

UNIVERSITY OF OKLAHOMA

GRADUATE COLLEGE

BRIDGING THE NASA GLOBAL PRECIPITATION MEASUREMENT AND SOIL
MOISTURE ACTIVE PASSIVE MISSIONS: VARIABILITY OF MICROWAVE
SURFACE EMISSIVITY FROM BOTH IN-SITU AND REMOTE SENSING
PERSPECTIVES

A THESIS

SUBMITTED TO THE GRADUATE FACULTY

in partial fulfillment of the requirements for the

Degree of

MASTER OF SCIENCE IN METEOROLOGY

By

YAOYAO ZHENG
Norman, Oklahoma
2016

BRIDGING THE NASA GLOBAL PRECIPITATION MEASUREMENT AND SOIL
MOISTURE ACTIVE PASSIVE MISSIONS: VARIABILITY OF MICROWAVE
SURFACE EMISSIVITY FROM BOTH IN-SITU AND REMOTE SENSING
PERSPECTIVES

A THESIS APPROVED FOR THE
SCHOOL OF METEOROLOGY

BY

Dr. Yang Hong, Chair

Dr. Pierre Emmanuel Kirstetter

Dr. Lance Leslie

Dr. Robert Palmer

Acknowledgements

I owe the most significant debt to my research advisor Dr. Kirstetter for his unfailingly supportive supervision and his fundamental role in assisting the accomplishment of this thesis. He showed me different ways to approach research scientific problems, provided the continuous systematic guidance and bountiful effort in realizing my potential to the scientific research. His attitude toward the research was contagious and motivational for me.

My academic mentor, Dr. Hong deserves my thanks for many aspects. He allowed me to join the hydro group, provided guidance at key moments, permitted me to work independently during the majority of the time, and supported my attendance at conferences. His mentorship was paramount in providing a well-rounded experience for my long-term career goals.

Boundless appreciation is for my co-advisor Dr. Joseph Turk. He provided the data that is the foundation of this research together with informative advices on the direction of this work, shared me many incisive questions and constructive comments. My profound gratitude also goes to the other members of my master committee Dr. Palmer and Dr. Leslie for their thoughtful input, valuable discussion and easy accessibility.

Without the financial support from the School of Meteorology and faithful support from Dr. Parsons and Dr. Fielder, my master study in University of Oklahoma would be impossible. The deepest gratitude is extended to the unwavering love and encouragement from my parents and brothers.

Table of Contents

Acknowledgements	iv
List of Tables	ix
List of Figures	xi
Abstract	xxi
1. Introduction	1
2. Instruments	10
2.1 GPM	10
2.1.1 DPR	12
2.1.2 GMI	14
2.1.3 GPM constellations	17
2.1.4 GMI products	19
2.1.5 GMI algorithm.....	19
2.2 SMAP	23
2.2.1 Soil moisture	23
2.2.2 SMAP mission.....	25
2.2.3 SMAP products	27
2.2.4 Challenges in the soil moisture algorithm.....	28
2.2.5 Soil moisture retrieval	30
2.2.6 SMAP soil moisture retrieval.....	33
3. Microwave Emissivity	35
3.1 Theoretical Basis of Emissivity.....	35
3.2 Emissivity in Precipitation Retrieval	37
3.3 Emissivity Estimation Methods	39

3.3.1 Physically based method	39
3.3.2 Satellite observation based methods	41
3.3.3 Statistical method	44
3.3.4 Data assimilation method	45
3.3.5 Theoretical model.....	46
3.3.6 A widely used tool.....	46
3.4 Challenges in Emissivity Retrieval.....	47
3.5 Emissivity Products	48
3.6 Relationship between the Surface Properties and the Emissivity	50
3.5.1 Soil moisture	51
3.5.2 Temperature	52
3.5.3 Vegetation	53
3.5.4 Other factors	55
4. Data and Methodology	57
4.1 Data	57
4.1.1 Emissivity data	57
4.1.2 Soil Moisture data	58
4.1.3 Surface temperature data	59
4.1.4 Vegetation indices	59
4.1.5 ISMN	62
4.2 Methodology	64
5. In-situ Measurement Perspectives	66
5.1 Grassland.....	70
5.1.1 Single parameter modeling.....	73
5.1.2 Multi-parameter modeling.....	83

5.1.3 Prediction	89
5.1.2 Forest	91
5.2.1 Single parameter modeling.....	92
5.2.2 Multi-parameter modeling.....	95
5.2.3 Prediction	98
5.3 Barren Region	100
5.3.1 Single parameter modeling.....	101
5.3.2 Multi-parameter Modeling	103
5.3.3 Prediction	105
5.4 Summary	107
6. A Remote Sensing Perspective	110
6.1 Minimal Vegetated Regions	113
6.1.1 Single parameter modeling.....	113
6.1.2 Multi-parameter modeling.....	115
6.1.3 Prediction	117
6.2 Moderate Vegetated Region	119
6.2.1 Single parameter modeling.....	119
6.2.2 Multi-parameter modeling.....	121
6.2.3 Prediction	123
6.3 Maximum Vegetated Surface	126
6.3.1 Single parameter modeling.....	126
6.3.2 Multi-parameter models	129
6.3.3 Prediction	132
6.4 Summary	135
7. Comparison	141

7.1 Comparisons between Remote Sensing and In-situ Measurement Perspectives	141
7.1.1 Comparison of single parameter models	144
7.2 Comparison of the Rainy Emissivity	155
7.3 Summary	158
8. Summary	162
References	165
Appendices	181
Appendix A: Distribution of Emissivity for In-situ Measurement from Three Stations	181
Appendix B: Comparison of the Distribution of Emissivity from In-situ Measurement and Satellite Observation	196
Appendix C: Comparison of the Rainy Emissivity from Model and from Satellite Retrievals	208

List of Tables

Table 2.1 GMI required technical performance.....	15
Table 2.2 Instrumentation comparisons between TMI and GMI.....	16
Table 2.3 list of constellation satellite in GPM.....	18
Table 2.4 Surface type index in GMI level 2 radiometer product	21
Table 5.1 Station information	68
Table 5.2 Different combinations of variables.....	83
Table 5.3. Best model and their correlation coefficient for all the channels for Abrams grassland station.....	88
Table 5.4 Best models and their correlation coefficient for all the channels over Mammothcave forest station.....	97
Table 5.5 Best models for all the channels and their correlation coefficients	104
Table 6.1 Sample sizes of different types of land surface in the remote sensing dataset	110
Table 6.2 Statistics of soil moisture, soil temperature, NDVI and EVI for maximum vegetated regions, moderate vegetated regions and minimal vegetated regions	112
Table 6.3 Rank of importance of different surface parameters in multi-parameter models for all the channels.....	116
Table 6.4 Rank of importance of different surface parameters in multi-parameter models for all the channels over moderate vegetated regions	123
Table 6.5 Rank of importance of different surface parameters in multi-parameter models for all the channels over maximum vegetated regions	132

Table 6.6. Variation trends of the emissivity as a function of surface properties for maximum vegetated regions	136
Table 6.7. Variation trends of the emissivity as a function of surface properties for moderate vegetated regions.....	137
Table 6.8. Variation trends of the emissivity as a function of surface properties for moderate vegetated regions.....	138
Table 7.1 Sample sizes of different surface types in the in-situ measurement datasets	142
Table 7.2 statistics of soil moisture, soil temperature, NDVI and EVI for maximum vegetation regions, moderate vegetation regions, low vegetation regions and minimal vegetation regions from the in-situ measurements	143
Table 7.3 Comparison between distributions of RS and IS emissivities over the maximum vegetated regions	159
Table 7.4 Comparison between distributions of RS and IS emissivities over the moderate vegetated regions.....	160

List of Figures

Figure 1.1.1 An illustration of a possible linkage between GPM and SMAP missions	8
Figure 2.1.1 GPM Swath Diagram	12
Figure 2.1.1 GMI scan patterns, KuPR (red circle), KuPR_HS (purple circles) and KuPR_MA (blue circles).....	13
Figure 2.1.2 GMI brightness temperature on March 10, 2014 (left); three-dimensional precipitation rate from DPR radar reflectivity (right)	14
Figure 2.1.3 GPM constellation partners.....	17
Figure 2.1.4 Surface type indexes from GMI, on June 10, 2015	22
Figure 2.2.1 SMAP mission (left); global soil moisture retrieved from SMAP.....	26
Figure 2.2.2 Contributions to TOA brightness temperature (Kerr et al. 2010)	31
Figure 3.3.1 Types of surface scattering, Lambertian reflection (left), specular reflection (right) (Guedj et al. 2010)	42
Figure 4.1.1 Example emissivity map from GMI on May 11 2015	58
Figure 4.1.2 Land cover classification for the SCAN/USCRN stations.....	63
Figure 5.1.1 Locations of Grassland station-Abrams, Barren region station-Stovepipe well and Forest station-Mammothcave	69
Figure 5.1.2 Temporal variation of soil moisture (upper), diurnal variation of soil temperature (Second) and air temperature (third) and seasonal variation of NDVI (fourth) /EVI (bottom).....	70
Figure 5.1.3 Distribution of Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) at the Abrams grassland station	72

Figure 5.1.4 Empirical (left) and statistical (right) single parameter models of 10V-emissivity as a function of soil moisture in a) and b), soil temperature in c) and d), air temperature in e) and f), NDVI in g) and h) and EVI in i) and j) over Abrams grassland station. The thick white line represents the median (50% quantile), the dark gray-shaded region represents the area between the 25% and 75% quantiles, the light gray-shaded region represents the area between the 10% and 90% quantiles. The dotted blue line represents the range of surface property values.....	76
Figure 5.1.5 Probability distribution function derived from statistical models.....	79
Figure 5.1.6 Scatter plot of emissivity derived from observed data and emissivity predicted using single-parameter statistical model over Abrams grassland station	80
Figure 5.1.7 Statistical modeling of all channel emissivity as a function of soil moisture over Abrams grassland station.....	82
Figure 5.1.8 Statistical model for single-parameter models over different channels ..	82
Figure 5.1.9 Framework of the transition from Single-Parameter Modeling to Multi-Parameter Modeling	83
Figure 5.1.10 Correlation coefficients between the 10V GHz emissivity derived from observed data and 10V GHz emissivity predicted using single-parameter statistical model over Abrams grassland station.....	85
Figure 5.1.11 Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted using single-parameter statistical model over Abrams grassland station.....	87
Figure 5.1.12 Cumulative distribution function of uncertainty for 10V GHz emissivity over Abrams grassland station.....	88

Figure 5.1.13 Prediction of 10V GHz hourly emissivity over Abrams grassland station from 2014, March to Feb 2016 (upper plot), and from May 20, 2014 to June 30, 2014 (middle plot), May 30 00:00 to June 1 00:00 (local time) (bottom plot)	90
Figure 5.2.1 Distribution of Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) over Mammoth cave forest station	92
Figure 5.2.2 Statistical model for single-parameter models over different channels for Stovepipewell barren region station; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot) and NDVI single parameter model (bottom plot)	94
Figure 5.2.3 Correlation coefficients between predicted emissivity using statistical models and the emissivity derived from observation data for all models over all the channels in the Mammoth Cave forest station	96
Figure 5.2.4 Prediction of 10GHz V hourly emissivity over MammothCave forest station from 2014, March to Feb 2016(upper plot), and from Sept 5, 2015 to Oct 16, 2015(middle second plot), Sept 7th 00:00 to Sept 9th 00:00 (local time)(middle third plot), Sept 9th 00:00 to Sept 11th 00:00 (local time)(bottom plot)	99
Figure 5.3.1 Distribution of Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) over Stovepipewell barren region station	101
Figure 5.3.2 Statistical model for single-parameter models over different channels; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot) and NDVI single parameter model (bottom plot)	103

Figure 5.3.3 Correlation coefficient between predicted emissivity and the emissivity derived from observation data for all models over all the channels in the Stovepipewell barren region station	104
Figure 5.3.4 Prediction of 10GHz V hourly emissivity over StovepipeWell barren region station from 2014, March to Feb 2016 (upper plot), and from Sept 5, 2015 to Oct 16, 2015 (middle second plot), Oct 2nd 00:00 to Oct 4th 00:00 (local time) (middle third plot), Oct 5th 00:00 to Oct 7th 00:00 (local time) (bottom plot).....	107
Figure 6.1.1 Distribution of soil moisture, surface temperature, NDVI and EVI over maximum vegetated (maxvg) regions (left column), moderate vegetated (midvg) regions (middle column) and minimal vegetated (minvg) regions (right column) ...	112
Figure 6.1.1 Single-parameter models over different channels for minimally vegetated region; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot), NDVI single parameter model (bottom plot)	115
Figure 6.1.2. Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted using single-parameter statistical model over minimal vegetated region	116
Figure 6.1.3 Prediction of 10GHz V emissivity modeled using two-parameter models over minimal vegetated regions.....	118
Figure 6.2.1 Statistical model for single-parameter models over different channels for moderate vegetated region; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot), NDVI single parameter model (bottom plot).....	121

Figure 6.2.2 Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted over moderate vegetated region (number one refers soil moisture, number two refers surface temperature, number 3 and 4 refer vegetation indices)	122
Figure 6.2.3. Prediction of emissivity using two parameter models at 10 GHz V channel (first row) and at 10 GHz H channel (second row), 89 GHz V channel (third row).....	125
Figure 6.3.1 Statistical model for single-parameter models over different channels for maximum vegetated region; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle second plot), NDVI single parameter model (middle third plot), and EVI single parameter model (bottom plot)	129
Figure 6.3.2 Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted using single-parameter models over maximum vegetation	131
Figure 6.3.3 Prediction of 10GHz V and 89V GHz V emissivity modeled using two-parameter models over maximum vegetated regions	133
Figure 7.1.1 Comparison of the distribution of emissivity as a function of soil moisture (first row), surface temperature (second row), NDVI (third row) and EVI (fourth row) at 10V-GHz channel from remotely sensed data based-models (blue profiles) and from in situ measurement-based models (grey profiles) over maximum vegetated regions (left), moderate vegetated regions (middle), low vegetated regions (right).....	146

Figure 7.1.2 Comparison of single parameter modeling of emissivity estimated from models based on the remote sensing data and models based on the in-situ measurements over five classifications of surface type for all the channels	151
Figure 7.1.3 Comparison of single parameter modeling (ST and NDVI) of emissivity estimated from models based on the remote sensing data and models based on the in-situ measurements over five classifications of surface type for all the channels	154
Figure 7.2.1 Time series of emissivity quantiles derived from our statistical models and type 1 rain emissivity over the Numm#1 station	156
Figure 7.2.2 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the grassland	157
Figure 7.2.3 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations for other types of landcover, such as mixed forest (10 GHz V channel), shrubland (89 GHz H channel) and cropland (37 GHz V channel)	158
Figure A.1.1 Distribution of emissivity from the soil moisture single parameter model for Abrams grassland station	182
Figure A.1.2 Distribution of emissivity from the soil temperature single parameter model for Abrams grassland station	182
Figure A.1.3 Distribution of emissivity from the air temperature single parameter model for Abrams grassland station	183
Figure A.1.4 Distribution of emissivity from the NDVI single parameter model for Abrams grassland station	184

Figure A.1.5 Distribution of emissivity from the EVI single parameter model for Abrams grassland station.....	185
Figure A.1.6 Distribution of emissivity from the soil moisture single parameter model for Mammothcave forest station.....	186
Figure A.1.7 Distribution of emissivity from the soil temperature single parameter model for Mammothcave forest station.....	187
Figure A.1.8 Distribution of emissivity from the air temperature single parameter model for Mammothcave forest station.....	188
Figure A.1.9 Distribution of emissivity from the NDVI single parameter model for Mammothcave forest station	189
Figure A.1.10 Distribution of emissivity from the EVI single parameter model for Mammothcave forest station	190
Figure A.1.11 Distribution of emissivity from the soil moisture single parameter model for Stovepipewell barren region station	191
Figure A.1.12 Distribution of emissivity from the soil temperature single parameter model for Stovepipewell barren region station	192
Figure A.1.13 Distribution of emissivity from the air temperature single parameter model for Stovepipewell barren region station	193
Figure A.1.14 Distribution of emissivity from the NDVI single parameter model for Stovepipewell barren region station	194
Figure A.1.15 Distribution of emissivity from the EVI single parameter model for Stovepipewell barren region station	195

Figure B.1.1 Comparison of distribution of the emissivity from the soil moisture single parameter models based on the satellite remotely sensed data and the emissivity from the soil moisture single parameter models based on in-situ measurements over the maximum vegetated regions	196
Figure B.1.2 Comparison of distribution of the emissivity from the surface temperature single parameter models based on the satellite remotely sensed data and the emissivity from the soil temperature single parameter models based on in-situ measurements over the maximum vegetated regions	197
Figure B.1.3 Comparison of distribution of the emissivity from the NDVI single parameter models based on the satellite remotely sensed data and the emissivity from the NDVI single parameter models based on in-situ measurements over the maximum vegetated regions	198
Figure B.1.4 Comparison of distribution of the emissivity from the EVI single parameter models based on the satellite remotely sensed data and the emissivity from the EVI single parameter models based on in-situ measurements over the maximum vegetated regions	199
Figure B.1.5 Comparison of distribution of the emissivity from the soil moisture single parameter models based on the satellite remotely sensed data and the emissivity from the soil moisture single parameter models based on in-situ measurements over the moderate vegetated regions	200
Figure B.1.6 Comparison of distribution of the emissivity from the surface temperature single parameter models based on the satellite remotely sensed data and	

the emissivity from the soil temperature single parameter models based on in-situ measurements over the moderate vegetated regions	201
Figure B.1.7 Comparison of distribution of the emissivity from the NDVI single parameter models based on the satellite remotely sensed data and the emissivity from the NDVI single parameter models based on in-situ measurements over the moderate vegetated regions	202
Figure B.1.8 Comparison of distribution of the emissivity from the EVI single parameter models based on the satellite remotely sensed data and the emissivity from the EVI single parameter models based on in-situ measurements over the moderate vegetated regions	203
Figure B.1.9 Comparison of distribution of the emissivity from the soil moisture single parameter models based on the satellite remotely sensed data and the emissivity from the soil moisture single parameter models based on in-situ measurements over the low vegetated regions	204
Figure B.1.10 Comparison of distribution of the emissivity from the surface temperature single parameter models based on the satellite remotely sensed data and the emissivity from the soil temperature single parameter models based on in-situ measurements over the low vegetated regions	205
Figure B.1.11 Comparison of distribution of the emissivity from the NDVI single parameter models based on the satellite remotely sensed data and the emissivity from the NDVI single parameter models based on in-situ measurements over the low vegetated regions	206

Figure B.1.12 Comparison of distribution of the emissivity from the EVI single parameter models based on the satellite remotely sensed data and the emissivity from the EVI single parameter models based on in-situ measurements over the low vegetated regions	207
Figure C.1.1 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the mixed forest.....	208
Figure C.1.2 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the cropland.....	209
Figure C.1.3 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the shrubland	210

Abstract

The overland precipitation retrievals from satellite passive microwave (PMW) radiometer such as the Global Precipitation Mission (GPM) microwave imager (GMI) suffer from the contamination of observed brightness temperatures from the land surface. Microwave land surface emissivity is the quantitative indicator of the magnitude of the microwave radiance from the land surface. Research has shown that the estimation of PMW emissivity faces challenges because emissivity cannot be directly measured but it is highly heterogeneous and highly variable under the influence of various surface properties such as soil moisture, surface roughness and vegetation. Our research aims to achieve an improved quantitative understanding of the emissivity by studying the relationship between the emissivity and different surface parameters.

