ABSTRACT

Title Confirming Distributed Snow Covered Area Model Results in a Small Arctic Watershed with MODIS Satellite Images

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Master of Science, 2007

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Environmental analysts face the problem of confirming distributed model maps with remotely-sensed measurement maps. Water resources managers and global change analysts, studying snow cover in particular, must consider how measurements are effected by snow-cloud confusion and low illumination. Finally, tools for managing swath data, a common format for snow and ice data products, are unable to efficiently batch processes multiple swath data.

The goal of this thesis is to confirm a time series of snow-covered-area (SCA) model maps with a time series of remotely sensed measurement maps. Specifically, SCA measurements remotely sensed by the National Aeronautics and Space Administration (NASA) are used to confirm SCA predictions modeled by the United States Agriculture Department (USDA). The measurements come from the two Moderate Resolution Imaging Spectroradiometer (MODIS) sensors aboard near-polar, sun-synchronous satellites named Aqua and Terra. The USDA calls the model TOPMODEL-Based Land-Atmosphere Transfer Scheme (TOPLATS). The Upper Kuparuk River Watershed (UKRW) on the North Slope of Alaska acts as the case study location.

To meet the map-comparison goal, the kappa statistic, kappa statistic variants, and probability density functions expressing measurement uncertainty in discrete scenes all evaluate the ability of MODIS measurements to confirm the accuracy of TOPLATS model maps both spatially and temporally. Data management objectives to make measured data accessible and comparable to the model output comprise a supporting goal.

Map comparison results show that individual composite statistics, like the proportion of agreement between two maps, can easily obscure spatiotemporally distributed confirmation information without additional statistics and side-by-side images of measurement maps and model maps. Map comparison results and data management result together reveal the importance of, and problems in, both the usability and quality of minimally processed (low level) MODIS measurements. Factors like clouds, malfunctioning sensors, and location-agnostic algorithms to discriminate between land coverage categories all impede, but do not stop, MODIS from potentially confirming a spatiotemporal process like snowmelt that occurs across less than 150 km$^2$ and less than a few days.
Keywords: arctic watershed, Cryosphere, distributed, kappa statistic, L2, map comparison, MODIS, remote sensing, snow covered area, swath.
CONFIRMING DISTRIBUTED SNOW COVERED AREA MODEL RESULTS IN A SMALL ARCTIC WATERSHED WITH MODIS SATELLITE IMAGES

By David F. Choy

Thesis submitted to the Faculty of the Graduate School of the University of Maryland, College Park, in partial fulfillment of the requirements for the degree of Master of Science 2008

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Date Date
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DEDICATION

This paper is dedicated to my grandpa Seymour Harrison and the engineers in my family: Sarah Ahmed, Cory Choy, Steven Choy, Arthur Harrison, Jesse Kovach, Amber Lee, Dean Lee, Megan Lee, and Marc Litz. We have catch-up work to do under an administration that is beginning to fund science and our planet.
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CHAPTER 1: INTRODUCTION

1.1 OVERALL RESEARCH GOALS
We sought to develop a method for confirming modeled snow maps with remotely-sensed measurements. This process inspired a second goal: to increase the usability of the remotely-sensed data. The following sections place this work in the context of global change research needs (1.2 Need & Problem); define research objectives (1.3 Objectives); introduce the Upper Kuparuk River Watershed (UKRW), the case study area, introduce the Moderate Resolution Imaging Spectroradiometer (MODIS), the satellite sensor, and introduce the TOPMODEL-Based Land-Atmosphere Transfer Scheme (TOPLATS), the model.

1.2 NEED & PROBLEM
The United States Senate and House of Representatives passed the Global Change Research Act of 1990 to establish the U.S. Global Change Research Program (USGCRP). The USGCRP aims to ―understand‖ and ―respond‖ to ―global change, including the cumulative effects of human activities and natural processes on the environment. . . .‖ Thirteen federal organizations, tabulated in Appendix A, participate in the program. Each organization contributes to seven research areas: (1) atmospheric composition, (2) climate variability and change, (3) global carbon cycle, (4) global water cycle, (5) ecosystems, (6) land use / land cover change, and (7) human contributions and responses (US Global Change Research Program, 2007). The U.S. Office of Management and Budget (2007) reports that the USGCRP spent $5.9 billion in FY 2006 and proposes $7.4 billion for FY 2008 to study global change.

1.2.1 Map Comparison Needs
Analysts in all seven of the USGCRP research areas are constructing models of the earth more frequently and with greater complexity than ever before. As desktop processing advancements and web-based communication tools drive this growth, the analysts struggle to systematically compare and confirm model results with measured data. Pontius (2002) describes this problem as it applies to landscape modeling:

\textit{Modeling Landscape Dynamics is an indication of the tremendous growth in the general field of landscape modeling. Our field abounds with variations on Markov Chain models, Cellular Automata models, agent-based models, multinomial logistic regression models, etc. In fact, we are now producing models faster than we can validate them.}

The research described in this thesis responds to the call from the USGCRP for better understanding of global changes by recommending mechanisms to confirm both spatially and temporally distributed model map results with remotely sensed measurement counterparts. We aim to answer water resources questions set forth by the USGCRP (2003) described in Chapter 5 of ―Strategic Plan for the U.S. Climate Change Science Program: Water Cycle.‖ In particular, we address ways to ―merge measurements from different satellite[s]‖ and review the effects of local extreme
events. We address aspects of Question 5.3, which asks for the “key uncertainties in seasonal . . . predictions . . . and . . . improvements . . . in . . . regional models to reduce these uncertainties,” “better understanding and improved model representations of . . . seasonal . . . interactions of the atmosphere with vegetation, soils, oceans, and the Cryosphere,” and “the role of mountains in the annual water cycle.” We also aspire to address new questions dealing with “Integration of Water Cycle Observations, Research, and Modeling” (USGCRP 2007) set forth in the 2008 strategic plan: “FY 2008 activities will focus on . . . an observing system aimed at measuring key elements required to close the terrestrial water cycle budget on a regional scale such as a river basin or watershed.”

To address the USGCRP needs, we sought to see if snowmelt in the Upper Kuparuk River Watershed – measured by MODIS and modeled by TOPLATS – could provide a sufficient case study. To do this, we defined the needs for the selection of an interest area and remotely sensed data. We decided that the selected interest area should lie in the Cryosphere, demonstrate seasonal variability, have a history of meteorological, geological, and hydrological measurements, have digital elevation information accessible, and exhibit spatial heterogeneity of snow cover during the melt season. We decided that the remotely sensed dataset should exhibit a fine enough temporal resolution to monitor a short snowmelt season, be accessible at a low level of processing, have other datasets available in the same location to check the measurements. With an interest area and dataset selected, we set a goal to define methods for testing model accuracy both spatially and temporally.

1.2.2 Data Management Needs

Simultaneous to the increasing need for map comparison, the USGCRP spurs a need for better management of remotely sensed data. Most-notably, the USGCRP funds management of three remote sensing projects: The POES and GOES program primarily developed NOAA and NASA, the LANDSAT program developed by NASA, USGS, and NOAA, and the overarching Earth Observing System (EOS) program maintained by NASA at the Goddard Space Flight Center in Maryland.

These programs, detailed in 2.2.1, contract, launch, and maintain satellite missions equipped with multi-spectral sensors. In space, sensors capture and broadcast images of the earth. On the ground, analysts receive, process, and archive the images. Growth of archived data at multiple levels of processing has created a need to better disseminate information over the World Wide Web. In Chapter 13 of “Strategic Plan for the U.S. Climate Change Science Program: Data Management and Information” (2003), the USGCRP set decade-long goals to make data free, available, and accessible via web-based technologies and GIS systems. The USGCRP calls for a “transparent” distribution service that allows end-users to focus on data. While first generation information systems are now in place, emerging web-based service technology indicate that “building this framework must be an evolutionary process” that will need to be “regularly updated . . . to respond to user requirements.” Such web-based technologies that could answer user requests for improved data management include the implementation of model view controller programming patterns through web-standard technologies and the developing semantic web standards. These technologies could answer requests for better conveyance of quality...
assurance datasets (MODIS conference 2006), data in user-specified geographic projections (MODIS conference 2006), and on-demand data delivery (CUAHSI 2009). Complementing USGCRP goals to make remotely-sensed data manageable, this thesis aims to employ web technologies, when appropriate, during the process of (a) converting low-level (Level 2), remotely sensed (MODIS) data into a geographical information system (GIS) compatible format and (b) comparing observed and simulated results.

1.2.3 Summary of Needs

In summary, we address two needs set forth by the USGCRP in the early 1990s which have been reevaluated and reinforced in 2008. First we aim to develop methods to access the accuracy and uncertainty of a time series of model maps in comparison to a time series of measured maps. Our comparison should provide an example for future researchers calibrating, validating, or evaluating the performance of a model predicting snow water equivalent or snow covered area in any small, mountainous watershed like the UKRW. Second we begin development of a tool for making low-level (MODIS Level 2) measurements manageable. Developing a MODIS data-management tool should reveal the ability and practicality of comparing MODIS measurement of snow and ice to modeled snow cover.

While these research needs are specific to snow cover during a quick snowmelt event, the methodology and results in this study should be practical to analysts comparing other types of MODIS land cover measurements to other types of simulated results during quickly-occurring events. For example, wildfire modelers could use MODIS forest-cover measurements and fire-cover measurements to calibrate their simulations. Flood modelers could similarly use MODIS water-cover measurements.

1.3 Objectives

We fulfilled preliminarily objectives to select an interest area, a time period, measurements, and a model (1.3.1) before we defined map comparison objectives (1.3.2) and data management objectives (1.3.3). The selection of resources to meet the preliminary objectives influenced the other two objectives and helped put this thesis in context with the overall goals of the USGCRP. A functional decomposition of objects, shown later in Chapter 3 (Table 3-1), defines the basis of the methodology.

1.3.1 Preliminary Objectives: Resource Selections

Section 1.2 defines the preliminary objectives to investigate whether the UKRW snowmelt, MODIS, and TOPLATS meet the requirements for an interest area, a time period, measurements, and a model that will both help understand global change according to the USGCRP and act as the case study for developing a methodology for spatiotemporal map comparison. Chapter three describes the reasons why these resources meet the needs of the USGCRP.
1.3.2 Map Comparison Objectives

Spatial map comparison and temporal map comparison compose the two parent map comparison objectives. After selecting TOPLATS as the model, we narrowed spatial map comparison objectives to evaluation of a single, binary land category because TOPLATS only assigns snow (in the form of a snow water equivalent) and snow-free categories to designated regions. It does not, for example, assign ice or water to any region. Given the decision to limit categories, and given the fact that the measurements include other categories like clouds and lake ice, we made another objective to develop a way to reduce the number of categories in the measured data. We realized that a no-data category would also need to be considered to account for potential problems from either the modeled or measured data.

In line with USGCRP goals to uncover small scale mechanisms described in the “Revised Research Plan for the U.S. Climate Change Science Program” (USGCRP 2008) and to exploit the high temporal resolution of the MODIS orbit, the temporal map comparison objectives were defined to emphasize the independence of each measured scene in a series. Given the high impact of elevation on snowmelt shown by Déry et al. (2004), we refined this objective to include provisions for analyzing a series of scenes for the entire watershed as well as a series of scenes for different elevation zones shown in Figure 4-4.

1.3.3 Data Management Objectives

Data management objectives in this thesis aim to make MODIS measurements comparable to the model output as explained in section 1.2.2. Specifically, the NSIDC distributes MODIS data that has been minimally processed in a swath data format, explained further in section 2.2 Remotely Sensed Measurements and Figure 2-5. For comparison of measured and model data, either measurements in the swath format need to be converted into model output format, or model output needs to be converted into the swath format. Data management objectives include evaluation of existing software tools that are able to manage swath measurements. Section 2.2.2.4 reviews these tools and reports results from attempting to benchmark them with measured data.

1.4 Potential Implications

Potential implications include the creation of a mechanism to compare measured and modeled maps, a way to manage swath data, and possibly the foundation for a web-based GIS application to manage swath data and similar HDF-EOS files described in 2.2.2 MODIS Snow Measurements. Other USGCRP projects will both potentially review and improve on the map comparison mechanism and develop new data management systems influenced by the findings in Chapter 4: Results and Discussion.
CHAPTER 2: LITERATURE REVIEW

Four topics contribute to the literature review:
- 2.1 Watershed Background
- 2.2 Remotely Sensed Measurements with a focus on MODIS snow cover
- 2.3 Distributed Models with a focus on TOPLATS
- 2.4 Map Comparison

2.1 Watershed Background

2.1.1 Location & Area

The Upper Kuparuk River watershed (UKRW), shown in Figure 2-1, spans 147.6 km² on the North Slope of Alaska in UTM zone 6. It is located at the foothills of the Brooks Mountain Range in the USGS Philip Smith Mountains quadrangle. The UKRW is flanked by Toolik Lake (east) and Imnavait Creek (west) tributaries. Figure 2-4 shows the UKRW shape projected in UTM zone 6.

Water flows from the mountains, northward, into the main Kuparuk River (Figure 2-3). For comparison, the entire Kuparuk River watershed is almost 60 times as large as the UKRW. It covers 8,421 km² and flows through three physiographic provinces: arctic mountain, foothills, and coastal plains. The Kuparuk River watershed pours into the Arctic Ocean at Prudhoe Bay.

The UKRW is accessible to researchers via the Dalton highway (Alaska 11), also known as “Haul Road” for its use during construction of the trans-Alaska oil pipeline in the 1970s. The road and pipeline run along the west boundary of the watershed as shown in Figure 2-1. The road crosses the Upper Kuparuk River, forming the north boundary. The road makes the UKRW a prime place for hydrological and meteorological stations.

2.1.2 Snowmelt

Statisticians describe winter-spring snowmelt as a secular event, usually lasting less than three months, occurring annually. The event starts with 100% SCA and ends in none. Plots of area-composite snow variables, like %SCA or mean SWE, against time show that hydrologists can describe snowmelt with a decreasing logistic function (biological death curve). Statistical models forecast snow using both autocorrelation relationships detected within past snow measurements and indirect correlations involving temperature (McCuen 2003). The effect of DEM on snowmelt exemplifies an indirect effect involving temperature.

Snowmelt, in the UKRW specifically, usually accounts for a third of the annual runoff (Kane et. al, 2000). This discharge from snow melt is due in part to both snow build up during the winter and thick permafrost limiting base flow in the

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*McNamara et al (1998) delineate a 142 km² watershed area for the Upper Kuparuk. This study uses the value 147.6 km², derived from a glacial geology map of the Toolik Lake and the UKRW created by Walker et al. in 2003. This number agrees with the product of the number of pixels (8557 pixels) and the pixel size (131.34 m by 131.34 m) used by S. Déry et al. in 2004.*
The largest snowmelt event of the year usually begins in May, during bird migration season, or sometime in June, when “hordes” of mosquitoes pester travelers, in the UKRW (Alaska Bureau of Land Management, 2006). This “winter-spring” (Liston, 1998) event usually causes the largest annual discharge shortly afterward. Chapter four shows that the UKRW snowmelt lasted six, ten, and seven days in years 2000, 2001, and 2002. Figure 4-2 shows the hydrographs and the proportions of SCA for these years. The peak discharge rationally occurs during the maximum change in %SCA with respect to time.

In addition to the importance of snowmelt on discharge, and in turn, traditional water resources and construction applications, Liston (1998) emphasizes the importance of snow cover on the balance of the earth’s climate cycle. He contributes the effect of snowmelt on radiation due to the high reflectance and the low thermal conductivity of snow covered areas.

### 2.1.3 Meteorological Measurements & Geology in the UKRW

Throughout the year, the U.S. National Weather Service (NWS) gauges the precipitation with a tipping bucket and Alter shields. During the snowmelt period, Kane, et al. (2003) make additional precipitation measurements. They measure precipitation twice daily. Wind contributes to the spatiotemporal variability of SCA along with accumulation and ablation (Zhang et al. 2000).

The Laurentide Ice Sheet shaped the foothills of the Brooks range (French 2007) during the Wisconsinan Glaciation (Kaufman and Manely 2004) of the late (Porter 1964) Pleistocene epoch (Hamilton 1986). Permafrost penetrates into the ground up to 600 meters in the Kuparuk River watershed near Prudhoe Bay (Osterkamp and Payne 1981), and up to 250 meters under the UKRW (Kane, et al. 2003).
### Table 2-1. Watershed Mask Characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Measurement</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>Raster 147.609924 km² (= 56.992510 mi²)</td>
<td>Small compared to the Kuparuk River watershed, which is 8,421 km². The watershed area is 18.12% of the model area.</td>
</tr>
<tr>
<td></td>
<td>Vector 147.61200 km² (= 56.99331 mi²)</td>
<td></td>
</tr>
<tr>
<td>Perimeter</td>
<td>56.6267 km</td>
<td>From vector area</td>
</tr>
<tr>
<td>Pixels</td>
<td>8,557</td>
<td>Includes only the Upper Kuparuk area shown in Figure 2-4</td>
</tr>
<tr>
<td>Maximum Stream Length</td>
<td>22.2354 km (= 13.8164 mi)</td>
<td></td>
</tr>
<tr>
<td>Elevation</td>
<td>Min 736.388 m</td>
<td>The watershed starts in alpine foothills and drains into a relatively flat tundra.</td>
</tr>
<tr>
<td></td>
<td>Max 1,492.230 m</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Range 755.842 m</td>
<td></td>
</tr>
<tr>
<td>Centroid</td>
<td>X 404,610.5309 m</td>
<td>Calculated with .Centroid.X and .Centroid.Y shape objects</td>
</tr>
<tr>
<td></td>
<td>Y 606,652.5374 m</td>
<td></td>
</tr>
<tr>
<td>Extent</td>
<td>UTM Zone 6</td>
<td>Global Coordinate System</td>
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<tr>
<td></td>
<td>Left 398,086.50 m</td>
<td>West -149.508205°</td>
</tr>
<tr>
<td></td>
<td>Right 413,190.60 m</td>
<td>East -149.121345°</td>
</tr>
<tr>
<td></td>
<td>Top 616,590.38 m</td>
<td>North 68.649343°</td>
</tr>
<tr>
<td></td>
<td>Bottom 598,334.12 m</td>
<td>South 68.480656°</td>
</tr>
</tbody>
</table>

### Table 2-2. Model Area Characteristics

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Measurement</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Area</td>
<td>814.485235 km² (= 314.474508 mi²)</td>
<td>Includes model area around the watershed shown in Figure 2-4</td>
</tr>
<tr>
<td>Pixels</td>
<td>Columns 208</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Rows 227</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Number 47,216</td>
<td></td>
</tr>
<tr>
<td>Pixel Size</td>
<td>Width (x) 131.34 m</td>
<td>Same as cell size.</td>
</tr>
<tr>
<td></td>
<td>Height (y) 131.34 m</td>
<td>1 pixel = 17,250.1956 m²</td>
</tr>
<tr>
<td>Projection</td>
<td>UTM Zone 6</td>
<td>Clarke 1866 Datum</td>
</tr>
<tr>
<td></td>
<td>False Easting 500 km</td>
<td></td>
</tr>
<tr>
<td></td>
<td>False Northing -7,000 km</td>
<td></td>
</tr>
<tr>
<td>Extent</td>
<td>UTM Zone 6</td>
<td>Global Coordinate System</td>
</tr>
<tr>
<td></td>
<td>Left 390,862.80 m</td>
<td>West -149.697228°</td>
</tr>
<tr>
<td></td>
<td>Right 418,181.52 m</td>
<td>East -148.998749°</td>
</tr>
<tr>
<td></td>
<td>Top 627,228.92 m</td>
<td>North 68.746202°</td>
</tr>
<tr>
<td></td>
<td>Bottom 597,414.74 m</td>
<td>South 68.469708°</td>
</tr>
</tbody>
</table>
Figure 2-1. Upper Kuparuk River Watershed.
This is a World Wind 1.4 render of LANDSAT 7 false-color mapped onto USGS 30-meter DEM. The image is from the perspective of a person looking upstream, north of the watershed outlet. The thin gray line represents the Dalton Highway, which delineates the northern watershed boundary.

Figure 2-2. Location of the Upper Kuparuk Watershed with respect to Alaska
From NSIDC (http://nsidc.org/data/arcss017.html)
Figure 2-3. Kuparuk River Watershed
The entire Kuparuk River watershed is 8,421 km². Water flows from the Upper Kuparuk, through the Kuparuk River into the Arctic Ocean at Prudhoe Bay.
Figure 2-4. Watershed Shape and Bounding Study Area
This figure shows the UKRW in context with other tributaries in UTM Zone 6.
2.2 **Remotely Sensed Measurements**

Remote sensing of the Earth from satellites creates opportunity to analyze both the lay and utilization of the land. The process complements aerial remote sensing. In general, aerial sensors deliver higher resolution images than satellite sensors because of their proximity to the Earth; but aircraft paths are limited by flight zones, funding, and fuel constraints. At times, analysts using aerial images must composite output from different flights and different sensors to get a complete picture of an interest area. Builders and city planners can schedule single aerial flights for constructability analysis while meteorologists, hydrologists, and other earth scientists cannot fund aircraft flights in order to monitor multi-day events and events that occur with little or no warning. These scientists, instead, use satellite imagery. Compared to sensors aboard aircraft, satellite sensors can potentially supply a persistent stream of images that blanket the earth. Satellites are expensive to build and maintain compared to aircrafts. When a problem occurs on a satellite, replacements parts (or a replacement satellite) cannot be as readily procured in comparison to a replacement part for an aircraft. Such problems, in conjunction with launches that are separated by years, lead to missing data.

2.2.1 **Satellite Measurements Overview**

As noted in 1.2.2 Data Management Needs, the USGCRP funds and manages the POES and GOES programs primarily developed by NOAA and NASA, the LANDSAT program developed by NASA, USGS, and NOAA, and the MODIS (Moderate Resolution Imaging Spectroradiometer) satellite programs developed by NASA. GOES, POES, LANDSAT, and MODIS missions compose part of NASA’s Earth Observing System (EOS). For sensing snow and ice, NOAA uses the Interactive Multisensor Snow and Ice Mapping System (IMS) to process POES and GOES measurements. The resulting images are best suited for large-scale (four to 25 km cell size) meteorological forecasting in the northern hemisphere. LANDSAT missions deliver imagery with relatively high spatial resolution (15 m cell size) and relatively low temporal resolution (16 day earth coverage) while MODIS missions deliver imagery with relatively low spatial resolution (30 m to 500 m cell size) and relatively high temporal resolution (two-day earth coverage). Only MODIS measurements provide sufficient spatial resolution and enough temporal resolution to monitor a seasonal land cover event like the snowmelt season in the UKRW.

2.2.1.1 **LANDSAT**

Scientists recognize the LANDSAT program as an old and comprehensive remote sensing project. Contractors are currently bidding on the development of the eighth LANDSAT satellite scheduled to replace the aging LANDSAT 5 (launched in 1984) and LANDSAT 7 (launched in 1999) satellites in 2011. Bergers (2006) estimates the value of the contract at $400 million. The LANDSAT 7 satellite orbits the earth once every 99 minutes in a near-polar, sun-synchronous pattern at an altitude of 705 km. While in orbit, the Enhanced Thematic Mapper Plus (ETM+) satellite sensor records a continuous strip of the Earth, called a swath, that is 185 km wide. Swaths are divided up into segments, called scenes, that are 170 km long. The LANDSAT 7
satellite takes 232 orbits or 16 days to record the entire earth (Williams 2007). Figure 2-5 evinces the components of a swath.

LANDSAT 7 takes digital images with pixels that have a cell size of 15m. This resolution makes LANDSAT 7 imagery especially useful in popular web-based mapping systems like Yahoo Maps and Google Maps. Additionally, desktop-based GIS like Google Earth and NASA World Wind uses false-color LANDSAT images in default views of Earth. While LANDSAT 7 provides enough resolution for many spatial applications, it does not provide enough temporal resolution for analysis of day-to-day events where significant change occurs in less time than the satellite takes to completely image the earth.

2.2.1.2 MODIS Satellites Aqua and Terra
In December 1999, NASA launched the first EOS mission by sending a Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, among a total of 5 sensors, into orbit aboard the satellite called Terra. In 2002, NASA launched a sister satellite to Terra, called Aqua, with a second MODIS sensor. The satellites and their launches are pictured in Figure 2-6 and Figure 2-7. Like LANDSAT 7, both Aqua and Terra follow a near-polar, sun-synchronous orbit. Terra, also called EOS-AM, crosses the equator in the morning while Aqua, called EOS-PM, crosses the equator in the afternoon.

MODIS reports observations of clouds, fire, ice, land, ozone, snow, temperature, vapor, water, and more. It senses 36 different wavelengths ranging from below near infrared to mid-infrared (0.405 to 14.385 μm) at an average data rate of 6.1 megabits (about three-quarters of a megabyte) each second. MODIS records swath scenes that are 2,330 km wide — an order of magnitude larger than the LANDSAT 7 swath. The wide swath size, in comparison to LANDSAT, enables MODIS to see every point on the earth every two days, or less.

The USGCRP has defined seven research topics based on MODIS data since Terra was initially launched: atmospheric composition, climate variability and change, global carbon cycle, global water cycle, ecosystems, land use / land cover change, and human contributions and responses (US Global Change Research Program, 2007). Riggs et al (2006) present both an overview of MODIS concepts and specific details pertaining to snow cover sensing. The overview favors Terra over Aqua because of the former satellite’s ability to better detect snow in the mid-infrared wavelengths. Some detection bands on Aqua have failed. This study uses data collected by both Terra and Aqua.

