

**APPLICATION OF OPEN SOURCE CODING TECHNOLOGIES IN THE
PRODUCTION OF LAND SURFACE TEMPERATURE (LST) MAPS USING
LANDSAT AND ASTER IMAGERY**

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MASTERS DEGREE THESIS

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ÖZET

ASTER VE LANDSAT GÖRÜNTÜLERİNDEN AÇIK KAYNAK KOD TEKNOLOJİSİ KULLANILARAK YÜZEY SICAKLIK HARİTALARININ ÜRETİLMESİ

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Uzaktan Algılama ve Coğrafi Bilgi Sistemleri Anabilim Dalı, Yüksek Lisans Tezi,

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Bu çalışmada, açık kaynak kodlu bir CBS yazılımı olan QGIS yazılımında çalışabilen ve ASTER, Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS uydularının termal bant, yakın kızılötesi çözümlemesini yapan bir eklenti geliştirilmiştir. Bu eklenti açık kaynak kodlu bir dil olan Python programlama dilinde kodlanmıştır. Geliştirilen eklenti ile, ASTER, Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS uydusunun elektromanyetik spektrumun görünebilen bantları, yakın kızıl ötesi ve termal kızıl ötesi bantları kullanılarak, yer yüzey sıcaklığı haritaları üretilebilmektedir.

Geliştirilen eklentide ASTER ve Landsat uydularının termal görüntülerinden yer yüzey sıcaklığı elde etmek için tasarlanmış olan farklı algoritmalar kullanılmıştır. Bu algoritmalar; Planck Kanunu (Planck function), Yayılım Aktarma Denklemi (Radiative Transfer Equation), Landsat Tek Pencere Algoritması (Single Channel Algorithm for Landsat), ASTER Tek Pencere Algoritması (Single Channel Algorithm for ASTER), Tek Pencere Algoritması (Mono Window Algorithm) ve Bölünmüş Pencere Algoritmasıdır (Split Window Algorithm).

Bu çalışmadan üretilmiş eklenti kullanılarak, Kanada, New Brunswick sahasında yer yüzey sıcaklığı haritaları üretilmiştir. Elde edilen yer yüzey sıcaklık değerlerinin doğruluk analizinde, meteoroloji istasyonlarında ölçülen sıcaklık değerleri kullanılmıştır. Bu değerlere göre; Landsat 5 TM uydu görüntüsü için RMSE: 1.58 °C, Landsat 7 ETM+ uydu görüntüsü için RMSE: 2.96 °C., Landsat 8 TIRS uydu görüntüsü için RMSE: 2.07 °C değerleri elde edilmiştir.

Bu çalışma kapsamında üretilen eklenti, QGIS yazılımının eklentilerinin yer aldığı resmi web sayfasından ücretsiz bir şekilde indirilebilmektedir (<https://plugins.qgis.org/plugins>). Bundan dolayı yüzey sıcaklıkları ile çalışan geomatik, peyzaj, çevre, hidroloji, iklim, jeoloji, enerji vb. alanlarda yapılacak çalışmalara ve araştırmacılara öncülük teşkil edecektir. Üretilebilecek yer yüzey sıcaklığı haritaları, değişim analizinde kullanılarak; iklim, meteoroloji, orman yangını, jeotermal, buharlaşma ve tarımı çalışmaları yapılabilecektir.

Anahtar Kelimeler: ASTER, Açık Kaynak Kod, Coğrafi Bilgi Sistemleri, Landsat 5, Landsat 7, Landsat 8, Python, QGIS, Yer Yüzey Sıcaklık.

ABSTRACT

APPLICATION OF OPEN SOURCE CODING TECHNOLOGIES IN THE PRODUCTION OF LAND SURFACE TEMPERATURE (LST) MAPS USING LANDSAT AND ASTER IMAGERY

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This study presents a Python QGIS plugin which has been developed to extract the Land Surface Temperature (LST) from ASTER and Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS Thermal Infrared (TIR), Visible and Near Infrared (VNIR) imagery. It has been written using a free and open source Python programming language to work in the QGIS software.

Due the difficulties arising from the implementation of the algorithms involved in LST extraction, most users have not managed to benefit enough from the data collected by the ASTER and Landsat sensors. This study has implemented the Mono Window Algorithm (MWA), the Single Channel Algorithm (SCA) for Landsat, the Radiative Transfer Equation (RTE), the Planck function, the Single Channel Algorithm (SCA) for ASTER and the Split Window Algorithm (SWA) for ASTER.

Through the use of the plugin developed in the study, the LST maps of New Brunswick-Canada have been produced from the data obtained from the sensors. The accuracy assessment was done against near surface temperatures measured by the meteorological stations of the area. The best results obtained from Landsat 5 TM had Root Mean Square Errors (RMSE) of 1.58 °C, while the ones of Landsat 7 ETM+ had RMSE of 2.96 °C and for Landsat 8 TIRS, the RMSE were 2.07 °C.

The plugin developed in this study is expected available for download through the official QGIS repository i.e. <https://plugins.qgis.org/plugins> without any cost. Through the plugin it is expected that users from other disciplines such geomatics, hydrology, energy, geothermal studies, evapotranspiration and other environmental related fields can manage to benefit from the plugin in the production of land surface temperature maps.

Keywords: ASTER, Geographic Information Systems, Landsat 5, Landsat 7, Landsat 8, Land Surface Temperature, Python, QGIS, Open Source Code

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Milton Isaya NDOSSI

July/11th/2016

STATEMENT OF CONFORMITY TO ETHICAL PRINCIPLES AND RULES

I hereby truthfully declare that this thesis is an original work prepared by me; that I have behaved in accordance with the scientific ethical principles and rules throughout the stages of preparation, data collection, analysis and the presentation of my work; that I have cited the sources of all data and information that could be obtained within the scope of this study, and included these sources in the references section; and that this document has been scanned for plagiarism with "a scientific plagiarism detection program" used by Anadolu University , and that "it did not plagiarize" whatsoever. I also declare that, if a case contrary to my declaration is detected in my work at any time, I hereby express my consent to all the ethical and legal consequences that might arise.

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LIST OF ABBREVIATIONS

K	: Kelvin
LSE	: Land Surface Emissivity
LST	: Land Surface Temperature
METI	: Ministry of Economy, Trade and Industry
MISIR	: Multi-angle Imaging Spectral Radiometer
MODIS	: Moderate-resolution Imaging Spectroradiometer
MODTRAN	: MODerate resolution atmospheric TRANsmission
MOPPIT	: Measurements of Pollution in the Troposphere
MWA	: Mono Window Algorithm
NASA	: National Aeronautics and Space Administration
NDVI	: Normalized Difference Vegetation Index
NIR	: Near Infrared
GDAL/OGR	: Geo-spatial Data Abstraction Library
OLI	: Operational Land Imager
QGIS	: Quantum GIS
RS	: Remote Sensing
RTE	: Radiative Transfer Equation
SCA	: Single Channel Algorithm
SWA	: Split Window Algorithm

TIR	: Thermal Infrared
TIRS	: Thermal Infrared Sensor
USGS	: United States Geological Survey
VNIR	Visible and Near Infrared

1. INTRODUCTION

Land Surface Temperature (LST) is the temperature of the surface of the Earth (Wu, Shen, Zhang, & Göttsche, 2015b). Rajeshwari and Mani defined land surface temperature as *“the temperature felt when the land surface is touched with the hands or it is the skin temperature of the ground”* (Rajeshwari & Mani, 2014) recently, the need to acquire the temperature of the surface of the Earth has been a matter of great importance to climatologists, environmental activists, farmers and many others. LST has been important in studies related to climate change, hydrology, evapotranspiration and geothermal energy. Modern Landsat and Advanced Space-borne Thermal Emission and Reflection Radiometer (ASTER) instruments are equipped with sensors with ability to detect electromagnetic radiation which belongs to the Thermal Infrared (TIR) region of the electromagnetic spectrum. As a result of this, these sensors provide researchers with an opportunity to collect temperature data from any place in the world, in relatively high spatial resolution even from inaccessible areas in a well-defined temporal resolution. Not only that but the cost per unit area of satellite data is lower in comparison to ground based measurements.

This study involves the use of Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS and the ASTER sensors as tools of thermal infrared data collection from space. There are numerous algorithms which have been developed for the purpose of extracting Land Surface Temperature (LST) from TIR and Visible and Near Infrared (VNIR) from space. Despite the opportunities which can be leveraged from these sensors, the extraction of temperature data from them has not been an easy task (Zhang, Wang, & Li, 2006). As a result of this, most of the researchers and other users who make use of land surface temperature data have failed to benefit enough from the data acquired from these sensors. Not only that but most of the Remote Sensing (RS) and Geographic Information Systems (GIS) software available in the market are very expensive and do not have these algorithms implemented to ease the extraction of land surface temperature from the imagery of these sensors. The availability of a tool to automate the extraction of LST provides an opportunity for arguments related to land surface temperature algorithms, improvement of the existing algorithms and even save costs.

1.1 Background of the Problem

Wu, Shen et al. 2015 defined LST as “the temperature felt when the land surface is touched with the hands or it is the skin temperature of the ground” (Wu, Shen, Zhang, & Göttsche, 2015a). LST is the temperature of the point of interaction between the surface and the atmosphere (T. Wang et al., 2014). Thermal infrared data is one of the most important data collected by satellites in the recent decades. However the estimation of LST from satellite imagery is a very complicated task (Zhang et al., 2006).

As a result of the development of Remote Sensing (RS) and Geographic Information Systems (GIS) technologies and the availability of sensors which have a significantly high temporal resolution, satellite remote sensing remains to be the unique way to be employed in the measurement of LST over the entire globe with a relative high spatial resolution with in mean values rather than point values (Z.-L. Li et al., 2013b). LST is an important constituent of the Earth’s surface energy budget and is generally necessary in applications of hydrology, evapotranspiration, vegetation monitoring, meteorology and climatology (Z.-L. Li et al., 2013b; Pandya et al., 2014).

Modern Landsat and ASTER sensors are equipped with thermal infrared sensors with the ability to detect thermal infrared electromagnetic radiation which lies between 8 – 12 μm in wavelength and as a result providing researchers with large quantities of thermal data. These instruments work on the basis of the physics principle that every object on the surface of the Earth radiates thermal infrared energy and the radiated energy is proportional to the temperature of the object.

Numerous algorithms have been designed to enable the extraction of land surface temperature from Visible, Near Infrared (VNIR) and Thermal Infrared (TIR) imagery acquired from space. Some of these algorithms include the Split Window Algorithm (SWA), Single Channel Algorithm (SCA), Mono Window Algorithm (MWA), the Radiative Transfer Equation (RTE) and many others. In this study, a total of six algorithms involved in the estimation of LST from VNIR and TIR imagery have been used. These algorithms have been used in the extraction of LST from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS and the ASTER instrument. These algorithms are; the Mono-Window Algorithm (MWA) (Qin, Karnieli, & Berliner, 2001; F. Wang et al., 2015), the Single Channel Algorithm (SCA) for Landsat (Jiménez-Muñoz & Sobrino, 2003), the

Radiative Transfer Equation (RTE) (Z.-L. Li et al., 2013b), the Split Window Algorithm (SWA) for ASTER (Mao et al., 2006), the Planck function (Artis & Carnahan, 1982) and the Single Channel Algorithm (SCA) for Landsat satellites (J. C. Jiménez-Muñoz et al., 2009) have been programmed to work as a plugin in QGIS. QGIS, previously known as Quantum GIS is a free and open source software which is used worldwide in Remote Sensing (RS) and Geographic Information Systems (GIS) studies. In order to enable the algorithms to be used successfully, the developed plugin also enables the conversion of digital numbers to radiance, calculate brightness temperature, calculate Normalized Difference Vegetation Index (NDVI) and estimate Land Surface Emissivity (LSE) through the use of NDVI based methods. To estimate LSE from NDVI a total of three algorithms have been implemented on the plugin depending on the sensor being used in the land surface temperature extraction. These algorithms are; the NDVI threshold algorithm (Sobrino & Raissouni, 2000), Zhang, Wang et. al's LSE algorithm (Zhang et al., 2006) and J.C. Jimenez-Munoz's et. al's ASTER LSE algorithm (J. C. Jiménez-Muñoz, Sobrino, Gillespie, Sabol, & Gustafson, 2006).

Despite the presence of a large number of algorithms for LST extraction from space, the implementation of these algorithms has not been an easy task. Many users have failed to benefit enough from the thermal infrared data collected by these sensors due to the unavailability of these algorithms in commonly used Remote Sensing (RS) and Geographic Information Systems (GIS) software. Most of the RS and GIS software available in the market are also very expensive and as a result limiting users from being able to make use of them. They also do not provide researchers with their source codes which can also play a great role towards algorithm improvement. The plugin developed in this study is free to download from the official QGIS repository (Team, 2016) so as to enable users to make use of it. As a result of the code being based on an open source development approach, users are allowed to view, modify and redistribute freely. It is expected that this would further encourage debates, discussions, the use and improvement of land surface temperature algorithms. The following objectives are to be met by the research:

- To develop a QGIS plugin with the ability to automatically estimate the Land Surface Temperature from the Visible, Near Infrared (VNIR) and Thermal

Infrared (TIR) bands of Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS and the ASTER instrument.

- To develop a tool with the ability to automatically calculate the Land Surface Emissivity (LSE) from a Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS and ASTER scene using NDVI based methods.
- To perform a comparison between the temperatures measured by the Landsat 7 ETM+ sensor and the ASTER instrument.
- To examine the differences in temperatures extracted by the different algorithms involved in LST extraction from the sensors involved.

1.2 Research Questions

This research typically attempts to answer the following questions:

- How suitable for use are the available algorithms in LST extraction for Landsat 5 TM, Landsat ETM+ and Landsat 8 TIRS?
- How different are the LST derived from ASTER different from Landsat 7 ETM+?

1.3 Description of Study Area

This part focusses on the description of the area where the study was conducted. It explains about the location from which the data was collected for the accuracy assessment of the land surface temperatures obtained from the sensors used in the study.

1.3.1. Location

This study involved data collected from New Brunswick, Canada. New Brunswick is located in both the northern and western hemispheres. It is specifically located in the Canadian Maritimes i.e. a region in eastern Canada which is part of North America. The area is bordered by the provinces of Nova Scotia and Quebec, the United States (US) province of Maine and by the St. Lawrence Gulf, Northumberland straight and the Bay of Fundy. The study area has been chosen because of the availability of the meteorological data.

1.3.2. Climate and Vegetation of New Brunswick Canada

New Brunswick is a Canadian province located on the eastern seaboard of the North American continent. Its climate is characterized by clearly distinguishable seasons with cold and snowy winters. Summers are mild and pleasant in the area. The area has falls with alternating cold nights and sunny warm days. Temperatures at Fredericton range from extremely low (-37°C) to an extreme high of (37°C). In January, the average daily temperatures are moderate in the southern coastal areas. The annual rainfall of the area is normally about 800 mm while snow averages at about 2,900 mm. The annual precipitation of the area is about 1,100 mm. The area is mostly covered by forests. Coniferous trees are mostly found in the northern temperate climates. Common tree species include balsam fir, red and black spruce, pine and hemlock. Deciduous trees which are mostly found along the river valleys consist of sugar and red maple, trembling aspen, and yellow and white birch. Areas with thin and soils are mostly covered with Wild blueberries and cranberries, especially in the southwestern areas (Patterson, 2016).

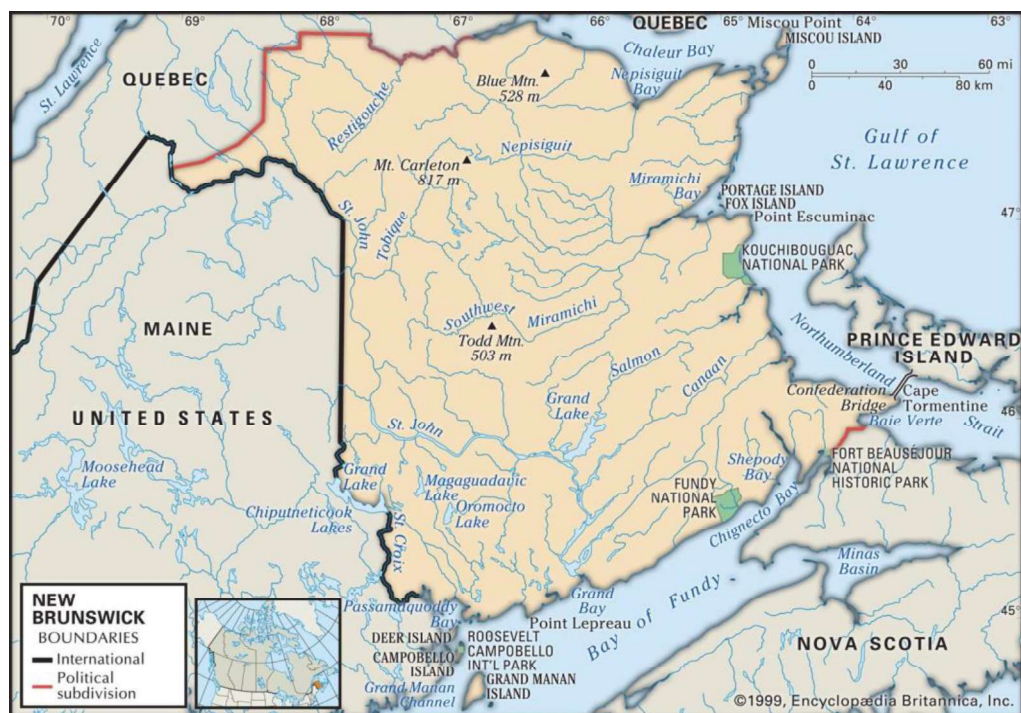


Figure 1.1. Map of New Brunswick, Canada

Source: Patterson, 2016

1.4 Theoretical Background

This part introduces the theoretical concepts involved in thermal remote sensing. It discusses the basis of the thermal electromagnetic theory and also attempts to do a literature study related to the algorithms of LST extraction from VNIR and TIR imagery acquired from space-borne sensors.

1.4.1. Literature review on the thermal infrared theory

Infrared radiation is the electromagnetic radiation in the wavelength range between the visible radiation ($\lambda 380\text{--}780\text{ nm}$) and the microwave region ($\lambda 1\text{ mm--}1\text{ m}$) of the electromagnetic spectrum. Any object on the surface of the Earth that has a temperature above absolute zero (i.e. -273 K) is said to emit Thermal Infrared (TIR) radiation. The average temperature of the Earth is about 300 K and its peak of electromagnetic emittance is located in the thermal infrared, TIR, domain at about $9.7\mu\text{m}$ (Kuenzer & Dech, 2013). This means that all the temperatures of all objects which are found on the surface of the Earth can be determined through the use of thermal infrared technologies. Figure 1.2 shows the position of the thermal infrared region in the electromagnetic spectrum.

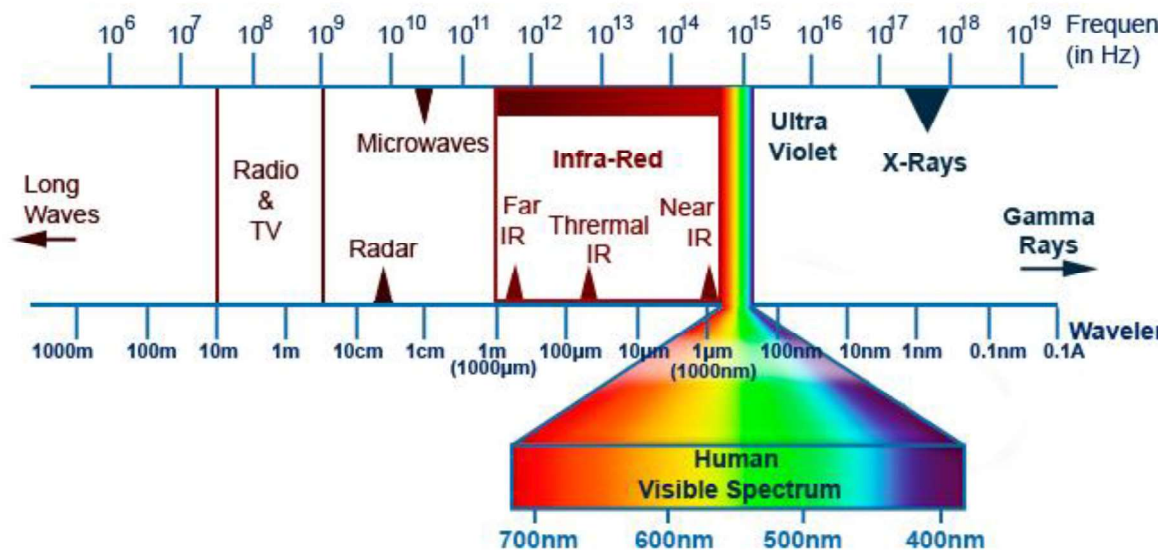


Figure 1.2. The Electromagnetic Spectrum

Source: Wubet, 2003

Every object with a temperature above the absolute zero radiates infrared radiation. The amount of radiation radiated at different wavelengths is been shown by Figure 1.3.

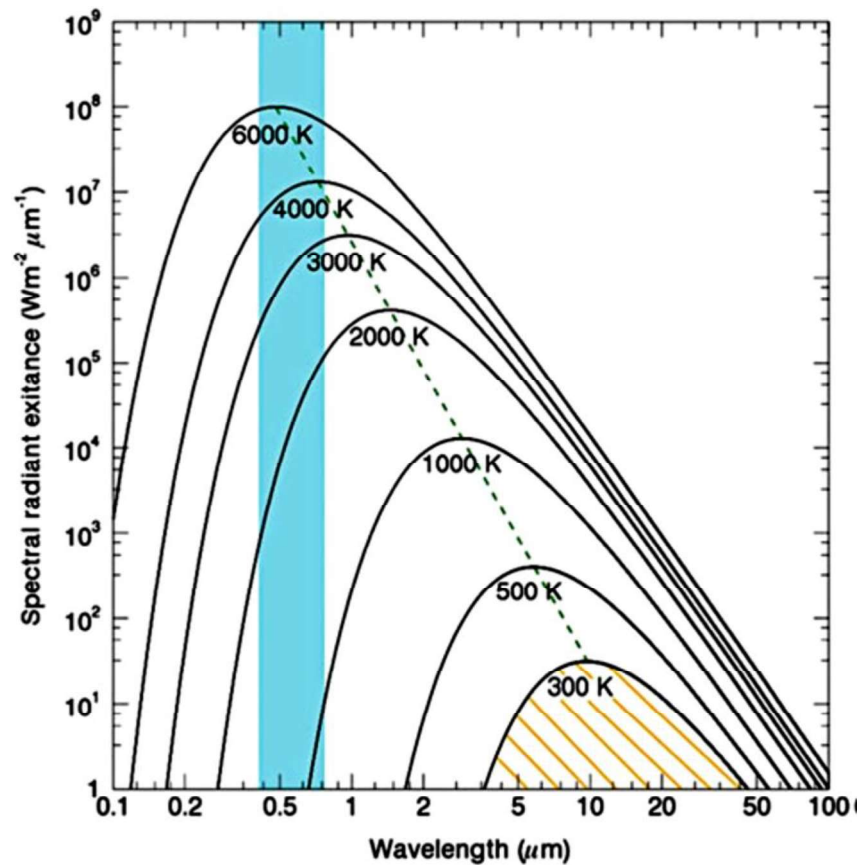


Figure 1.3. Blackbody radiation curves at different selected temperatures, as derived from Eq. (1.1). the laws of Planck, Stefan-Boltzmann (marked area under the 300 K curve) and Wien (green dotted line) are depicted in this figure. The blue bar indicates the VIS region

Source: Wubet, 2003

1.4.2. Planck's law

The Planck's law is the law that governs the amount of radiation absorbed and emitted by a blackbody. The law is sometimes known as Planck's law of radiation or just Planck's law. It operates based on the radiation of a black body. A blackbody is an object that has the ability to radiate and absorb all the energy. It is a hypothetical model which is used in the modelling of temperature values emitted from an object. In real world scenarios, an object that meets the properties of a blackbody doesn't exist, however, there exist objects which have properties which are close to those of black

bodies. The law describes the amount of electromagnetic radiation that is emitted by a blackbody at a known wavelength M_λ as a function of the blackbody's absolute temperature (Kuenzer & Dech, 2013). The law is expressed mathematically in Equation (1.2).

$$M_\lambda = \frac{2\pi hc^2}{\lambda^5 (e^{\frac{hc}{\lambda kT}} - 1)} \quad (1.2)$$

Where M_λ stands for the spectral radiant exittance, h represents the Planck's constant, c is the speed of light 2.9979246×10^8 m/s, k is the Boltzmann constants, T is the absolute temperature and λ is the wavelength [μm]

1.4.3. Wien's law

This law is also known as Wien's law of displacement. According to the law, there exists an inverse relationship between wavelengths and emittance (Kuenzer & Dech, 2013). The law describes the maximum wavelength at which the maximum spectral radiant emittance occurs. It is expressed mathematically as shown in Equation (1.3).

$$\lambda_{\max} = \frac{A}{T} \quad (1.3)$$

In Equation (1.3), $\lambda_{\max}$ stands for the wavelength of maximum spectral radiant exittance [μm], A stands for the Wien's constant [$2897.8 \mu\text{m K}$] and T is the absolute kinetic temperature. According to the law, with the increase of the temperature of an object, its maximum emittance $\lambda_{\max}$ shifts to shorter wavelengths.

1.4.4. Black body emissivity and radiant temperature

Temperature is the measurement of the degree of hotness or coldness of an object. The concentration of kinetic heat of a body is also known as kinetic temperature. It is measured by a thermometer placed on direct contact with the material. With

reference to the Planck's law, very few terrestrial surfaces act as perfect black bodies. Most objects emit less than predicted from their kinetic temperature (Kuenzer & Dech, 2013). The emissivity of a body varies from one place to another depending on the nature of the surface of an area and the wavelength of the emitted radiance and does not relate to the temperature of a body (Flynn, Harris, & Wright, 2001). Land surface temperature is strongly influenced by the ability of a substance to radiate thermal radiation i.e. emissivity, therefore it is important for the emissivity of the surface to be known for the successful estimation of LST from space.

1.4.5. Literature review on algorithms of land surface temperature extraction

Many algorithms have been developed for the purpose of extracting land surface temperature from visible, near infrared and thermal infrared imagery. These algorithms can generally be classified into two major groups. Which are; algorithms based on a single thermal infrared band and algorithms based on more than one thermal band. Examples of single channel algorithms include; the Radiative Transfer Equation (RTE) (Chandrasekhar, 2013; A. P. Wang), the Single Channel Algorithm (SCA) (J. C. Jiménez-Muñoz & J. Sobrino, 2010; Jiménez-Muñoz & Sobrino, 2003), the Planck function (Stathopoulou & Cartalis, 2007) and the Mono Window Algorithm (Qin et al., 2001; F. Wang et al., 2015). The algorithms based on more than thermal band include; Split window algorithms (SWA) (Becker & Li, 1990; J.-C. Jiménez-Muñoz & Sobrino, 2008; Kerr, Lagouarde, & Imbernon, 1992; Mao et al., 2006) and many others.

The RTE is also known as the equation of transfer. Thermal infrared data has a direct relationship with the radiative transfer equation (Z.-L. Li et al., 2013b). It is an equation which shows the relationship between the atmospheric processes of absorption, emission and scattering of electromagnetic radiation. The equation is based on the radiative transfer theory which states that the amount of radiation that is measured by a sensor is determined by the atmosphere and the ground that it is emitted from (Z.-L. Li et al., 2013b). In accordance to the theory on blackbodies, the emittance of a substance can be expressed by the Planck equation. The equation was derived while ignoring the solar irradiance and assuming that the land surface was flat. This poses a challenge in the accuracy of the algorithm as it does not take the surface roughness in

the estimation of land surface temperature. The blackbody theory is also a hypothetical theory as a result of the absence of a true blackbody (Qin et al., 2001). As a result of this, it is important for researchers to estimate the land surface emissivity of the land surface when using the RTE in the extraction of land surface temperature. The RTE is expressed mathematically as shown in Equation (1.4).

$$\lambda_i = [\varepsilon_i B_i(T_s) + (1 - \varepsilon_i) L_{d,i}] \tau_i + L_{u,i} \quad (1.4)$$

Where $L_{u,i}$ and $L_{d,i}$ are the atmospheric upwelling and down-welling radiance, respectively. Land Surface Emissivity (LSE) and atmospheric parameters ($L_{u,i}$, $L_{d,i}$ and τ_i) should be known before the LST can be solved from the equation. Assuming that the LSE of an area is known, the method can be applied with the inversion of the Planck's function. It is however difficult to put this equation into application as the atmospheric temperature and humidity are usually difficult to obtain (S. L. L. Wang, 2012).

Due to the presence of the atmosphere between the surface of the Earth and the sensor involved for measurements of the top of atmosphere radiance, there arises a need to perform atmospheric corrections on the radiances acquired from space-borne sensors. These radiances are obtained mainly from emission/reflection at the surface altered by the effects of attenuation, emission and emission-reflection. Making these correction requires accurate knowledge of the vertical and horizontal profiles of the atmospheric water vapour and temperature which are highly variable (Z.-L. Li et al., 2013a; Perry & Moran, 1994; P. K. Srivastava et al., 2014). It is however difficult to perform atmospheric corrections involved in the radiative transfer equation especially because the atmospheric profile information during the satellite overpass time is in most of the times not available. The estimation of the atmospheric transmission, upwelling radiance and the down-welling radiance of the atmosphere during the satellite overpass time is also difficult to determine. Although there is a presence of methods such as Moderate Atmospheric Transmission (MODTRAN) (AGPA Berk et al., 1999; Alexander Berk, Bernstein, & Robertson, 1987) and 6S (Kotchenova & Vermote, 2007) which are used to simulate the atmospheric conditions and perform atmospheric corrections during the satellite overpass, atmospheric transmission may vary from

place to place and as a result hampering the accuracy of the temperatures derived from the algorithm. According to previous researchers, the process of deriving land surface temperature from space is mathematically underdetermined and unsolvable (Hook, Gabell, Green, & Kealy, 1992; Kealy & Hook, 1993; Z.-L. Li et al., 2013a). When attempts are made to derive land surface temperature using the radiative transfer equation, if the radiance is measured in N number of channels, there is always a presence of $N+1$ number of unknowns corresponding to N emissivities in each channel and an unknown land surface temperature for N number of equations even if the quantities such as the emissivities and land surface temperature are known in priori (Z.-L. Li et al., 2013a). The measurements which are made in the thermal infrared region of the electromagnetic spectrum are highly correlated. This means that, the instrumental noise and errors which may arise from atmospheric corrections may exert a great influence to the accuracy of the retrieved land surface temperatures. This correlation poses a challenge even if the land surface temperature is made solvable either through the reduction in the number of unknowns or through making reasonable assumptions or constrains in land surface emissivities. As a result of these correlations, land surface temperature becomes unstable and have hampered the methodological development of land surface retrieval (Z.-L. Li et al., 2013a). Figure 1.4 illustrates the radiative transfer model of the atmosphere.

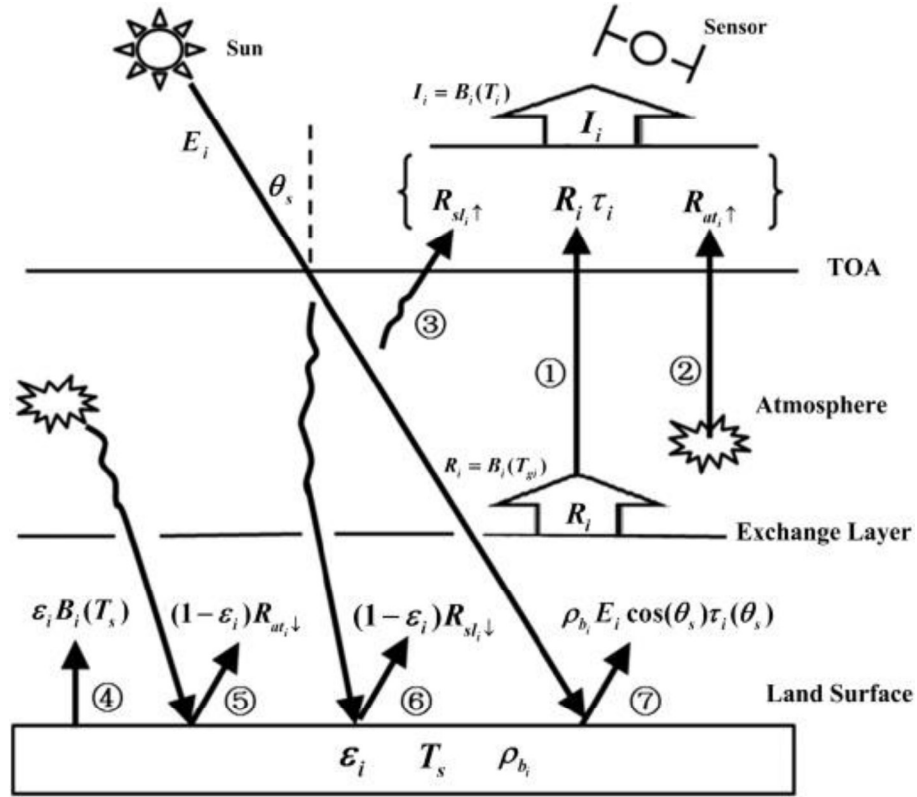


Figure 1.4. The Radiative transfer model of the atmosphere

Source: Z-L. Li et al., 2013a

Where I_i represent the radiance measured by a thermal infrared channel i at the top of atmosphere. Path ① represents the radiance measured at ground level attenuated by the atmosphere. Paths ② and ③ represent the upwelling atmospheric thermal radiance and the upward solar diffusion radiance, respectively. Path ④ represents the radiance which is directly emitted by the surface. While paths ⑤ and ⑥ represent the downward atmospheric thermal radiance and solar diffusion radiance reflected by the surface, respectively. Path ⑦ represents the direct solar radiance reflected by the surface.

In order to derive LST through the use of the RTE and the SCA, the atmospheric parameters of upwelling radiance, down-welling radiance and transmission during the satellite overpass time are required. This implies the availability of atmospheric sounding data during the satellite overpass time. This is difficult as these parameters change from one place to another and are also variable with time. In order to solve the problem, The National Centers for Environmental Prediction (NCEP) modeled

atmospheric profiles. However, these data are only usable in studies at a global scale and they need to be interpolated to a specific date, location and time (J. C. Jiménez-Muñoz et al., 2009). As a solution to the problem, Barsi, Barker et al. introduced the National Aeronautics and Space Administration (NASA) atmospheric parameters calculator (J. Barsi, Barker, & Schott, 2003) which can be used to simulate the atmospheric functions as from January 2000 (Isaya Ndossi & Avdan, 2016).

Jimenez-Munoz, Cristobal et al. introduced five different atmospheric sounding databases to create simulated data for Landsat 4 TM, Landsat 5 TM and Landsat 7 ETM+ (J. C. Jiménez-Muñoz et al., 2009). These atmospheric databases can also be used in the determination of the atmospheric functions required when deriving LST. These databases were tested and proved to provide results with Root Mean Square Errors (RMSE) of less than 1 K in most situations whenever the atmospheric water vapour was less than 2 g·cm⁻². However, for atmospheric water vapour values of more than 3 g·cm⁻², the errors were not acceptable (J. C. Jiménez-Muñoz et al., 2009).

The single channel method is also known as the model emissivity method (Hook et al., 1992). The algorithm uses the radiance which has been measured by a sensor in a single thermal band chosen within an atmospheric window and corrects the radiance for possible attenuation and emissivity through atmospheric transmittance or radiance code which requires input data on the atmospheric profiles. In order to obtain accurate measurements using the single channel algorithm, there is a need to have high quality atmospheric transmittance and radiance code to estimate the atmospheric quantities involved in the radiative transfer equation (Z.-L. Li et al., 2013a). The Single Channel Algorithm (SCA) has been used successfully to derive land surface temperatures using Landsat 5 TM, Landsat 7 and the ASTER sensors. Mathematically, the algorithm is expressed as shown in Equation (1.5).

$$T_s = \frac{[a(1 - C - D)] + (b(1 - C - D) + C + D)T_i - DT_a}{C} \quad (1.5)$$

Where T_i is the brightness temperature the thermal infrared band which is involved in the study, $a = -67.355351$, $b = 0.458606$, $C = \varepsilon_i \tau_i$ and $D = (1 - \tau_i) [1 + \tau_i (1 - \varepsilon_i)]$ while ε_i and τ_i are the land surface emissivities of the thermal infrared band.

The input parameters involved in the Single Channel Algorithm (SCA) are the atmospheric transmittance and the average temperature of which the atmospheric transmittance and average temperature can be obtained from meteorological data. The limitation of this algorithm is that the estimation of atmospheric transmittance and average temperature only makes use of standard atmospheric profile data. As a result of standard atmospheric data being representing statistical results of a large area, this may not reflect the actual atmospheric condition and as a result limit the applicability of the algorithm (S. L. L. Wang, 2012). As an attempt to reduce the limitations resulting from the single channel algorithm, Jiménez-Munoz and Sobrino (2003) introduced a generalized single channel algorithm for land surface retrieval from thermal infrared data obtained from any sensor (Jiménez-Muñoz & Sobrino, 2003). As compared to the single channel algorithm, the only inputs required in the algorithm are land surface emissivity and atmospheric water vapour. Jiménez-Munoz and Sobrino (2003) also introduced an atmospheric profile database of regressing atmospheric function coefficients and recalculating the atmospheric functions needed for Landsat 4 TM, Landsat 5 TM and Landsat 7 ETM+ (S. L. L. Wang, 2012).

