas not commonly considered forests (e.g., shrub-scrub wetlands). Forest area accounted for 43.9% (± 2%) of Minnesota land area in 1973, expanding to 52.5%

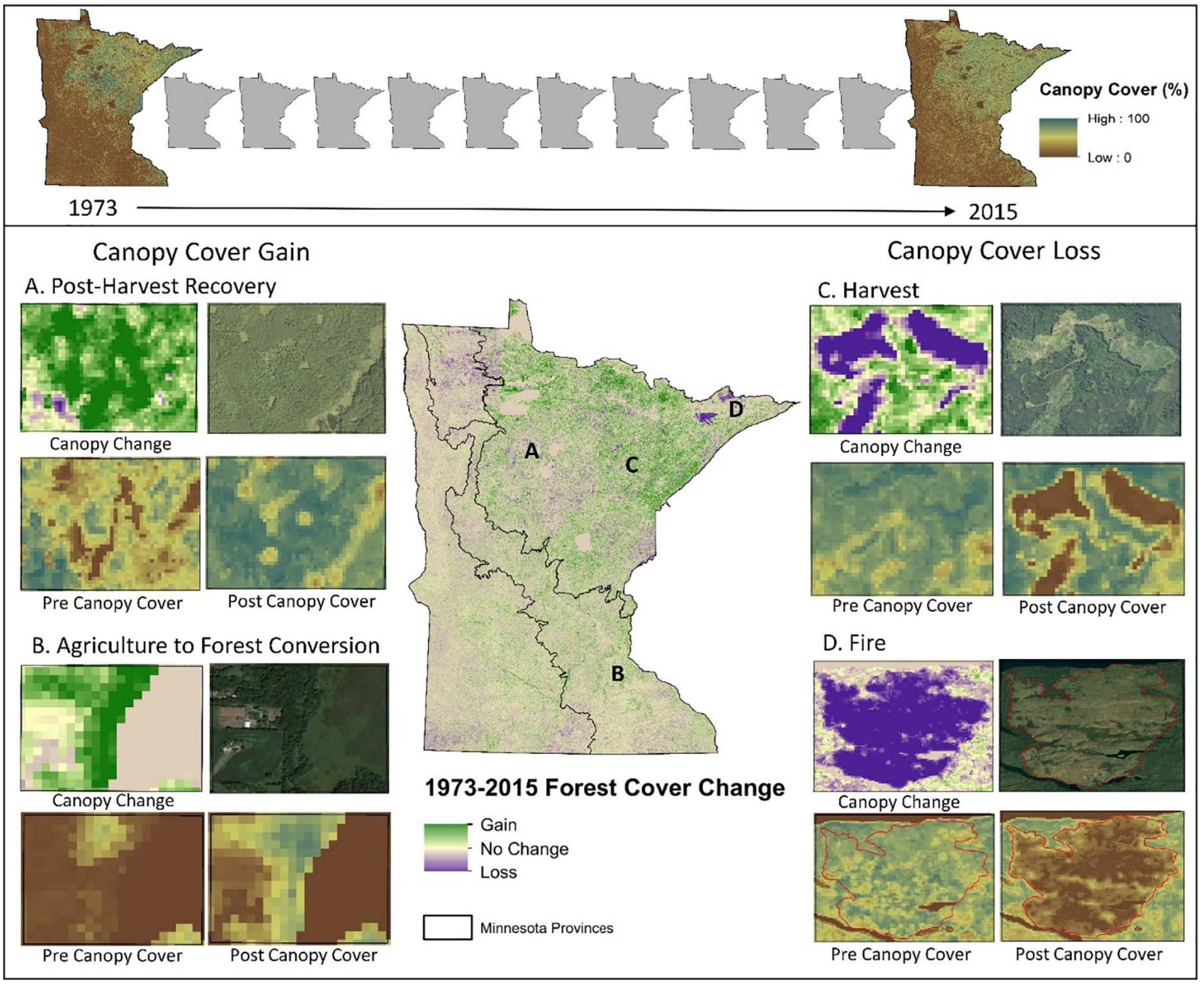

Fig. 4. Representation of the annual stacks of forest canopy cover maps created for 1973–2015 including summary maps of canopy cover change within the Minnesota ecological provinces over the 43 year study period. Subsets are provided for example sources of canopy cover gain and loss observed during the study period (note that we make no claim that these examples represent dominant agents of change for Minnesota as this is beyond the scope of this study). Each example includes a local view of the change event from cover change (1973–2015) maps, a google earth photo corresponding to the post change condition, and pre- and post-change percent canopy cover for years directly prior and following each specific change event.