2.2.1.3 POES and GOES Satellites
NASA, NOAA, the United Kingdom, and France developed the Geostationary Operational Environmental Satellite (GOES) project and Polar Operational Environmental Satellite (POES) project for weather forecasting among other environmental and social causes (GOES 2008 and POES 2008). Both projects currently launch several satellites each equipped with an Advanced Very High Resolution Radiometer (AVHRR) among other payloads. AVHRR is comprised in part by a channel (3A) for sensing snow and ice at 1.58 μm to 1.64 μm wavelengths and channels (1, 3B, 4) for sensing cloud coverage (AVHRR 2008). While AVHRR
can produce relatively high resolution images with a pixel size as low as 1.1 km (Robinson 2003), the final IMS product currently produces relatively lower resolution images with a larger pixel size of four kilometers. POES and GOES projects contribute to the oldest record of the northern hemisphere started by NOAA in 1966 when weekly products were created (Matson et al. 1986 and Robinson et al. 1993).

Table 2-3. Satellite and Instrument Characteristics for Sensing Snow & Ice

<table>
<thead>
<tr>
<th>Satellite</th>
<th>LANDSAT</th>
<th>AQUA &amp; TERRA</th>
<th>POES</th>
<th>GOES</th>
</tr>
</thead>
<tbody>
<tr>
<td>Instrument</td>
<td>ETM+</td>
<td>MODIS</td>
<td>AVHRR</td>
<td></td>
</tr>
<tr>
<td>Flight Pattern</td>
<td>near polar sun-synchronous</td>
<td></td>
<td></td>
<td>geosynchronous</td>
</tr>
<tr>
<td>Orbit Time</td>
<td>98.9 min</td>
<td>[98,102] min</td>
<td></td>
<td>36,000 km</td>
</tr>
<tr>
<td>Nominal Satellite Altitude</td>
<td>705 km</td>
<td>810 km &amp; 850 km</td>
<td></td>
<td>36,000 km</td>
</tr>
<tr>
<td>Swath Width</td>
<td>185 m</td>
<td>2,330 km</td>
<td>1,500 km†</td>
<td></td>
</tr>
<tr>
<td>Scene Area§</td>
<td>3,145 m²</td>
<td>3,154,820 km²</td>
<td>1,000 km²</td>
<td></td>
</tr>
<tr>
<td>Scene Spatial Resolution (Cell Size)</td>
<td>15 m</td>
<td>500 m for snow and ice products</td>
<td>After processing through IMS: 25 km before 2004 4 km since 2004</td>
<td></td>
</tr>
<tr>
<td>Time to sense every point on the earth.</td>
<td>16 days</td>
<td>2 days</td>
<td>1 day (14.1 polar orbits / day)</td>
<td></td>
</tr>
</tbody>
</table>

† Johnson 1996
‡ Swath width varies between a “few” and 1500 km.
http://www.oceanexplorer.noaa.gov/technology/tools/satellites/satellites.html
§ For comparison, the surface area of the earth spans 510,065,600 km².
Figure 2-5. Swath
A swath is a continuous strip of land sensed from a satellite in orbit. A swath scene is a portion of a swath. This figure depicts the parts of a single swath taken from two consecutive orbits. It also highlights an individual swath scene. The swath shown is similar to the one produced by LANDSAT 7 in that the “swath orbits” converge near the poles. The swath is drawn on a pseudo-cylindrical Robinson projection.
Figure 2-6. Moderate Resolution Imaging Spectroradiometer (MODIS)
MODIS is one of 5 instruments aboard Terra and one of 6 instruments aboard Aqua. (a) The relative size of Terra is shown as it is being prepared for loading into the C-5 aircraft. (b) Aqua is shown with (c) the MODIS sensor highlighted.
Figure 2-7. Terra and Aqua Launch Photos
(a) C-5 aircraft lifting Terra on December 18, 1999 and (b) Delta II rocket lifting Aqua, at 2:55 a.m. PDT on May 4, 2002. Both satellites were launched from Vandenberg Air Force Base, CA. Photos from Wolfe (2002).
2.2.2 MODIS Snow Measurements

2.2.2.1 Sensing Snow

While clouds, snow, and water all highly reflect light in the visible spectrum, only clouds highly reflect light in the near infrared spectrum; snow and water absorb most near infrared light. Additionally, water reflects infrared light less than snow. The visible spectrum, therefore, cannot solely distinguish between snow, clouds, and water. The infrared spectrum, similarly, cannot solely distinguish between snow-covered areas and snow-free land. AVHRR, EDM+, and MODIS utilize both the visible spectrum (0.4–0.7 \( \mu \)m) and near infrared spectrum (0.75–5 \( \mu \)m) to discriminate between snow, clouds, and water according to Table 2-4. Analysts can only estimate land coverage in areas where clouds block the earth (detailed further in 2.4.3.1 Missing Data in Partially Obscured Scenes).

Hall et al. (2001) and Riggs et al. (2006) developed a snow mapping algorithm to test each point of the earth detected by MODIS for the presence of snow. The algorithm depends on the visible and near infrared bands of MODIS categorized in Table 2-5 and consists of three Boolean requirements. Each point of the earth that MODIS detects must satisfy all three requirements in order for the algorithm to indicate the presence of snow at that point.

Hall and Riggs define the first of the three requirements to detect snow as the Normalized Difference Snow Index (NDSI)

\[
NDSI = \frac{\text{band}4 - \text{band}6}{\text{band}4 + \text{band}6} \geq 0.4 \, \mu \text{m}
\]

which considers the difference between the visible reflectance on the 0.555 \( \mu \)m wavelength (band 4) less the near infrared reflectance on the 1.640 \( \mu \)m wavelength (band 6), all normalized over the sum of these two reflectance values. Normalizing the difference between visible and near infrared reflections help determine the presence of snow in varying light conditions throughout the day.

The second requirement distinguishes water from snow. It checks the near-infrared signal on the 0.865 wavelength (band 2). A reflectance greater than 0.11 indicates snow. Smaller values indicate water.

\[
\text{band}2 > 0.11 \, \mu \text{m}
\]

The third, final requirement ensures enough visible reflectance on the 0.555 \( \mu \)m wavelength is available to make a reading:

\[
\text{band}4 > 0.10 \, \mu \text{m}
\]

The last requirement, in other words, tests to make sure there is enough visible light to make a dependable reading of snow.

The conjunction of all three requirements, expressed in equations 2-1, 2-2, and 2-3, form the snow mapping of the MODIS snow and sea ice Algorithm Theoretical Basis Document (ATBD) in practice (Hall et al. 2001):

\[
(NDSI \geq 0.4 \, \mu \text{m}) \land (\text{band}2 > 0.11 \, \mu \text{m}) \land (\text{band}4 > 0.10 \, \mu \text{m})
\]

Expanding 2-4 in terms of bands only yields

\[
\left( \frac{\text{band}4 - \text{band}6}{\text{band}4 + \text{band}6} \geq 0.4 \, \mu \text{m}\right) \land (\text{band}2 > 0.11 \, \mu \text{m}) \land (\text{band}4 > 0.10 \, \mu \text{m})
\]

The accuracy of the snow mapping algorithm varies with land cover, grain size, and pollution. Hall et al. (2001) explains that
exclusive of clouds, the maximum, aggregated Northern Hemisphere snow-mapping error is expected to be about 7.5%. The error is expected to be highest (around 9-10%) when snow covers the boreal forest, roughly between November and April.

and that sensors detect snow best at solar noon. At this time, they are facing nadir — directly at the earth.

Table 2-4. Relative Visible and Near-Infrared Reflectance of Clouds, Land, and Snow

<table>
<thead>
<tr>
<th>Coverage</th>
<th>Visible</th>
<th>Near Infrared</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Snow</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Water</td>
<td>High</td>
<td>Very Low</td>
</tr>
<tr>
<td>Snow-Free Land</td>
<td>Low</td>
<td>Low</td>
</tr>
</tbody>
</table>

Table 2-5. MODIS Bands

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength (µm)</th>
<th>Spectrum</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.645</td>
<td>Visible</td>
</tr>
<tr>
<td>2</td>
<td>0.865</td>
<td>Near Infrared</td>
</tr>
<tr>
<td>4</td>
<td>0.555</td>
<td>Visible</td>
</tr>
<tr>
<td>6</td>
<td>1.640</td>
<td>Near Infrared</td>
</tr>
</tbody>
</table>

NDSI and other snow-mapping tests depend on these MODIS bands to detect the presence of snow.
2.2.2.2 Snow Products

The Distributed Active Archive Center (DAAC) at the National Snow and Ice Data Center (NSIDC) provides a web-based service for researchers to order MODIS snow and ice data products (NSIDC 2008a). The NSIDC DAAC is one of a eight DAACs in the EOS Distribution System (EOSDIS) sponsored by NASSA. NSIDC DAAC label products according to sensor satellite (either Terra or Aqua) and processing information. The processing information of a product indicates the unit spatiotemporal size (i.e., the amount of compositing) and spatial-format for that product. MOD and MYD comprise the two possible sensor abbreviation representing, respectively, MODIS aboard Terra and MODIS aboard Aqua (NSIDC 2006). Six processing information abbreviations, 10_L2, 10A1, 10A2, 10C1, 10C2, and 10CM, indicate, respectively, 5-minute 500m swaths, 500m sinusoidal grids composited daily, 500m sinusoidal grids composited every eight days, 0.05 degree climate model grids (CMG) composited daily, 0.05 degree CMGs composited every eight days, and 0.05 degree CMGs composited monthly (NSIDC 2008a). Two satellites and six kinds of processing yield a total of 12 products. Of these 12 products, NSIDC refers to the two swath products (MOD10_L2 and MYD10_L2) as level two products. NSIDC builds level two products from fundamental MODIS reflectance data, MODIS geolocation data, and a cloud mask using the ATBD described in 2.2.2.1 Sensing Snow. Table 2-6 describes the characteristics of the level two product further. The remaining, gridded products comprise level three, which NSIDC builds from level two products.

All products are stored in the EOS-specified hierarchal data format (HDF) called HDF-EOS. This means, in application, researchers download product files, also called product granules in this context, that have a “.HDF” file extension. The National Center for Supercomputing Applications (NCSA) funded by the National Science Foundation (NSF) at the University of Illinois oversees continued development of the HDF file format. The HDF-EOS file format stores spatial information in three formats: swath, point, and grid. NSIDC distributes XML side-car files with each HDF-EOS granule that include metadata like database references, contributing products, time references, orbit number, the time the granule was last processed, and whether or not a granule is scheduled to be reprocessed.

NSIDC advances products by reprocessing them based on both current scientific research and NCSA updates to make HDF more manageable. NSIDC assigns a version number, synonymously called a collection number, to each reprocessing initiative. Version five, the current version in the completion stages of being processed, improves on version four by, for example, using a more conservative cloud mask, adding fractional snow information to the MOD10_L2 products and the MOD10A1 products, making products more manageable with new HDF compression techniques, and rendering preview images for each granule. Researchers have, in the past, found errors in data collections. NSIDC, when researchers correctly report processing errors, confirm the errors and temporarily remove access to error-effected data to patch it. NSIDC eventually deletes outdated collections.

Hall et al. (2001) describes the level three CMG products composited every eight days and recommends them for most model confirmation experiments (pers.
com. 2006) because of their ease-of-use and the accessibility of data tools built around them. Our review of level three products confirms that they are easy to use with the NASA’s HDF-EOS to GeoTIFF Conversion Tool (HEG-TOOL) developed by Raytheon Company, scripting libraries included with The MathWorks™ MATLAB® and ITT Visual Information Solutions™ Interactive Data Language® (IDL). We, however, do not employ level three products in this research. We use, instead of level three products, level two measurement-derived maps as explained further in section 3.1.

Hall acknowledges that the level three eight-day composite period is an arbitrary period in many applications (pers. com. 2006). The level three CMGs, also, “do not simulate the present Arctic climate very well” (Hall 2001 summarizing Bromwich et al. 1994). The compositing process that NSIDC uses to create level three products, finally, marks pixels snow-covered if the snow mapping algorithm (2-5) is satisfied for at least one pixel among all location-coincident pixels in a composite period (Hall 2001). This means that the composite process will map a pixel as snow-covered even if only one location-coincident pixel within the composite period satisfies the snow requirements (2-5). Level three temporal composites, therefore, are inadequate to confirm model results where model periods are close to or smaller than the measurement composite periods.

2.2.2.3 Quality Assurance

NSIDC 2006 explains that collection four, level two products include a layer called “Snow Cover PixelQA” that reports an eight-bit quality assurance report “ for each point recorded by the MODIS sensor in the swath. Bits zero and one represent the general quality of the product. The first two bits, bit zero and bit one read right to left, with values of [0,0] indicate nominal, usable quality. Values [0,1] (i.e. bit zero equals one and bit one equals zero) indicate abnormal quality. Values [1,0] indicate clouds, and values [1,1] indicate invalid data.

Abnormal quality, cloudy, and invalid reports, all according to NSIDC 2006, indicate respective locations were sensed both out of an acceptable 150 degree to 210 degree range and with an observation coverage area limited to than 20% of the potential coverage area. The NSIDC does not further differentiate between these three quality assurance labels — abnormal quality, cloudy, and invalid — beyond the physical meaning inherent in the “cloudy” label. Data analyzed later in this thesis (e.g. Figure 4-8b, Figure 4-9b, Figure 4-10b), however, infer that MODIS reports invalid locations throughout the day and night but reports abnormal locations predominantly during the daylight.

Bits two through seven detail supporting quality information. Bit three flags measurements taken with broken (“dead”) detector bands. Bit four flags

** Various websites and literature use the word “quality assurance” and the word “quality assessment” interchangeably. This thesis uses the word “quality assurance.” Further, a quality assurance report describes a multi-point layer of — or multi-pixel layer of — quality assurance eight-bit values in the context of swaths and grids, whereas a quality assurance report describes single-point quality assurance eight-bit values in the context of a single coordinate or a single pixel.
measurements taken at sensor view angles greater than 45 degrees. Bit five flags measurements derived from “highly uncertain” band 6 radiance calculations. Bit six flags results given an undetermined cloud mask. Bit seven flags unusable sub-
calculations. Bit eight is unused.

All other collection four (non level two) snow coverage products include a unique “Spatial QA” index, which is derived from the level two “Snow Cover PixelQA” and reported in four bits of eight bits. The first two bits report the same general quality information reported in the first two bits of the level two products. Bit three indicates a sensor azimuth angle between 150 degrees and 210 degrees. Bit four indicates an observation coverage of more than 20% of the are covered by the product. Bits five through eight are unused.

2.2.2.4 Swath To Grid Conversion Tools
Many software tools exist to project and interpret MODIS snow data. Most of these tools, however, read grid data only. Few tools read and project data originally in the swath format, and of these tools, even fewer work the MOD10_L2 product. Before we wrote our own set of scripts to convert swaths for the UPRW into a format comparable to TOPLATS as described in 3.3.1, we reviewed and tested the following three tools:

2.2.2.4.1 MODIS Swath To Grid Toolbox (MS2GT)
NSIDC distributes a combination of C programs, IDL scripts, and Perl scripts called MODIS Swath To Grid Toolbox (MS2GT) specifically for converting swaths to grids (NSIDC 2003). MS2GT requirements, however, exceed our accessible resources: full access to a UNIX platform with IDL and Level 1 MODIS data. NSIDC has only tested MS2GT on a SGI O2 workstation.

2.2.2.4.2 HDF-EOS to GeoTIFF Conversion Tool (HEG-TOOL)
HDF-EOS to GeoTIFF Conversion Tool (HEG-TOOL) converts most swath files into grids. HEG-TOOL converts and composites HDF-EOS products of all levels from all eight DAACs. The general tool works especially well compositing several level three granules (like MOD10C1) into a mosaic. The conversion tool, however, works only intermittently with our level two data. It seems to fail, although we have not confirmed this, when converting swath granules with a large amount of no-data within bounds of an interest area. In a batch conversion process for our granules, implemented using HEG-TOOL’s scripting interface, HEG-TOOL often halts mid-conversion.

2.2.2.4.3 MODIS Reprojection Tool for Swath Data (MRT Swath)
The Land Process DAAC (LP DAAC) created the MODIS Reprojection Tool (MRT) for Swath Data (MRT Swath). The LP DAAC created the tool especially for LP data. MRT Swath incorporates Delaunay triangulation to map swath points to cells. MRT Swath, in our attempt to automate the conversion process of MOD_10L2 and MYD10L2 products with batch scripts, failed in situations similar to those that failed with HEG-TOOL. MRT Swath often halts mid-conversion. Neither HEG-
TOOL or MRT Swath created files that were completely compatible with the projection descriptions used by ArcGIS Desktop.
<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Spatiotemporal Properties</strong></td>
<td></td>
</tr>
<tr>
<td>Pixel Size</td>
<td>$(500 \text{ m})^2$ or $0.25 \text{ km}^2$</td>
</tr>
<tr>
<td>Nominal Swath Coverage</td>
<td>$2,000 \text{ km}$ across track</td>
</tr>
<tr>
<td></td>
<td>$1,354 \text{ km}$ along track</td>
</tr>
<tr>
<td>Scan Time</td>
<td>5-minute (1 Scene)</td>
</tr>
<tr>
<td><strong>Contributing Products</strong></td>
<td></td>
</tr>
<tr>
<td>Cloud</td>
<td>MOD35_L2</td>
</tr>
<tr>
<td>Geolocation</td>
<td>MOD03</td>
</tr>
<tr>
<td>Radiance</td>
<td>MOD02HKM</td>
</tr>
<tr>
<td></td>
<td>MOD021KM</td>
</tr>
<tr>
<td><strong>Pixel Categories (Snow_Cover SDS)</strong></td>
<td></td>
</tr>
<tr>
<td>Missing Data</td>
<td>0</td>
</tr>
<tr>
<td>No Decision</td>
<td>1</td>
</tr>
<tr>
<td>Night</td>
<td>11</td>
</tr>
<tr>
<td>Snow-Free</td>
<td>25</td>
</tr>
<tr>
<td>Lake</td>
<td>37</td>
</tr>
<tr>
<td>Ocean</td>
<td>39</td>
</tr>
<tr>
<td>Cloud</td>
<td>50</td>
</tr>
<tr>
<td>Lake Ice</td>
<td>100</td>
</tr>
<tr>
<td>Snow</td>
<td>200</td>
</tr>
<tr>
<td>Detector Saturated</td>
<td>254</td>
</tr>
<tr>
<td>Fill</td>
<td>255</td>
</tr>
</tbody>
</table>

This table data from Riggs et al (2006) is applicable to both MOD10\_L2 (Terra) and MYL10\_L2 (Aqua) products.
2.3 DISTRIBUTED MODELS

“No real advance will be made if we continue to force lumped models based on empirical relationships to represent the complexity of distributed runoff.”

Hydrologists have long relied on model concepts based on empirical observations, like the unit hydrograph, and parameters that lump spatiotemporal-varying watershed characteristics into single values. The Natural Resources Conservation Service (NRCS) approach for estimating rainfall runoff and channel routing (Mucus 1972) exemplifies a lumped-parameter model. Soil group, impervious area, land cover, hydrologic condition, and land use are all lumped into the single NRCS curve number. A watershed-averaged storage parameter is another example of a lumped parameter. Lumped conceptual models, in general, are called grey-box models (Abbot et al. 1996) because they are not based on purely black-box empirical relationships and they do not fully account for “white-box” sub-watershed processes.

Lumping concepts based on empirical observations of one type of watershed (e.g. a relatively large watershed) into a particular parameter can lead to problems if that parameter is used to predict runoff in a different type of watershed (e.g. a relatively small watershed). Further, a parameter developed for one application could be useful in another application for the wrong physical basis. As lumped-parameter models are scaled to meet the needs of different applications, the number of calibration parameters can increase and the inter-correlation between calibration parameters can increase. Modelers, to compensate for these problems, package application-specific calibration parameters alongside matching, application-specific run-time processes.

Remotely sensed measurements that uncover sub-watershed discrepancies between observations and lumped simulations drive the need to lump concepts over smaller areas and smaller time intervals. Such models that account for sub-watershed processes are called are called distributed models. The level a model is distributed is subjective and discussed further in relation to map comparison (2.4.1). “The Saint Venant equations for overland and channel flow, Richards’ equations for unsaturated zone flow and Boussinesq’s equation for groundwater flow” are examples of partial differential equations used in distributed modeling (Abbot et. al. 1996).

The traditional comparison between empirical (black box), lumped-conceptual (grey box), and distributed physically-based (white box) models can be misleading. The common use of the words “physically-based” in combination with the word “distributed” makes sense; distributed models readily enable the simulation of physical processes and produce maps that are comparable to remotely-sensed measurements. The words “physically-based,” however, are not exclusive of lumped conceptual models. Most models and model parameters have a physical basis, including lumped-parameters like the NRCS curve number.

Although the vintage of the programming techniques employed by a model does not determine if it is more lumped or more distributed, to efficiently create application-specific modules for time-tested lumped programs, programmers compartmentalize legacy procedural code into object-oriented classes. These classes can be used in combination with distributed processes when, for example, distributed
calibration data is unavailable. Using a combination of lumped concepts and distributed concepts can, ideally, result in smaller errors of prediction with modest gains in model complexity. These models are called semi-distributed models. TOPMODEL, which stands for Topographic Model, exemplifies semi-distributed models (Vieux 2004 and Bevin 1998a). Hydrological Simulation Program--Fortran (HSPF) is another model that incorporates “theory, laboratory experiments, and empirical relations from instrumented watersheds” (USGS 2008) with distributed modules. Critics of semi-distributed models like HSPF complain that there is a danger in significantly increasing model complexity to a point where here are minimal returns in increased model accuracy.

While it is important to consider model complexity in combination with model rationality, the process of creating distributed models has recently become more practical as a result of accessibility to geospatial products over the internet, desktop GIS, and cheap computer processing. Distributed models are now advancing the state of the art. Abbot et. al. (1996) contend that models distributed in space and time “nearly always” limit uncertainty in comparison to lumped-parameter models. Abbot et. al. (1996) site this advantage of distributed models over lumped-parameter models in water resources applications for irrigation, erosion and land restoration, surface and ground water pollution remediation, flood and drought control, maintenance of aquatic ecosystems, and climate change assessment. “In mountainous terrain, topographically induced spatial variability makes distributed snowmelt models [especially] attractive” (Colee 200).

2.3.1 TOPLATS
Déry et al. (2004) implemented TOPMODEL-Based Land-Atmosphere Transfer Scheme (TOPLATS) for studying the UKRW at the USDA. TOPLATS applies TOPMODEL surface water processes (Famiglietti and Wood 1994a,b) on a cell-by-cell basis. The model incorporates a soil–vegetation–atmosphere transfer (SVAT) scheme to simulate near-surface soil column energy balances (Peters-Lidard et al. 1997) and models physical representations of moss, snow, soil, and forest. The snow module divides snowpack into a thin surface layer and a thick subsurface layer. The surface snow layer interacts with the atmosphere and the sub surface snow layer exchanges heat with the soil. The forest module discriminates between an understory and an overstory.

Déry et al. (2004) add “key topographic effects” to TOPLATS: the effect of elevation on air temperature, the effect of slope on radiation, and the of effect of an adiabatic lapse rate of 6 °C / km² on the ambient air temperature with elevation. Déry et al. (2004) report that although a difference of 5.58 °C persists between the highest and lowest points of the watershed throughout each model run, “the mean air temperature change for all pixels in the Upper Kuparuk is only 20.48C.” TOPLATS calculates the position of the sun using the method developed by Gates (1980) combined with DEM data. Of all TOPLATS parameters, DEM and the adiabatic lapse rate of 68 °C / km² drive model results. TOPLATS prediction results consist of a time series of maps separated by regular time intervals. Déry et al. (2004) use a 10 minute time interval and maps projected in UTM Zone 6 grid with a 131.34 m cell size. Input variables include precipitation (mm), relative humidity (%), temperature (°C),
incoming solar radiation (W/m²), wind speed (m/s), air pressure (mbar). Model parameters include the UKRW DEM (m) and snow albedo (a dimensionless ratio of reflected to incident solar radiation). Initial conditions include the beginning of season SWE (mm of water).

Déry et al. (2004) review the possibility of confirming model results in the UKRW with MODIS measurements. They conclude that although MODIS measurements could be reviewed, MODIS measurements “do not provide the location covered by snow within a single grid cell, nor the SWE contained in the snow cover” and “the persistence of low-level clouds in the Arctic during spring may also compromise its applicability.” While the last two points — that MODIS does not measure SWE and that clouds can block the near infrared radiation that MODIS senses — are problems, the first point — that measurements are not provided in grid cells can be overcome by either interpolating swath measurements into grid values or interpolating model predictions into a sinusoidal projection. In this thesis, the former is complete as described in Resources and Methodology.

2.4 Map Comparison

2.4.1 Background

Analysts evaluate prediction capabilities of spatiotemporal models by comparing modeled map series with measured map series. Point, line, polygon, and pixel features delineate these maps into categorical (e.g. snow, ice, snow-free) or scalar (e.g. %SCA) space. Maps with points (e.g. well locations) and maps with lines (e.g. topographic steps) that are relatively close together, and maps with polygons (e.g. land use) and maps with pixels (e.g. snow cover) that are relatively small, best describe physical processes that span relatively small areas and take place in relatively small interest areas. Analysis call such maps with high spatial resolution highly spatially distributed. The time difference between scenes and the time interval of composite scenes indicate, likewise, the relative degree of temporal distribution in a map. The granularity of measurements available in an interest area help modelers limit the physical processes that they employ when formulating a model. The increasing resolution of newer model results, in return, define needs for developing sensors that capture images with higher resolutions for purposes of calibration and validation.

Model and instrument error statistics indicate confidence in observed and simulated maps respectively. The most relevant error statistics for a data product are often distributed within that data product as complementary series of maps. The MODIS L2 Collection Five product, for example, includes quality assurance estimates for every coordinate measured in each swath scene. Sometimes analysts need to derive error information from data that is not necessarily included in a product. For example, supplementary meteorological measurements, elevation measurements, and detection band information can be used to infer error in MODIS measurements. The error statistics derived from supplementary sources like these are not necessarily reported in the same measurement system or coordinate systems as measurements themselves. For instance, if there is a high correlation between a land-use feature and an error, that error may be presented spatially as a polygon which
masks many pixels. In this case, error is spatially lumped. Error may be lumped temporally as well. The continuous volatility of the stock market, for example, may be lumped into individual variances that represent periods of time between abrupt events like interest rate cuts. An analogous example in hydrology is the lumping of error in a rainfall-runoff model into two periods, before channelization and after channelization.