Qin, Karnieli and Berliner introduced the Mono Window Algorithm (MWA) in order to increase the use of thermal infrared remote sensing from Landsat TM sensor (Qin et al., 2001). As a result of the algorithm being suitable for the retrieval of land surface temperature from only one thermal band, it was named as the “Mono Window Algorithm” in order to distinguish it from the Split Window Algorithm (SWA) which makes use of two thermal infrared channels in land surface temperature extraction (Qin et al., 2001). For the MWA to be successfully applied, three parameters are required. These are land surface emissivity, atmospheric transmittance and the effective mean atmospheric temperature. The sensitivity analysis which was done by the researchers revealed that the errors which may result from the estimation of land surface emissivity which is difficult to estimate, have considerably a low effect to the probable land surface temperature estimation error which is much more sensitive to errors which may arise

from atmospheric transmittance and mean atmospheric temperature (Qin et al., 2001). The MWA has been used in several studies for LST estimation (Huang, Li, Zhao, & Zhu, 2008; Liu & Zhang, 2011; Zhang et al., 2006; Zhang, Wang, & Wang, 2007). The MWA also faces the challenges which face the other algorithms involved in the estimation of LST from space. The near surface temperature which is used in the algorithm may vary rapidly depending on the topography of an area, the estimation of the atmospheric transmission which is also used as a parameter in the algorithm may as well lead to the occurrence of errors in the LST estimation process. This in turn limits the application of the algorithm.

The Split Window Algorithm (SWA) was developed for the purpose of extracting land surface temperature from multispectral thermal infrared sensors such as Moderate Resolution Imaging Spectral Radiometer (MODIS), Advanced Very High Resolution Radiometer (AVHRR), Landsat 8 Thermal Infrared Sensor (TIRS) and the Advance Space-borne Thermal Emission and Reflection Radiometer (ASTER). The algorithm has been used successfully in a number of studies (Kerr et al., 1992). It was initially introduced by McMillin for the purpose of estimating sea surface temperature from remote sensing data (McMillin, 1975) and it was later on modified for use in different types of sensors. Its algorithm takes advantage of different atmospheric absorption features in two different channels in between the (10.5 – 12.5 μm) atmospheric window. In order to reduce the influence of the atmosphere from the estimated LST, the brightness temperatures of the two thermal infrared channels are used (S. L. L. Wang, 2012).

In this study, the Mono Window Algorithm, (MWA), the Single Channel Algorithm (SCA) for Landsat sensors, the Single Channel Algorithm (SCA) for the ASTER sensor, the Radiative Transfer Equation (RTE) and the Planck function and the Split Window Algorithm (SWA) have been implemented to work as a Quantum GIS (QGIS) plugin for land surface temperature estimation. To implement the plugin development, the Python programming language was used. This is because the language is supported in the QGIS Application Programming Interface (API), it is robust and developed in the Free and Open Source Framework (FOSS) and also because the Python programming language is independent of platform therefore the users of the plugin will manage to

use it in the commonly used operating systems platforms i.e. Windows, Linux and Mac OSX operating systems.

2. MATERIALS AND METHODS

In order for the research to solve and meet the anticipated objectives, the study was divided into the preliminary phase, data collection, development phase and analysis.

2.1. Preliminary Preparation

In this phase, literature and materials which are related to the study were read. This included going through the libraries available for Python geo-processing of raster data obtained from the sensors, acquisition of satellite imagery and understanding the algorithms which are used in the extraction of LST from the sensors used in the study.

2.2. Data Collection

This stage involved the familiarization and collecting the meteorological data which was collected during the satellite overpass time. In this step, the near surface air temperature and relative humidity data of the study areas was collected.

2.3. Development Phase

This is the phase which used most of the time of the project. The development stage involved the writing of the geo-processing script which is used in the implementation of the algorithms which have been used in the study and the development of the Graphical User Interface (GUI) of the plugin.

2.4. Data Processing and Analysis

This phase involved the analysis of the data using the plugin which was developed in the study. The results obtained from the plugin were compared to the results which were obtained ArcGIS 10.2.2 and ERDAS Imagine 2014 in order to make sure that the outputs were correct.

2.5. Materials and Data Used in The Study

2.5.1. Landsat

Landsat is the longest series of Earth Observation Satellites (EOS) in use today. The first satellite of the series was known as Earth Resources Technology Satellite and it was put into orbit in 1972. The satellite was later on renamed to Landsat 1. Since the launch of Landsat 1, there has been a launch of a total of 8 satellites. Out of the satellites, Landsat 8 failed to attain orbit and fell down to Earth in 1993. The rest of the seven have proven to be successful and have been used in a great number of studies related to change research, agriculture, urban studies, climate studies and many more. This study involves the use of the data collected from Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS. Table 2.1, Table 2.2 and Table 2.3 show the technical specifications of Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS respectively. Landsat is available for download without any cost through the United States Geological Survey (USGS) i.e. <http://earthexplorer.usgs.gov>. Table 2.4 shows the Landsat scenes which have been used in the study.

Table 2.1. *Landsat 5 TM technical specifications*

Thematic Mapper (TM)	Bands	Wavelength (micrometres)	Resolution (meters)
	Band 1	0.45-0.52	30
	Band 2	0.52-0.60	30
	Band 3	0.63-0.69	30
	Band 4	0.76-0.90	30
	Band 5	1.55-1.75	30
	Band 6	10.40-12.50	120* (30)
	Band 7	2.08-2.35	30

Source: *USGS, 2015a*

Table 2.2. *Landsat 7 ETM+ technical specifications*

Enhanced Thematic Mapper Plus (ETM+)	Landsat 7	Wavelength (micrometres)	Resolution (meters)
	Band 1	0.45-0.52	30
	Band 2	0.52-0.60	30
	Band 3	0.63-0.69	30
	Band 4	0.77-0.90	30
	Band 5	1.55-1.75	30
	Band 6	10.40-12.50	60 * (30)
	Band 7	2.09-2.35	30
	Band 8	0.52-0.90	15

Source: *USGS, 2015a*

Table 2.3. *Landsat 8 technical specifications*

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) Launched February 11, 2013	Bands	Wavelength (micrometres)	Resolution (meters)
	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 - Blue	0.45 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
	Band 6 - SWIR 1	1.57 - 1.65	30
	Band 7 - SWIR 2	2.11 - 2.29	30
	Band 8 - Panchromatic	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
	Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
	Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)

Source: USGS, 2015a

Table 2.4. *Landsat Scenes used in the study*

Sensor	Date	Path	Row
Landsat 5 TM	13 th November 2010	009	028
Landsat 5 TM	31 st December 2010	009	028
Landsat 7 ETM+	21 st November 2010	009	028
Landsat 7 ETM+	23 rd February 2016	009	028
Landsat 8 TIRS	29 th May 2013	009	028
Landsat 8 TIRS	4 th June 2015	009	028

2.5.2. The Advanced Space Thermal Emission and Reflection Radiometer (ASTER)

The ASTER sensor is one of the five modern instruments found in the Terra spacecraft. Terra was launched on December 18, 1999 at Vandenberg Air Force Base, California - USA. The spacecraft carries a total of five payloads. These include; ASTER, Clouds and the Earth's Radiant Energy System (CERES), Multi-angle Imaging Spectroradiometer (MISR), Moderate-resolution Imaging Spectroradiometer (MODIS) and Measurements of Pollution in the Troposphere (MOPITT). The imagery acquired from the ASTER instrument is expected to contribute to a wide range of global change-related studies, including vegetation and ecosystem dynamics, hazard monitoring, geology and soils, land surface climatology, hydrology, land cover change, and the generation of Digital Elevation Models (DEMs) (USGS, 2014). The ASTER sensor is a product of a cooperative effort between the National Aeronautics and Space Administration (NASA), Japan's ministry of Economy, Trade and Industry (METI) and Japan Space Systems (J-Space systems). The sensor is used to create in depth maps of

Land Surface Temperature (LST), reflectance and elevation (NASA, 2012). Following the announcement which was made in 1st April 2016, ASTER imagery will be provided free of charge (Buis, 2016). This provides researchers with an opportunity to extract LST from space at different spatial and spectral resolutions in comparison to other sensors. ASTER imagery is available for download without any cost through the United States Geological Survey (USGS) i.e. <http://earthexplorer.usgs.gov>. Table 2.5 shows the technical specifications of the ASTER sensor.

Table 2.5. *Technical specifications of the ASTER instrument*

Launch Date	18 December 1999 at Vandenberg Air Force Base, California, USA
Equator Crossing	10:30 AM (north to south)
Orbit	705 km altitude, sun synchronous
Orbit Inclination	98.3 degrees from the equator
Orbit Period	98.88 minutes
Grounding Track Repeat Cycle	16 days
Resolution	15 to 90 meters

Source: NASA, 2012

The ASTER instrument consists of three separate instrument subsystems: VNIR (Visible Near Infrared), a backward looking telescope which is only used to acquire a stereo pair image SWIR (Shortwave Infrared), a single fixed aspheric refracting telescope TIR (Thermal Infrared). The sensor consists of 14 bands. Table 2.6 shows the bands, their spectral ranges and spatial resolution of the ASTER instrument. Table 2.7 shows the ASTER scenes which have been used in the study.

Table 2.6. *ASTER sensor bands, wavelengths and spatial resolution*

Subsystem	Band	Spectral Range (μm)	Spatial Resolution	Quantization
VNIR Subsystem	1	0.52 – 0.60	15 m	8 bits
	2	0.63 – 0.69		
	3N	0.78 – 0.76		
	3B	0.78 – 0.76		
SWIR Subsystem	4	1.60 – 1.70	30 m	8 bits
	5	2.145 – 2.185		
	6	2.185 – 2.225		
	7	2.235 – 2.285		
	8	2.295 – 2.365		
	9	2.360 – 2.430		
TIR Subsystem	10	8.125 – 8.475	90 m	12 bits
	11	8.475 – 8.825		
	12	8.925 – 9.275		

13	10.25 – 10.95
14	10.95 – 11.65

Source: NASA, 2012.

Table 2.7. *ASTER Scenes used in the study*

Sensor	Date	Path	Row
ASTER Level 1T	21 st November 2010	009	028
ASTER Level 1T	23 rd February 2016	009	028

2.5.3. Meteorological data

In order to perform the accuracy assessment of the land surface temperatures used in the study, this study made use of historical data. The meteorological data was obtained from the Canadian weather and meteorological website i.e. <http://www.climate.weather.gc.ca> (Canada, 2016). The meteorological data was collected in an hourly basis during the satellite overpass time. To solve the time differences arising from day light saving, one hour was added to the data which was collected when daylight saving was observed. Environment Canada requires one hour to be added to the time when daylight saving is observed. One hour was added to the satellite overpass times of the scenes belonging to the months of November, December and February therefore the meteorological data for 12:00 hours was used. The scenes belonging to the months of June, May and September was compared to meteorological data measured at 11:00 am., as daylight saving was not observed.

2.5.4. Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics (Hetland, 2008). The Python programming language offers a number of features. Some of them include;

- It reflects a number of developing styles in software development.
- It is a very simple language surrounded by a wide range of libraries and add-on modules.
- It is an open source project supported by a large community of developers.
- It is an object-oriented language. The language is organized in the form of objects which may contain data in the form of attributes and methods.

- The language has an ability to run in all the commonly used operating systems. It is a platform-independent, scripted language, with complete access to operating system Application Programming Interfaces (APIs).
- It supports incorporation of complex solutions from pre-built components.
- The Python code has an ability to run more flexibly and in a dynamic manner as compared to statically compiled languages.

Additionally, Python is a scripting language with an ability of having full access to Operating System (OS) services. As a result, it can create high level solutions built up from other complete programs. This allows someone to integrate applications without a glitch, creating high-powered, highly-focused meta-applications. This kind of very high level programming is sometimes termed as scripting. The Python programming language is a programming language of its own class which allows a powerful combination of existing application programs and unique processing (Linuxtopia, 2015).

2.5.5. The Geo-Spatial Data Abstraction Library (GDAL/OGR)

The library is the most widely used geospatial data access library (OSGeo, 2015). It is a platform independent C++ translator library intended for raster and vector geospatial data formats. It is released under an X/MIT style open source license by the Open Source Geospatial Foundation. Being a library, it presents a single abstract data model to the calling application for all supported formats. The library comes with numerous command line utilities used for data translation and processing. GDAL supports more than fifty raster formats while OGR supports more than twenty vector formats. The library provides the primary data access engine for many applications such as; MapServer, GRASS, QGIS and OpenEV. It is also used by software such as OSSIM, Cadcorp SIS, FME, Google Earth, VTP, Thuban, ILWIS, MapGuide and ArcGIS. GDAL provides functions to open raster files and retrieve their metadata as well as their image data. Through the use of the library, it is possible to perform mathematical operations to the data.

2.5.6. PyQt4

In order to develop a graphical user interface for the LST extraction tool for the study, PyQt4 has been used. Qt is a platform independent framework for the design of User Interfaces (UI) for developers in C++ or QML (a CSS and JavaScript like language). The Integrated Development Environment (IDE) of Qt is known as Qt Creator. PyQt is a collection of Python bindings for Qt that are distributed in two licenses which are; General Public License (GPL) 2 and 3 with additional license exceptions. PyQt exposes much of the functionality of Qt to Python, including (Project, 2015):

- A complete set of widgets,
- Flexible layout managers,
- Standard Graphical User Interface (GUI) features for applications i.e. menus, toolbars, and dock windows.
- It has the ability to facilitate easy communication between application components through the use of signals and slots.
- It is a unified painting system with transparency, anti-aliasing, OpenGL integration and SVG support.
- It allows internationalization (i18n) support and integration with the Qt Linguist translation tool and as a result enabling its applications to be available in a wide range of languages.
- It has an ability to process rich text, displaying and printing facilities, including support for exporting PDFs.
- It supports databased based applications such as the Structured Query Language (SQL) and model/view features.
- PyQt4 is a multithreading environment which supports the execution of a program in more than one instance and as result managing to make use of processing power in an efficient manner.
- Widget styles, including support for widget style sheets (from Qt 4.2 onwards),
- Input/output (I/O) and networking.

2.6. Land Surface Temperature (LST) Extraction

This part discusses the methodology used in the study. It discusses the processes involved in the conversion of Digital Numbers (DNs) to LST. Typical discussions made in this part include the Conversion of DNs to radiance, conversion of radiance to brightness temperature, Normalized Difference Vegetation Index (NDVI), Land Surface Emissivity (LSE) and the algorithms involved in the estimation of LST from VNIR and TIR satellite imagery. Figure 2.1 and Figure 2.2 show the methodology used in the extraction of LST using imagery acquired from the Landsat sensors and the ASTER instrument respectively.

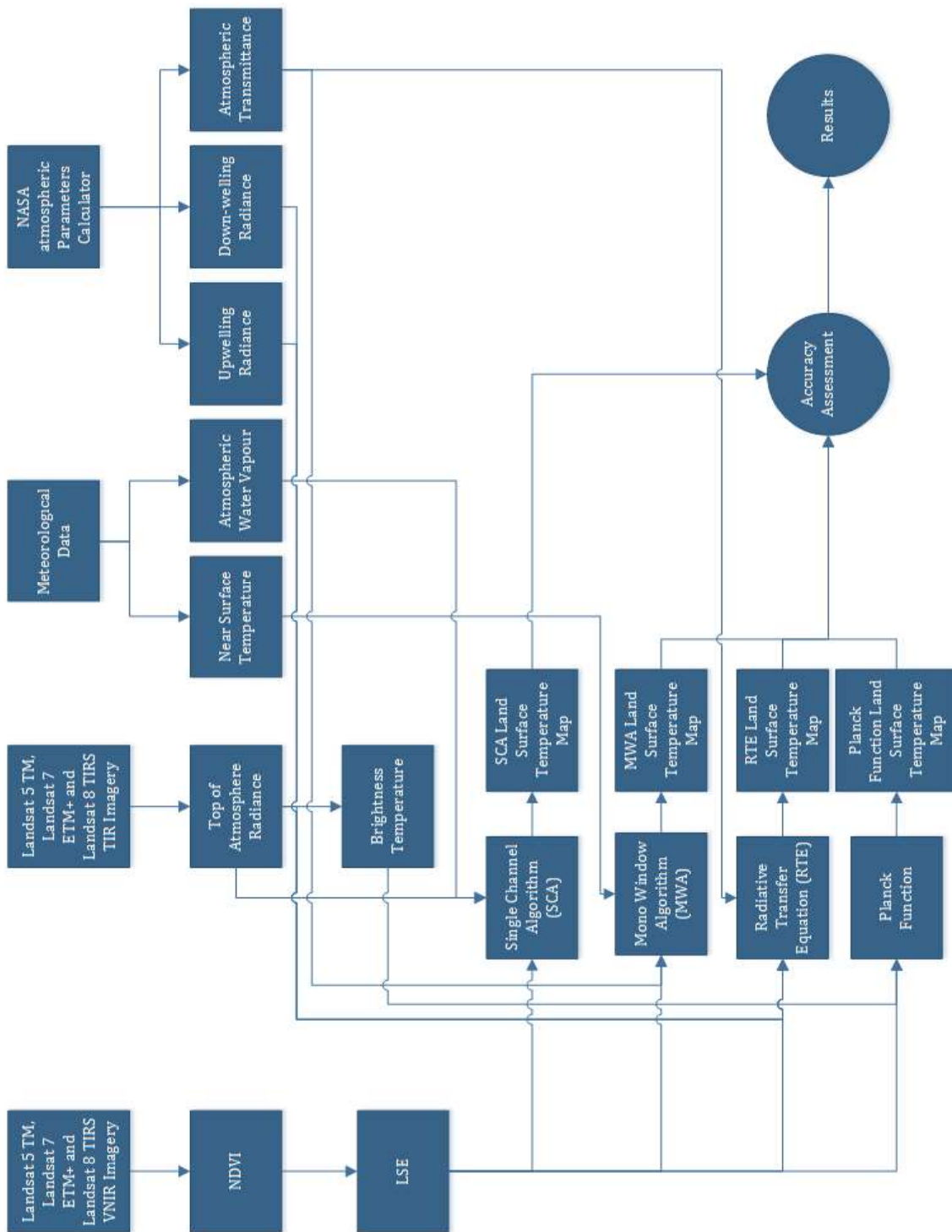


Figure 2.1: Methodology used in the extraction of LST using Landsat imagery

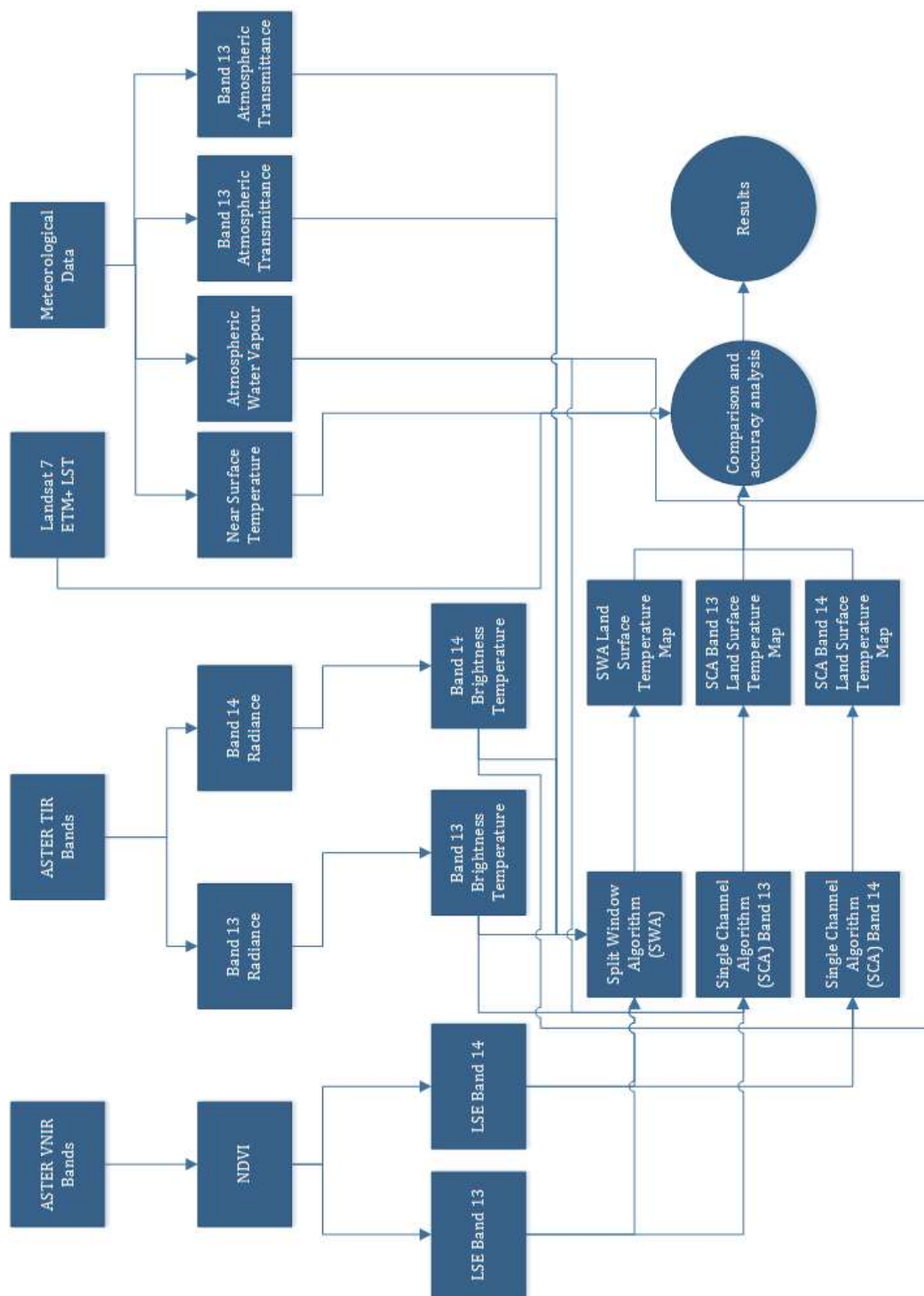


Figure 2.2: Methodology used in the extraction of LST using ASTER imagery

2.6.1. Conversion of digital numbers to radiance

Satellite imagery store thermal data in the form of Digital Numbers (DNs). DNs are a way to represent differences in levels of radiation intensities before they have been processed in meaningful units. In order to extract LST from these imagery, the first process involved is the conversion of DNs to radiance. For Landsat 8 TIRS, Equation (2.1) has been used in the study.

$$L_{\lambda} = M_L Q_{cal} + A_L - O_i \quad (2.1)$$

Where; L_{λ} is the Top-of-Atmosphere (TOA) spectral radiance in $W/(m^2 \cdot sr \cdot \mu m)$, M_L is the band specific multiplicative rescaling factor from the metadata, A_L is the band-specific additive rescaling factor, Q_{cal} is the quantized and calibrated standard product pixel values (DN), and O_i is the offsets issued by USGS for the calibration of the TIRS bands. Due to the uncertainties arising from the use of Landsat 8's thermal infrared band 11, only data from band 10 are reliable for use (J. A. Barsi et al., 2014; USGS, 2015b). This study has only employed the use of band 10 in the extraction of LST. Table 2.8 shows the constants which have been used in the study during the conversion of DNs to radiance.

Table 2.8. Constants for the conversion of DN to radiance using Landsat 8 TIRS

M_{10}	A_{10}	O_{10}	O_i
0.0003342	0.1	0.32	0.29

Source: F. Wang et al., 2015

In Table 2.8, M_{10} is band 10's specific multiplicative rescaling factor, A_{10} is the band 10's additive factor and O_{10} is the offset calibration factor for band 10. With the exception of the offset calibration factor, the rest of the values are read automatically from the metadata file of Landsat 8 TIRS through the use of the plugin.

There are two equations available for the conversion of DNs to radiance from the data obtained from Landsat 5 TM and Landsat 7 ETM+. Namely; "The gain and bias equation" and the "spectral radiance rescaling method". The equations are however a different representation of each other. Equation (2.2) and Equation (2.3) show the "gain

and bias equation” and the “spectral radiance rescaling equations” respectively (USGS, 2015a).

$$L_{\lambda} = \text{gain} * Q_{\text{cal}} + \text{bias} \quad (2.2)$$

$$L_{\lambda} = ((L_{\text{MAX}\lambda} - L_{\text{MIN}\lambda}) / (Q_{\text{CALMAX}} - Q_{\text{CALMIN}})) * (Q_{\text{CAL}} - Q_{\text{CALMIN}}) + L_{\text{MIN}\lambda} \quad (2.3)$$

Where L_{λ} is the spectral radiance at the sensor's aperture in watts/(meter squared * ster * μm), gain is the rescaled gain (the data product "gain" contained in the Level 1 product header or ancillary data record) in watts/(meter squared * ster * μm), bias is the rescaled bias in watts/(meter squared * ster * μm), Q_{CAL} is the quantized calibrated pixel value in DN. $L_{\text{MIN}\lambda}$ is the spectral radiance that is scaled to Q_{CALMIN} in watts/(meter squared * ster * μm), $L_{\text{MAX}\lambda}$ is the spectral radiance that is scaled to Q_{CALMAX} in watts/(meter squared * ster * μm), Q_{CALMIN} is the minimum quantized calibrated pixel value and Q_{CALMAX} is the maximum quantized calibrated pixel value (corresponding to $L_{\text{MAX}\lambda}$) in DN = 255. The plugin which has been developed in this study has been programmed in such a way that the variables used in these equations are read automatically from the metadata.

In order to convert the DNs to radiance when using the data obtained from the ASTER sensor, Equation (2.4) is used (Abrams, Hook, & Ramachandran, 2002).

$$L_{\lambda} = (\text{DN} - 1) * \text{UCC} \quad (2.4)$$

Where L_{λ} is the spectral radiance in $\text{W}/(\text{m}^2 \cdot \text{sr} \cdot \mu\text{m})$, DN stands for the Digital Numbers and UCC is the unit conversion coefficient. Table 2.9 shows the Unit Conversion Coefficients (UCC) which have been used in the study (Finn, Reed, & Yamamoto, 2012).

Table 2.9. Unit Conversion Coefficients of the Thermal Infrared (TIR) ASTER bands

Band	Band 10	Band 11	Band 12	Band 13	Band 14
UCC	0.006822	0.006780	0.006590	0.005693	0.005225

Source: Finn, Reed & Yamamoto, 2012

Figure 2.3 shows the application interface of the plugin for the conversion of DNs to radiance.

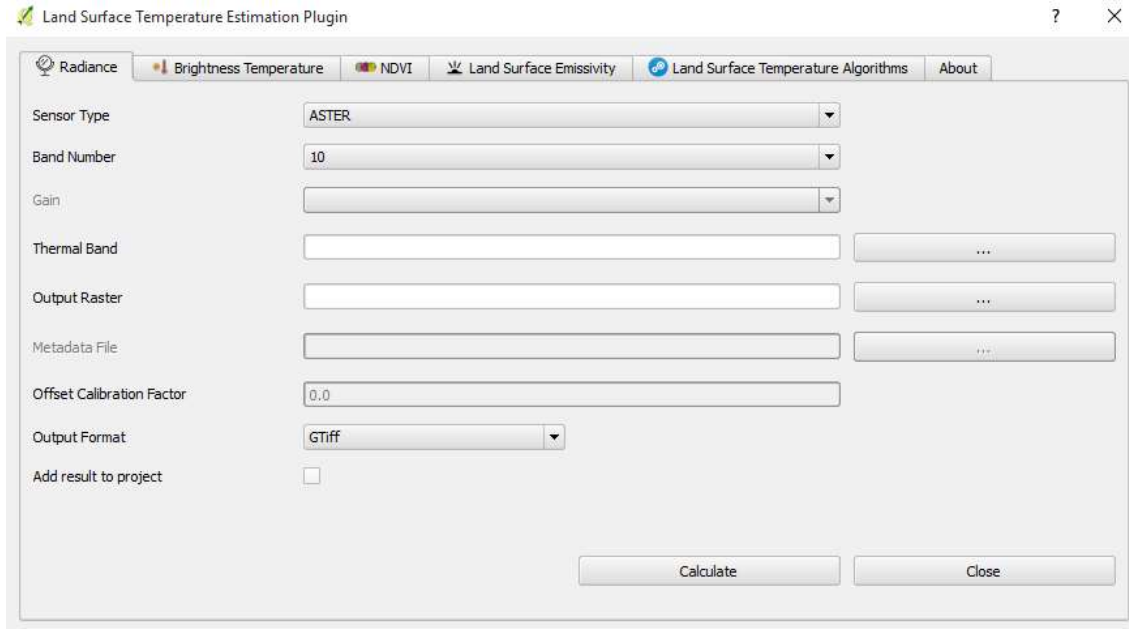


Figure 2.3: Application's Interface for calculating radiance

2.6.2. Conversion of radiance to brightness temperature

Brightness temperature is the measure of the intensity of received radiation, it is the temperature that a blackbody is required to have so as to be able to emit the same amount of radiation per unit of surface area as the body being observed (Kruse, McGlauchlin, & McQuistan, 1962). When the radiance of an object is the same as the one for a blackbody, the physical temperature of this blackbody is termed as the brightness temperature of the object. Brightness temperature has the ability to represent temperature measurements but it doesn't have the physical meaning of temperature (S. L. L. Wang, 2012). After the DNs have been converted to radiance, the next step is to convert the radiance to brightness temperature. In order to convert the radiance to brightness temperature, Equation (2.5) has been used in the study (USGS, 2013).

$$T_{\text{sen}} = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)} \quad (2.5)$$

Where, T_{sen} stands for the at-sensor brightness temperature (K)/Top-of-atmosphere brightness temperature, L_{λ} is the temperature of atmosphere spectral radiance, K_1 and K_2 are the band specific thermal conversion constants from the metadata. The same equation is used for Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS and ASTER sensors. The values for K_1 and K_2 variables may vary depending on the sensor and the wavelengths by which the thermal channels operate. Table 2.10 shows the K_1 and K_2 values of the sensors used in this study.

Table 2.10. K_1 and K_2 values of ASTER, Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS

Sensor	Band	K_1	K_2
Landsat 5 TM	Band 6	607.76	1260.56
Landsat 7 ETM+	Band 6	666.09	1282.71
Landsat 8 TIRS	Band 10	774.89	1321.08
ASTER	Band 10	3047.47	1736.18
	Band 11	2480.93	1666.21
	Band 12	1930.80	1584.72
	Band 13	865.65	1349.82
	Band 14	649.60	1274.49

Source: J.C. Jimenez-Munoz & J. Sobrino, 2010; F.Li et al. 2004

Figure 2.4 shows the application's interface to convert the radiance to brightness temperature.

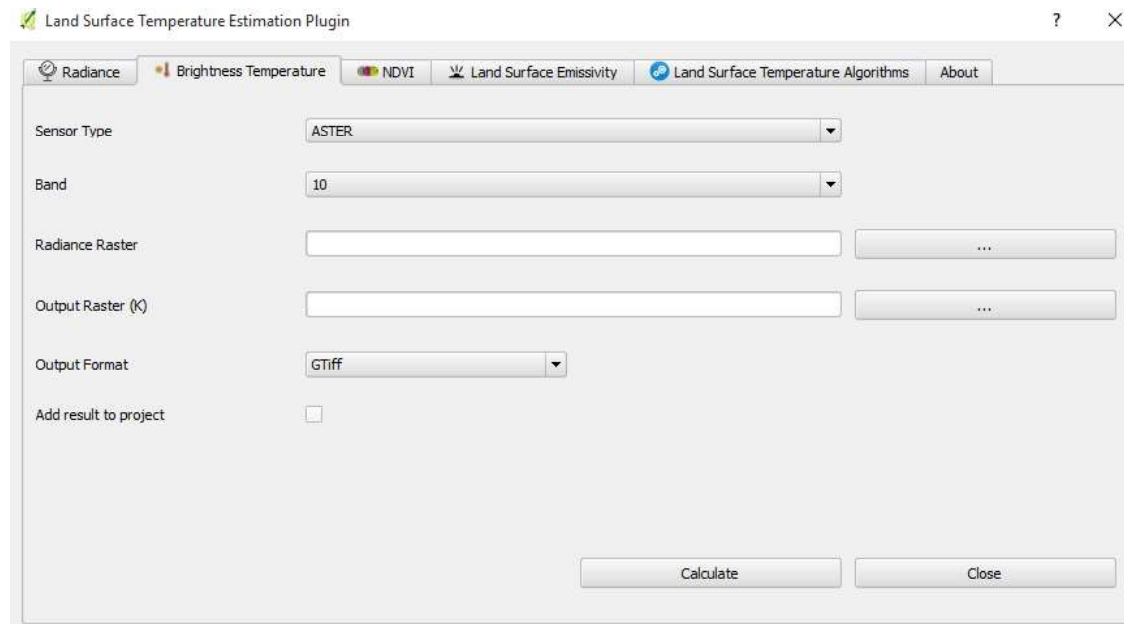


Figure 2.4. Application's Interface for calculating brightness temperature

2.6.3. Estimation of Land Surface Emissivity (LSE)

Emissivity is a measure which is used to show the relationship between the amount of heat that can be radiated by an object in comparison to a blackbody at the same temperature. The emissivity of materials on the surface differs from one another and it has a high impact to the land surface temperatures derived from thermal infrared sensors. This makes it important to estimate the land surface emissivity during the extraction of land surface temperature. Estimating land surface emissivity is important as it can reduce errors during the estimation of land surface temperature from thermal satellite infrared data (Mallick, Singh, Shashtri, Rahman, & Mukherjee, 2012). Land surface emissivity is used in energy balance assessment studies, land cover assessment and other environmental studies (J. C. Jiménez-Muñoz et al., 2006). Emissivity obtained from remote sensing techniques varies depending on observation conditions, wavelengths and the angle of observation. There are several methods which can be used in the extraction of LSE. Some of them include; Temperature Emissivity Separation (TES) or Radiative Transfer Equation (RTE) (Gillespie et al., 1998) and emissivity retrieval from Normalized Difference Vegetation Index (NDVI) values. The TES algorithm is prone to scaling errors in estimating the emissivity ϵ of vegetation if atmospheric correction is inaccurate whereas the NDVI method identifies vegetated areas for which ϵ is known a-priori. The TES algorithm is the basis of the development of the Radiative Transfer Equation (RTE) shown by Equation (1.4). The LSE of an area can also be determined through the use of Normalized Difference Vegetation Index (NDVI) values. The composition of the land surface changes over time, it is therefore important to estimate the LSE of an area during the satellite overpass time. Thanks to the availability of the Near Infrared (NIR) and the Red band on board the Landsat and ASTER sensors as they have made it possible to estimate the NDVI of a scene during the satellite overpass time. Through NDVI it is possible to estimate LSE of different terrestrial materials in the 10-12 μ m wavelength range (F. Wang et al., 2015). To calculate the NDVI of the surface, Equation (2.6) has been used in the study (Vandegriend, Owe, Vugts, & Ramothwa, 1992).

$$\text{NDVI} = \frac{\text{NIR} - \text{R}}{\text{NIR} + \text{R}} \quad (2.6)$$

In Equation (2.6) NIR represents the reflectance of the near infrared band and R stands for the reflectance of the Red band. To estimate the LSE from the NDVI, two algorithms have been implemented in the study. These algorithms are: Zhang, Wang et al's algorithm based on the NDVI image (Zhang et al., 2006) and the NDVI threshold algorithm (Sobrino & Raissouni, 2000). During the estimation of land surface emissivity using the NDVI based approach, the data obtained may be affected by the atmospheric processes of scattering, absorption and attenuation. These may sometimes lead to lower NDVI values and as a result affect the estimated land surface emissivities derived from the NDVI based approach. To solve such errors algorithms such as 6S are used to perform atmospheric correction (P. K. Srivastava et al., 2014). This study has been done by assuming the absence of atmospheric interference in the red and near infrared channels used in the calculation of NDVI. In order to extract LST from the visible and near infrared bands through NDVI, two NDVI based land surface emissivity estimation algorithms have been implemented in the plugin. These are Zhang, Wang et al's algorithm based on the NDVI image (Zhang et al., 2006) and the NDVI threshold algorithm (Sobrino & Raissouni, 2000).

2.6.3.1. *Zhang, Wang et al's algorithm based on the NDVI image*

According to Zhang, Wang et al (Zhang et al., 2006), it is possible to estimate the LSE from the NDVI of an area. To determine the LSE of a pixel through the use of the algorithm, the algorithm checks on the value of the NDVI. When a pixel has a value that is below -0.185, then the pixel is considered to represent water and as a result, the emissivity water is assigned to the pixel, when the NDVI of a pixel is between -0.185 and 0.157, then the algorithm considers the pixel to be covered by soil/rocks and as a result the emissivity of soil/rocks is assigned to the pixel. The algorithm makes use of a logarithmic relationship between LSE and NDVI in the determination of LSE of pixels with mixed land covers of soil and vegetation cover. Pixels with NDVI values which are greater than or equal to -0.185 and less than or equal to 0.727 are considered to be covered by a mixed land cover of soil and vegetation. For NDVI values which are greater

than 0.727, the algorithm considers the pixel to be covered by a full vegetation cover and as a result the emissivity of vegetation is assigned to the pixel as it is shown in Table 2.11.