(± 2%) by 2015 (water bodies were removed from this analysis). This significant positive trend was consistent across all Minnesota provinces (Fig. 6), where the Eastern Broadleaf and Laurentian Mixed Forest provinces experienced the greatest growth. While most of the provinces exhibited a constant positive trend across the 43-year study, the Tallgrass Aspen Parkland province began with 10 years of decline followed by an increase in forest for the remainder of the time series (Fig. 6). Examinations of the prediction maps revealed a slight overestimation of forest area within agricultural dominated areas on the western edge of Minnesota, primarily within the Prairie Parkland province.

The five cover classes including a non-forest class derived from the continuous canopy cover values facilitated further evaluation of the canopy cover mapping products and temporal trends for additional context and utility (Fig. 7). The histogram of cover values from the photo interpretation plots used in model creation were well represented by those of the corresponding 2008 cover map, with the exception of a slight under representation of the highest cover class in the map (≥75% cover). Across the time-period of the study, all ecological provinces with the exception of the Tallgrass Aspen Parkland exhibited significant decreases in the non-forest cover class, corresponding to the significant increase in overall forest cover observed through our forest mask maps (Fig. 8). Trends within the moderate cover classes (10–24% and 25–49%) varied across the provinces (Fig. 8). All regions of the state experienced significant growth in the land area within the two highest cover classes with the exception of a non-significant trend for the 50–74% class within the Tallgrass Aspen Parkland (Fig. 8). The greatest growth in these two high cover classes occurred in the Laurentian Mixed Forest province.

4. Discussion

Through the use of the freely available Landsat archive, we created forest masks and maps of canopy cover for the state of Minnesota from 1973 to 2015, a valuable data set for a variety of research and management applications. This was in large part facilitated by the automation of processing steps by LandsatLinkr for the creation of spatially and spectrally harmonized image data from all Landsat sensors and multiple scenes. The harmonized spectral index predictors were further enhanced with the use of the LandTrendr segmentation algorithm for the smoothing of year-to-year spectral variations not associated with forest change dynamics. Many of the previous studies utilizing Landsat time series products for the mapping of forest attributes are temporally restricted to the post-MSS years (> 1984; Potapov et al., 2015; Powell et al., 2010). The harmonization of MSS imagery to the later sensors allowed us to add an additional 11 years to our stacks of mask and cover maps, adding over a decade of identified patches of forest cover change and expanding the records of general forest area and cover class trends.