The simplest process for comparing modeled maps and measured maps includes laying the two series out side-by-side, in chronological order. The comparison is easiest when the maps between each series have a one-to-one relationship. Models, therefore, should ideally be setup to simulate maps corresponding to the times the data in the measured maps were collected. Additionally, all maps should be presented in the same spatial resolution and the same coordinate systems. Analysis will be subject to unwanted rounding and lumping, or needlessly smaller sample sizes, if model output times cannot be made to correspond to measurement times or spatial mismatches are present between the two series. This side-by-side comparison process of displaying information for every feature (e.g. pixel) in every scene is simple to execute. The format of this comparison, however, becomes increasingly onerous to visually analyze with an increasing number of scenes. The comparison problem provokes the need to find goodness-of-fit statistics that both preserve the independence of each scene in time and the independence of each given spatial feature (either point, line, polygon, or pixel).

2.4.2 Spatial Comparison

2.4.2.1 Cohen’s Kappa Statistic

Calculating the change of a criterion that is spatially lumped over an entire interested area accounts for the independence of each scene with respect to time, but ignores spatial processes within the interest area. A comparison between observed video frames and model frames that, in this study, explain the decline of %SCA across a watershed during a winter-spring melt season could indicate good agreement in the overall decline of snow. This comparison, however, does not confirm the correctness of — or reveal the absence of needed — sub-watershed processes in the model. The effect of local elevation on the distribution of snow is an example of one of these sub-watershed processes. Researchers using such a comparison exclusively could calibrate a model to correctly predict the change in a spatially lumped coverage for the wrong physical reasons. Confirming model predictions of the decline of fuel in a wildfire is another example in which a spatially lumped agreement could lead to the oversight of small-scale, model failures.

Without tediously comparing model maps and measured maps side by side, Cohen’s Kappa goodness-of-fit statistics, $K$ (Cohen 1960 and, for a more abstract case, Fleiss 1971), give analysts insight into spatial agreement of feature-scale physical processes. The statistic “gives a quick indication of the level of agreement between two maps.” It is, more explicitly, “an indication of goodness-of-fit in comparison to a random situation” in which the pixels from each of the two maps being compared are relocated at random (Hagen 2002).
Kappa varies from negative infinity to one. Negative values of Kappa and Kappa equal to zero both indicate no agreement between two maps beyond what would be expected in the random relocation situation. Increasing, positive values of Kappa indicate increasing agreement between two maps. A positive value of Kappa close to zero indicates almost no agreement between two maps. A positive value of Kappa close to one indicates a strong agreement between two maps. Landis and Koch (1977) call negative values of Kappa “poor,” and values from zero to one, in 0.2 intervals: “slight” (0 to 0.20), “fair” (0.21 to 0.40), “moderate” (0.41 to 0.60), “substantial” (0.61 to 0.80), and “almost perfect” (0.81 to 1). They call these labels “arbitrary” but “useful benchmarks.” Sim and Write (2005), in response to this scale, note that Kappa decreases with increasing categories because an increase in categories decreases the chance of agreement between two maps in the random relocation situation.

Cohen (1960) popularized the Kappa statistic to measure the agreement between two judges, categorizing single items in a series of trials. Fleiss (1971) extended the comparison to include multiple judges. “Smeeton (1985) traces [Kappa’s] history to Galton (1892)” (Pontius 2000). Two maps in a spatial comparison are analogous to two judges considered by Cohen’s Kappa. Location-coincident pixels in the two maps are analogous to individual trials being exclusively-categorized by the two judges.

For the simple comparison of two raster maps I and II with pixels exclusively in any number of categories, Cohen’s Kappa statistic answers the following question: How well does the agreement between map I and map II compare to the agreement between theoretical maps, III and IV; where, the probability that location-coincident pixels in III and IV assume the same category equals the product of the fraction of that category in map I and the fraction of that category in map II? The remainder of this section further details the calculation of Kappa and discusses complementary statistics Kno, Klocation, Kquantity all explained by Pontius (2000) and Khisto derived by Hagen (2002).

The first step in making a fair comparison between a model map and a measured map, which is also the first step in calculating Kappa, is to calculate the proportion of agreement, PA, between the two maps.

\[
PA = \frac{\text{area in agreement}}{\text{total area}}
\]

Two square maps, each with four-pixels and two-categories (snow or snow-free), for example, that both have their two left-side pixels marked as snow and their two right-side pixels marked as snow-free have perfect agreement. In this example, there are no errors of commission (a false-positive detection of snow) and there are no errors of omission (a false-negative missing detection of snow). In the case that the two left pixels of the measured map are observed to be snow-covered, and the model map shows the top two pixels as covered with snow, there is a 50% agreement: There is an error of commission in the upper right cell, there is an error of omission in the lower left cell, leaving two cells out of four (50% of the map) in agreement.

Calculating the proportion of agreement between two maps show how well two maps agree on a pixel-by-pixel basis. Success, however, is measured with the assumption that there are the same number of pixels, for each category, between each
of the two maps being compared. (This is not to say each category has the same number of pixels as every other category.) If there are an unequal number of pixels of a particular category between maps, there can never be 100% agreement. We call this issue the “unequal category size limitation” of the PA comparison.

The Kappa goodness of fit statistic addresses the “unequal category size limitation” of the simple PA calculation by comparing the PA with the proportion of expected agreement of a random rearrangement of cells (PE).

\[ K = \frac{PA - PE}{1 - PE} \]  
\[ 2-7 \]

The calculation of PA and PE with a confusion matrix explains the two statistic further. Figure 2-8 shows the confusion matrix (boxed) for the abstract case with n categories. The row header cells and the column header cells contain category labels \( C_1, C_2, \ldots, C_n \). The rows correspond to map one and the columns correspond to map two. The proportion of cells of \( C_i \) in map one with coincident cells of \( C_j \) in map two, \( p_{ij} \), appear in the cell at row \( i \) and column \( j \). For example, the proportion of category-three cells in map one with coincident category-four cells in map two would be expressed as \( p_{34} \) and appear in row three and column four of the confusion matrix. The matrix diagonal contains proportions map categories agree. The matrix trace, therefore, equals the sum-total proportion of agreement, PA, between the two maps:

\[ PA = tr(confusion matrix) = \sum_{k=1}^{n} p_{kk} \]  
\[ 2-8 \]

Summing the number of cells of each category for each map begins the calculation of the proportion expected agreement due to a random relocation of cells within each map, PE. The sum of proportions in each row \( i \) equal the proportion of category \( i \) cells in map one. These totals are expressed in an \( n \)-by-one column to the right of the confusion matrix.

\[ \bar{p}_{i*} = \begin{bmatrix} p_{1*} \\ p_{2*} \\ \vdots \\ p_{n*} \end{bmatrix} \]  
\[ 2-9 \]

The number of cells containing category \( i \) in map one equal

\[ p_{i*} = \sum_{k=1}^{n} p_{ik} = sum([p_{i1} \ p_{i2} \ \ldots \ p_{in}]) \]  
\[ 2-10 \]

The proportion of category \( j \) cells in map two are similarly expressed in a one-by-\( n \) row below the confusion matrix. Map two proportion totals are expressed as

\[ \bar{p}_{*j} = [p_{*1} \ p_{*2} \ \ldots \ p_{*n}] \]  
\[ 2-11 \]

The number of cells containing category \( j \) in map two equal

\[ p_{*j} = \sum_{k=1}^{n} p_{kj} = sum \left( \begin{bmatrix} p_{1j} \\ p_{2j} \\ \vdots \\ p_{nj} \end{bmatrix} \right) \]  
\[ 2-12 \]

The product of the total proportion vectors, \( \bar{p}_{*j} \) and \( \bar{p}_{i*} \) (2-9 and 2-11), equal PE,
\[ PE = \tilde{p}_{i_j} \tilde{p}_{n*} = [p_{1*} \ p_{2*} \ \ldots \ p_{n*}] \]

where, each \( k \) component product
\[ p_{kj} \cdot p_{ik} \]
for \( k = 1, 2, \ldots, n \), represents the probability of agreement for category \( k \) in every combination of cell pairs between — or, for random relocation of cells in — map one and map two. \( PE \), thus, depends on the quantity of cells in each category in each map; \( PE \) does not depend on the location of cells within either map.

Comparing two four-pixel maps with two categories \( C_1 \) and \( C_2 \), for instance, if each map contains three \( C_1 \) pixels and one \( C_2 \) pixel, there are nine pairs of pixels in which both pixels are in category \( C_1 \) and there is one pair of pixels in which both pixels are in category \( C_2 \) out of sixteen possible pairs in a random situation. \( PE \) in this instance equals \( 9/16 \) (for \( C_1 \)) \( + 1/16 \) (for \( C_2 \)) \( = 10/16 = 0.625 \). Replacing a \( C_1 \) pixel from map two with a \( C_2 \) pixel doubles the probability of \( C_2 \) pairs to \( 2/16 \) in the calculation of \( PE \), but lowers the probability of \( C_1 \) pairs from \( 9/16 \) to \( 6/16 \) and lowers the overall \( PE \) to \( 2/16 \) (for \( C_2 \)) \( + 6/16 \) (for \( C_1 \)) \( = 8/16 = 0.5 \).

**Figure 2.8. Generic Confusion Matrix.**

The generic confusion matrix (boxed) can be used to calculated \( PA \) and \( PE \) for the abstract case in which there are an unlimited number of categories in the maps being compared. \( PA \) equals the trace of the matrix. \( PE \) equals the product of the total vectors: \( PE = \tilde{p}_{i_j} \tilde{p}_{n*} \).
<table>
<thead>
<tr>
<th>( \text{H}_0: ) Snow Free</th>
<th>Type I Error of Commission (False Positive)</th>
<th>Agreement of SCA (Hit)</th>
<th>Proportion Snow in Modeled Map</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \bar{p}_{ij} )</td>
<td>Proportion Snow-Free in Measured Map</td>
<td>Proportion Snow in Measured Map</td>
<td>1</td>
</tr>
</tbody>
</table>

**Figure 2-9. Two-Category Confusion Matrix.**
The two-category confusion matrix (boxed) shows four possible coincident-cell outcomes.

### 2.4.2.2 Cohen’s Kappa Statistic for Two Categories

Figure 2-9 simplifies the generic confusion matrix used in Cohen’s calculation of Kappa for multiple categories (Figure 2-8), into a confusion matrix limited to two-categories, snow-free and snow, that we used in this thesis. Figure 2-9 shows that the calculation of Kappa in this thesis can be thought of \( n \) hypothesis tests, where \( n \) equals the number of cells in two maps being compared. We call each of these hypothesis tests a pixel test to distinguish them from the overall evaluation of agreement between two maps expressed by Kappa. In each pixel test, the null hypothesis indicates the absence of snow (snow-free) and the alternative hypothesis indicates the detection of snow:

\[
\begin{align*}
\text{H}_0: & \text{ Snow Free} \quad \text{2-15} \\
\text{H}_A: & \text{ Snow} \quad \text{2-16}
\end{align*}
\]

We call the situation in which the model falsely indicates that snow is present in a pixel test a type I error of commission. In other situations, a type I errors have been called \( \alpha \) errors, false alarms, false positives, and producer’s risk. We call the situation in which the model falsely indicates that snow is absent in a pixel test a type II error of omission. Type II errors have been called \( \beta \) errors, non-detects or misses, false negatives, and consumer’s risk.

The terms “producer risk” and “consumer risk,” are only sensible if the alternative hypothesis is undesirable (e.g. a polluted water sample or a defective product). A producer, in the case that an alternative hypothesis is undesirable, could incur unnecessary expenses (e.g. extraneously increase quality control in an acceptable system) due to a producer risk. A consumer, in the case that an alternative hypothesis is undesirable, could suffer worse, unexpected ill-effects (e.g. sickness) due to a consumer risk. In this thesis both type I and type II errors are equally undesirable. False detection of snow is simply different, not worse, than a non detection of snow. We, therefore, avoid the terms “producer risk” and “consumer risk. The calculation of Kappa, further, lumps both types of errors into \( PE \) (2-9, 2-11, and 2-13). Isolating type I and type II two errors could, however, reveal a systematic bias in the model.

### 2.4.2.3 Kappa Variants

We cannot solely rely on Kappa to compare two maps. Cohen (1960) and Pontius (2000) warn that Kappa is best used only when the two judgments of a trail are
independently made. Kappa, for example, appropriately explains a test of agreement between two biologists individually categorizing species of a random samples of nematodes, each isolated in separate Petri dishes. In this example, there is no known correlation between samples to the judges; judgments on a single sample are made separately from each other. In the general case of comparing model and measurement maps, in contrast, pixels are often dependent on spatial information (e.g. DEM, location) and the model map is dependent on model calibration. Researchers using Kappa to compare maps, therefore, best complement Kappa with additional information about model dependency, and model ability to predict, both the quantity of pixels in each category and the location of pixels.

Pontius (2000) generalizes Cohen’s the calculation of Kappa (2-7) into,

\[
K = \frac{PA - PE}{1 - PE} \rightarrow K = \frac{PA - PC}{PP - PC}
\]

where \(PC\) (compare to \(PE\) in Cohen’s Kappa) equals the expected proportion of correctly categorized coincident cells made by a model, and \(PP\) (compare to unity in Cohen’s Kappa) equals the expected proportion of correctly categorized cells when the model is perfect. This generalization provides the foundation to develop Kappa variants that account for situations in which models choose categories based on

1. No
2. Medium
3. Perfect

ability to specify

1. The quantity pixels in each category
2. The location of individual pixels

2.4.2.3.1 Kno

Models with “no ability” (Pontius 2000) to select either the quantity of pixels in each category or the location of individual pixels have a chance of \(1/n\) to correctly predict a category at a pixel. Kappa for no ability, Kno (Pontius 2000) — also called \(k_{noe}\) by Lantz & Nebenzahl in (1996), PABAK by Byrt, Bishop & Carlin (1993), and random coefficient (RC) by Maxwell (1997) — exchanges \(PC\) in the generalized calculation of Kappa (2-17) with this chance that a model pixel could have the correct category at random, \(1/n\),

\[
Kno = \frac{PA - \frac{1}{n}}{1 - \frac{1}{n}}
\]

where, \(n\) is the number of categories. Hagen (2002) appropriately calls \(1/n\) in this case the probability expected by the model due to the random selection of a category by the model, \(P(E)_{RC}\).

Pontius contends that Kno improves Kappa because it considers the quantity of cells that could agree in a completely random situation. Figure 2-10 illustrates this point with a nine-pixel comparison in which snow rests in exactly one cell in each map. The strong agreement of snow-free pixels in this Figure 2-10 produces a
relatively high $PE = 0.8025$ (2-7), but yields a misleading negative Kappa of -0.1250. Kno, comparatively, only considers the number of categories, $1/n = 0.5000$, yielding a rationally-positive Kno value of 0.7500.

\[ Kno = \frac{n PA - 1}{n - 1} = \frac{n}{n - 1} PA - \frac{1}{n - 1} \]  

(2-19)

which has a redundant linear dependency on the probability of agreement, $PA$, despite the subjectively more-rational positive and negative values.

2.4.2.3.2 Klocation and Khisto

Both Kappa and Kno “fail to distinguish . . . between quantification error and location error” (Pontius 2000). Poor (low and negative) values of Kappa and Kno, in other words, do not explain whether a model has poorly predicted the quantity of pixels in each category or whether a model has located the correct quantity of pixels in the wrong locations.

Klocation (2-20), introduced by Pontius (2000) attempts to correct Kappa and Kno by substituting $PP$ in the generalized calculation of Kappa (2-17) with the maximum success rate of agreement that a model could achieve in the situation in which the number of pixels in each category predicted by that model does not change (2-21).

\[ Klocation = \frac{PA - PE}{P_{max} - PE} \]  

(2-20)

where

\[ P_{max} = \sum_{k=1}^{n} \min(p_{k}, p_{k'}) \]  

(2-21)

Think of the calculation of $P_{max}$ (2-21) in comparison to the calculation of $PE$ (2-13). In the calculation of $PE$, the product the two map proportions for each category are summed. In the calculation of $P_{max}$, alternatively, the minimums of the two proportions (one for each map) are summed. $P_{max}$, therefore is likely to be less than one except in the perfect-quantity case in which the proportion of pixels in each category are equal between maps.

Klocation reports a lower agreement in comparison to the Kappa value when a cell of one category is displaced. Klocation, however, fails to consider the distance of
a displaced cell. For example, in a mountain scene where it is known that snow is present on the mountain tops, but not in the valleys, a comparison between actual and simulated maps is made. In this example, Klocation will report identical values no matter if a pixel falsely reporting snow coverage is found either on a peak or in a valley. Despite this fallacy, Klocation is still valuable. It replaces the ideal 100% agreement used for $PP$ (2-17) in standard Kappa calculation (2-7) with a realistic calculation for the maximum possible agreement, $P_{\text{max}}$.

Kquantity, also introduced by Pontius (2000) attempts to correct Kappa errors resulting from differences in the quantity of cells for each category between two different maps. It is “the success due to the simulation’s ability to specify quantity divided by the maximum possible success due to a simulation’s ability to specify quantity perfectly.” Hagen (2002) renounces the statistic as “incomprehensible” and reports, with personal agreement from the Pontius, that the statistic is unstable. “Minor changes in the maps can lead to major change in the statistic” in cases where the denominator of the calculation is close to zero.

Hagen introduces an alternative to Kquantity, named Khisto, which is used in this study. It is called Khisto because it can be calculated from the histograms of two maps. The product of Khisto and Klocation equals Kappa:

$$\text{Khisto} = \frac{P_{\text{max}} - PE}{1 - PE} = \frac{K}{K_{\text{location}}}$$

2-22

2.4.3 Temporal Comparison

2.4.3.1 Missing Data in Partially Obscured Scenes

Scalar statistics like %SCA or basin SWE summarize spatially-distributed properties of a map scene for a point in time. Measuring model performance by comparing modeled and measured summary statistics over period of time (e.g. comparing two SCA depletion curves) presents the problem of accounting for uncertainty in partially obscured measured scenes. While models predict complete results and complementary summary statistics, sensors yield incomplete measurements. Satellite orbit limitations (Table 2-3), for example, limit both the resolution and the frequency of scenes that a sensor can measure. Smoke that obscures the video camera mentioned in the previous wildfire example (described 2.4.2.1), or clouds that block a remote sensing instrument, as shown in this study, leave measured maps spatially incomplete. Smoke and clouds are only two possible physical causes of why a sensor could tag a spatial-feature with a no-data label.

To compensate for missing data in measurement summary statistics, due to partially obscured scenes or other sensor problems, one could report a likely value based on either surrounding areas, surrounding scenes, or other spatiotemporal trends. (Decreasing soil moisture along the slope of a hill illustrates a spatiotemporal trend.) Making educated guesses like these, based on physical relationships and past observations, creates complete, usable products. Making these guesses in measurements, however, defeats the theoretical basis of comparing observed and modeled data; a “simulated measurement” is an oxymoron. Creating an artificial measurement, based on the same physical theories used in a model that the
measurement is being compared to, can lead to artificially increased goodness-of-fit statistics. This problem reveals the need to calculate the uncertainty of a summary statistic for individual measured scenes, not based on external factors, but based on data from within the scene itself.

Many remotely sensed measurements, including many MODIS products (2.2.2), actually are composted over time to fill in the gaps of the missing data from clouds. NSIDC, for example, composites sea and snow ice data over time in the MODIS level three products as explained in 2.2.2.2. NSIDC reports time intervals with level three composites — not just mean points in time — so that analysts understand the implications of comparing model results to composite measurements. When composite time intervals are large compare to the time for physical processes to occur (like snow blown overnight by wind), those physical processes that occur out of sensing range (e.g. behind clouds), are missed. In the case of quick winter-spring snowmelt (2.1.2), which occurs in a matter of days in the Upper Kuparuk, level three MODIS data hides too much information from analysts to make reasonable judgments about physical processes in models.

2.4.3.2 Using Probability to Express Measurement Uncertainty

Brubaker, Pinker, and Deviatova (2005) present a solution for comparing MODIS SCA measurements and IMS SCA measurements to surface station snow/no-snow reports across the continental United States while accounting for no-data fields. They develop a single triangle-shaped probability density function (PDF) of %SCA for each remotely-sensed map in a time series. Each PDFs relies on the quantity of categorical data, including missing data, exclusively from within its respective scene. They plot the PDFs on a probability density (ordinate) versus %SCA (abscissa) axis.

Brubaker et al. use snow cover information in cloud-free areas of each scene to estimate a possible range of snow cover for the entire scene. They assume that the likely estimate of %SCA in a scene is proportional to the fraction of the cloud-free part of the scene which is snow-covered.

\[
\text{%SCA}_{\text{likely}} = \frac{\text{%SCA}_{\text{cloud-free}}}{100\% - \text{CCA}}
\]

In equation 2-23, all percentages are relative to the entire scene: %SCA_{\text{likely}} is the likely estimate of %SCA relative to the entire scene, %SCA_{\text{cloud-free}} is the cloud-free %SCA relative to the entire scene, %CCA is the percentage of cloud-covered area relative to the entire scene, and 100% – CCA% equals the percentage of cloud-free area relative to the entire scene.

The mathematically minimum possible %SCA equals %SCA_{\text{cloud-free}}. Snow-free land, in this hypothetical case, lies under the cloud-covered area. The mathematically maximum possible %SCA equals %SCA_{\text{cloud-free}} plus %CCA. Snow, in this opposite case, completely blankets the land under the cloud-covered area. In either case, the area under any PDF equals unity. Therefore,

\[
1[\%] = \frac{\left( \frac{\text{%SCA}_{\text{cloud-free}} + \text{CCA} - \text{%SCA}_{\text{cloud-free}}}{\text{max} \: \text{%SCA}} \right)_{\text{triangle base}} - \left( \frac{\text{%SCA}_{\text{cloud-free}}}{\text{min} \: \text{%SCA}} \right)_{\text{triangle height}}}{\text{PD}(%\text{SCA}_{\text{likely}})}
\]

35
where \( PD(\%SCA_{likely}) \) equals the probability density of the most likely percentage of snow cover over the entire scene. Solving 2-24 for \( PD(\%SCA_{likely}) \) yields,

\[
PD(\%SCA_{likely}) = \frac{2\%}{\%CCA} \tag{2-25}
\]

Take, for example, a PDF for an area measured with 30% snow, 30% snow-free, and 40% cloud-covered shown in Figure 2-11a. Solving equation 2-23 for the most likely percentage of snow cover in this example yields

\[
\%SCA_{likely} = \frac{30\%}{100\% - 40\%} = 50\% \tag{2-26}
\]

Solving equation 2-24 for the probability density of most likely percentage of snow cover yields

\[
PD(\%SCA_{likely}) = \frac{2\%}{40\%} = 0.05 \tag{2-27}
\]

A congruent calculation for snow-free land yields a 0.05 probability density of likely snow-free area. A second example, plotted in Figure 2-11b, shows how ratio of a the same 30% SCA used in the first example to a reduced 20% snow-free area raises the overall likely %SCA. The apex %SCA in this case equals 60% (equation 2-25) and has a probability density of 0.04 (equation 2-27). In a final example, not shown, the probability density of the likely %SCA in a map with 100% coverage approaches infinity. In this case, the maximum and minimum %SCA equal the %SCA likely.

![Figure 2-11. Example Triangle Probability Density Functions](image)

**Figure 2-11. Example Triangle Probability Density Functions**

Example PDFs for two cases where %SCA equals 30% and (a) %CCA = 40% (b) %CCA = 50%. The likely %SCA in the cloud-covered area depends directly on the proportion of snow-covered area in the cloud-free area. The likely %SCA in the cloud-covered area only depends on the quantity of cells in that scene; it does not depend on the location of known values in the scene or in scenes measured within a time period.

We can generalize the triangle-PDF approach of estimating the most likely %SCA under a cloud-covered area to estimate the percentage of any category in an unknown
area based on a known area. It’s a quantity-only, scene-independent approach. The method, in other words, estimates uncertainty in obscured areas irrespective either the coverage within a map and the coverage in previous and subsequent scenes. Review section 2.4.2.1 for a spatial example of how elevation could influence estimates within a map. Review section 2.2.2.2 for a temporal example of how MODIS products are derived from a series of scenes. Using this method in a comparison of modeled and measured maps, triangle PDFs of remotely sensed %SCA can be compared to model predictions of %SCA on a scene-by-scene basis.
CHAPTER 3: RESOURCES AND METHODOLOGY

This chapter explains the rational for selecting resources (3.1) mentioned in Chapter One, describes the approach for comparing maps (3.2), and lists procedures for managing measured and modeled data (3.3). Table 3-1, a functional decomposition of objectives (1.3.1 Preliminary Objectives: Resource Selections, 1.3.2 Map Comparison Objectives, and 1.3.3 Data Management Objectives), summarizes the basis of the methodology.

Table 3-1. Functional Decomposition of Objectives

1. Select resources
   a. Select an interest area
      i. In the Cryosphere.
      ii. Is subject to past analysis, including . . .
         1. Hydrologic study
         2. Meteorological study
         3. Other studies in the 7 USGCRP research areas listed in “Need & Problem”
      iii. Has measurements available
      iv. Has seasonal mechanisms
   b. Select a time period
      i. Over a seasonal event.
      ii. That includes an extreme event
      iii. That has obtainable measured and modeled data
   c. Select both remotely sensed measurements and a model
      i. With enough temporal resolution to monitor the seasonal event
      ii. With enough spatial granularity to see the impact of DEM
      iii. That reports snow and ice
   d. Select a model
      i. That has all the objective properties of the measurements listed above
      ii. That is ideally available to modify
      iii. That can be calibrated
      iv. That ideally has been validated in the past

2. Compare maps
   a. Spatially, by
      i. Statistical comparison, that accounts for
         1. Proportion agreement
         2. Location errors
         3. Category errors
      ii. Visual inspection
   b. Temporally, by statistical comparison of independent scenes, for the entire watershed and DEM zones

3. Manage Data.
   Make measured data and model output compatible, by either . . .
   a. Converting measured data into the model format, or,
   b. Converting model output into measured the measured format
3.1 **Resource Selection**

As introduced in 1.3.1 Preliminary Objectives: Resource Selections, we selected the Upper Kuparuk River watershed (UKRW) for the interest area, an annual snowmelt season for the time period, MODIS data for the measurements, and TOPLATS to produce model results.