Table 2.11. *Algorithm based on the NDVI image*

NDVI	LSE
NDVI < - 0.185	0.995
-0.185 ≤ NDVI < 0.157	0.985
0.157 ≤ NDVI ≤ 0.727	1.009 + 0.047ln(NDVI)
NDVI > 0.727	0.990

Source: Zhang et al., 2006

2.6.3.2. NDVI Threshold Algorithm

The NDVI threshold emissivity estimation algorithm uses known NDVI values to differentiate the pixels which represent soil (NDVI < NDVI_s) from the ones representing vegetation (NDVI > NDVI_v). During the estimation of land surface emissivity from NDVI, authors have proposed the use of 0.2 and 0.5 as NDVI of soil and NDVI of vegetation in global scales (Sobrino & Raissouni, 2000). In the NDVI threshold algorithm, there might be an occurrence of three possible scenarios depending on the content of a pixel.

- (NDVI < NDVI_s) in this scenario, the algorithm considers the pixel being analyzed to be made up of bare soil or rock and as a result, the emissivity of soil is assigned to the pixel.
- (NDVI > NDVI_v) in this scenario, the algorithm considers the pixel being analyzed to be made up of full vegetation cover and as a result, the emissivity of vegetation is assigned to the pixel.
- (NDVI_s ≤ NDVI ≤ NDVI_v) in this scenario, a pixel is considered to be made up of a mixture of vegetation and rocks/soil; and as a result, a mathematical relationship is used. Authors (Sobrino & Raissouni, 2000) introduced Equation (2.7) to represent the relationship between NDVI and LSE.

$$\varepsilon_{\lambda} = \varepsilon_{v\lambda}P_v + \varepsilon_{s\lambda}(1 - P_v) + C_{\lambda} \quad (2.7)$$

In Equation (2.8), ε_v stands for emissivity of vegetation, ε_s stands for the emissivity of soil, P_v stands for the Fractional Vegetation Cover (also known as Proportion of Vegetation) and C is a value which represents the surface roughness; ($C = 0$ for flat surfaces). The value of C takes into consideration the cavity effect due to surface roughness. The authors in (Sobrino & Raissouni, 2000) proposed the cavity term for a mixed area and near-nadir view is given by Equation (2.8).

$$C_\lambda = (1 - \varepsilon_{s\lambda})\varepsilon_{v\lambda}F'(1 - P_v) \quad (2.8)$$

The value of F' is a surface roughness factor with a value which ranges between 0 and 1, depending on the geometrical structure of the surface. Assuming the presence of geometric distributions which differ from one place to another, an average value of 0.55 is chosen (Sobrino, Caselles, & Becker, 1990).

In order to calculate the proportion of vegetation (sometimes known as fractional vegetation cover) of a pixel through the use of NDVI, Equation (2.9) has been used in the study (Carlson & Ripley, 1997; Yu, Guo, & Wu, 2014). The proportion of vegetation has a value between 0 and 1 where 1 represents full vegetation cover while 0 represents no vegetation cover. The emissivity values shown in Table 2.12 have been used (F. Wang et al., 2015).

$$P_v = \left[\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right]^2 \quad (2.9)$$

Table 2.12 *LSE values for various terrestrial materials*

Terrestrial material	Soil	Built-up areas	Vegetation	Water
Emissivity	0.966	0.962	0.973	0.991

Source: *F. Wang et al., 2015*

Figure 2.5 and Figure 2.6 show the application's interface to estimate the LST from NDVI using Zhang, Wang et al's algorithm and the NDVI threshold LSE estimation algorithm respectively.

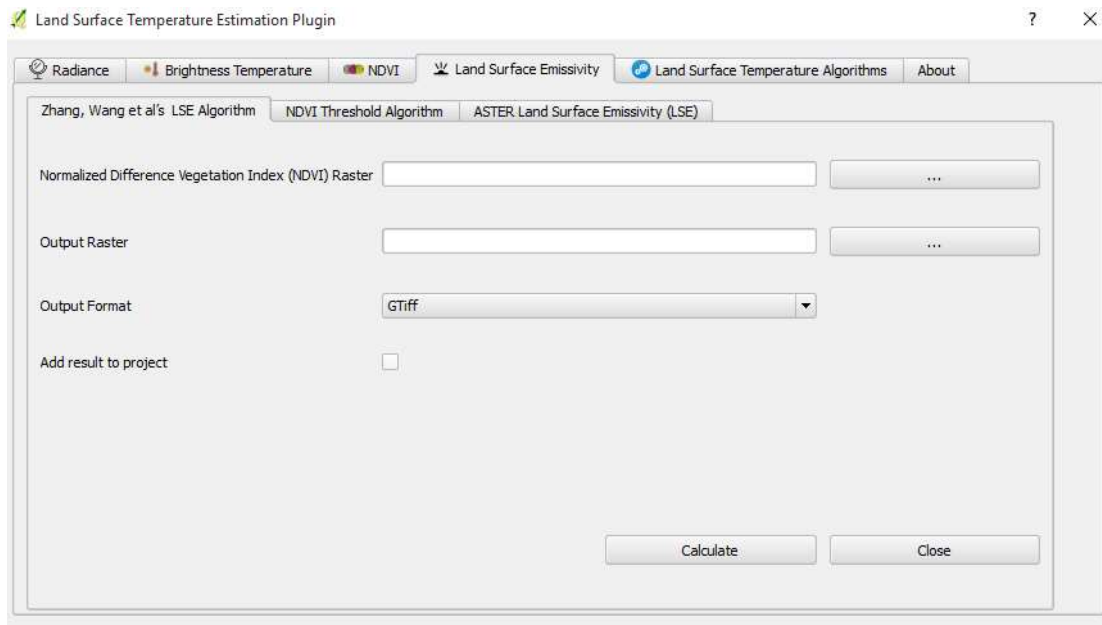


Figure 2.5. Application Interface for the estimation of LSE using Zhang, Wang et al's algorithm

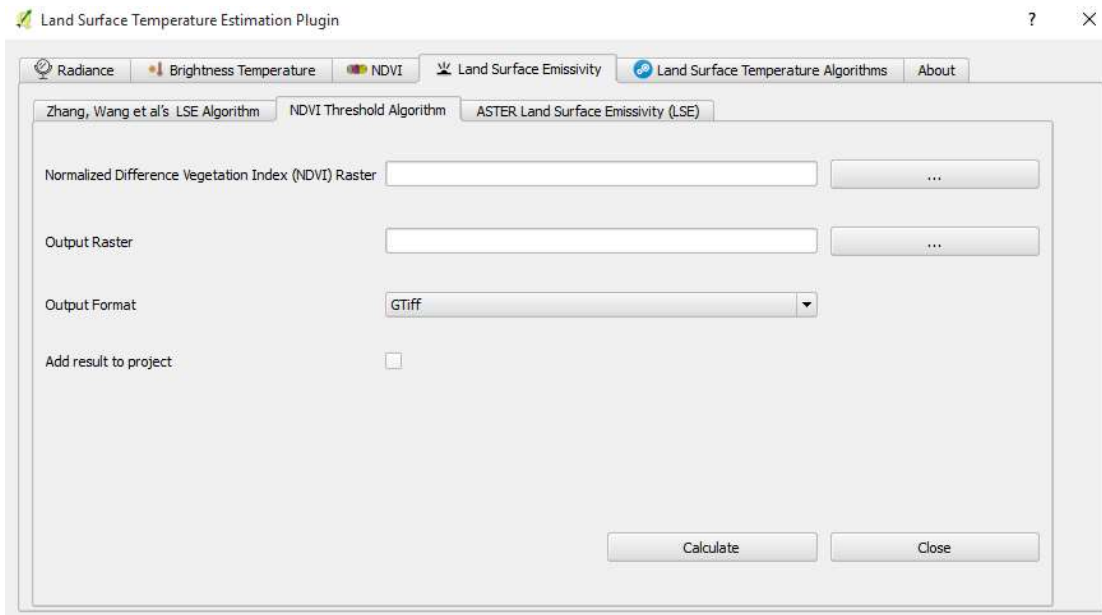


Figure 2.6. Application's interface for Land Surface Emissivity (LSE) estimation using the NDVI Threshold LSE estimation algorithm.

2.6.3.3. ASTER Land Surface Emissivity Estimation

In order to estimate the LSE for ASTER, Juan C. Jimenez-Munoz et al.'s algorithm has been used in the study (J. C. Jiménez-Muñoz et al., 2006). The algorithm has been tested against *in situ* data and has proven to provide results which have a Root Mean

Square Error (RMSE) of less than 0.005 over vegetated areas. The algorithm is based on Equation (2.7). All the parameters involved are estimated in the same way as the Landsat sensors. According to Juan C. Jimenez-Munoz et al, the most sensitive issue during the estimation of LSE from NDVI using ASTER imagery is the choice of the emissivity of soil. In order to get the values to apply on Equation (2.7), Juan C. Jimenez-Munoz et al introduced Equation (2.10), Equation (2.11), Equation (2.12), Equation (2.13) and Equation (2.14) for ASTER TIR band 10 to 14 respectively.

$$\varepsilon_{10} = 0.946 + 0.044P_v \quad (2.10)$$

$$\varepsilon_{11} = 0.949 + 0.041P_v \quad (2.11)$$

$$\varepsilon_{12} = 0.941 + 0.049P_v \quad (2.12)$$

$$\varepsilon_{13} = 0.968 + 0.022P_v \quad (2.13)$$

$$\varepsilon_{14} = 0.970 + 0.020P_v \quad (2.14)$$

2.6.4. Determination of up-welling radiance, down-welling radiance and atmospheric transmittance

In this study, the estimation of the atmospheric parameters (transmittance, upwelling and down-welling radiance) of Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS has been done through the use of the NASA'S atmospheric parameters calculator (J. Barsi et al., 2003). The tool uses the National Centers for Environmental Prediction (NCEP) modeled atmospheric global profiles interpolated at a particular date, time, and location as inputs (J. Barsi et al., 2003). Through this tool, the atmospheric profile of the study area was simulated to the conditions during the satellite overpass time. The tool supports the simulation of atmospheric parameters as from January 2000. The obtained atmospheric transmittance, upwelling and down welling radiance used in the study is as shown in Table 2.13.

Table 2.13. *Simulated atmospheric parameters for the study.*

Sensor Type	Date	Time (UTC)	Atmospheric Transmittance	Upwelling radiance (W/(m ² ·sr·μm))	Down-welling radiance (W/(m ² ·sr·μm))
Landsat 5 TM	13th November 2010	14:57	0.89	0.72	1.20

Landsat 5 TM	31 December 2010	14:57	0.89	0.58	0.97
Landsat 7 ETM+	21st November 2010	15:00	0.96	0.18	0.31
Landsat 7 ETM+	23 February 2016	15:09	0.97	0.11	0.20
Landsat 7 ETM+	2nd September 2010	14:59	0.59	3.31	4.97
Landsat 7 ETM+	19th September 2013	14:56	0.88	0.89	1.48
Landsat 7 ETM+	29th July 2009	14:57	0.55	3.43	5.20
Landsat 7 ETM+	30th July 2015	15:07	0.65	2.59	4.03
Landsat 8 TIRS	04th June 2015	15:06	0.87	0.91	1.52
Landsat 8 TIRS	29 May 2013	15:09	0.89	0.72	1.22

To determine the atmospheric transmittance of ASTER band 13 and band 14, the relations shown in Equation (2.15) and Equation (2.16) were used.

$$\tau_{13} = 1.02 - 0.104 \times w_{13} \quad (2.15)$$

$$\tau_{14} = 1.04 - 0.113 \times w_{14} \quad (2.16)$$

Where; W_{13} and W_{14} represent the atmospheric water vapour content while τ_{13} and τ_{14} represent the band atmospheric transmissions for ASTER band 13 and ASTER band 14 respectively.

2.6.5. Determination of near surface air temperature

In order to obtain the near surface air temperature to use in the study, the meteorological data was used. Mean temperatures were calculated from the meteorological data measured during the satellite overpass time. The average values were thereafter used as mean atmospheric temperatures in the study. The near surface air temperatures which have been used in this study are shown in Table 2.14.

2.6.6. Determination of atmospheric water vapour

The atmospheric water vapour is among the data required for the successful application of the SCA. As a result of the SCA being one of the algorithms used in this study, it's estimation was crucial. To estimate the atmospheric water vapour during the satellite overpass time, Equation (2.17) was used in the study. (J. Li, 2006; Liu & Zhang, 2011; Yang & Qiu, 1996). The relative humidity used in the equation has been obtained from the meteorological data during the satellite overpass time.

$$w_i = 0.0981 \times \left\{ 10 \times 0.6108 \times \exp \left[\frac{17.27 \times (T_0 - 273.15)}{237.3 + (T_0 - 273.15)} \right] \times RH \right\} + 0.1679 \quad (2.17)$$

In Equation 4.11, W_i represents the atmospheric water vapour, T_0 represents the near surface air temperature in Kelvin and RH represents the relative humidity. Table 2.14 shows the relative humidity, near surface air temperature and the atmospheric water vapour used in the study.

Table 2.14. *Atmospheric water vapour, relative humidity and near surface air temperature used in the study.*

Sensor Type	Date	Time (UTC)	Relative Humidity (%)	Near Surface Air Temperature (K)	Atmospheric Water Vapour (g/cm ³)
Landsat 5 TM	13 th November 2010	14:57	42.778	285.994	0.790
Landsat 5 TM	31 December 2010	14:57	75.889	271.983	0.585
Landsat 7 ETM+	21 st November 2010	15:00	63.500	269.450	0.457
Landsat 7 ETM+	23 February 2016	15:09	49.125	265.475	0.333
Landsat 7 ETM+	02 nd September 2010	14:59	55.500	301.625	2.284
Landsat 7 ETM+	19 th September 2013	14:56	58.500	292.175	1.431
Landsat 8 TIRS	04 th June 2015	15:06	54.571	287.821	1.062
Landsat 8 TIRS	29 May 2013	15:09	37.444	291.706	0.953
ASTER Level 1T	02 nd September 2010	15:24	55.500	301.625	2.284
ASTER Level 1T	19 th September 2013	15:18	58.500	292.175	1.431

2.6.7. Brightness atmospheric and land surface emissivity correction

It is necessary to correct brightness temperature against atmospheric profiles during the satellite overpass time. Numerous algorithms have been developed in order to do enable LST to be derived from space through thermal infrared imagery. These algorithms are dependent on the sensor in use and each one has its limitations and strengths. In this study, a total of six algorithms have been used in the plugin. These algorithms are; The Radiative Transfer Equation (RTE), the Single Channel Algorithm (SCA) for Landsat, the Single Channel Algorithm (SCA) for ASTER, the Planck function, the Mono Window Algorithm (MWA) and the Split Window Algorithm (SWA) for ASTER.

2.6.7.1. Inversion of Planck's function

The Planck function represents the relationship between the emissivity and temperature of a blackbody. After the brightness temperatures have been computed, the brightness temperatures can be corrected against emissivity. To do so, the Planck's function has been implemented in the plugin. Equation (2.18) shows the Planck function (Artis & Carnahan, 1982).

$$T_s = \frac{BT}{\left\{1 + \left[\frac{\lambda \cdot BT}{\rho}\right] \cdot \ln \varepsilon\right\}} \quad (2.18)$$

Where T_s represents the land surface temperature (K); BT represents the at-sensor brightness temperature (K), λ stands for the wavelength of the emitted radiance; ρ stands for the $(h \times c/\sigma) = 1.438 \times 10^{-2} \text{mK}$; ε stands for the spectral emissivity. Figure 4.5 shows the application's interface for the Plank equation.

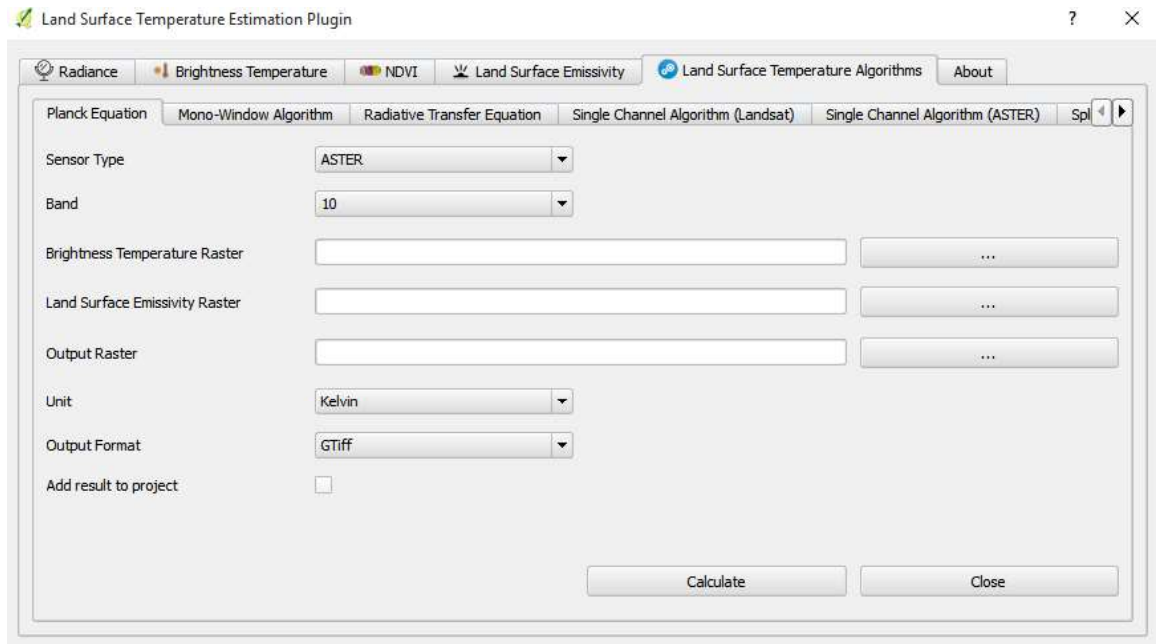


Figure 2.7. Application's interface for the Planck Equation

2.6.7.2. *The Mono Window Algorithm (MWA)*

Due to the atmospheric processes of absorption, scattering and attenuation of electromagnetic radiation, there arises a need to do brightness temperature atmospheric and land surface emissivity correction. The MWA was used by Liu L. and Y. Zhang (Liu & Zhang, 2011) in order to obtain LST with a considerably high quality (Qin et al., 2001). To make use of the algorithm, the knowledge atmospheric transmittance, the effective mean atmospheric temperature and the land surface emissivity of a study area is crucial. According to the results of a sensitivity analysis which was done to the MWA, the algorithm is less sensitive to errors which may arise from the probable errors arising from the estimation of LSE. The algorithm is however more sensitive to errors arising from the estimation of atmospheric transmission and mean atmospheric temperature (Qin et al., 2001). According to a validation which was done using data collected from seven typical atmospheres, it was determined that the algorithm has an ability to retrieve LST from Landsat 5 TM and Landsat 7 ETM+ data whereby, the differences between the data retrieved by the algorithm and the simulated ones were less than 0.4°C for most conditions (Qin et al., 2001). The MWA is mathematically expressed as shown in Equation (2.19) (Qin et al., 2001).

$$T_s = \frac{a_i(1 - C_i - D_i) + [b_i(1 - C_i - D_i) + C_i + D_i]T_i - D_iT_a}{C_i} \quad (2.19)$$

Where T_s is the Land Surface Temperature (LST), T_i is the brightness temperature from Equation (2.5), T_a is the effective mean atmospheric temperature, $a_i = -67.355351$ and $b_i = 0.458606$. The values of C_i and D_i can be calculated using the Equation (2.20) and Equation (2.21) respectively (Qin et al., 2001).

$$C_i = \varepsilon_i \tau_i \quad (2.20)$$

$$D_i = (1 - \tau_i)[1 + (1 - \varepsilon_i)\tau_i] \quad (2.21)$$

Where ε_i is the land surface emissivity and τ_i is the atmospheric transmittance. T_a , ε_i and τ_i are the three parameters needed to convert the brightness temperature to LST. In order to acquire the effective mean atmospheric temperature of an area, Qin,

Karnieli et al. (Qin et al., 2001) introduced linear relations for the approximation depending on the location of the atmosphere of an area of study. These are as shown in Table 2.15. In this study, the mid latitude winter atmospheric profile was considered to be the most suitable for the Landsat 5 TM scene dated 31 December 2010, Landsat 5 TM scene dated 13 November 2010, Landsat 7 ETM+ scene dated 21 November 2010 and Landsat 7 ETM+ scene dated 23 February 2016. For the Landsat 7 ETM+ scene dated 2 September 2010, Landsat 7 ETM+ scene dated 19 November 2013 and for Landsat 8 TIRS scenes dated 4 June 2015 and 29 May 2013, the mid latitude summer was considered.

Table 2.15. Linear relations for the approximation of effective mean atmospheric temperature T_a from the near surface air temperature.

Atmospheres	Linear Relations Equations
For USA 1976	$T_a = 25.9396 + 0.88045T_0$
Tropical model	$T_a = 17.9769 + 0.91715T_0$
Mid-latitude Summer	$T_a = 16.0110 + 0.92621T_0$
Mid-latitude winter	$T_a = 19.2704 + 0.91118T_0$

Source: Qin et al., 2001

In the equations, the temperatures T_a and T_0 are both expressed in Kelvin. These formulas imply that, under normal atmospheric conditions with a clear sky and absence of turbulence; the effective mean atmospheric temperature T_a has a linear relationship with near surface air temperature T_0 . This is because under standard conditions, the distribution of atmospheric temperature T_a the distribution of water vapour and atmospheric temperature are assumed to be constant. Due to the presence of NASA's atmospheric parameters calculator (J. Barsi et al., 2003), researchers are now able to simulate the atmospheric conditions of during the satellite overpass time in order to determine the atmospheric transmittance, the up-welling and down-welling radiances. Figure 2.8 shows the interface of the MWA in the developed application.

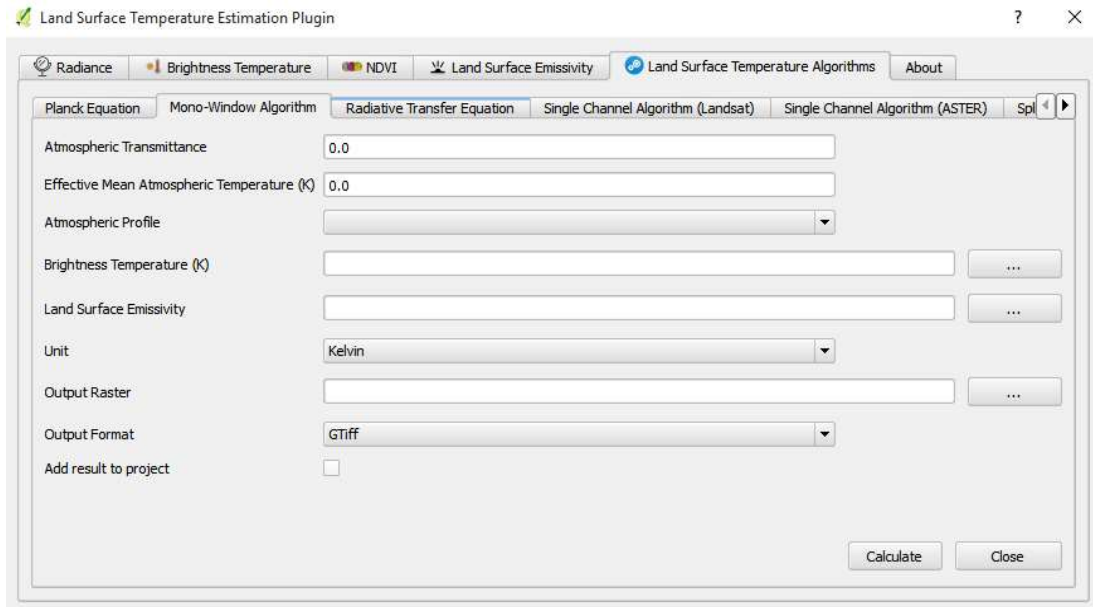


Figure 2.8. Application's interface for Mono-Window Algorithm

2.6.7.3. The Radiative Transfer Equation (RTE)

The radiative transfer equation has also been considered in this study. The algorithm has been implemented in the plugin to enable users to extract LST from the VNIR and TIR imagery acquired Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 TIRS. The equation makes use of one thermal infrared channel during land surface temperature extraction. Landsat 5 TM and Landsat 7 ETM+ sensors are equipped with a single thermal infrared channel. Due to this, it is not possible to make use of split window algorithms in during the extraction of LST from these sensors. Nevertheless, the high spatial resolution of these sensors offers the users of its data to make use of the imagery obtained from these sensors for regional and local studies (P. Srivastava, Majumdar, & Bhattacharya, 2009). Many studies have successfully used single channel algorithms in land surface temperature extraction (Goetz, Halthore, Hall, & Markham, 1995; Schott & Volchok, 1985; Weng, Lu, & Schubring, 2004; Wukelic, Gibbons, Martucci, & Foote, 1989). The RTE is shown in Equation (2.22).

$$L_{\lambda} = [\varepsilon_{\lambda} L_{\lambda}(T_s) + (1 - \varepsilon_{\lambda}) L_{\text{down}}] \tau + L_{\text{up}} \quad (2.22)$$

Where; L_{λ} is the at-sensor radiance measured by a sensor in space(it mainly consists of surface radiance, down-welling radiance from the atmosphere and up-

welling radiance to the atmosphere (J. A. Barsi et al., 2003)); τ is the atmospheric transmittance; ε is the land surface emissivity; $L_{\lambda}(T_s)$ is the radiance of a blackbody target of kinetic temperature T_s . $L_{\lambda up}$ is the upwelling or atmospheric path radiance and $L_{\lambda down}$ is the down-welling or sky radiance.

Due to the limitations arising from the missing of the atmospheric parameters of study areas during the satellite overpass time. The atmospheric parameters used in the RTE in this study were obtained from NASA's atmospheric parameters calculator (J. Barsi et al., 2003) (<http://atm-corr.gsfc.nasa.gov>). Through the use of the calculator, the atmospheric conditions of the study area were simulated to those of the satellite overpass time. With the required parameters in hand, the land surface radiance, $L_{\lambda}(T_s)$ of kinetic temperature T_s has been calculated by Equation (2.23).

$$L_{\lambda}(T_s) = \frac{L_{\lambda} - L_{\lambda up}}{\tau \varepsilon_{\lambda}} - \frac{1 - \varepsilon_{\lambda}}{\varepsilon_{\lambda}} L_{\lambda down} \quad (2.23)$$

After the radiance has been calculated, they are thereafter converted to LST through a relationship resembling the Planck function with two prelaunch calibration constants of K_1 and K_2 . To do this, Equation (2.24) has been used in the study (P. Srivastava et al., 2009).

$$T_s = \frac{K_2}{\ln\left(\frac{K_1}{L_{\lambda}(T_s)} + 1\right)} \quad (2.24)$$

Where; T_s is the LST in Kelvin which is changed to degree Celsius ($^{\circ}\text{C}$) by subtracting 273.15; K_1 and K_2 are thermal constants whose values are obtained from the metadata file (P. Srivastava et al., 2009). Figure 2.9 shows the application's interface for the RTE.

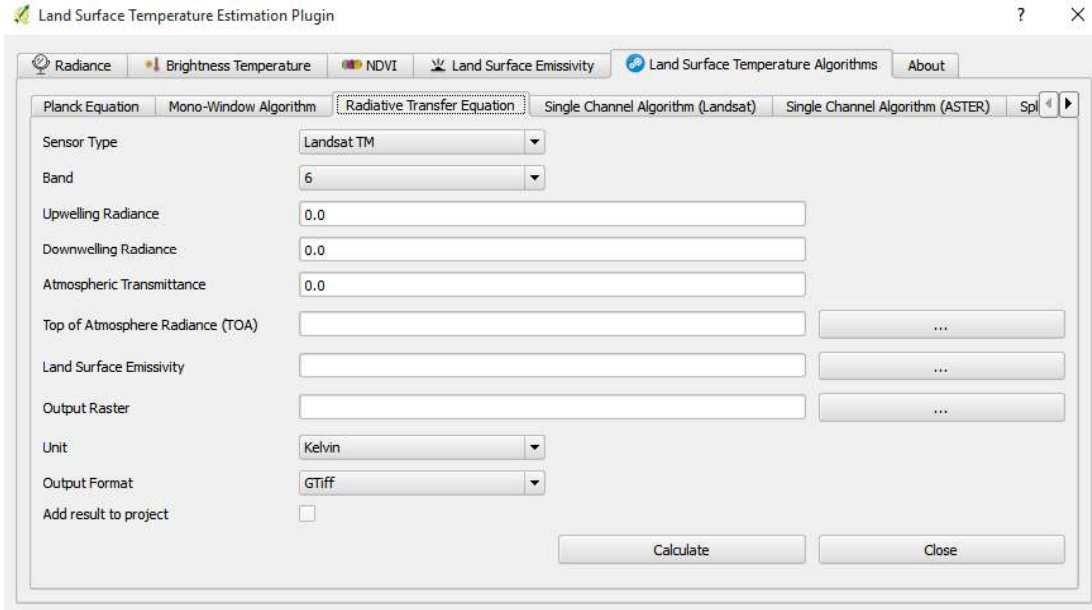


Figure 2.9 Application's interface for the RTE

2.6.7.4. The Single Channel Algorithm (SCA) for Landsat Sensors

The generalized SCA (Jiménez-Muñoz & Sobrino, 2003) was developed for the purpose of extracting LST from a single thermal infrared band. According to the algorithm, the LST is expressed as shown in Equation (2.25), Equation (2.26) and in Equation (2.27).

$$T_s = \gamma[\varepsilon^{-1}(\Psi_1 L_{\text{sensor}} + \Psi_2) + \Psi_3] + \delta \quad (2.25)$$

$$\gamma = \left\{ \frac{C_2 L_{\text{sensor}}}{T_{\text{sensor}}^2} \left[\frac{\lambda^4}{C_1} L_{\text{sensor}} + \lambda^{-1} \right] \right\}^{-1} \quad (2.26)$$

$$\delta = -\gamma L_{\text{sensor}} + T_{\text{sensor}} \quad (2.27)$$

From the equations T_s stands for LST, T_{sensor} is the at sensor brightness temperature in Kelvin, λ is the effective wavelength of a thermal infrared band in use, $C_1 = 1.19104 \times 10^8 \text{ W}\mu\text{m}^4\text{m}^{-2}\text{sr}^{-1}$ and $C_2 = 14387.7 \mu\text{m K}$. The Ψ_1 , Ψ_2 , and Ψ_3 atmospheric parameters can be estimated from Equation (2.28), Equation (2.29) and Equation (2.30) respectively. Figure 7 shows the application's interface for the SCA.

$$\Psi_1 = 0.14714w^2 - 0.15583w + 1.1234 \quad (2.28)$$

$$\Psi_2 = -1.1836w^2 - 0.3760w - 0.52894 \quad (2.29)$$

$$\Psi_3 = -0.04554w^2 + 1.8719w - 0.39071 \quad (2.30)$$

Studies have proven that an error of one percent in land surface emissivity may result to an error of between 0.3K for hot and arid areas to an error of 0.7 K for cold and dry atmospheres. Due to the fact that the single channel algorithms is mostly chosen at around $10\mu\text{m}$ where the land surface emissivity for most of the land surfaces can be known, the uncertainty in land surface emissivity may result to an error of between 1K and 2K if the algorithm is used (Z.-L. Li et al., 2013a). Figure 2.10 shows the application's interface for the SCA.

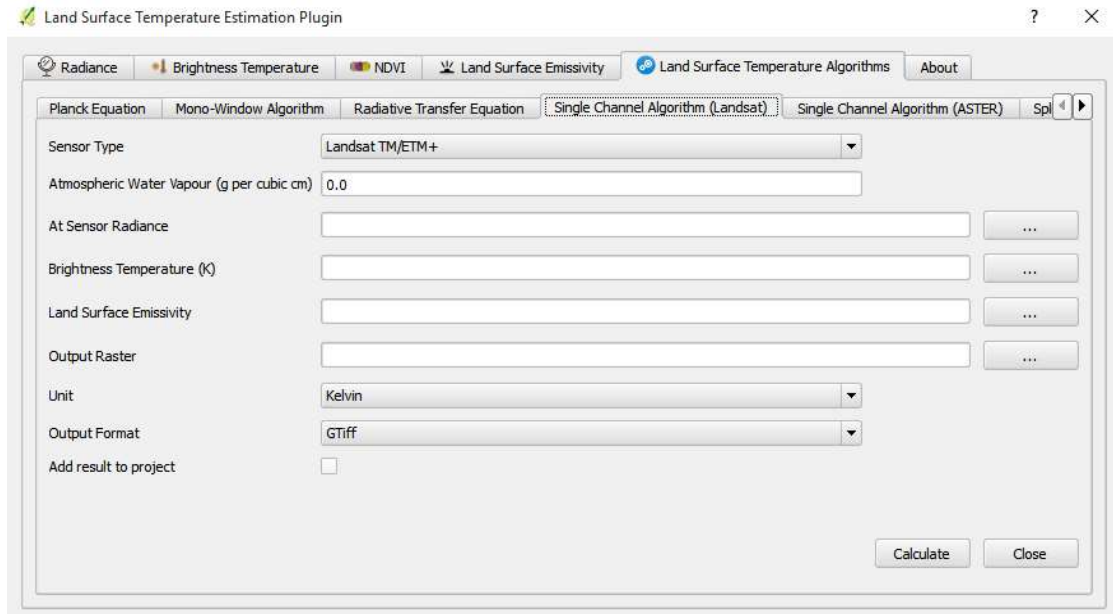


Figure 2.10. Application's interface for the SCA

2.6.7.5. The Single Channel Algorithm (SCA) for ASTER

J.C. Jimenez-Munoz and A. Sobrino adopted the single channel algorithm for the extraction of LST from the ASTER sensor (J. C. Jiménez-Muñoz & J. Sobrino, 2010). As a result of the presence of high atmospheric transmission and the lower emissivity variations in the $10\text{-}12\mu\text{m}$ spectral window as compared to the $8\text{-}9\mu\text{m}$ spectral window, it was proposed that in order to extract LST using the algorithm from the ASTER sensor,

then band 13 and band 14 should be used in the algorithm (J. C. Jiménez-Muñoz & J. A. Sobrino, 2010). The algorithm is shown in Equation (2.31).

$$T_s = \gamma \left[\frac{1}{\varepsilon} (\Psi L_{sen} + \Psi_2) + \Psi_3 \right] + \delta \quad (2.31)$$

In Equation (2.31), ε stands for the land surface emissivity, L_{sen} is the at-sensor radiance, γ and δ are parameters which are based on the Planck function and Ψ_1 , Ψ_2 and Ψ_3 are referred to as Atmospheric Functions (AFs). These AFs can be estimated using Equation(2.32), Equation (2.33) and Equation (2.34).

$$\Psi_1 = \frac{1}{\tau} \quad (2.32)$$

$$\Psi_2 = -L^\downarrow - \frac{L^\uparrow}{\tau} \quad (2.33)$$

$$\Psi_3 = L^\uparrow \quad (2.34)$$

Where τ is the atmospheric transmittance, $L^\uparrow$ is the upwelling radiance and $L^\downarrow$ is the down-welling atmospheric radiance.

Table 2.16. *Effective wavelengths of the ASTER thermal infrared bands*

ASTER Band	Effective Wavelength (μm)
Band 10	8.287
Band 11	8.635
Band 12	9.079
Band 13	10.659
Band 14	11.289

Source: *J.C. Jimenez-Munoz & J. Sobrino, 2010*

In order to determine the gamma (γ) and delta (δ) parameters used in the algorithm, J.C. Jimenez-Munoz and A. Sobrino used Equation (2.35) and Equation ((2.36) respectively.

$$\gamma \approx \frac{T_{sen}^2}{K_2 L_{sen}} \quad (2.35)$$

$$\delta \approx T_{sen} - \frac{T_{sen}^2}{K_2} \quad (2.36)$$

Where T_{sen} is computed from Equation (2.5) and the K_1 and K_2 variables are as shown in Table 2.10.

The atmospheric functions which are used in the single channel algorithm for the ASTER sensor can be obtained in the following ways:

- Through the use of atmospheric transmittance, down-welling and upwelling atmospheric radiances which can be obtained through the atmospheric soundings such as Moderate Atmospheric Transmission (MODTRAN) 4 (AGPA Berk et al., 1999).
- Through empirical approaches using only one input parameter like the total-atmospheric water vapour content (J. C. Jiménez-Muñoz et al., 2009; Jiménez-Muñoz & Sobrino, 2003).
- Through the use of empirical methods with two or more parameters such as atmospheric water vapour and air temperature (Cristóbal, Jiménez-Muñoz, Sobrino, Ninyerola, & Pons, 2009).
- Through the use of lookup tables (J. C. Jiménez-Muñoz et al., 2009).

In this study, the empirical approach obtained from the second order polynomial fits against the atmospheric water vapor content has been used to determine the AFs (J. C. Jiménez-Muñoz et al., 2009; Jiménez-Muñoz & Sobrino, 2003). This is as shown in Equation (2.37).

$$\begin{bmatrix} \Psi_1 \\ \Psi_2 \\ \Psi_3 \end{bmatrix} = \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \begin{bmatrix} w^2 \\ w \\ 1 \end{bmatrix} \quad (2.37)$$

Where C_{ij} are obtained from simulated data which was constructed from atmospheric profiles included in different databases and MODTRAN4 radiative transfer code. In this study, both TIGR61 and STD66 databases of the MODTRAN4 code were implemented in the plugin. Though them the number of cases have been reduced and a result reducing the amount of time required for simulation but are still applicable for

global conditions (J. C. Jiménez-Muñoz & J. A. Sobrino, 2010). Table 2.17 shows the coefficients for the atmospheric functions in a matrix notation.