Surface parameter information can be obtained through in-situ measurements (International Soil Moisture Network stations) and satellite measurements. In particular, the Soil Moisture Active and Passive mission (SMAP) provides global scale soil moisture data. The overarching goal of our work is to incorporate the SMAP soil moisture to improve the precipitation retrieval from GPM in order to bridge two satellite missions on the water cycle by linking remotely sensed precipitation with soil moisture.

Our results quantitatively and holistically describe the variation of the emissivity with soil moisture, surface temperature and vegetation at various frequencies / polarization over different type of land surfaces. This sheds light into the processes governing the emission of the land and provides reliable support to the development of a physically based emissivity model.

Moreover, while most of the emissivity retrieval approaches apply only to cloud-free scenes, the analyses established in this study can be used to reproduce and predict the emissivity also for the rainy/cloudy conditions when surface parameters such as soil moisture and vegetation are available.

Furthermore, the analyses based on in-situ measurements serve as a benchmark for satellite-based models established using the satellite observations, which paves a way toward a global scale dataset of emissivity based on our models.

1. Introduction

Precipitation is a primary component in both global water and energy cycles (Held et al. 2006; Michaelides et al. 2008; Bengtsson et al. 2014). The distribution of water, its phase transition and associated energy affects the earth system (atmosphere, hydrosphere and cryosphere) (Oliver et al. 1995). Precipitation transfers the atmospheric water vapor to the surface, releasing latent heat and impacting the atmospheric circulation (Allen et al. 2002; Trenberth et al. 2011). Processes such as evaporation converts liquid water to atmosphere water vapor, absorbing energy, cooling the atmosphere and contributing to the formation of clouds and storms (Middleton et al. 1966; Yau et al. 1996). These clouds and storms will again produce precipitation (Pruppacher et al. 1988; Rosenfeld et al. 2014). With types and intensities varying from drizzle to large hail, precipitation can bring natural disasters such as flash floods and blizzards and redistribute the regional water resources that are essential for agriculture, industry and life (Rosenzweig et al. 2002; Jiang et al. 2005). Therefore, the study of precipitation is vital to a holistic understanding of our planet's weather and climate, and is also influential to aspects of our life and society (Chahine et al. 1992; Hernández et al. 2005).

Quantitative precipitation estimation (QPE) has long been a topic of extensive research in hydrology and meteorology (Huffman et al. 2009). It is challenging to maintain a long-term and consistent quantitative database of rain, snow, and other precipitation types such as hail and sleet, around the globe. Rain gauge, invented thousands of years ago, was the most common method to observe surface precipitation

before the era of remote sensing (Strangeways et al. 2007). However, ocean and remote areas are not accessible to rain gauge networks. Due to the discrepancies of rain device and measurement setup among different stations or networks, precipitation measurement using rain gauge suffers serious quality problems. In addition, because a rain gauge provides only a small sample volume, it is not representative over the large areas and is unable to depict the spatial variability of the whole precipitation systems.

A few decades ago earth-observing satellites started to carry numerous instruments designed to measure various characteristics of a variety of hydrometeor (Bellerby et al. 2000; Ushio et al. 2003), which led to a number of studies to distinguish between precipitation types, to identify the location and coverage of precipitation, to observe the structure and dynamics of storms to cite a few (Levizzani et al. 2007; Sorooshian et al. 2008). Precipitation measurement using satellite presents recognized advantages over the traditional rain gauge. First, satellites have a broader observation coverage as they fly over the regions where surface measurement is scarcely available, such as ocean. Second, measurement is often more consistent in data quality and sensitivity. The third point is that satellite sensors can provide high spatial and temporal resolution data. Additionally, when combined with land-surface data, it can support and improve a number of applications such as weather forecasting, climate and hydrologic modeling, as well as natural disaster monitoring.

The remote sensing techniques fall into two general categories, passive remote sensing (Kawanishi et al. 2003; Joyce et al. 2004) and active remote sensing (Brandes et al. 1975; Kozu et al. 2001; Villarini et al. 2010). Weather radar is an exemplar of active remote sensor (Harrison et al. 2000), operating by transmitting a pulse of

electromagnetic radiation and measuring the returned signals that are backscattered by the targets (Doviak et al. 1992; Bringi et al. 2001). In contrast, passive remote sensors do not send signal but simply measure the incoming radiation (Ulaby et al. 1981). Examples are microwave and infrared imagers that use passive sensing techniques (Kidd et al. 2003).

Passive remote sensing of precipitation is theoretically possible over the microwave and infrared spectral region (Ulaby et al. 1981). The wavelength of microwave radiation is around 1 cm, which is 1000 times larger than that of the infrared radiation that corresponds to a higher spatial resolution. Consequently, a geostationary orbit (36,000km) is appropriate for infrared sensors and low earth orbit (350-850 km) for microwave sensors. The following discussion excludes the infrared sensors.

An electromagnetic wave in the microwave spectrum (1 to 200 GHz or 0.15-30cm) can penetrate through clouds to collect information about the atmosphere (temperature, humidity, clouds, rain, etc.) as well as the earth's surface (temperature, vegetation, roughness, moisture, etc.) (Kidder et al. 1995). The physical basis for retrieving precipitation from passive microwave (PMW) measurements depends on distinguishing the radiation of the earth's surface from the radiation coming from precipitation. Over the ocean, the microwave emission from the surface is strongly polarized while the emission from raindrops is non-polarized. Thus, by utilizing both the vertically and horizontally polarized radiation, precipitation can be efficiently separated from the underlying ocean surface. The microwave emission over land is more difficult to distinguish from rain because the emission from the land surface is highly variable in terms of polarization. Ongoing efforts in the satellite retrieval

community aim to characterize the passive microwave emission from land surface. Had we acquired a quantitative estimation of the land surface microwave emission, it could be subtracted from the total observed radiation to perform the precipitation retrieval.

One method prevalent in PMW sensing of precipitation relies on the emission from cloud water and precipitation observed against a radiatively cold surface background. Rainfall rates are related to the magnitude of radiance difference. This method, unlike another method discussed below, is applicable to clouds with little or no ice. Nevertheless, terrestrial radiance without cloud must be ascertained beforehand, so it is generally only useful over ocean but not land. Another widespread method use the brightness temperature that is defined as the measurement of the radiance of the microwave radiation traveling upward from the top of the atmosphere to the satellite and expressed in units of the temperature of an equivalent black body (Petty et al. 2006). This method supposes that ice in clouds scatters terrestrial radiation downward, producing a cold area in the imagery and thus establishing a linkage between the rainfall rate and the magnitude of brightness temperature depression. Notwithstanding the second method's infeasibility for clouds without water, this method is quite effective in high-frequency channels where the surface effects can be minimized.

A typical microwave radiometer is intended to receive the thermally emitted microwave radiation in two orthogonal polarizations, which are related to the vertical and horizontal polarizations of radiation emitted at the earth's surface or can be defined relative to either the normal to the surface or the viewing direction of antenna (Classen et al. 1974). Many PMW imagers designed for precipitation estimation have been operating over the last decades, such as the Tropical Rainfall Measuring Mission

(TRMM) Microwave Imager (TMI) (Simpson et al. 1996), Global Precipitation Measurement Microwave Imager (GMI) (Hou et al. 2014), Special Sensor Microwave Imager (SSM/I) (Ferraro et al. 1997), Special Sensor Microwave Imager Sounder (SSMIS) (Bommarito et al. 1993), Advanced microwave Sounding Unit (AMSU) (Weng et al. 2003) and Advanced Microwave Scanning Radiometer (AMSR-E) (Kawanishi et al. 2003). Among them, TMI and GMI attract special attention thanks to their unique colocation with active sensors -- precipitation radar (Kozu et al. 2001), which has revolutionized the measurement of precipitation from space by providing high-resolution 3-dimensional rain echoes in terms of radar reflectivity (Steiner et al 2007). Inter-calibration between active and passive sensor in the some spacecraft has been used to assess the accuracy of PMW measurements, substantially contributing to improve the satellite QPE (Furuzawa et al. 2005).

The current method used in GMI for overland QPE is based on the assumption that microwave scattering by frozen hydrometers is an indicator of rain rate. The retrieval algorithm builds upon physical or empirical models associating the scattering signature to surface rain rates. Nonetheless, this approach might be problematic due to its poor detection ability of precipitation produced by warm clouds. Undoubtedly, such retrieval method is inadequate and calls for improvements. In particular, the scattering signal can be complemented with the precipitation emission signal of precipitation. But the contribution from the surface to the measurements needs to be filtered out beforehand.

Both electromagnetic theory and past research (Weng et al. 2001; Karbou et al. 2005; Turk et al. 2012; Ferraro et al. 2013; Prigent et al. 2015) have implicitly

illustrated that the land surface emission is evidently influenced by the water in the soil. Thus it might be feasible to model emissivity quantitatively using the information of land surface variables. However, how the surface property impacts the land surface emissivity is not well understood yet and awaits more research.

Soil moisture is one of the most important surface properties to characterize the surface status. Soil moisture is a primary state variable of hydrology and the water cycle over land, and is an initial or boundary condition of earth science models. An assessment of surface soil moisture is necessary for applications such as weather forecasting, climate change modeling, monitoring of agricultural productivity, water resources management, drought prediction, flood area mapping, and ecosystem health monitoring (Robock et al. 2000).

Past researches (Koster et al. 2003; Hohenegger et al. 2009; Ruscica et al. 2015; Fort et al. 2015) suggest the existence of feedback between soil moisture and precipitation. Rain wets the soil and increases the soil moisture. In turns, the increasing soil moistures cause an increase in evaporation and change the low level humidity-temperature profile in the boundary layer atmosphere, potentially leading to a higher probability of precipitation.

However, traditional in-situ soil moisture measurements are incomplete, sparsely distributed, limited in area of coverage, short of standardization and handicapped by low sensitivity and resolution (Dorigo et al. 2011). For instance, the instrument can be Electrical Resistance Blocks or tensiometers while the sensor configuration can be stationary or portable. Lack of standardization bears potential

systematic errors. Therefore, measurements with high levels of accuracy and resolution in addition to standardization are imperative for scientific and societal applications.

Satellite remote sensing is anticipated to mitigate some insufficiencies in the current soil moisture observation. The active or passive microwave satellite observations from AMSR-E (Owe et al. 2008; Njoku et al. 2003), ERS AMI, MetOp ASCAT (Bartalis et al. 2007), SMMR, SSM/I, WindSat (Li et al. 2010; Parinussa et al. 2012) and SMOS (Kerr et al. 2010; Mecklenburg et al. 2012) have been used to develop the soil moisture databases. However, only SMOS was the only instrument specifically designed for soil moisture retrieval until January 31st, 2015, when the Soil Moisture Active and Passive (SMAP) mission was launched. SMAP, a new mission specifically dedicated to soil moisture retrieval is supposed to provide a global mapping of near surface soil moisture (Entekhabi et al. 2010). In our study, this newly available remotely sensed soil moisture data is incorporated in the development of a rigorous overland microwave emissivity model.

The sensitivity of PMW emissivity to vegetation also underwent assessment (Weng et al. 2001; Karbou et al. 2006; Turk et al. 2014; Prigent et al. 2015; Tian et al. 2014; Norouzi et al. 2015). Therefore, apart from soil moisture, other parameters such as vegetation and surface temperature are taken into account in this study.

The motivation of our research can also stem from a large number of recent operational work in assimilating the microwave land surface emissivity into the numerical weather prediction model to improve the model's accuracy (Weng et al. 2003; Boukabara et al. 2011).

This study mainly attempts to disentangle the various parameters that might contribute to the microwave land surface emissivity (e.g., vegetation, soil moisture and surface temperature). The initial motivation is to better understand about how the surface properties can modify the variation of the overland passive microwave emissivity, to establish robust statistical models to quantify the emissivity using the measurements of surface parameters, to investigate the frequency-and-polarization dependence of the effect of surface parameters on the emissivity, to evaluate the sensitivity of the established statistical models over various underlying surface. The established emissivity models for different frequency and polarization over different surface types can be incorporated into the PMW algorithm to improve the precipitation retrieval for PMW radiometers in GPM constellation and to take effective utilization of low-frequencies channels in GPM radiometer. Furthermore, this study aims to bridge SMAP and GPM, to achieve a synergistic use of the two promising NASA emissions, facilitating the new understanding of the interaction between soil moisture and precipitation and the air-land interaction, as shown in the Figure 1.1.1

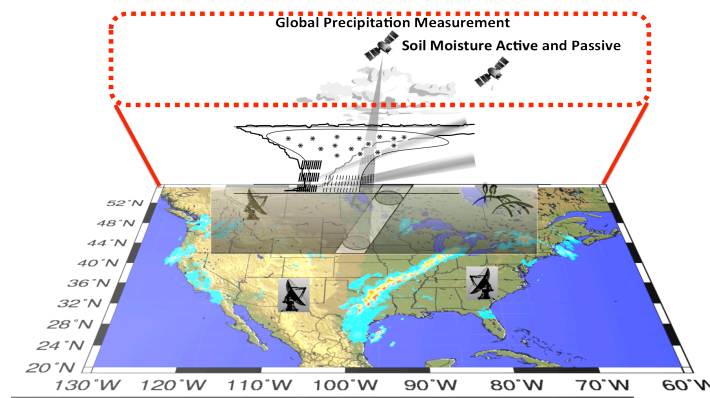


Figure 1.1.1 An illustration of a possible linkage between GPM and SMAP missions

Introduction in the section 1 will be followed by section 2 in which the instrument and algorithm of GPM and SMAP will be described. Section 3 provides the theoretic basis of microwave emissivity, the past and ongoing research on emissivity including the typical calculation methods and the currently available products. Data and methodology used in this study are presented in section 4. Section 5 presents the results and analyses based on the in-situ measurements. Section 6 focuses on a model developed with remotely sensed data, along with a comparison between the two models.

2. Instruments

2.1 GPM

The joint National Aeronautics and Space Administration and Japanese Aerospace Exploration Agency (JAXA) Global Precipitation Measurement (GPM) Mission is an international satellite constellation aimed to provide the next generation observations of both liquid and solid precipitation observation every three to four hours around the world.

The GPM is an extension to the Tropical Rainfall Measurement Mission (TRMM) that produced over 17-year scientific database of precipitation over tropical and subtropical regions. In order to continue and expand TRMM's consistent precipitation observation, the GPM core observatory was launched on Feb 27, 2014 as the principal component of the GPM. It carries an active microwave sensor, the Dual Frequency Radar (DPR), and a passive microwave sensor, the GPM Microwave Imager (GMI). GMI is supposed to sample the amount, size, intensity and type of precipitation, from heavy-to-moderate rain to light rain and snowfall. The DPR returns the 3D profiles and intensities of liquid and solid precipitation. DPR and GMI do not only provide their measurement of geophysical parameters, but also act as a calibration reference to unify precipitation estimates from other operational and research satellites of the GPM constellation.

The GPM core observatory, characterized by a 65° inclination and a 407-km mean altitude orbit, allows for a broad latitudinal coverage free from being locked into a sun-synchronous polar orbit, which enables frequent crossings with other constellation members and facilitates diurnal sampling of precipitation (Draper et al. 2015). The

GPM core observatory is noted for several new characteristics compared to its TRMM predecessor. First, differing from TRMM whose coverage is restricted to the tropics between 35°S-35°N, the GPM core observatory flies over higher latitude regions up to 65° in latitude. Solid precipitation is more common in the higher latitude regions. Correspondingly, compared to the previous generation of instruments of TRMM, the accuracy and reliability in estimating solid precipitation become more urgent and await more effort. Moreover, TRMM primarily addressed the moderate and heavy rain in the tropics and subtropical areas, whereas GPM is extended to detect light rain and snow as well. Ice crystals produce a much weaker radar backscattered signal than liquid water, necessitating a improvement in the measurement sensitivity. These new requirements are tackled by enabling new high frequency channel (165.5 and 183.3 GHz) on GMI, and a Ka-band (35.5GHz) radar on the DPR.

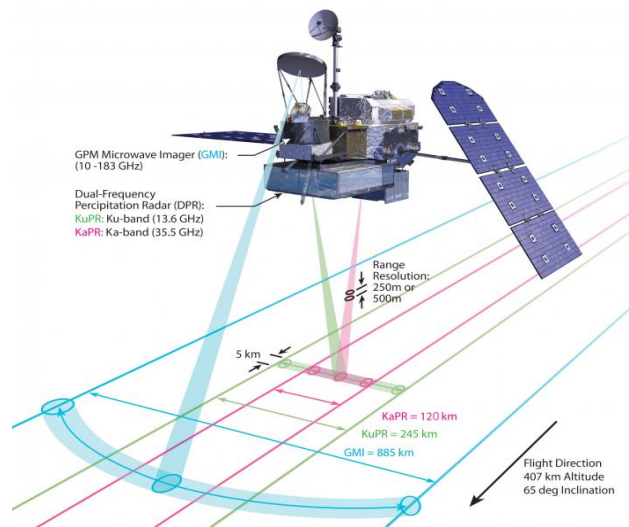


Figure 2.1.1 GPM Swath Diagram

2.1.1 DPR

One of the noteworthy breakthroughs in remote sensing of precipitation is the introduction of active sensors. Despite that weather radar emerged during World War II, the first space-borne radar was not launched until 1997. Advantages of space-borne precipitation radar include a much lower dependence to the relief from the vantage point of space (decreased land surface contamination), uniquely direct and high-resolution observation of vertical rain profiles. The typical challenges in the retrieval of precipitation with radar involve the phase state of hydrometeors and drop size distribution, temperature of precipitation particles, and inhomogeneity of rain distribution with the radar resolution.

