Supporting large-area, sample-based forest inventories with very high spatial resolution satellite imagery

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Abstract

Information needs associated with forest management and reporting requires data with a steadily increasing level of detail and temporal frequency. Remote sensing satellites commonly used for forest monitoring (e.g., Landsat, SPOT) typically collect imagery with sufficient temporal frequency, but lack the requisite spatial and categorical detail for some forest inventory information needs. Aerial photography remains a principal data source for forest inventory; however, information extraction is primarily accomplished through manual processes. The spatial, categorical, and temporal information requirements of large-area forest inventories can be met through sample-based data collection. Opportunities exist for very high spatial resolution (VHSR) (i.e., < 1 m) remotely sensed imagery to augment traditional data sources for large-area, sample-based forest inventories, especially for inventory update.

In this communication we synthesize the state-of-the-art in the use of high spatial resolution remotely sensed imagery for forest inventory and monitoring. Based upon this review, we develop a framework for updating a sample-based, large-area forest inventory that incorporates VHSR imagery. Using the information needs of the Canadian National Forest Inventory (NFI) for context, we demonstrate the potential capabilities of VHSR imagery in four phases of the forest inventory update process: stand delineation, automated attribution, manual interpretation, and indirect attribute modeling. Although designed to support the information needs of the Canadian NFI, the framework presented herein could be adapted to support other sample-based, large-area forest monitoring initiatives.

I Introduction

Forest ecosystems influence human well-being through the provision of natural resources as well as other economic and ecological benefits. Inventory and subsequent monitoring of forested ecosystems across large areas is paramount to the development and evaluation of effective sustainable forest management practices and policies (Gillis, 2001). Baseline data and knowledge of forest dynamics are required to monitor and better understand interactions between forests, human activities, and the atmosphere (IPCC, 2000). Early forest inventories were commodity driven and therefore primarily relied upon *in situ* field measurements to estimate timber quantity and quality across small tracts of forestland (Köhl *et al.*, 2006). Increasing concerns over various environmental issues—coupled with sustainable forest management needs—have expanded the spatial, temporal, and categorical details demanded of forest inventories (Corona *et al.*, 2003). Today, forest inventories are aimed at informing a variety of long term objectives including biodiversity monitoring, carbon accounting, habitat protection, and sustainable timber production (Wulder *et al.*, 2004a; McRoberts and Tomppo, 2007). Supporting these objectives often requires timely forest inventory data across large spatial extents.

The synoptic spatial coverage provided by remote sensing can facilitate the timely characterization of forest ecosystems across large areas (Wulder *et al.*, 2004b; McRoberts and Tomppo, 2007). However, the efficacy of supporting large-area forest inventories with remotely sensed data depends upon the relationship between the scale of the object of interest (e.g., individual trees, disturbance events) and sensor-specific characteristics such as resolution (including spatial, spectral, and temporal aspects) and spatial extent (Coops *et al.*, 2007). For instance, remote sensing systems that acquire images with large spatial extents will have a lower spatial resolution, and will ultimately measure less spatial detail compared to images acquired by higher spatial resolution sensors that provide detailed depictions of forest characteristics across small spatial extents (Table 1; Figure 1). In terms of operational forest inventory and assessment, objects of interest (e.g., trees) are much smaller than the pixel size of medium spatial resolution remotely sensed data (i.e., with spatial resolutions ranging from 10–30 m), thereby prohibiting the direct measurement of object properties (e.g., tree locations, tree crown dimensions) with such data. Conversely, when considering very high spatial resolution (VHSR) sensors (i.e., with a spatial resolution ≤ 1 m), objects of interest (e.g., trees) are larger than the image pixel size, making is possible to directly measure certain object properties (Strahler *et al.*, 1986).

Large-area forest inventories could benefit from the increased spatial detail provided by VHSR remote sensing. We propose a scenario whereby VHSR imagery is integrated with an existing large-area, sample-based forest inventory framework for inventory update where *a priori* data exist. In this communication, we review the role of remotely sensed data in a sample-based, large-area forest inventory, with a specific focus upon synthesizing the state-of-the-art in VHSR remote sensing for forest inventory and assessment. Based upon this review we develop a large area forest inventory framework that incorporates VHSR remotely sensed data. Although we focus on developing capacity to service the information needs of the Canadian National Forest Inventory, the framework presented herein is portable to other regional, national, international, or global forest inventory and monitoring initiatives.

II Remotely sensed data in support of national forest inventories

Current National Forest Inventory (NFI) systems aim to provide comprehensive characterizations of forest ecosystem conditions across large areas. Data collected by NFIs are commonly employed to assess the status and sustainability of forest resources, evaluate forest management practices, and to support national and international reporting requirements such as the State of the Forests, the United Nations Framework on Climate Change, the Kyoto Protocol, or the Montréal Process (Gillis, 2001; McRoberts and Tomppo, 2007). In order to provide inventory data in an efficient, timely manner, NFIs typically employ statistical sampling protocols to generate nationally consistent estimates of forest characteristics. NFIs also rely upon multiple sources of information, often including both *in situ* field measurements and remotely sensed data (Kohl *et al.*, 2006), the latter of which can increase sampling efficiency and improve the characterization of forest resources across large spatial extents.

Remotely sensed data have long been used to augment traditional field-based forest inventories. Manually deriving forest inventory data from analog aerial photography has historically been the primary application of remotely sensed data in support of forest inventories (Franklin, 2001; Hall, 2003). Since no other optical remote sensing system can compete with the spatial resolution and affordability of analog aerial photography, it remains an attractive data source for forest inventory and assessment (Hall, 2003). However, the continual development and improvement of remote sensing technology and related analysis techniques result in an increased utilization of such data in forest inventory applications. Today there are a myriad of options available for supporting NFI efforts with remotely sensed data. For example, NFIs often leverage remotely sensed data to (i) improve the accuracy, precision, and efficiency of forest inventories, (ii) develop wall-to-wall maps of forest inventory attributes, or (iii) generate basic forest inventory information in lieu of *in situ* field measurements (McRoberts and Tomppo, 2007).