Table 2.17. Coefficients of the atmospheric functions

Database	Band	C _{ij}	i=1	i=2	i=3
STD66	13	J=1	0.06524	-0.05878	1.06576
		J=2	-0.55835	-0.75881	0.00327
		J=3	-0.00284	1.35633	-0.43020
TIGR61	13	J=1	0.05327	-0.03937	1.05742
		J=2	-0.484444	-0.74611	-0.03015
		J=3	0.00764	1.24532	-0.39461
STD66	14	J=1	0.10062	-0.13563	1.10559
		J=2	-0.79740	-0.39414	-0.17664
		J=3	-0.03091	1.60094	-0.56515
TIGR61	14	J=1	0.07965	-0.09580	1.08983
		J=2	-0.66528	-0.48582	-0.17029
		J=3	-0.01578	1.46358	-0.52486

Source: J.C. Jiménez-Munoz & J. Sobrino, 2010

Figure 2.11 shows the application's interface for the Single Channel Algorithm (SCA) for the ASTER sensor.

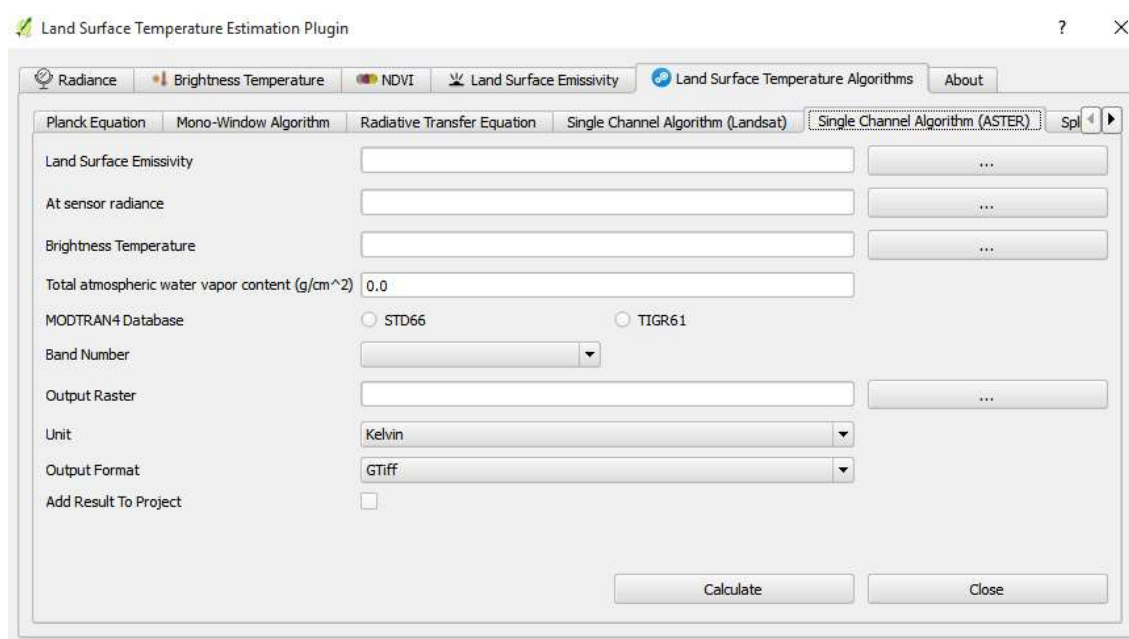


Figure 2.11. Application's interface for the SCA for the ASTER sensor

2.6.7.6. *The Split Window Algorithm (SWA) for the ASTER Sensor*

The SWA is a LST estimation algorithm which was developed for the purpose of extracting LST from instruments with more than one TIR channel. The algorithm was initially introduced to estimate Sea Surface Temperature (SST) and was later adopted for the extraction of LST. It takes full advantage of the differences in absorption between two thermal infrared channels in the atmospheric window between 10.5 - 12.5 μm . Many SWA equations have been derived by numerous researchers for LST estimation (Becker & Li, 1990; Caselles, Coll, & Valor, 1997; Price, 1984). In this study, Mao et al's SWA has been used. The algorithm used is as shown in Equation (2.38).

$$T_s = \frac{\{[C_{14}(D_{13} + B_{13})] - [C_{13}(D_{14} + B_{14})]\}}{C_{14}A_{14} - C_{13}A_{14}} \quad (2.38)$$

$$A_{13} = 0.145236 \times \varepsilon_{13} \times \tau_{13} \quad (2.39)$$

$$B_{13} = 0.145236 \times T_{13} + 33.685 \times \varepsilon_{13} \times \tau_{13} - 33.685 \quad (2.40)$$

$$C_{13} = (1 - \tau_{13}) \times [1 + (1 - \varepsilon_{13}) \times \tau_{13}] \times 0.145236 \quad (2.41)$$

$$D_{13} = (1 - \tau_{13}) \times [1 + (1 - \varepsilon_{13}) \times \tau_{13}] \times 33.685 \quad (2.42)$$

$$A_{14} = 0.13266 \times \varepsilon_{14} \times \tau_{14} \quad (2.43)$$

$$B_{14} = 0.13266 \times T_{14} + 30.273 \times \varepsilon_{14} \times \tau_{14} - 30.273 \quad (2.44)$$

$$C_{14} = (1 - \tau_{14}) \times [1 + (1 - \varepsilon_{14}) \times \tau_{14}] \times 0.13266 \quad (2.45)$$

$$D_{14} = (1 - \tau_{14}) \times [1 + (1 - \varepsilon_{14}) \times \tau_{14}] \times 30.273 \quad (2.46)$$

Where τ_{13} and τ_{14} stand for the atmospheric transmissions for band 13 and band 14 respectively, ε_{13} and ε_{14} stand for the land surface emissivities of band 13 and band 14 respectively and T_s represents the land surface temperature. Figure 2.12 shows the application's interface for the split window algorithm.

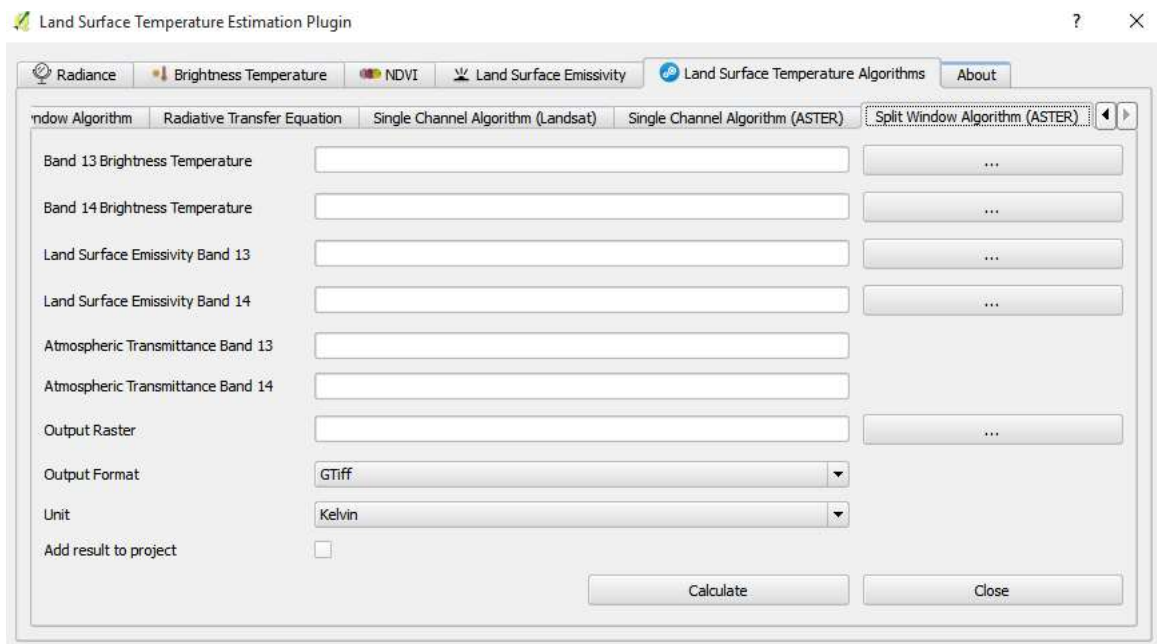


Figure 2.12. Application's interface for the SCA for the ASTER sensor

3. RESULTS AND DISCUSSION

In order to assess the accuracy of the land surface temperatures derived from the sensors in space, this study used near surface temperatures measured by meteorological stations during the hour of the satellite overpass. The coordinates of the meteorological stations were converted to shape files in order to determine the pixel containing the LST of which its value was being tested. The vector layers containing the meteorological stations were thereafter placed on top of the raster layers containing the LST derived from space and their corresponding pixel values were read. The meteorological stations used in the study were located in areas with different land covers and elevation. Meteorological data was used for accuracy assessment due to the absence of *in situ* measurements made during the satellite overpass time. Meteorological data was considered in the accuracy modelling as it has been used by researchers in previous studies for land surface temperature validation (Liu & Zhang, 2011). Near surface temperatures were also considered in the accuracy assessment of the LST derived from space as previous researchers found out that there's an existence of a relationship between near surface temperature and land surface temperatures. Researchers also used LST to derive near surface temperatures (Cresswell, Morse, Thomson, & Connor, 1999; Prihodko & Goward, 1997; Stisen, Sandholt, Nørgaard, Fensholt, & Eklundh, 2007).

Doing an accuracy assessment of LST derived from sensors in space through the use of data measured on the ground is usually a challenging task. This is because a satellite scene covers a large area with variations in vegetation cover and topography. For example, a Landsat scene covers an area of approximately 170 km from north to south and about 183 km from east to west. The spatial resolution of a satellite pixel can also pose a challenge as meteorological stations usually collect data from a certain point while a pixel containing a LST value covers a wider area and stores an average value of a larger area (a Landsat pixel covers an area of about 900 m²).

The atmospheric conditions of a study area during the satellite overpass time may also play a great role in the determination of the accuracy of the LST derived from space. The presence of cloud cover on a satellite scene can seriously hamper the

accuracy analysis process. For this reason, the scenes used in this study have a cloud cover of less than 10%.

Some of the Landsat 7 ETM+ scenes used in this study have been affected by the Scan Line Corrector (SLC) error. The SLC error has affected the sensor as from 31 May 2003 and resulting to the presence of stripes on Landsat 7 ETM+ imagery. Stripped imagery has been used in this study as a result of the absence of enough meteorological data before the occurrence of the error, the number of scenes not affected by the error are also very few in number. Some of the meteorological stations used in the study are located on the areas where the stripes crossed the imagery. The data recorded from these meteorological stations has only been used in the estimation of atmospheric water vapour and effective mean atmospheric temperature but has not been used in the accuracy assessment as the LSTs were missing. These stations have been shown in Table 3.3 and in Table 3.4.

In this study, the LST maps of the study area have been produced using imagery acquired from Landsat 5 TM, Landsat 7 ETM+, Landsat 8 TIRS and the ASTER instrument. The MWA (Liu & Zhang, 2011), SCA for Landsat (Jiménez-Muñoz & Sobrino, 2003), the Planck function and the RTE have been used to derive the LST maps from the Landsat sensors while the LSTs obtained from the ASTER instrument have been derived using the SCA for ASTER (J. C. Jiménez-Muñoz & J. A. Sobrino, 2010) and the SWA for ASTER (Mao et al., 2006). In the study, Zhang, Wang et al.'s algorithm (Zhang et al., 2006) was used to derive the LSE of the scenes from the VNIR imagery of the Landsat sensors while J.C. Jimenez-Munoz's algorithm was used in the estimation of LSE from the ASTER imagery (J. C. Jiménez-Muñoz et al., 2006). Meteorological data was used in the modelling of the LST derived from the imagery of the sensors used in the study.

Table 3.1 and Table 3.2 show the comparisons of the land surface temperatures derived from the SCA, MWA, Planck function and the RTE using Landsat 5 TM in relation to the pixel in which the meteorological stations were located. For Landsat 5 TM, the best results were obtained from the RTE for the scene dated 31 December 2010; where by the algorithm produced results with a Root Mean Square Error (RMSE) of 2.64°C. For the Landsat 5 TM scene dated 13 November 2010, the best result was obtained from the Planck function which produced temperatures with a RMSE of 1.58 °C. The LST

maps produced by the SCA, RTE, MWA and Planck function for the Landsat 5 TM scene dated 31 December 2010 are shown in Appendix 1, Appendix 2, Appendix 3 and Appendix 4 respectively. For the Landsat 5 TM scene dated 13 November 2010, the LST maps extracted using the SCA, RTE, MWA and the Planck function are shown in Appendix 5, Appendix 6, Appendix 7 and Appendix 8 respectively. The meteorological stations used in the accuracy assessment have also been shown on the maps.

Table 3.3 and Table 3.4 show the comparisons of the land surface temperatures derived from the SCA, MWA, Planck function and the RTE using Landsat 7 ETM+ in relation to the location of the meteorological stations. For the Landsat 7 ETM+ scene dated 21 November 2010, the best results were obtained from the RTE which produced results with a RMSE of 3.75 °C while for the Landsat 7 ETM+ scene dated 23 February 2016, the Planck function produced the best results with LST values which had a RMSE of 3.58 °C in relation to the near surface temperatures acquired from the meteorological stations. The LST maps produced by the SCA, MWA, Planck function and the RTE for the Landsat 7 ETM+ scene dated 21 November 2010 are shown in Appendix 9, Appendix 10, Appendix 11 and Appendix 12 respectively. For the Landsat 7 ETM+ scene dated 23 February 2016, the LST maps derived by the SCA, MWA, Planck function and the RTE are shown in Appendix 13, Appendix 14, Appendix 15 and Appendix 16 respectively. The meteorological stations used in the accuracy assessment have also been shown on the maps.

In this study, a comparison of the LST derived from Landsat 7 ETM+ and the ASTER sensor was done. The Terra spacecraft is positioned on a sun synchronous orbit and passes thirty minutes after Landsat ETM+. It crosses the equator at 10:30 am solar time (Abrams et al., 2002). This provides researchers with an opportunity to make use of cross validation techniques which involve the use of land surface temperatures derived from two or more instruments in order to assess the accuracy of the temperatures calculated. Table 3.5 and Table 3.6 show the comparisons of land surface temperatures derived from the Landsat 7 ETM+ scenes dated 2 September 2010 and 19 September 2013 respectively in relation to the near surface temperatures measured by the meteorological stations. The LST maps derived by the SCA, MWA, Planck function and the RTE using the scene dated 2 September 2010 are shown in Appendix

17, Appendix 18, Appendix 19 and Appendix 20 respectively. For the Landsat 7 ETM+ scene dated 19 September 2013, the LST maps produced by the SCA, MWA, Planck function and the RTE are as shown in Appendix 21, Appendix 22, Appendix 23 and Appendix 24 respectively. The meteorological stations used in the accuracy assessment have also been shown on the maps. The LST maps which were produced by the ASTER imagery dated 2 September 2010 using the SCA for ASTER band 13, SCA for ASTER band 14 and the SWA for ASTER are as shown in Appendix 25, Appendix 26 and Appendix 27 respectively. For the ASTER imagery dated 19 September 2013, the LST maps produced by the SCA band 13 for ASTER, SCA band 14 for ASTER and the SWA for ASTER are as shown in Appendix 28, Appendix 29 and Appendix 30 respectively.

The spatial resolution of the thermal infrared bands of the ASTER instrument is 90 meters and the one for Landsat 7 ETM+ is 60 meters. After resampling the, the spatial resolution of Landsat 7 ETM+ sensor becomes 30 meters. In order to perform a comparison in a correct manner, the spatial resolution of the land surface temperature maps obtained from Landsat 7 ETM+ were resampled using ERDAS Imagine 2014 to a pixel resolution of 90 meters.

The ASTER instrument is equipped with a total of five thermal bands i.e. band 10 - band 14. All thermal bands (i.e. band 10, band 11, band 12, band 13 and band 14) of the ASTER sensor have the ability to detect thermal infrared electromagnetic radiation, it is however important to select the optimal thermal band when deriving LST (J. C. Jiménez-Muñoz & J. A. Sobrino, 2010). It is expected that accurate land surface temperatures are retrieved in the spectral region with wavelengths between 10 and 12 μm . This is because the region has a higher atmospheric transmittance and lower emissivity variations as compared to the spectral window with wavelengths between 8 and 9 μm . Although band 12, 13 and 14 show the highest transmittance in the ASTER instrument, band 13 and band 14 are the mostly preferred ones due to band 12 being around 9 μm in wavelength (J. C. Jiménez-Muñoz & J. A. Sobrino, 2010). For this reason, this study has only made use of ASTER band 13 and band 14 for LST retrieval. Figure 3.1 shows the comparison of the spectral regions of ASTER and the Landsat 7 ETM+ sensor.

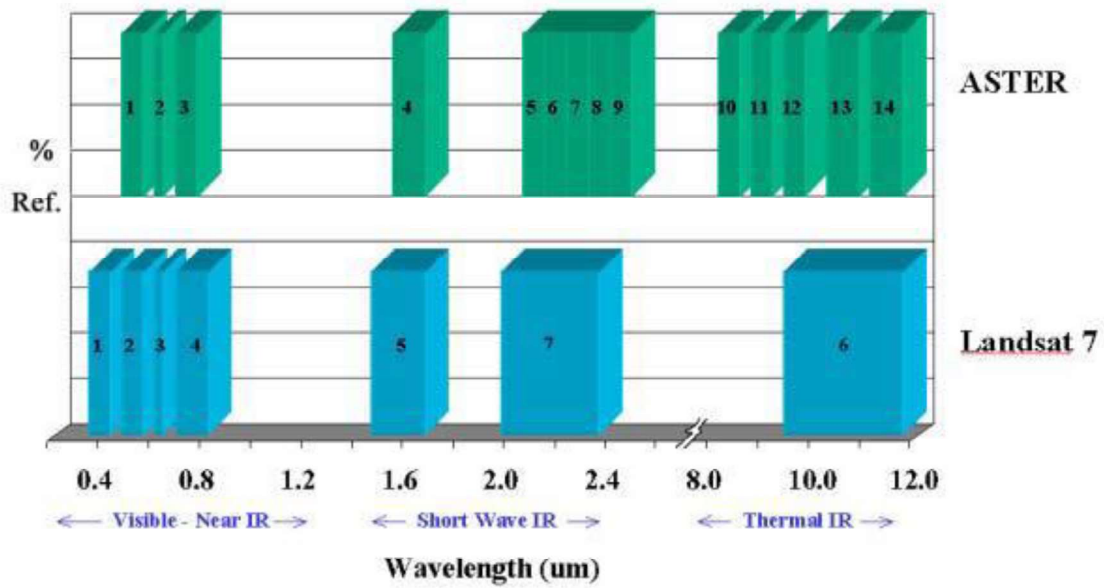


Figure 3.1. Comparison of the spectral regions of the ASTER and Landsat 7 ETM+ sensors

Source: Abrahams et al, 2002

In order to compare the LSTs derived from Landsat 7 ETM+ to those measured by the ASTER instrument 10 control points were randomly created for each scene. A shape file containing the points was thereafter placed on top of the LST maps created from the data obtained from the sensors. These points and their coordinates have been shown in Table 3.7 and Table 3.8 for the imagery dated 2 September 2010 and 19 September 2013 respectively. These control points have also been shown in Appendix 25, Appendix 26 and Appendix 27 for the image dated 2 September 2010. For the image dated 19 September 2013, the control points used in the accuracy assessment are shown in Appendix 28, Appendix 29 and Appendix 30. The temperatures obtained from the algorithms of the ASTER sensor were very close. In this study, the land surface temperatures derived from ASTER band 14 using the SCA of ASTER were generally higher as compared to the ones obtained from ASTER band 13. There was a big variation in LSTs derived from the two sensors. The LSTs derived from the ASTER instrument were generally higher in comparison to the ones derived from Landsat 7 ETM+. Figure 3.2 and Figure 3.3 show the comparison of the different land surface temperature values obtained from the algorithms used in the study and the

corresponding control points used in the accuracy assessment. The values have been shown in detail in Table 3.7 and Table 3.8.

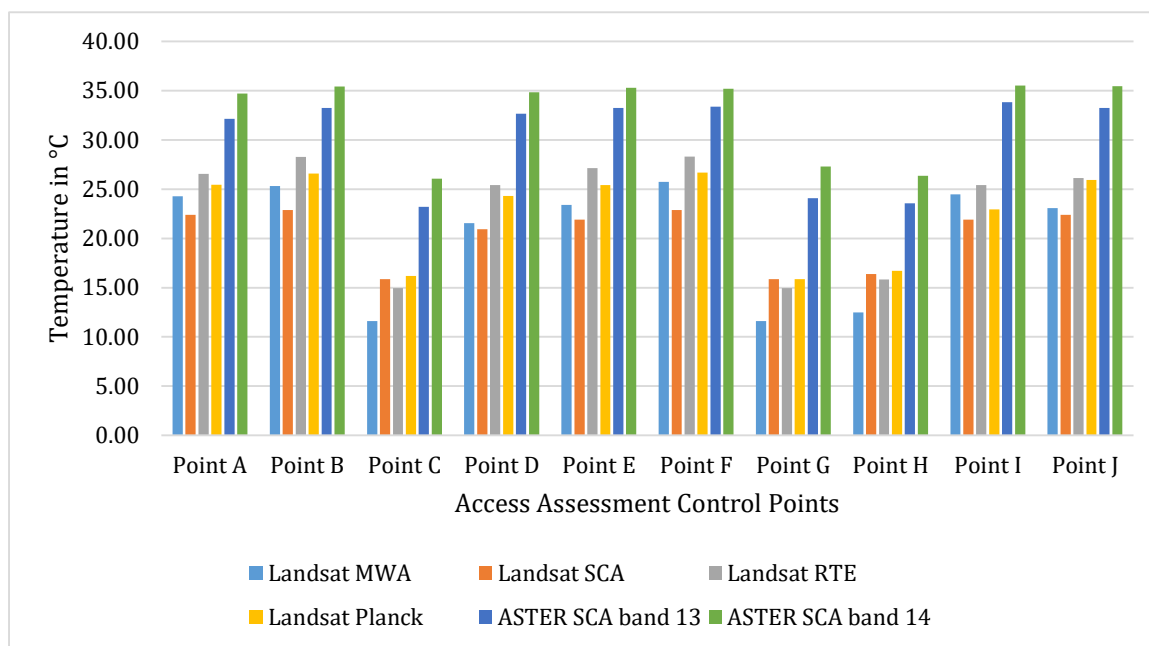


Figure 3.2. Comparison of the land surface temperatures derived from the Landsat 7 ETM+ and the ASTER imagery dated 2 September 2010 using the MWA, SCA for Landsat, RTE, Planck function, SWA for ASTER, SCA for ASTER using band 13 and the SCA for ASTER using band 14.

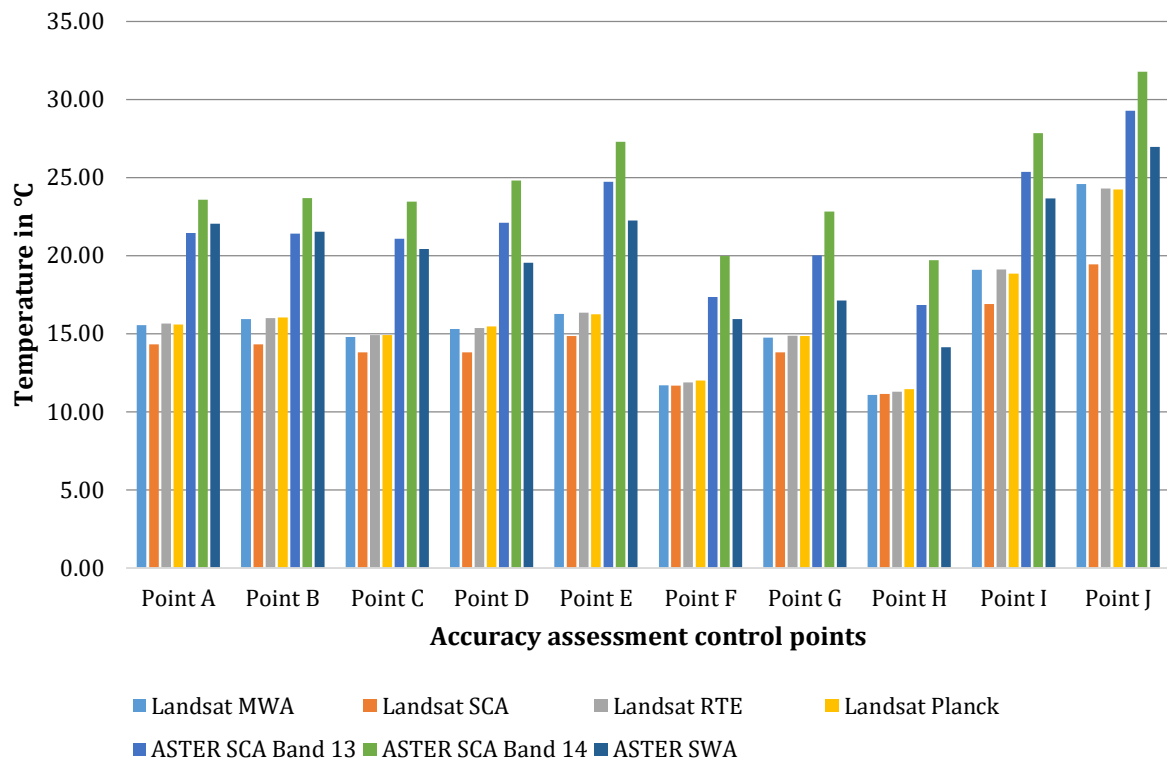


Figure 3.3. Comparison of the land surface temperatures derived from the Landsat 7 ETM+ and the ASTER imagery dated 19 September 2013 using the MWA, SCA for Landsat, RTE, Planck function, SWA for ASTER, SCA for ASTER using band 13 and the SCA for ASTER using band 14.

There was a big variation between the LST values obtained from the Landsat 7 ETM+ and the ASTER instrument. The land surface temperature differences measured by the sensors for the scenes dated 2 September 2010 exhibited differences ranging from 1.3 °C to 15.7 °C while those for the scenes dated 19 September 2013 exhibited differences ranging from 2.26 °C to 12.46 °C. Such differences in land surface temperature values between the two sensors have also been previously reported by researchers in a previous study (Chen & Zhou, 2004). It is not possible for such temperature differences to take place within a period of thirty minutes especially considering the fact that;

- Both scenes covered the same area,
- It is not possible for such temperature changes to take place within such a short period of time,
- The two sensors have similar specifications such as a similar spectral resolution between the bands involved in the study, similar spatial

resolution, both sensors are positioned in sun-synchronous orbits, altitudes and viewing angles (Chen & Zhou, 2004).

According to the tests done by Chen and Zhou, there was an existence of a correlation between the surface temperatures of derived from the ASTER sensor with the brightness temperatures under clear conditions as all the correlations were above 0.99 regardless of the sampling technique used. The temperatures of these sensors are however still correlated with values ranging from 0.85 to 0.95 (Chen & Zhou, 2004). Chen and Zhou also revealed that the differences between the temperatures obtained from the two sensors are not caused by the differences in spatial resolution between the Landsat 7 ETM+ and the ASTER instrument. Considering the fact that the ASTER products have been tested and proven to be suitable for scientific research. This variation implies that there is a presence of performance errors in the Landsat 7 ETM+ sensor. This proves that there is a need to do more calibration to the LST bands of the Landsat 7 ETM+ instrument and users should be careful when making use of LST data derived from the sensor.

Table 3.9 and Table 3.10 show the comparisons between the LST derived using the MWA, SCA, RTE and the Planck function for the Landsat 8 TIRS imagery dated 4th June 2015 and 29th May 2013 respectively. For the Landsat 8 TIRS scene dated 4th June 2015, the best results were obtained from the Planck function with temperatures with a RMSE of 2.07 °C in comparison to the near surface temperatures measured on the meteorological stations. The best results for the Landsat 8 TIR sensor scene dated 29th May 2013 were obtained from the SCA which produced LST with a RMSE of 3.06 °C in comparison to the near surface temperatures. The LST maps produced from the scene acquired on 4th June 2015 using the SCA, RTE, MWA and the Planck function are shown in Appendix 31, Appendix 32, Appendix 33 and Appendix 34 respectively. The LST maps produced using the Landsat 8 TIRS scene dated 29th May 2013 using the SCA, RTE, MWA and the Planck function are shown in Appendix 35, Appendix 36, Appendix 37 and Appendix 38 respectively. The meteorological stations used in the accuracy assessment have also been shown on the maps.

Table 3.1. Comparison between LST values obtained from Landsat 5 TM using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 31st December 2010.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 12:00	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	-3.1	99	-4.75	-4.70	-4.55	-5.56
Fundy Park (Alma) Cs	45°36'00.000"N	64°57'00.000"W	42.7	3.6	62	-0.91	-1.29	-0.73	-2.17
Buctouche CDA Cs	46°25'49.006"N	64°46'05.009"W	35.9	-0.9	78	-8.06	-7.64	-7.85	-8.48
Nappan Auto	45°45'34.400"N	64°14'29.200"W	19.8	-7.9	73	-3.46	-3.55	-3.26	-4.42
Saint John A	45°19'05.000"N	65°53'08.050"W	108.8	-0.2	69	-0.29	-0.73	-0.11	-1.62
Parrsboro	45°24'48.000"N	64°20'49.000"W	30.9	2.1	68	-0.29	-0.73	-0.11	-1.62
Gagetown A	45°50'00.000"N	66°26'00.000"W	50.6	-2.2	79	-0.91	-1.29	-0.73	-2.17
Gagetown Awos A	45°50'20.000"N	66°26'59.000"W	50.6	-1	77	-0.29	-0.73	-0.11	-1.62
Summerside	46°26'28.000"N	63°50'17.000"W	12.2	-0.9	78	-3.46	-3.55	-3.26	-4.42
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	-3.1	99	-4.75	-4.70	-4.55	-5.56
Root Mean Square Error (RMSE)						2.67	2.78	2.64	3.17

NST Near Surface Temperature (Day light saving was observed); PLANCK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; RH Relative Humidity.

Table 3.2. Comparison between LST values obtained from Landsat 5 TM using the MWA, Planck function, RTE, SCA and meteorological data obtained on 13th November 2010.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 12:00	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	15.4	40	15.15	14.97	15.32	13.28
Fundy Park (Alma) Cs	45°36'00.000"N	64°57'00.000"W	42.7	13.1	53	15.70	15.80	15.73	10.86
Buctouche CDA Cs	46°25'49.006"N	64°46'05.009"W	35.9	12.4	39	12.70	12.58	12.90	10.36
Nappan Auto	45°45'34.400"N	64°14'29.200"W	19.8	12.1	52	14.17	14.26	14.30	10.36

Saint John A	45°19'05.000"N	65°53'08.050"W	108.8	12.2	41	14.83	14.25	15.14	13.27
Parrsboro	45°24'48.000"N	64°20'49.000"W	30.9	13.2	48	14.56	14.57	14.70	10.85
Gagetown A	45°50'00.000"N	66°26'00.000"W	50.6	11.6	36	10.11	10.27	10.40	8.37
Gagetown Awos A	45°50'20.000"N	66°26'59.000"W	50.6	12.0	36	10.96	10.82	11.30	9.86
Summerside	46°26'28.000"N	63°50'17.000"W	12.2	13.6	40	12.63	12.55	12.88	10.36
Root Mean Square Error (RMSE)						1.64	1.58	1.68	2.33

^{NST} Near Surface Temperature (Day light saving was observed); ^{PLANCK} Planck Function; ^{RTE} Radiative Transfer Equation; ^{SCA} Single Channel Algorithm; ^{RH} Relative Humidity.

Table 3.3. Comparison between LST values obtained from Landsat 7 ETM+ using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 21st November 2010.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 12:00	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	-6.8	78	-11.75	-11.52	-11.43	-12.34
Fundy Park (Alma) Cs	45°36'00.000"N	64°57'00.000"W	42.7	-1.9	58	-5.50	-5.53	-5.21	-6.39
Buctouche CDA Cs	46°25'49.006"N	64°46'05.009"W	35.9	-4.4	64	-9.62	-9.48	-9.31	-10.31
Nappan Auto	45°45'34.400"N	64°14'29.200"W	19.8	-4.4	70	-8.23	-8.14	-7.92	-8.98
Saint John A	45°19'05.000"N	65°53'08.050"W	108.8	-3.6	55	-6.18	-6.18	-5.88	-7.03
Parrsboro	45°24'48.000"N	64°20'49.000"W	30.9	-2.6	60	N/A	N/A	N/A	N/A
Gagetown Awos A	45°50'20.000"N	66°26'59.000"W	50.6	-2.9	55	-3.51	-3.62	-3.22	-4.49
Summerside	46°26'28.000"N	63°50'17.000"W	12.2	-3	68	-8.23	-8.14	-7.92	-8.98
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	-6.8	78	-11.75	-11.52	-11.43	-12.34
Root Mean Square Error (RMSE)						4.03	3.94	3.75	4.73

^{NST} Near Surface Temperature (Day light saving was observed); ^{PLANCK} Planck Function; ^{RTE} Radiative Transfer Equation; ^{SCA} Single Channel Algorithm; ^{RH} Relative Humidity; N/A—Data not available as a result of Scan Line Corrector (SLC).

Table 3.4. Comparison between *LST* values obtained from Landsat 7 ETM+ using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 23rd February 2016.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 12:00	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	-8.1	35	-14.46	-14.31	-14.04	-15.12
Fundy Park (Alma) Cs	45°36'00.000"N	64°57'00.000"W	42.7	-6.9	50	-10.17	-10.15	-9.77	-10.98
Buctouche CDA Cs	46°25'49.006"N	64°46'05.009"W	35.9	-8.9	45	-5.40	-5.53	-5.03	-6.39
Nappan Auto	45°45'34.400"N	64°14'29.200"W	19.8	-7.9	68	N/A	N/A	N/A	N/A
Parrsboro	45°24'48.000"N	64°20'49.000"W	30.9	-5.9	49	-7.41	-7.48	-7.03	-8.33
Moncton International Airport	46°06'44.000"N	64°40'43.000"W	70.7	-8	44	-4.08	-4.25	-3.72	-5.12
Gagetown A	45°50'00.000"N	66°26'00.000"W	50.6	-8.4	47	N/A	N/A	N/A	N/A
Summerside	46°26'28.000"N	63°50'17.000"W	12.2	-7.3	55	N/A	N/A	N/A	N/A
Root Mean Square Error (RMSE)						3.68	3.58	3.61	3.80

NST Near Surface Temperature (Day light saving was observed); PLANCK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; RH Relative Humidity; N/A—Data not available as a result of Scan Line Corrector (SLC).

Table 3.5. Comparison between *LST* values obtained from Landsat 7 ETM+ using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 2nd September 2010.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 11:00	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	28.3	0.51	45°41'37.040" N	Mechanic Settlement	28.3	24.42	26.63	27.09	21.91
Fundy Park (Alma) Cs	24.2	0.67	45°36'00.000" N	Fundy Park (Alma) Cs	24.2	18.33	23.30	21.09	18.44
Buctouche CDA Cs	30.5	0.5	46°25'49.006" N	Buctouche Cda Cs	30.5	24.75	24.40	27.85	23.37
Nappan Auto	29.5	0.53	45°45'34.400" N	Nappan Auto	29.5	24.75	24.40	27.85	23.37
Saint John A	29.6	0.5	45°19'05.000" N	Saint John A	29.6	31.28	28.24	34.11	27.18
Parrsboro	25.1	0.66	45°24'48.000" N	Parrsboro	25.1	N/A	N/A	N/A	N/A
Gagetown Awos A	31	0.52	45°50'20.000" N	Gagetown Awos A	31	N/A	N/A	N/A	N/A

Summerside	29.6	0.55	46°26'28.000" N	Summerside	29.6	23.09	23.43	26.24	22.39
Root Mean Square Error (RMSE)					5.01	4.22	2.96	6.06	

NST Near Surface Temperature (Day light saving was observed); PLANKK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; RH Relative Humidity; N/A—Data not available as a result of Scan Line Corrector (SLC).

Table 3.6. Comparison between LST values obtained from Landsat 7 ETM+ using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 19th September 2013.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 11:00	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Fundy Park (Alma) Cs	45°36'00.000" N	64°57'00.000" W	42.7	20.1	54	15.64	16.01	15.59	13.28
Nappan Auto	45°45'34.400" N	64°14'29.200" W	19.8	19	57	17.84	17.57	17.92	16.39
Parrsboro	45°24'48.000" N	64°20'49.000" W	30.9	18.2	67	N/A	N/A	N/A	N/A
Summerside	46°26'28.000" N	63°50'17.000" W	12.2	18.8	56	16.44	16.29	16.55	15.36
Root Mean Square Error (RMSE)						2.99	2.89	2.97	4.66

NST Near Surface Temperature (Day light saving was observed); PLANKK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; RH Relative Humidity; N/A—Data not available as a result of Scan Line Corrector (SLC).

Table 3.7. Comparison between LST values obtained from Landsat 7 ETM+ and ASTER using the MWA, Planck equation, RTE, Landsat SCA, ASTER SCA and ASTER SCA band 13 and ASTER SCA band 14 data obtained on 02 September 2010.