The GPM Dual-frequency Precipitation Radar (DPR) consists of a Ku-band precipitation radar (13.6 GHz) and a Ka-band precipitation radar (35.5 GHz). DPR provides three-dimensional profiles of precipitation water content and rainfall rate. The first upgrade of DPR, in comparison to the TRMM PR of single frequency setup, is that dual-frequency data of DPR can provide valuable information of particle size distribution (PSD) or drop size distribution (DSD) in rain and snow. In particular, the addition of Ka-band frequency can reveal the non-Rayleigh scattering effect in the higher frequency (e.g. multiple scattering, Battaglia et al. 2016). Therefore, the retrieval of DSD information can be considerably improved along with the accuracy and reliability of solid and liquid precipitation estimation, and the investigation of microphysical properties of storms. Secondly, the differential attenuation between the Ku-band and the Ka-band frequencies can help in the rain/snow delineation, such as

determining the freezing heights at which the solid precipitation transitions into liquid precipitation. This meets the objective and performance requirement of GPM to provide from solid precipitation observation at high latitude to characteristics of convective storms. Furthermore, the Ka-band radar (sensitivity 12 dBZ) is more sensitive to the light rainfall and snowfall that might not be detected by the Ku-band radar (sensitivity 17 dBZ). In conjunction with the variable pulse repetition frequency (VPRF) technique, the number of samples at each IFOV is increased to achieve the 0.2 mm/h sensitivity.

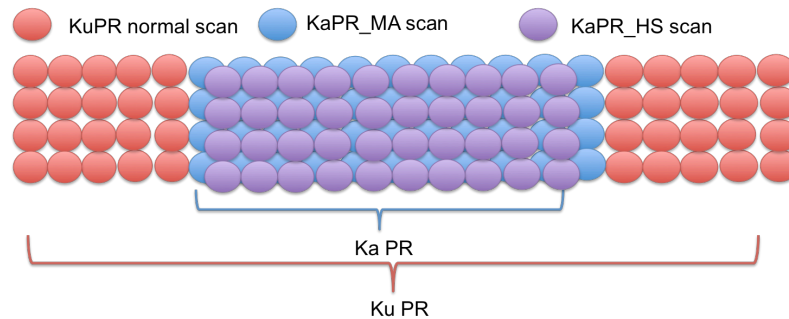


Fig 2.1.2 GMI scan patterns, KuPR (red circle), KuPR_HS (purple circles) and KuPR_MA(blue circles)

As shown in Fig 2.1.2, DPR has three types of scan pattern that are KuPR normal scan, KaPR Matched beam (KaPR_MS) scan and KaPR high sensitivity beam (KaPR_HS) scan. All of them share the same centerline but the KaPR scan is wider than KuPR. The beams of the KaPR_MA scan are overlapped with the central 25 beams of the KuPR, whereas KaPR operates in the high sensitivity mode in Ka_HS scan, attempting to detect the light rain and snow with the minimum measurable rain rate of 0.2mm/h, compared to the minimum measurable rain rate of KuPR of 0.5 mm/hr. KuPR has a lower sensitivity but a wider swath. Collocated measurements of KuPR and KaPR

can supplement each other and advance their capability to detect both deep convective storm in tropics and light rain and snow in the high latitude region, overcoming technical limitations in the previous generation of instruments.

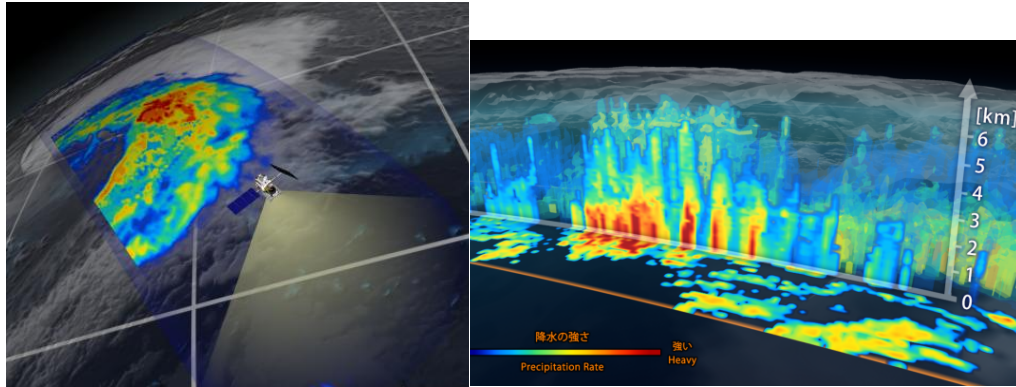


Figure 2.1.3 GMI brightness temperature on March 10, 2014 (left); three-dimensional precipitation rate from DPR radar reflectivity (right)

2.1.2 GMI

The GPM Microwave Imager (GMI) provides radiometric measurements from space at multiple microwave frequencies and polarizations. It is a multi-channel, conical-scanning, microwave radiometer with 13 radiometric channels ranging in frequency from 10.65 to 183.31 GHz. GMI is placed together with DPR. Thus, GPM core observatory is the only satellite carrying both active sensor and passive sensor, while other constellation satellites only have passive sensors. This co-location of DPR and GMI provides a unique opportunity to compare the high precision of precipitation radar measurement directly with radiometric measurement. Starting from GMI, the comparison can be extended to more passive microwave (PMW) sensors in GPM constellation. Therefore, the GMI instrument is a key component to achieve the GPM scientific goals because it serves as the link between the core observatory and the

constellation sensors. It allows the GPM core observatory to perform both as a ‘precipitation standard’ and as a ‘radiometric standard’ for cross-calibration of the other GPM constellation members.

Table 2.1 GMI required technical performance

Channel #	Center Frequency (GHz)	Polarization	Earth Incidence Angle (degree)	Beam width (degree)	Footprint (km×km)	Band width (MHz)
1,2	10.65	V/H	52.821	1.72	32.1×19.4	100
3,4	18.7	V/H	52.821	0.98	18.1×10.9	200
5	23.8	V/H	52.821	0.85	16.0×9.7	400
6,7	36.64	V/H	52.821	0.81	15.6×9.4	1000
8,9	89	V/H	52.821	0.38	7.2×4.4	6000
10,11	166	V/H	49.195	0.37	6.3×4.1	4000
12	183.31 ±3	V	49.195	0.37	5.8×3.8	2000
13	183.31 ±7	V	49.195	0.37	5.8×3.8	2000

GMI shares similar features and channel set with other constellation radiometers listed in the following section (Draper et al. 2015). The low-altitude orbit and 1.22-m diameter antenna provide GMI with a finer spatial resolution than most of the instruments in the GPM constellation. Up to 6-km resolution is available at high-frequency channel and approximately 25 km resolution at 10.65 GHz, in terms of

effective field of view (EFOV). GMI adopts conical-scanning geometry similar to its predecessor TMI instrument, as shown in Fig 2.1. With an earth-incidence-angle of 52.8 degrees and 49.1 degrees respectively for 10.64- through 89-GHz channels and the 166/183.3-GHz channels, GMI scans over a sector of 140 degrees wide centered about the spacecraft ground track vector, equivalent to an arc of 1190 km on the earth surface. In contrast, cross-track swaths of the KuPR and KaPR are 245 km and 120 km in width, respectively, overlapping the central portion of GMI swath. The overlapping part is essential for improving the retrieval algorithm. Other instrumentation information can be seen in Table 2.1. A comparison between the TMI and GMI can be found in Table 2.2.

Table 2.2 Instrumentation comparisons between TMI and GMI

Instruments	Number of channel	Frequency range	Swath width
TMI	9	10-85.5Ghz	758.5km
GMI	13	10-183	885km

GMI directly measure the Level 0 counts, which is converted into the geolocated antenna temperature (T_a) by means of the sensor radiometric calibration. And antenna temperature is converted into brightness temperature (T_b) after antenna pattern correction (APC) and vicarious calibrations (GMI L1B manual cited). Besides derived top-of-atmosphere brightness temperature (T_b), other secondary ocean data products such as cloud liquid water, column-integrated precipitable water, sea surface temperature, wind speed, and vertical atmospheric water vapor profiles can be derived

from GMI as well. The disadvantage of using PMW sensor is its larger field of view compared to the space radar and lower vertical resolution.

2.1.3 GPM constellations

Precipitation exhibits time-scale-dependent variability, ranging from the diurnal scale to sub-seasonal Madden-Julian Oscillation (30-90 days) to El Nino-Southern Oscillation (ENSO) (one to two years). Capturing precipitation variability at the global scale on temporal scales less than one day calls for measurements from as many sensors as possible. Capturing the variability on time scales longer than one year requires continuous records from consistently calibrated sensors.

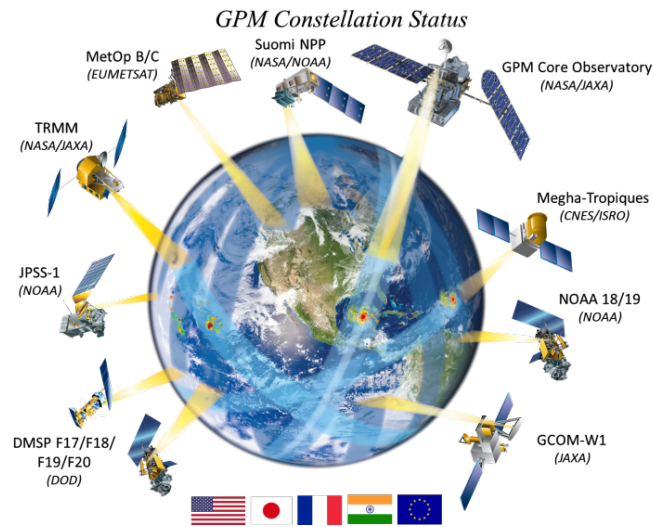


Figure 2.1.4 GPM constellation partners

In order to achieve the required every-three-hour-updating and worldwide precipitation estimates and make data available in a near-real-time manner, a number of passive microwave sensors from other agencies are also included in the GPM constellation. Multiple constellation spacecraft allow for frequent spatial sampling of

precipitation everywhere in the world every 3h, as is shown in Fig 2.1.4. Additionally, the orbital overpasses between GMI and other constellation members allow to compare the measurements of each constellation member, and help establishing the inter-comparison algorithm to understand the physics of various microwave scenes. Other constellation radiometers are listed in Table 2.3.

Table 2.3 list of constellation satellite in GPM

Constellation Radiometers	Launch Date	End Date
AMSR 2	May 18th, 2012	Active
SSMIS	F-16, Oct. 18, 2003	Active
	F-17, Nov. 4, 2006	Active
	F-18, Oct. 18, 2009	Active
Windsat	Jan. 6, 2003	Active
ATMS	NPP, Oct. 28. 2011	Active
AMSU A/B	NOAA-15, May. 13,1998	Active
	NOAA-18, Aug. 30, 2005	Active
	MetOp-A, May. 21, 2007	Active
	NOAA-19, Jun. 02, 2009	Active
	MetOp-B, Sep 17, 2012	Active
SSM/I	F-16 Oct 18, 2003	Active

2.1.4 GMI products

GMI precipitation products can be classified as follows; Level-1 GPM Microwave Imager (GMI) and partner radiometers brightness temperatures and Level-2 Goddard Profiling Algorithm (GPROF) GMI and partner radiometers precipitation retrievals (Liu et al. 2016)

2.1.5 GMI algorithm

The passive microwave precipitation retrieval algorithm employed in GPM uses a-priori retrievals databases, consisting of the observed precipitation profiles and their associated brightness temperature (T_b) signals from the physical measurement from GPM core observatory. The a-priori databases are constructed by matching the GMI observed brightness temperature and the coincident DPR radar-derived surface rainfall and vertical hydrometer structure. The retrieval bases on a Bayesian inversion where the uncertainty weighed proximity of the observed T_b to the database T_b is used to compute a weighted average of the precipitation profiles. Consistent databases across sensors are employed to design consistent retrieval algorithms for all the GPM radiometers. The following discussion exclusively addresses the PMW retrieval over land surface.

2.1.5.1 GPROF 2010

In the previous version of Goddard profiling algorithm (GPROF 2010), the retrieval over land was not Bayesian because of our poor knowledge about land surface emissivity and the resulting inability to quantify the microwave emission from hydrometeors (Gopalan et al. 2010). Instead, the scattering signal by ice particles in the high frequency channels (i.e., 85-GHz), observed as a depression of the brightness temperature, was used through an empirical relationship with the surface rain rate.

Before retrieving precipitation, screening procedures were applied to determine the probability of rain for each pixel without regards to surface emission. However, this scattering index approach, though effective for convective storms with the existence of large frozen hydrometeors, exhibits inferior performance during the winter season typically characterized with stratiform precipitation. Brightness temperatures from PMW sensors alone fail to discern precipitation from cold surface because of the absence of scattering particles (Meyers et al. 2015).

2.1.5.2 GPROF 2014

The overland GPROF 2014 retrieval algorithm is fully Bayesian. It uses a database of co-located surface rainfall obtained from the ground-radar based Multi-Sensor Quantitative Precipitation Estimation project (Zhang et al. 2011), and brightness temperatures coincidentally observed during GPM overpasses. This database is segregated according to the land surface temperature, TPW and surface type. Unlike the GPROF 2010 primarily using the 85-GHz vertically polarized T_b values, all-channel brightness temperature vectors are utilized to search the best match in terms of brightness temperatures and surface precipitation in order to estimate the surface precipitation rate (Kummerow et al. 2015).

Preliminary versions of this algorithm use the surface skin temperature (T_{skin}), Total Column Water Vapor (TCWV) or Total Precipitable Water (TPW) as ancillary data to constrain the Bayesian retrieval (Berg et al. 2006). A significant improvement in the present version is the addition of the Land Surface Class as an ancillary parameter to further constrain the searching work for the appropriate rain profiles corresponding to the observed brightness temperature. Land Surface Classes are clustered according to

their emissivities. In the GPM level-2 product output, the surface type index is a parameter indicating the land surface classes and is defined numerically using value from number 1-15, according to the land surface emissivity class/ocean/ coast/sea ice classification (see Table 2.4).

Table 2.4 Surface type index in GMI level 2 radiometer product

Values	Surface type classification
1	Ocean
2	Sea-Ice
3-7	Vegetation
8-11	Snow
12	Inland
13	Non-frozen Coastline
14	Sea-ice/Ocean
15	Frozen Water/land Boundary

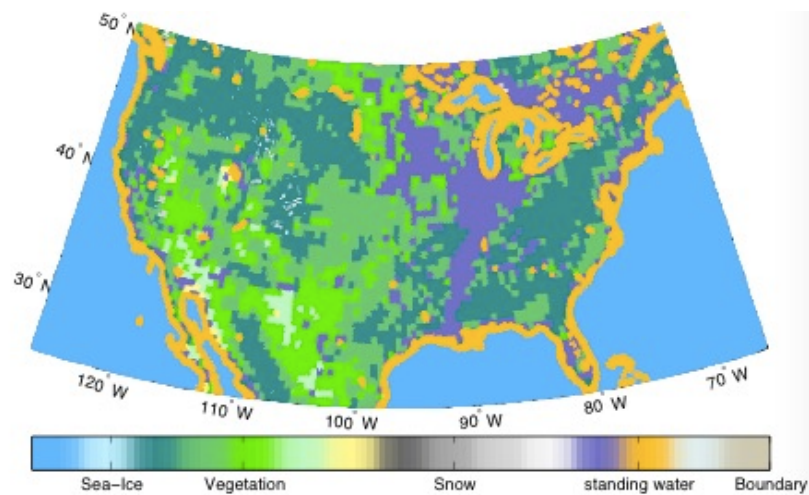


Figure 2.1.5 Surface type indexes from GMI, on June 10, 2015

Recognizing the challenge of using emissivity, GPROF 2014 implements three types of overland retrievals: S0, S1 and S2 type. The S0 type retrieval assumes that when the land emissivity is unknown and applies a linear channel combinations. S1 type of retrieval applies when the land surface emissivity is known to some extent and specifically believed to have significant covariance across channels. It involves tabulated climatology of emissivity. The S2 retrieval type is used when the surface emissivity is either known or retrievable. Therefore, the GPM algorithm is intended to function differently over type S0 (the surface is unidentified), type S1 (the surface has unknown but consistent and repeatable emissivity properties) and type S2 (the surface emissivity is adequately understood and predictable using ancillary data). The last type is not applied at this time, as further research is needed to implement a robust scheme for the emissivity quantification. A latitude/longitude classification by land, ocean (or inland water), snow/ice and the three different boundaries (land-ocean; land-sea ice and ocean-sea ice) is given priority in the surface type classification. Further subdivision is executed using the mean climatological emissivity. All the clear-sky-scene SSM/I observations from 1993 to 2008 (Prigent et al. 1997) are used to derive a climatological land surface emissivity database with a spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ at the equator (equal-area grid) at monthly averaged intervals, and incorporating the correlation structure and the covariance matrices from A Tool to Estimate Land Surface Emissivities at Microwave frequency (TELSEM) (Aires et al. 2011).

The major systematic errors inherent in the GPROF 2014 algorithm stem from the quality of the a-priori database, the estimate of the forward model uncertainty and the ancillary information used to subset the a-priori database. Undoubtedly, an improved understanding of land surface emissivity would be a prerequisite to the construction of a more robust a-priori database. Further improvements in the GMI precipitation retrieval are essential for achieving the GPM performance requirements. Although active sensors such as DPR can provide refined observations of vertical precipitation profiles, active sensors are not available in other constellation radiometers. Besides, GMI has a larger swath than the radar and covers a larger surface as the constellation radiometers. Finally, translating the observed GMI Tbs to equivalent Tbs observed by the constellation radiometers requires that the computed Tb for the constellation radiometers are fully consistent with the a-priori database, even if other sensors have a variety of incidence angle and orbital parameters. An improved knowledge of the emissivity can ensure the consistency between the GPM DPR and GMI, but also across the microwave passive radiometer sensors of the GPM constellation.