Satellite remote sensing has been recognized as an attractive data source for forest inventory and assessment as no other data acquisition system or protocol can match the spatial coverage, timeliness, and data consistency provided via satellite platforms (Cohen *et al.*, 1996; Franklin, 2001). A number of satellite remotely sensed data sources have been used in support of forest inventory. For example, medium spatial resolution remote sensing platforms are particularly useful for estimating and mapping broad-scale forest characteristics (e.g., forest area, land cover (Wulder *et al.*, 2008a; 2008b)) and for monitoring forest change across large spatial extents (e.g., Kennedy *et al.*, 2007).

Data collected via medium spatial resolution satellite sensors have been used in conjunction with *in situ* field data to generate large area estimates of forest characteristics such as vegetation cover type (Wulder *et al.*, 2008a; 2008b), timber volume (Meng *et al.*, 2007), biomass (Zheng *et al.*, 2004), crown closure (Xu *et al.*, 2003), and leaf area index (Pocewicz *et al.*, 2004), among others. The spatial resolution, extent, and comprehensive coverage provided via medium spatial resolution sensors are also ideal for characterizing and monitoring phenomena such as deforestation and reforestation across large spatial extents (Steininger *et al.*, 2001; Schroeder *et al.*, 2007). Since medium spatial resolution sensors do not resolve individual trees, detailed forest inventory attributes are not easily discernable, leading some to question the efficacy of medium spatial resolution imagery for forest inventory because these data do not provide information at scales relevant to meet particular operational forest management and planning needs (e.g., Meyer and Werth, 1990; Holmgren and Thuresson, 1998). Furthermore, the mixed-pixel nature of medium spatial resolution data (Cracknell, 1998) can lead to errors (e.g., under-detection of subtle changes in forest condition) when employing such data to monitor changes through time (Foody, 2001).

Remotely sensed images acquired via VHSR sensors (spatial resolution ≤ 1 m) are able to resolve individual trees, and thereby enable more accurate estimates of detailed forest inventory attributes (e.g., Chubey *et al.*, 2006; Kayitakire *et al.*, 2006; Ozdemir, 2008). In addition to improving the precision of satellite based estimates of forest inventory attributes, the increased spatial detail of VHSR data could facilitate the characterization of subtle changes in forest structure through time.

III Forest inventory via VHSR satellite remote sensing

VHSR satellite sensors have emerged as promising data sources for forest inventory and assessment. The sub-meter spatial resolution of new satellite sensors (e.g., QuickBird and WorldView-1; 0.61, and 0.5 m panchromatic spatial resolution, respectively) affords the detection of individual tree characteristics such as tree crown diameter and shadow length (Ozdemir, 2008), leading to improved estimates of many forest inventory attributes including crown closure, tree density, and stand volume (Wulder, 1998). The continual development of VHSR sensors and associated data processing algorithms, coupled with an increase in data availability, will likely improve our ability to conduct spatially detailed forest inventories across large spatial extents (Culvenor, 2003).

There are numerous satellite platforms in orbit acquiring imagery with spatial resolutions ≤ 1 m over panchromatic wavelengths (Table 2). The ability of these acquisition systems to provide consistent, timely data with a high degree of geometric fidelity (Aguilar *et al.*, 2008) makes them attractive data sources for forest inventory and assessment. Supporting large area forest inventories with VHSR imagery presents a number of unique challenges. For instance, small image extents will lead to high data acquisition costs as many scenes are required to characterize large areas (Table 1) (Wulder *et al.* 2008c). If costs are not a limitation, the off-nadir view angles and differing solar and atmospheric conditions associated with multiple scenes would require substantial image processing to reduce edge effects and to facilitate image mosaicking; otherwise, time and computationally intensive single scene processing and attribution would be required. Using VHSR images in a sampling mode and restricting image acquisition to sample plot areas (i.e., following the sampling protocol and photo plots established by the NFI program) reduces these aforementioned problems, and enables the generation of desired information in a manner analogous to national ongoing large-area forest inventory frameworks.

Other challenges associated with using VHSR imagery include the use of relatively new processing techniques specifically developed for analyzing VHSR data. In some cases, these techniques may not yet be as robust as more established methods, or may not be widely available in commercial image processing software. Furthermore, the overall accuracy of many VHSR image processing techniques is dependent upon structural characteristics of the forest (e.g., forest type, canopy structure, tree size) and upon sun-sensor-surface geometry, especially in northern environments characterized by low sun angles and open canopy, low stature forests.

Incorporating VHSR satellite imagery into existing large-area, sample-based forest inventory frameworks may provide a means to increase overall inventory efficiency and precision. Image processing techniques for the automatic extraction of forest inventory attributes from VHSR images are increasingly mature, with the option of either modeling or manually interpreting attributes that are difficult to extract via automated techniques. As a caution, extracting forest inventory information from VHSR images often requires relatively new processing techniques specifically developed for analyzing VHSR data. Furthermore, the application of such techniques may be regionally specific or only applicable in certain forest structural types. Some of the most promising approaches for estimating forest inventory attributes for VHSR imagery include image segmentation, texture analysis, and shadow analysis, among others (Table 3). In the following sections, we discuss each of these methods in the context of forest inventory and assessment.

1 Image segmentation

Image segmentation refers to the use of automated algorithms to partition remotely sensed images into homogenous, mutually distinct spatial units. In terms of forest inventory applications, image segmentation can further be characterized as either forest stand segmentation or individual tree crown segmentation. The goal of forest stand segmentation is to partition an image into spatial units that are homogenous in terms of forest composition and structure (i.e., forest stands). The basic assumption associated with forest stand segmentation is that spectral and spatial image features serve as reasonable proxies for forest attributes used to define stands; spatial aggregations of these image features should therefore represent forest units that are homogenous in terms of structure and composition (e.g., Pekkarinen, 2002; Chubey *et al.*, 2006; Wulder *et al.*, 2008d). Automated stand segmentation has shown to have utility as a surrogate method for manual stand delineation from aerial photography. For example, Radoux and Defourny (2007) implemented a region-merging segmentation algorithm to partition an IKONOS image into unique forest stands, and found that the image segments conformed to 1:20,000 scale mapping standards. In a separate study, Wulder *et al.* (2008d) evaluated the efficacy of stand segmentation as compared to manual stand delineation techniques. They conclude that automated image segmentation of VHSR satellite imagery was a viable alternative to manual stand delineation in areas where aerial photography is difficult to acquire or where there is limited forest inventory information available (Wulder *et al.*, 2008d).