The interest area lies in the Cryosphere, in a mountainous region. The entire Kuparuk area is well studied. “It has the longest history of research of any basin within Arctic Alaska, as both the Toolik Lake and Innnavait Creek watersheds are part of this system” (Nolan 2003). The area has glacial geology measurements (Walker et al. 2003), hydrological measurements (Kane and Hinzman 2009), and meteorological measurements (Kane and Hinzman 2009) all available online. Hinzman and Kane (2009) provide detailed hydrological and meteorological measurements during snowmelt.

For remotely sensed measurements, we selected MODIS level two products, LANDAT, and high resolution DEM (Nolan 2003) measurements for their online availability and use in past research. Déry et al. (2005) has compared the MODIS measurements in this area to LANDSAT measurements in the area. MODIS level two products, although not as widely used or readily available to use in existing software packages, describe daily information compared to the eight day composites in level three products.

The model, TOPLATS, shows spatial heterogeneity in the snow and considers interactions with environmental factors of interest to USGCRP including vegetation and radiation from the sun. Déry et al. (2004) showed that TOPLATS can be used to model the UKRW with a time step as small as 10 minutes. TOPLATS outputs results in the same mask and the same coordinate system defined by Walter et al. (2003).

3.2 **Map Comparison**

Two methods compare model and measurement maps. In the first method, the proportion of agreement (PA), Cohen’s Kappa goodness of statistic (2.4.2.1) and Kappa variants (2.4.2.3) show the agreement between maps accounting for the quantity and location of pixels categorized as either snow, snow-free, or not available. The second method compares model and measured %SCA depletion curves, where the quantity of categorized pixels in each independent scene is used to measure the uncertainty of MODIS %SCA. (See section 2.4.3.2 to review how Brubaker et al. (2005) used this second method for comparing MODIS SCA measurements and IMS SCA measurements to surface station measurements.)

In both methods, MODIS measurements and TOPLATS predictions need to be put into comparable formats. TOPLATS predicts SWE depths over grids of pixels in UTM zone 6 while MODIS reports arrays of categories codes, each corresponding to a snow or sea ice feature, across point features in swath scenes. While we could have developed a procedure to convert TOPLATS grids to MODIS-comparable swaths, we instead defined a way to convert MODIS swaths into a TOPLATS-comparable grid format. We selected the latter procedure because (a) it is easier to visualize and analyze data in a grid format compared to a swath format and (b) it
would be hard to assign MODIS categories like lake ice, night, and ocean to TOPLATS SWE values without updating the theoretical basis of the model and modifying the model code. The last part of this chapter, Section 3.3, lists the data management procedures used to make the model predictions and measurements comparable.

After completing the data management procedure, we put MODIS measurement codes listed in Table 2-6 into groups. Table 3-2 shows these groups, where

- The “Available” group includes points that have been successfully identified by the sensor as either snow, lake, ocean, lake ice, or snow.
- The “Frozen” group includes points reported as either lake ice or snow; a subset of available measurements
- The “Snow” group is an exclusive subset of the frozen group
- The group labeled “Not Available” contains member points that MODIS has not decidedly identified or detected. This group also includes points reported by MODIS as night and points for a given granule in which those points were outside the respective swath coverage

MODIS measurement groups are independent of quality assurance values and satellite detection angles. For purposes of evaluating a pixel as either snow-covered or snow-free in map comparison, the word “snow” is generalized to include “frozen” pixels including lake ice.
### Table 3-2. MODIS Measurement Groups

<table>
<thead>
<tr>
<th>Group</th>
<th>Members</th>
<th>Characteristic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Available</strong></td>
<td>25</td>
<td>Snow-Free</td>
</tr>
<tr>
<td></td>
<td>37</td>
<td>Lake</td>
</tr>
<tr>
<td></td>
<td>39</td>
<td>Ocean</td>
</tr>
<tr>
<td></td>
<td>100</td>
<td>Lake Ice</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>Snow</td>
</tr>
<tr>
<td><strong>Frozen</strong> (called snow during map comparison)</td>
<td>100</td>
<td>Lake Ice</td>
</tr>
<tr>
<td></td>
<td>200</td>
<td>Snow</td>
</tr>
<tr>
<td><strong>Snow</strong></td>
<td>200</td>
<td>Snow</td>
</tr>
<tr>
<td><strong>Not Available</strong></td>
<td>0</td>
<td>Missing Data</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>No Decision</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>Night</td>
</tr>
<tr>
<td></td>
<td>254</td>
<td>Detector Saturate</td>
</tr>
<tr>
<td></td>
<td>255</td>
<td>Fill</td>
</tr>
</tbody>
</table>

**MODIS Map Categories**

- **H₀**: Snow-Free
- **Hₐ**: Snow

**TOPLATS Map Totals, \( \tilde{p}_{t,s} \)**

<table>
<thead>
<tr>
<th>Agreement of Snow-Free Area</th>
<th>Type II Error of Omission (False Negative or Miss)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>H₀</strong>: Snow-Free Area</td>
<td><strong>Hₐ</strong>: Snow</td>
</tr>
<tr>
<td><strong>Hₐ</strong>: Snow</td>
<td><strong>H₀</strong>: Snow-Free Area</td>
</tr>
</tbody>
</table>

**Proportion Snow-Free in TOPLATS Map**

**Proportion Snow in TOPLATS Map**

**Proportion Snow-Free in MODIS Map**

**Proportion Snow in MODIS Map**

### Figure 3-1. MODIS-TOPLATS Confusion Matrix.
The MODIS-TOPLATS confusion matrix (boxed) shows four possible coincident-cell outcomes: Agreement of snow free area (upper-left box), agreement of snow covered area (lower-right box), error of commission where TOPLATS falsely predicts snow cover (upper-left box), and an error of omission where TOPLATS predicts a snow free area in an area that MODIS reports to be snow covered (upper-right box).
### Table 3-3. Kappa and Kappa Variant Interpretation

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Criteria</th>
<th>Agreement Strength</th>
</tr>
</thead>
<tbody>
<tr>
<td>PA</td>
<td>0.00</td>
<td>None</td>
</tr>
<tr>
<td></td>
<td>0.01 – 0.40</td>
<td>Poor</td>
</tr>
<tr>
<td></td>
<td>0.41 – 0.60</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>0.61 – 0.80</td>
<td>Moderate</td>
</tr>
<tr>
<td></td>
<td>0.81 – 0.90</td>
<td>Substantial</td>
</tr>
<tr>
<td></td>
<td>0.91 – 1.00</td>
<td>High</td>
</tr>
<tr>
<td>K, Klocation, Khisto</td>
<td>&lt; 0.00</td>
<td>Poor</td>
</tr>
<tr>
<td></td>
<td>0.01 – 0.10</td>
<td>Slight</td>
</tr>
<tr>
<td></td>
<td>0.11 – 0.30</td>
<td>Low</td>
</tr>
<tr>
<td></td>
<td>0.31 – 0.60</td>
<td>Moderate</td>
</tr>
<tr>
<td></td>
<td>0.61 – 0.80</td>
<td>Substantial</td>
</tr>
<tr>
<td></td>
<td>0.81 – 1.00</td>
<td>High</td>
</tr>
</tbody>
</table>

This criteria for interpreting agreement strength solely reflects the two categories, snow and snow-free, in this particular study location. Reevaluate this interpretation for different category quantities, different cell areas, and different physical traits of categories.

---

**Figure 3-2. Interactive Map Comparison**

Visit [http://terpconnect.umd.edu/~dchoy/thesis/Kappa/](http://terpconnect.umd.edu/~dchoy/thesis/Kappa/) to interact with, and visually inspect, Kappa statistics for two categories. See the effect of varying grid size on Kappa and varying category assignments on Kappa.
3.2.1 Spatial Comparison with Kappa and Kappa Variants
To compare MODIS and TOPLATS scenes, we calculate PA, K, Kno, Klocation, and Khisto and we evaluate the results according to Table 3-3. We also report $P_{\text{max}}$ and PE. The criteria for interpreting the strength of agreement of the Kappa statistics in Table 3-3 reflects the number of categories being compared (two, snow and snow-free, rather than a multi-categorical test), the Kappa evaluation scale developed by Landis and Koch (1977), and visual comparison of maps. Reevaluate this scale in reproducing this methodology for a different location and/or for different categories.

We plot these statistics using a set of MATLAB® comparison scripts (Appendix I) that filter model results and projected measurements with the following parameters: initial model albedo, SWE threshold, number of elevation zones, elevation zone, percent available threshold, and time of day. The initial model albedo parameter is determined by the model input files. The SWE threshold parameter determines the minimum height of snow, at a particular pixel, simulated by the model, that we can consider snow-covered. The threshold is important to making SWE predictions comparable to SCA measurements. The number of elevation zones parameter determines the elevation boundaries between each elevation zone by dividing the difference of the maximum elevation and the minimum elevation into equal parts. The elevation zone parameter determines the elevation zone to report results for. The percent available threshold parameter determines the scenes to include in the comparison based on the percentage of cells available — where available means reporting either snow or snow-free, opposed to for example, cloud-covered or missing — in the MODIS scenes. If the percent available threshold is set to 50%, for example, than the comparison script only evaluates scenes in which MODIS reports at least 50% of the pixels within the scenes as either snow or snow-free. Scenes that report more than 50% of cells as cloud or no-data, in this example, are excluded from the comparison. The time of day input parameter determines the scenes to include based on the time of day — morning or evening relative to solar noon. In each comparison we show the effect of changing each parameter relative bias, bias, and correlation.

3.2.2 Temporal Comparison
Varying the same parameters from the spatial comparison — initial model albedo, SWE threshold, number of elevation zones, elevation zone, percent available threshold, and time of day — we compare MODIS and TOPLATS %SCA depletion curves and evaluate the sensitivity of changing the percent available threshold on the upper and lower limits of MODIS uncertainty. In this comparison, we report the correlation coefficient for the most likely MODIS %SCA, the minimum possible MODIS %SCA, and the maximum possible MODIS %SCA.

Finally, we compare TOPLATS performance to an inverse logarithmic model with both a chi squared and a KS1 test goodness of fit tests, each with 5% rejection probabilities. In this comparison, we report and discuss correlation, explained variance, unexplained variance, standard error, bias, and relative bias.
3.3 DATA MANAGEMENT

3.3.1 Measured Data

Each MOD10_L2 and MYD10_L2 swath needs to be converted into a projected grid in order to compare TOPLATS model results with MODIS measurements. After we failed to batch-convert series of measurements using MS2GT, HEG-TOOL, and MRT Swath (reviewed in 2.2.2.4), and after exploring layers of swath information using NCSA’s HDFView (version 2.3) application, MATLAB®, and IDL, we created our methodology to convert swaths to grids. Our conversion procedure builds on the theory and procedures documented by MS2GT, HEG-TOOL, and MRT Swath and produces grids comparable to TOPLATS output described in Table 2-2. We name our procedure Level 2 Swath to TOPLATS Grid Tool for the Upper Kuparuk River Watershed and abbreviate it as Swath to Kuparuk (S2K). S2K creates grids with the same coordinate system (UTM Zone 6) used by Walker, D.A. (2003) and the same cell size (131.34 m) used by that Déry, S.J. et al. (2004). S2K relies on MATLAB® to convert swath points to grid cells and ESRI ArcGIS to project, resample, and mask the grids that MATLAB® creates. ESRI has yet to functionally realize hearsay plans for natively supporting HDF-EOS swaths in the ArcGIS application suite. S2K can be modified to accommodate other watersheds by modifying interest area and projection variables, including a watershed polygon. S2K could, for example, capture measurements from nearby research areas like Toolik Lake with minimal modification.

To complete the S2K procedure we adhere to the following general steps for MOD10_L2 and MYD10_L2 swath scenes overlapping our interest area:

3.3.1.1 Download Swaths
3.3.1.2 Transform Swaths into Grids
3.3.1.3 Make Grids Comparable to Model Results

The remainder of this section operationalizes this procedure. Section 4.1 shows intermediate results from its execution.

3.3.1.1 Download Swaths

We query the NSIDC DAAC for MOD10_L2 and MYD10_L2 measurements via a web-based interface (NSIDC 2008c) in which we specify a square bounding box in GCS coordinates (latitude and longitude) and time period. A query with coordinates bounding the watershed only, as expected, yields fewer granules than a query with coordinates bounding the entire model interest area. (Compare Table 2-1 and Table 2-2 to see the difference between the watershed-only area and the model interest area.) The difference in the number of granule the DAAC returns, however, is not significant (e.g. <3% difference during the 2005 winter-spring snow melt). It is not impractical, therefore, for us to conservatively select the larger area to build a query.

The temporal correspondence between the winter-spring snowmelt and runoff shown in hydrographs (described in 2.1.2 and plotted in Figure 4-2 for years 2000 through 2002) guides our selection of the snowmelt time period in each query. For each year, we initially select a time period before the peak seasonal discharge. Plots of %SCA versus time reveal whether or not an initial time period inferred from
hydrographs captures the melt period. In the case that a time period does not overlap with the melt period, we modify the query period in another trial. We repeat this trial and error process until we find a query that returns a time window in which the first couple days of scenes show at least 99% snow- and ice-covered (frozen) area and the last couple days of scenes show at most 1% frozen area. In all queries, we seek to limit the number of granules returned to limit download time and S2K processing time. If download time and processing time could be executed one or two orders of magnitude faster (through, for example, a web-based controller of a server-side processing tool), we could practically mitigate the trial and error query process by initially selecting three months of data instead of a few weeks of data based on hydrograph plots. The NSIDC, in that vein, provides an option to skip night data in queries. We always opt-in to exclude night data from our query. This choice limits the number of scenes that cannot be well evaluated by the snow mapping algorithm (2-5) and halves processing time.

Most queries run shy of one hour and require a persistent connection to the internet to complete. After queries are complete, we purchase granules (currently free) via a shopping cart interface. Next, NSIDC DAAC processes, compresses, and makes-available the selected granules via an FTP connection. The time it takes NSIDC to process the granules and copy them to an FTP location often occurs within a couple hours, but can take up to an entire day. We always request NSIDC to compress all requested granules (using zip compression; HDF compression is currently unavailable) to limit the hard disk requirements for each year of data.

Extracting 200 MB of compressed granule files yield about 5GB of uncompressed information. We, therefore, need to check there is enough available disk space at a particular location before we uncompress the HDF files to it. At the end of a query we always save a copy of the search result summary. This search result summary, converted into a spreadsheet, keeps track of the scenes selected by a query. Search result summaries ensure the time periods encompassing results of each query trial overlap and therefore scenes are not overlooked.

3.3.1.2 Transform Swaths into Grids

3.3.1.2.1 Overview

The MATLAB® script “animate_series.m” (Appendix XXX) simultaneously animates a directory of HDF-EOS swaths in the GCS and creates a series of GCS ASCII files formatted for ArcGIS. The script depends on two subroutines, “expandgrid2.m” and “proccessDuplicates.m” Warning: “animate_series.m” and its subroutines fully utilize a single processor and require at least 2GB of memory to interpolate up to 200 swaths in the UKRW. Without at least 2GB of memory, disk caching operations excessively increase the time to complete the interpolation of the swaths. If MATLAB® depletes all physical memory and starts paging information to the hard disk, break the script and run it again after moving the HDF files that have been already converted into a new folder. Be sure to delete, in this case, the last ASCII file the script created because that file is probably incomplete. The scripts instructs MATLAB®, for each file in a user-specified directory, to:
1. Read Data
   a. Use the inherent MATLAB® function, “hdfinfo,” to read HDF granule data into a MATLAB® structure.
2. Extract three grids of points from the HDF MATLAB® structure into three matrices:
   a. Snow categories
   b. Latitudes
   c. Longitudes
3. Assign latitude and longitude coordinates to each snow category point by resampling latitude grids and longitude grids ten-fold.
4. Assign categories to duplicate coordinates using a modal decision.
5. Fit an evenly spatially-spaced grid to the surface defined by the three duplicate-free snow category, latitude, and longitude grids using Delaunay triangulation built into the MATLAB® function “griddata.”
6. Write fitted data to an ASCII file formatted for ArcGIS

After “proccessDuplicates.m” runs, “animate_series.m” could logically perform another modal decision to make measurement categories more comparable to TOPLATS categories by compositing all categories, listed in Table 3-2, into two categories: snow and snow-free. The “animate_series.m” script, however, does not perform this secondary processing so that we can evaluate MODIS measurement groups during map comparison. By not consolidating all categories at this step, S2K could be readily modified to confirm results from distributed snow-cover models that, unlike TOPLATS, account for categories like water and ice.

3.3.1.2.2 Extract and Resample Location Grids
The snow category matrix, the latitude matrix, and the longitude matrix, although presented in the HDF-EOS file as two dimensional grids and visualized by HDF View in a similar manner, are not regularly spaced in the GCS because the MODIS sensor, while in its sun-synchronous orbit, collects these grids in a 10-minute “long” flyby. If the points were regularly spaced, NSIDC could replace the latitude matrix and longitude matrix in the MODIS product with relatively simple metadata containing the position of a fixed point (e.g. the top left corner of a map) and a pair of values representing the x- and y-spacing between points.

The resolution of each snow category matrix, additionally, is ten times finer than both the latitude matrix and the longitude matrix. If, for example, a snow category matrix contained 20 rows and 20 columns, then both corresponding location matrices would contain two rows and two columns — a total of four cells in each location matrix. The first (upper left) cell in a snow category matrix maps to the first cell in both the latitude matrix and the longitude matrix. The tenth cell (ten cells below the first cell) in the snow matrix maps to the second cell (directly below the first cell) in the location matrices.

The “animate_series” script creates intermediate latitude values and intermediate longitude values spaced evenly between original location values to enable a one-to-one matching of snow category values with location values. To do this, the script instructs MATLAB® to perform a bilinear interpolation on each
location grid with the “interp2” function built into MATLAB®. MATLAB® executes this interpolation process in the “expand_grid.m” subroutine. (The subroutine does not increase the spatial extent of a grid.) The “expand_grid.m” subroutine, for example, expands a two cell by two cell square in an original matrix into a ten cell by ten cell square. Equation 3-1 demonstrates this example for a case in which the original cells are expanded by a factor of two rather than by a factor of ten.

\[
\begin{bmatrix}
100 & 50 \\ 
5 & 1
\end{bmatrix}
\rightarrow
\begin{bmatrix}
100 & 75 & 50 \\ 
52 & 39 & 25 \\ 
5 & 3 & 1
\end{bmatrix}
\]

Equation 3-1 greatly exaggerates the actual expansion of GCS coordinates and shows interpolated values in bold. The values of neighboring cells in the latitude and longitude matrices vary only slightly, if at all, compare to the demonstration values shown in equation 3-1. The distance between originally spaced location points decreases between scenes as the MODIS sensor approaches nadir in relation to the UKRW as described in Figure 3-3.

Figure 3-3 Effect of Satellite Angle on Sample Point Quantity
Assuming MODIS measures points at evenly spaced angles, the point density on the interest area is the greatest when MODIS is close to nadir. The sample point density under the acute angle (in red) is greatest on the left-hand side of the interest area and the smallest on the right-hand side of the interest area. The sample point density under the obtuse angle (in blue) is greatest at the center of the interest area and smallest at the edges of the interest area.

3.3.1.2.3 Assign Categories to Duplicate Coordinates
Given a limited floating point size for coordinate values, the “expand_grid.m” subroutine may produce duplicate coordinates while creating intermediate coordinates to match all snow category points in a granule. The “expand_grid.m” subroutine more-likely produces duplicate coordinates from points that are sensed by MODIS.
close to nadir in comparison to coordinates that are relatively far apart on the earth. These duplicate coordinates, further, may have conflicting snow categories. When duplicate coordinate points all share the same snow category, “animate_series.m” removes all but one of the points from the surface. When duplicate coordinate points report conflicting snow categories, “proccessDuplicates.m” replaces these points with a single point in the same location with a snow category derived by a modal decision algorithm: For an n-size sample of points with the same location

1. Eliminate L1BMissingData points if there are points with other values.
2. Eliminate DetectorSaturated points and NoDecision points if there are points with other values.
3. Eliminate cloud-obsurred points if there are points with other values.
4. Eliminate night points if there are points with other values.
5. Determine the frequency of categories reported by the remaining points.
6. If there is a maximum category frequency, replace all duplicate points with a single point marked with the maximum category frequency. If, otherwise, there is a “category-tie” among the remaining points, pick one of the tied categories at random.

S2K alerts the MATLAB® command window in the case it finds duplicate coordinates. While running S2K, if many (e.g. 5%) duplicate coordinates are found, consider modifying the procedure by increasing the floating point size of coordinate variables. In this case, if the physical memory of a computer limits increasing the floating point size of coordinate variables, consider dividing the interest area up if the interest area is large, or ignoring snow-cover values at interpolated coordinates if the interest area is small.

3.3.1.2.4 Surface Fitting

After “proccessDuplicates.m” determines the snow category for points with duplicate coordinates in the swath surface, “animateSeries.m” creates an evenly spaced location grid from the swath surface in the GCS. Input variables, that “animateSeries.m” reads at the beginning of the script, describe the evenly spaced surface

```matlab
west = -149.53; %lons
east = -149.10;
north = 68.67; %lats
south = 68.47;
west_to_east_inc = .001;
south_to_north_inc = .001;
```

where the bounding variables (west, east, north, and south) describe the UKRW extent in the GCS and the increments (west_to_east_inc and south_to_north_inc) describe the spacing between each point in the evenly spaced grid. The MATLAB® function “griddata.m” performs Delaunay triangulation to populate the evenly spaced grid with categorical values from the swath surface. Note that west_to_east_inc and south_to_north_inc values smaller than 0.001 cause “griddata.m” to produce unexpected, irrational results in which categorical values are averaged rather than selected based on nearest neighbor sampling. Delaunay triangulation is used by other swath-to-grid conversion tools like the LP DAAC MRT Swath Tool (2.2.2.4.3). After “griddata.m” fits each swath surface into evenly spaced
3.3.1.3 Make Grids Comparable to Model Results

Projecting GCS (WGS 1984) maps created by “animate_series.m” into the model projection system, Clarke 1966 UTM Zone 6, begins the third step in the S2K process. When an ArcMap user attempts to directly project an UKRW map from the GCS into the model coordinate system and model extent, using for example an “ArcToolbox” wizard, ArcGIS unexpectedly shuts down. To compensate for this problem, the Python script “ascii2kuparuk.py” instructs the ArcGIS processor, called the “geoprocessor,” to first project GCS maps into the Albers Equal Area Conic coordinate system, and then to secondly project the maps from the equal area coordinate system into the model coordinate system. Note that ESRI makes the intermediate coordinate system, Albers Equal Area Conic, a standard that is easily available to ArcDesktop users. This coordinate system is available to users under the hierarchy of labels: Continental, North American, Alaskan. Note that the Albers Equal Area Conic system could be useful in confirming model results spanning larger arctic areas like the entire Kuparuk River.

In a final step, “ascii2kuparuk” masks the raster in the model coordinate system with a watershed raster defined by a cell size and extent comparable to TOPLATS output

```python
gp.extent = "390862.8 597414.74 418181.52 627228.92"
gp.cellSize = "131.34"
```

where the values, in order, of “gp.extent” define minimum easting, minimum northing, maximum easting, and maximum northing values all in meters. The parameter, “gp.cellSize,” defines the cell size of the mask, 131.34 m, which equals the cell size output by TOPLATS. The mask is simply a rectangular grid in the model projection system with the extent of the interest area. Watershed pixels in the mask report unity while all other pixels report zero (re-classed from null values). Once a granule is masked, “ascii2kuparuk” saves it in a floating point file for comparison to the model.

**Figure 3-4 Python Script, “ascii2kuparuk” Processes**
The python script, “ascii2kuparuk,” instructs the geoprocessor to transforms GCS grids created by “animate_series.m” into raster images that are comparable with model output.

Figure 3-4 charts the process “ascii2kuparuk” performs on each GCS grid. In order to reproduce this procedure ArcMap users must set up their workspace; they must

1. Add the “ascii2kuparuk.py” script to their tool box or load it from an existing toolbox.
2. Obtain the spatial analyst extension and set the spatial analyst options to match the extent of the mask:
   a. top: 627228.92
3. Set the cell size variables in the Spatial Analyst options (accessible in ArcMap via Spatial Analyst → Options > Cell Size Tab) and the environment settings (accessible via Tools menu → Options → Geoprocessing Tab → Environment Settings Button) to:
   a. Cell size: 131.34
   b. Number of rows: 227
   c. Number of columns: 208

Warning: Only raster multiplication will correctly mask the watershed for an individual gradual. The “Extract by Mask” command consistently produces and offset error and, sometimes, produces maps with a number of cells incomparable with model output.

### 3.3.2 Model Data and Calibration

The entire modeling process consists of model conceptualization, model formulation, model calibration, and model confirmation. The following steps describes how to calibrate TOPLATS (2.3.1) for measured data and select a SWE threshold to discriminate between snow-free and -covered areas.

1. Determine the winter-sprint melt time period from MODIS measurements
2. Define input parameters…..
Chapter four presents MODIS measurements independent of TOPLATS results (4.1), presents results from calibrating TOPLATS with three different albedo values and varying the SWE threshold (4.2), and presents, finally, map comparison results to show how well MODIS confirms TOPLATS (4.3). Chapter four limits its discussion of implications of each result to their effects on steps described in the methodology, (including evaluation of statistics via Table 3-3), while chapter five summarizes all results, critiques our methodology, and suggests future work. Note: Throughout chapter four and chapter five, unless lake ice is specifically mentioned, snow refers to both members of the MODIS measurement group “frozen” defined in Table 3-2 — lake ice and snow.