The accuracy of our canopy cover model is comparable to those

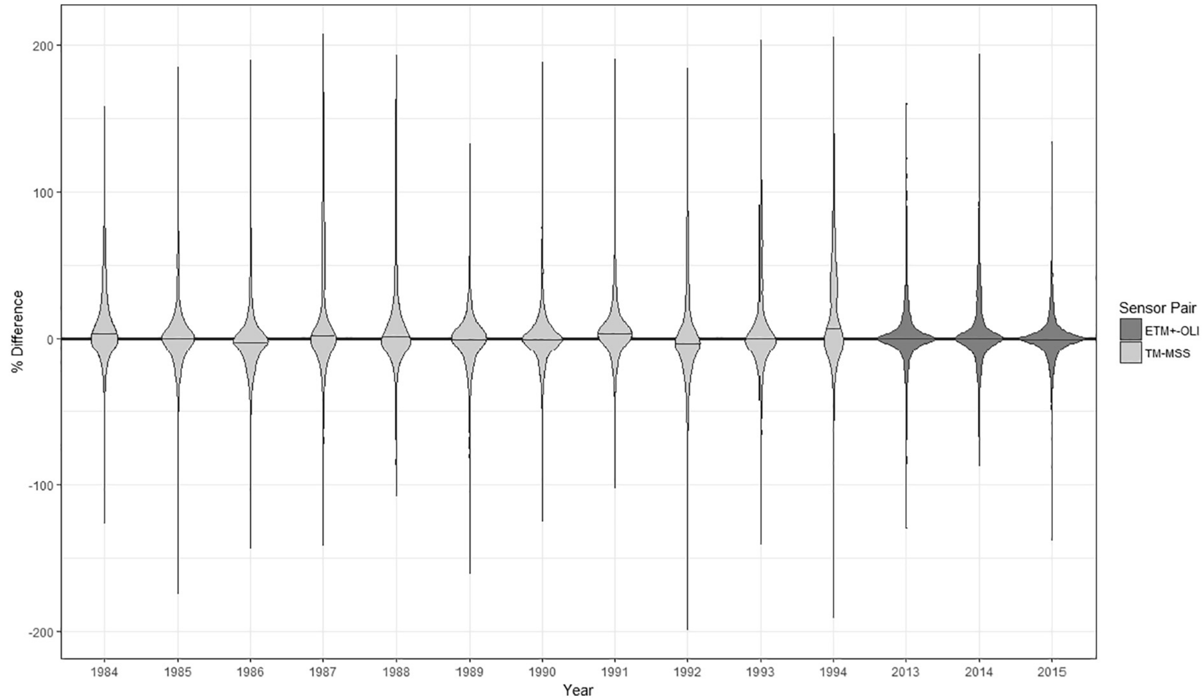

Fig. 5. Distributions of pair-wise difference between LandsatLinkr (LLR)-produced Tasseled Cap Wetness (TCW) annual image composites for years when two sensors concurrently acquired data. Differences between sensor data is cast as a percent of the range between two standard deviations surrounding the mean of TCW for Minnesota. Positive differences indicate that MSS and OLI TCW values are greater than TM and ETM+, respectively, and less, when negative.

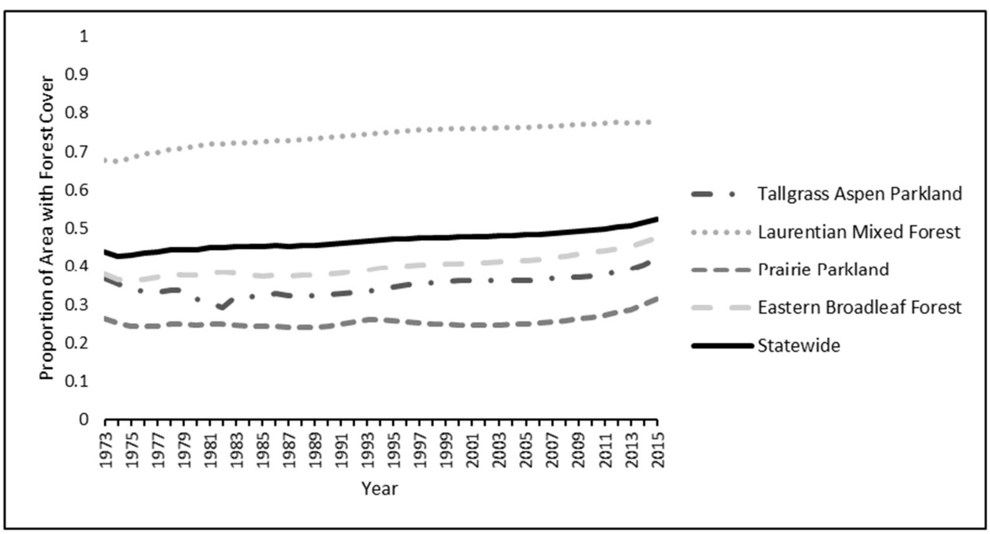

Fig. 6. Temporal trends (1973–2015) in the proportion of land statewide and within ecological provinces with forest cover derived from annual forest mask maps.