Once an image has been segmented into unique spatial units representing forest stands, many different techniques can be used to generate forest inventory attributes within each of these unique segments. These include manual interpretation, tree crown isolation, and texture analysis, among others. For example, Chubey *et al.* (2006) classified crown closure, stand height, and stand age based upon texture metrics calculated within stand segments derived from IKONOS imagery.

Although image segmentation has shown promise for automatically delineating forest stands, some limitations have been identified in the literature. For example, when compared to manually delineated stand boundaries, automatically derived stand boundaries can be more convoluted where there are complex or indistinct edges between objects. Edge smoothing algorithms are common (e.g., McMaster, 1987) enabling mitigation of this concern. More notable and less easily addressed is the grouping of objects that are categorically different yet appear similar on imagery. For instance, roads may be coupled with newly harvested areas, or wetland areas may be grouped with mature conifer forests. When additional algorithm developments cannot decouple features in these types of instances, some manual editing may be required (Wulder *et al.* 2008d). Furthermore, segmenting VHSR forest scenes can be particularly challenging as there are often multiple features occurring at different scales within the same image (e.g., shadows, tree crowns, stands, lakes, rivers) (Tian and Chen, 2007), indicating a need for a multi-scale segmentation approach or for users to be mindful of the computation scale and expected features.

2 Crown segmentation

Crown segmentation or isolation is focused upon delineating individual tree crowns from VHSR remotely sensed data. A variety of techniques have been developed to automatically isolate individual trees. Some of the most widely applied methods include (i) local maximum filtering (Wulder *et al.*, 2004c), (ii) multi-scale, object-based methods (Wang *et al.*, 2004; Strand *et al.*, 2006; Palenichke and Zeramba 2007; Chubey *et al.*, 2006; Falkowski *et al.*, 2008), (iii) valley following algorithms (Gougeon and Leckie, 2006; Leckie *et al.*, 2003), and (iv) feature matching techniques (Greenberg *et al.*, 2006). Following delineation, individual tree crown dimensions can be used to directly estimate many forest inventory attributes including stand density and canopy closure (Wulder, 1998; Leckie *et al.*, 2006). Following tree crown segmentation, other attributes such as timber volume, biomass, or diameter distributions can be modeled via allometry (Palace *et al.*, 2008; Popescu, 2007).

A shortcoming of many automatic tree crown segmentation techniques is that the resultant accuracy of the segmentation is often dependent upon the structural complexity and density of the forest stands being segmented: greater delineation accuracy is attained in open single-story stands, while comparatively lower accuracy is attained in closed multi-story stands (Maltamo *et al.*, 2004). The overlap of individual tree crowns also influences the accuracy of automated tree detection algorithms (Wang *et al.*, 2004; Palenichke and Zeramba, 2007; Falkowski *et al.* 2008). Furthermore, the efficacy of tree crown detection techniques is generally lower in areas exhibiting large variation in crown shapes and sizes, or where the canopy is relatively planophile (e.g., deciduous forests (Warner *et al.*, 1999; Culvenor, 2003)).

3 Texture analysis

Texture analysis refers to using local image patterns to characterize the spatial structure of remotely sensed imagery. Texture quantifies the spatial variation in image digital numbers and may be determined using a variety of methods (Wulder et al., 1996). One simple measure of texture summarizes the image digital numbers within a fixed window (i.e., kernel). The local spatial structure of the digital numbers is a function of the forest structure present and the image spatial resolution, and this link between forest structure and image spatial structure provides opportunities to glean supplementary information about forests from the imagery. For example, a mature forest and a young forest will have different tree sizes, tree distributions, and within-stand shadowing. Computing the standard deviation of digital numbers for a small kernel of pixels will result in a larger standard deviation for a mature forest compared to a younger forest (See Cohen et al. 1995; Wulder et al. 2004b). Passing such a kernel systematically over an entire image results in output that can provide complementary interpretation and computation information (i.e., spatial context information for inclusion in image segmentation).

Image texture has been identified as one of the most important visual cues for manual photo interpretation (Lillesand and Kiefer, 1994). The digital calculation of texture is analogous to how human photo interpreters exploit image texture when manually interpreting aerial photography (Franklin *et al.*, 2001). Simple first order texture measures, such as the standard deviation example described above, can be generated directly from the digital numbers present in an image. More complex measures of texture may be produced when digital numbers are placed in a virtual matrix, such as the grey level co-occurrence matrix (see Haralick *et al.* 1973).

Texture features can be used to empirically estimate forest inventory information from remotely sensed imagery. For example, Franklin *et al.* (2001) used variance and homogeneity texture features to distinguish forest age classes from IKONOS imagery, while Rao *et al.* (2002) and Mallinis *et al.* (2008) demonstrated that texture features could be used to classify land cover in forested environments. In a separate study, Kayitakire *et al.* (2006) used several image texture features to characterize numerous forest structural parameters including age, height, basal area, and stand density from IKONOS imagery.

One major limitation of using texture analysis for forest inventory purposes is that the relationship between texture features and forest structure often changes between images (Franklin, 2001). Changes in sensor type, viewing angle, and time of image acquisition (i.e., sun angle and phenologic changes) will also alter this relationship. As a result, *in situ* data are often required for calibration. Texture analysis is also scale dependent; texture features derived from a medium spatial resolution image will be quite different than texture features derived from a coincident high spatial resolution image (Wulder *et al.* 2004a).