2.2 SMAP

2.2.1 Soil moisture

Soil moisture is usually defined as the water present in the unsaturated part of the soil profile, i.e., between the soil surface and the ground water level. It can be expressed in terms of soil water content or soil water potential (tension). The units of soil water content can be percent water by weight, percent water by volume or inches of water per foot of soil (Robock et al. 2000).

Soil moisture has been involved in both operational application and scientific research for diverse disciplines (Yeh et al. 1984; Seneiratne et al. 2010). It governs hydrological processes such as evaporation, infiltration and runoff, and contributes to various hydrological applications to support water managers and water resource decision-makers, Soil moisture drives ecosystem models (Daly et al. 2005), assists epidemiological modeling of water borne diseases, helps to predict agricultural productivity and supports the establishment of a bottom-up fire emission inventory for fire management. High-resolution soil moisture observations used in numerical modeling and data assimilation (Reichle et al. 2008) is anticipated to enhance the forecast of local storms and seasonal climate anomalies as well as drought and flooding monitoring. In respect of science, soil moisture holds the meteorological memory for the climate system over the land and serves an important boundary condition for seasonal climate predictability over continental interiors.

Atmospheric forcing is responsible for the long-term (approximately 1-4 months) and large-scale (about 400-800 km) variability of soil moisture, while small-scale spatial and temporal variability of soil moisture can be attributed to complex topography of natural landscapes, with spatially varying vegetation and soil types, and gravitational drainage and infiltration of water after heavy rains (Vachaud et al. 1985; Rodriguez-Iturbe et al. 1995).

Research and operational applications of soil moisture have been long circumscribed by the unavailability of a long-term and high-resolution soil moisture database. In an effort to resolve this predicament, several in-situ soil moisture networks have been established and operating in the United States during the past decade, such as

Oklahoma Mesonet. However, current soil moisture networks are geographically constrained and unevenly distributed. For instance, only a few networks exist in Africa and South America. Moreover, these point measurements are insufficient to capture the spatial and temporal variation of soil moisture. Thus, remote sensing observations are expected to pave the way to complement the traditional ground-based soil moisture observing system. For example the European Space Agency (ESA) Soil Moisture and Ocean Salinity Mission (SMOS) mission currently flies an aperture synthesis L-band radiometer, which produces soil moisture derived from brightness temperature data at multiple incidence angles over the same ground location.

2.2.2 SMAP mission

The Soil Moisture Active Passive (SMAP) mission, launched by NASA on January 31, 2015, is designed to study the global soil moisture at the top surface with a revisit frequency of 2-3 days. This new mission can help investigate the processes involved in water, energy and the carbon cycle, augment the monitoring capability of flood and drought, and support numerical weather forecast and climate prediction (Entekhabi et al. 2014).

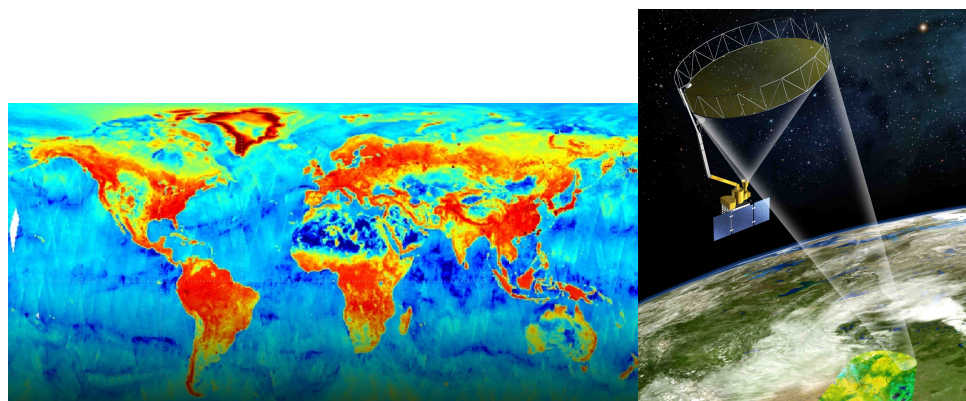


Figure 2.2.1 SMAP mission (left); global soil moisture retrieved from SMAP

SMAP carries two instruments which are a 1.41GHz L-band radiometer and a L-band synthetic aperture radar (SAR) (Spencer et al. 2010). The combination of high-resolution radar and high-accuracy radiometer observations was expected to provide enhanced soil moisture estimates. Unfortunately, the radar stopped operation on July 7, 2015. Thus, our study will exclusively focus on the data derived from the radiometer measurements with a spatial resolution of 40 km and a relative accuracy of 1.3 K in brightness temperature. The SMAP retrieval algorithms identify a pixel as retrievable only if the vegetation water content (VWC) is less than 5 kg/m², urban fraction is less than 0.25, water fraction is less than 0.1 and DEM slope standard deviation is less than 3 degree (Entekhabi et al. 2014).

The SMAP orbit is a 685-km altitude, near-polar, sun-synchronous 6am/6pm, 8-day exact repeat, frozen orbit. Sun-synchronous orbit provides observations of the surface at close to the local solar time for each orbit throughout the mission, enhancing SMAP sensors' ability to detect the anomalies of soil moisture and hence improving the overall science accuracy of soil moisture measurements. The sun-synchronous at 6am/6pm orbit attempts to minimize the Faraday rotation impact and also minimize the difference between canopy and soil temperature, and thermal difference between land cover types within a footprint.

The reason to choose microwave radiometer for SMAP is discussed below. For visible infrared sensors, soil is masked by clouds and vegetation. Optical sensors operate by measuring scattered sunlight and are "daytime only". In contrast, microwaves can penetrate through clouds and vegetation, can operate both day and

night, and are highly sensitive to the water in the soil due to the change in the soil microwave dielectric properties (Njoku et al. 1995).

The effective sensing depth always decreases with increasing measurement frequency and vegetation attenuation increases with the measurement frequency (Kong et al. 1990;). Low frequency is preferred because we hope to achieve larger sensing depths and minimized vegetation attenuations. Therefore L-band (approximately 1 GHz) was chosen and its advantages are discussed as follows (Wang et al. 1995). Firstly, atmosphere is almost completely transparent in the all-weather sensing in the L-band frequency. Secondly, the transmission of signals from the underlying soil can pass through sparse and moderate vegetation layers (up to at least 5 kg/m² of vegetation water content). Moreover, both day and night observations are available owing to the independence of solar illumination from the measurement (O'Neill et al. 2015).

2.2.3 SMAP products

SMAP products include the Level 1 calibrated, geo-located surface brightness temperature, Level 2 swath-based and Level 3 daily averaged surface soil moisture products both from radiometer measurements on a 36 km grid, Level 3 freeze/thaw products from radar measurements on a 3 km grid (Polson et al. 2012), Level 4 surface and root zone soil moisture and Level 4 Net Ecosystem Exchange (NEE) of carbon on a 9 km grid.

Our study mainly uses SMAP level 2 radiometer products. They provide high-resolution of global mapping of surface soil moisture (0-5 cm) in cm³/cm³ derived from brightness temperatures on a earth-fixed, global, cylindrical 36 km EASE-Grid 2.0, globally between 85°N and 85°S (Dunbar et al. 2009).

2.2.4 Challenges in the soil moisture algorithm

Though soil moisture is a technically possible target at L-band, the retrieval problem is complicated mainly by the requirement of ancillary information and the challenges posed by complex land conditions such as inland water bodies, snow cover, and the freeze/defreeze cycle.

Apart from soil moisture, the L-band radiance measured overland by a passive microwave sensor over a non-frozen and snow-free surface is also a function of vegetation opacity and effective surface temperature. Other surface properties such as soil texture and surface roughness might have a significant impact as well. Therefore, any physically based soil moisture retrieval algorithm requires static parameters such as topography, soil type soil texture and landcover, as well as dynamic parameters such as vegetation coverage, surface temperature, snow coverage and freeze states, and surface precipitation. In order to assess the contribution of vegetation, the SMOS makes use of multi-angular information whereas the SMAP uses the vegetation indices derived from other satellites.

The spatial resolution of the radiometer used in SMAP is 40 km, which is the same as SMOS and is a typical for the PMW sensors for soil moisture application. However, a footprint with such large coverage is subject to non-uniformity of the surface properties within the footprint, and can always include some water bodies, low to high vegetation coverage, possibly frozen and snow-covered surfaces, with varying topography. The heterogeneous land surface leads to a large variability of the surface emission at L-band and render the retrieval more challenging because the temporal

resolution of the heterogeneity of surface is typically smaller than the footprint size of radiometer.

Different types of landcover (grassland, forest, cropland, etc.) might coexist within a single pixel. The soil moisture retrieval is only valid over certain types of surface. For example, let's assume a pixel encompassing areas of low vegetation, dense forest and a lake. The signal contribution from the lake and the forest needs be estimated and eliminated when retrieving the soil moisture. Hence the radiance from a single pixel is divided into two parts, one in which the soil moisture is retrieved, and the other in which the signal contribution is estimated without retrieving the soil moisture. The latter part is always believed to be constant and can be evaluated using external data, while the retrieval is applied only in the first part.

Another challenge is associated with the concept of the penetration depth, which is related to the real part of the dielectric constant and determines the emissivity to the great extent. As a rule of thumb, the penetration depth can be approximately equivalent to one-tenth of the wavelength (Wilheit et al. 1978). Therefore, for a L-band passive microwave radiometer, the depth can be less than the top 2 cm of the soil layer. However, the penetration depth in reality depends on the magnitude of the soil moisture and soil profiles, leading to a potential source of error for the soil moisture estimation by means of the satellite PMW sensor.

2.2.5 Soil moisture retrieval

The microwave portion of the electromagnetic spectrum, whose wavelengths range from a few centimeters to a meter, has long been the most promising for soil moisture remote sensing (Njoku et al. 1996; Owe et al. 2008). The theoretical basis of the microwave remote sensing of soil moisture is discussed herein.

The dielectric constants of liquid water and dry soil are 80 and 5, respectively. Clearly, the dielectric property of a mixture of water and dry soil will be much subjected to the amount of water. Therefore, the dielectric constant of a soil layer will increase with soil moisture, resulting in a decrease in soil emissivity or an increase in soil reflectivity (Dobson et al. 1985). It indicates the potential to obtain information on soil moisture given the soil emissivity or reflectivity. However, frozen soil free from any water content is also characterized by a low dielectric constant similar to the dry soil (Hoekstra et al. 1974). Therefore, a freeze/thaw flag is required to avoid such ambiguity. As discussed in section 2.1.3, the brightness temperature is proportional to the emissivity for a given surface soil temperature in the microwave spectral region (O'Neill et al. 2014). Thus, an increase of soil moisture comes with a decrease in microwave emissivity and a decrease in the brightness temperature. This relationship between the soil moisture, soil dielectric property, microwave emissivity and brightness temperature serves as the physical basis for the passive remote sensing of soil moisture.

The observed brightness temperature in conjunction with the effective temperature, surface roughness parameter, vegetation opacity and vegetation single scattering albedo can be used to solve the soil reflectivity or emissivity and then the soil dielectric constant. Then a dielectric model (Wang et al. 1980; Dobson et al. 1985;

Mironov et al. 2009) incorporating the derived dielectric constant and ancillary soil texture can be used to estimate the soil moisture.

Passive microwave sensors measure the natural thermal emission from the soil surface. The intensity of radiance is determined by both the dielectric properties and physical temperature of the target medium. The near surface soil layer is assumed as a mixture of water, inorganic minerals, organic material and air. Water always has a much larger dielectric constant compared to inorganic minerals and organic material. As a consequence, the radiance emitted from the near-surface soil layer can be approximated as a function of water content in the thin layer.

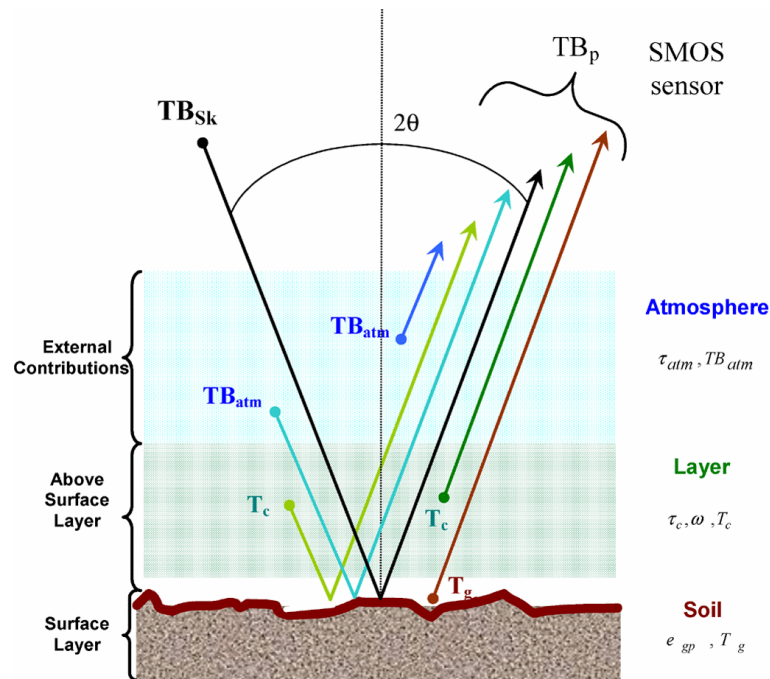


Figure 2.2.2 Contributions to TOA brightness temperature (Kerr et al. 2010)

As mentioned in section 2.2.3, the intensity of the observed emission is proportional to the Tb. If the microwave sensor is in orbit above the earth, the observed Tb is a combination of the emitted energy from the soil attenuated by any overlying

vegetation, the emission from the vegetation, the downwelling atmospheric emission and the cosmic background emission as reflected by the surface and attenuated by the vegetation, and the upwelling atmospheric emission (Figure 2.6; Kerr et al. 2010). At L-band, atmosphere is nearly transparent and the atmospheric emission is negligible.

A zero-order microwave emission model, commonly known as the tau-omega model (Mo et al. 1982; Brunfeldt et al. 1984; Jackson et al. 2013), is a well-known approximation to the radiative transfer equation. In the tau-omega model, the scattering within the vegetation and reflection at the vegetation-air interface are negligible by treating the vegetation layer primarily as an absorbing layer. Vegetation opacity is related to the total vegetation water content by taking the vegetation type and microwave frequency and polarization into consideration. The surface roughness is parameterized by a linear relationship of the root-mean-square surface height.

Therefore, the ancillary data used in the soil moisture retrieval are the surface temperature, vegetation opacity (or vegetation water content and vegetation opacity coefficient), vegetation single scattering albedo, surface roughness information, land cover type classification, soil texture and identification of land, water, precipitation, mountain terrain and permanent ice/snow and dense vegetation (O'Neill et al. 2014). At time near to 06:00am (the time of the SMAP descending pass), air, vegetation and near-surface soil layer are most likely in thermal equilibrium, the vegetation temperature is also most likely equal to the soil temperature and both of them are surrogated by a single effective temperature (Jackson et al. 2009; O'Neill et al. 2014). Then the soil moisture can be retrieved by solving the surface reflectance using the Fresnel equation and the dielectric-soil moisture model. The Fresnel equation is shown to reveal the

behavior of an electromagnetic wave at a smooth dielectric interface. Most dielectric models share the same dependence on soil moisture, soil texture and frequency. Three typical soil dielectric models are Dobson, Wang and Schmugge and Mironov (Wang et al. 1980; Dobson et al. 1985; Mironov et al. 2009).

2.2.6 SMAP soil moisture retrieval

A baseline and four optional soil moisture algorithms are used in the radiometer's retrieval of soil moisture. They are named as Baseline Single channel Algorithm V-pol (SCA-V), Single Channel Algorithm H-pol SCA-H, Dual Channel Algorithm (DCA), Microwave Polarization Ratio Algorithm (MPRA), and Extended Dual Channel Algorithm (E-DCA), respectively (O'Neill et al. 2015).

There are five general steps in the passive microwave retrieval of soil moisture: normalize brightness temperature to emissivity, eliminate the vegetation effect, correct for the soil surface roughness, retrieve the soil dielectric properties from emissivity and retrieve the soil moisture from dielectric models.

In essence, this tau-omega model in SMAP retrieval algorithm relates the brightness temperature (SMAP L1 observations) to soil moisture (SMAP L2 retrievals) through ancillary information (e.g. soil texture, soil temperature, and vegetation water content) and a soil dielectric model. The algorithms differ in their approaches to solve for soil moisture from the model in terms of constraints and assumptions.

The baseline algorithm converts the observed vertically polarized brightness temperature to emissivity. Retrieved emissivity is corrected for vegetation and surface

roughness to obtain the soil emissivity (Jackson et al. 1993). The dielectric constants are determined from the soil emissivity by the Fresnel equation. Eventually, the soil moisture is retrieved using a dielectric mixing model and ancillary knowledge of soil texture.

The second and the third algorithm use the same retrieval procedure as SCA-V and the only difference is that SCA-H uses the horizontal polarized brightness temperature as the preliminary input data and DCA uses both horizontal and vertical polarized brightness temperature as the input. In DCA, a cost function (Φ_2) that consists of the sum of squares of the differences between the observed and estimated Tbs is minimized iteratively along with the simultaneous adjustment of soil moisture and vegetation opacity (Njoku et al. 1999; O'Neill et al. 1995).

The fourth algorithm MPRA is based on the Land Parameter Retrieval Model (Owe et al. 2001). It also uses both vertically and horizontally polarized brightness temperatures but it assumes equal soil and canopy temperature and same vegetation transmissivity and single-scatter albedo for both H and V polarization. The fifth algorithm, a variant of DCA, uses a different formulation of cost function trying to minimize the sum of squares of the difference between the observed and estimated normalized polarization differences.

3. Microwave Emissivity

3.1 Theoretical Basis of Emissivity

We recall some basic radiation concepts for the sake of completeness. Radiation flux is a measure of the total energy per unit time per unit area transported by an electromagnetic radiation through a plane or deposited on a surface (Petty et al. 2006). Radiance is the flux measured on a surface normal to the beam per unit solid angle in a particular direction. The Rayleigh-Jeans approximation can be expressed as,

$$L_{\lambda} = \varepsilon \frac{2kc}{\lambda^4} T = \frac{2kc}{\lambda^4} T_B \quad (3.1)$$

for spectral radiance of wavelengths much greater than the wavelength of peak in the black body radiation formula, which corresponds to the microwave spectral range. For example, given the earth's body temperature at 300 K, the Rayleigh-Jeans approximation can be valid with a wavelength larger than 2.57 cm.