Point Name	X Coordinate (UTM Zone 20 N Meters)	Y-Coordinate (UTM Zone 20 N Meters)	Landsat 7 ETM+ MWA (°C)	Landsat 7 ETM+ SCA (°C)	Landsat 7 ETM+ RTE (°C)	Landsat 7 ETM+ PLK (°C)	ASTER SCA Band 13 (°C)	ASTER SCA Band 14 (°C)	ASTER SWA (°C)
Point A	340,104.58	5,104,728.23	24.27	22.40	26.55	25.44	32.16	34.70	27.93
Point B	346,260.15	5,126,000.88	25.32	22.89	28.29	26.60	33.25	35.43	30.30
Point C	397,042.02	5,135,686.27	11.60	15.88	14.96	16.20	23.21	26.06	18.71
Point D	381,310.91	5,110,072.44	21.54	20.93	25.43	24.30	32.68	34.83	29.88
Point E	356,398.13	5,100,474.19	23.41	21.91	27.15	25.43	33.26	35.29	30.88

Point F	357,483.55	5,149,626.86	25.74	22.89	28.33	26.67	33.40	35.22	31.81
Point G	383,374.23	5,146,459.03	11.60	15.88	14.96	15.87	24.07	27.31	18.34
Point H	406,885.75	5,141,442.09	12.48	16.39	15.84	16.71	23.57	26.37	19.20
Point I	390,705.47	5,103,279.45	24.48	21.91	25.42	22.94	33.84	35.52	32.75
Point J	373,484.50	5,093,156.85	23.09	22.39	26.15	25.94	33.25	35.48	30.14

PLK Planck Equation; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; SWA Split Window Algorithm.

Table 3.8. Comparison between LST values obtained from Landsat 7 ETM+ and ASTER using the MWA, Planck equation, RTE, Landsat SCA, ASTER SCA and ASTER SCA band 13 and ASTER SCA band 14 data obtained on 19 September 2013.

Point Name	X Coordinate (UTM Zone 20 N Meters)	Y-Coordinate (UTM Zone 20 Meters)	Landsat 7 ETM+		Landsat 7 ETM+ SCA		Landsat 7 ETM+ RTE		Landsat 7 ETM+ PLK		ASTER SCA Band 13		ASTER SCA Band 14		ASTER SWA	
			(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)	(°C)
Point A	360,723.97	5,116,004.13	15.55	14.32	15.65	15.60	21.45	23.59	22.04							
Point B	364,467.01	5,113,601.73	15.94	14.32	16.00	16.05	21.42	23.70	21.54							
Point C	382,589.95	5,102,412.81	14.80	13.80	14.92	14.91	21.08	23.46	20.43							
Point D	378,117.34	5,085,584.78	15.30	13.80	15.36	15.48	22.11	24.82	19.54							
Point E	352,055.18	5,068,433.96	16.26	14.84	16.35	16.26	24.73	27.30	22.25							
Point F	377,456.35	5,070,840.17	11.70	11.68	11.89	11.99	17.35	19.99	15.95							
Point G	362,431.43	5,080,911.60	14.76	13.80	14.88	14.86	20.02	22.83	17.14							
Point H	373,804.08	5,058,939.05	11.09	11.14	11.28	11.46	16.83	19.71	14.14							
Point I	397,157.90	5,074,703.15	19.09	16.91	19.12	18.86	25.37	27.84	23.67							
Point J	361,786.91	5,105,964.24	24.58	19.44	24.29	24.25	29.29	31.79	26.97							

PLK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; SWA Split Window Algorithm.

Table 3.9. Comparison between LST values obtained from Landsat 8 TIRS using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 4th June 2015.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 11:00 am	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	13.1	57	9.27	9.65	9.43	8.15
Fundy Park (Alma) Cs	45°36'00.000"N	64°57'00.000"W	42.7	12.4	56	13.42	13.36	13.51	11.33
Buctouche CDA Cs	46°25'49.006"N	64°46'05.009"W	35.9	15.1	58	16.66	16.14	16.73	14.20
Nappan Auto	45°45'34.400"N	64°14'29.200"W	19.8	15.4	63	14.84	14.40	15.01	13.18
Parrsboro	45°24'48.000"N	64°20'49.000"W	30.9	15.9	42	11.70	12.10	11.69	9.17
Summerside	46°26'28.000"N	63°50'17.000"W	12.2	13.9	62	13.44	13.55	13.45	10.82
Moncton International Airport	46°06'44.000"N	64°40'43.000"W	70.7	16.9	44	17.74	17.55	17.84	14.25
Root Mean Square Error (RMSE)						2.30	2.07	2.28	3.65

NST Near Surface Temperature; PLK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; RH Relative Humidity.

Table 3.10. Comparison between LST values obtained from Landsat 8 TIRS using the MWA, Planck Function, RTE, SCA and meteorological data obtained on 29 May 2013.

Station Name	Latitude	Longitude	Elevation (Meters)	NST (°C) at 11:00 am	RH (%)	MWA (°C)	PLANCK (°C)	RTE (°C)	SCA (°C)
Mechanic Settlement	45°41'37.040"N	65°09'54.040"W	403	17	27	22.24	21.80	23.07	18.85
Fundy Park (Alma) Cs	45°36'00.000"N	64°57'00.000"W	42.7	18.1	38	18.41	18.41	19.31	15.53
Buctouche CDA Cs	46°25'49.006"N	64°46'05.009"W	35.9	20.1	35	23.07	22.28	23.98	20.62
Nappan Auto	45°45'34.400"N	64°14'29.200"W	19.8	19.3	35	21.66	21.06	22.59	19.29
Parrsboro	45°24'48.000"N	64°20'49.000"W	30.9	16.2	49	22.04	21.60	22.88	18.77
Moncton International Airport	46°06'44.000"N	64°40'43.000"W	70.7	20.2	41	29.74	28.78	30.24	23.70
Gagetown A	45°50'00.000"N	66°26'00.000"W	50.6	20	31	15.36	17.58	16.34	13.32
Gagetown Awos A	45°50'20.000"N	66°26'59.000"W	50.6	20	31	22.02	21.74	22.79	18.06
Summerside	46°26'28.000"N	63°50'17.000"W	12.2	16.1	50	20.26	19.67	21.26	18.65
Root Mean Square Error (RMSE)						4.83	4.33	5.35	3.06

NST Near Surface Temperature; PLK Planck Function; RTE Radiative Transfer Equation; SCA Single Channel Algorithm; RH Relative Humidity.

4. CONCLUSION AND RECOMMENDATIONS

This study has proven how much open source tools can be powerful in the processing of geospatial data. With the presence of geo-spatial tools such as GDAL, Python and QGIS it is possible to implement complex algorithms which can ease geo-processing tasks. With this plugin, it is expected that users from other disciplines such as the ones related to hydrology, urban planning, vegetation studies, climate change and energy will make use of it in the extraction of LST. As a result of the source code being provided freely and different users being allowed to do modification of the code for more improvements, it is expected that more users will benefit from it.

In order to get better results when doing the accuracy assessment of the LST derived from space it is recommended that accuracy assessment should be done with *in situ* data collected during the satellite overpass time. It is also important to take the effects arising from atmospheric processes of scattering, attenuation and absorption into consideration as these processes affect the VNIR bands which are used in the estimation of NDVI and LSE. This study recommends that the General Directorate of Meteorology “*Meteoroloji Genel Müdürlüğü*” of Turkey to consider the provision meteorological data to the public through the use of a web portal like the one used by Environment Canada as a way to encourage researchers to do researches which will use case studies in Turkey.

The land surface temperatures obtained from the algorithms involved in this study revealed that all algorithms involved have the ability to be applied in LST extraction. It is important for Landsat 7 ETM+ users to be careful and note that there may be a presence of errors in land surface temperatures derived from Landsat 7 ETM+ band 6 and the errors may vary by up to 10°C or more, therefore users should be cautious when using the instrument.

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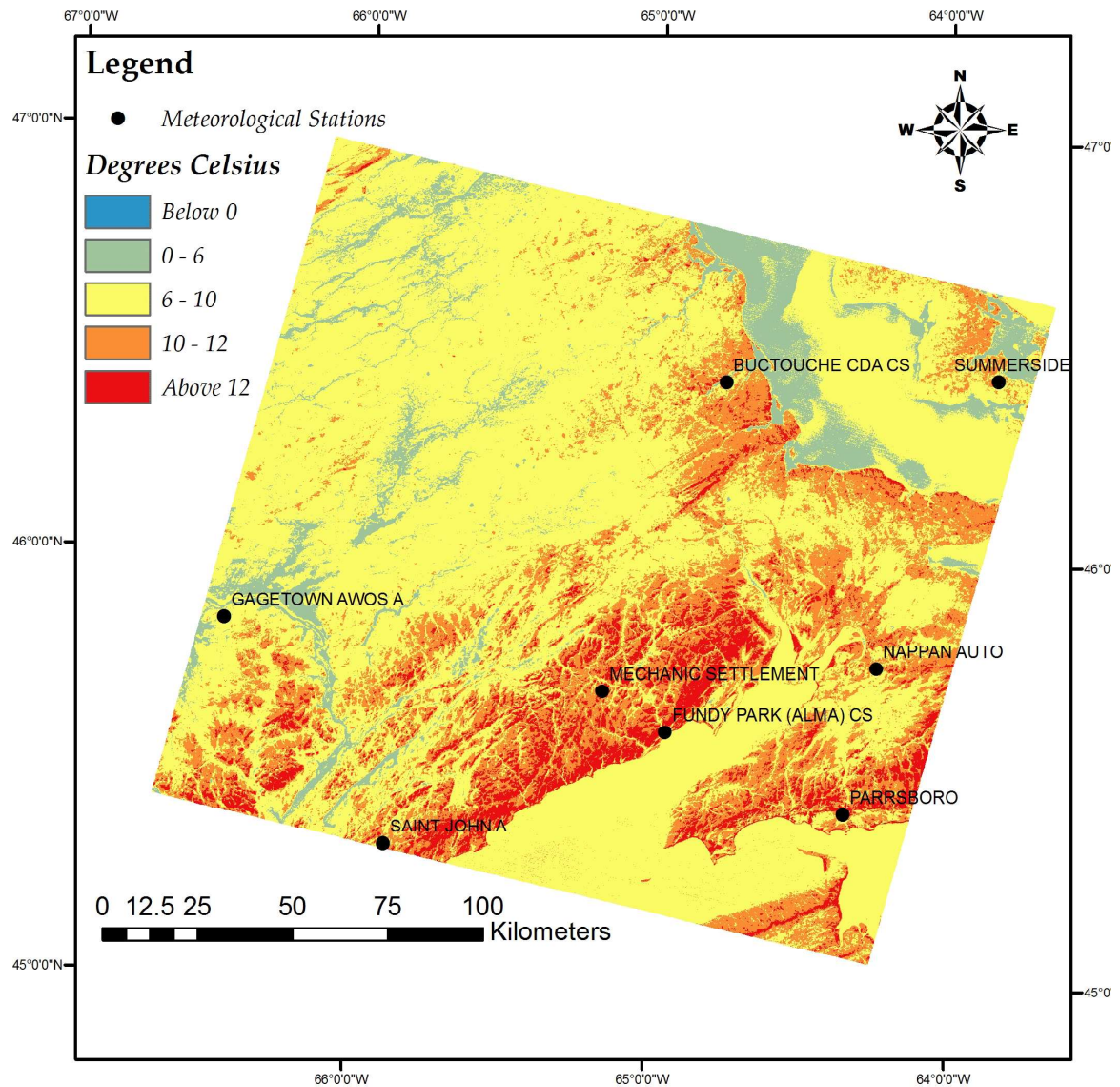
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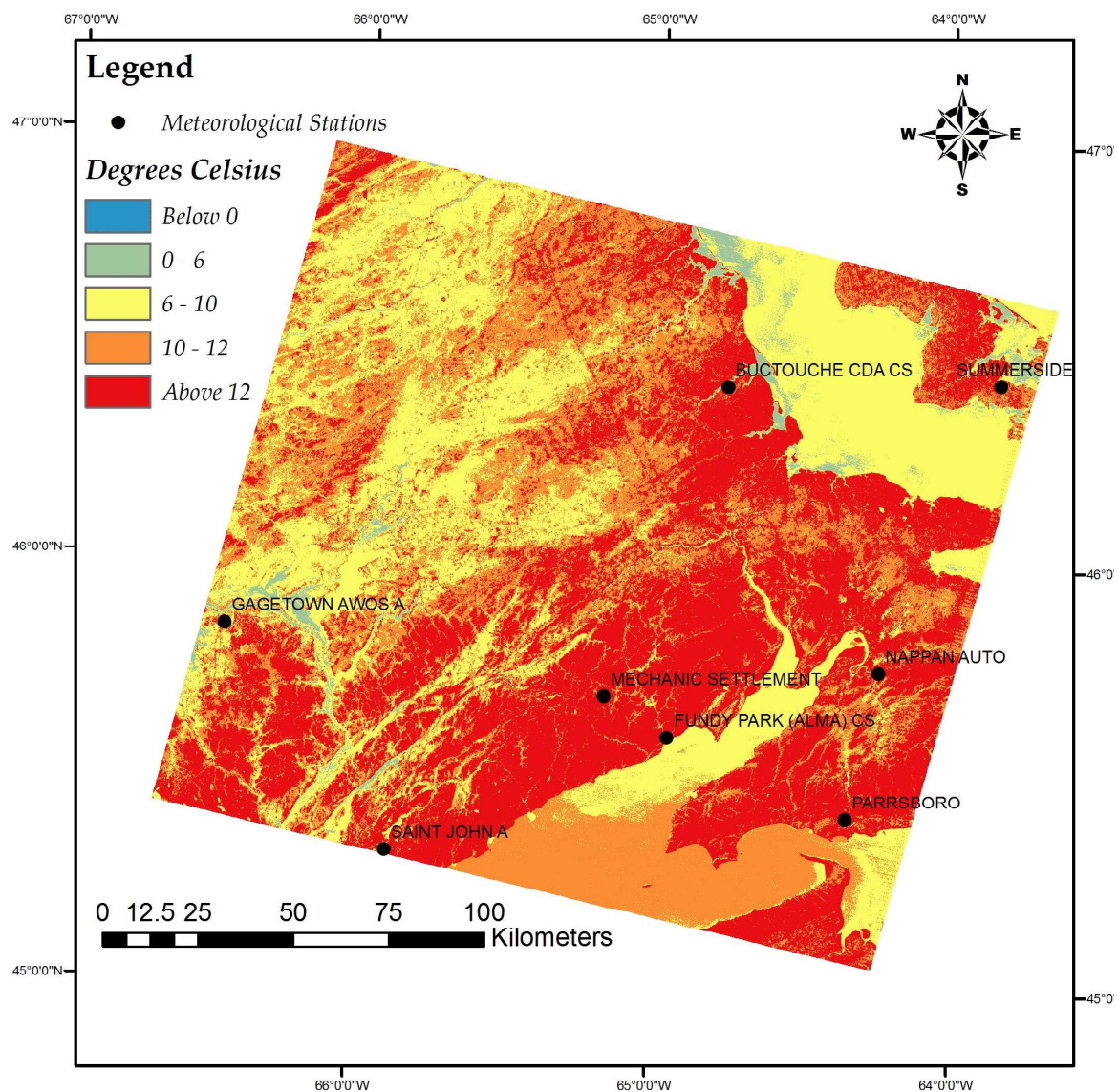
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APPENDICES

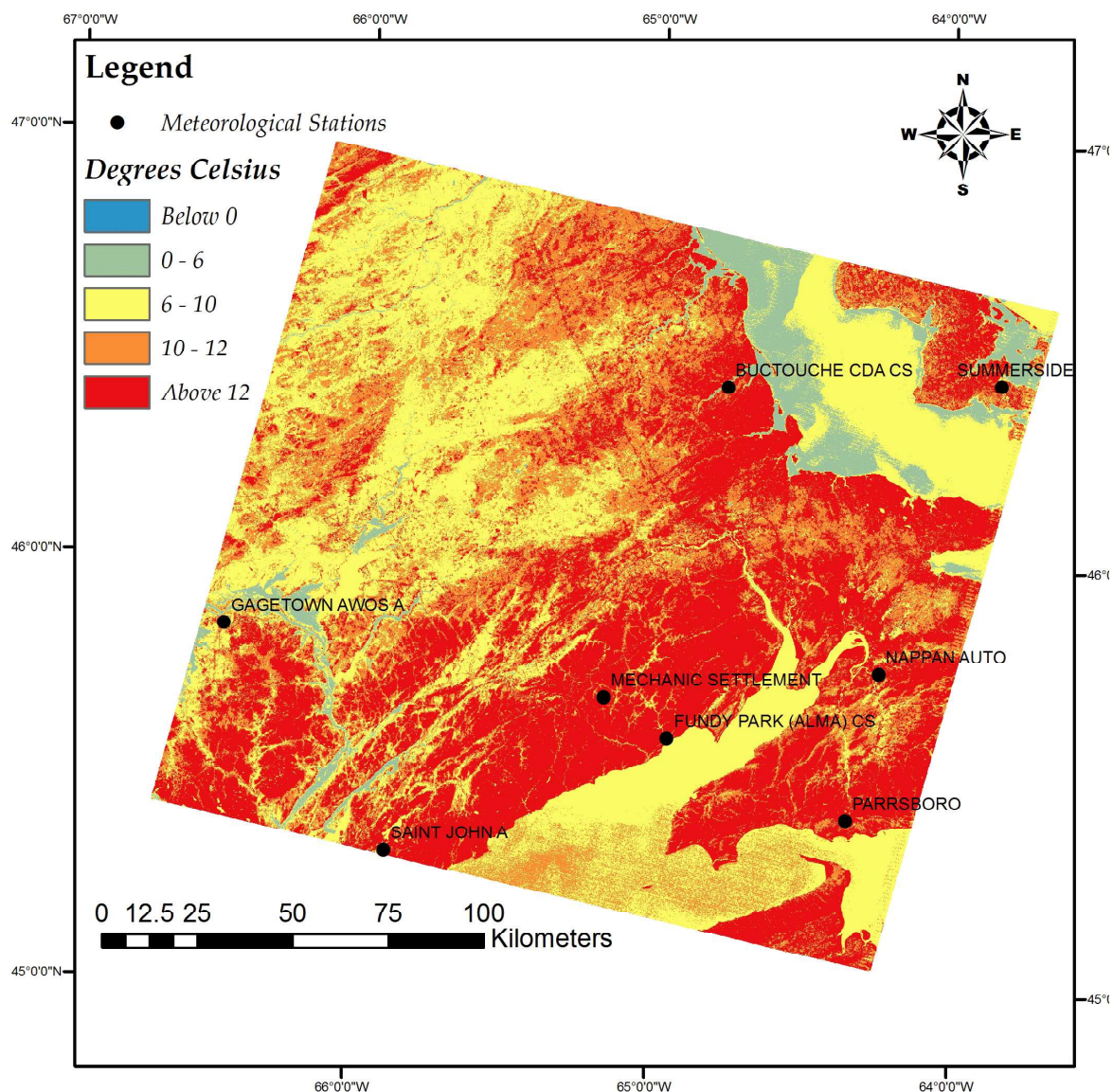
Appendix 1. Landsat 5 TM LST map produced by the SCA using the image dated 13 November 2010



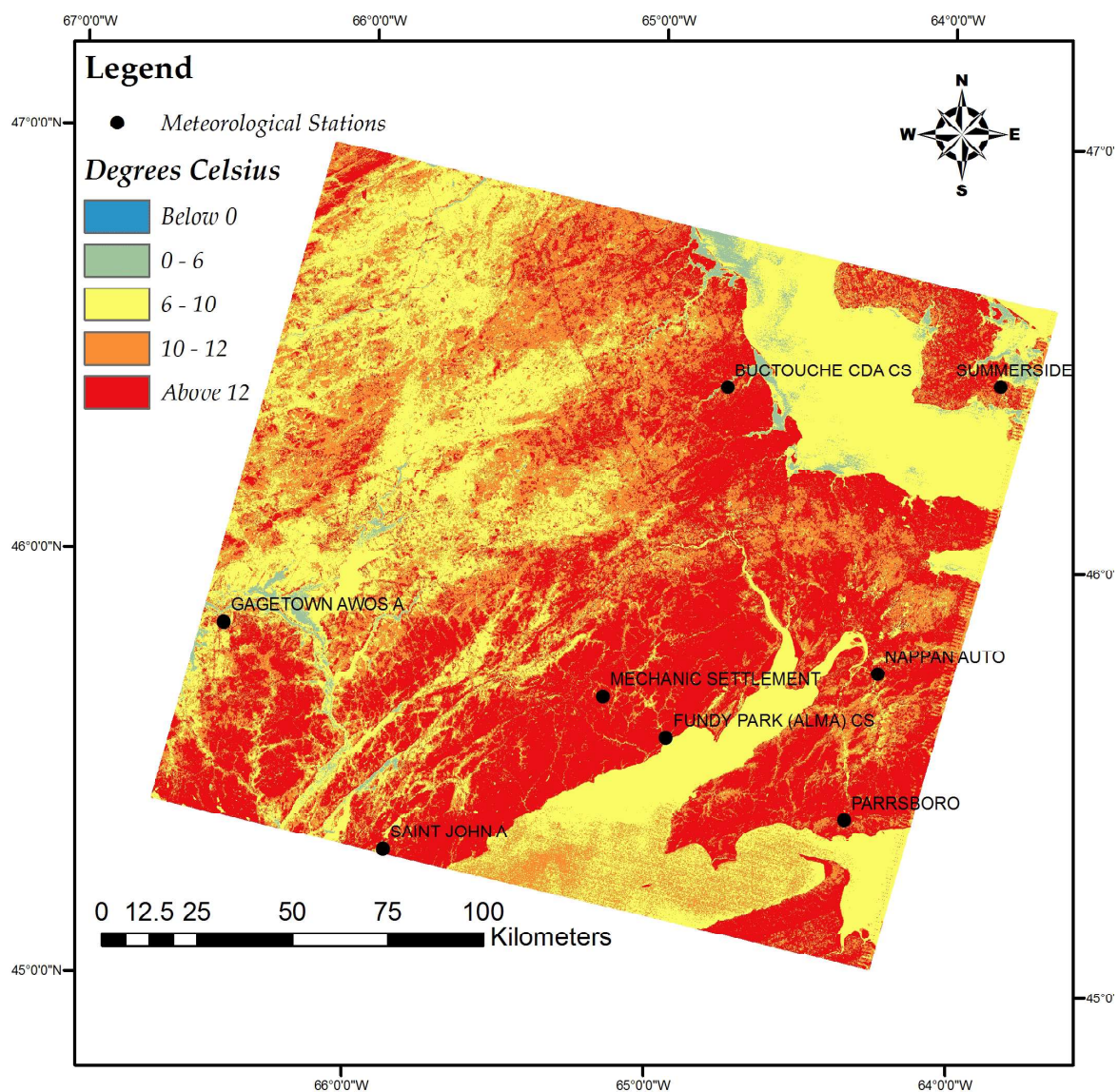
Appendix 2. Landsat 5 TM LST map produced by the RTE using the image dated 13 November 2010



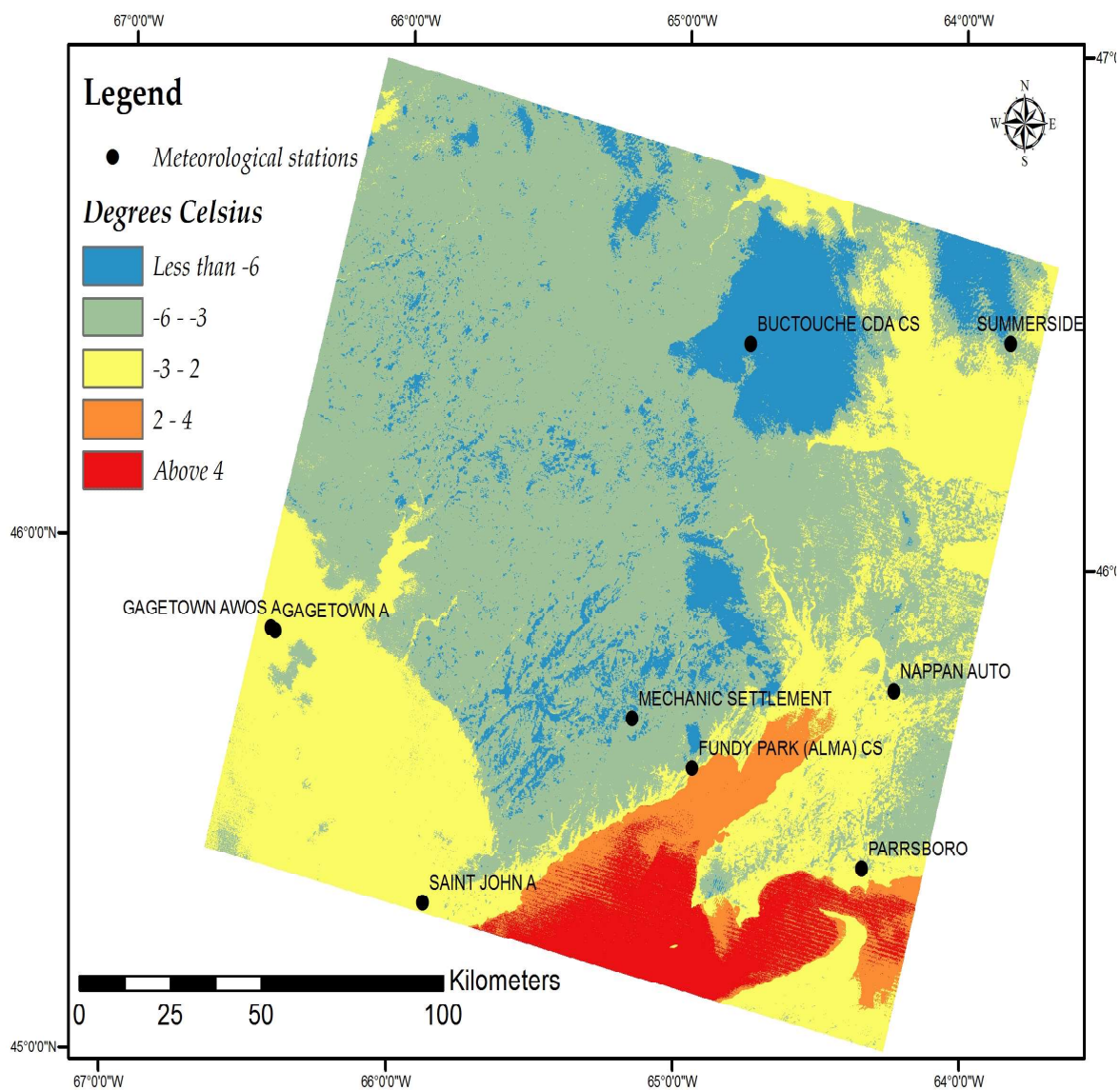
Appendix 3. Landsat 5 TM LST map produced by the MWA using the image dated 13 November 2010



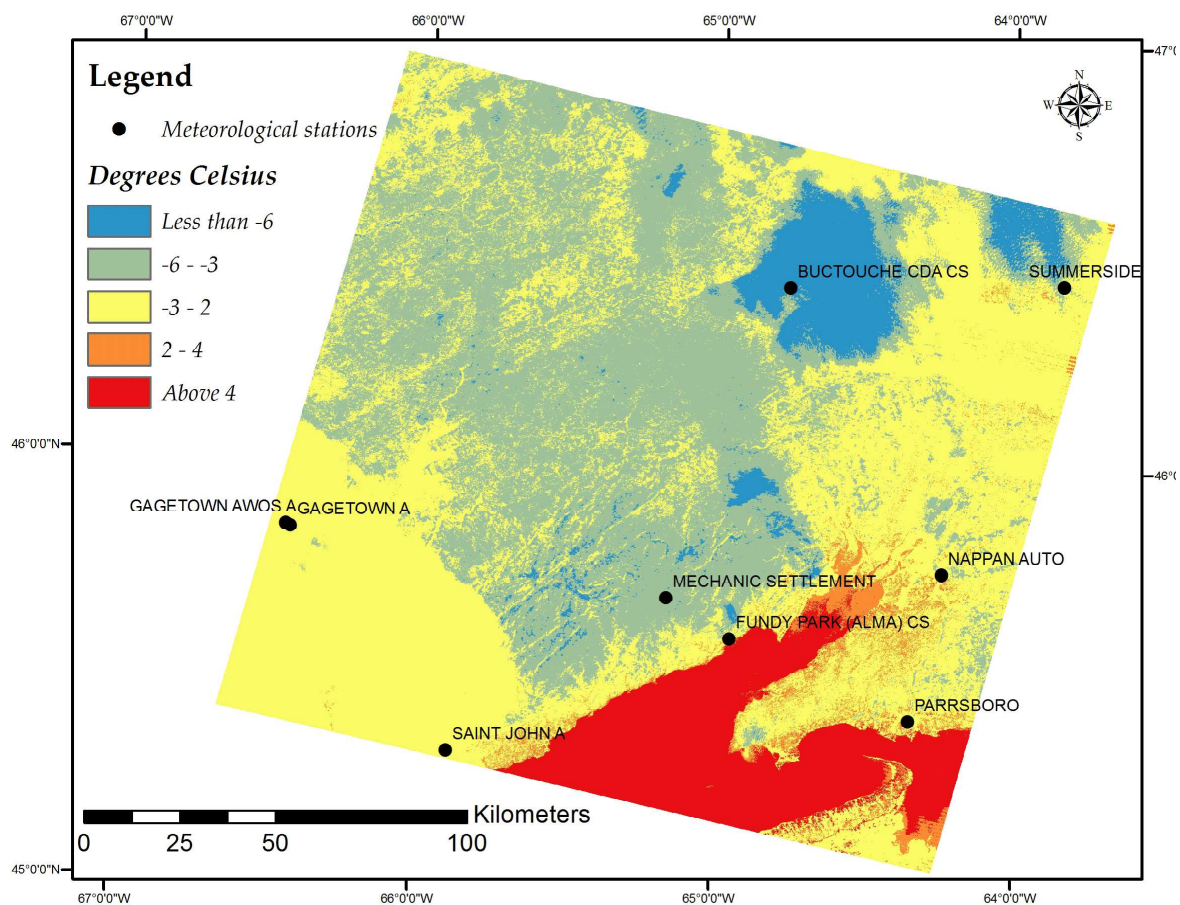
Appendix 4. Landsat 5 TM LST map produced by the Planck function using the image dated 13 November 2010



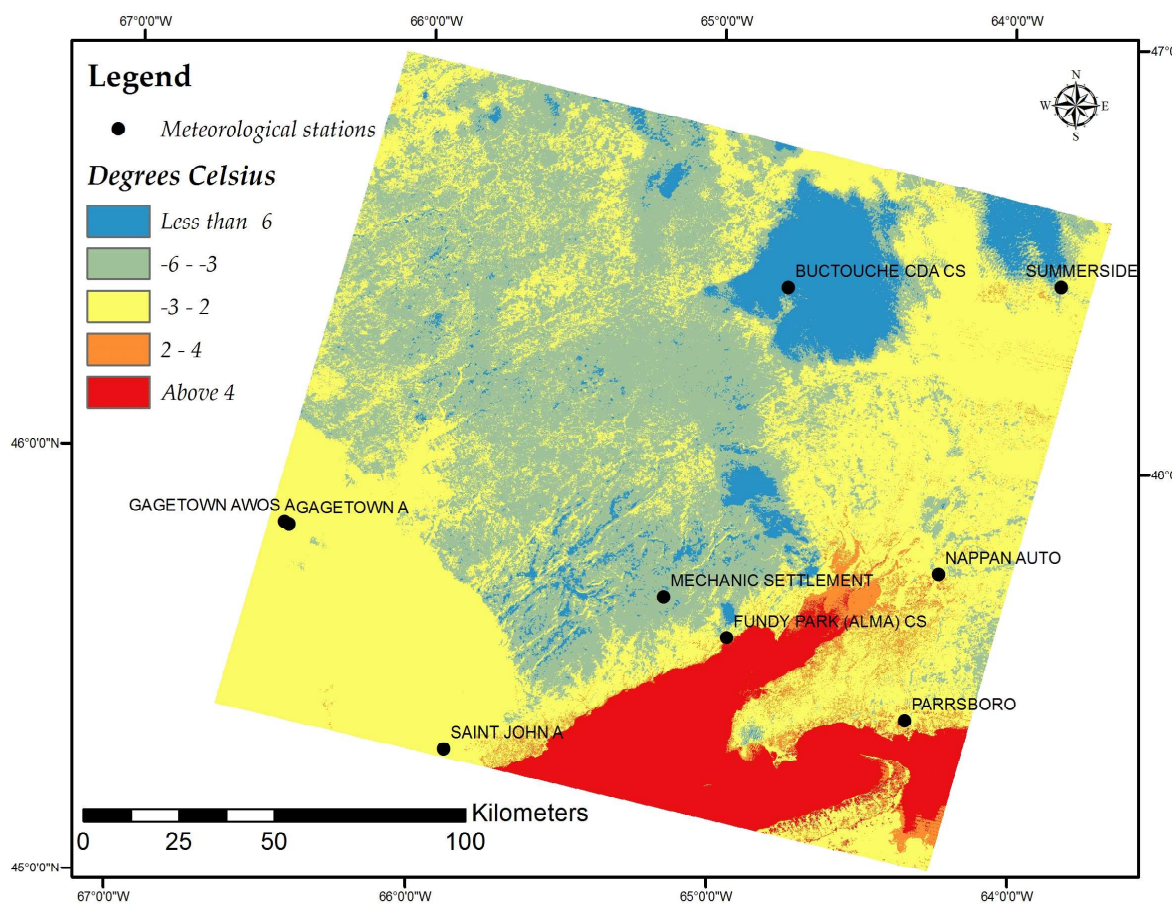
Appendix 5. Landsat 5 TM LST map produced by the SCA using the image dated 31 December 2010



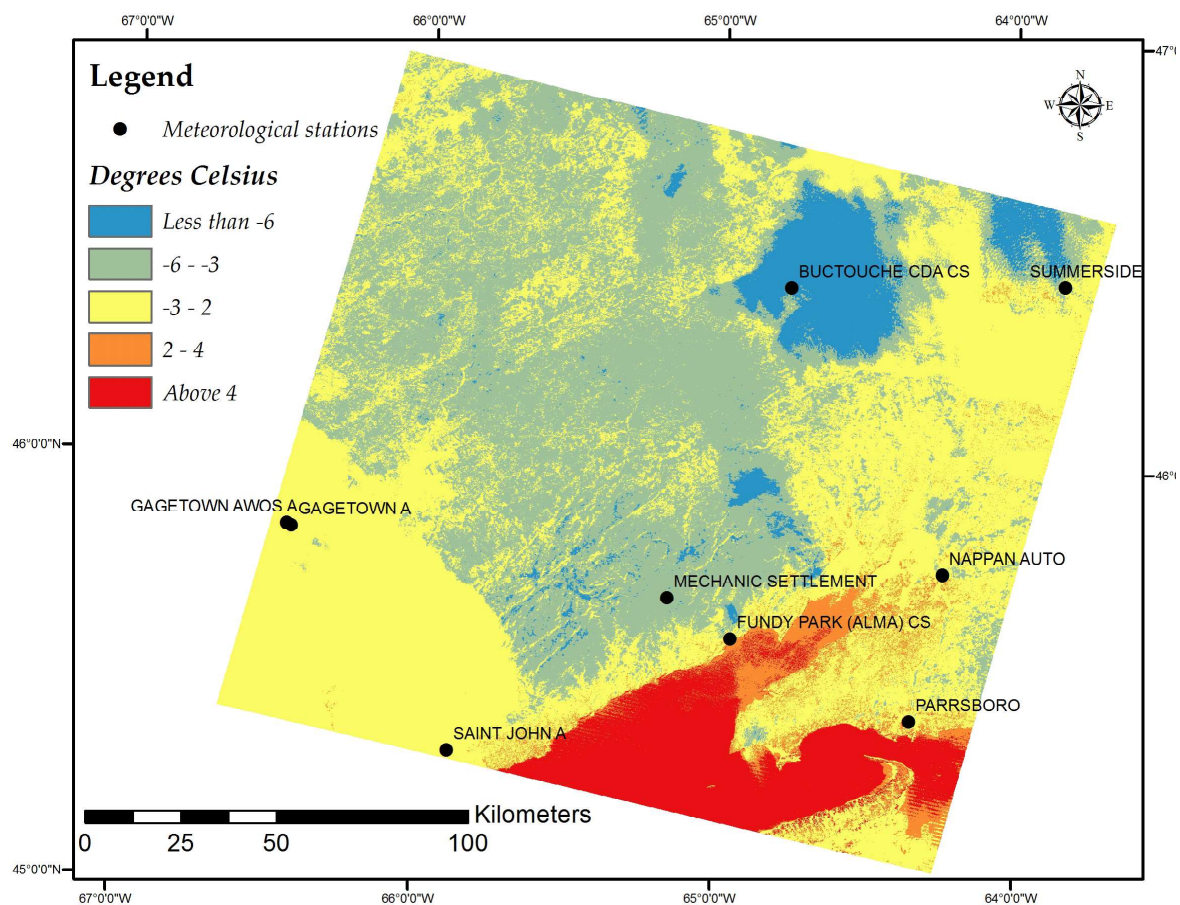
Appendix 6. Landsat 5 TM LST map produced by the RTE using the image dated 31 December 2010