4 Shadow analysis

In remotely sensed imagery, shadows cast by tree canopies can often be related to forest inventory parameters as well as biophysical characteristics. Spectral mixture analysis and geometric-optical models, which model the fraction of shadow in a forest scene, have been applied to medium resolution remotely sensed data to infer structural properties of forested canopies. For example, the Li-Strahler model, which models pixel reflectance based upon tree crown reflectance, shadows, and background reflectance components, can be inverted to predict forest cover and tree crown size from Landsat imagery (Woodcock *et al.*, 1994; 1997). Spectral mixture analysis models pixel reflectance as linear or non-linear combinations of pure sub-pixel components (e.g., trees, soil, shadow), and has been used to estimate forest canopy cover, biomass, and leaf area index for medium resolution remotely sensed data (e.g., Hall *et al.*, 1995; Pu *et al.*, 2003; Chen *et al.*, 2004). More recently, other techniques have been used to relate shadow fraction to forest structure from VHSR remotely sensed data. For example, Leboeuf *et al.* (2007) used image thresholding and segmentation to create a shadow fraction map, which was then employed to empirically estimate biomass across a black spruce forest in northeast

Canada, while Greenberg *et al.* (2005) used a shadow allometry approach to estimate crown area, tree bole diameter, stem density, and biomass from IKONOS imagery. In a recent study, Ozdemir (2008) employed shadow fraction analysis of QuickBird imagery to empirically estimate stem volume in an open canopy juniper forest.

Kane *et al.* (2008) concluded that shadow analysis was an effective way to measure canopy complexity in a structurally diverse forest of the Pacific Northwest, USA; however, due to variations and interactions between topography, tree spacing, and tree size, the correlation between image shadows and forest inventory attributes such as tree height and stem density was low. In addition to variations in topography and forest structure, results attained via shadow analysis will also be impacted by sun-sensor-surface geometry (Wulder *et al.*, 2008e). This is of particular importance when considering the use of shadow analysis to measure forest inventory attributes via VHSR sensors capable of providing multiple look angles. For example, Wulder *et al.* (2008e) found statistically significant differences in stems counts derived from coincident QuickBird images acquired via different look angles. Therefore, to ensure consistency in the application of shadow analysis, satellite tasking specifications that reduce acceptable acquisitions to nadir or near-nadir images are necessary.

IV Application

1 The Canadian NFI

Canadian forests comprise 10% of total global forest cover, and forested ecosystems encompass approximately 60% of Canada's land mass (Wulder *et al.*, 2008a; 2008b). Canadian forests are an important component of many global processes including biogeochemical cycles and climate dynamics as well as local environmental systems (e.g., air and hydrological cycles). The forests of Canada are also of great economic importance, contributing 3% of Canada's GDP and providing 373,000 direct jobs and 900,000 indirect jobs (Natural Resources Canada, 2001). Currently, Canada implements a multi-phase, plot-based NFI to assess and monitor forest condition. In the first phase of the NFI, 1% of Canada's landmass is surveyed via a systematic network of approximately 19,000 plot locations. The plots are 2 x 2 km photo plots centered upon a 20 x 20 km national grid (Figure 1). In the second phase of the NFI, ground plots are installed at 10% random subset of photo plot locations, with a minimum of fifty ground plots surveyed within each Canadian ecozone. Attributes measured at each photo and ground plot location are listed in Table 4 (Gillis, 2001).

In the more actively managed south of Canada photo plots are primarily inventoried based upon manual interpretation of 1:20,000 scale aerial photography. In the first step of the interpretation process, photo interpreters manually delineate forest stand boundaries within the photo plot. Manual photo interpretation techniques and allometric models are then employed to populate each delineated stand with forest inventory attributes (Table 4). Although manual interpretation techniques are effective, financial and logistical constraints often limit the acquisition of aerial photography in Canada's north. As a result, a Landsat-based land cover classification developed by Canada's Earth Observation for Sustainable Development of Forests (EOSD) initiative (Wulder *et al.*, 2008a) was used to estimate a limited number of forest inventory attributes (e.g., cover type, density, volume, and biomass) in areas where recent 1:20,000 scale aerial photographs could not be acquired (Gillis, *et al.*, 2005).

2 Developing a framework for supporting Canada's NFI with VHSR remote sensing

Canada's NFI program is currently endeavoring to supplement its sample-based forest inventory with data acquired via VHSR satellite sensors, primarily in northern Canada. The development and implementation of a forest inventory framework incorporating VHSR satellite data is intended to circumvent the aforementioned limitations associated with air photo acquisition in Canada's north, and ultimately provide a higher degree of data consistency across both the north and south of Canada. The automated processing of VHSR satellite imagery in combination with attribute modeling and manual interpretation techniques are desired to enable such improvements. Based upon the preceding review, there is potential for supporting Canada's NFI with samples of VHSR remotely sensed data. In order to develop a framework for updating Canada's NFI with VHSR data, we employed the following logic:

- In order to provide forest inventory estimates that are comparable to the current Canadian NFI, the VHSR sampling protocol should mimic the sampling protocol used by the current NFI (e.g., 2 x 2 km photo plots centered upon a 20 x 20 km national grid (Figure 1).
- In order to achieve a high degree of data consistency, the VHSR inventory update framework should incorporate automated image processing techniques whenever possible; however, since not all forest inventory attributes can be automatically derived in a consistent manner, modeling and manual interpretation techniques should also be considered.
- Given logistical constraints to collecting *in situ* data at the national level, the framework should employ automated processing techniques that directly derive forest inventory information from the VHSR data; methods requiring empirical data for parameterization or calibration should be avoided.
- Since this is an update of the previous NFI, existing inventory data will guide the update process via the VHSR remotely sensed data.
- Given the dichotomy in previous NFI data content (between north and south), the framework for update developed in Canada's north will be slightly different than the update framework developed in Canada's south.
- A framework permitting the use of VHSR data from a variety of sensors (e.g., Table 2) will facilitate timely data acquisition across Canada's vast landmass. Allowing for the use of additional data sources may improve estimates of inventory attributes not related to forest structure (e.g., lower spatial resolution remotely sensed data could be employed to estimate species composition as well as disturbance or growth related inventory attributes).