Microwave radiometers measure the spectral radiance emitted by the target medium. If the microwave brightness temperature is defined as the product of emissivity and physical temperature, according to Rayleigh-Jeans approximation, microwave radiometers equivalently measure the brightness temperature. Therefore, if brightness temperature can be obtained from radiometer measurements and physical temperature can be ascertained beforehand, emissivity can be calculated by dividing the brightness temperature by the physical temperature.

The brightness temperature emerging at the top of the atmosphere (TOA) as seen by a satellite radiometer is expressed as a sum of the upwelling atmospheric radiation including scattering, downwelling atmospheric radiation that is reflected

upward by the surface and direct emission of land surface attenuated by the intervening atmosphere.

Theoretically, the brightness temperature observed by the satellite sensor is further modified by atmospheric emission and attenuation. The formula is expressed as follows,

$$T_{B_p} = T_{B_u} + \exp(-\tau_a) (T_{b_p} + r_p T_{B_d}) \quad (3.2)$$

where T_{B_u} and T_{B_d} are the upwelling and downwelling atmospheric emission; τ_a is the slant atmospheric opacity and r_p is the surface reflectivity.

Microwave signal emanating at TOA is the combination of the surface and atmospheric contribution and the microwave emission of land surface itself being the product of the physical temperature and the surface emissivity.

Basically, ocean and land surfaces exhibit distinctively different microwave emissions. For ocean, the surface is radiometrically cold and strongly polarized at microwave frequencies under low and moderate wind speeds conditions, contrasting with the randomly polarized microwave emission from hydrometeors. Thus, it is relatively easy to distinguish between microwave emissions from the ocean surface and rain. In contrast, the microwave emission from the radiometrically warm and highly unpolarized land surface is not easily distinguishable from the hydrometeors over land. Furthermore, land surfaces are typically highly nonhomogeneous and their associated emissivities are characterized by significant variability. Therefore, rainfall estimation techniques over land have primarily relied on the depression in the 85-GHz Tb from ice scattering. The corresponding algorithm is empirical in nature (Gopalan et al. 2010).

3.2 Emissivity in Precipitation Retrieval

In the precipitation retrieval framework, different microwave emission characteristics from between land, ocean and coastal regions necessitate the development of different precipitation retrieval algorithms for the three types of surface.

Most passive microwave techniques for precipitation estimation depend on the high-frequency channels, scattering-based schemes, due to the fact that the low-frequency emission scheme is useless over the land surface. For instance, the previous overland precipitation retrieval for GMI is based on empirically derived Tb–rain-rate relationships, rather than relying on the physically based radiative transfer modeling of rainfall as is the case in ocean surface algorithm. In addition land surfaces are highly variable and associated with specific challenges. Some surfaces such as rain forests have been characterized while others such as semi-arid regions still require significant work before a truly physical model of the emissivity can be constructed over land. Regardless, the study of microwave land surface emissivity is essential. In particular, the GPM observations are more likely to be affected by the land surface emissivity because of its larger coverage with more complex surface characteristics than TRMM. The surface information can enable to exploit all-channel information for other applications such as retrieving soil moisture, snow water equivalent, sea-ice extent, sea surface temperature, atmospheric water vapor over ocean, and sea surface wind speed. Besides, accurate estimates of land surface emissivity can help numerical weather prediction model and development of reliable weather forecast products. Furthermore, emissivity estimates can also help research about global land surface characteristics,

such as vegetation monitoring, wetland extent and seasonality, soil moisture estimates, and snow characterization

In order to develop a physically based overland precipitation retrieval algorithm, our understanding of the microwave emission, or quantitatively, of the land surface emissivity should be improved. However, there are many challenges in general. First, emissivity is not a quantity that is directly measurable; the microwave emissivity is fundamentally influenced by dielectric properties of materials within the top several centimeters near the land surface. Basically, the subsurface layer can be composed of a variety of earth materials, different types of minerals, organic matter, water and ice. Their dielectric constants change with external environment conditions and it is impossible to determine the relative amount of each earth material and estimate their individual contribution quantitatively and for each site.

The heterogeneity of the land surface is also responsible for the large variability of emissivity. As mentioned above the typical footprint size of a PMW sensor is of at least 10 km, possibly including inhomogeneous surface areas consisting of different kinds of land cover (grassland, crop, forest, desert, urban area, shrubland, etc.), each of them with their own variability in surface emissivity. Simultaneously, microwave emissivities vary tremendously between different types of land surface, such as the notable contrasting behavior between rainfall forest and semi-arid region.

The variability also results from the dynamic nature of emissivity. The large contrast in terms of dielectric constants between liquid water (~ 80) and dry soil (~ 5) explains that the dielectric property of a mixture of water and dry soil omitting vegetation is substantially subjected to the amount of water. Emissivity can be

anticipated to be lower in conditions of higher soil moisture, as driven by the occurrence of rainfall. The emissivity of grassland, for instance, typically decreases abruptly when it rains and gradually regains higher values during the subsequent dry period.

3.3 Emissivity Estimation Methods

Two main categories of PMW emissivity estimation approaches can be land surface modeling and observational approaches (Turk et al. 2014). The merits and demerit of another category, physical retrieval, together with the two categories above have been discussed (Ferraro et al. 2013). Forward modeling (Ringerud et al. 2014; Boukabrar et al. 2011; Weng et al. 2001) are also attempted to estimate the emissivity (Norouzi et al. 2015). The performance of three categories of emissivities estimation approaches including physically modeling based on radiative transfer models, statistical modeling (Turk et al. 2014; You et al. 2014) and a hybrid of physical and statistical modeling (Ringerud et al. 2014) are assessed and compared (Tian et al. 2015). The hybrid approach is defined as use of the physically based retrievals in some channel while statistical covariance across channels is used to infer the emissivity in the other channels. A summery of the principles as well as the cons and pros of these emissivity estimation methods are presented below.

3.3.1 Physically based method

Physical modeling of surface emissivity using the surface parameters is a complex problem. Such a model must include radiative transfer from subsurface soil (which requires knowing soil type and soil moisture) to air and then scattering and

absorption-emission through the vegetation canopy that varies based upon frequency, vegetation type, and density [leaf area index (LAI)] as well as the water content of the plants themselves and any intercepted water or dew (Ringerud et al. 2013). Weng (Weng et al. 2001) introduced a method for physical modeling of emissivity by dividing the surface into three layers (i.e., soil, vegetation, and air) and by performing radiative transfer through these three media and their boundaries

The retrieval methods referred to as “physical” are by the reason of the utilization of geophysical parameters coupled with a radiative transfer model. The relationship between the microwave emissivity and other land surface parameters (soil composition, soil moisture, vegetation water content and surface roughness, etc.) are applied in the radiative transfer model to estimate the physical-based emissivity. Typically such a model must involve radiative transfer from subsurface soil to air, which requires information of soil texture characteristics and soil moisture, and scattering and absorption-emission through the vegetation canopy medium, which is variable with the varying frequency, vegetation type, and density or leaf area index, as well as the vegetation water content and other forms of surface water in such as intercepted water or dew (Ringerud et al. 2014). The current prevalent radiative transfer models are the Community Microwave Emission Modeling Platform (CMEM) developed by European Center for Medium-Range Weather Forecasts (ECMWF) (Holmes et al. 2008; de Rosnay et al. 2009), and Community Radiative Transfer Model (CRTM) in the Land Information System-Community RTM developed at the NSAS Goddard Space Flight Center (GSFC) and at the Joint Center for Satellite Data Assimilation (JCSDA) (Kumar et al. 2006).

One impediment in the physical model is the input geophysical parameters. The large-scale or global-scale input variables which are required in physical models, such as soil moisture, surface roughness, and vegetation water content, are either unavailable, or with large errors and uncertainties. Therefore, the land surface model-driven emissivity model, whereby the hourly output of land surface model including the soil moisture, soil temperature, land surface temperatures, vegetation fraction and snow depths are used to drive the CRTM land surface emissivity models (Ferraro et al. 2013; Ringerud et al. 2014). CRTM is based on a two-stream radiative approximation (Weng et al. 1999). For instance, the community Noah LSM was used to assist the computation of emissivity (Kumar et al. 2006). This method relies on the dense media radiative transfer theory but its feasibility is dependent upon the availability of specific surface parameters (soil type, vegetation, etc.). It is also suggested that a dew/intercepted water layer may be a useful addition to the physical emissivity model (Ringerud et al. 2014).

3.3.2 Satellite observation based methods

The generic method uses radiative transfer calculation using satellite brightness temperatures in conjunction with temperature and humidity profiles as input, under cloud-free scenes and given a corrected cloud estimation. Then the results from the radiative transfer calculation are combined with corrected skin temperature to obtain the emissivity. In this satellite retrieval, the surface can be assumed as Lambertian reflection or specular reflection (Figure 3.3.1; Guedj et al. 2010). Lambertian reflection is typical proper for the very rough surfaces where radiation is isotropically reflected by the surface, while spectral reflection typically occurs over the flat surface and this

approximation is widely used (Prigent et al. 1997; Hewison et al. 1999; Morland et al. 2001; Karou et al. 2006). This observationally based approach (Prigent et al. 1997; Karou et al. 2005) can directly derive the cloud-free emissivity from satellite observation if the atmospheric transmissivity and land surface temperature is ascertained.

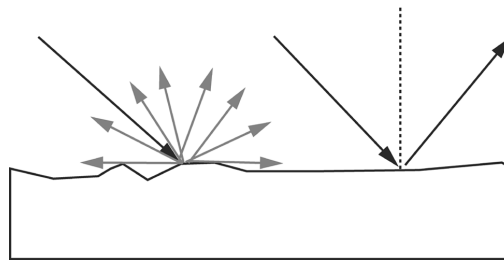


Figure 3.3.1 Types of surface scattering, Lambertian reflection (left), specular reflection (right) (Guedj et al. 2010)

Satellite observation based method is supposed to be most accurate for the cloud-free scenes (Turk et al. 2014) and has been widely used (Felde et al. 1995; Prigent et al. 1997; Karou et al. 2005). For instance, microwave land surface emissivities were derived from cloud-free SSM/I all-channel (19, 22, 35, 85 GHz) observations (Prigent et al. 1998) by simultaneous inversion of the surface temperature, emissivity, atmospheric water vapor content and cloud liquid water. Using cloud distribution, surface skin temperature and clear/cloud sky flags from the International Satellite Cloud Climatology Project (ISCCP) along with water vapor from the National Center for Environmental Prediction (NCEP) model, the microwave radiative transfer model simulates the SSMI brightness temperatures over 7 channels. Then adopting the same data from ISCCP as first guess, the simulated brightness temperatures are ingested in a neural network framework to calculate the surface skin temperature, water vapor,

cloud liquid water path and emissivity vectors. The absence of in-situ measurement of skin temperature is coped with near surface air temperature data by considering the solar zenith angle, surface humidity and cloud cover.

Another example is emissivity product from AMSU observations. Identification of cloud-free observation and skin temperature are extracted from ISCCP, humidity and temperature profile are from the ECMWF reanalysis (Karbou et al. 2005).

Retrievals were also attempted using the 91-GHz and 150-GHz cloud-free observations from collocated SSM/T-2 and radiosonde measurements (Felde et al. 1995). The dual-polarized 19-GHz and 37-GHz emissivity for specific land surfaces including sand deserts, rainforest and savanna were carried out using SSM/I (Choudhury et al. 1993), whereby the comparison of the satellite observation retrieval of emissivity is compared to the prediction of emissivity from Fresnel equation, radiative transfer model and field data respectively. Microwave radiative emissivity was retrieved with simultaneous retrieval of surface skin temperature and dynamical cloud discrimination (Lones et al. 1997), apart from the auxiliary information of in-situ atmospheric sounding used for atmospheric correction. The high frequency channels of the AMSU-B radiometer in conjunction with the radiation transfer model and the database of previously reported emissivities for a given snow cover amount are used to retrieve the falling snow over and adjust the surface emissivity (Skofronick-Jackson et al. 2004). More recently, the multichannel physical retrieval developed for the WindSat-based soil moisture retrieval algorithm (Li et al. 2010) has been adapted for TMI emissivity estimation (Turk et al. 2012).

Usually the above emissivity models are hampered by the lack of accurate input data. An uncertainty on the skin temperature with $\pm 4\text{K}$ leads to a 3% uncertainty in emissivity, $\pm 15\%$ uncertainty in humidity profiles increases the emissivity uncertainty by 3%, and $\pm 1\text{K}$ uncertainty in temperature profiles contributes to 1% uncertainty in emissivity, while the effect of $\pm 1\text{K}$ brightness temperature is negligible. Besides, if the emissivity falls into the range from 0.9 to 1, it does not make difference for using the spectral or Lambertian assumptions.

3.3.3 Statistical method

In contrast, the statistical modeling is established on the basis of statistical relationships derived from a long-term record data to predict the emissivity using some predictor variables (Aires et al. 2001; Turk et al. 2014; You et al. 2014).

The network approach in addition to a training database of simulated data is used to retrieve surface temperature, integrated water vapor content, cloud liquid water path, and microwave land surface emissivities in the 19–85-GHz range from SSM/I Tbs over land (Aires et al. 2001).

The principal component analysis together with empirical orthogonal functions (PCA-EOF) approach is also used to retrieve the emissivity from a dataset of historical instantaneous Tbs (Turk et al. 2014; You et al. 2014). This method is advantageous for the real-time application because only the instantaneous Tb data are needed as input once the statistical model is established.

Statistical models show better prediction performance compared to other approaches (Tian et al. 2015), if the current challenges and the limits in the physical modeling of emissivity are taken into consideration. However, the strength of the statistical methods does not invalidate the physical modeling approach. The robustness of the physical-based model is an ultimate test of our knowledge of the land surface radiative processes. Basically, the current physical-based emissivity model is largely practical rather than theoretical because lots of empirical relationship and parameterizations are used. Nevertheless, the statistical methods also have some drawbacks. Their performance is determined by the quality of sufficient long record dataset of Tb and emissivity. Moreover, the statistical retrieval is only applicable for the frequencies and view angles available in the historical data.

3.3.4 Data assimilation method

The Microwave Integrated Retrieval System retrieval and data assimilation system (Boukabara et al. 2011) simultaneously retrieves atmosphere and surface states in a 1DVAR approach starting with a first guess surface emissivity from mean retrieved clear sky values. While this approach yields an estimate of surface emissivity, it does so using an emissivity climatology including mean state and covariance matrices rather than a physical model directly computing emissivity as a function of the surface properties.

3.3.5 Theoretical model

For completeness, we also brief the early work on the theoretical calculation of emissivity. Theoretical analyses are usually restricted to finding an effective emissivity for wet soil and vegetation at these frequencies (Weng et al. 2001). In the RADTRAN surface emissivity model (Isaacs et al. 1989), soils with varying wetness and vegetation are modeled as layers of continuous random media bounded by an underlying homogeneous soil layer.

3.3.6 A widely used tool

Realistic emissivity first guesses are required for many PMW emissivity retrievals discussed above and should be independent from the data to be used in the retrieval procedure. Pre-calculated monthly-mean emissivity climatology was calculated from TELSEM (Aires et al. 2011). TELSEM utilizes a parameterization of land-surface emissivities between 19 and 100-GHz, which was derived on basis of an exhaustive analysis of the frequency, angular and polarization dependence of emissivities obtained from SSM/I, TMI and AMSU (Prigent et al. 2008). The emissivity in the GMI algorithm is from TELSEM, which was developed with the Radiative Transfer for the Television and infrared Observation satellite operational Vertical Sounder (RTTOV) model. TELSEM can not only provide the global monthly estimates of emissivity over the 19-100Ghz range, and their uncertainties which are typically lower than 0.02 in snow-free regions, but also climatology of the error-covariance matrices that include the reference climatology uncertainties and the emissivity interpolation errors for a given frequency, viewing angle, and polarization state.

3.4 Challenges in Emissivity Retrieval

Two categories of factors are responsible for the inconsistency among current land emissivity databases (Norouzi et al. 2015). The first category relates to the sensor parameters such as incident angle, data acquisition time, footprint size, frequency and polarization. For instance, shifts in instrument footprint locations, different acquisition times and calibration process would enhance the uncertainties originating from the heterogeneity of the land-surface radiometric properties.

Retrieval methods and ancillary data represent the second category of factors explaining the discrepancies among different land emissivity products. For example, the physically based method benefits from an exhaustive analysis of parameters but its success relies on the quality of input data, some of which are unattainable or exhibit a poor quality at the global scale. On the other hand, the emissivity calculation based on satellite observation together with radiation transfer models is only suitable for cloud-free sceneries, because of the intricacy in eliminating the atmospheric contribution and the associated strong atmospheric scattering and absorption of land-surface signals under the cloudy/rainy scenarios (Tian et al. 2015). Specifically, at higher frequencies over 19GHz, the atmospheric contribution might be significant, making the cloud-free retrieval erroneous. Even for a cloud-free atmosphere, there are many error sources that are accounted for uncertainties in emissivity retrievals, including instrumental errors, inaccuracies in the atmospheric profile data, imperfect cloud screening, and misrepresentation of the land-surface temperature (Jones et al. 1997; Prigent et al. 2005; Yang et al. 2011; Tian et al. 2013). Additionally, observations from different satellites

(SSM/I, AMSR-E, TMI etc.) and different kinds of ancillary might be used in these satellite-observation based retrievals. For instance, land surface temperature might be from reanalysis data (such as MERRA) or from satellite sensors (MODIS/GOES-5). These can contribute to the discrepancies and inconsistency of the emissivity estimates.

One major problem in estimating emissivity is the lack of “ground-truth” data for validation and comparison, especially on the global scale. A few field campaigns for land emissivity studies existed in the past but most of them are limited to small-scale areas and short-term, and are seldom abreast with any specific satellites (Tian et al. 2014). The robustness of emissivity retrievals have to be evaluated by checking the spatial and temporal consistency of the known surface properties, or by checking the spectral, angular and polarization variation from different instruments, or by comparing to emissivity models. However, this exercise is limited since the emissivity radiative transfer models themselves are not reliable enough to reproduce the spatial structure due to the complex radiative transfer interaction and because of the inputs uncertainties on variables such as texture and roughness.