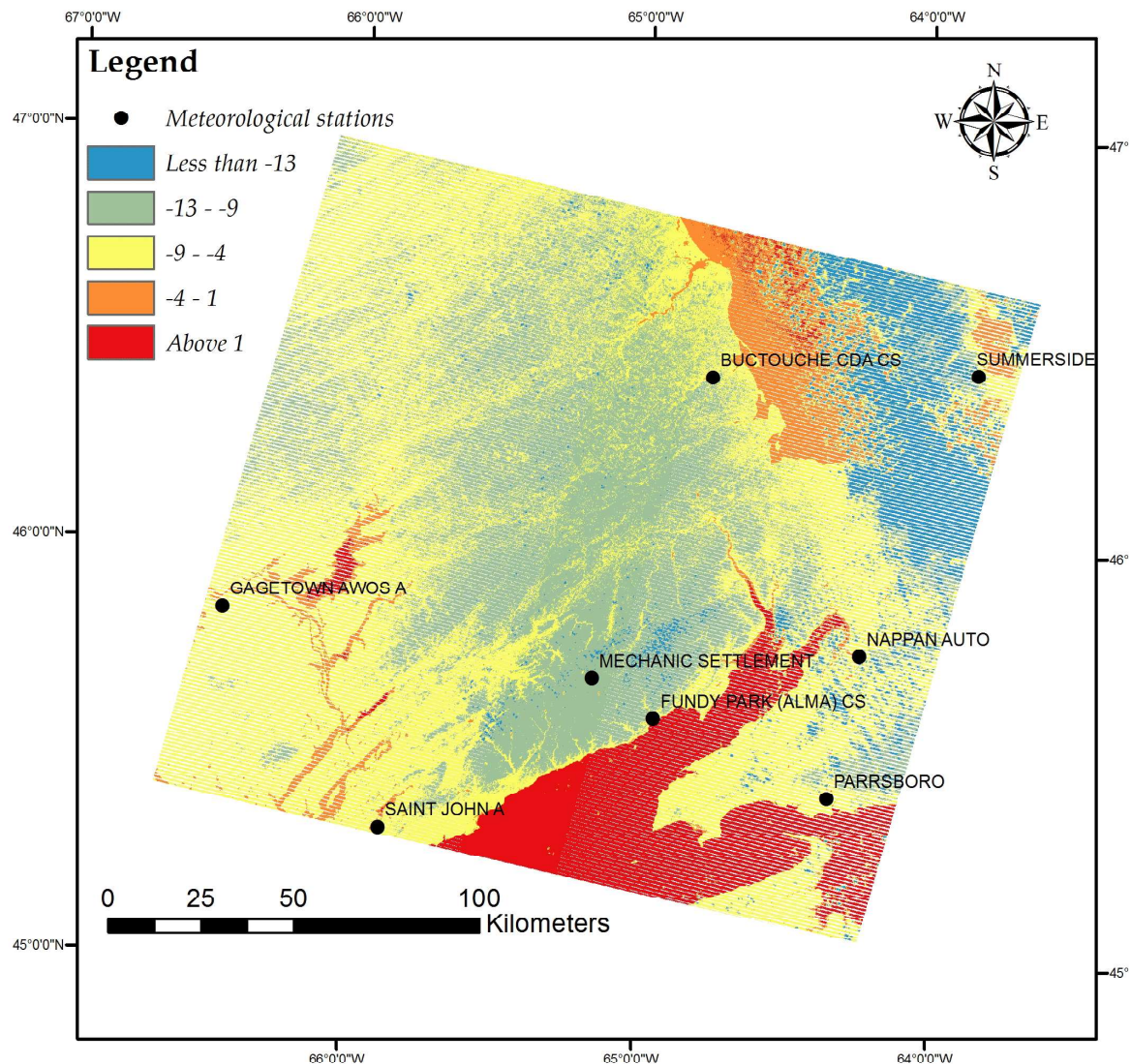
Appendix 7. Landsat 5 TM LST map produced by the MWA using the image dated 31 December 2010



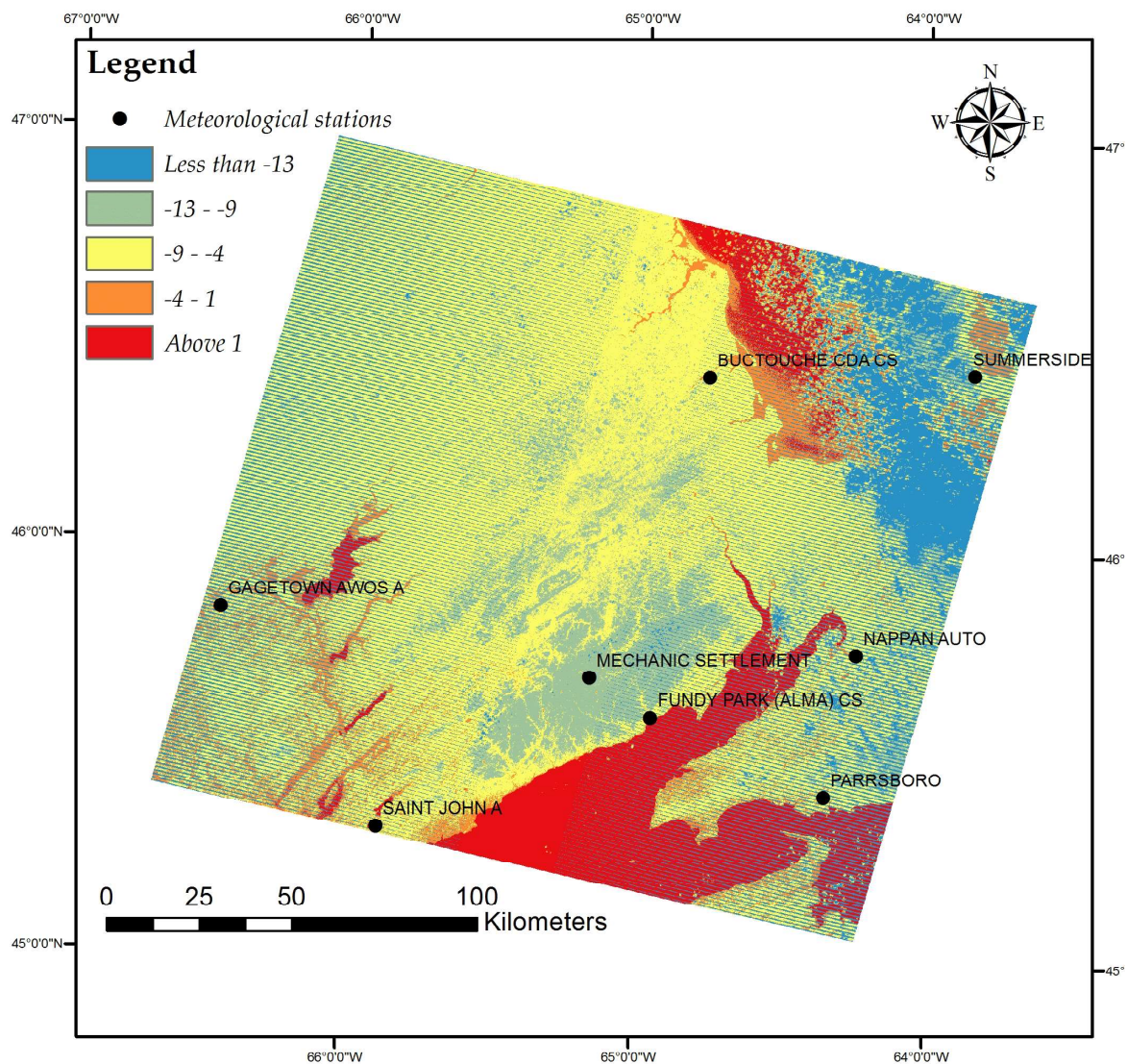
Appendix 8. Landsat 5 TM LST map produced by the Planck function using the image dated 31 December 2010



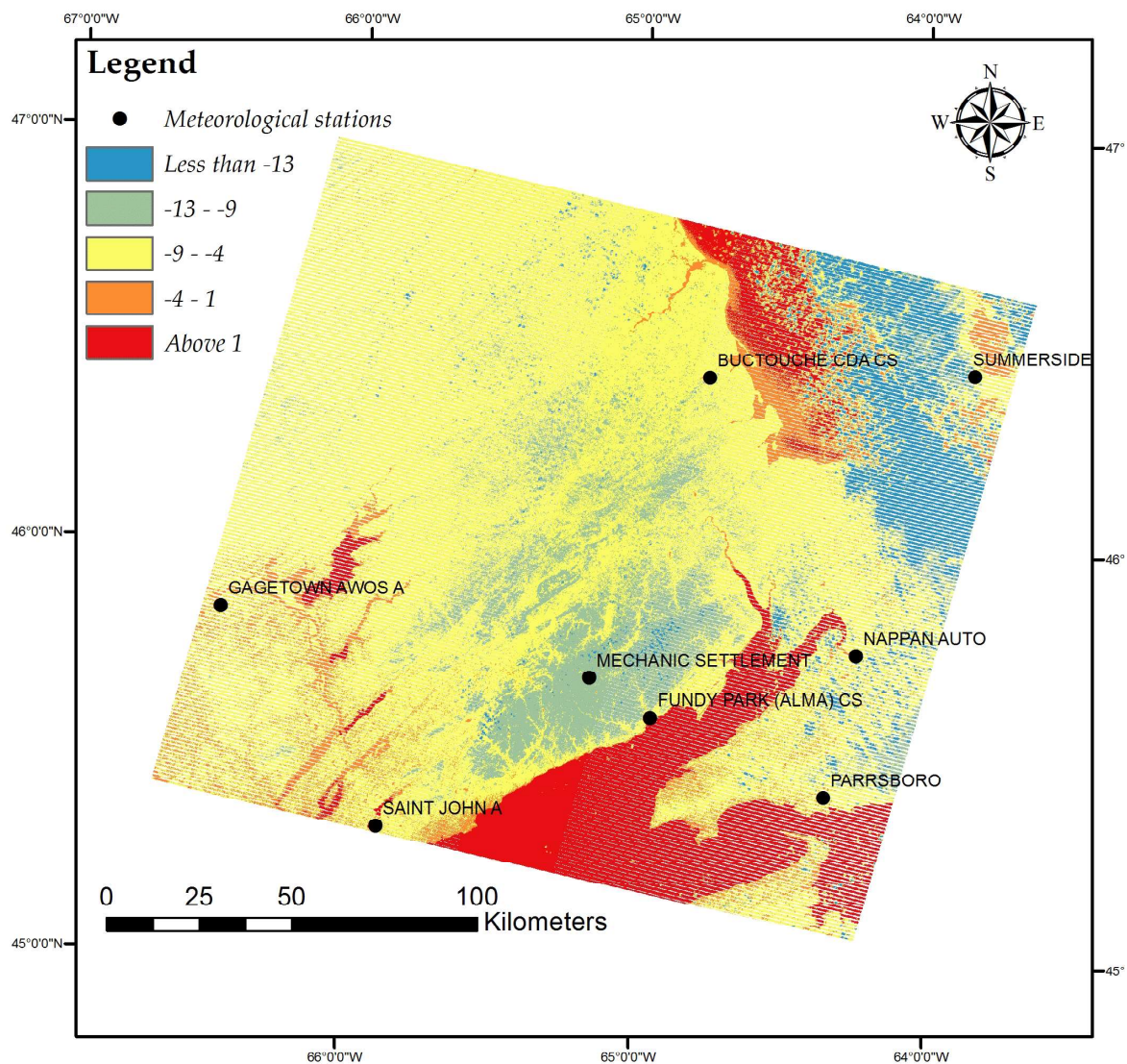
Appendix 9. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010



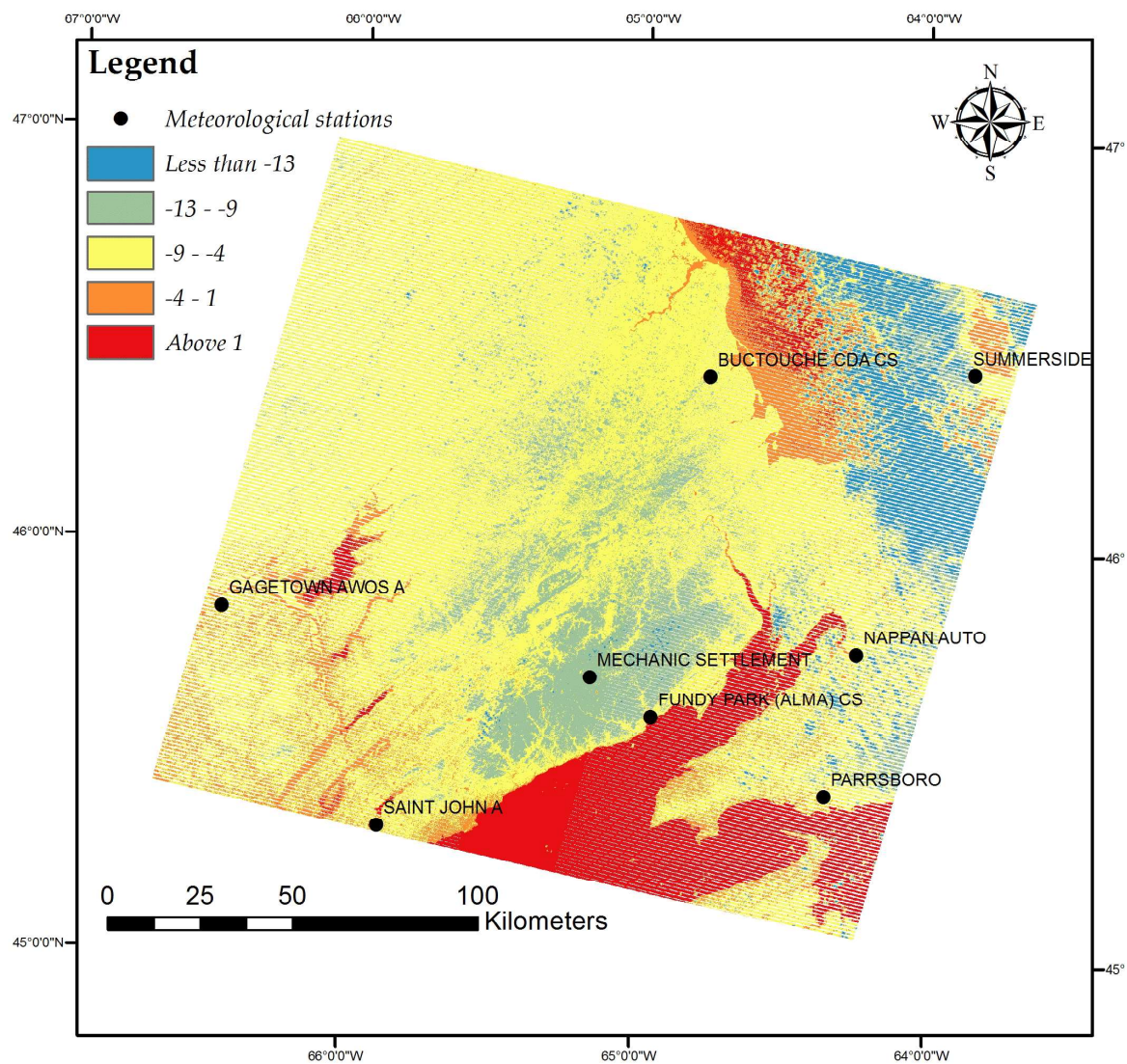
Appendix 10. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010



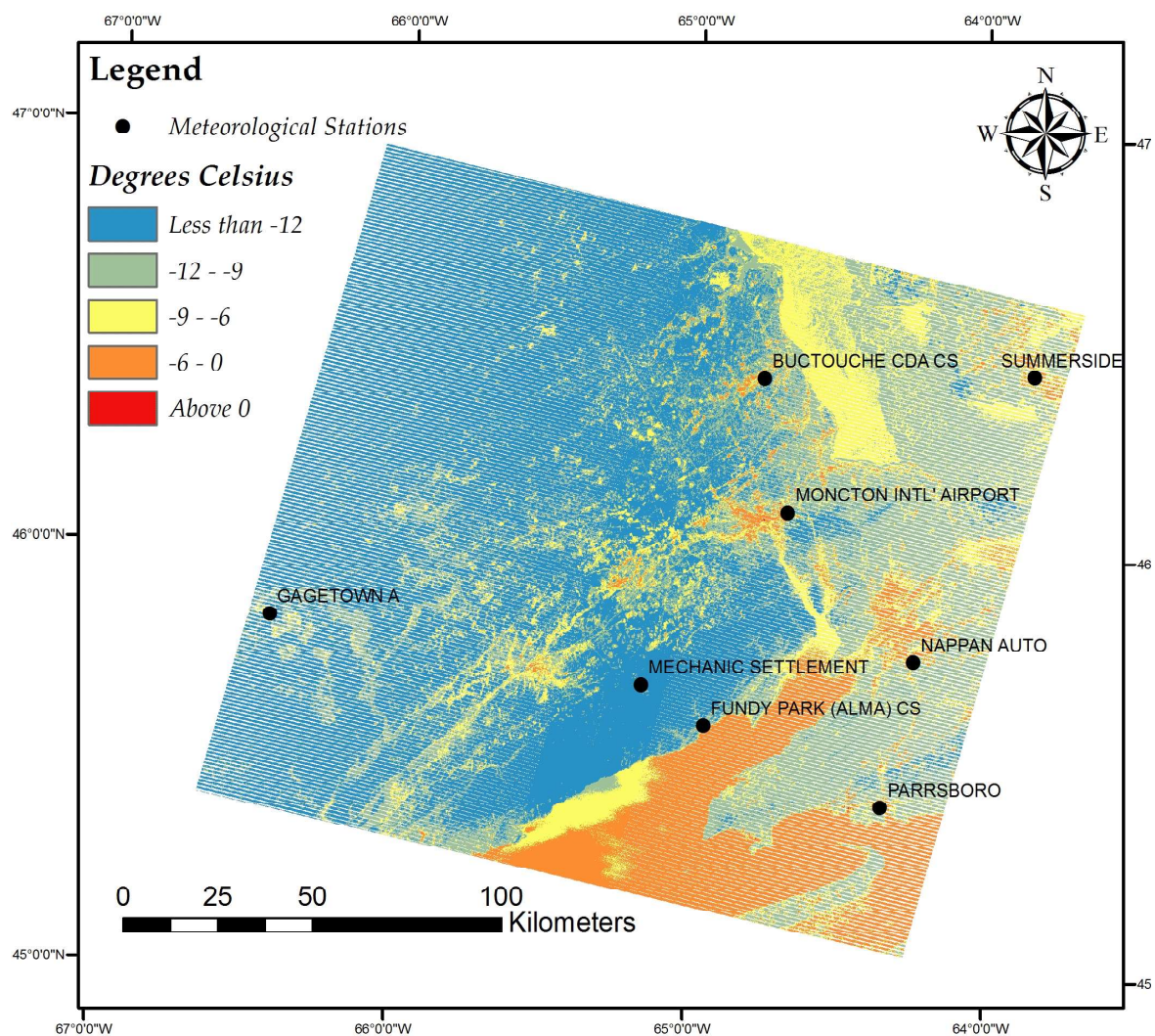
Appendix 11. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010.



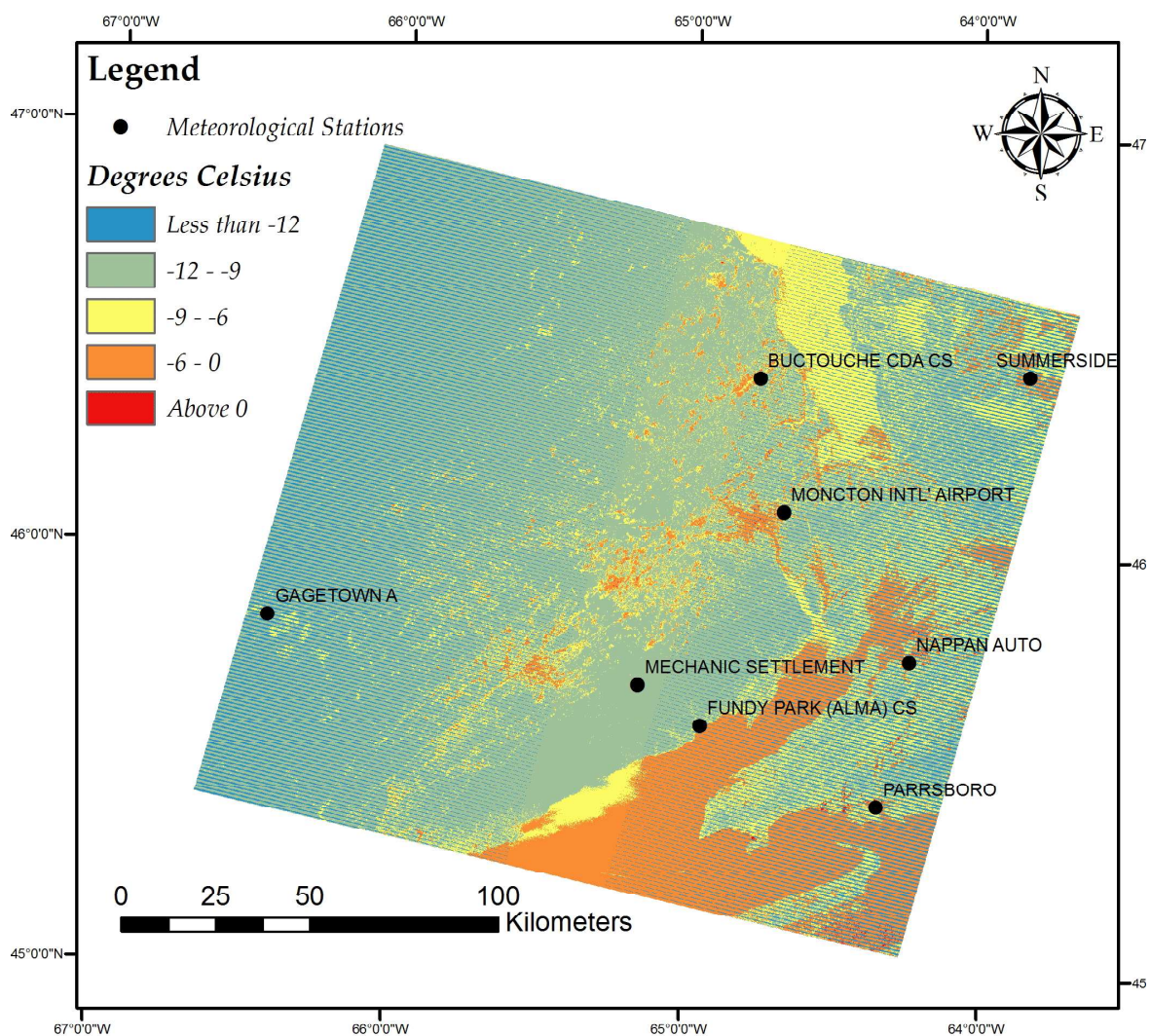
Appendix 12. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010.



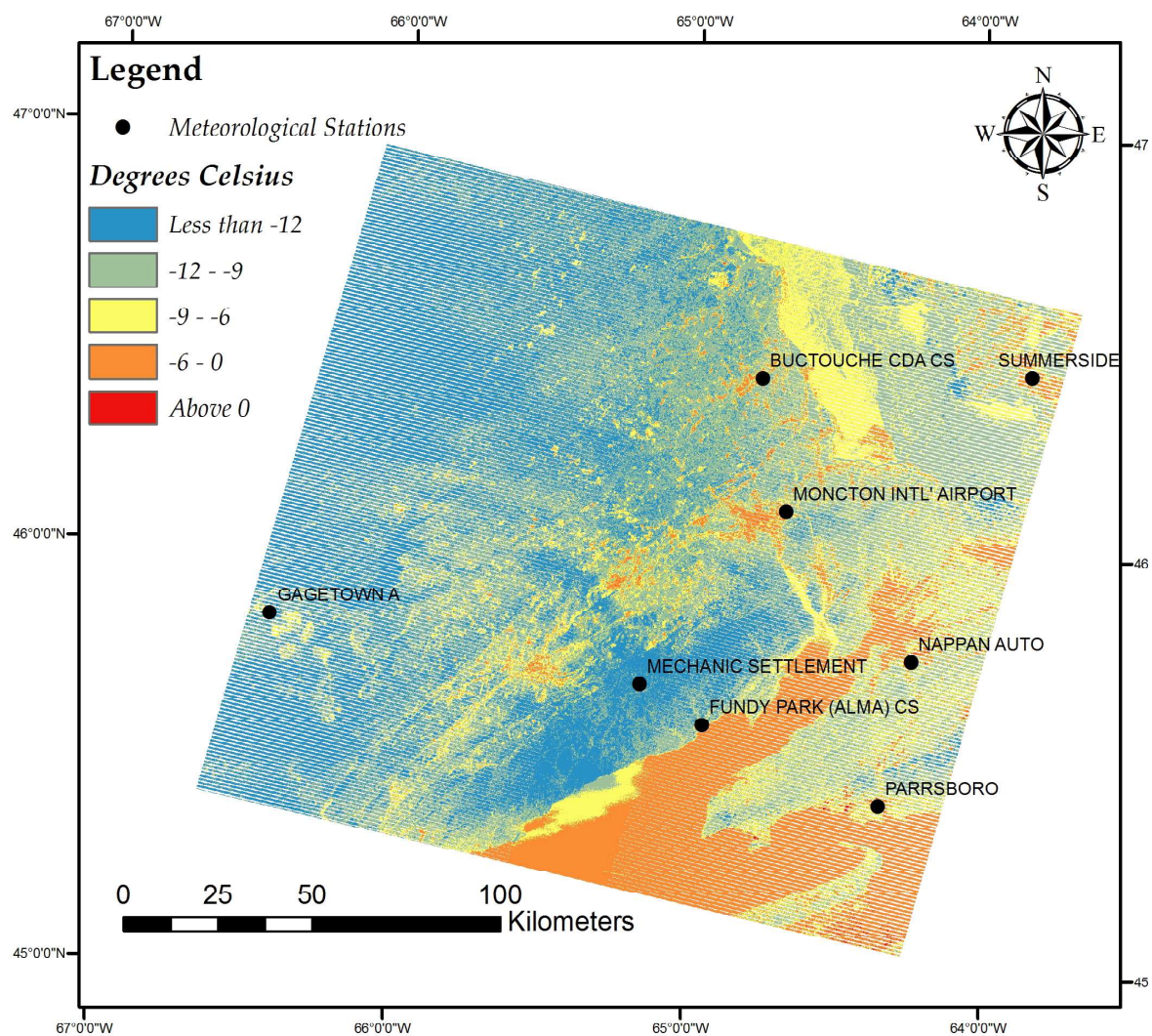
Appendix 13. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010.



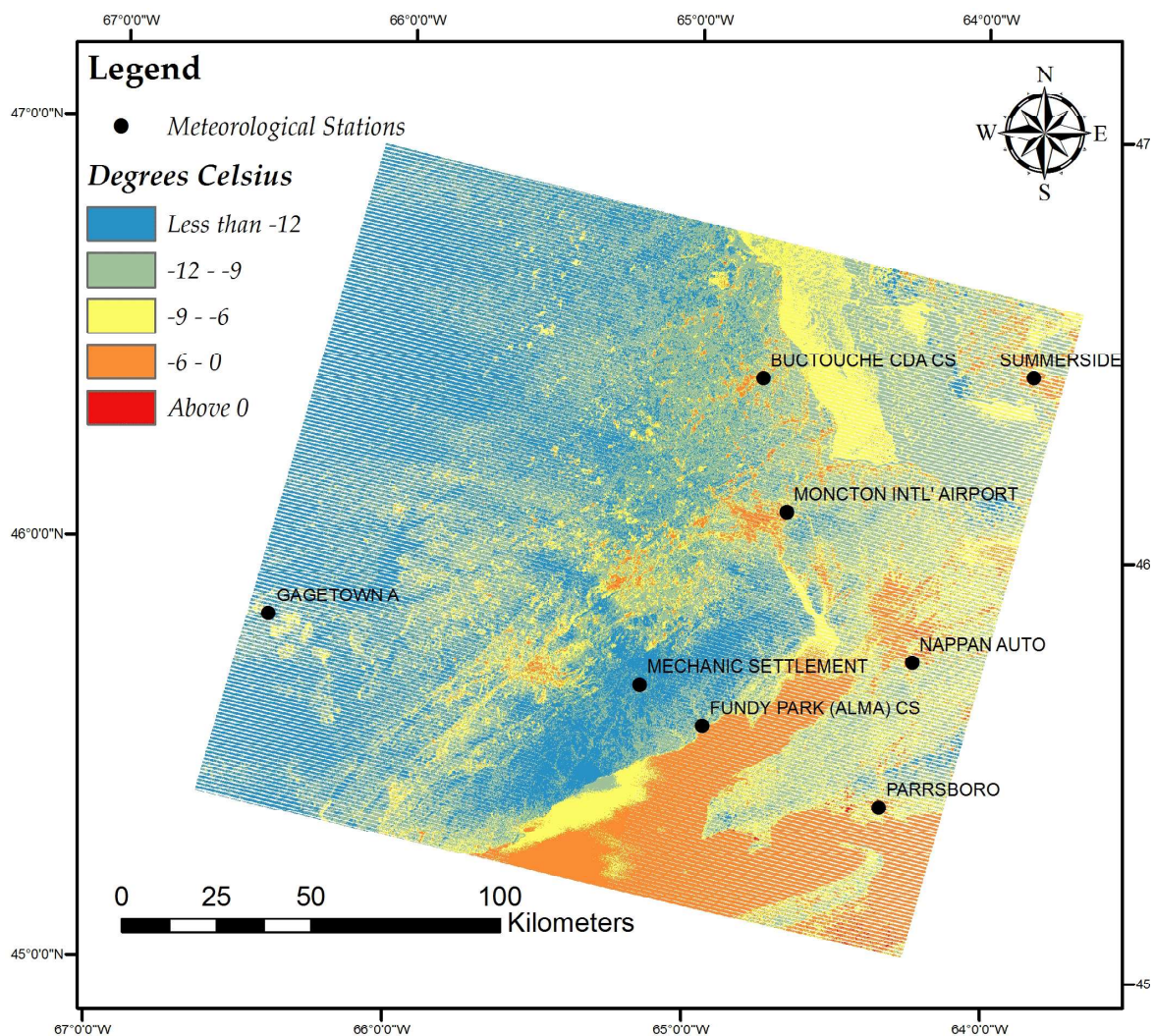
Appendix 14. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010.



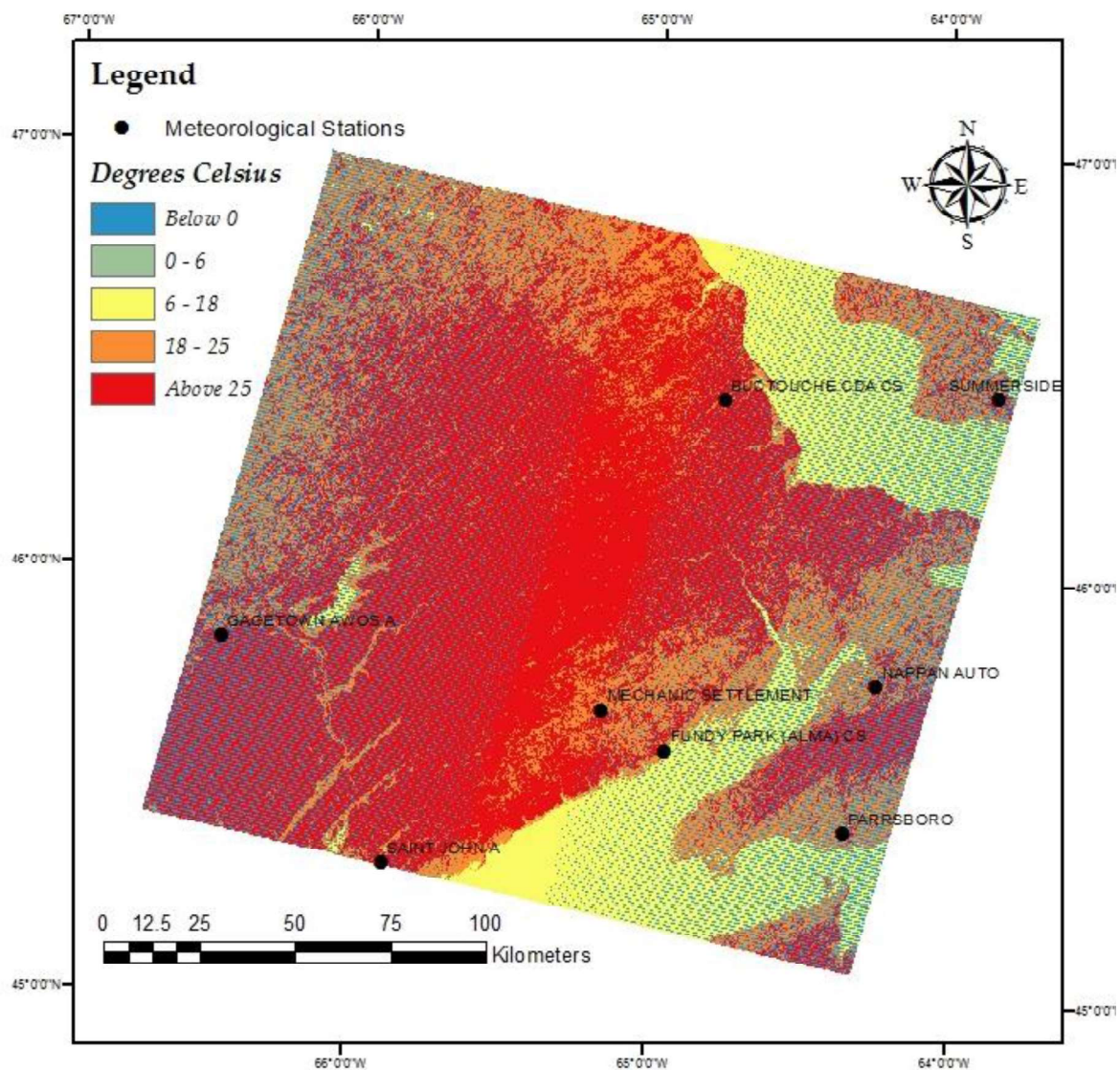
Appendix 15. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010.



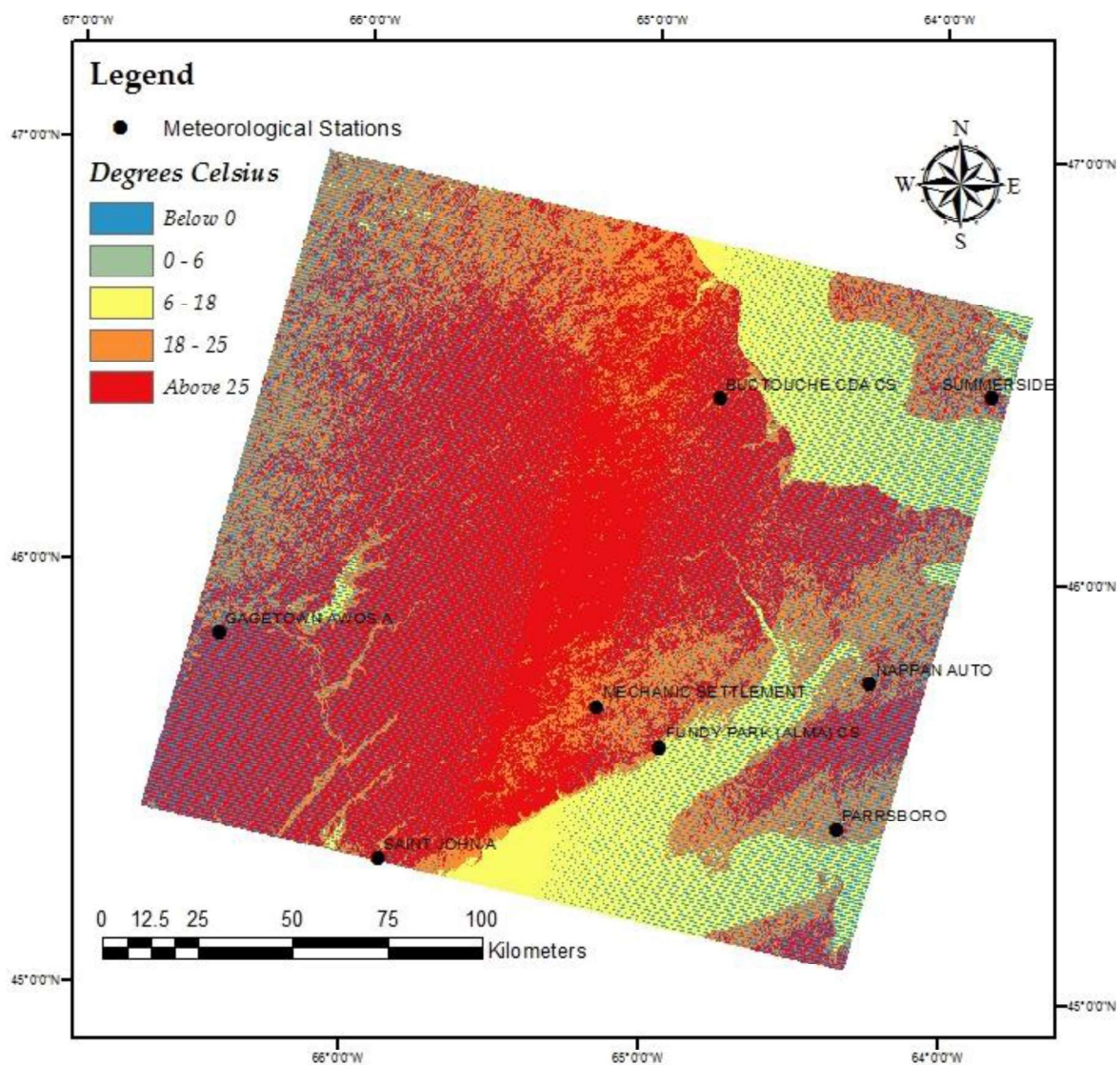
Appendix 16. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 21 November 2010.