4.1 MEASUREMENTS
We need to download and review MODIS measurements before running TOPLATS because model input parameters depend on the winter-spring melt period revealed by MODIS. Additionally, the quality assurance of MODIS measurements determines the usability of individual scenes in model confirmation. This section shows measurement results from this review exclusive of model results. It shows swath plots and grid plots of MODIS snow cover, cloud cover, quality assurance, and other categorical data throughout the S2K procedure described in section 3.3.1. It shows the effect of observation time during the day, the effect of cloud coverage, and the effect of elevation on snow cover measurements. The results in this section reveal ambiguities in MODIS measurements, and ultimately aid us in selecting a set of observations that we believe are closest to “ground truth.” We use these observations — the ones that we have the most confidence in — for both selecting the times to get model results in section 4.2 and confirming model results via map comparison in section 4.3. Probability quantifies our uncertainty of measurements at each scene through the triangle-shaped probability density function described in section 2.4.3.2. Plots of %SCA versus time of day and plots of %SCA versus day of the year, along with plots of supporting quality assurance information like cloud coverage and like overall quality, support qualitative explanations of our confidence in individual MODIS scenes to confirm model results.

4.1.1 DAAC Query Results
Given the peak annual discharge usually occurs shortly after the winter-spring snow melt in the UKRW, as explained in section 2.1.2, the peak winter-spring discharges shown in the UKRW hydrographs for years 2000, 2001, and 2002 (Figure 4-1) guide the time period for our initial queries to the NSIDC DAAC. Figure 4-2 shows final results of the trial and error process described in section 3.3.1.1 of downloading granules and plotting %SCA versus day of the year in relationship to the these hydrographs. Notice that the %SCA data Figure 4-2 shows many, unrealistically rapid (within time intervals of less than one day) melt and accumulation periods during the course of an overall melt period confined by a smooth, logistic-shaped, upper envelope. The reason why the Figure 4-2 reports an unrealistic result, is because the figure shows %SCA results irrespective of the following filters (a) supporting quality...
assurance information described in section 2.2.2.3, (b) collection time information (besides night time), (c) elevation information, and (d) satellite. This unfiltered†† %SCA series only considers categories listed in Table 3-2 and our decision to request only daytime granules from the DAAC. Table 3-2 categories plus the daytime query flag, even though they yield the overall unrealistic %SCA series in Figure 4-2, do sufficiently indicate a rough (plus or minus a few days) time period to narrow collection of model input parameters and perform map comparison in. Figure 4-2 indicates that model confirmation for the winter-spring snowmelt depends on model results between day 150 and day 165 in the year 2000, day 145 and day 165 in the year 2001, and day 135 and day 150 in the year 2002. Appendix XXX shows the MATLAB® script, “plot_hydrographs.m”, which shifts the hydrograph data from Kane (2009) in Alaska local time into coordinated universal time (UTC) and plots results with MODIS snow cover.

View all MODIS scenes using the application at http://choy.me/david/research/thesis/filter.php, where MODIS maps can be sorted by the filters described in Table 4-1. The application colors unavailable pixels, including cloud-covered pixels, grey; it colors snow blue; and it colors snow-free land brown. Complete sets of unfiltered MODIS snow cover maps support their unrealistic %SCA series counterparts from Figure 4-2. The unfiltered maps show patches of snow cover that appear and disappear from one scene to the next. The maps suggest that either physical factors like wind possibly moved snow across the watershed in between measurement times, or that the snow cover observations do not fully consider the impact of supporting quality assurance information — like a broken detector band, an obtuse sensing angle, an uncertain radiance calculation, or clouds detailed in section 2.2.2.3. Section 5.XXX suggests additional factors, not necessarily completely inherent to HDF-EOS quality assurance information, that could contribute to measurement error.

4.1.2 Influence of Availability, Collection Time, and Quality Assurance Filters on Measurement Uncertainty

While the unfiltered maps seem to indicate patches of snow moving from one scene to the next in short time intervals (under one day), time-composite maps of the sum of SCA over the entire melt period of each year, shown in Figure 4-3, indicate that snow consistently persists the longest during the melt period at locations in the lower elevations zones across all three years evaluated. The color of each pixel this figure represents the number scenes in a series that show that pixel covered with snow. Figure 4-3a does not provide clear results compared to Figure 4-3b because clouds and invalid data influence the plots shown in Figure 4-3a while Figure 4-3b considers three filters: 90% available coverage, 50% or greater quality of points, and the

†† The word “unfiltered,” when exclusively describing measurement maps in this study or comparison results in this study, refers to the scenes corresponding to the measurement times described in this passage. “Filtered” scenes, alternatively, refer to a subset of scenes defined by one or more variables Table 4-1 lists most of these filters.
morning time period (close to solar noon) times. Note: Reference the DEM in Figure 4-4 while reviewing elevation-specific results throughout this chapter.

Figure 4-5, Figure 4-6, and Figure 4-7 shows sets of filtered scenes from respective years 2000, 2001, and 2002. Each set contains images that start with close to 100% likely SCA and end in none. The filter selections in each of these figures maximize the useful information for each year. In Figure 4-5, nine sequential morning scenes from year 2000 between noon (UTC) at day 151 and the end of day 154 reveal unavailable pixels, resulting from mainly clouds, obscure the melt window. Changing the morning filter to an evening filter in this figure reveals a series which include a similar amount of cloud coverage and likely, mis-detected points. View these evening scenes by adjusting Figure 4-5 at the website location specified in the caption of this figure.

Figure 4-6 shows nine sequential morning scenes from year 2001 between day 151 and day 159 with 0.40 or greater proportion of good quality swath points. These scenes represent the beginning of the melt period inferred from Figure 4-2, which appears to last from day 150 to 160. The middle of the melt period, occurring between day 154 through day 157, is absent from these filtered results. During this time, in the middle of the melt period, the proportion of good quality swath points falls below 0.40. The figure reveals a strong correlation between the proportion of points available in the scene and the quality assurance information. Changing the time-of-day filter parameter to evening yields nine scenes with unavailable information, blanketing the series. See these evening scenes by adjusting this Figure 4-6 at the website location specified in the caption of this figure.

Figure 4-7 shows fifteen sequential morning scenes with a proportion of quality swath points greater that 0.50 between day 138 and day 146 during the year 2002. The year 2002 contains more available coverage with higher quality measurements during the melt period than either the year 2000 or the year 2001. Unlike the series shown in Figure 4-5 for the year 2000, this figure shows no cloud coverage. Unlike the series shown in Figure 4-6 for the year 2001, this figure contains scenes that are more evenly sampled across time during the melt period. Notice that all of the scenes in this figure have 100% available coverage, which means the estimate of uncertainty in these measurements due to unavailable pixels is zero. Like Figure 4-5 and Figure 4-6, adjust Figure 4-7 at the website location specified in the caption of the figure.

Extending the time periods in Figure 4-5, Figure 4-6, and Figure 4-7 to days both before and beyond their respective melt periods reveal some scenes that have high data availability, but unrealistic coverage. MODIS reports near complete SCA, for example, on day 144 of the year 2000 and almost no SCA on the local evening of day 145 at 5:25 UTC. The sensor, subsequently, reports almost 100% SCA later in the day after a period of low availability due to cloud coverage. The time that a given measurement was collected explains the poor quality of this scene, and many others like it. Figure 4-8, Figure 4-9, and Figure 4-10 show effect of measurement time and quality on SCA for all the unfiltered scenes from 2000, 2001, and 2002. The first plot in each of these figures (a) shows the proportion of four supporting quality assurance measures at each swath point cropped by the model area in the GCS. The second plot in each of these figures (b) shows the data from data from a on an hourly basis in
relationship to sunset, sunrise, and solar noon. These plots define two measurement time periods — morning, which is close to solar noon and evening, which extends past sunset. The third plot in each of these figures (c) summarizes plot a, plot b, and SCA reports. The larger, bluer, circles in these plots represent increasing proportions of good quality swath points. Note that the evening data in the second plot of each figure includes night scenes even though our DAAC queries included the request to ignore night data. See Figure 4-8 for this description of the three plots specific to year 2000.

The 2000 data in Figure 4-8 shows MODIS collected the highest quality measurements (> 0.90) before and after the three days of quick snow melt. During the melt, almost all the scenes with 50% or higher quality assurance are morning scenes. Figure 4-9 shows 2001 data in the same types of plots described in Figure 4-8. Figure 4-9a shows a high proportion of abnormal quality points during the melt period which are reflected by the gray areas in Figure 5 maps. Figure 4-9b shows that while MODIS reports the highest cloud coverage after sunset, it also reports many good quality points. This could suggests that MODIS could mistake low-lit ground for clouds after sunset. In each day during the begging of the melt shown in Figure 4-9c, the points that deviate from the upper SCA envelope the most are all evening points. The quality of these points, however range from 0% good quality points to over 50% good quality points. The scenes on day 148 and 149 with the lowest SCA and medium-good quality, for example, both occur in the evening. We suspect that these points are invalid outliers due to poor measurement capabilities of MODIS in the evening.

Figure 4-7a, which plots supporting quality assurance information versus the time of year 2002, shows the proportion of good quality points scattered across the month of May starting on day 121. Abnormal points are also scattered over the month. The proportion of cloud obscured points remains consistently below 0.3 or over 0.9 with the exception of four outliers, half of which contain mostly invalid points of data among the remaining cloud free points. The other two outliers contain mostly good points of data among remaining cloud free points. Figure 4-7a shows that the fourteen scenes with a proportion of invalid points greater than 0.01 all occur before day 133 with the exception of one scene occurring on day 139 with a proportion of invalid points under 0.05. The apparent drop off of invalid points later in the month cannot easily be explained by this figure alone. Figure 4-7b shows there are exactly 47 scenes in the morning set and 47 scenes in the evening set. Looking at the proportion of quality assurance information in Figure 4-7b in relationship to apparent sunset, notice how the set of data collected later in the evening includes many invalid points after sunset between hour seven and hour nine UTC. We can conclude, based on the apparent correlation between invalid points and time after apparent sunset, that perhaps the drop off of the proportion of invalid points on day 133 unexplained by figure Figure 4-7a alone is due to DAAC results successfully limiting night scenes starting on day 133. Also notice in the evening period that the median proportion of the good quality points in the model interest area above 0.10 at night is higher than the median of all other proportions of good quality points above 0.10. In other words, at night, MODIS reports that measurements are either very poor quality or very high quality. There is no proportion of good quality points between
0.20 and 0.80 at night and we have not found an explanation for this result in the literature. We can, however, attribute the lack of “abnormal” points and increase of “invalid points” at night to the poor reflectance of snow in low light. The evening points, in summary, contain less trustworthy information based on the night scenes with a high proportion of invalid points. Finally, compare the frequency of the proportion of cloud-covered points in the model area during the morning times and the evening times: There are no points in the morning time interval with more than a 0.05 proportion of cloud coverage while every hour in the evening time interval has at least one scene with a 0.15 proportion of cloud coverage. We, therefore, based on both these observations and conclusions made by Hall et al. in 2001 explained in section 2.2.2.1, prefer the set of measurement scenes captured in the morning over set of measurement scenes captured in the evening.

Given the results described in this section, above, and the availability of TOPLATS input parameters for 2000, 2001, and 2002, the remainder of this study discusses the morning scenes for the year 2002, and focuses in particular, on the filtered in Figure 4-7. Of the three years discussed, we have the most confidence in the measurements from the year 2002. The MODIS data from the year 2000 contains too many invalid scenes as shown in Figure 4-5 and Figure 4-8. Data from 2001 does not contain any scenes in the middle third of the melt period. Although scenes like the one on day 143 at 20:15 in 2002 shown in Figure 4-7 look out of place in context with the two filtered scenes occurring before and after it, the number of available (including cloud-free) scenes in the year 2002 out numbers the available scenes in the other two years. The 2002 measurements show two areas persistent snow, that get smaller and smaller, shown in Figure 4-3b and Figure 4-7 more clearly than the 2000 measurements or the 2001 measurements do in their respective figures. MODIS observations for the year 2002, therefore, can most-appropriately verify model output in comparison to year 2000 and year 2001.

Figure 4-11 plots the minimum, likely, and maximum proportion SCA values that define the triangle-shaped probability density (PD) distributions described in 2.4.3.2. Plots are shown for (a) all scenes, (b) all morning scenes, and (c) all morning scenes with a 0.50 or greater proportion of good quality swath points. The figure reinforces our conclusion that a combination of measurement availability, collection time information, and supporting quality assurance information determines the overall usefulness of a series of measurements. The black circles in each scene represent likely PD and the black lines represent the PD distribution. The red x points represent the minimum PD and the green cross points represent the maximum PD. In cloud-free scenes with 100% availability, the maximum SCA and minimum SCA PD values are equal. Figure 4-11 marks these scenes with overlapping a red x points and green + points; but for clarity, does not include black PDF lines which would extend infinitely on the PD axis. Additionally, Figure 4-11 hides the black PDF lines for scenes with 100% unavailable (in-part cloud obscured) pixels. The figure does show, however, the opposing minimum and maximum %SCA values. In the hypothetical case our baseline measure of uncertainty of SCA per independent scene was 50% snow or 50% snow free, we could plot PDF functions for the scenes with 100% unavailability. These hypothetical PDFs that would have a PD of 2 at 0.50 proportion SCA.
Figure 4-12 and Figure 4-16 show the morning scenes and morning scenes with a 0.50 or greater proportion of good quality swath points shown in Figure 4-11 across the entire watershed and four elevation zones. The plots show more scatter in the higher elevation zones. The scatter, however, looks correlated to the smaller sample sizes. This study does not investigate this apparent correlation.
Table 4-1. Scene Filters  
View [http://choy.me/david/research/thesis/filter.php](http://choy.me/david/research/thesis/filter.php) to apply these filters on MODIS data in the TOPLATS model system where each cell is 131.34 square meters. Grey cells represent clouds, blue cells represent snow, and brown cells represent snow-free land.

<table>
<thead>
<tr>
<th>Filter</th>
<th>Description / Values</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Temporal</strong></td>
<td></td>
</tr>
<tr>
<td>Year</td>
<td>All (2000, 2001, 2002)</td>
</tr>
<tr>
<td></td>
<td>2000</td>
</tr>
<tr>
<td></td>
<td>2001</td>
</tr>
<tr>
<td></td>
<td>2002</td>
</tr>
<tr>
<td>Day of Year Range</td>
<td>Time since the beginning of a year in decimal days</td>
</tr>
<tr>
<td>Time of Day</td>
<td>All (Morning and evening)</td>
</tr>
<tr>
<td></td>
<td>Morning (Near solar noon)</td>
</tr>
<tr>
<td></td>
<td>Evening (Near night)</td>
</tr>
<tr>
<td>Sequence Number</td>
<td>Rank of a map among all unfiltered maps for a year</td>
</tr>
<tr>
<td><strong>Spatial</strong></td>
<td></td>
</tr>
<tr>
<td>Quality Range</td>
<td>Proportion of good quality swath points in a GCS bounding box</td>
</tr>
<tr>
<td>Proportion Available Range</td>
<td>Proportion of snow-covered or snow-free pixels</td>
</tr>
</tbody>
</table>

Figure 4-1 Winter-Spring Hydrographs  
The peak discharge collected by Hinzman and Kane (2009) time during May and June, for each 2000, 2001, and 2002, guides the time period selection in our initial queries for snow cover. It also allows us to cross reference MODIS Quality Assurance information for those times. Note that the day of year references UTC time, not UKRW local time which is nine hours ahead. May 1 occurs on day 135. (See [http://modland.nascom.nasa.gov/QA_WWW/](http://modland.nascom.nasa.gov/QA_WWW/)). See MATLAB® script "plot_hydrographs.m" to reproduce this figure.
The beginning of the winter-spring melt in the UKRW occurs within ten days prior to the peak winter-spring discharge in each of the years, 2000, 2002, and 2002, shown. The %SCA series shows results of each scene returned by the DAAC from the day-time query, irrespective of cloud coverage, day of year, measurement quality, or any other scene-excluding factor. %SCA in this plot is calculated over the watershed area, not the model bounding box. See MATLAB® scripts “compare_calculate_all.m” and “plot_hydrographs.m” to reproduce these figure.
Figure 4-3 Sum of Snow-Covered Pixels Across Unfiltered and Filtered Melt Series' 
Brightness-normalized plots of the sum of the number of pixels where snow lasts during a melt series indicates either the location of possible physical features that should be considered by a model to limit snow melt, or the location of features that limit MODIS from correctly sensing snow. In the UKRW, clouds and poor quality measurements confuse the plots derived from the unfiltered scenes (a). The plots derived from the filtered scenes (b), however, clearly show two areas flanking the river path where snow lasts the longest. Maps are shown in the model coordinate system where southing and easting units are pixels widths of 131.34 m. See MATLAB® script "plot_cumulative_sca.m" to reproduce these figure.
Figure 4-4 UKRW Elevation Zones

Elevations equally spaced at 736.4 m (minimum elevation), 925.4 m, 1,114.3 m, 1,303.3 m, and 1,492.2 m (maximum elevation) above sea level bound four 189.0 m elevation zones in the UKRW. In the 131.34 m model grid (Table 2-2), zone one covers 3,015 pixels (52.01 km$^2$), zone two covers 4,173 pixels (71.99 km$^2$), zone three covers 1,184 pixels (20.42 km$^2$), and zone four covers 185 pixels (3.191 km$^2$). Note that easting and southing units are pixel widths in the model grid. See MATLAB® script “elevationszones.m” to reproduce this figure and see a side views of the watershed elevation zones.
Figure 4-5 2000 Select MODIS Scenes
Unavailable data, caused predominantly by cloud coverage, obscures the most important scenes during the 2000 melt period. This figure shows morning scenes during the melt period. See evening scenes, which include a similar amount of cloud coverage and likely, mis-detected points by adjusting this figure at http://choy.me/david/research/thesis/filter.php?Y=2000&Tmin=151.5&Tmax=154.9&M=Morni ng&Qmin=0.00&Qmax=1.00&Amin=0.00&Amax=1&Nmin=1.00&Nmax=500&go=Submit.
Morning scenes with 0.40 or greater proportion of good quality swath points show the beginning of the melt period inferred from Figure 4-2, which appears to last from day 150 to 160. The middle of the melt period, occurring between day 154 through day 157, is absent from these filtered results. At these times the proportion of good quality swath points falls below 0.40. View these points and modify this figure at http://choy.me/david/research/thesis/filter.php?Y=2001&Tmin=151&Tmax=158.91&M=Mornin g&Qmin=0.4&Qmax=1.00&Amin=0.00&Amax=1&Nmin=1.00&Nmax=500&go=Submit.
Continued on the next page, the fifteen 2002 morning images with a proportion of good quality swath points greater than 0.50 shows more clear information than the images from previous two years. Unlike year 2000, this figure shows no cloud coverage. Unlike year 2001, this figure contains scenes that are evenly sampled during the melt period. View more at http://choy.me/david/research/thesis/filter.php?Y=2002&Tmin=138&Tmax=145.85&M=Mornin g&Qmin=0.5&Qmax=1&Amin=0.00&Amax=1&Nmin=1.00&Nmax=500&go=Submit.
Figure 4-7 2002 Select MODIS Scenes Continued from Previous Page
Figure 4-8a. Supporting Quality Assurance Information Versus Day of Year

Figure 4-8b. Supporting Quality Assurance Information Versus Hour of Day
**Figure 4-8c. SCA Versus Day of Year, Morning or Evening, and Quality Assurance**

**Figure 4-8 Year 2000 Quality Assurance, Collection Time, and Proportion SCA**

MODIS reports four supporting quality assurance measures at each swath point. Figure 4-8a shows the proportion of each of these measures in every scene cropped by the model area in the GCS. Figure 4-8b shows the data from Figure 4-8a on an hourly basis in relationship to sunset, sunrise, and solar noon. The plot define two measurement time periods — morning, which is close to solar noon and evening, which extends past sunset. Figure 4-8c combines Figure 4-8a, Figure 4-8b, and SCA reports. In Figure 4-8c, the larger, bluer, circles represent increasing proportions of good quality swath points within a model area scene. Figure 4-8a and Figure 4-8c share the same x-axis scale and range.

The 2000 data shows good quality scenes during the melt are almost all morning scenes. Read more about this figure in section 4.1.2.
Figure 4-9a. Supporting Quality Assurance Information Versus Day of Year

Figure 4-9b. Supporting Quality Assurance Information Versus Hour of Day
Figure 4-9c. SCA Versus Day of Year, Morning or Evening, and Quality Assurance

Figure 4-9. Year 2001 Quality Assurance, Collection Time, and Proportion SCA
This figure shows 2001 data in the same types of plots described in Figure 4-8. We suspect evening points, like one with the medium-good quality but no SCA during the beginning of the melt on day 148, report invalid information due to the poor ability of MODIS to detect snow at times of the day far from solar noon. Section 4.1.2 analyzes this figure further.
Figure 4-10a. Supporting Quality Assurance Information Versus Day of Year

Figure 4-10b. Supporting Quality Assurance Information Versus Hour of Day
Figure 4-10c. SCA versus Day of Year, Morning or Evening, and Quality Assurance

**Figure 4-10. Year 2002 Quality Assurance, Collection Time, and Proportion SCA**

This figure shows 2002 data in the same types of plots described in Figure 4-8.

Figure 4.9a shows a high proportion of abnormal quality points during the melt period which are reflected by the gray areas in Figure 4.5 maps. Figure 4.9b shows that while MODIS reports the highest cloud coverage after sunset, it also reports many good quality points. This could suggest that MODIS could mistake low-lit ground for clouds after sunset. In each day during the beginning of the melt shown in Figure 4.9c, the points that deviate from the upper SCA envelope the most are all evening points. The quality of these points, however range from 0% good quality points to over 50% good quality points. The scenes on day 148 and 149 with the lowest SCA and medium-good quality, for example, both occur in the evening. We suspect that these points are invalid outliers due to poor measurement capabilities of MODIS in the evening.
Figure 4-11a. All Scenes

Figure 4-11b. Morning Scenes
Figure 4-11c. Morning Scenes with a 0.50 or Greater Proportion of Good Quality Points

**Figure 4-11. 2000 Probability as a Measure of Uncertainty**
Probability density (PD) plots indicate increasing certainty of measurements from (a) all scenes to (b) morning scenes to (c) morning scenes with a 0.50 or greater proportion of good quality swath points. In each figure, the black lines represent the PD distribution, the red x points represent the minimum PD and the green cross points represent the maximum PD. The black circles represent the likely PD for scenes with any available points or scenes where the maximum PD does not equal the minimum PD.
Figure 4-12a. Watershed

Figure 4-12b. Zone One

Figure 4-12c. Zone Two
Figure 4-12. 2002 Morning Scenes Across The UKRW and Four Elevation Zones
The proportion minimum, likely, and maximum SCA shown in Figure 4-11b are plotted for (a) the entire watershed and four elevation zones (b-e). Only, and all, morning scenes are shown.
Figure 4-13a. Watershed

Figure 4-13b. Zone One

Figure 4-13c. Zone Two
Figure 4-13. 2002 Morning Scenes with a Proportion of 0.50 or Greater Good Quality Swath Points Across The UKRW and Four Elevation Zones

The proportion minimum, likely, and maximum SCA shown in Figure 4-11c are plotted for (a) the entire watershed and four elevation zones (b-e). Only, and all, morning scenes with a proportion of 0.50 or greater good quality swath points are shown.
4.2 Model Results

Two parameters, in addition to DEM and adiabatic lapse rate (discussed in 2.3.1), drive model %SCA results: (a) the snow albedo, measured in a percentage of light reflected by the snow surface, and (b) the SWE threshold, that indicates the minimum millimeters of SWE to consider a model cell snow-covered. (Recall that the model predicts a continuous SWE value at each pixel in comparison to the snow/snow-free categories that MODIS implies. In order to make a comparison between these measures, a new parameter — SWE threshold — defines the value of SWE at a model pixel where that pixel is considered snow covered.) A sensitivity study where snow albedo varies between trials, the model produced two simulated SWE maps for each trial: an overstory map and an understory map. This study uses the sum of the understory SWE and the overstory SWE. Raising the snow albedo, as expected, increases the melt period; it causes the snow to reflect more energy than absorb it. In some cases, when we set the snow albedo high, TOPLATS simulated snow accumulation during the expected melt period.

Section 4.2.1 discusses TOPLATS results independent of MODIS measurements and independent of any the SWE threshold. It maps three TOPLATS scenes corresponding to the select 2002 scenes from Figure 4-7, and shows the effect of elevation on SWE results. Section 4.2.2 shows the effect of three SWE thresholds on SWE results in conjunction with MODIS SCA results. This section only discusses results from the year 2002.

4.2.1 Snow Water Equivalent

Figure 4-14 shows TOPLATS SWE maps for snow albedo values of 0.75, 0.80, and 0.85 for the (a) first, (b) middle (seventh), and (c) last scene of the select 2002 MODIS scenes shown in Figure 4-7. Figure 4-15, Figure 4-16, Figure 4-17, Figure 4-18, and Figure 4-19 show SWE means, SWE standard deviations, and box plots grouped by day for the entire watershed and each of four elevation zones during the 2002 melt period.

Figure 4-14 shows the effect of elevation on model results. Snow in the higher elevation zones, framed by Figure 4-4, depletes the quickest. The whitest areas in both Figure 4-14b for a 0.80 albedo and Figure 4-14c for a 0.85 albedo show that snow remains the longest along the river path. Figure 4-14 also indicates the model with the 0.80 albedo, without consideration to a SWE threshold, best predicts the 2002 MODIS measurements because the other two scenarios show complete snow melt on day 142 (albedo = 0.75) and incomplete snow depletion at the end of the melt period (albedo = 0.85). The mean watershed SWE and daily SWE boxplots shown in Figure 4-15 confirm this result.