3 The four VHSR forest inventory phases

Based upon the logic outlined above, the VHSR inventory update will be comprised of the following four phases (Figure 2): (i) an automated stand boundary delineation phase, (ii) an automated attribution phase where image processing techniques are employed to extract basic forest inventory data directly from the VHSR data, (iii) a manual interpretation phase where forest inventory attributes that cannot be directly extracted from the VHSR imagery will be generated via manual image interpretation techniques, and (iv) a modeling phase where additional indirect inventory attributes (e.g., volume and biomass) are modeled from the automatically extracted and manually interpreted forest inventory data. The following section details the general VHSR inventory framework in terms of the four phases outlined above. Expected results are discussed and differences between the VHSR inventory update strategy in Canada's north and south are highlighted.

a Automated stand delineation: We propose to employ automated image segmentation to generate stand boundaries delineating homogenous forest conditions from the VHSR images. In Canada's south, where stand boundaries were manually delineated from aerial photography during the previous NFI, the VHSR image segments will only be used to update the pre-existing segments where disturbances, or harvest-related depletions, have markedly altered stand boundaries; in all other cases, the manually generated stand boundaries from the previous NFI will be used in all other cases. In Canada's north, where stand boundaries were not generated during the previous NFI, the VHSR image segments will be used as forest inventory units.

A variety of image processing techniques will be explored to address the previously discussed challenges associated with segmenting VHSR images (e.g., the presence of multi-scale features and boundary convolution). For example, median filters across a variety of window sizes could be applied to minimize the influence that small scale features (e.g., shadows and trees in open canopy forests) have upon the accuracy of the automated stand delineation procedure. Segmenting median filtered images, rather than the VHSR image, will likely produce more homogenous image segments and may reduce the amount of convolution in the final segmented stand boundaries. Furthermore, image acquisition parameters will restrict acceptable images to those acquired within ± 15° of nadir.

b Automated attribution: Following automated stand delineation, forest inventory attributes will be generated within each stand boundary. Numerous image processing techniques have been successfully employed to extract forest inventory attributes from VHSR imagery in an automated manner (Table 3), however many of these techniques generate estimates of forest inventory attributes based upon empirical relationships between VHSR images and *in situ* data. Given logistical constraints to collecting *in situ* data across the diversity of forest ecosystems and structural types found across the Canada's extensive landmass, automated image processing algorithms employing empirical relationships are not ideal for national-level implementation. Nevertheless, techniques such as crown segmentation that do not require *in situ* data could be used to generate estimates of basic forest inventory attributes in a nationally consistent manner. Therefore, the proposed VHSR inventory framework will also employ image segmentation to automatically isolate individual tree crowns within each delineated stand boundary. Basic forest inventory attributes will then be directly estimated based upon the segmented tree crowns within each stand. In open stands for example, tree density can simply be the number of segmented crowns within each stand (e.g., Greenberg *et al.*, 2005; Hirata, 2008), while canopy cover can be determined by calculating the ratio of total segmented crown area to total stand area. Other inventory attributes such as mean stand crown diameter can also be directly estimated from the segmented tree crowns, while the distribution of crown sizes within a stand could be indicative of stand age class (Nelson *et al.*, 2004). In addition to crown segmentation, shadow analysis may prove useful for extracting basic forest inventory data from the VHSR images, especially in northern environments where the interaction between low sun angles and open forest canopies result in VHSR images dominated by shadows.

c Manual interpretation: Given the high degree of geometric fidelity of VHSR images, manual photo interpretation techniques could easily be applied to generate estimates of forest inventory attributes that are difficult to extract via automated image processing. For example, forest inventory attributes related to land cover, species composition, and disturbance type would be difficult to extract via the automated processing of VHSR images, especially when considering only the panchromatic image bands. However, as demonstrated by Wulder *et al.* (2008d), experienced photo interpreters could efficiently estimate these attributes directly from the VHSR images.

The proposed VHSR inventory framework will also employ additional datasets to help guide the manual interpretation of the panchromatic VHSR images. In Canada's south, for example, data regarding land cover and species composition generated during the previous NFI will aid in the interpretation of these attributes from the VHSR images, while data from the Landsat-based land cover classification developed by Canada's Earth Observation for Sustainable Development of Forests (EOSD; Wulder *et al.*, 2008a; 2008b) project will guide species composition calls in Canada's north. Furthermore, the low species diversity generally found in Canada's northern environments (Wulder *et al.*, 2007) will further enable the efficient and accurate interpretation of forest inventory attributes related to land cover and species composition.

Information available from lower spatial resolution optical remote sensing instruments is envisioned to aid in capture of disturbance information within the national inventory cycle. Lower spatial resolution imagery, such as MODIS, can be utilized to produce annual regionally-based estimates of disturbance, especially fire. The high temporal frequency of this low spatial resolution change information can be compared to long-term expectations of change rates, thereby supplementing our understanding of the spatial variability of disturbance. Further, the low spatial resolution change information can also be used to flag individual photo plots as having a likelihood of being disturbed. While the information may be too coarse to enable an update of the photo plot, the presence of disturbance can be noted and considered in the update planning.

d Indirect attribute modeling: The last phase of the proposed VHSR forest inventory update framework will be to combine data generated from the previous three phases to indirectly estimate forest inventory attributes such as stem volume and biomass. In the southern portion of Canada, the current NFI protocol produces model-based estimates of tree volume and biomass through the application of provincial- or territorial-specific allometric equations parameterized via manually interpreted photo plot attributes (Gillis *et al.*, 2005), while these attributes are modeled from EOSD data in Canada's north. Following completion of the first three VHSR inventory phases, the same allometric equations could be applied to generate nationally consistent estimates of volume and biomass for both northern and southern photo plots.

V Implementation

Prior to the successful implementation of the previously described VHSR forest inventory update framework, a number of unique challenges must be addressed. Generating estimates of forest inventory attributes that are consistent across the wide variety of forest types and structures contained within the vast landmass of Canada will be particularly challenging, requiring a combination of stable automated image processing algorithms, consistent manual image interpretation techniques, and robust allometric models.

An understanding of how VHSR forest scene properties change as a function of sun-sensor-surface geometry will also be required for remeasurement (Wulder *et al*., 2008), particularly for northern environments where low sun angles and open canopy forest result in VHSR imagery that is dominated by shadow. Although pointable sensors potentially increase the amount of image data available over NFI plots, images acquired from obliquely pointed sensors will introduce an additional source of variation in the VHSR image forest inventory framework that will be particularly problematic for segmentation routines. Image acquisition constraints will be used to ensure that only images with collected within ±15° are acceptable and will be acquired for the VHSR framework.