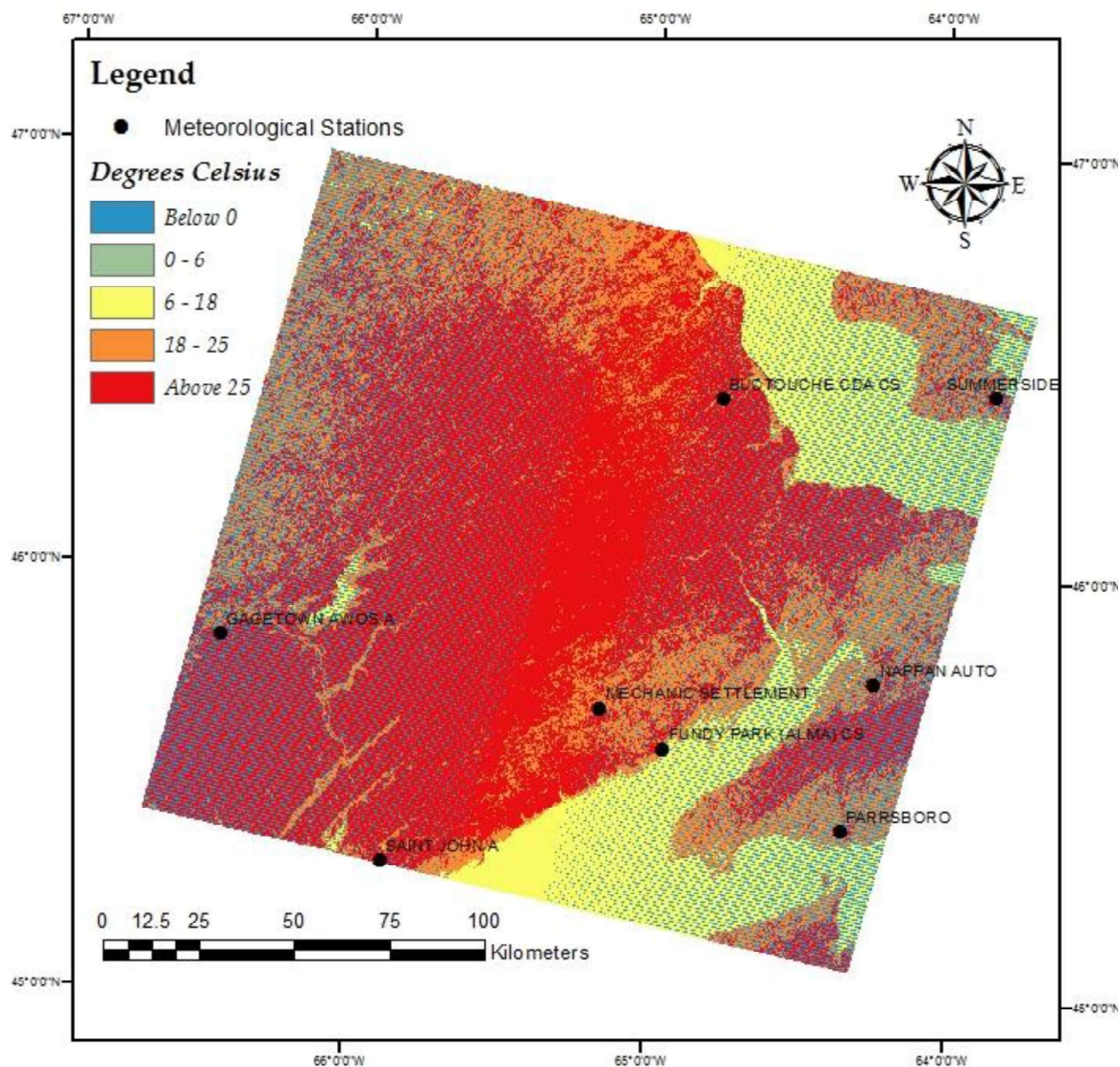
Appendix 17. Landsat 7 ETM+ LST map produced by the SCA using the image dated 2 September 2010.



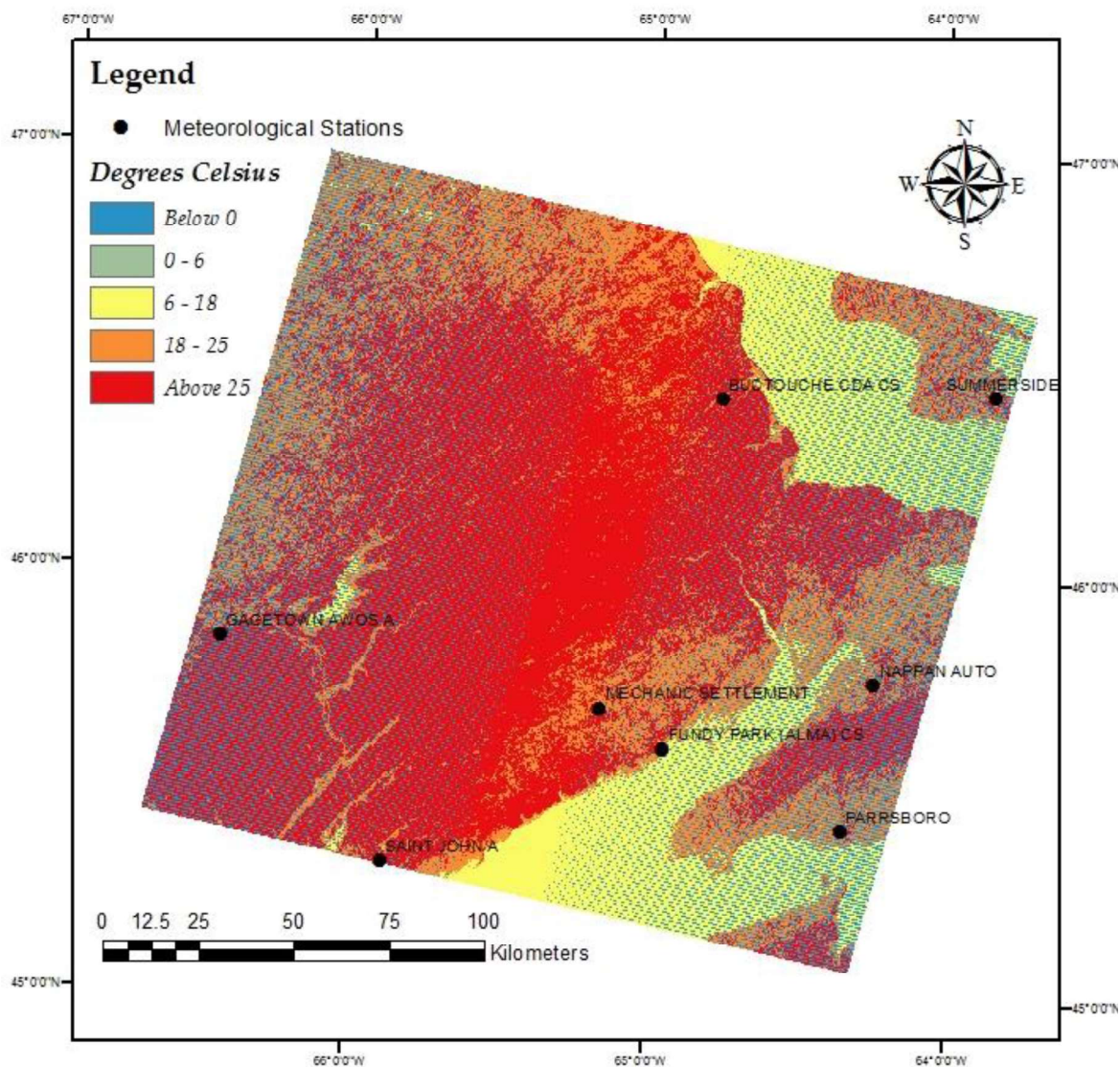
Appendix 18. Landsat 7 ETM+ LST map produced by the RTE using the image dated 2 September 2010.



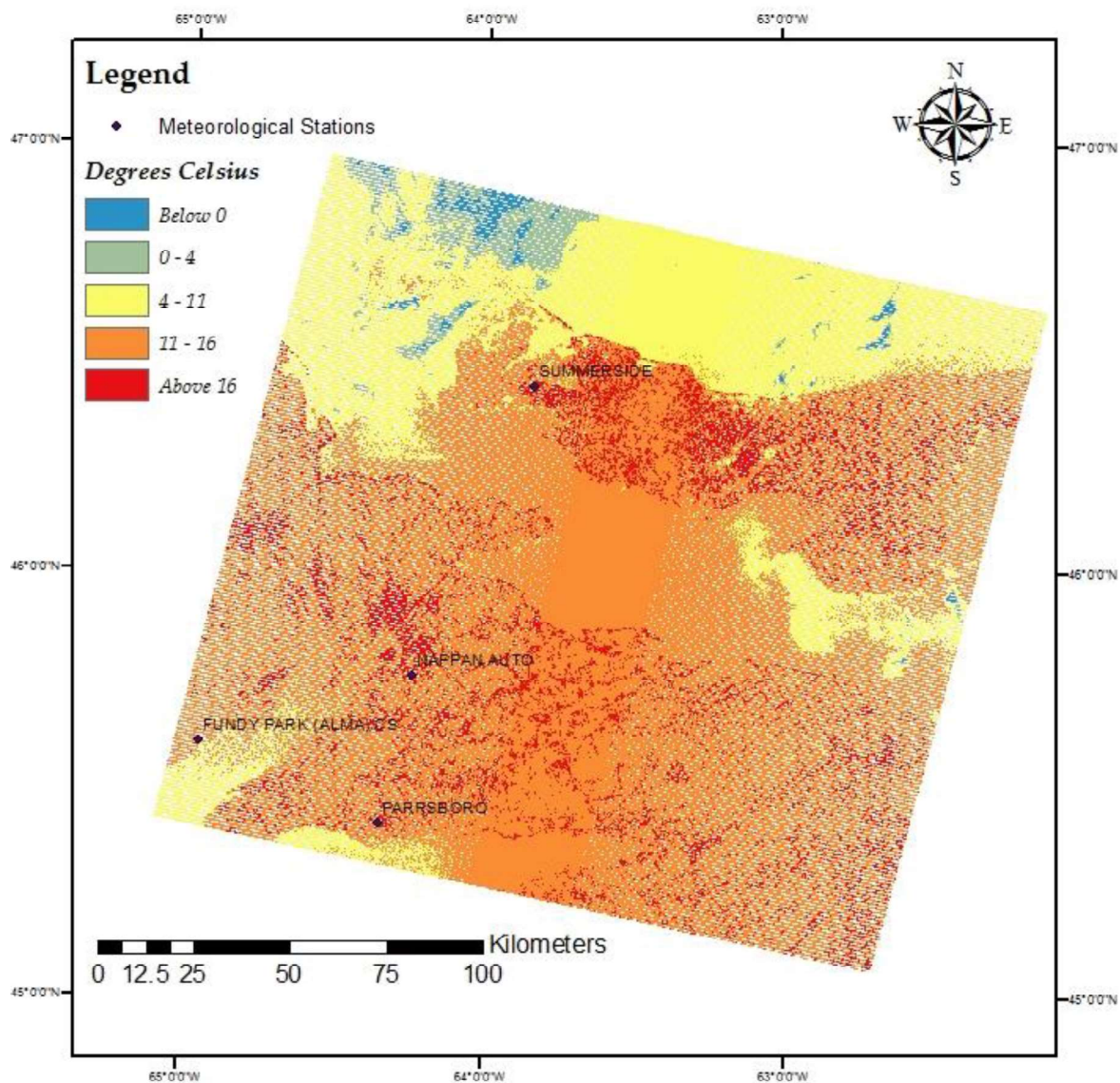
Appendix 19. Landsat 7 ETM+ LST map produced by the MWA using the image dated 2 September 2010.



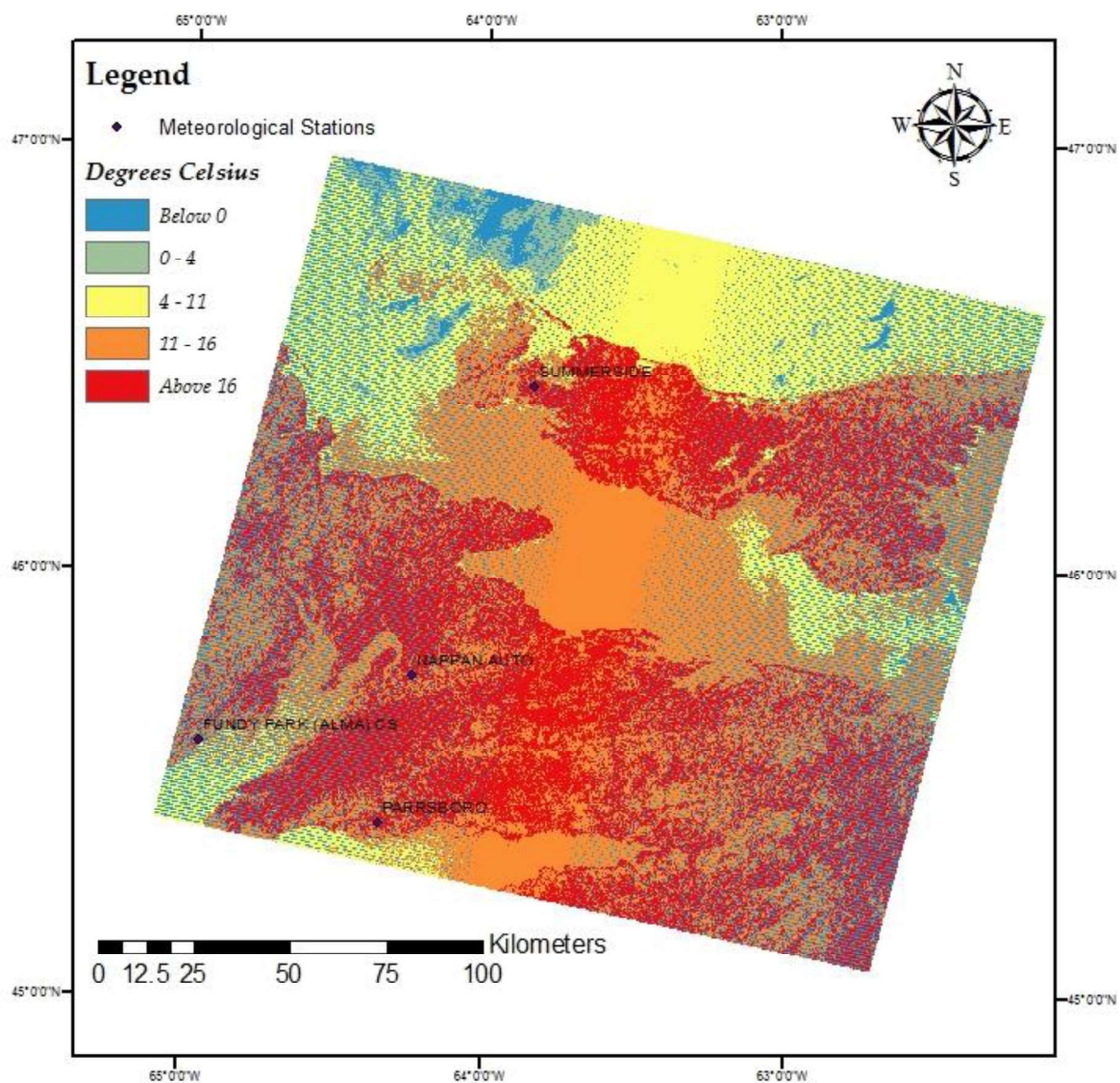
Appendix 20. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 2 September 2010.



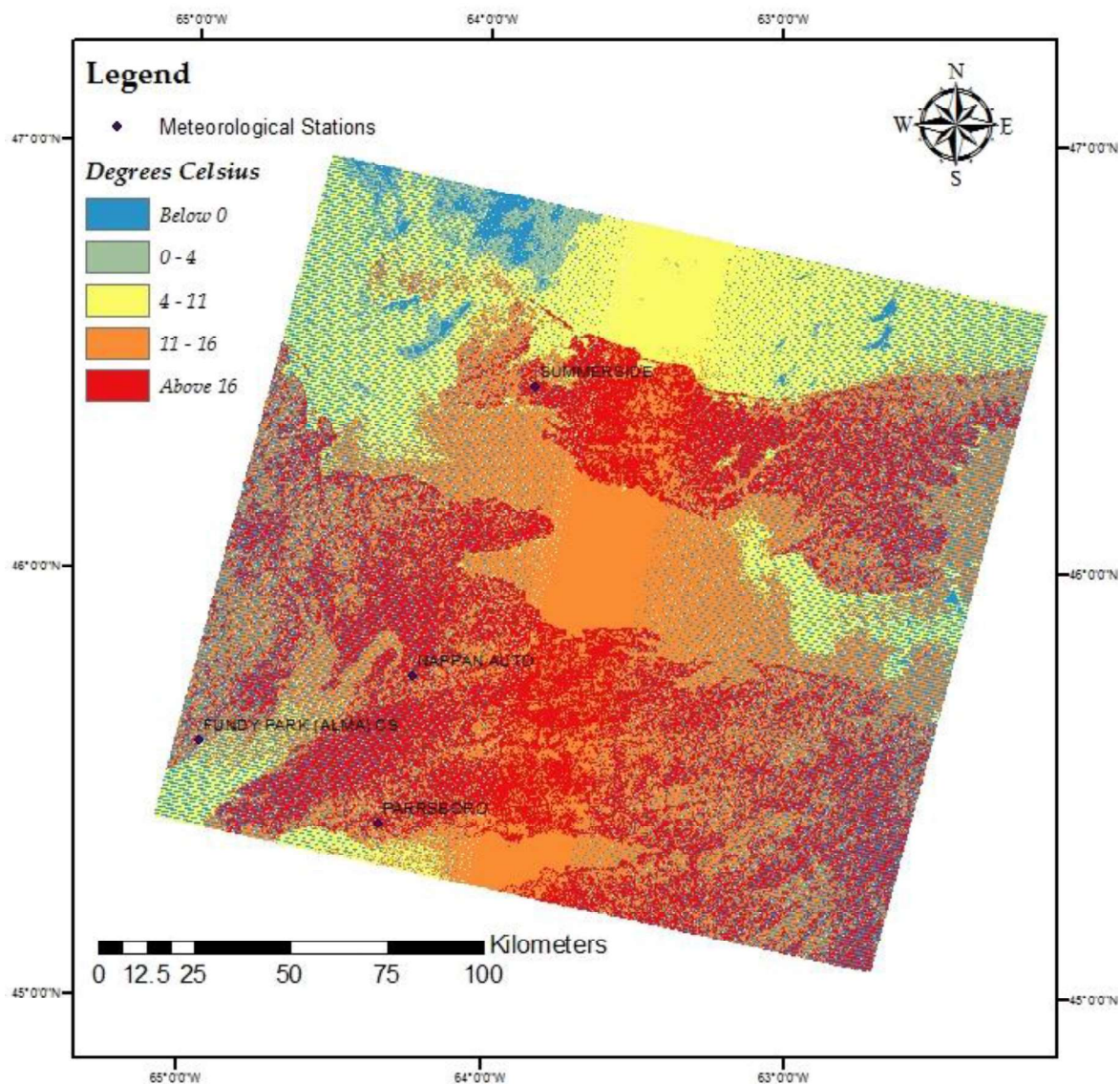
Appendix 21. Landsat 7 ETM+ LST map produced by the SCA using the image dated 19 September 2013.



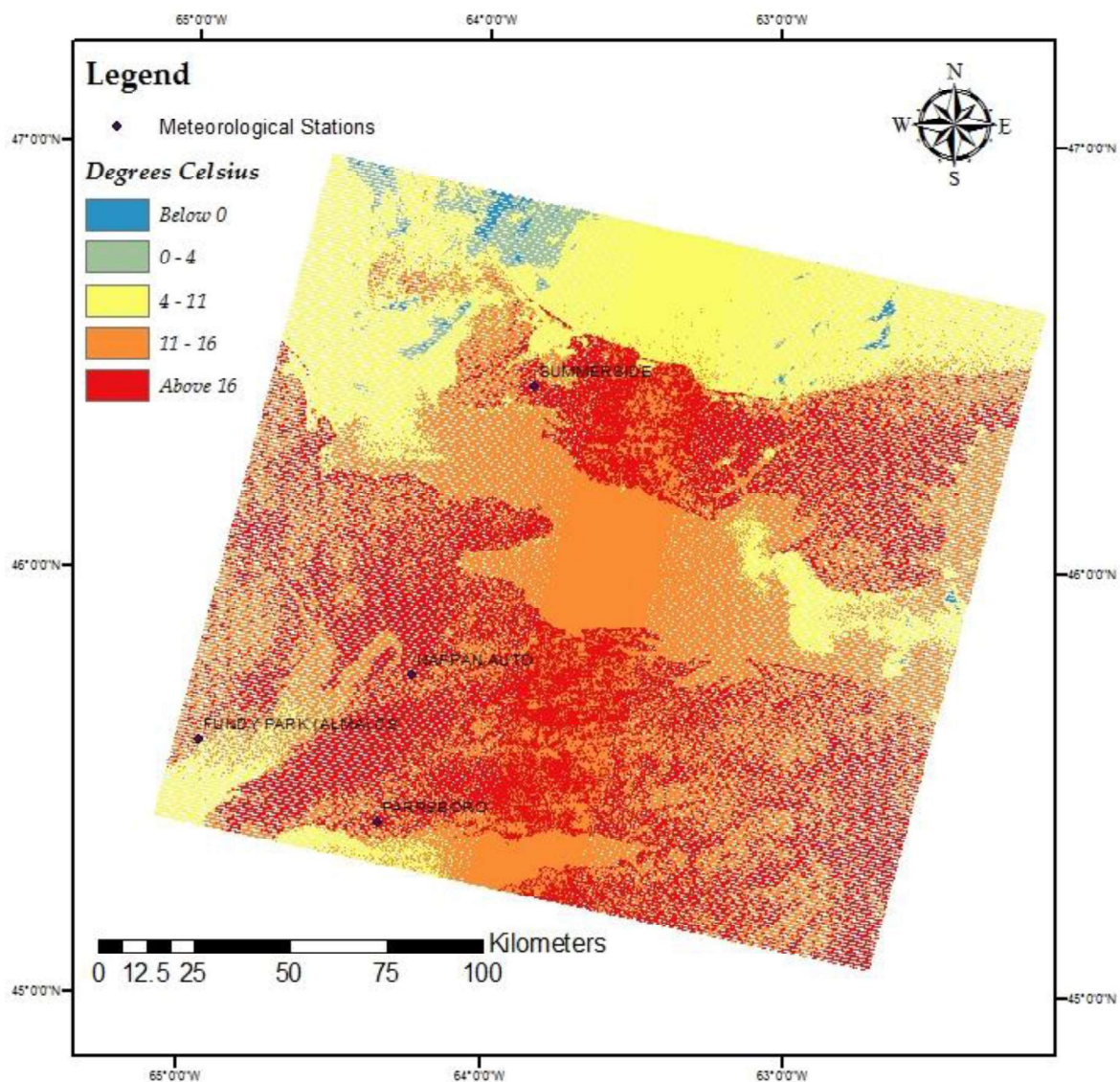
Appendix 22. Landsat 7 ETM+ LST map produced by the RTE using the image dated 19 September 2013.



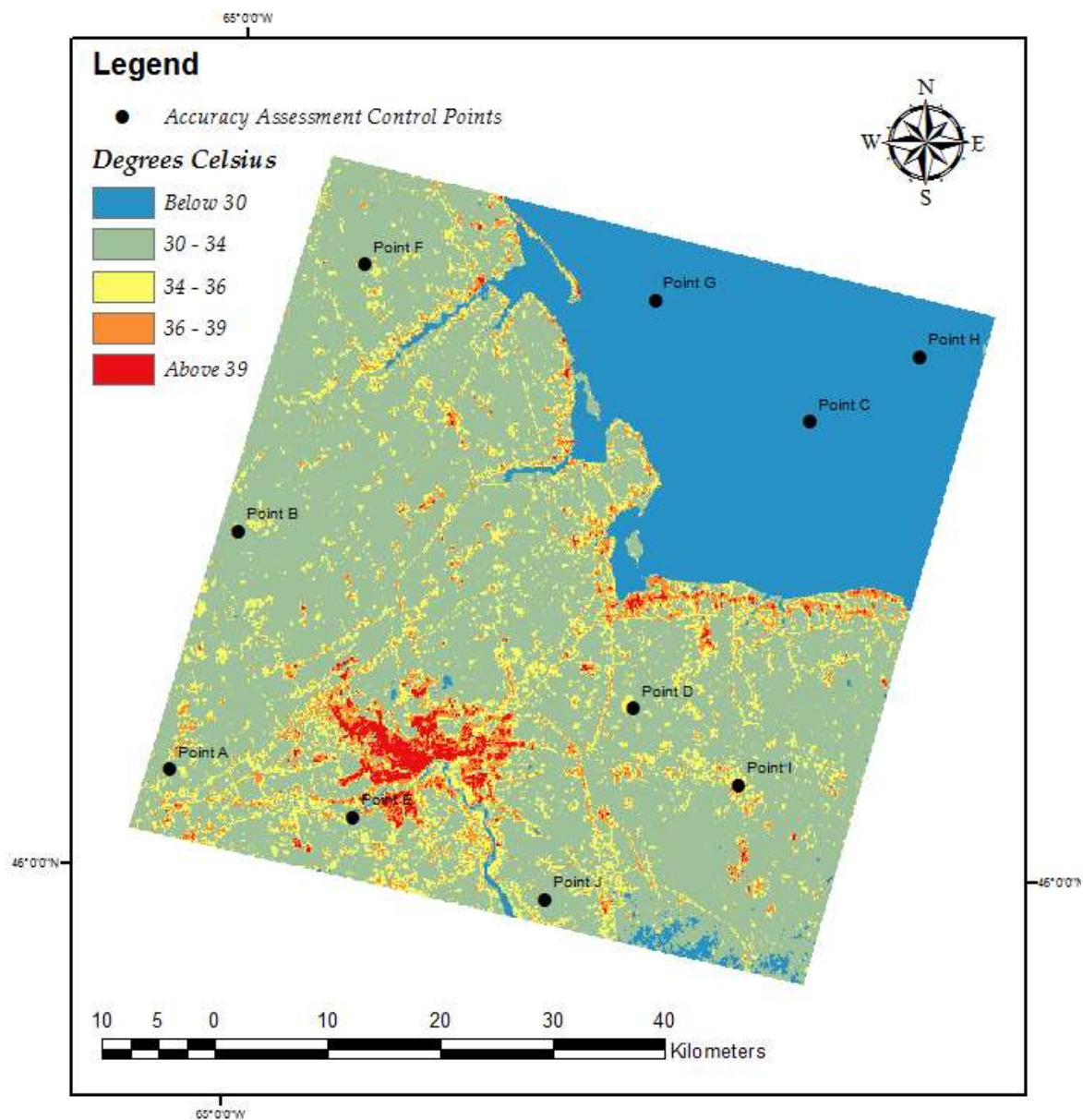
Appendix 23. Landsat 7 ETM+ LST map produced by the MWA using the image dated 19 September 2013.



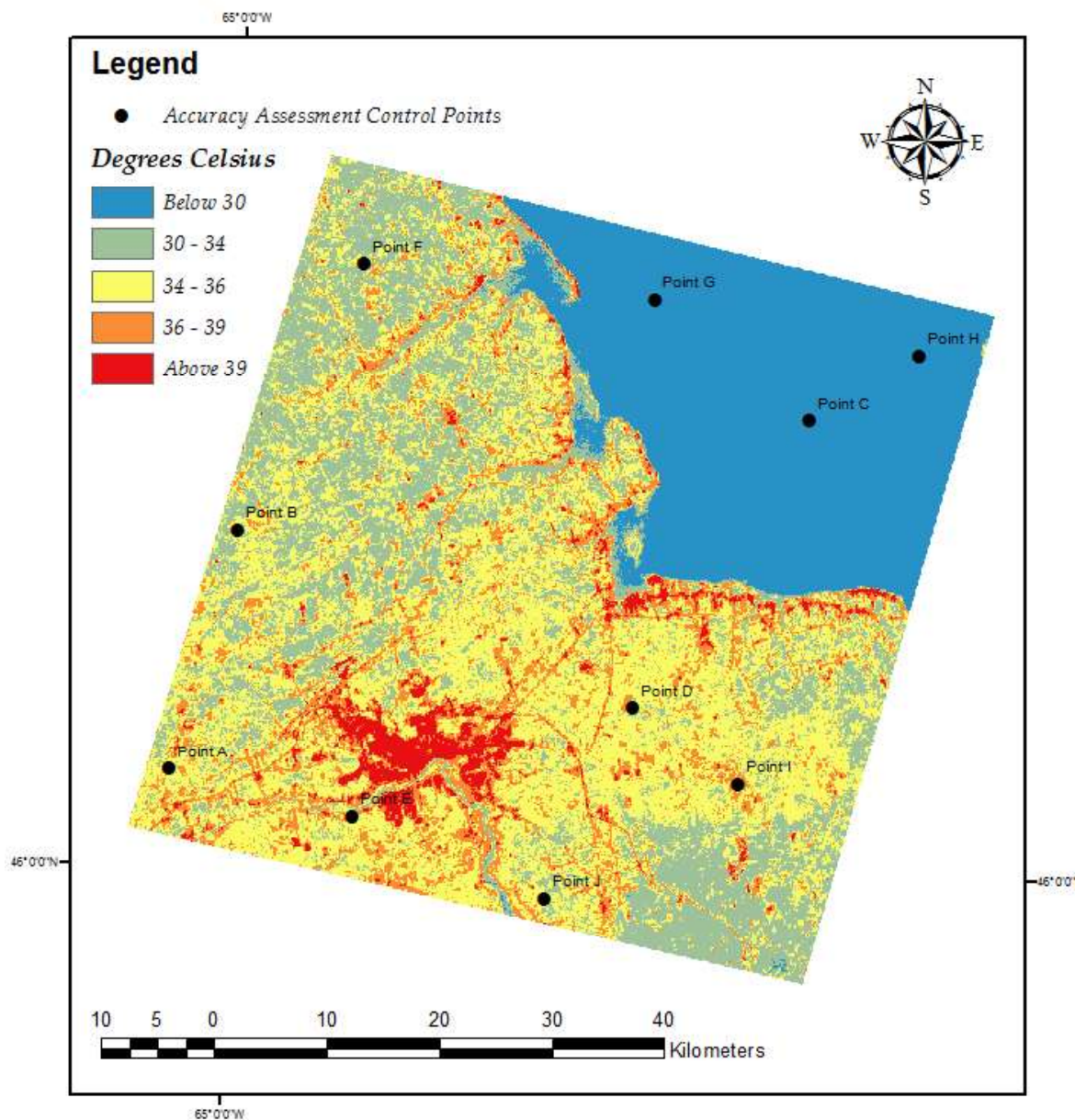
Appendix 24. Landsat 7 ETM+ LST map produced by the Planck function using the image dated 19 September 2013.



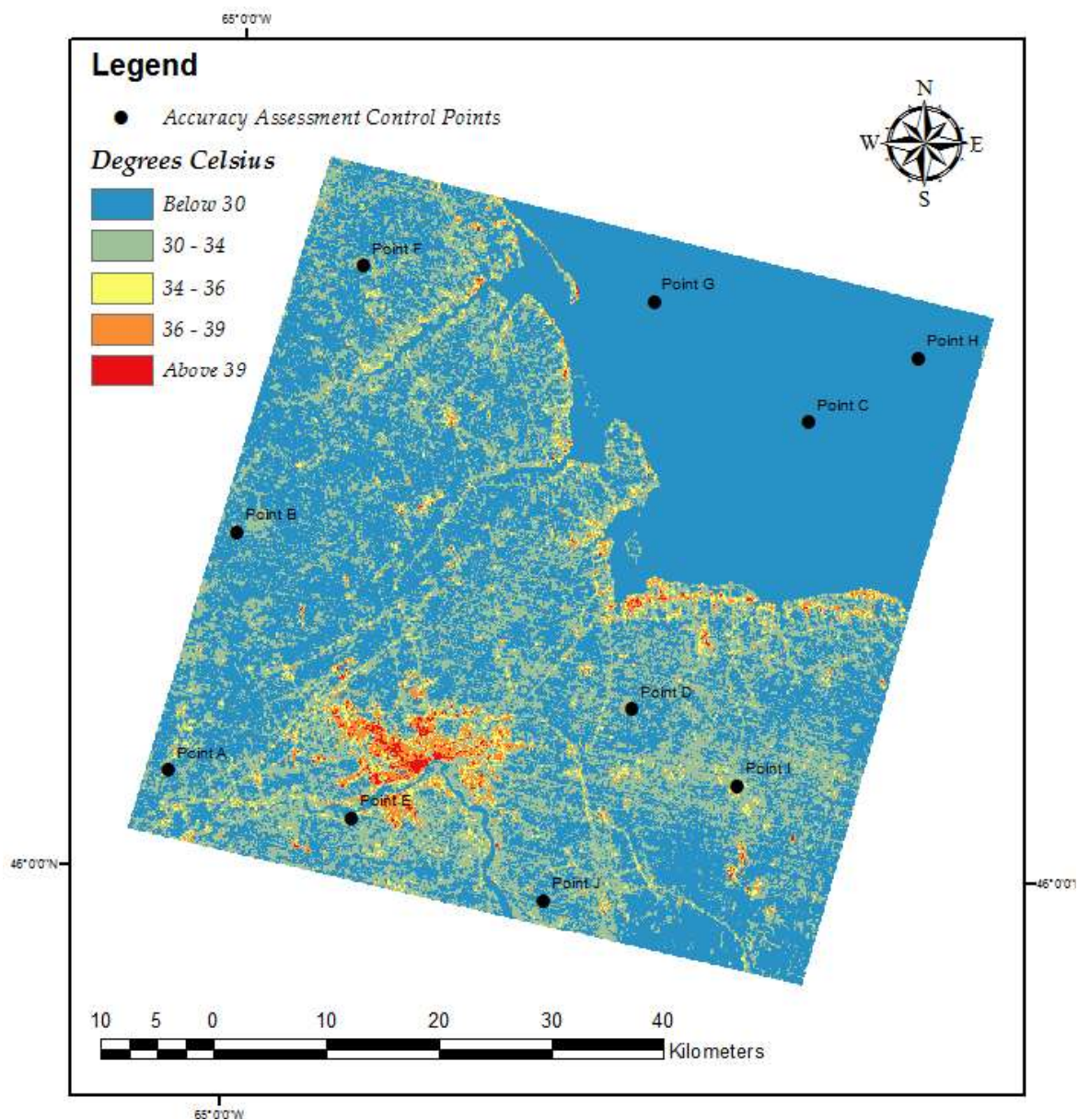
Appendix 25. ASTER LST map produced by the SCA for ASTER band 13 using the image dated 2 September 2010.