3.5 Emissivity Products

Global land emissivity retrieval was first developed (Prigent et al. 1998) using the brightness temperatures from the Special Sensor Microwave Imager (SSM/I). Other available products were proposed later from other sensors, such as the Advanced Microwave Scanning Radiometer – Earth Observing System (AMSR-E) (Norouzi et al. 2011; Moncet et al. 2011), the Advanced Microwave Sounding Unit (AMSU) (Karbou et al. 2005), and the Tropical Rainfall Measuring Mission (TRMM)

Microwave Imager (TMI) (Furuzawa et al. 2012). Four microwave emissivity products (Norouzi et al. 2015) are discussed as follows.

The SSM/I-derived emissivity product is produced by the Centre National de la Recherche Scientifique (CNRS) in France (Prigent et al. 1998, 2006). SSM/I started to operate since 1987, allowing this dataset to have the longest record of emissivity estimates at frequencies over the range 19 to 85 GHz. The 3-hour International Satellite Cloud Climatology Project (ISCCP) skin temperature and the NCEP reanalysis for air temperature and water vapor column are ancillary data in this dataset. The satellite observations and the ancillary data are all gridded on a $0.25^\circ \times 0.25^\circ$ equal-area grid (Prigent et al. 2006).

The 6-year $0.25^\circ \times 0.25^\circ$ global emissivity data from the AMSR-E instrument over the channels of 6.9, 10.65, 18.7, 23.8, 36.5, and 89.0 GHz is available on monthly basis. It is processed by the National Oceanic Atmospheric Administration (NOAA) Cooperative Remote Sensing and Technology (CREST) center (Norouzi et al. 2013). This data uses TIROS Operational Vertical Sounder (TOVS) for skin temperature, ISCCP for cloud mask, and atmospheric information (Rossow et al. 1999).

Another $0.25^\circ \times 0.25^\circ$ AMSR-E-based monthly emissivity database from Atmospheric and Environmental Research Inc. (Moncet 2011) is also derived from AMSR-E brightness temperature with using MODIS LST to represent the emitting temperature of the surfaces and ancillary data (the $1^\circ \times 1^\circ$ National Centers for Environmental Prediction (NCEP) Global Data Assimilation System (GDAS) analysis) to define the atmospheric contribution. Monthly mean values are obtained from the daily product with the highest possible level of clear condition that yields an adequate

number of samples passing quality control. The microwave emission depth and effective emissivity are estimated by fitting the solution of a thermal diffusion equation to a one-month time series of clear-sky measurements, assuming sinusoidal diurnal surface forcing.

TMI observations have also been used to derive an emissivity database, processed by Nagoya University at the monthly scale (Furuzawa et al. 2012). Japanese 25-year Reanalysis (JRA-25) dataset is used as ancillary data (Onogi et al. 2007) in conjunction with an interpolation technique based on TMI acquisition time for each pixel.

Another Windsat-based emissivity estimates use ancillary data from the Atmospheric Infrared Sounder (AIRS) and NCEP data (Turk et al. 2014) by adopting a maximum likelihood estimation (Li et al. 2010).

3.6 Relationship between the Surface Properties and the Emissivity

The past ground experiments and theoretical studies have demonstrated strong relationship between the microwave land surface emissivities and the variation of soil moisture and crop canopy (Ulaby et al. 1986; Norouzi et al. 2012). It is widely accepted that the emissivity is notably variable and prone to the surface properties (Ferrao et al. 2013) and a robust description of microwave emission requires the knowledge of several parameters that include soil moisture and temperature, surface roughness, vegetation structure and vegetation water content (Raju et al. 1995; Njoku et al. 2006).

Moreover, this relationship is frequency-dependent. Many studies (Choudhury et al. 1987; Kerr et al. 1990; Njoku et al. 1999; Owe et al. 2001; Fily et al. 2003; Gao et al. 2006) have shown the multifrequency sensitivities of satellite microwave observations to soil moisture and vegetation. In turn, there are some studies retrieving the information of near-surface soil moisture using the microwave radiance which is based on the relationship between the microwave radiance and surface properties (Bauer et al. 2005).

In general, the vegetation has large emissivity whereas desert is characterized by low emissivities. And emissivity is larger and stabilizes under larger vegetation water contents (e.g., becomes less sensitive to soil moisture conditions) and very low soil moisture conditions (where there is often little or no vegetation) (Turk et al. 2013).

3.5.1 Soil moisture

The primary soil characteristics affecting emissivity are the volumetric moisture content, surface roughness, and the volume structure and texture (Njoku et al. 2006). The surface roughness is supposed to increase scattering and surface area, resulting in an increasing soil emissivity. However, among these characteristics, soil moisture invites most research and the large soil moisture value is closely related to low surface emissivity (Ulaby et al. 1986; Calvet et al. 1995a, 1995b; Le Vine et al. 1996) and associated the low observed brightness temperature (Ferraio et al. 2013). It can be theoretically explained by the discrepancy of large dielectric constants between water and soil. Soil moisture increases the dielectric constant of the soil–water mixture and thus decreases the soil emissivity. It is supported by the real scenarios soaking of the

near-surface soil layer by rain inevitably triggers a notable decrease in emissivity. Additionally, it is believed that the emissivity from horizontally polarized channels exhibits a higher sensitivity to the moisture than that from the vertically polarized channels (Lin et al. 2000).

Soil layer can obtain moisture from both condensation and infiltration during the night owing to radiative cooling and resultant rewetting of surface, resulting to the noticeable diurnal variation of soil moisture. The diurnal variation of emissivity accounts for a large part of the original variation of emissivity if there is no near-time precipitation events, which is the abreast with the diurnal variation of the shallow-layer soil moisture (Jackson et al. 1997). Specifically, the more uniform soil moisture vertical profile during the early morning can be responsible for the relative low early morning emissivity (Lin et al. 2000). The dependence of emissivity on the soil moisture varies in terms of soil texture. When clay content increases, more bound water is in the soil system, leading to a lower dielectric constant (Owe et al. 1998; Ringerud et al. 2014).

3.5.2 Temperature

Emissivity estimated from the satellite observation can be sensitive to the surface skin temperature (Prigent et al. 1997). Most variation of emissivity on the absence of precipitation appears in form of diurnal variation, which might correspond to the diurnal variation of the surface temperatures (Lin et al. 2000). Increasing the temperature of the first layer of soil under the vegetation produces a slight decrease in emissivity in all channels, with a slope that increases with frequency (Ringerud et al. 2014). Studies have pointed out that (Norouzi et al. 2012) the discrepancies between

emissivity of the nighttime overpasses and emissivity of the daytime overpasses and one possible explanation is that the brightness temperatures do not origin from the same penetration depth as the surface skin temperatures that use the retrieved infrared skin temperature as the surrogate. Therefore a few emissivity retrievals (Moncet et al. 2011) take the effect of penetration effect of brightness temperature and skin temperature into consider.

Skin temperature is believed to be about 0.5-5 K lower than air temperature and similar to or less than the dew point temperature. However, it is not easy to define surface skin temperature as “seen” by the radiometer. The radiometric temperature depends upon the vegetation and associated evaporation. Through the latent heat exchange that occurs during evapotranspiration, the vegetation canopy actively controls its temperature in contrast to bare soil, as suggested by the smaller amplitude diurnal variability observed over densely vegetated areas (Norouzi et al. 2012). Skin temperature may also depend upon soil properties, and emission depth varies with frequency (Galantowicz et al. 2011).

3.5.3 Vegetation

Microwave radiance has been used in the retrieving information about vegetation, including water content, canopy height, density, structure, and phenology (Calvet et al. 2011; Jones et al. 2011). Vegetation alters the soil emission through scattering and attenuation (Sibley et al. 1973; Eagleman et al. 1976), and very dense vegetation can completely obscure the soil MWE signal (Harrison et al. 2016). Vegetation acts as an attenuating and emissive layer above the soil, with characteristics

determined by its water content, geometric structure, and spatial distributions of stem (trunk, branch) and leaf components (Njoku et al. 2006) and canopy architecture (shape, orientation, density). Among these vegetation characteristics, the vegetation water content is most likely to affect the microwave radiation (Jackson et al. 1991; Calvet et al. 1995a; Wigneron et al. 1997).

In the tau-omega model, the emission emitted from a two-layer medium consists of the direct vegetation emission, the vegetation emission reflected by the soil and attenuated by the canopy layer, and the soil emission attenuated by the canopy. If the soil temperature and canopy temperature are assumed equal, the emissivity over a vegetated surface is theoretically given by

$$e_p = (1 - \omega_p)(1 - \gamma_p)(1 + \gamma_p \Gamma_{s_p}) + (1 - \Gamma_{s_p})\gamma_p \quad (3.3)$$

$$\gamma_p = \exp\left(-\frac{\tau_p}{\cos\theta}\right) \quad (3.4)$$

$$\tau_p = b_p W_c \quad (3.5)$$

where γ_p is the attenuation factor, ω_p is the single scattering albedo that depends on the vegetation structure and water content (Njoku et al. 2006), Γ_{s_p} is soil reflectivity, and τ_p is the optical depth and could be empirically related to the total vegetation water content $W_c(kg/m^2)$ using the so-called b_p parameter (Jackson et al. 1991; Wigneron et al. 1995).

A linear relationship between attenuation and vegetation water content (Jackson et al. 1991; Le Vine et al. 1996) also supports the effect of vegetation canopy on the microwave surface emission. However, the vegetation effect might be nonlinear and

suggested by a sharp increase, the leveloff and a decrease trend from the scatterplot of the emissivity and LAI (Ringerud et al. 2014). Moreover, the vegetation effect is supposed to be dependent on the vegetation types, climate regimes, and soil background (Hunt et al. 2011). Besides, the influence of polarization and vegetation structure is assumed to be weak for a randomly organized canopy, particularly at coarse scale satellite footprint resolutions (Turk et al. 2014). Under vegetated conditions, a flat or slight increase in emissivity with frequency is expected whereas a more dramatic increase in emissivity with frequency would be expected when vegetation is low.

3.5.4 Other factors

Precipitation modulates the emissivity dynamically. Emissivity might return back to its normal level approximately 2-3 days after the rain.

It is also suggested by other studies (Lin et al. 2000) that the reason why emissivities for cloudy scenes are lower than those for the clear-sky scenes is owing to the less evaporation from the underlying surfaces in the cloudy skies.

Liquid water in the form of dew or interception of precipitation by a vegetation canopy can also have observable effects on emission in the passive microwave regime. The dew effect typically covered over the vegetated surface is quite similar to that of soil moisture, whereby the water layer absorbs part of microwave radiation emitted from the soil and vegetation and reflected downwelling microwave radiation back into the atmosphere (Jackson et al. 1999; Lin et al. 2000). The water held by leaves after the rain can also increase the backscattering of microwave emission, which then gradually

drop to the normal levels as a result of the evaporation of the water on the leaf surfaces (Lin et al. 2000). Therefore, the absence of rainwater interception by vegetation can lead to an even larger decrease in emissivity after precipitation (Wigneron et al. 1996).

After reviewing and consider the possibility of effect of surface parameters on the variation of emissivity, our research works toward a dynamic emissivity database, especially uses these surface information (soil moisture, temperature and vegetation) to better characterized the surface emissivity under both cloud-free and precipitation scenes, to get a knowledge of the variability of the overland PMW emissivity under a variety of conditions. Our model might work in the rainy emissivity. This adjustment of the emissivity following precipitation events may provide a more realistic emissivity structure, for example, during or after sustained precipitation (where clear-scene emissivity retrievals are not designed to function) (Ferrazzoli et al. 2010; You et al. 2013).

4. Data and Methodology

4.1 Data

4.1.1 Emissivity data

The emissivity data used in this work are derived from the methodology (Turk et al. 2014), which is briefly recalled hereafter. A principal component (PC) analysis of a global emissivity dataset is performed over a variety of surface conditions. The emissivity PC structure is expressed as a function of nonlinear TB combinations and converted into the desired emissivity vector without any ancillary information of atmospheric profiles or surface temperature. There are several benefits coming with applying this technique. Firstly, it uses the brightness temperature as the only input so avoids using auxiliary data that might be low-quality. Secondly, emissivity adjustments are allowed in the PC space and the adjustments can be used to estimate the emissivity under precipitating scenes, in contrast to the other emissivity retrievals that are only valid for clear-sky cases. One example is shown in Figure 4.1.1. As is shown in Figure 4.1.1, the emissivity of the horizontally polarized channel is lower than the vertically polarized channels and the spatial variation of the horizontal polarized emissivity is more heterogeneous than that for the vertically polarized channels. Specifically for the 10GHz H channel, a very low region (blue dot) is located in the north Texas but this low-value region gradually diminishes for the 89GHz channel. And with the increasing frequency, the spatial variation, no matter for horizontally or vertically polarized emissivity, becomes more homogeneous, indicating being less prone to the surface heterogeneity.

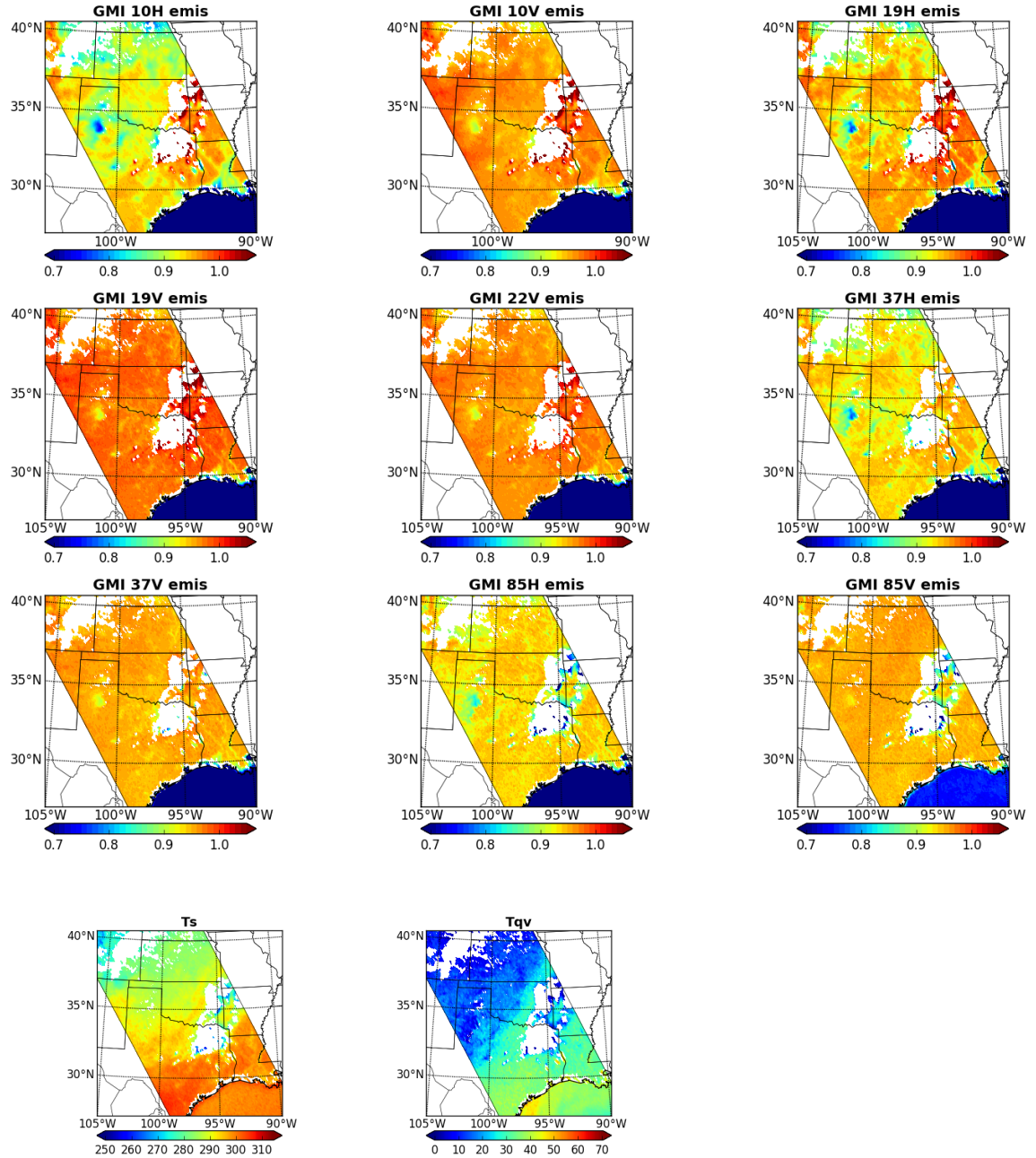


Figure 4.1.1 Example emissivity map from GMI on May 11, 2015

4.1.2 Soil Moisture data

As discussed above, SMAP L2 Radiometer Half-Orbit 36km EASE-Grid Soil Moisture (SPL2SMP) data is used for the statistical modeling of remotely sensed datasets.

4.1.3 Surface temperature data

For the purpose of consistency, the operational land surface model surface temperature product used as an ancillary data for the SMAP level 2 product is used herein (Ancillary Data Report: Surface Temperature). It is from the NASA Goddard Earth Observing System Model, Version 5 (GEOS-5) forward processing system. GEOS-5 is a near-real time atmospheric modeling and assimilation system (Lucchesi et al. 2013) that is of the same lineage as the NASA/GMAO global atmospheric reanalysis (MERRA). GEOS-5 currently provides data at 0.25 x 0.25 degree spatial resolution, which is similar to the spatial resolution of the SMAP level 2 soil moisture retrievals.

4.1.4 Vegetation indices

Two kinds of vegetation indices (VIs) are used: the normalized difference vegetation index (NDVI) and the enhanced vegetation index (EVI) from the Moderate Resolution Imaging Spectroradiometer (MODIS) (Justice et al. 1998; Justice et al. 2002). Vegetation Indices (VI) are empirical but robust indicators of the vegetation activity (Tucker et al. 1979; Huete et al. 2006b).

VIs product from MODIS are produced on 16-day intervals and at multiple spatial resolutions including 250 m, 500 m, 1 km and 0.05 degree spatial resolutions (Huete et al. 1999). In this research, both 250m-resolution MOD13Q1/MCD13Q1 and 500m-resolution MOD13A1/MCD13A1 are used for in-situ data modeling and remote sensing data modeling, respectively.