from previous Landsat studies (Ahmed et al., 2015; Pierce et al., 2012), although utilizing predictor data available for the entire Landsat time series and encompassing a larger spatial extent and species composition gradient compared to many of the previous studies. With a few exceptions (Sexton et al., 2013; Hansen et al., 2011) including the NLCD tree cover products (Homer et al., 2015), many of the previous Landsat based canopy cover modeling efforts have been conducted within restricted forest types and/or small geographic areas (Ahmed et al., 2015; Carreiras et al., 2006). Pierce et al. (2012) utilized Landsat TM data for modeling aspects of canopy structure including cover for inclusion in fire behavior models within the coniferous dominated forests of Lassen Volcanic National Park, CA (42,900 ha). The study incorporated band reflectance and additional spectral indices to a similar set of tasseled cap and topographic metrics as our study with moderate model performance ($R^2 = 0.66$; Pierce et al., 2012). Through the incorporation of Landsat-derived disturbance information, Ahmed et al. (2015) were able to stratify the forests in their 2600 ha study area on Vancouver Island, BC Canada, into mature and young classes prior to canopy cover modeling efforts. The initial stratification improved model performance for mature forests ($R^2 = 0.72$) over the combined data set ($R^2 = 0.67$), although resulting in weaker model performance for the young forest class with an R^2 of 0.59; RMSE remained constant at 7% for the divided and combined cover models (Ahmed et al., 2015). In our study, we were able to create a single canopy cover model for the entire state of Minnesota (> 22 million ha; $R^2 = 0.75$, RMSE = 5%) which includes 15 NLCD land cover classes, distinguishing forest from non-forest and estimating cover for forest types representing a range of composition from deciduous to coniferous and wetland to upland stands. Tasseled cap wetness was the strongest spectral predictor in our canopy cover models, consistent with findings of previous studies (Hadi et al., 2016;