The VHSR forest inventory framework described herein will incorporate elements of automated image processing, manual interpretation, and attribute modeling to update photo plot attributes inventoried during the previous NFI (Table 4). Based upon the literature review (Table 3) we expect that image segmentation can be employed to directly estimate basic forest inventory attributes from the VHSR images. Specifically, crown size, canopy closure, and stem density will be estimated from individual tree crown segments within each delineated forest stand. These basic attributes can be used in conjunction with other image analysis techniques (e.g., shadow analysis and texture analysis) to model additional forest inventory attributes such as stand age and height. For example, the distribution of crown sizes in an inventory polygon, image texture metrics, or shadow analysis, could be employed to estimate stand age (e.g., Nelson *et al*., 2004; Franklin *et al*., 2001) and stand height (e.g., Kayitakire *et al*., 2006; Chubey *et al*., 2006); although, doing so would require well-calibrated empirical models. Therefore, manual image interpretation techniques will likely be employed to estimate age and height related forest inventory attributes from the VHSR images. Furthermore, since the NFI's update strategy will only employ panchromatic VHSR data, determining species composition and disturbance related attributes will be difficult; however, a photo-interpreter could estimate these attributes directly from VHSR images or supported by other ancillary data (e.g., previous NFI attributes). Finally, existing models (Boudewyn et al., 2008) will be employed to estimate volume and biomass from NFI attributes (e.g., crown closure and height) updated via the VHSR inventory framework.

VI Conclusions

Successful inventory and subsequent monitoring of forest ecosystems across large spatial extents provides information necessary for sustainable forest management practices and policies. Remote sensing has increased our ability to characterize and monitor forest ecosystems across large areas in a timely manner, especially broad-scale forest characteristics, as captured using medium (or larger) spatial resolution remotely sensed data. Until recently, it has been difficult to quantify detailed forest characteristics via satellite VHSR remotely sensed data, largely due to data availability, cost, and processing requirements. However, as these limitations diminish, the utility of VHSR data for forest inventory and assessment has been realized and data acquired via VHSR have been used to measure many forest inventory attributes including crown closure, crown size, and stem density, among others (Table 3). The limited spatial extent of VHSR images typically constrains large-area forest inventory applications; however, VHSR is well-suited to a sample-based large-area forest inventories such as Canada's NFI. Furthermore, the use of VHSR digital satellite data will provide new opportunities for automated attribute estimation, improving precision and consistency, while also enabling the collection of detailed data over remote areas of Canada's forests, where the acquisition of traditional data sources such as aerial photography is often precluded by logistics and cost.

Based upon our review of the state-of-the-art in VHSR remote sensing for forest inventory and assessment, we developed a framework that incorporates VHSR satellite images into a sample-based, large-area forest inventory and monitoring process. The framework integrates elements of automated image processing and segmentation, manual interpretation, and statistical modeling to generate forest inventory attributes from the VHSR satellite images. We have identified several methodological challenges that will need to be addressed as we further develop and proceed with implementation of this framework in the context of Canada's NFI. The framework presented herein could easily be adapted to support other national, international, or global forest inventory and monitoring initiatives by enabling the reporting of detailed forest ecosystem attributes and trends, and by providing forest managers and policy makers with new information for planning and decision making purposes.

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Table 1. Resolutions, extents, and costs for example sensors.

Sensor	Spatial Resolution	Spectral Resolution	Temporal Resolution	Swath Width	Cost
MODIS	250 - 1000 m	36 bands (multispectral, thermal)	1 - 2 Days*	2330 km	Free
Landsat 7	15 m (panchromatic) 30 m (multispectral) 60 m (thermal)	8 bands (panchromatic, multispectral, and thermal)	16 Days	185 km	Free†
IKONOS-2	1 m (panchromatic) 4 m (multispectral)	1 Panchromatic 4 multispectral	141 Days (nadir) 3 days (60^{o} off-nadir)‡	11 km	29.00 USD km^{-2}

* MODIS is aboard two separate platforms (Terra and Aqua)

† Prior to January 2009 data cost was 0.02 USD km^{-2}

‡ Off-nadir images have a lower spatial resolution and an increased swath width

Table 2. Data characteristics of select very high spatial resolution (VHSR) sensors.