Figure 4-15, additionally, shows (a) a period of relatively constant SWE from day 146 to day 150 given an albedo of 0.85, (b) a decreasing SWE standard deviation in the 0.75 albedo series compare to an increasing SWE standard deviation in the 0.80 albedo series and the 0.85 albedo series, and (c) SWE values further below the 25% quartile than above the 75% quartile. The shape of the simulated SWE appears to match that of an arc more than a logistic function.
In the 0.75 albedo series, the snow melts relatively quickly compared to the other two albedo series. The model reports no snow at the end of day 140. The mean SWE plot reveals snow melting in downward “steps” that each, shown in a zoom view, incline upward slightly with time. The mean SWE starts at 1.97 cm. In the 0.80 albedo series, snowmelt completes exactly four days (96 hours) after the melt completes with an albedo of 0.75 and the total SWE starts at 2.56 cm. During this time period, the SWE standard deviation and range increases over the melt. In the 0.80 albedo series snowmelt completes well after the expected time period. The range and standard deviation of the SWE values increase throughout the simulation. The mean SWE starts at 2.89 cm and exceeds 1 cm through day 150.

Figure 4-16a mean model results, limited to elevation zone one, start higher and end lower than the mean watershed SWE values for an albedo of 0.85. Figure 4-16b standard deviation values are lower than those for the entire watershed and increase during the beginning of the melt defined by the mean values. Figure 4-16c box plots show that the range of SWE at each day in zone one is smaller than that shown in the entire watershed. The zone one boxes, whiskers, and minimum values are all larger than those in the entire watershed. The maximum values are close to those in the watershed. Zone two through four SWE values, therefore, should have lower SWE values than zone one. The time to melt in zone one appears to mirror that of the watershed.

Zone two SWE values shown in Figure 4-17a and Figure 4-17c are lower than zone one values shown in Figure 4-16a and Figure 4-16c. Given the 0.80 albedo box-plots in zone one and zone two, while melt completes in both series at day 145, the mean SWE value approaches zero more quickly (day 144) in zone two. The magnitude of the spread and standard deviation of the SWE values in zone two is close to that of zone one because they have similar sample sizes compared to the watershed. A shorter melt period in zone two compared to zone one causes the standard deviation of the 0.80 series to increase more rapidly from the beginning of the melt period through day 143 where it drops down to close to zero at the end of the 0.80 albedo melt on day 144. The standard deviation of the 0.75 series, conversely, decreases in zone two during the melt period compared to the increase in zone one.

Figure 4-18 shows that zone three SWE values decrease faster than the lower zones. Unlike zone one and zone two, during end melt for both the 0.80 albedo and the 0.85 albedo, on day 142, the standard deviation of the SWE values for the 0.80 albedo series is higher than that of the 0.85 albedo series. Also unlike lower zones, the 0.80 albedo series completely melts at day 144 compared to day 145. At the top of the watershed, SWE values shown in Figure 4-19 are the lowest and the melt period is the quickest. There is still snow on the ground, however, on the last simulated day (day 151). The standard deviation values for all three albedo values in zone four are almost the same until day 141 when the 0.75 albedo series melts. On day 143, the 0.80 series standard deviation series diverges from the 0.85 series standard deviation series because TOPLATS, at this time, completely depletes the snow in some partial areas of zone four.

Two plots in Figure 4-20 compare SWE values from Figure 4-15a with MODIS SCA values on a second, overlapping axis. The first plot (Figure 4-20a) shows mean SWE values and the second plot (Figure 4-20b) shows the mean SWE
values normalized by the minimum mean and maximum mean SWE values in the series. In each plot, blue circles mark the likely MODIS proportion SCA for each scenes. Blue lines, capped with blue points, connect the minimum and maximum possible proportion SCA values explained by section 2.4.3.2. Figure 4-21 shows a subset of the information in Figure 4-20 filtered by the morning scenes with a proportion of 0.50 good quality swath points. The MOIDS measurements in this figure are the same as those plotted in Figure 4-13a. The uncertainty of MODIS measurements in this figure are the same as those plotted in Figure 4-11c. Fewer uncertainty lines in Figure 4-21 compare to Figure 4-20 confirm our finding described in 4.1 that morning scene measurements are less ambiguous than evening scene measurements. The two figures also confirm that the 0.75 albedo series depletes too quickly and the 0.85 series, even when it is normalized, depletes too slowly. Figure 4-21 suggests that the 0.85 series, normalized by the maximum mean SWE at the start of the series (2.89 cm) and the minimum mean SWE at the end of the apparent MODIS melt period, around day 145, could be more comparable to the 0.80 series. Figure 4-22 tests this idea and reveals that if the normalized SWE series’ were used to indicate proportion SCA, the 0.85 albedo series would over estimate the MODIS proportion SCA more than the 0.80 albedo series would underestimate it. In summary, plots of SWE and SCA show that the 0.75 albedo series time to melt is too short. The 0.80 albedo series and 0.85 albedo series, however, could both predict MODIS SCA depending on both the spatial variability of SWE values (shown in Figure 4-15 through Figure 4-19) and a SWE threshold.

Chapter four presents MODIS measurements independent of TOPLATS results (4.1), presents results from calibrating TOPLATS with three different albedo values and varying the SWE threshold (4.2).

Section 4.1 reviewed the MODIS measurements in terms of filters including collection time of day and quality assurance information. The section shows that measurements from the year 2002 can be trusted more than those from the year 2000 and 2001. In section 4.2.1, the SCA measurements from 2002 are compared with TOPLATS SWE model results in a sensitivity study for values of varying albedo. This section shows that while the 0.80 albedo simulation or the 0.85 albedo simulation could possibly predict the measured data, at least on a time-to-melt basis, the 0.75 simulation produces a brief melt time that under-predicts the observed melt time.

4.2.2 Snow Covered Area Threshold

The SWE threshold parameter, explained in section 3.2.1, determines the minimum SWE for any pixel in any scene for us to consider that pixel snow covered. We can seed our selection of a SWE thresholds to analyze based on the mean SWE and normalized mean SWE plots: Figure 4-21a suggests the SWE threshold seed for the 0.80 albedo series starts at 0 m because the mean SWE series depletes before the MODIS SCA series does; raising the threshold for this series would lower the mean SWE values yielding an even earlier time of depletion at some locations. For the 0.85 albedo series, Figure 4-21a suggests seeding the SWE threshold between 1 cm and 1.5 cm where the snow melts at day 145. The SWE distributions marked with box-plots in Figure 4-15c, however, shows that these thresholds need to be expanded to
consider the distribution of SWE values about the mean. Therefore, given these seed values and box-plots, a fair comparison between the 0.80 albedo series and the 0.85 albedo series considers SWE thresholds from 0.00 cm to 3.00 cm in 0.25 cm increments.

The first two plots in Figure 4-23a through Figure 4-23f (i) compare MODIS and TOPLATS proportion SCA and (ii) show the proportion of agreement between the two maps, both due their initial arrangement and in consideration of a random relocation of cells, for a 0.80 albedo. The first two plots in Figure 4-24a through Figure 4-24f show similar information for a 0.85 albedo simulation. Both Figure 4-23 and Figure 4-24 only show select plots relevant to their respective albedo values.

The proportion SCA comparison in Figure 4-23a, which employs the 0.00 cm SWE threshold seed value inferred from Figure 4-21a shows the 0.80 albedo TOPLATS series over predicting for the MODIS observations. In Figure 4-23b, the 0.75 cm SWE threshold model data gets closer to the TOPLATS data, especially at the beginning and end of day 141. The modeled proportion of SCA at the end of day 141 in Figure 4-23c, for a 1.00 cm SWE threshold, lies the closest to the measured SCA data than that in any marker shown in Figure 4-23 – but the prediction of SCA on day 143 is too close to zero compare to a measurement of 0.40 proportion SCA. Therefore, based on the SCA and proportion of agreement plots alone, the 0.75 cm SWE threshold series shown in Figure 4-23b best predicts the MODIS measurements for the 0.80 albedo. Figure 4-24, similarly, shows that the 2.50 cm SWE threshold series (Figure 4-24d) best predicts the MODIS observations for the 0.85 albedo. Note that we prefer Figure 4-24d over Figure 4-24e partially because we know that the higher measured SCA points in the series between day 140 and day 144 exhibit higher quality than the lower points as shown in Figure 4-22. Figure 4-25 shows the absolute maximum error in the 0.80 series is higher than then the 0.85 series on every day except for day 142. The plot suggests the 0.85 albedo series with a 2.50 cm SWE threshold best matches the MODIS measurement scenes.
Figure 4-14 Select TOPLATS SWE Scenes for Albedo Values 0.75, 0.80, and 0.85
(a) On day 138, TOPLATS blankets each watershed with snow. (b) On day 142, the 0.75 albedo watershed has no snow and the 0.80 watershed has very little snow. (c) On day 151, after the measured melt, TOPLATS shows snow on the 0.85 map. Southing and easting coordinates reference the model coordinate system and interest area. Figure 4-7 shows respective MODIS scenes.
TOPLATS Watershed SWE (8,557 pixels)

(a) 8,557 SWE pixel values averaged over the watershed versus time confirm that the time for snow to melt increases with albedo. (b) The slope of the standard deviation of SWE for all pixels increases with Albedo. (c) Box and whisker plots grouped by day show that the distribution is skewed with a relatively long tail below the twenty-fifth percentile. For each box, the line in the box is the median and the “+” in the box is the mean. The box encloses points above the twenty-fifth percentile and points below the seventy-fifth percentile. The “+” whisker lines outside the box are the tenth percentile and the ninetieth percentile.
Figure 4-16 TOPLATS Zone One SWE (3,015 pixels)
(a) 3,015 zone one SWE pixel values start higher and end lower than the watershed SWE values for an albedo of 0.85. (b) Standard deviation values are lower than those for the entire watershed. (c) The range of SWE at each day in zone one is smaller than that shown in the entire watershed. See section 4.2.1 for further analysis.
4,173 zone two SWE pixel values are overall lower than zone one values. The shorter melt causes the standard deviation values for the 0.80 albedo simulation and 0.85 albedo simulation to rise above standard deviation values in the zone one simulation.
Figure 4-18 TOPLATS Zone Three SWE (1,184 pixels)
Zone three SWE values decrease faster than the lower elevation zones.
The SWE in the 185 pixels in zone four are the lowest compare to the other four zones. The time to melt, therefore, is the quickest compare to the other zones.

Figure 4-19 TOPLATS Zone Four SWE (185 pixels)
Figure 4-20a. Mean SWE (m)

Figure 4-20b. Mean SWE Normalized by the Minimum Mean and Maximum Mean SWE

**Figure 4-20 2002 Effect of initial Albedo on SWE Model Results**

TOPLATS pixel SWE values, averaged over the watershed, for initial snow albedo values 0.75, 0.80, and 0.85 (left axes) are shown with MODIS SCA (right axis, blue circles) from day 134 through 152. Plot b shows the SWE values normalized by the minimum mean and maximum mean SWE values in the watershed area.
Figure 4-21a. Mean SWE (m)

Figure 4-21b. Mean SWE Normalized by the Minimum Mean and Maximum Mean SWE

**Figure 4-21 2002 Effect of initial Albedo on SWE Model Results for Good Quality Morning Points**

The morning scenes with a 0.50 or greater proportion of good quality swath points are shown on the same types of plots described in Figure 4-20.
Figure 4-22 2002 Effect of initial Albedo on SWE Model Results for Good Quality Morning Points Ending for All Scenes Measured Before The Apparent end of Melt on Day 146.

Compare to Figure 4-21, normalizing the 0.85 series over the shorter time interval makes the 0.85 series more comparable to the 0.80 series. The proportion of good quality swath points at each scene, labeled with black text, however, shows that higher quality scenes lie closer to the 0.80 series and the 0.85 series. Therefore, if the normalized mean SWE series were indicators of SCA and not SWE, then we could conclude that the 0.85 albedo model results overestimate the MODIS measurements on a watershed basis.
Figure 4-23a 0.00 cm SWE Threshold (Year 2002, 0.80 Albedo)
Figure 4-23b 0.75 cm SWE Threshold (Year 2002, 0.80 Albedo)
Figure 4-23c cm 1.00 SWE Threshold (Year 2002, 0.80 Albedo)
Figure 4-23d 1.25 cm SWE Threshold (Year 2002, 0.80 Albedo)
Figure 4-23e 1.50 cm SWE Threshold (Year 2002, 0.80 Albedo)
Figure 4-23f 2.50 cm SWE Threshold (Year 2002, 0.80 Albedo)

Figure 4-23 Year 2002 0.80 Albedo Map Comparison for the Entire Watershed (Zone 0)
Select plots from a complete set of plots for SWE thresholds from 0.00 to 3.00 cm.
Figure 4-24a 0.00 cm SWE Threshold (Year 2002, 0.85 Albedo)
Figure 4-24b 1.50 cm SWE Threshold (Year 2002, 0.85 Albedo)
Figure 4-24c 2.25 cm SWE Threshold (Year 2002, 0.85 Albedo)
Figure 4-24d 2.50 cm SWE Threshold (Year 2002, 0.85 Albedo)
Figure 4-24e 2.75 cm SWE Threshold (Year 2002, 0.85 Albedo)
Figure 4-24f 3.00 cm SWE Threshold (Year 2002, 0.85 Albedo)

Figure 4-24 Year 2002 0.85 Albedo Map Comparison for the Entire Watershed (Zone 0)
Select plots from a complete set of plots for SWE thresholds from 0.00 to 3.00 cm.
Figure 4-25 Year 2002 0.80 Albedo and 0.85 Albedo SCA Error
SCA error from both the 0.80 albedo 0.75 SWE Threshold series and the 0.85 albedo 2.50 SWE Threshold series.
4.3 Model Confirmation

Section 4.2.2 describes results from selecting a SWE threshold for each of two snow albedo values using only (a) overlaying, filtered model and measurement SCA plots and (b) plots of the proportion of agreement between the two map series’ to confirm the best quality observed scenes shown in Figure 4-22. We should additionally, however, should consider (c) the Kappa statistics, (d) the effect of elevation on the overall map comparison, and (e) the uncertainty in the MODIS measurements for scenes with less than 100% coverage in order to both calibrate the model and use the best MODIS measurements to evaluate the model performance. This section completes item c and item d for the select series’ from section 4.2.2, plots filtered modeled and measured maps side by side, and shows the zone-specific comparison statistics. The section skips item e because the given filters based on QA and collection time in the 2002 reduced the series of measurement scenes to those with only 100% available coverage. This completely cloud-free series raises our overall confidence in the measurement series to report truth and leaves confirmation subjective to the QA information in each scene, which ranges from 0.50 to 0.92 (Figure 4-22), side-by-side maps, and elevation information.

Figure 4-26 and figure Figure 4-27 separate the series of statistics in Figure 4-23b and Figure 4-24d into four elevation zones. The SCA plots in these series show SCA agreement across the watershed as a whole agrees much better than the SCA on a zone-basis. This explains the poor Kappa and $K_{location}$ values in Figure 4-23b and Figure 4-24d showing the watershed composite results. Even though the proportion of agreement on a watershed-basis is good; the Kappa statistics reveal poor agreement in by pixel-pixel comparisons. The zone statistics in Figure 4-26 and figure Figure 4-27 show the Kappa values are best for zone one at the beginning of the melt period and that the 0.80 simulation confirms the start and middle of the melt period across zones two through four better than the 0.85 series.

Figure 4-28 shows the two series side by side with MODIS observations. The maps confirm the result from Kappa statistics, both across the watershed and separated into zones, that TOPLATS poorly confirms MODIS results. Further, the figure reiterates that TOPLATS relies primarily on DEM information and shows that additional physical processes should be incorporated, or further emphasized, in order for TOPLATS to well confirm MODIS results.
Figure 4-26a Zone 1
Figure 4-26b Zone 2
Figure 4-26d Zone 3
Figure 4-26d Zone 4

Figure 4-26 Year 2002 0.80, 0.75 SWE Threshold Comparison for Four Elevation Zones
Select plots from a complete set of plots for SWE thresholds from 0.00 to 3.00 cm.
Figure 4-27a Zone 1
Figure 4-27b Zone 2
Figure 4-27d Zone 3
Figure 4-27 Year 2002 0.85, 2.50 SWE Threshold Comparison for Four Elevation Zones
Select plots from a complete set of plots for SWE thresholds from 0.00 to 3.00 cm.
Figure 4-28 SCA Maps for Measured, and Two Sets of Model SCA Results
Continued on the following pages, the 15 MODIS scenes selected for 2002 in Figure 4-7 (column one) are shown to the left of TOPLATS results for an albedo (A) of 0.80 and a SWE threshold (SWE) of 0.75 cm (column two) and the TOPLATS results for an albedo of 0.85 and a SWE threshold of 2.50 cm (column three).
CHAPTER 5: CONCLUSIONS

This chapter
1. Summarizes findings and implications
2. Critiques the methodology describes the value of the data
3. Suggests future work

5.1 FINDINGS AND IMPLICATIONS

5.1.1 Response to Déry et al.

Results confirm Déry et al. (2004) conclusions that clouds hinder MODIS from making complete measurements. MODIS snow cover maps shown in Figure 4-5 and supporting quality assurance information show that clouds, during the winter-spring snowmelt of the year 2000 in particular, obscure the MODIS view of the ground during the brief three and a half day period between noon (UTC) at day 151 and the end of day 154. The results also show that, in conjunction with cloud coverage, other factors help determine the usability of MODIS measurements. These factors include MODIS supporting quality assurance information described by NSIDC (2006) to create the Snow Cover PixelQA eight-bit layer — invalid data, broken detector bands, obtuse sensor angles, “highly uncertain” band 6 radiance, unusable sub-calculations — and also include time-of-day information. A combination of filters, described in chapter four, sift out the most usable MODIS measurements.

This research also agrees with Déry et al. (2004) in that both level two and level three MODIS results do not well confirm SWE maps. For level two measurements, MODIS does not measure SWE nor does MODIS report results in a grid format. For level three MODIS measurements, while they are more readily projected into grids because they are delivered in the GCS, the temporal composite inherent in them is longer than the melt-period in the UKRW. Level three measurements, therefore, are better suited to confirm snow predictions of longer melt periods occurring across larger, global regions like the entire Kuparuk River watershed. For level two MODIS measurements, however, the methodology in-part overcomes these problems through the S2K procedure and a modal decision to generalize multi-category swaths into grids containing three category groups of cells: snow, snow-free, and unavailable. (For these groups, the snow group includes all “frozen” locations including ice, and the snow-free group includes both snow-free land and water.) Plots of MODIS and TOPLATS maps side-by-side, like those in Figure 4-28, show that despite factors that limit the spatiotemporal measurement information in MODIS measurements, during relatively cloud-free years, MODIS data can reveal sub-watershed problems with a model. In the case of TOPLATS predictions for the year 2002, Figure 4-28 suggests TOPLATS relies on DEM information at, perhaps, the expense of other physical factors and other processes that need to be determined. Our confidence in this conclusion is limited largely by the measurement quality assurance proportions in these cloud-free scenes, which range from 0.57 to 0.94, with an average proportion of 0.73 good quality cells.

We can make the positive conclusion that image spectrometers on sun synchronous satellites like Aqua and Terra potentially have the spatiotemporal
resolution to monitor, and confirm SCA predictions for short snow melt periods in watersheds that are a similar size as the UKRW. If the scattered quality of MODIS measurements during melt periods over areas like the UKRW does not increase, however, in years to come — which is limited by both natural (cloud coverage) and human (small number of satellites and broken sensor) factors — an unknown number of years will need to pass before analysts can make conclusive results about the ability of computer models to predict snow cover in areas where field studies are unavailable.

5.1.2 Measurement Uncertainty at Locations where Measurements are Unavailable

Addressing the attempt to use probability to express measurement uncertainty in this research, as described in section 2.4.3, we define unavailable locations in scenes as those that are cloud obscured or otherwise deemed poor quality by MODIS as described in chapter three and chapter four. Determining the probability of SCA at a locations with unavailable measurements, based only on known information within a respective scene, only slightly increases our confidence in confirmation results because most scenes with any unknown coverage are generally filtered out based on time of day and quality assurance information before they can be considered. The final year 2002 series analyzed in chapter four, for example, contains zero cloud-obscured areas. In summary, after filtering out MODIS data based on a combination of quality assurance layers inherent to the HDF-EOS granules, observed cloud coverage, and time of day, for each of three years, we found only a small amount of — and sometimes no — remaining usable data during the melt period to confirm TOPLATS results. Of the usable scenes, only a marginal amount of unavailable data was left which could bear any impact on our conclusions for the UKRW.

5.1.3 Applicability of Kappa Statistics

With a limited sample size, the Kappa statistic and Kappa statistic variants plotted over the melt period do not show much more than the proportion of agreement between measured MODIS SCA measurements and inferred TOPLATS SCA model results over the same time period, but they do show some useful information. Three figures — (1) plots of Kappa comparison statistics in Figure 4-23b for the 0.80 albedo, 0.75 SWE threshold series, (2) plots of Kappa comparison statistics in Figure 4-24d for the 0.85 albedo, 2.50 cm SWE threshold series, and (3) the side-by-side measured and modeled results from Figure 4-28 — show the usefulness of Kappa statistics in comparison to the proportion of agreement. The remainder of this section reviews these plots systemically from the begging of the melt period to the end of the melt period. The beginning of the melt period for the 0.85 series shows the most useful information.

During the beginning of the melt period, from day 138 through day 140, shown in the first three rows of images in Figure 4-28, notice the 0.80 simulated series remains blanketed with snow while MODIS and the 0.85 simulated series both report snow depletion. In this beginning-of-melt period, therefore, the Kappa statistic cannot be calculated for the 0.80 series because there are uneven number of
categories between the measured and modeled maps. There are always two categories in the measured data and only one category — snow — in the modeled data. In this case, the proportion of agreement can be considered the “alternative” Kappa. In the 0.85 series alternatively, two categories exist in each of the three early scenes. Kappa reveals, in this case, more than the proportion agreement does. While the proportion of agreement shows relatively high values, and the proportion SCA points are close together in the SCA vs time plot, the low Kappa values hint at problems in the model maps without showing them. The side-by-side plots in Figure 4-28 of measured and modeled data for the 0.85 albedo series confirm the problems detected by the Kappa summary statistic. On the first scene shown in this plot (Day 138 at 00:05), for example, notice that while the bulk of the maps look the same where snow covers the ground, the snow-free areas are in almost completely different locations. The two scenes from day 140 shows similar problems that the proportion of agreement does not show. On all three scenes notice that Klocation is always lower than Khisto indicating that the spatial problems in the model are due to location problems more than quantity problems. In other words, the quantity of pixels in each of the two categories predicted by the model contributed less to the poor Kappa statistic than the location of the those pixels. The high maximum success rate of agreement $P_{\text{max}}$ and the relatively low proportion of agreement, as described by equation 2-7, are the contributing factors to the lower Klocation.

During the middle of the melt period from day 141 through day 143 low and negative Kappa values confirm what the proportion of agreement already shows and does not reveal much more. When Kappa falls to values between 0.50 and -0.50 in the 0.80 albedo series for example, the proportion of agreement fall to values between 0.80 to 0.30. The 0.85 Kappa values show similar information. In both cases, however, the proportion of agreement and the Kappa values show more than the side-by-side proportion SCA plot where the proportion SCA values between the model and the measurements are relatively close together. The Klocation and Khisto values in both the 0.80 albedo series and the 0.85 albedo series show that, like at the beginning of the melt, spatial location errors influence the poor proportion of agreement and poor Kappa values in comparison to the influence of the quantity of cells in each category. This explains the close proportion of SCA results.

At the end of the melt period from day 144 through day 145 the Kappa statistics are the least relevant and show little compare to the proportion of agreement. During these times when there are two categories in the simulated maps to calculate Kappa, Klocation shows, like it did in the beginning of the melt, the misplacement of by TOPLATS and demonstrates the difficulty the model has in predicting patchy snow cover during the melt period as shown in Figure 5-1.
Figure 5-1 Patchy Snow in the Kuparuk River
TOPLATS poorly predicts the patchy location of where snow melts, as shown in this south-facing photo, picture toward the end of the melt period. This photo was taken by G. W. Kling from the University of Michigan on May 28, 1996.

5.2 Critique and Future Work
In this research, model output is compared to measurements in the model coordinate system, Clark 1866 UTM Zone 6. The sensitivity of the error of measurement, however, has not been propagated through the intermediate Albers Equal Area projection. For interest areas that are smaller than, or on the order of magnitude in size of the resolution of the MODIS sensor (in this case 500 meters), the swath to grid operations could be suspect to reduced comparison accuracy. A sensitivity analysis should be conducted in the future to verify this guess. One way to overcome the intermediate projection is to test other GIS products in performing directional transformations from GCS to UTM zone 6 for the UKRW data.

Another piece of information that could be used is the MODIS Collection 5 fractional snow cover information. Besides reporting a quality assurance information and Boolean snow information compare to unavailable information, fractional snow information could show how close a model might be in predicting snow-cover. Fractional snow information, further, could be more easily comparable to SWE values that TOPLATS predicts before we assign the SWE threshold.
5.3 **Recommendations of Future Work**

5.3.1 Other Statistics

Our conclusions call for a similar analysis in a larger area with a longer melt period to determine the applicability of Kappa statistics over in these kinds of areas and timeframes. The entire Kuparuk river could be a candidate for such a study. These two factors — space and time, however, are not dependent on each other and an analysis of Kappa on the comparison between MODIS measurements and spatially simulated results over either a larger area or a longer time frame would increase the sample of cells and make the Kappa statistics more relevant to review they are in this research. Alternatively, several watersheds the size of the UKRW with a similar snow melt time frames as the UKRW could be reviewed in tandem to further determine the applicability of the Kappa statistics.