4.1.4.1 Physical basis for VIs

Vegetation indices are composite indicators of the vegetation canopy greenness, a property of the leaf area, leaf chlorophyll, canopy cover and canopy structure (Myneni et al. 1995; Huete et al. 2006a). And VIs can be used to estimate the canopy state variable (e.g., leaf area index, fraction cover) and canopy biophysical processes (e.g. photosynthesis, net primary production) (Huete et al. 2006b).

They are derived from daily, atmosphere-corrected, bidirectional surface reflectance in the red, near-infrared, and blue wavebands. They are designed to enhance the vegetation reflected signal from measured spectral responses by combining two (or more) wavebands, often in the red (0.6 - 0.7 μm) and NIR wavelengths (0.7-1.1 μm) regions (Huete et al. 1999). The NDVI product is the continuity index of the NOAA-AVHRR derived NDVI global dataset covering approximately 27-year (Huete et al. 2006b). The NDVI is commonly expressed as a normalized transform of the NIR to red reflectance ratio and designed to standardize VI values to between -1 and $+1$. EVI minimizes canopy-soil variations and is characterized by improved sensitivity over dense vegetation conditions or high biomass regions through a de-coupling of the canopy background signal and a reduction of atmosphere influences. The formula of the VIs can be written as follows (Rouse et al. 1973; Huete et al. 2002)

$$NDVI = \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + \rho_{red}} \quad (4.1)$$

$$EVI = 2.5 \frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + 6\rho_{red} - 7\rho_{red} + 1} \quad (4.2)$$

Both indices are positive with the presence of the vegetation and increase with the increasing vegetation density, while they are negative for the clouds, water and snow, and are near zero for the rock and bare soil (Felde et al. 1998). The difference between NDVI and EVI is that EVI depends on the near-infrared canopy reflectance that is less likely to saturate and can remain sensitive to the canopy greenness even in high leaf area index (LAI) canopies, especially for the forest regions (Huete et al. 2002; Thenkabail et al. 2015)

4.1.4.2 MODIS VIs algorithm

A higher temporal resolution can be achieved if each 16-day composite products from Terra and Aqua satellites are combined because the two satellite are identical and orbit eight days apart.

The reflected energy in the visible spectral region is quite low due to high absorption by photosynthetically active pigments, with maximum absorption values in the blue (470 nm) and red (670 nm) wavelengths. Nearly all of the near-infrared radiation (NIR) is scattered (reflected and transmitted) with very little absorption back, in a manner dependent upon the structural properties of a canopy (LAI, leaf angle distribution, leaf morphology). As a result, the contrast between red and near-infrared responses (called the red shift) is a sensitive measure of vegetation amount, with maximum red–NIR differences occurring over a full canopy and minimal contrast over targets with little or no vegetation. For low and medium amounts of vegetation, the contrast is a result of both red and NIR changes, while at higher amounts of vegetation, only the NIR contributes to increasing contrasts as the red band becomes saturated due

to chlorophyll absorption. Vegetation indexes are measures of the red-NIR contrast and thus are integrative functions of canopy structural (%cover, LAI, LAD) and physiological (pigments, photosynthesis) parameters (Huete et al. 1999; Friedl et al. 2002)

4.1.5 ISMN

In-situ measurements of soil moisture are typically used for validating the land surface models and satellite-based soil moisture retrievals. Therefore before using remote sensing soil moisture SMAP data, in-situ soil moisture measurements will be used in the analysis.

The international Soil Moisture Network (ISMN) collects and unifies soil moisture datasets from an assortment of individually operating in-situ networks and validation campaigns, and makes the data available through a centralized data portal (Dorigo et al. 2011). Appropriate and standardized quality control and assessment procedures are employed to resolve the inconsistency between sensor types, measurement quality and setup of different networks. ISMN has become recognized by many scientific communities as a dedicated platform for in-situ soil moisture measurements (Liu et al. 2011; Albergel et al. 2012; Gruber et al. 2013; de Jeu et al. 2015). Presently, approximately 50 networks including more than 2100 stations contribute to the ISMN dataset.

In this research, we need the simultaneous precipitation and soil temperature measurements along with soil moisture. Two networks named as Soil Climate Analysis

Network (SCAN) and United States Climate Reference Network (USCRN)(Bell et al 2013) satisfy such requirement. Both networks convey soil moisture data from different depths in the common volumetric soil moisture unit. Simultaneous measurement of precipitation and soil temperature are taken at the same depths as the soil moisture.

In SCAN, precipitation, snow water equivalent, air temperature, soil moisture, snow depth, and soil temperature at depths ranging from 2-cm to 2-meter are measured. The dielectric-constant-based soil moisture sensors such as Hydraprobe Analog, Hydraprobe Digital Sdi-12, and Hydraprobe Digital Sdi-12 Thermistor are used. Besides, 115 commissioned stations in USCRN measure the air temperature, precipitation, wind speed, global solar radiation, ground surface temperature, relative humidity, soil moisture and soil temperature at depths of 5-cm, 10-cm, 20-cm, 50-cm and 1-meter. The soil moisture sensor used is Stevens Hydraprobe II Sdi-12.

The location and landcover classification for the stations used in this study can be found in Figure 4.2.

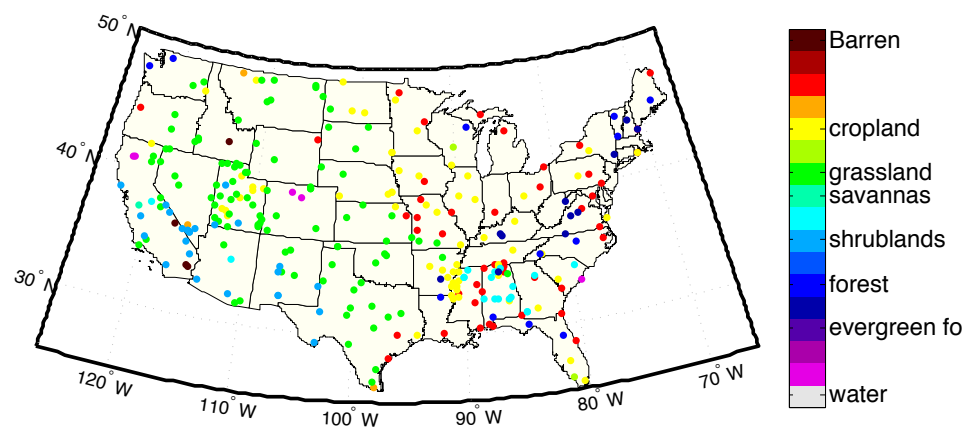


Figure 4.1.2 Land cover classification for the SCAN/USCRN stations

4.2 Methodology

Two dataset are constructed. The first data combines in-situ measurements and remotely sensed data. Specifically, emissivity data directly calculated from the GMI level-1 brightness temperatures and vegetation index from MODIS are remapped to match ground-based station measurements: hourly 5-cm soil moisture, air temperature and 5-cm soil temperature. The second dataset consists of purely remotely sensed data, with the emissivity data and MODIS vegetation index data matched with coincident and co-located SMAP overpasses. Differing from the first dataset, soil moisture/surface temperature data are obtained from SMAP.

Two surface classifications are applied to split the two datasets above. The first one is using a surface type index from the GMI level-2 product. It focuses on the maximum vegetated, high vegetated, moderate vegetated, low vegetated and minimal vegetated regions respectively. The other classification is based on the landcover classification from the International Geosphere-Biosphere Programme (IGBP) classification. Grassland, mixed forest and barren region are categories discussed herein.

The statistical modeling will be applied to these subsets individually. The analysis will be performed with the GAMLSS package in the R language. Generalized Additive Models for Location, Scale and Shape (GAMLSS) are (semi) parametric regression models, where all the variables of the assumed distribution for the response variable can be modeled with additive functions of the explanatory variables. The additive functions can be P-splines, Cubic splines, loess smoothing, ridge regression, lasso regression, simple random effects, varying coefficient models and so on. The

variables can be the mean, or other parameters of the distribution as linear parametric or additive non-parametric functions of the explanatory variables. The distribution for the response variable in GAMLSS can be chosen from a large number of distributions including highly skew or kurtotic continuous and discrete distribution. GAMLSS has been used in a variety of fields including actuarial science, biology, biosciences, energy economic, genomics, finance, fisheries, food consumption, marine research, medicine, meteorology and so on.

5. In-situ Measurement Perspectives

To analyze the effect of surface properties such as soil moisture, surface temperature (surface skin temperature or near-surface air temperature), vegetation structure, and vegetation phenology on the variability of the overland passive microwave (PMW) emissivity, a database of coincident and collocated in-situ-measurements of surface properties and satellite-derived emissivity is established following the methods discussed in section 4. The surface properties involved in this section include Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI).

Grassland, shrubland, forest, cropland are common types of land cover over the Contiguous United States (CONUS). They are characterized by different spatial and temporal variability of soil moisture and temperature. Provided the theoretical basis of PMW emissivity, the relationship between PMW emissivity and surface properties is supposed to vary from one land cover to another. And the research has shown that emissivity is sensitive to the landcover conditions (Norouzi et al. 2015). Therefore, in order to develop an understanding of the similarities and differences of PMW emissivity over different types of land cover, the emissivity for each land cover should be studied individually first.

Herein, in-suit measurements from a number of stations are used to analyze the behavior of emissivity over grassland, forest and barren regions. Grassland dominates central North America and thus is one of our primary research targets. It is recognized as prairies and grass is the main vegetation. Due to a relative lack of precipitation, trees

are scarce. Grassland embraces the apparent seasonal trends and the growing season ranges from spring to fall.

In order to investigate the role of vegetation in the variability of PWM emissivity, the land cover of forest is also taken into consideration and serves as a reference. Contrasting forest and grassland will be used to illustrate the exclusive effect of vegetation on modulating the variability of overland PMW emissivity. Besides, different types of trees coexist in the forests, which can help us study the influence of vegetation height and structure.

Another kind of surface, the barren region with little vegetation, will also be considered to study the scenario that is characterized by the strong microwave signals resulting from soil moisture and surface temperature and by the negligible signals from the vegetation.

Among the hundreds of stations in ISMN (as shown in Figure. 4.3), three stations (Abrams, MammothCave and Stovepipe-Wells-1-SW) are selected in our study (see Figure 5.1.1). Abrams is located in the North of Oklahoma and is a typical station over the grassland of the U.S. Great Plain. MammothCave station is located in the MammothCave National Park and represents the forest land cover. And Stovepipe-Wells-1-SW station is near Death Valley National park and represents the barren area land cover short of vegetation. All the data is from March 4, 2014 to May 20, 2016. The sample size that is equivalent to the number of the in-situ measurement matched up with GMI overpasses for these three stations is shown in the Table 5.1. The temporal variation of soil moisture, diurnal variation of soil temperature and air temperature together with the seasonal variation of NDVI/EVI are shown in the Figure 5.1.2. For

soil moisture, data of the time period from April 1, 2014 to March 30, 2015 is shown and the variation is random and mostly subjective to precipitation events. For soil temperature and air temperature, data of the time period from September 1, 2014 to September 30, 2014 is plotted and the figures for the temperatures reveal the apparent diurnal variation. At 00:00 UTC, the soil temperatures always reach the peaks, then decrease until around 15:00UTC and then recover. For the NDVI/EVI, data of the time period from February 2014 to May 2016 is plotted, demonstrating the clear seasonal variation according to the phenomena that the higher vegetation indices tend to occur during the summers and the early autumns.

Table 5.1 Station information

Station	Landcover type	Sample Size
Abrams	Grassland	383
MammothCave	Forest	364
Stovepipe-Wells-1-SW	Barren region	432

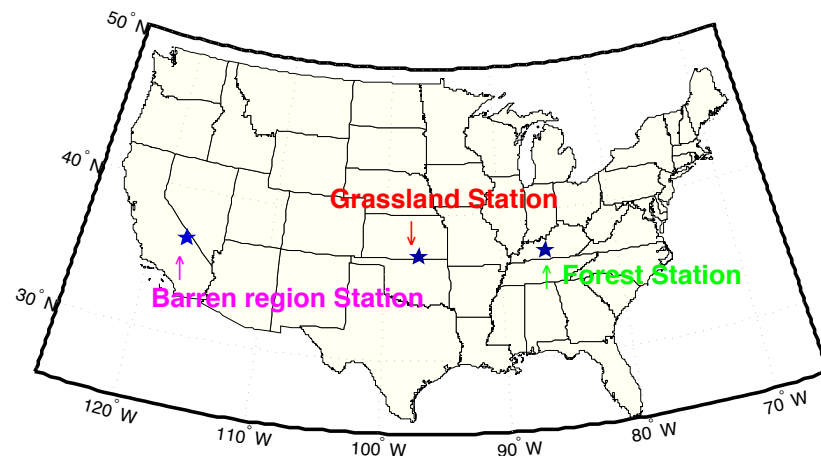
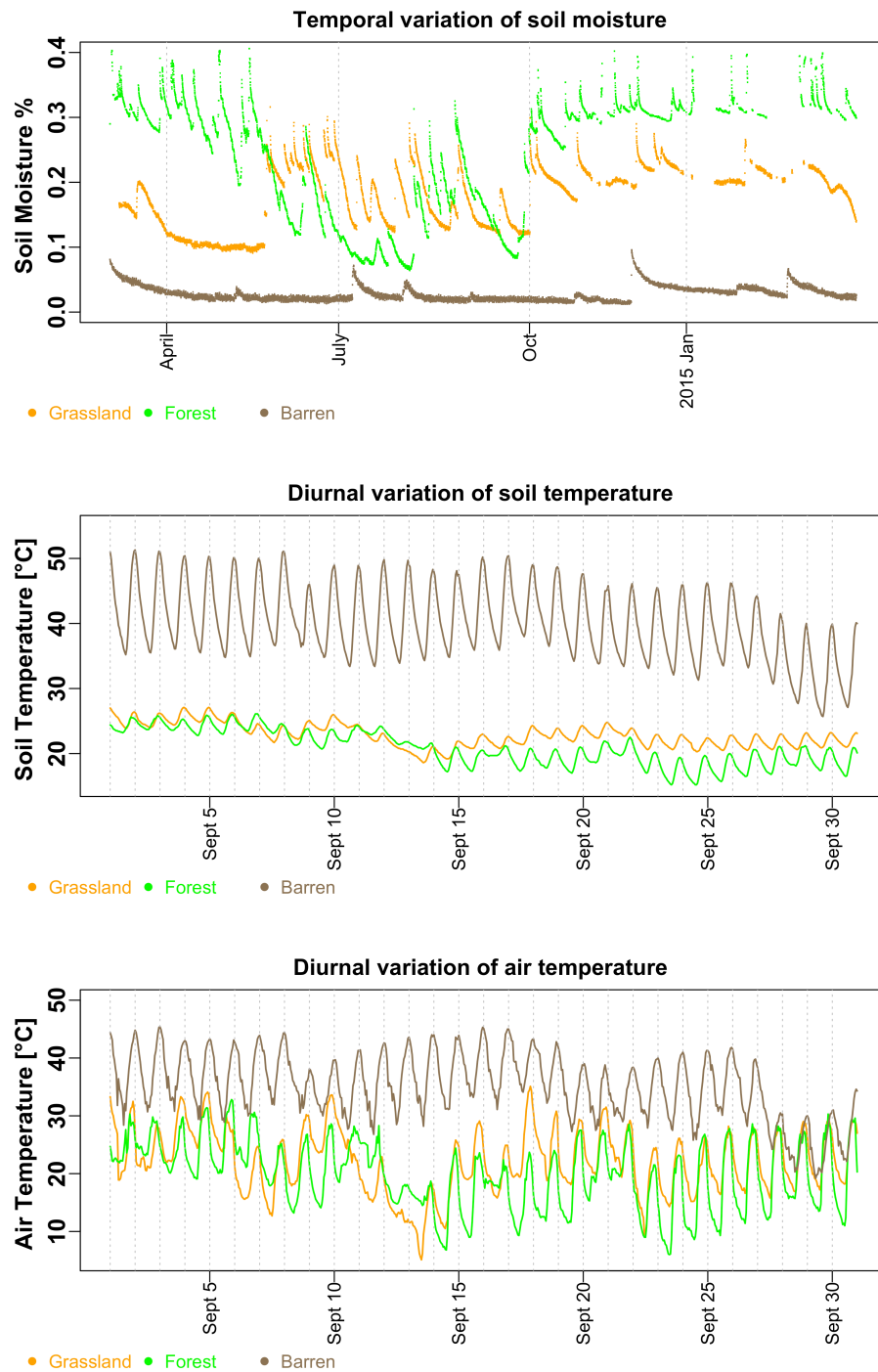


Figure 5.1.1 Locations of Grassland station-Abrams, Barren region station-
Stovepipe well and Forest station-Mammothcave



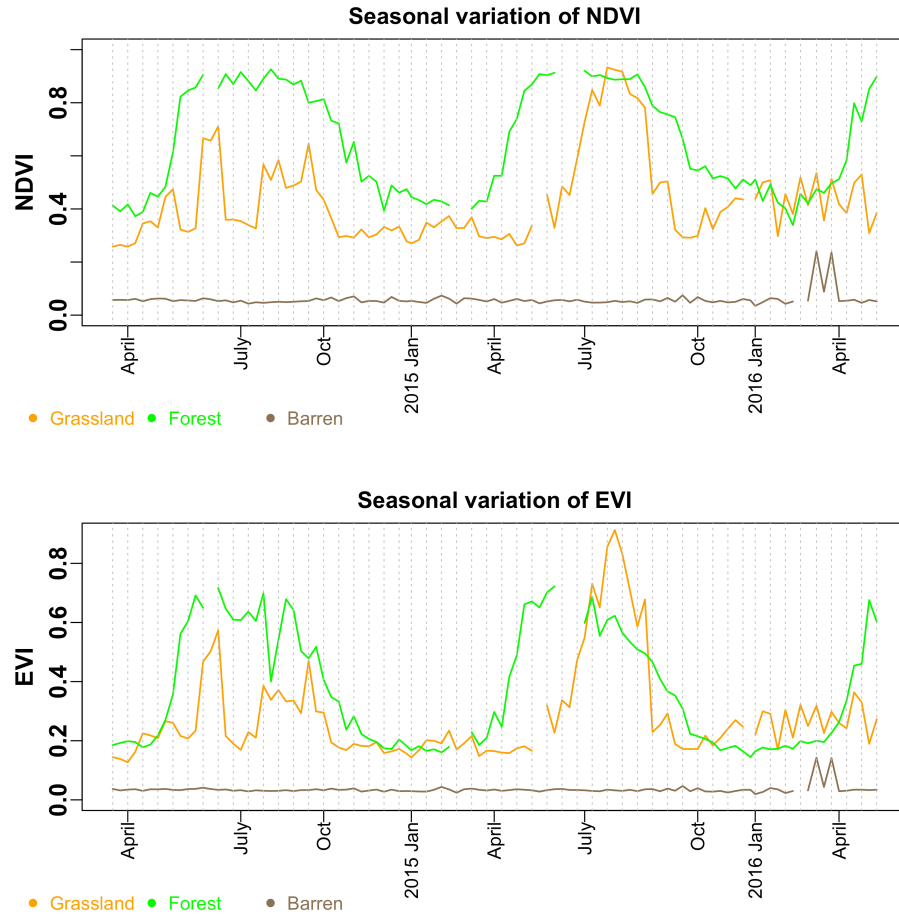


Figure 5.1.2 Temporal variation of soil moisture (upper), diurnal variation of soil temperature (Second) and air temperature (third) and seasonal variation of NDVI (fourth) /EVI (bottom)

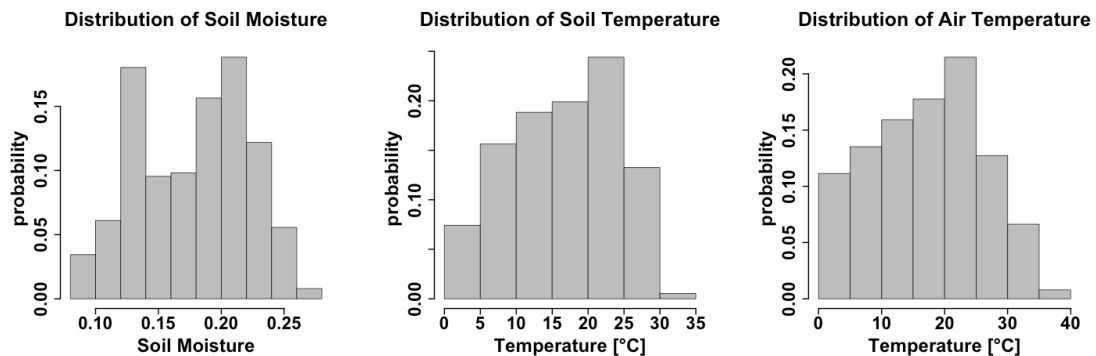
The study on the PMW emissivity for the grassland, forest and barren region will be discussed as follows in section 5.1.1, 5.1.2 and 5.1.3, respectively.