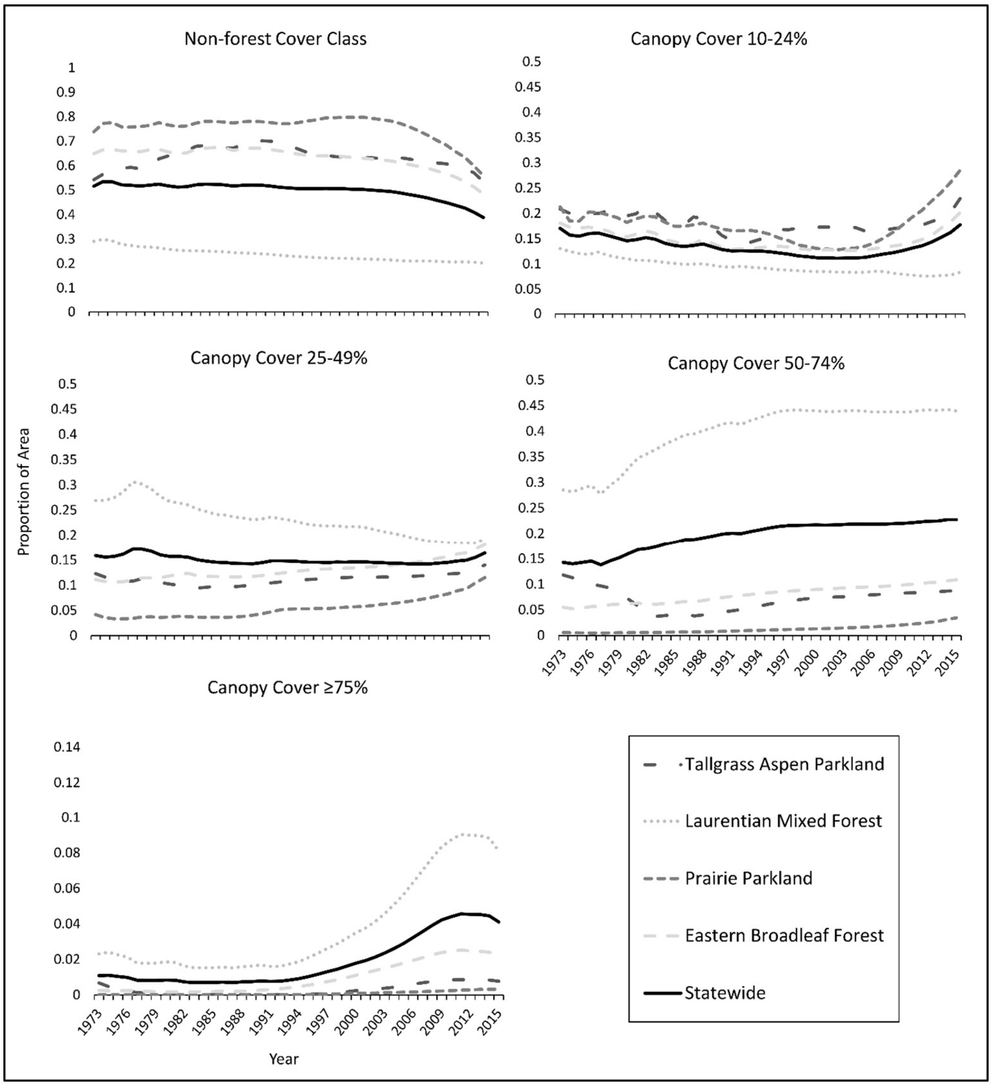

Fig. 7. Temporal trends (1973–2015) of proportion of land within forest canopy cover classes statewide and within Minnesota ecological provinces. Water bodies have been masked out and are not reflected in proportions. Note that the y-axis ranges vary to better depict the trends for each canopy cover class by province.

Healey et al., 2006).

Several continental to global scale tree cover products incorporating Landsat data do exist, although restricted in their ability to be applied to the Landsat archive due to the predictors utilized in their approach (Sexton et al., 2013; Coulston et al., 2012). The national tree cover models from the 2011 NLCD project achieved a range of predictive strengths when models were tested in the five focal areas across the country (R^2 values from 0.65–0.87; Coulston et al., 2012); our results fall within this range. In addition to the NDVI and tasseled cap predictors, the 2011 NLCD cover models also incorporated the previously created 2001 tree cover maps and land cover data (Coulston et al., 2012). The NLCD tree cover product provides an extremely useful spatial data set for a large suite of applications across the continuous United States, although the need for land cover classifications as model inputs complicate the repeatability on an annual basis. Our approach may be an alternative for monitoring change at local or regional extents in the interim of more spatially continuous decadal projects such as NLCD. On a global scale, Sexton et al. (2013) utilized Landsat TM and ETM+ surface reflectance with additional axillary data at two time steps (2000 and 2005) to model the global MODerate-resolution Imaging Spectroradiometer (MODIS) Vegetation Continuous Fields (VCF) Tree Cover product, rescaling the 250 m tree product to the 30 m Landsat scale. When results were summarized across four validation areas where the study utilized lidar canopy products as reference data, the Landsat-based model had an R^2 of 0.811 and an RMSE of 14.637 (Sexton et al., 2013). Our utilization of spectral indices, which can be created for the entire Landsat archive, provides the opportunity to create annual historic records of forest cover for over four decades into the past and that are repeatable into the future. Through the harmonization of MSS and OLI imagery to TM/ETM+, our study assumes that the model created for a single time will be applicable to other years in the time series. We acknowledge that the accuracies presented here are for the single year model and the change products derived from the time series application of this model may have reduced accuracies.