Other statistics could be used in a future analysis including a ratio of Kappa to the proportion of agreement. Simplifying this ratio where Kappa is defined by equation 2-7

$$\frac{K}{PA} = \frac{1 - PE/PA}{1 - PE}$$

This ratio could show analysts if category location problems or category quantity problems in the model results could be present where the proportion of agreement between the two maps in the comparison fails to show any, or little, problems. This ratio is driven by the proportion of expected agreement due to a random relocation of cells ($PE$) over the proportion of agreement ($PA$). As $PE$ gets higher in comparison to $PA$ in the $PE/PA$ ratio, we expect the $K/PA$ ratio to get lower indicating more information is being shown by Kappa then the Proportion of Agreement. In future work, calculating this ratio for several watersheds like the UKRW during like snow-melt periods could reveal the significance of the Kappa statistic in comparison as an objective function for model evaluation.

Another statistic that could be evaluated is a fuzzy Kappa statistic. Fuzzy statistics simply summaries of individual statistics taken at various resolutions. For example, a sixty-four-pixel, square map could be composited into a forty-nine pixel, square map and these two maps could be compared in a fuzzy analysis. Most of the time, the composites are conducted irrespective of physically-distributed features. If physical features are believed to influence criterions, however, perhaps the compositing process inherent in reducing the resolution of an image could be taken over physical features instead of in a grid. The following question could be addressed for a simple physical feature like DEM in determining if this feature influences snowmelt: Given two fuzzy kappa series (a) Kappa statistics for increasingly coarse resolution maps and (b) Kappa statistics for maps with decreasing elevation zones representing individual trials, can ratios of results from these two series quantify the dependence of a distributed snow-cover model on elevation at a particular interest area?
5.3.2 Variable Time-Rate Composite MODIS Data

This research, by employing level two MODIS data, highlights the fundamental problem with level three MODIS data described by Hall (2001, pers. com. 2006) in Chapter Two: The information in level three MODIS data is composited over an arbitrary fixed eight-day time interval. While this temporal composite potentially “eliminates unknown” measurement information at locations from cloud obscured and other unavailable regions in individual scenes, it (a) could hide sub-scene changes and physical process and (b) could composite information where no compositing is needed — between sense with 100% measurement coverage. These problems from eight-day temporal compositing could greatly hinder the ability of level three MODIS data to evaluate the capabilities of a model during a relatively short time period. In the example of the UKRW where snow melts in less than eight days, the level three MODIS data is useless. Level two data, in comparison however, is hindered by clouded and poor quality measurements. In conclusion, a variable time-rate composite could be created out of level two MODIS data that composites sequential scenes over variable timelengths. The criteria for determining the time length could be spatial measurement availability and quality assurance information from the MODIS product. In an extreme example, if a ten-scene series contains all unavailable data during scenes one, two, four, five, seven, eight, and ten and all cloud-free, high quality scenes on days three, six, and nine, a variable time-rate composite could consist of three composites for (1) days one through four, (2) days five through seven, and (3) days eight through ten. In this example the composites last for four, three, and three days each with periods of no-data divided as evenly as possible between them. Similar to a variable bit-rate (VBR) music file on a computer (like modern mp3 file formats) where file size is optimized by varying the bit-rate dependent on the waveforms in a song, variable time-rate composites would optimize the useful information in a series of MODIS measurements for a given interest area. The composite scenes in such a series could depend on user-specified thresholds like maximum number of scenes in a composite, minimum number of scenes in a composite, maximum time period of a composite, minimum time period of a composite, minimum proportion of available information in an interest area, and the product of the minimum probability of certainty – measured across time – with the number of cells in a scenes. Note that “cells” could be determined on a pixel-basis, or on a vector basis, grouped by physical areas like DEM as described in suggestions for Kfuzzy statistic analysis.

5.3.3 Comparing Data in Swath Format

In the case of UKRW, the DEM data is given in UTM zone 6. Comparing measurements in the raster coordinate system of the model is the most common method of using MODIS data to confirm model results. This way is usually used because common MODIS products, such as three products, are already provided in grid formats which may easily be projected using GIS packages like those reviewed in Chapter Two. These packages, which did not work well to batch-convert level two MODIS data, are made specifically to convert level three data into UTM zone data. In future work, a second method could be used to confirm model results. Point data
could be extrapolated from the raster model data and compared more directly with the measurements. In this analysis, the model would idealistically produce results in the measurement format. It would reduce the need to propagate measurement uncertainty and error through multiple projections, but would also create the need to spatially weight kappa statistic values—greater near at points further away from to the convex hull of respective swaths where there is generally a relatively greater point density, and lower at locations with a relatively high point density. The weighting algorithm would need to be developed in future work.

Another way to compare the model and measurement maps, both given SCA categories (opposed to SCA and SWE categories), could be comparing raster model results with swath points projected, without bitmap resampling, in the model projection system. Maps of these comparisons, visually, would contain measurement swath points—likely only those matching the latitude and longitude grid—overlaid on simulated model cells with color-coded categories. We can call this type of analysis a raster-point comparison. A raster-point comparison, like this, would enable use of hdf-eos information without geographic transformations where certainty in measurements could be reduced. The analysis would require maximum distances to determine the influence of a measurement point on the simulated model cell. For example, a like analysis could evaluate the prediction of a model cell on only the data points within it or with data points in a region nearby that model cell. This region could be defined by a distance or, perhaps, a physical feature.

5.3.4 Reevaluate HEG-TOOL

Raytheon Company updated HEG-TOOL during the 2007-2008 International Polar Year since it was first evaluated for converting MOD10_L2 and MYD10_L2 swath graduals into projected grids. One notable update, the ability of HEG-TOOL to project data in the Albers Equal Area, could possibly solve the batch-conversion problems described in Chapter Three. HEG-TOOL, thus, should be reevaluated. If HEG-TOOL no longer halts during conversion of some HDF-EOS products, it could be used in place of a subset of the methods for converting swaths to grids created in this thesis.

5.3.5 Select Only High Quality Scenes Within Sub Time Intervals

In section 4.1 we narrowed our selection of scenes down to morning scenes with a 0.50 or greater proportion of good quality swath points. In section 4.2.1 we showed that the 0.80 albedo simulation and the 0.85 albedo simulation performed better than the 0.75 series in terms of matching normalized SWE values to SCA values. From Figure 4-22, we can narrow our set selection of scenes further to calibrate the model by selecting the scenes with a higher proportion of good quality points within close proximity: For example, at the end of day 136, we can trust the point with 0.87 QA more than the point with 0.79 QA; and at the end of day 137, we can have the most confidence in the scene with 0.84 QA.
5.4 **Research Summary**

In summary, MODIS level two data and use of the Kappa statistic could be used in evaluating spatiotemporally distributed models. Level two MODIS data best describes snow-melt situations with slightly longer melt periods and larger areas than the UKRW — but still shows more than level three data. Funding for more satellites and funding to repair existing satellite sensors would increase the chance of collecting good quality coverage data. A report generated by an online web-service found toward the end of this research called “Product Quality Documentation for MOD10_L2, C4,” located at the “MODIS Land Quality Assessment web site” (NASA 2009), confirms our findings on the usability of data collected between the end of April in the year 2002 (day 120) and the end of the year 2002 (day 365). For these times, “Snow cover is mapped with reasonable accuracy. However, snow/cloud confusion and false snow detection do occur in some situations. Analysis of inaccuracies in snow mapping continues. Discretion should be exercised in use of this product.” The report warns further that, “Snow mapping errors may occur on the perimeters of snow fields, cloud edges, and water boundaries,” and the data is “being investigated” for further errors. For collection five data, not reviewed in this report, the web service reports similar problems. Additionally, while the collection five report confirms the data collected by MODIS during the 2002 UKRW melt has been “inferred” to pass a science quality test, the report marks the times right before (April 14 at day 104 through April 15 at day 105) and right after (three hours on June 19 at day 170) the winter-spring melt-window as “suspect” for quality errors. While the Kappa statistic shows a small amount of information beyond the proportion of agreement statistic in the map comparison of the year 2002 data – different datasets for different times, with perhaps a model that directly outputs SCA vs SWE, could further reveal the usefulness of the Kappa statistic in map comparison for evaluation of a spatially distributed snow-melt model.
## Table I-1. USGCRP Organizations

<table>
<thead>
<tr>
<th>Organization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agency for International Development</td>
</tr>
<tr>
<td>Dept. of Agriculture</td>
</tr>
<tr>
<td>Dept. of Commerce, Natl. Oceanic &amp; Atmospheric Admin.</td>
</tr>
<tr>
<td>Dept. of Defense</td>
</tr>
<tr>
<td>Dept. of Energy</td>
</tr>
<tr>
<td>Dept. of Health and Human Services, National Institutes of Health</td>
</tr>
<tr>
<td>Dept. of State</td>
</tr>
<tr>
<td>Dept. of Transportation</td>
</tr>
<tr>
<td>Dept. of the Interior, US Geological Survey</td>
</tr>
<tr>
<td>Environmental Protection Agency</td>
</tr>
<tr>
<td>National Aeronautics &amp; Space Administration</td>
</tr>
<tr>
<td>National Science Foundation</td>
</tr>
<tr>
<td>Smithsonian Institution</td>
</tr>
</tbody>
</table>
APPENDIX B. PROJECTED MODIS MEASUREMENTS

See separate online images.
APPENDIX C. CUMULATIVE SPATIAL DISTRIBUTION OF SNOW COVER

APPENDIX D. SOFTWARE REQUIREMENTS

The following software is required to repeat or modify the methodology described in chapter three and generate the results in chapter four.

1. Microsoft Windows XP
2. Mathworks MATLAB® 7 with HDF-EOS support
3. Python 4 for Windows and Pythonwin
4. ESRI ArcGIS 9.1 or 9.2 with the Spatial Analyst extension
APPENDIX E. COMPARISON OVERVIEW DATAFLOW

Hydrographs

Snow Melt Research

Define Query (Time/Space)

Query

NSIDC Website

Query Results (Email)

Receive Order Information (Email)

FTP Request

NSIDC DAAC

Swaths (HDF-EOS)

Receive Swaths

Compare Measurements To Model

Model Grid (FLT)

Local File System

GCS Snow Files (ASCII)

Swaths (HDF-EOS)

Model Formatted Measurements

UTM 6 (Raster)

Convert to Model Format

Boundary & Grid (Matlab)

GCS

ASCII

Project & Mask (GP)

Raster

DEM

MET

USDA

Distributed Model Output

Model

128
APPENDIX F. MODIS SWATH SCENE OBJECTS

- **Scene**
  - (HDF-EOS Swath Band)

- **Snow Cover**
  - (Data Field Band)

- **Reduced Cloud**
  - (Swath Data Grid)

  - **Snow Cover**
    - (Swath Data Grid)

  - **Quality Assessment**
    - (Swath Data Grid)

  - **Fractional Snow Cover**
    - (Swath Data Grid In Collection 5 Only)

- **Extend**
  - (Geolocation Band)

- **Time**
  - (In File Name)

- **Satellite**
  - (Defined in DAAC Query)

- **Latitudes**
  - (Swath Geolocation Grid)

- **Longitudes**
  - (Swath Geolocation Grid)
## APPENDIX G. GLOBAL CHANGE ONLINE RESOURCES

<table>
<thead>
<tr>
<th>Agency</th>
<th>Global Change Website Information</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dept. of Commerce, National Oceanic &amp; Atmospheric Admin. (also, National Institute of Standards and Technology)</td>
<td><a href="http://www.climate.noaa.gov/">http://www.climate.noaa.gov/</a></td>
</tr>
<tr>
<td>Environmental Protection Agency</td>
<td><a href="http://cfpub.epa.gov/gcrp/">http://cfpub.epa.gov/gcrp/</a></td>
</tr>
<tr>
<td>Smithsonian Institution</td>
<td><a href="http://www.serc.si.edu/research/searchresults.jsp?themeId=21">http://www.serc.si.edu/research/searchresults.jsp?themeId=21</a></td>
</tr>
</tbody>
</table>
APPENDIX H. SWATH TO KUPPARUK (S2K) CODE

Python Code for Projecting, Masking, and Converting Maps to Little Endian Floating Point Format

```
# Input Parameters
file_limit = 1000
directory = "C:/Data/Research/Data/2002"
directory = "C:/Data/Research/Data/2001/ASC"
directory = "C:/Data/Research/Data/2000/ASC"
directory = "C:/Data/Research/Data/2000/May/ASC"
directory = "C:/Data/Research/Data/2002a"

# Import system modules
import sys, string, os, win32com.client
# Create the Geoprocessor object
gp = win32com.client.Dispatch("esriGeoprocessing.GpDispatch.1")
# Load required toolboxes
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Conversion Tools.tbx")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Data Management Tools.tbx")
gp.CheckOutExtension("spatial")
gp.AddToolbox("C:/Program Files/ArcGIS/ArcToolbox/Toolboxes/Spatial Analyst Tools.tbx")
gp.AddMessage('Starting ascii2kuparuk.py...\n')
filelist = os.listdir(directory)
acounter = 1;
for afile in filelist:
    aextension = os.path.splitext(afile)[1]
    if os.path.normcase(aextension) == '.asc' and acounter <= file_limit:
        # Input, output, and naming
        afilebasename = os.path.splitext(os.path.splitext(afile)[0])[0]
time_y = afilebasename[10:14]
time_d = afilebasename[14:17]
time_h = afilebasename[18:20]
time_m = afilebasename[20:22]

        input_file = directory+'/'+afile
        gcs_raster = directory+'/'+"gcs_"+time_d+"-"+time_h+time_m
        alaska_raster = directory+'/'+"ala_"+time_d+"-"+time_h+time_m
        kuparuk_raster = directory+'/'+"kup_"+time_d+"-"+time_h+time_m
        masked_raster = directory+'/'+"mas_"+time_d+"-"+time_h+time_m
        float_file = directory+'/'+"flt_"+time_d+"-"+time_h+time_m+'.flt'
        mask = "C:/Data/Research/Data/Mask/mask"

        if os.path.isfile(float_file):
            # Float file already created, no need to process.
            gp.AddMessage("Skipping "+input_file+"; "+float_file+" already exists.")
        else:
            gp.AddMessage('Now creating '+kuparuk_raster+' from '+input_file)
            gp.AddMessage('Year: '+time_y+'; '+'Day: '+time_d+'; '+'Hour: '+time_h+'; '+'Minute: '+time_m)

        # ASCII to Raster Conversion (GCS)
        gp.ASCIIToRaster_conversion(input_file, gcs_raster, "INTEGER")
```
gp.AddMessage('ASCII to raster conversion complete for day:'+time_d+', time:'+time_h+':'+time_m)

# Project Raster into GCS
gp.DefineProjection_management(gcs_raster,
"GEOGCS['GCS_WGS_1984',
  "DATUM['D_WGS_1984',
    "Spheroid['WGS_1984',6378137.0,298.25723563],
    "PRIMEM['Greenwich',0.0],
    "UNIT['Degree',0.0174532925199434]"
  ],
  "PROJECTION['GEOGCS']",
  "PARAMETER['False_Easting',0.0],
  "PARAMETER['False_Northing',0.0],
  "PARAMETER['Central_Meridian',0.0],
  "PARAMETER['Standard_Parallel_1',55.0],
  "PARAMETER['Standard_Parallel_2',60.0],
  "PARAMETER['Latitude_Of_Origin',50.0],
  "UNIT['Meter',1.0]"],
-10000.000000 -10000.000000 100000.000000 0.000000 100000.000000
  )"
);
gp.AddMessage('WGS projection definition complete for day:'+time_d+', time:'+time_h+':'+time_m)

# Project Raster into the Continental > North America > Alaska System
gp.ProjectRaster_management(gcs_raster, alaska_raster,
"PROJCS['Alaska_Albers_Equal_Area_Conic',
  "GEOGCS['GCS_North_American_1983',
    "DATUM['D_North_American_1983',
      "Spheroid['GRS_1980',6378137.0,298.257223563],
      "PRIMEM['Greenwich',0.0],
      "UNIT['Degree',0.0174532925199434]"
    ],
    "PROJECTION['Albers']",
    "PARAMETER['False_Easting',500000.0],
    "PARAMETER['False_Northing','-7000000.0'],
    "PARAMETER['Central_Meridian','-147.0'],
    "PARAMETER['Scale_Factor',0.9996],
    "PARAMETER['Latitude_Of_Origin',0.0],
    "UNIT['Meter',1.0]"],
-10000.000000 -10000.000000 100000.000000 0.000000 100000.000000
  ),
  "NEAREST", "262.68"
);gp.AddMessage('Alaska_Albers_Equal_Area_Conic projection complete for day:'+time_d+', time:'+time_h+':'+time_m)

# Project Raster into Clark 1866 UTM Zone 6
gp.ProjectRaster_management(alaska_raster, kuparuk_raster,
"PROJCS['Clarke_1866_Transverse_Mercator',
  "GEOGCS['GCS_Clarke_1866',
    "DATUM['D_Clarke_1866',
      "Spheroid['Clarke_1866',6378206.4,294.9786982],
      "PRIMEM['Greenwich',0.0],
      "UNIT['Degree',0.0174532925199434]"
    ],
    "PROJECTION['Transverse_Mercator']",
    "PARAMETER['False_Easting',500000.0],
    "PARAMETER['False_Northing','-500000.0'],
    "PARAMETER['Central_Meridian','-147.0'],
    "PARAMETER['Scale_Factor',0.9996],
    "PARAMETER['Latitude_Of_Origin',0.0],
    "UNIT['Meter',1.0]"],
-10000.000000 -10000.000000 100000.000000 0.000000 100000.000000
  ),
  "NEAREST", "131.34"
);gp.AddMessage('Clark 1866 UTM Zone 6 projection (Kuparuk Watershed) complete for day:'+time_d+', time:'+time_h+':'+time_m)

# Mask the raster
temp_extent = gp.extent #Do this, or the extent for the other systems, above will be set to these!
temp_cellSize = gp.cellSize
gp.extent = "390862.8 597414.74 418181.52 627228.92"
gp.cellSize = "131.34"
gp.Times_sa(kuparuk_raster, mask , masked_raster)
gp.extent = temp_extent #Restore original, temp extent and temp cell size
gp.cellSize = temp_cellSize

gp.AddMessage('Mask complete for day:' + time_d + ', time:' + time_h + ':' + time_m)

# Creating Floating Point File for Analysis
gp.RasterToFloat_conversion(masked_raster, float_file)
gp.AddMessage('Little Endian Floating Point File Created for day:' + time_d + ', time:' + time_h + ':' + time_m)

# Increment Limiting Counter
counter = counter + 1

# Complete with this run - show stats
gp.AddMessage('Files complete: ' + str(counter) + '; Files limit: ' + str(file_limit) + '
')
MATLAB® Code for Converting HDF-EOS Files To ASCII Files

% This script looks through a directory of MODIS hdf-eos files and outputs
% an animation of the reduced cloud snow coverage for a particular area.
% It also outputs a series of ASCII files to read into ESRI software
% This script depends on expandgrid2.m and proccessDuplicates.m
% format
clear; close all;

% INPUT PARAMETERS
% MAX FILES TO PROCESS
number_of_files_limit = 200;

% MOVIE DISPLAY
make_movie_as_images_are_computed = 0; % 1=yes, 0=no Makes the movie at the end of the
% program, instead of making a movie as the images are computed.
number_of_times_to_play_movie = 0;
movie_frames_per_second = 2;

% NO DATA VALUE
no_data_value = 0;

% DECIMAL Rounding FOR LAT AND LON .001 is e-3.
% This is OK b/c there are about 42.6844322 km/lon line on average
% and there are about 107.829318 km/lat line on average.
% Therefore, .001 lon line is .108 km - less than the measurement precision,
% which is 5km
rounding_dec = -3;

% INPUT LOCATION
% path = 'E:\Research\Data\MODIS\2002\';
% path = 'C:\Data\Research\Data\2001\MODIS\';
% path = 'C:\Data\Research\Data\2000\PullDir\0800617529LJwmEB\';
path = 'C:\Data\Research\Data\2000\May\PullDir\0800617805bGLIrB\';

% SPATIAL BOUDARIES USED TO CROP DATA
% This window is too small.
% west = -149.505848; %lons
% east = -149.118133;
% north = 68.651338; %lats
% south = 68.481948; %
% New values from projecting the raster mask, and measuring on screen.
% This window covers the mask. This is a good window.
west = -149.53; %lons
east = -149.10;
north = 68.67; %lats
south = 68.47;

% New values from projecting the raster mask, not the vector, into GCS + .1 for error
% This window more than covers the mask, and yields more consistent results.
west = -149.697227815679 - .1; %lons
east = -148.99748804145 + .1;
north = 68.7462023674783 +.01; %lats
south = 68.4697083181439 -.01;

% SPATIAL INCRIMENTS
west_to_east_inc = .001; %.001 is good.
south_to_north_inc = .001; %.001 is good.

% SCALES (to increase speed of computations)
subScale = 1; % 1: The data will be subset by this factor. Ex: a 15x15 subset by 3
% will be 5x5. For the most detail this number should be 1.
LatLonSubScale = 10;
% 10: This is the subscale the Lat Lon is at. For terra snow data, there is generally
one lat and one lon for each 10x10 square of data. (swaths.MapInfo Incrememt)
% for modis snow, subScale * LatLonSubScale should = 1, because the lat
% lons are measured for every 10 points of grid data.
To make a world file, the following affine matrix would be used:
\[ R = \begin{bmatrix} \text{south-to-north inc} & 0 & \text{north-to-south inc} \\ 0 & \text{west-to-east inc} & \text{west-to-east inc} \end{bmatrix}; \]

BUILD LIST OF FILES TO GO THROUGH
\[ a = \text{ls(path)}; \]
output = '';
runs = 0;
[a_cols, a_rows] = size(a);
for ii = 1:a_cols,
s = strrep(a(ii,:), ' ', '');
if (~length(findstr(s, '.hdf.met')) & length(findstr(s, '.hdf')) & (s(length(s)-3:length(s)) == '.hdf'))
    runs = runs + 1;
    % filenames is a cell array denoted by brackets {}. 
    filenames(runs,:) = {[path, s]}; % char(filenames) lists the files
end
number_of_files = length(filenames);
if (number_of_files_limit < number_of_files & number_of_files_limit ~= 0)
    number_of_files = number_of_files_limit;
end
number_of_files_left = number_of_files;
disp(['There are ', num2str(number_of_files), ' of ', num2str(length(filenames)), ' files that will be processed in: ', path]);
avgtime = []; % initial estimate
estimated_time_remaining = avgtime * number_of_files_left; % seconds
disp(['Estimated processing time remaining: ', num2str(estimated_time_remaining), ' seconds']);
tic;
framenum = 0;
runtimes = [];

FOR EACH FILE
for jj = 1:number_of_files
    % Mark the start time for this iteration
    start_iteration_time = toc;
    % Define filename for this iteration
    filename = char(filenames(jj));
    % Read MODIS Snow Information.
    eosInfo = hdfinfo(filename, 'eos'); % Read eos data into a matlab structure
    swaths = eosInfo.Swath; % Isolate the swath data
    % Extract the data, the lats, and the lons. Note:
    rcSnowName = swaths.DataFields(3).Name; % 3 = 'Snow Cover Reduced Cloud'
    rcSnow = double(hdfread(swaths, 'Fields', rcSnowName, 'Index', {[1 1], [subScale subScale], []]));
    oLats = hdfread(swaths, 'Fields', 'Latitude'); % o stands for original
    oLons = hdfread(swaths, 'Fields', 'Longitude');
    [rows, cols] = size(rcSnow);
    % Interpolate lat lons to the data grid scale
    % This takes the most time. The size of the latitude grid and the
    % longitude grid are "expanded." In other words, points are added
    % inbetween the given points. A second degree spatial interpretation is
    % used (interp2). The east and south edges might include NaN points
    % because for each point on the lat or lon grid coorisponds to the
    % NW point in the data grid.
    [rows, cols] = size(rcSnow);
    tLats = expandGrid2(oLats, LatLonSubScale);
    tLons = expandGrid2(oLons, LatLonSubScale);
    % remove the few points from the south and east of the grid
    % that are outside of the rcSnow grid
    Lats = tLats(1:rows, 1:cols);
    Lons = tLons(1:rows, 1:cols);
Delaunay triangulation needs double arrays and produces errors if the
values are not rounded sufficiently. Six decimal places are used
because this number is greater than or equal to most Latitude and
Longitude measurements.