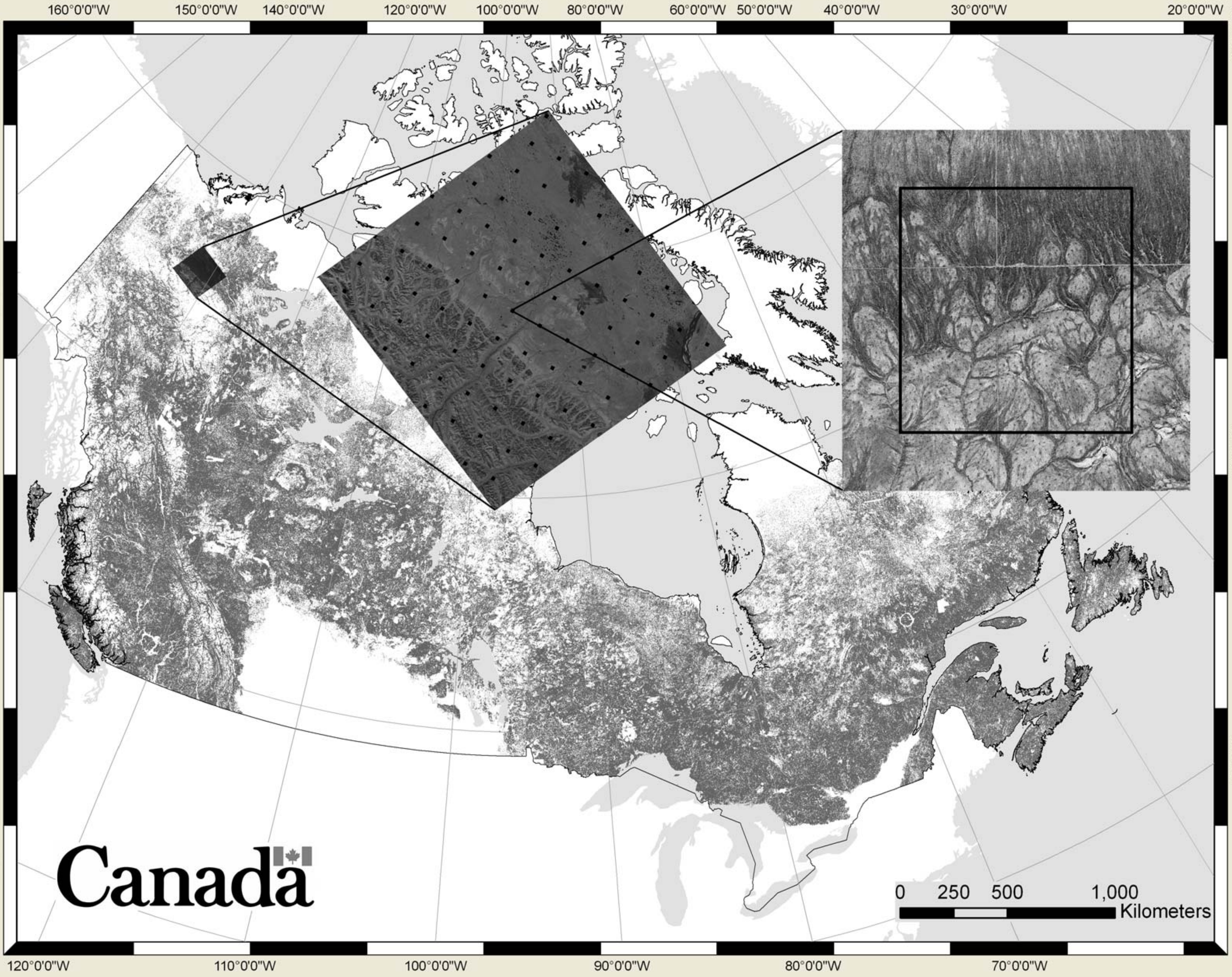
Sensor	Spectral Resolution	Spatial Resolution (GSD)	Temporal Resolution	Radiometric Resolution	Swath Width	Max Viewing Angle
QuickBird	Pan, B, G, R, NIR	Pan: 0.61 m (nadir) to 0.72 m (25^o off-nadir) MS: 2.44 m (nadir) to 2.88 m (25^o off-nadir)	Daily (off-nadir) to 3.5 days (nadir)	11-bit	16.5 km (nadir)	±45^o off-nadir
WorldView-1	Pan	0.50 m (nadir) to 0.59 m (25^o off-nadir)	1.7 days (1 m GSD) 4.6 days ≤ 25° off-nadir (0.59 m GSD)	11-bit	17.6 km (nadir) to 20.8 km (25^o off-nadir)	±45^o off-nadir
RapidEye	B, G, R, R. Edge, NIR	5 m (nadir)	Daily (off-nadir) to 5.5 days (nadir)	12-bit	77 km	±25^o off-nadir
IKONOS	Pan, B, G, R, NIR	Pan: 0.82 m (nadir) to 1m (60^o off-nadir) MS: 4 m (nadir)	3 days (60^o off-nadir) to 141 days (nadir)	11-bit	11.3 km (nadir)	±60^o off-nadir
GeoEye-1	Pan, B, G, R, NIR	Pan: 0.41 m (nadir) to 0.50 m (60^o off-nadir)	4 days (60^o off-nadir)	11-bit	15.2 km (nadir)	±60^o off-nadir
EROS-B	Pan	0.7 m (nadir)	3 days (off-nadir)	10-bit	7 km (nadir)	±45^o off-nadir
KOMPSAT-2	Pan, B, G, R, NIR	Pan: 1 m (nadir) MS: R,G,B 1 m (nadir), NIR 4 m (nadir)	3 days (off-nadir)	10-bit	15 km (nadir)	±30^o off-nadir

Table 3. Studies employing VHSR data for forest inventory and assessment. SS = stand segmentation, CS = crown segmentation, TA = texture analysis, SA = shadow analysis, SpecA = spectral analysis, and SMA = spectral mixture analysis.

e	Sensor	Spatial Resolution	Spectral Resolution	RS Method	Estimation Method	Source	Accuracy/Goodness of Fit	Error
/	Aerial Photography	0.25, 0.5, and 1 m	G, R, NIR	SMA, TA	Empirical - Stepwise multiple regression	Levesque and King, 2003	$R^2 = 0.96$	Not Reported
	IKONOS	1 and 4 m	B, G, R, NIR, Pan	SS, Spec. A, TA	Empirical - CART	Chubey et al., 2006	Accuracy = 85%	Error = 15%
	IKONOS	1 and 4 m	B, G, R, NIR, Pan	SA	Empirical - CART	Goetz et al., 2003	Accuracy = 97.3%	Error = 12.7%
	Aerial Photography	0.25, 0.5, and 1 m	G, R, NIR	SMA, TA	Empirical - Stepwise multiple regression	Levesque and King, 2003	$R^2 = 0.99$	Not Reported
	IKONOS	0.82 m	Pan	TA	Empirical - linear regression	Kayitakire et al., 2006	$R^2 = 0.82$	RMSE = 0.305 Trees Ha^{-1}
	IKONOS	1 m	B, G, R, NIR (Pansharpened)	CS	Direct - Number of segmented crowns	Greenberg et al., 2005	R = 0.87	Not Reported
	QuickBird	0.61 m	Pan	CS	Direct - Number of segmented crowns	Hirata, 2008	R = 0.82	RMSE = 108.9 Trees Ha^{-1}
	IKONOS	0.87	Pan	CS	Direct - Number of segmented crowns	Gougeon and Leckie, 2006	Accuracy = 83%	Error = 17%
	Aerial Photography	1 m	Pan	TA	Empirical - Linear regression	Couteron et al., 2005	$R^2 = 0.80$	Not Reported
	Digital Camera	0.25, 0.5, and 1 m	G, R, NIR	SMA, TA	Empirical - Stepwise multiple regression	Levesque and King, 2003	Adj. $R^2 = 1.00$	Not Reported
	QuickBird	0.61 m	B, G, R, NIR (Pansharpened)	CS	Direct - Area of segmented crowns	Ozdemir, 2008	$R^2 = 0.67$	RMSE = 12.5%
	IKONOS	1 m	B, G, R, NIR (Pansharpened)	SA, CS	Empirical - Multiple regression	Greenberg et al., 2005	R = 0.71 and 0.83	RMSE = 0.641 and 0.627 m^2

Table 4. Canadian NFI photo and ground plot attributes. Adapted from Gillis (2001).