Annual canopy cover maps may serve as model inputs for wildlife habitat relationships and additional forest attributes at single points in time, as well as providing the opportunity to monitor and interpret trends through time. Vogeler and Cohen (2016) reported that almost 80% of the US Fish and Wildlife Service habitat suitability models for forest inhabitants included some measure of canopy cover, highlighting the value of this metric for predicting and monitoring wildlife habitat for many species. In an effort to identify potential habitat for Myanmar's endangered Eld's deer (*Cervus eldi*), Koy et al. (2005) found significant relationships between their Landsat-derived canopy cover maps and deer distributions. There is increasing interest in leveraging historic datasets such as Landsat to map forest disturbance patches through

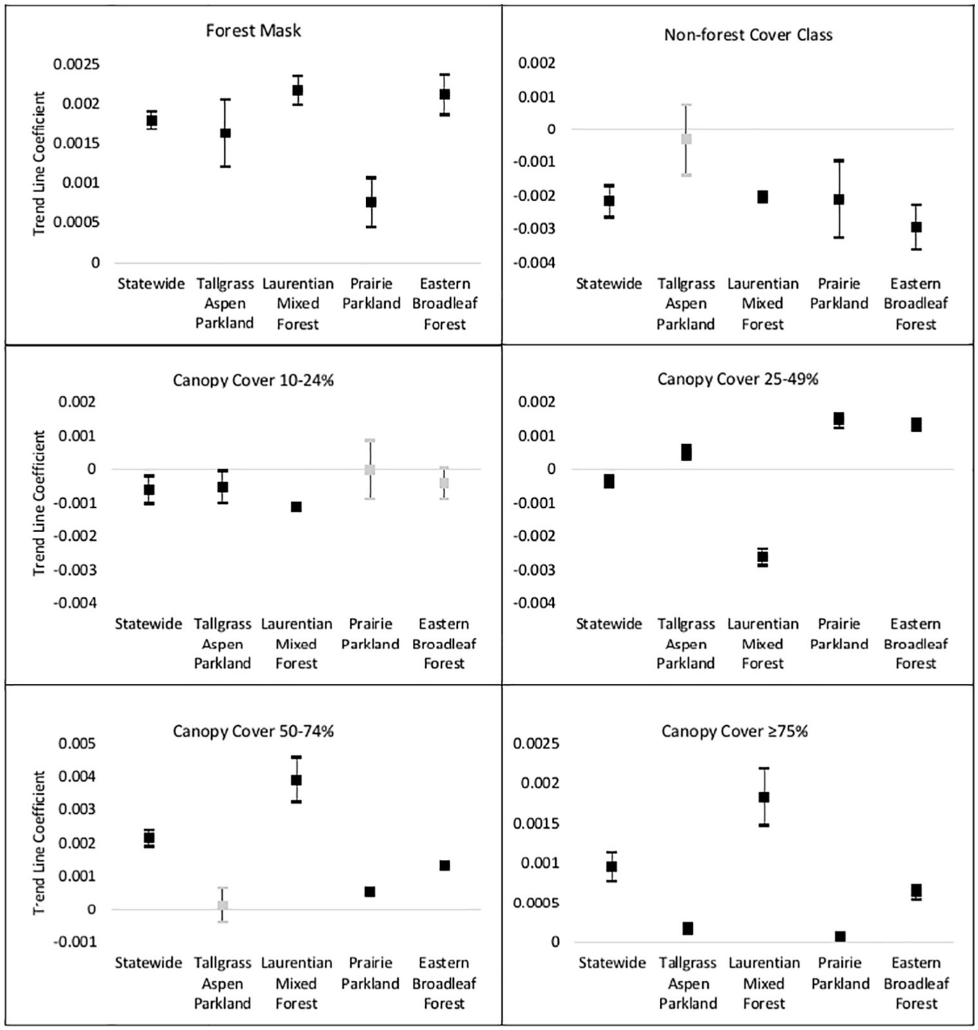

Fig. 8. Linear time series trend line coefficients with 95% confidence intervals for error-adjusted forest area from the forest mask maps, in addition to the proportion of the state represented by the 5 canopy cover classes derived from continuous canopy cover products (1973–2015). Non-significant coefficients shown in gray.

change algorithms such as LandTrendr (Kennedy et al., 2010). Information about changes in canopy cover within a disturbance patch may aid in classifying the agent of change which is of great interest to forest managers. The few studies that have incorporated imagery from the full time span of the archive have tended to focus on quantifying disturbance history to estimate current forest structure (Pflugmacher et al., 2012). Our stack of Landsat imagery was spatially and spectrally harmonized and cover models created for one time step should be applicable to additional years, but further research is needed to assess the accuracy of these models for application in future years.