Lats = roundn(double(Lats),rounding_dec);
Lons = roundn(double(Lons),rounding_dec);

bound interest area
in_bound_positions = find( (Lons<=east) & (Lons>=west) & (Lats<=north) &
(Lats>=south) );

create a "grid" of three columns: Lats, Lons, and Values
grid = {Lats(in_bound_positions), Lons(in_bound_positions),
rcSnow(in_bound_positions)};

if isempty(grid)
% if the grid is empty, there are no points in this granule
        disp(['Note: There are no points in the interest area bounded by
        ',filename,'.']) ; toc;
else
    % Process duplicate coordinate unique data values through a modal decision
    % Specifically, set duplicate values equal for equal coordinates.
    grid(:,3)= processDuplicates(grid(:,1),grid(:,2),grid(:,3));

% Now remove duplicates - this is not necessary as averages are
% taken. However, it cleans things up a little bit.
    before_remove = length(grid);
    [not_used_vals,unique_rows]=unique(grid(:,1)+sqrt(-1)*grid(:,2));
    grid=grid(unique_rows,:);
    number_of_duplicates_removed = before_remove - length(grid)

% Project Data into LatLon(griddata(LonsVector,LatsVector,rcSnowVector,X,Y,'nearest'))
% Matlab reads from north to south!
    [X,Y] = meshgrid(west:west_to_east_inc:east,north:south_to_north_inc:south);
    projected_data = griddata(grid(:,2),grid(:,1),grid(:,3),X,Y,'nearest');

    % The unique values;
    unique_values_found = unique(projected_data)

    % Replace out of bound points with the value "no_data_value".
    minLat = min(Lats(in_bound_positions));
    maxLat = max(Lats(in_bound_positions));
    minLon = min(Lons(in_bound_positions));
    maxLon = max(Lons(in_bound_positions));
    out_of_bound_positions = find( (X<minLon) | (X>maxLon) | (Y<minLat) |
    (Y>maxLat) );
    projected_data(out_of_bound_positions) = no_data_value;

% Extract Date From Filename
    a = find(filename == '\'); a = a(length(a));
    myyear=filename(a+11:a+14);
    myday=filename(a+15:a+17);
    mytime=filename(a+19:a+22);

% Save the current frame
    framenum = framenum + 1;
    projected_data_set(:,:,framenum) = projected_data;
    if (make_movie_as_images_are_computed == 1)
        close all; figure; image(projected_data); title(['Year: ',myyear,' Day:
        ',myday,' Time: ',mytime]);
        timeSeriesFrames(framenum) = getframe;
    end

% Write an ESRI ascii file for projection into another system
    writeESRIAsciiFile(projected_data,[filename,'.asc'],west,south,west_to_east_inc,no_data_value);
end
% Estimate Time

number_of_files_left = number_of_files_left - 1;
iteration_time = toc - start_iteration_time;
runtimes = [runtimes, iteration_time];
avgt ime = mean(runtimes);
estimated_time_remaining = avgt ime * number_of_files_left; % seconds
disp(''); disp(['Files left: ', num2str(number_of_files_left)]);
disp(['Estimated time remaining: ', num2str(estimated_time_remaining), ' seconds']);
toc;
end

if (number_of_times_to_play_movie > 0)
    if (make_movie_as_images_are_computed == 0)
        a = size(projected_data_set);
        total_frames = a(3);
        for kk = 1:total_frames
            close all; figure; image(projected_data_set(:,:,kk)); title(['Year: ', myyear, ' Day: ', myday, ' Time: ', mytime]);
            timeSeriesFrames(kk) = getframe;
        end
    end
end

close all;
if (number_of_times_to_play_movie > 0)
    movie(timeSeriesFrames, number_of_times_to_play_movie, movie_frames_per_second);
end
APPENDIX I. COMPARING MODEL AND MEASUREMENTS

clear all; close all; colormap('cool'); hold off;

%input path
path = 'C:\Data\Research\Data\2002\';
year = 2002;
% path = 'C:\Data\Research\Data\2001\FLT\';
% year = 2001;
% path = 'C:\Data\Research\Data\2000\ALLFLT\';
% year = 2000;

%input percent available to circle
percent_available_threshold = .90;

%input grid size and number pixels in the mask
grid_size = [208,227];
number_of_mask_pixels = 8557;

%intro message
disp('-----------------------------------------------------------');
disp(['Starting %SCA analysys of ',path]);

generate file list of floats
a = ls(path);
[a_cols,a_rows] = size(a);
rates = 0;
filenames = generate_files_list_of_floats(path);
number_of_files = length(filenames);
testgrid=zeros([227,208]);
tic;
%for each file
for jj = 1:number_of_files
    simplegrid=zeros([227,208]);
    filename = char(filenames(jj));
    %Extract Time From Filename
    [myday(jj),myhour(jj),mymin(jj),days_since_new_years(jj)] =
    get_time_from_file(filename);
    % Open the file and position north up
    grid = fread(fopen(filename),grid_size,'float');
    grid = fliplr(rot90(rot90(rot90(grid))));
    %Get the pixel indexes
    [location_index_frozen,...
    location_index_unavailable,...
    location_index_not_frozen,...
    location_index_not_in_mask,...
    location_index_unavailable_in_mask,...
    = divide_watershed_into_frozen_and_not(grid,filename);
    %Calculate the percent frozen and the percent available
    [percent_frozen(jj),...
    percent_frozen_min(jj),...
    percent_frozen_max(jj),...
    percent_available(jj)...]
    = get_percentage_frozen_and_available(...
    location_index_not_frozen,...
    location_index_frozen,...
    location_index_unavailable_in_mask,...
    number_of_mask_pixels);

    %Calculate upper and lower error bars
    percent_frozen_upper_error(jj) = percent_frozen_max(jj) - percent_frozen(jj);
    percent_frozen_lower_error(jj) = percent_frozen(jj) - percent_frozen_min(jj);
frozen_grid_for_time_i = zeros(size(testgrid));
frozen_grid_for_time_i(location_index_frozen) = 1;
testgrid = testgrid + frozen_grid_for_time_i;

% Show grid during computation
simplegrid(location_index_frozen) = 60;
simplegrid(location_index_not_frozen) = 30;
simplegrid(location_index_not_in_mask) = 0;
simplegrid(location_index_unavailable) = 0;
image(simplegrid); title(["Year: ",num2str(year)," Day: ",num2str(myday(jj)),' Time: ",'num2str(myhour(jj)),':',num2str(mymin(jj))]);
colorbar; timeSeriesFrames(jj) = getframe;

allhours(jj) = myhour(jj);
end
toc;

good_values = find(percent_available > percent_available_threshold);

% PLOT SINGLE PICTURE
hold on;
% errorbar(...
  days_since_new_years,percent_frozen,...
  percent_frozen_lower_error,...
  percent_frozen_upper_error,...
  '+b');
plot(days_since_new_years(good_values),percent_frozen(good_values),'or');
for count = 1:length(days_since_new_years)
  text(days_since_new_years(count),
  percent_frozen(count),['\leftarrow',num2str(myhour(count)),':',num2str(mymin(count))]);
end
xlabel('Julian Day');
ylabel('Percent Snow Covered Area (SCA)');
legend('All Values with Error Bars Accounting for Unavailable Pixels',
'Values with more than ',num2str(percent_available_threshold*100),'% available','Location','SouthOutside');
title(["MODIS Snow Depletion For ",num2str(year)]);

% DRAW 4 PICTURE SUMMARY
figure; colormap('cool');
% subplot(2,2,4); hold on;
% plot(days_since_new_years,percent_frozen,...
% plot(days_since_new_years(good_values),percent_frozen(good_values),'ok');
% xlabel('Julian Day');
% ylabel('Percent Snow Covered Area (SCA)');
% legend('All Values','Values with more than ',num2str(percent_available_threshold*100),'% available','Location','SouthOutside');
% title(["MODIS Snow Depletion For ",num2str(year)]);
% subplot(2,2,3);
% hist(percent_available);
% xlabel('Percent Available Bins');
% ylabel('Count');
% title('Percent Available Histogram');
% subplot(2,2,2);
% image(64.*testgrid./max(testgrid(:)));
% xlabel('Easting Pixels');
% ylabel('Northing Pixels');
% title('Sum of Frozen Pixels over Melt');
% colorbar;

% subplot(2,2,1);
% mesh(testgrid); view([90,-45,45]);
% xlabel('Easting Pixels');
% ylabel('Northing Pixels');
% zlabel('Sum of Frozen Pixels over Melt')
% title('Sum of Frozen Pixels over Melt');

% %ROTATE
% for i=0:1:45
%     view([90,i,45]);
%     pause(1/180)
% end

% %TIME HISTOGRAM
% figure;
% hist(allhours); xlabel('Hours Of The Day'); ylabel('Frequency');
GLOSSARY

**Aqua** EOS satellite launched in. Collects MODIS data. To compliment Terra, Aqua crosses the equator in the afternoon. ([http://aqua.nasa.gov/](http://aqua.nasa.gov/))

**Advanced Very High Resolution Radiometer (AVHRR)** Instrument aboard POES.

**Catchment-Based Land Surface Model (CLSM)** A catchment-based model used by Koster et al. (2000) and Ducharne et al. (2000) in a general circulation model.

**Collection, MODIS** A MODIS collection of data sets. Collection 5 includes fractional snow coverage.

**Confusion Matrix** (or Contingency Table) Shows agreement and disagreement between categorical results. The transformed confusion matrix with only two categories shows type 1 errors (producer risk) and type 2 errors (consumer risk). Confusion matrix has been used in computer science for testing data mining algorithms.

**Coverage** Not a grid…

**Deterministic**

**Distributed Active Archive Center (DAAC)** Center for storing and distributing HDF-EOS data. The NSIDC DAAC stores relevant snow and ice MODIS measurements.

**Enhanced Thematic Mapper Plus (ETM+)** LANDSAT Sensor


**GOES** sd

**Granule** A single HDF-EOS dataset taken at a set time. Represents a single MODIS “scene” or “snapshot.”

**Grid** sd

**griddata.m** MATLAB® script used to fit swath surfaces to evenly spaced grids.

**Earth Observing System (EOS)** Project developed by NASA to study the earth. Includes the launch of Aqua and Terra. ([http://eospso.gsfc.nasa.gov/](http://eospso.gsfc.nasa.gov/))

**Feature (called Feature Class by ESRI)** Either a point, line, polygon, or pixel where the term line is generalized to include Bezier curves. ESRI excludes pixels from their definition of a feature and groups features into classes that can be assigned to layers of a map. ArcMap users cannot mix features within a layer, but can overlay layers in a single map. Three dimensional and four dimensional measurements can theoretically be called features. In practice however, such measurements are usually described by composite layers across time series of maps.

**HDF (Hierarchal Data Format)** A data storage file format developed by NCSA. ([http://www.hdfgroup.com/](http://www.hdfgroup.com/))

**HDF-EOS** Extension of the HDF file format used to store EOS data. Geographic data is stored in Swath, Grid, or Point formats in HDF-EOS files. ([http://hdf.ncsa.uiuc.edu/hdfeos.html](http://hdf.ncsa.uiuc.edu/hdfeos.html))
Interactive Multisensor Snow and Ice Mapping System (IMS) Software written by NOAA to create 25km, daily snow and ice data products.  
http://www.ssd.noaa.gov/PS/SNOW/ims.html

Kolmogorov-Smirnov (KS) Test See page Ayyub page 316…

MOD10_L2
MOD10_L2G
MOD10A1
MOD10A2
MOD10C1
MOD10C2
MOD10CM
MS2GT The MODIS Swath-to-Grid Toolbox  
(http://nsidc.org/data/modis/ms2gt/)

Land Surface Model (LSM) A model that yields results that are distributed in a projected, Cartesian grid.

Moderate Resolution Imaging Spectroradiometer (MODIS) The tool that measures snow albedo, among other qualities, aboard AQUA and TERRA.

Multinomial A modifier for regression equations and distributions. Also expressed as a hyphenated word (Pontius).

Nadir The direction directly below an observer, opposite from the zenith. In the case of a satellite, the direction towards the earth.

National Aeronautics and Space Administration (NASA) U.S. government agency that both observes the earth and explores space.  
Developed the HDF-EOS format based on the NCSA HDF format.

National Center for Supercomputing Applications (NCSA) Developed the HDF format.  
(http://www.ncsa.uiuc.edu/)

National Snow and Ice Data Center (NSIDC) Maintains a DAAC of MODIS snow and ice data in HDF-EOS format.  
(http://nsidc.org/)

National Oceanographic Agency

Point

Polar Operational Environmental Satellite (POES) Satellite program launched by NASSA and operated by NOAA.  
Used primarily for meteorological forecasting.

Permafrost Rock or soil that has been frozen for two or more years.

Physically-Based

Projection

Albers Equal Area An equal area projection from the view of a pole

Cylindrical Equidistant A global project with latitude an longitude units

Robinson A common Pseudo-Cylindrical global projection.

Sinusoidal

qHull or QuickHull. Algorithm used by MATLAB® script “griddata.m” to perform nearest-neighbor Delaunay triangulation. See http://qhull.com.

Scene A segment of a swath.

Swath One of three ways HDF-EOS data is stored (Swath, Grid, Point)
Snow Covered Area (SCA)

Solar Noon The time midway between sunrise and sunset. At Solar Noon, MODIS sensors view the earth near nadir, the best possible angle.

Level 2 Swath to TOPLATS Grid Tool for the Upper Kuparuk River Watershed (S2K) Procedure to convert MODIS swaths to grids comparable to TOPLATS output in the Upper Kuparuk River Watershed.

Terra EOS satellite launched in . Collects MODIS data. To compliment Aqua, Terra crosses the equator in the morning. *(http://terra.nasa.gov/)*

TOPMODEL-based Land-Atmosphere Transfer Scheme (TOPLATS) A distributed snowmelt model created by Pauwels and Wood 1999.

United States Global Change Research Program (USGCRP) U.S government program that appropriates funds to 13 federal agencies to study global change, with a focus on climate change.

REFERENCES


This section contains unused paragraphs and thoughts – good, bad, right and wrong:

CHAPTER 2

Quality assurance Grids

147.6 km² Watershed (< 60mi^2)
500 m granule resolution (about relevant 590 pixels)

Cloud and Snow Albedo: 40 to 80 percent difference depending on hydration

Future work could include creation of Variable Time Rate datasets.

There are a few options to projecting swath data. The MODIS Swath-to-Grid Toolbox (MS2GT), offered by the NSIDC,

As models are built by the ### organizations that collaborate with the USGCPR….

Figure 5-2: Discharge and Snow-Covered Area during the Winter-Spring Snowmelt of 2002

Distributed Models

a. “talk about the idea of distributed modeling”

b. Ask mccuen about hspf
i. Model complexity and accuracy

On Kappa — thinking about relationship to Bernoulli trials and the binomial distribution — that was ruled out:

We can discuss the calculation of the proportion expected agreement, \( PE \), in terms of Bernoulli trials. The total number of trial pairs equal the square of the number of location features (e.g. cells) being compared. The proportion of successfully matched pairs . . .

Cells surrounding a particular cell during the calculation of Kappa do not influence the category of that particular cell as they might in a fuzzy calculation.

In addition to the cell-by-cell map comparison using the Kappa statistic, Hagen (2002) evaluates two other methods for comparing maps which are not used in this study: a fuzzy interference system method and a fuzzy set method. These methods best compare model and measurements with a third reference map. In this study, however, a third reference map is absent.

Hagan (2002) reviews three statistics that are complementary to Kappa and that were introduced by Pontius in 2000 for map comparison purposes: \( K_{no} \), \( K_{location} \), and \( K_{quantity} \). Hagan, additionally, defines a fourth statistic, \( K_{histo} \), which overcomes problems with \( K_{quantity} \).

Pontius (2000) uses the term “no ability” because replacing \( PE \) with \( 1/n \), compares the \( PA \) to the situation in which a model has “no ability” to account for the quantity or location of categorized cells.

VBR composites

Errors for both model and measurements, plotted alongside results, justify the level of confidence

Examples include the spread and depletion of a forest fire over days, the decreasing habitat of a species of centuries

, for nominal (e.g. snow/snow-free) and multi-criterion (e.g. land-cover) accuracy

Spatiotemporal model results
A simple procedure for comparing two time series of SCA maps consists of (a) plotting %SCA for the watershed. Plotting both measured and modeled SCA, lumped over a watershed, versus time

…show a simple comparison…

Geographic information systems combined with satellite imagery enable researchers to virtually traverse harsh terrains and virtually cross political boundaries. Resulting maps reveal the influence of the environment on developments as well as effect of developments on the land and water.

Simultaneous to an explosion of satellite measurements being made available to the public through web services, models are being developed more quickly than ever. These models need

In Déry et al. (2004)…
Two snow models are evaluated: Catchment-Based Land Surface Model (CLSM) and TOPLATS…

- Catchment-Based Land Surface Model (CLSM)

- TOPMODEL-based Land-Atmosphere Transfer Scheme (TOPLATS).
  - Distributed.

deconvolution
solar radiation
air temp variation from dem
south facing slopes melted faster
95% snow cover variations due to solar radiation
Fotran

Papers to be sure to include in lit review:
- Modeling Snow-Cover Heterogeneity over Complex Arctic Terrain for Regional and Global Climate Models (S. Déry, W. T. Crow, M. Stieglitz, E. F. Wood)

CHAPTER 3
Delaunay triangulation is used to interpolate swath measurements into GCS grid data. This format is, in turn, projected into the Clarke UTM Zone 6 grid for comparison against the model output. Procedures and best practices for transforming swath data
are detailed. MATLAB® and Python code are made available for further research efforts.

a. Make associated quality assurance data, inherent to swath data, accessible
i. Develop a procedure for converting swath information to GIS readable GCS grid data.
ii. Consider both spatial and temporal distributions information in each available MOD10_L2 MODIS granule.
iii. Review measurement quality by evaluating
   1. Information inherent to HDF-EOS
      a. Quality assurance information
      b. Fractional snow coverage
      c. Time from solar noon
   2. Information inherent to the DEM
      a. Slope
      b. Elevation
   3. Source satellite
iv. Suggest RDF triplets for future map comparisons.
v. Evaluate feasibility of creating a web-service to perform data management tasks.
   1. On demand processing
   2. Distribution
      a. Technology survey

CHAPTER 4

Original Opening Paragraph... too redundant...
Model input parameters depend on the melt period revealed by MODIS measurements, and model confirmation depends on the usability of MODIS measurements as discussed in section 2.3.1 and section 3.3.2. We need, therefore, to download and review MODIS measurements before running TOPLATS. In this review we (a) look for the apparent winter-spring melt period and (b) determine the usability of MODIS measurements during this time.

From 4.1
Hang a picture on a wall and put a water bubble level on the frame. Two independent observers, depending on physical factors like their viewpoint angle and influencing factors like their taste for the picture, will read the level differently and give different advice on whether or not to use the picture. Similarly,

Figure XXX shows

Figure XXX shows the uncertainty of measurements as a function of probability described in section 2.4.3.2. The plot marks likely, maximum, and minimum snow cover for each MODIS scene.
In order to increase our confidence in the results to confirm TOPLATS, we filtered these results by (a) time of day, (b) coverage of available pixels, and (c) supporting quality assurance information.

We created arrays of scene indexes corresponding to measurement times for each of these factors and plotted %SCA over time for each of these indexes (figure XXX). We also plotted %SCA over time for the intersections of several of these indexes (figure XXX).

MODIS reads snow cover differently depending several factors like angle, cloud coverage, daylight, satellite (Aqua or Terra), and physical sensor damage.

Talk about night data and QA. Explain why we choose data based on time of day.

On describing the second supporting quality information plot:
The plots shows that there are two time periods in which MODIS senses the UKRW; once between hour twenty and hour one UTC and once between hour four and hour nine UTC. The measurement interval between hour twenty and hour four UTC occurs at solar noon relative to the end of May. We call this time interval “morning,” even though it ends after solar noon, because it starts in the morning. The second time period starts in the evening between XXX and XXX. We call this time period “evening” even though a third of it extends past the apparent sunset as determined by XXX. Note that the evening data includes night scenes even though our query to the NSIDC DAAC for these data included the request to ignore night data.

Figure XXX plots SCA for 2000, 2001, 2002 and figure XXX shows the decline of SCA vs time for the entire watershed and four elevation zones. While the %SCA plots show 100% SCA at the start of the melt and 0% SCA at the end of the melt, there is a lot of scatter during the melt and, initially, we predicted that this scatter must be due to either wind or cloud coverage. To test this first prediction, we plotted %SCA points over time from the data that had more than 90% of the data “Available” as defined by 3-2. Figure XXX circles this series in relationship to all points but still shows a lot of unexplained scatter in the data.

Plotting TOPLATS SWE time series’ for various albedos, overlaid with the a MODIS %SCA time series (that we believe to report measurements closest to the true melt as explained in 3.X and 4.X), we narrowed the number of albedo values down to three: 0.75, 0.80, and 0.85.

Figure 4-20 shows mean SWE measurements for each cell in the watershed overlaid with MODIS %SCA measurements (>90% available morning scenes). Error! Reference source not found. decomposes Figure 4-20 results into the four elevation zones shown in Figure 4-4. Error! Reference source not found. summarizes appendix XXX, showing the SWE depletion curve for each value of
initial albedo for the entire watershed. From visual inspection of these figures, the SWE depletion curve from the model run with an albedo of 0.80 seems to follow the path of the MODIS %SCA deletion curve best. Snow in the 0.75 albedo simulation completely ablates more than two days earlier than the snow in both the other two simulations and the snow reported by MODIS. The maximum mean SWE in the 0.75 simulation is Notice, however, total SWE for the trial with an initial albedo of 0.85 never reaches zero.

After directly comparing TOPLATs SWE predictions to MODIS %SCA measurements, we set thresholds for %SWE to be considered snow-covered and compared the %SCA graphs.

Thoughts for conclusions: Just because you are told a sensor delivers a particular temporal resolution, it doesn’t mean that all the points are usable within that temporal resolution. The largest factor limiting measurement frequency in the case of snow and ice data is time of day. Night-time data is unusable.

More thoughts: Reference 4.1 and talk about why QA data could have provided different results.

New figure list
- Map series / animations for all years.
- Cumulative series / animations for all years.
- Filtered series / animations for 2002.
- Filtered SCA plots….

Figure list
- Lat Lon Geolocation Course Grid GCS (put in chapter 3?)
- Lat Lon Geolocation Course Grid masked by watershed (put in chapter 3?)
- Interpolated Geolocation Grid masked by watershed
- Reduced Snow Cover on interpolated geolocation grid masked by watershed
- QA on interpolated geolocation grid masked by watershed
- Effect of Time of Day on Watershed %SCA
- Projected UTM zone 6 Cumulative %SCA

Notes
- Night data

Number of useful points = f(aqua, terra, area, daylight)

Daylight has a profound effect.
Kappa statistics confirm more about the quality of MODIS measurements during the 2002 sprint-winter melt period than they confirm model predictions. Figure XXX show plots of $\%$SCA, PA, $P_{RL}$, $P_{max}$, K, Klocation, Khisto for the entire watershed and each elevation zone. Notes from each of these plots are summarized in

This section shows spatial and temporal map comparison results for the 2002 MODIS data and the TOPLATS simulation data calibrated with a 0.80 albedo using a 0.015 SWE threshold. Map comparison results for other years depends on additional model input data.

Figure XXX takes the information plotted in figure XXX and extends it to include Kappa statistics described in XXX.

?? Figure XXX shows the temporal autocorrelation between the maximum discharge and peak decline of $\%$SCA with respect to time between years 2000 and 2002.
KS1 results for both methods, time series for both methods, Pearson correlation coefficient, relative accuracy of the model se/sy, other stats….

<table>
<thead>
<tr>
<th>Table 5-2. 2002 0.80 Albedo 0.75 SWE Threshold Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Watershed</td>
</tr>
<tr>
<td>----------</td>
</tr>
<tr>
<td>e&lt;sub&gt;min&lt;/sub&gt; (m)</td>
</tr>
<tr>
<td>e&lt;sub&gt;max&lt;/sub&gt; (m)</td>
</tr>
<tr>
<td>n (pixels)</td>
</tr>
<tr>
<td>%Area</td>
</tr>
<tr>
<td>PA</td>
</tr>
<tr>
<td>P&lt;sub&gt;RL&lt;/sub&gt;</td>
</tr>
<tr>
<td>P&lt;sub&gt;max&lt;/sub&gt;</td>
</tr>
<tr>
<td>K</td>
</tr>
<tr>
<td>K&lt;sub&gt;location&lt;/sub&gt;</td>
</tr>
<tr>
<td>K&lt;sub&gt;histo&lt;/sub&gt;</td>
</tr>
<tr>
<td>Bias ̂e</td>
</tr>
</tbody>
</table>

Compare values across

<table>
<thead>
<tr>
<th>Table 5-3. 2002 0.85 Albedo 2.50 SWE Threshold Statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>PASTE TABLE HERE</td>
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</tbody>
</table>

5.5 **CONTEXT: A SEMANTIC WEB OF HYDROLOGY**

Civil and environmental science engineers expect more, organized, and searchable information from modern technology such as web services, geographical information systems (GIS), and remote sensing: Web services provide on-demand datasets; portable GIS brings analysis into the field; radar and remote sensing provide measurements previously impossible to collect on the earth without destroying the environment or wasting time.

Water resources data is served in a variety of formats; from tab delaminated nitrogen data to XML specified rating curve information. Researchers can process data given a schema (e.g. document type definition), and understand it through a specification; computer systems, however, have no way of “understanding” data. Systems can be programmed to parse a particular syntax, but do not comprehend the English language. Programming objects, currently, can only abstract data meaning with additional specification knowledge. As storage and compute clouds are forming, more detailed hydrologic information is becoming available. More information will lead to better understanding of hydrologic systems only if processing and organizing this information becomes more efficient.

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The approaching semantic web will give computers, in addition to scientists and engineers, access to data defined by the Resource Description Framework (RDF) standard. RDF will enable both computers and humans, to not only comprehend and parse the syntax of a data, but also understand the needs and relevance of data in relation to water resources problems.

In this research, a time series of snow covered area (SCA) predictions are compared to remotely sensed measurements. Queries are currently made for snow coverage through one system and queries for digital elevation model (DEM) data are made, for that same location, using a different system. While it is feasible for an application to be developed in order to query for a snow coverage scene, for a given elevation zone, in a particular location — and in this work that is what is completed — there is no syntax for a computer system to understand the semantic connections between DEM data and snow coverage data. Once semantic web standards perpetuate data and data tools used in the field of water resources, relational queries like these may be easier to execute by both humans and services. Machine-readable ontology will enable intelligent agents to understand and solve queries that regularly take an engineer the time to learn application-specific programming objects and build analysis functions to relate what is not inherent in data itself. With increased convenience, model parameters will be lumped during the later stages of analysis, and measurement composites will be taken over further spatial reaches and longer time intervals.

A need to better understand distributed data in water resources will rise with a semantic web of information. Specific to remotely sensed data, once a semantic web is in place, it is assumed that map properties, map “needs,” and map relationships to other earth science information will be described more completely on a pixel-by-pixel basis. In this work, although RDF is not implemented for any data set, the hierarchal data format (HDF) that the SCA information is encapsulated in, contains self-describing statistics. Statistics include quality assurance information and, in Collection 5 described in XXX, fractional snow coverage. With greater accessibility to this kind of information through association of other data defined by RDF in the future, especially in measurements, it is assumed that more often future models will be created that take in account both spatial distributions and temporal distributions. Whether a model accurately predicts truth or not, the process of comparing distributed information will become more and more important. This work attempts to compare maps on said time and space distributions, composting information only in the final steps of analysis. In this approach, the process of comparison is emphasized as much as the result is, and the most basic datasets are selected from variety of available composites.