Photo plot attributes	Ground plot attributes
Polygon:	***Site:***
Landcover class	Land cover
Stand structure	Plot origin
Stand:	Plot treatment
Species composition	Plot Disturbance
Age	***Large tree list:***
Height	Species
Crown closure	Volume
Volume	Growth
Origin:	Biomass
Treatment	***Small tree list:***
Disturbance	Species
Land use	Biomass
Ownership	***Shrub and Herb:***
Protection status	Species
Conversion of landuse	Percent Cover
Exotics:	Biomass
Origin of exotics	***Woody debris:***
	Volume and biomass
	Soil:
	Soil features
	Soil horizon



160°0'0"W
150°0'0"W
140°0'0"W
120°0'0"W
100°0'0"W
80°0'0"W
60°0'0"W
50°0'0"W
40°0'0"W
30°0'0"W
20°0'0"W
60°0'0"N
50°0'0"N
40°0'0"N
120°0'0"W
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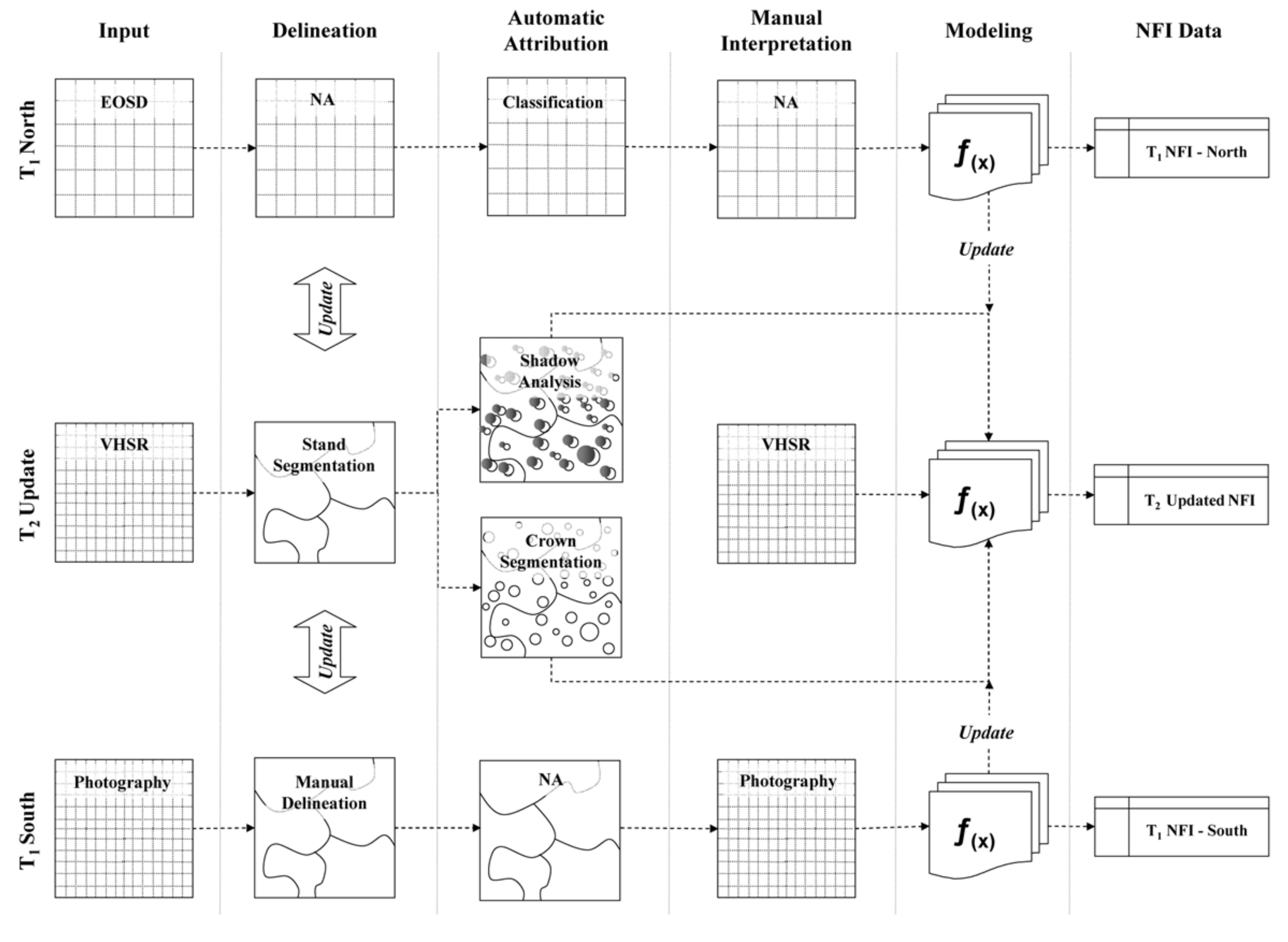
Canada
0 250 500 1,000
Kilometers



Input
Delineation
Automatic Attribution
Manual Interpretation
Modeling
NFI Data
T1 North
EOSD
NA
Classification
NA
f(x)
T1 NFI - North
Update
Update
Shadow Analysis
T2 Update
VHSR
Stand Segmentation
VHSR
f(x)
T2 Updated NFI
Crown Segmentation
Update
Update
T1 South
Photography
Manual Delineation
NA
Photography
f(x)
T1 NFI - South