During the four decades of our forest mask and cover products, we observed a significant increase in overall forest cover across the state of Minnesota, although this trend was not consistent across all cover classes. In a USDA Forest Service resource bulletin based on Forest Inventory and Analysis (FIA) data for Minnesota, live trees were reported to have increased during 1977–2003, as well as an increase of 5.6% in live tree biomass on timberlands within the same time-period (Miles et al., 2007), supporting the results of this study. Within the shorter time-period of 1990–2003, the study reported an overall decrease in Minnesota forest land of 4% (Miles et al., 2007). When we tested the forest area trend within our data for this truncated time-period, the significant increase in forest cover remained as found within the greater 1973–2015 study period. These contrasting results could be due to differences in the definitions of forest cover by FIA compared to this study, as well as a sampling-based vs. our spatially continuous predictive mapping assessments. In our forest delineation, we take a snap-shot approach where there must be current forest cover to be classified as forest at a specific time period. FIA considers forest land as more of a land cover classification where even recently cleared areas with the absence of current cover will still be considered forest as long as the potential treed area is > 1 acre or at least 36.6 m (120 ft) wide for roadside, riparian, and shelterbelt strips. Updated Minnesota USDA forest resources reports for all years following the 1990–2003 time period found increases in overall forest area (e.g. Miles and Heinzen, 2008; Miles and VanderSchaaf, 2012, 2015), consistent with our findings. Miles et al. (2007) reported that during 1990–2003, there was greater timber growth than removal rates suggesting an increase in growing-stock volume. This may support our observation of the greatest increases occurring within the two higher forest cover classes.

While there were a variety of sources of forest cover loss and gain during our study, one example of forest gain was the encroachment of forest cover in land previously used for agriculture and pasture. We mostly observed this agriculture to forest conversion within the Eastern Broadleaf Forest province, which, along with the Laurentian Mixed Forest province, experienced the greatest gain in overall forest area. Marshlands reverting back to forest cover are an additional potential source of forest gain within Minnesota reported by Miles et al. (2007). This, along with forest regeneration within harvest patches may have contributed to the greatest increases we observed within the Laurentian Mixed Forest province for the two highest cover classes. That said, the highest cover class (≥75%) also appeared to be under represented when histograms of data from the photo interpretation samples were compared to that of the corresponding 2008 predictive map (visual comparison, data not shown). The under representation of the highest cover class could potentially be a bias of photo interpretation methods for underestimating cover values (Greenfield et al., 2009) or an underestimation of higher cover values within the model.

5. Conclusions

In this study, we utilized the Landsat archive to create annual spatial records of canopy cover across the state of Minnesota from 1973 to 2015, a valuable resource for a multitude of research and management applications. We demonstrate the utility of the R package LandsatLinkr for expanding the temporal record of comparable Landsat spectral indices through the harmonization of Landsat MSS and OLI imagery to the spatial and/or spectral qualities of TM and ETM+. We found value in the further enhancement of the LandsatLinkr products with the use of the LandTrendr segmentation algorithm for the smoothing of year-to-year spectral variations not associated with forest change dynamics. While the accuracy of our canopy cover models were comparable to previous Landsat studies, and our temporal trends suggest that the forest area in Minnesota is expanding and moving towards more closed canopy conditions, all temporal trends presented here should be observed with caution as our study did not include a multi-year validation procedure. While the statewide and within province trends discussed here are a way to immediately assess our products, we believe the full value of our maps will be extracted when used in conjunction with additional datasets for applications such as evaluating habitat drivers for Minnesota wildlife species of conservation interest, as well as aiding in interpreting and classifying agents of change across the state, a project currently underway. Future studies should also assess the utility of these image stacks for characterizing local scale dynamics within specific disturbance events and associated recovery patterns. Within more specific applications of the mapping products for change, additional validation should be considered if reference data sets are available. Future studies should continue to assess the range of forest attributes able to be modeled and mapped using LandsatLinkr spectral products.

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