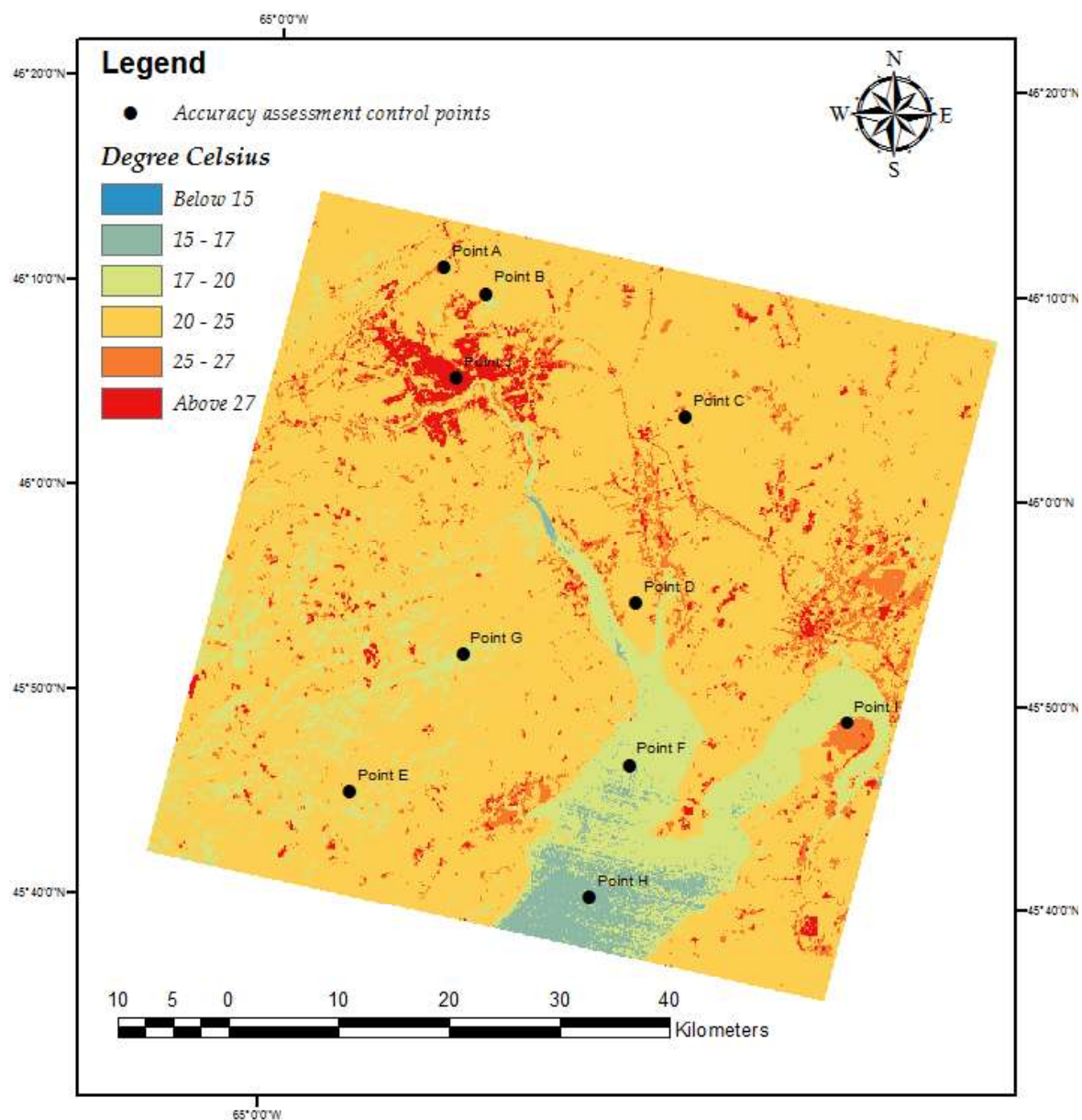
Appendix 26. ASTER LST map produced by the SCA for ASTER band 14 using the image dated 2 September 2010.



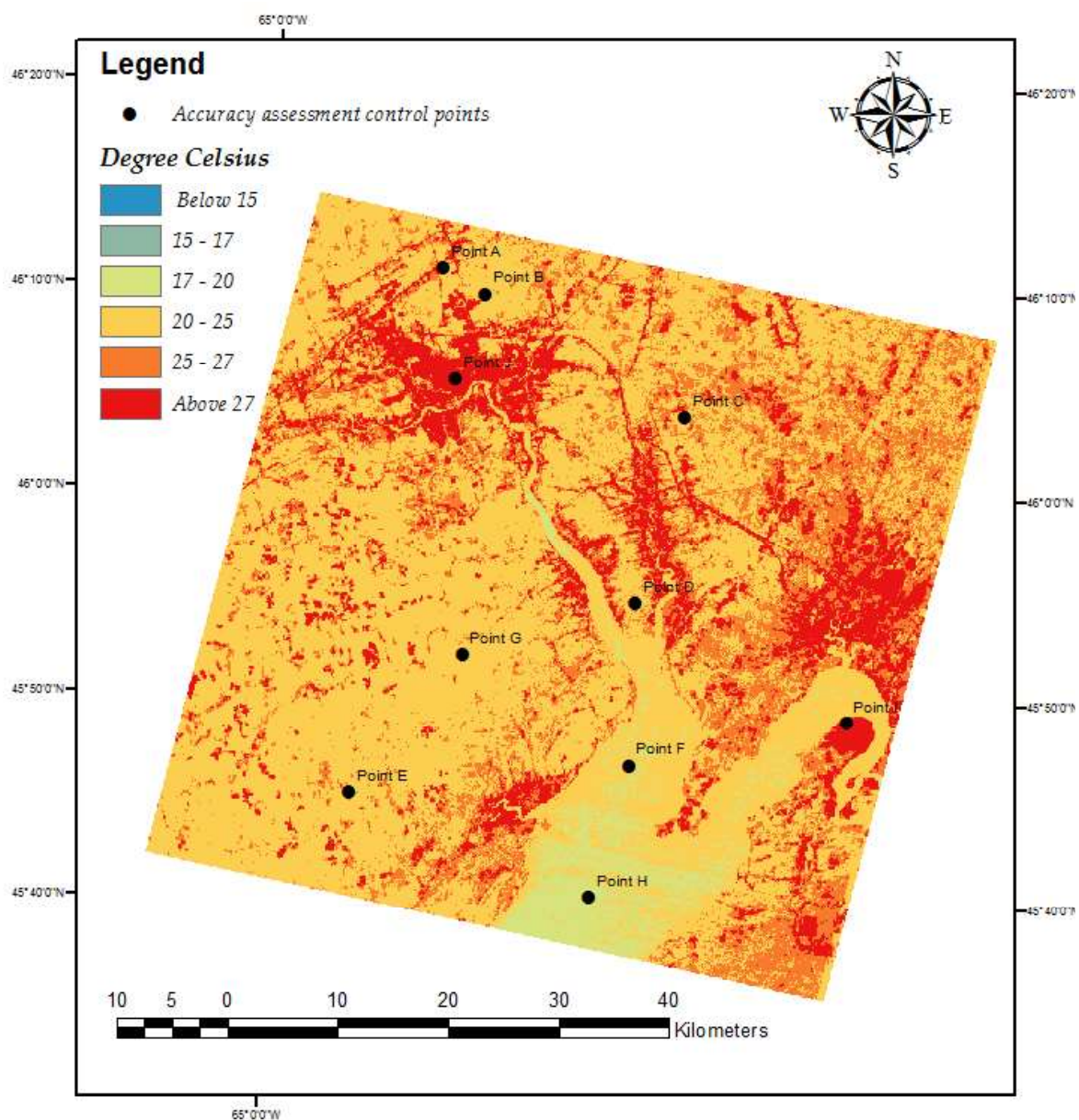
Appendix 27. ASTER LST map produced by the SWA for ASTER using the image dated 2nd September 2010.



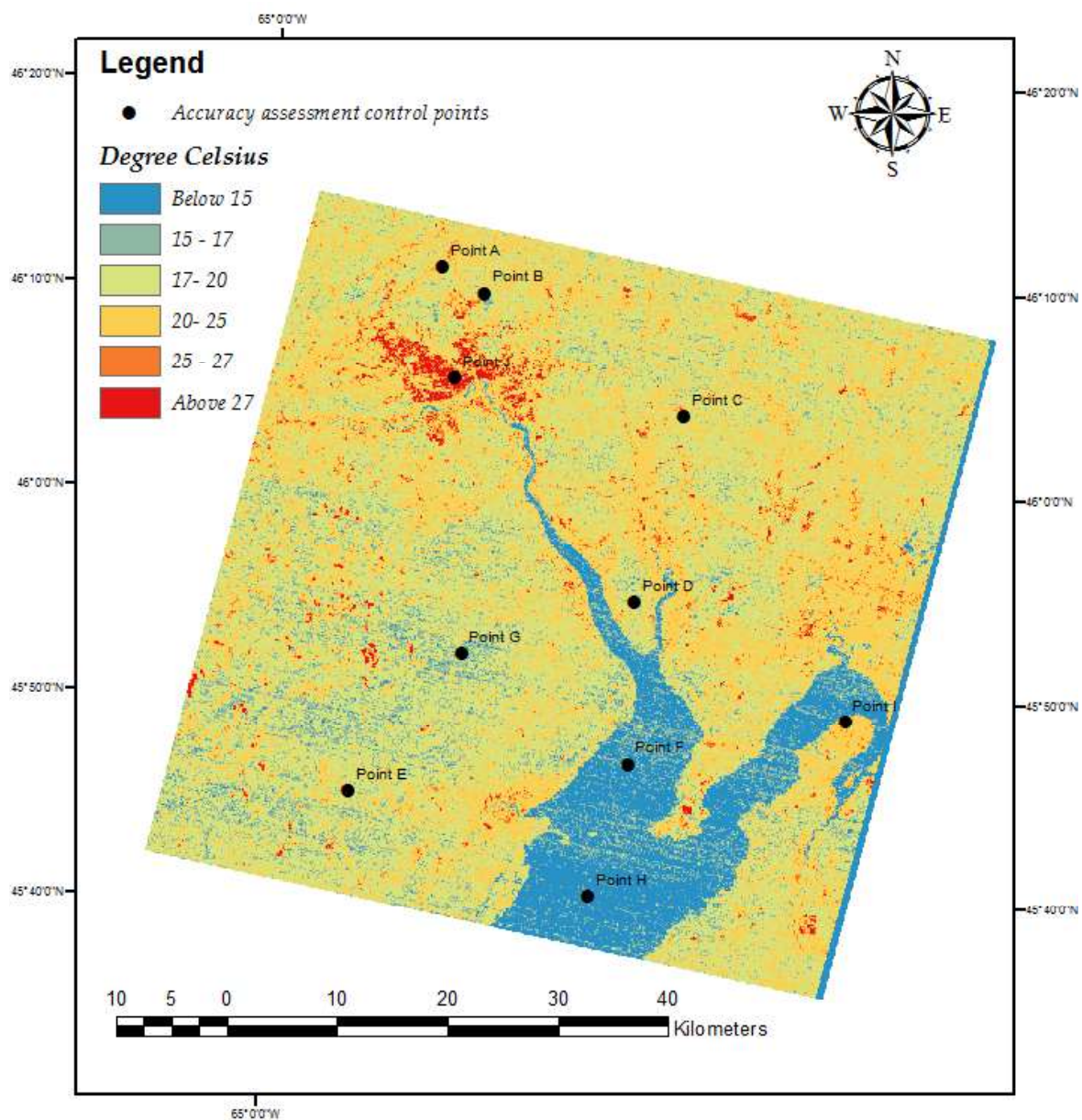
Appendix 28. ASTER LST map produced by the SCA band 13 for ASTER using the image dated 19 September 2013.



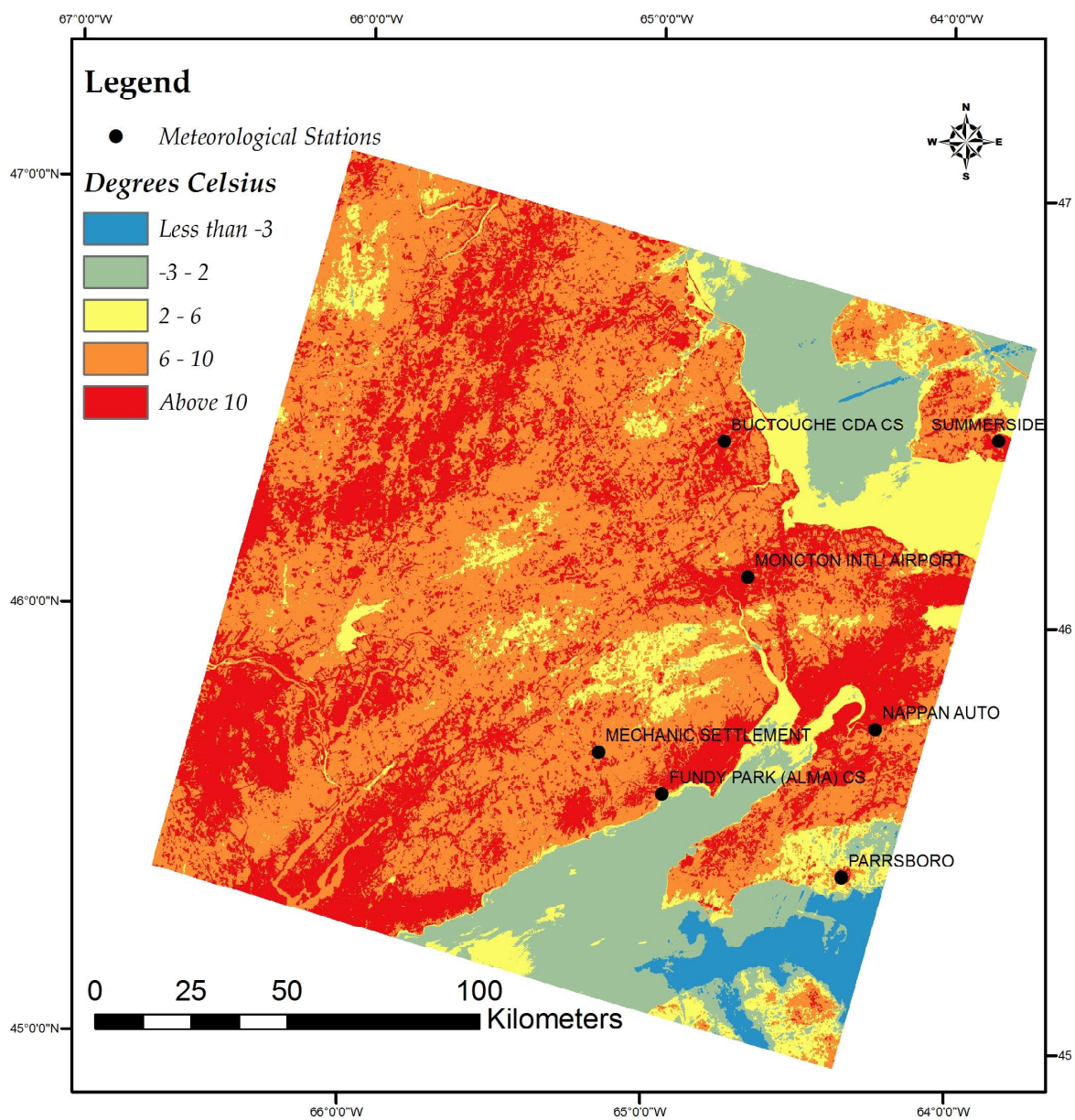
Appendix 29. ASTER LST map produced by the SCA band 14 for ASTER using the image dated 19 September 2013.



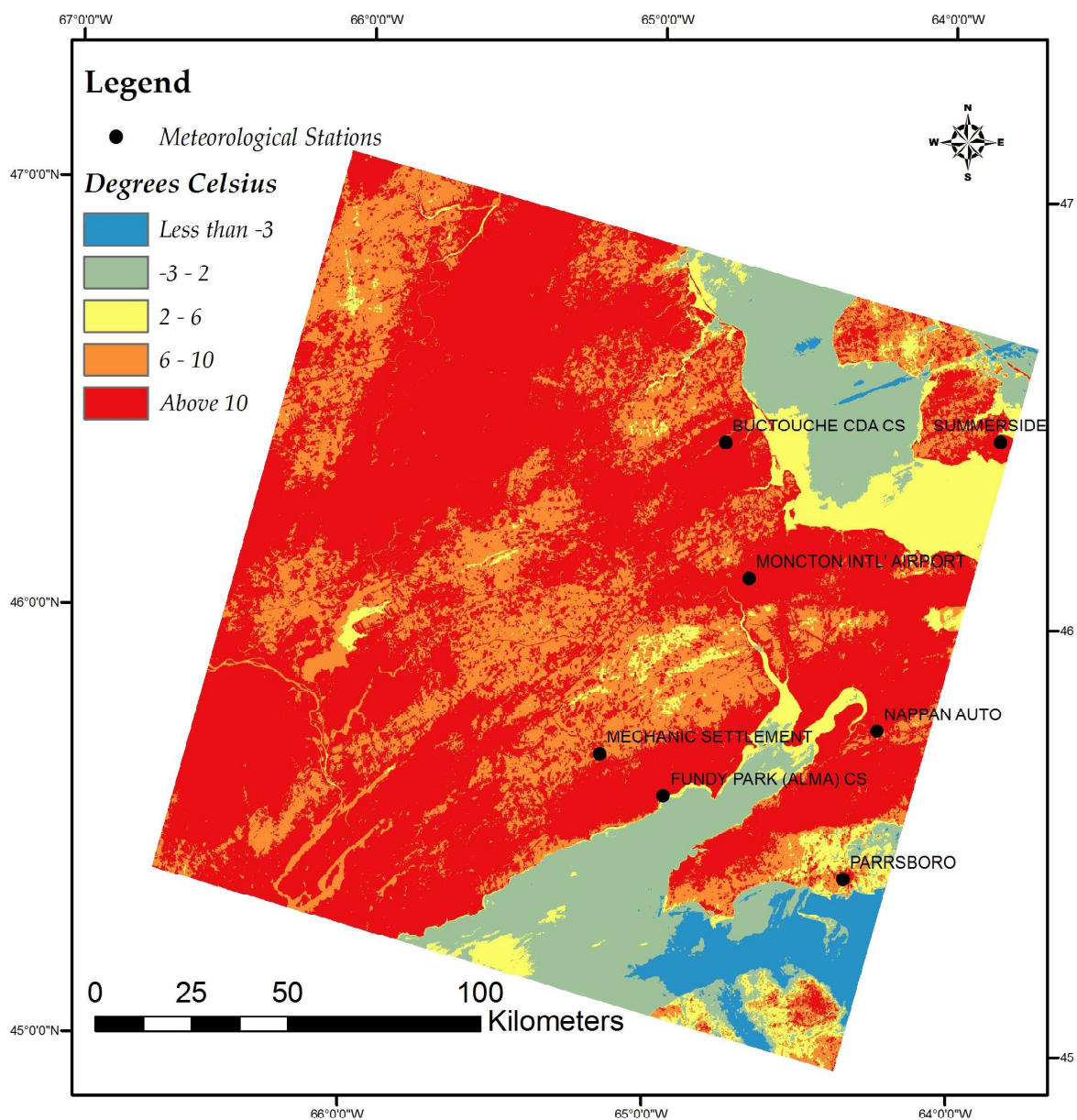
Appendix 30. ASTER LST map produced by the SWA band 14 and band 13 for ASTER using the image dated 19 September 2013.



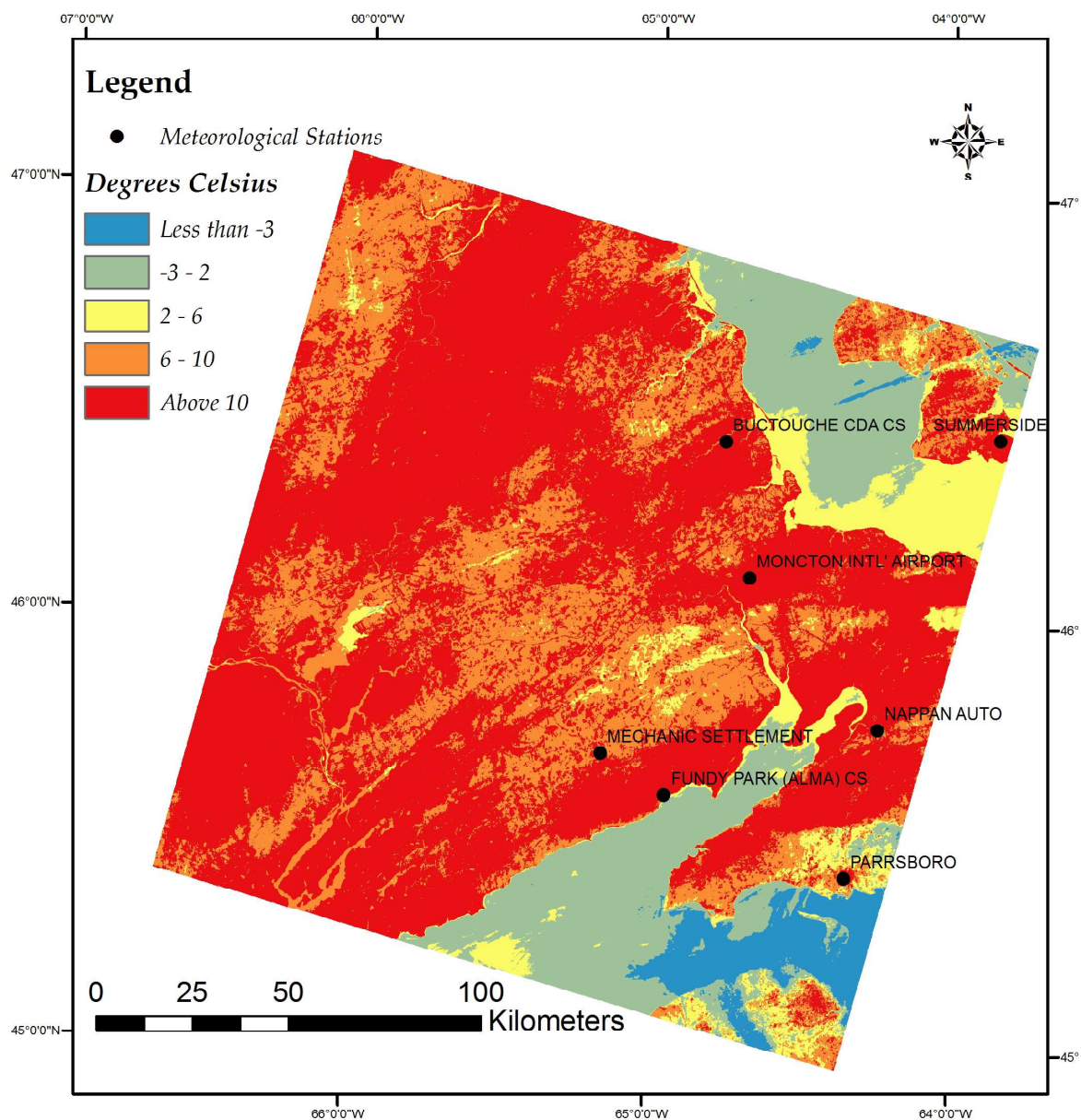
Appendix 31. Landsat 8 TIRS LST map produced by the SCA using the image dated 4 June 2015.



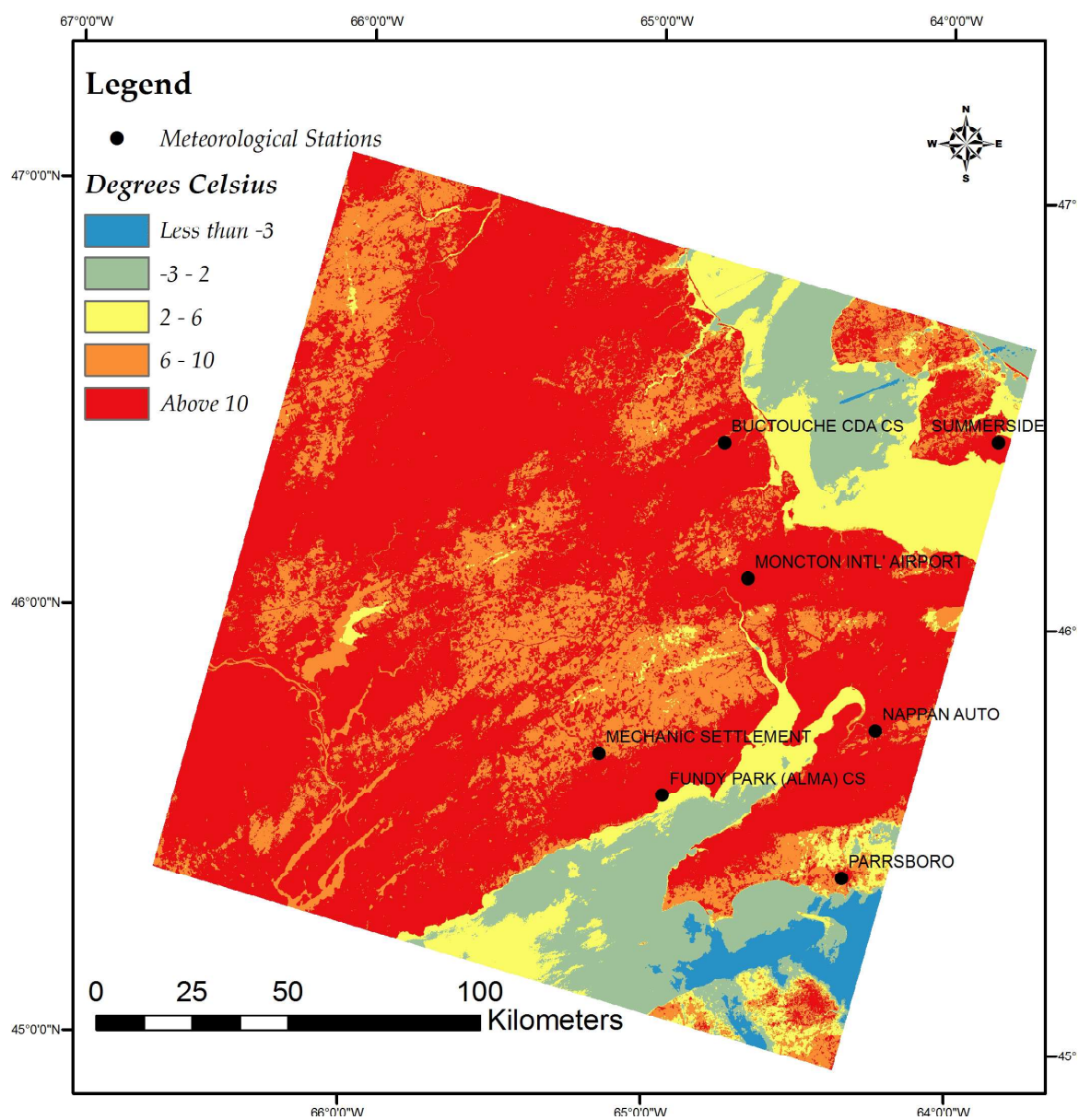
Appendix 32. Landsat 8 TIRS LST map produced by the RTE using the image dated 4 June 2015.



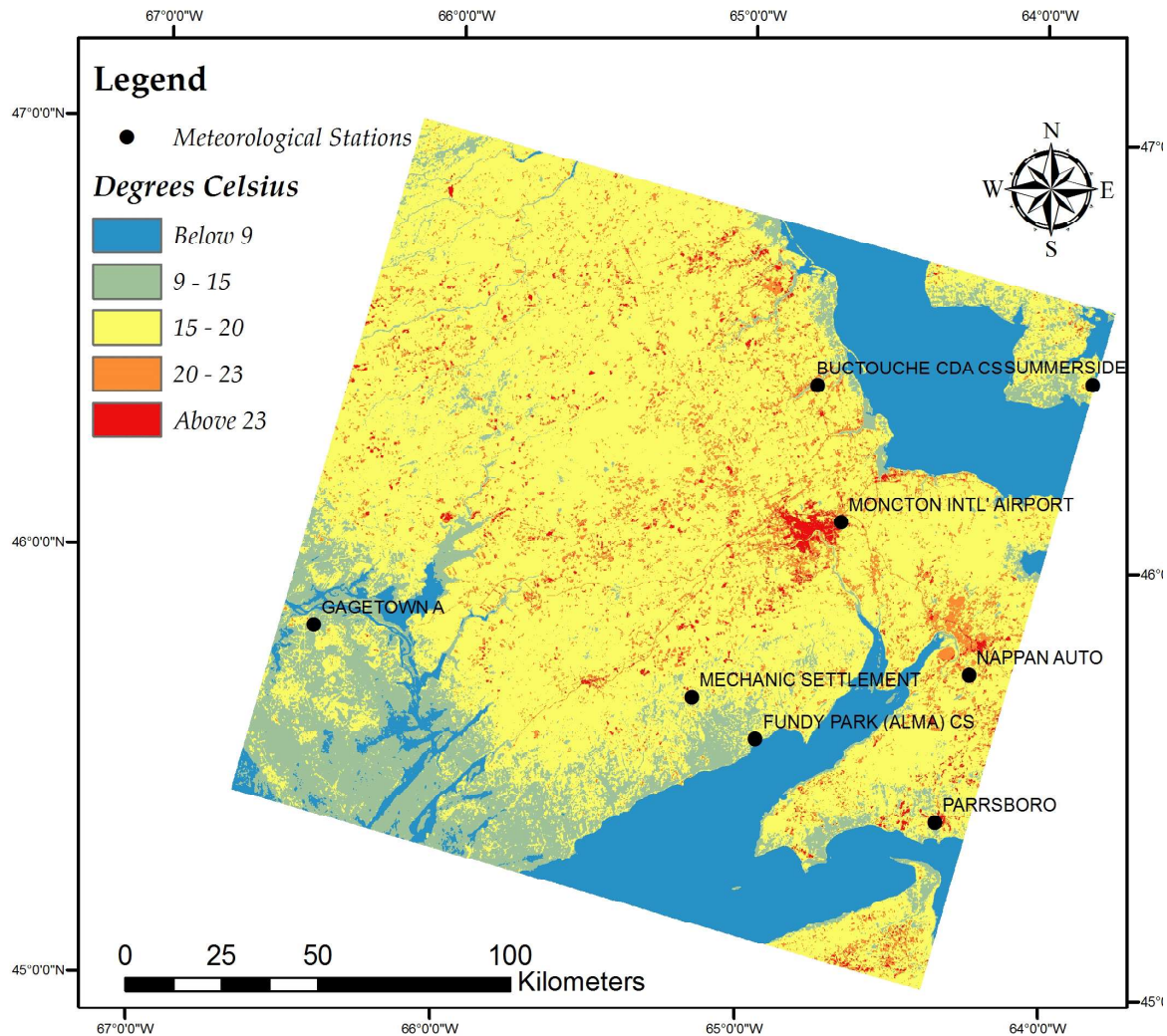
Appendix 33. Landsat 8 TIRS LST map produced by the MWA using the image dated 4 June 2015.



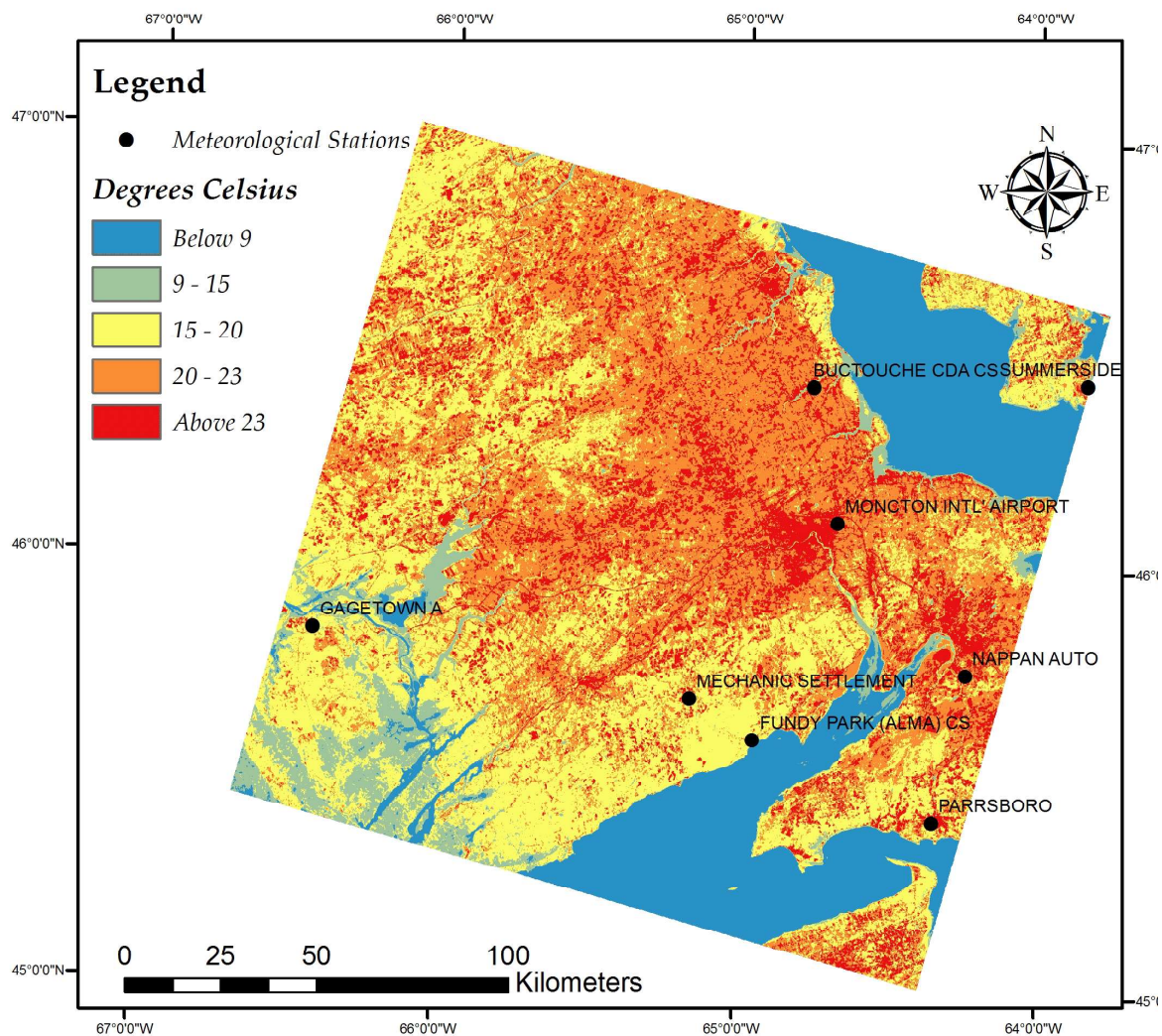
Appendix 34. Landsat 8 TIRS LST map produced by the Planck function using the image dated 4 June 2015.



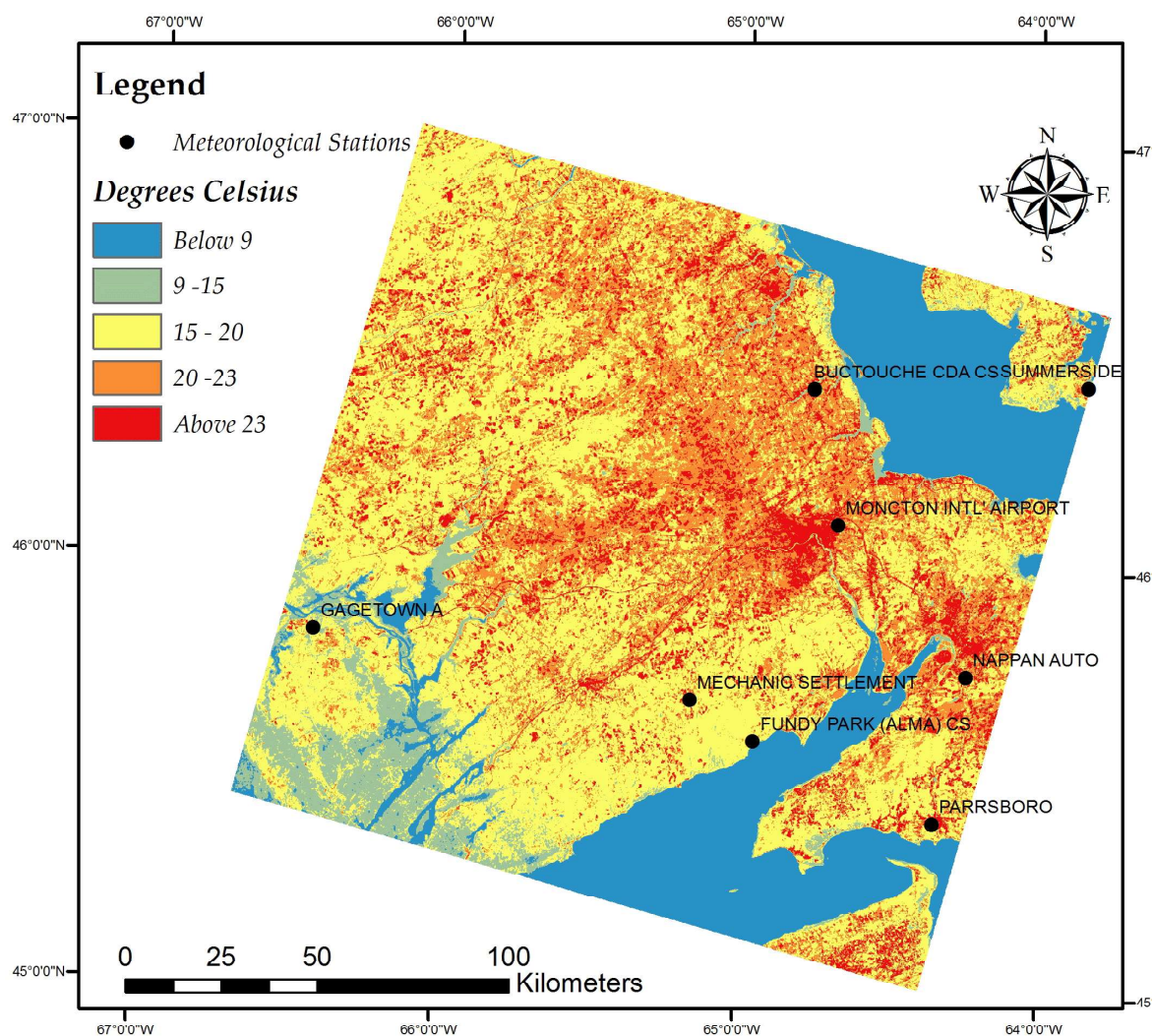
Appendix 35. Landsat 8 TIRS LST map produced by the SCA using the image dated 29 May 2013.



Appendix 36. Landsat 8 TIRS LST map produced by the RTE using the image dated 29 May 2013.



Appendix 37. Landsat 8 TIRS LST map produced by the MWA using the image dated 29 May 2013.



Appendix 38. Landsat 8 TIRS LST map produced by the Planck function using the image dated 29 May 2013.