5.1 Grassland

Unconditional distributions of soil moisture (SM), soil temperature (ST) at 5-cm depth, 2-meter height air temperature (AT), vegetation indices (VIs) including

Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) are shown in Figure 5.1.2. The soil moisture ranges from 0.1 to 0.25. Frozen soil layer conditions are kept out of the scope of our study. Therefore, soil temperature and air temperature discussed herein are above zero Celsius degree. Most of soil temperatures are less than 30°C while most of air temperatures are within the range from 0°C-35°C, indicating a larger variability of near surface air temperature and that soil has a larger heat capacity. The air temperature is highly correlated with the soil temperature because the near surface soil layer is strongly affected by the atmosphere. The detection depth of the PMW high-frequency channels is less than 5-cm and soil temperatures at depth less than 5-cm are most likely to have temperatures bounded by that of the 5-cm soil temperature and the near-surface air temperature. Therefore both soil temperature and air temperature are involved in our research. Emissivity might require both information from soil temperature and air temperature to some extent.

NDVI ranges from 0.3 to 0.8 while EVI ranges from 0.2 to 0.6. Typically the value of EVI is smaller than NDVI. Both vegetation indices are kept in our research because NDVI and EVI are believed to represent the vegetation activity from different perspectives, as we discussed the difference between NDVI and EVI in the section 4.1.4.



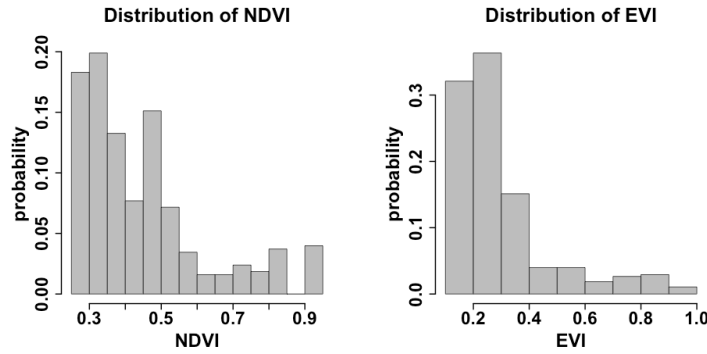


Figure 5.1.3 Distribution of Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) at the Abrams grassland station

We propose here a novel approach to estimate emissivity. The dependency of emissivity with soil properties is analyzed to identify factors directly impacting the distribution of probable emissivity values. The purpose is to generate probabilistic emissivity in acknowledgement of the possible range of values that might exist. A novel aspects is that it helps identify general levels of uncertainty associated with emissivity estimates.

The relationship between the surface properties and “true” emissivity is acknowledged to contain many factors that arise from environmental, observational and algorithmic influences. This is conceptually described by relating the surface properties to a distribution of possible precipitation emissivity (Figure 5.1.4). The distribution depends on the conditioning by the aforementioned factors. The spread of the distribution - and associated uncertainty - can be attributed to factors not explicitly considered in the conditioning. Note that there is theoretically no “wrong” or “biased” estimate whatever the conditioning is, since it still reflects the actual distribution of

possible emissivity values under these conditions. The output distribution of emissivity is broader when considering fewer factors. It is better defined with less uncertainty (along with the expected precipitation rates) with including additional conditioning factors. This approach assumes that the relationship between surface properties and distribution of emissivity is representative and stationary, and that the emissivity can be evaluated with reasonable accuracy.

The soil properties-to-emissivity uncertainty approach overcomes challenges encountered in previous works. It allows a more complete description of the emissivity error estimation because error information is included into the distribution moments. By design, this formulation yields unbiased estimates with respect to the emissivity used to build the distribution. The diagnostic power and prognostic capabilities of factors are preserved. This enables deriving stationary characterization to be potentially generalized over large areas or periods of time for emissivity modeling. Other factors rather than the surface properties considered here have a potential influence on the distributions and will be considered in the conditioning in future studies.

5.1.1 Single-parameter modeling

Emissivity is assumed a function of surface properties (soil moisture, soil temperature, air temperature, vegetation etc.).

$$E = E(SM, ST, AT, VI, etc.) \dots\dots\dots (5.1)$$

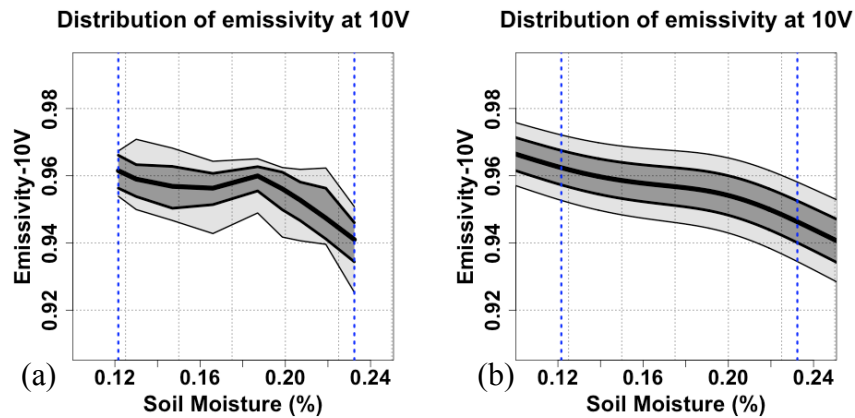
Due to the complex nature of emissivity, a robust and accurate emissivity model is much likely to be multi-parametric on the basis of these surface variables. However we start with a single-parameter modeling approach in an attempt to investigate the

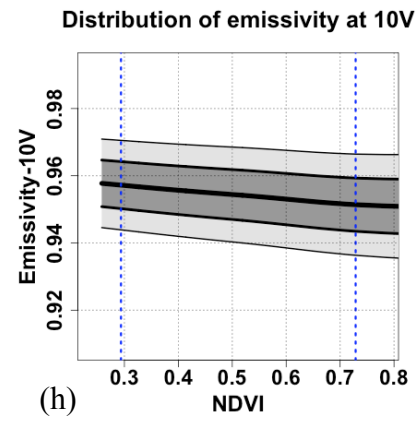
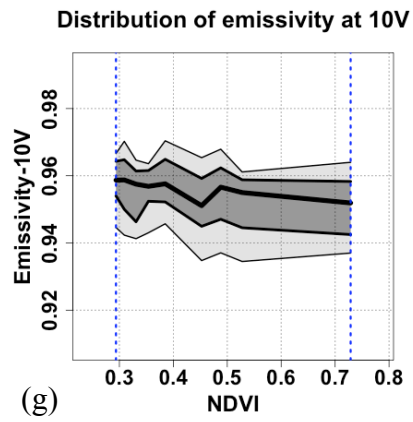
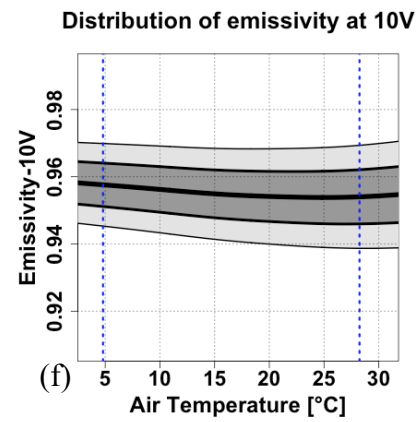
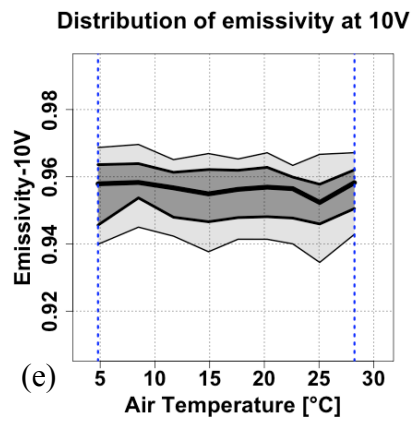
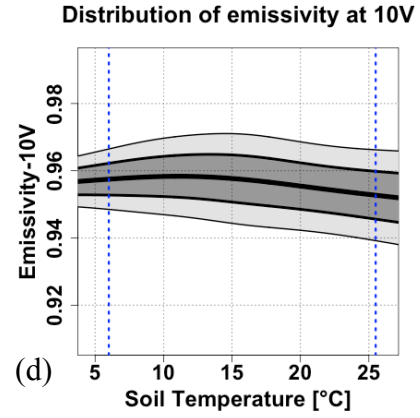
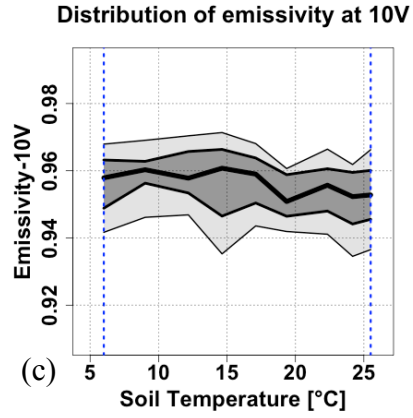
individual effect of each surface property on the emissivity. Taking soil moisture for example, it is assumed that emissivity can be a function of soil moisture solely.

$$E = E(SM) \quad (5.2)$$

The empirical model is established on the concept of conditional probability distribution function. The empirical model of emissivity as a function of soil moisture is shown in the first line on the left column in Figure 5.1.3. The 50%, 25-75%, and 10-90% quantiles have been computed for the emissivity distributions at 10V-GHz and are plotted in the figure. Empirical models of the emissivity conditioned by other surface properties are shown in other plots on the left column of Figure 5.1.3.

Panel (a) in Figure 5.1.4 shows a shift toward lower emissivity as the soil moisture increases in line with expectations. The spread of each distribution remains quite constant across the range of soil moisture values. This feature indicates constant uncertainties in quantifying the emissivity with increasing soil moisture. The 10V-GHz emissivity also decreases slightly with the increasing soil temperature, air temperature or vegetation indices. However, the decreasing trend from SM-SPM holds the sharpest slope, thus it is inferred that the soil moisture is a primary factor accountable for the variation of 10V-GHz emissivity.





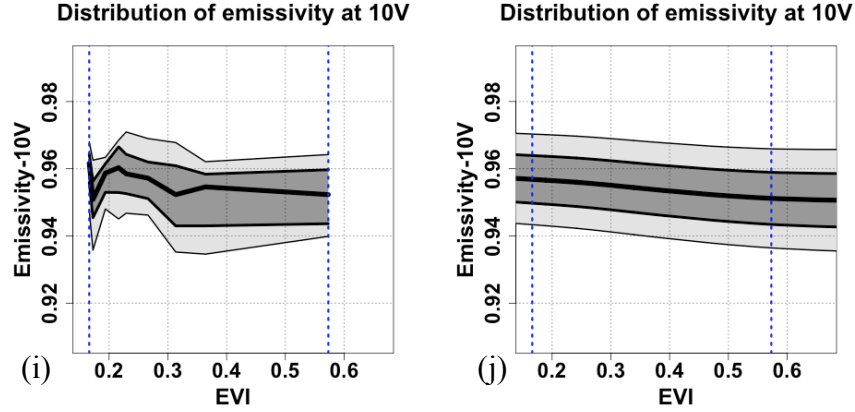


Figure 5.1.4 Empirical (left) and statistical (right) single parameter models of 10V-emissivity as a function of soil moisture in a) and b), soil temperature in c) and d), air temperature in e) and f), NDVI in g) and h) and EVI in i) and j) over Abrams grassland station. The thick white line represents the median (50% quantile), the dark gray-shaded region represents the area between the 25% and 75% quantiles, the light gray-shaded region represents the area between the 10% and 90% quantiles. The dotted blue line represents the range of surface property values

Probabilistic emissivities computed in this study are modeled from the conditional distribution of emissivity for a given set of surface conditions. For example, the statistical model as a function of soil moisture can be expressed as follows,

$$PDF(Emissivity) = Function(SM) \quad (5.3)$$

Probabilistic emissivities computed in this study are modeled from the conditional distribution of emissivity for a given set of surface conditions. The conditional distribution parameterized to a simple theoretical model. For the sake of formulation efficiency, a number of conditional densities with the first two moments as parameters are considered here: the mean describing the average surface property -

emissivity relationship and the standard deviation. This eases analyzing the dependence with each factor and generating ensembles of emissivities. We assume the distribution has the same parametric form for all surface conditions by using the generalized additive models for location, scale, and shape approach (GAMLSS; Rigby et al. 2005). To evaluate the most appropriate model, the goodness-of-fit has been checked by investigating different parametric density fits (e.g., normal, lognormal, gamma, Weibull, logistic, etc.) for emissivity subsamples corresponding to the neighborhood of a selected surface property bin. Such checks have been performed for different surface property values. The distributions of emissivity were generally found to be uni-modal and symmetric, making the Gaussian model appropriate. More complex models could be evaluated, such as mixtures of distributions to improve the flexibility of the distribution model. These would be justified if additional factors driving the distribution features were considered. These aspects will be analyzed in future studies. In this prototype study, we strike a balance between model complexity, accuracy, and efficiency.

Additional tests on the emissivity distributions were performed on the whole dataset for each precipitation type by using the GAMLSS technique. Generalized linear models for location, scale, and shape aim at modeling the parameters of a response variable's distribution (emissivity) with the following assumptions: 1) emissivity is a random variable following a known distribution with density $f(emissivity|\mu, \sigma)$ conditional on the parameters (μ, σ) and 2) the emissivity observations are mutually independent given the parameter vectors (μ, σ) . Each parameter is a function of surface properties using monotonic (linear/nonlinear or

smooth) link functions. The emissivity trends for each parameter are fitted using cubic splines with three degrees of freedom. A variety of two-parameter distributional forms (not shown) were also tested. The goodness-of-fit on the whole dataset has been checked for each of the density fits by investigating the Akaike information criteria (AIC), computing the residuals, first four moments, their Filliben correlation coefficient, and quantile-quantile plots (Stasinopoulos et al. 2007). The results confirmed the findings above that the normal model is most appropriate for describing the variability exhibited by the data. Using the distributions, the location parameter μ is related to the deterministic component of the surface properties - emissivity relationship and the scale σ is related to the variability of this relationship. Both depend on the magnitude of the surface variables, e.g. in order to account for the shift toward lower emissivity with soil moisture (Figure 5.1.4a). These models are compact and simple as described with rather simple mathematical expressions, which minimizes computational costs.

The modeled conditional distributions of emissivities are plotted for each surface variable in Figure 5.1.4 left. Note that the models enable (supervised) extrapolation outside the range of the predictors in the training datasets. Five different single-parameter models were obtained, and referred as soil moisture single-parameter model (SM-SPM), soil temperature single parameter model (ST-SPM), air temperature single-parameter model (AT-SPM), NDVI single parameter model (NDVI-SPM) and EVI single-parameter model (EVI-SPM)

$$PDF(Emissivity) = Function(ST)$$

$$PDF(Emissivity) = Function(AT) \quad (5.4)$$

$$\text{PDF(Emissivity)} = \text{Function(NDVI)} \quad (5.5)$$

$$\text{PDF(Emissivity)} = \text{Function(EVI)} \quad (5.6)$$

These models present visual consistency with empirical conditional distributions, and particularly account for the proportionality of emissivity uncertainty. They can be used to analyze the distribution of emissivity. For example for a given value of soil moisture, the corresponding probability distribution function (Figure 5.1.5) yields the mean, median, standard deviation, or other quantiles and statistical parameters providing qualitative and quantitative information on the emissivity.

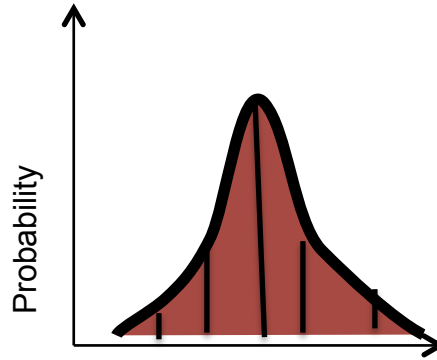


Figure 5.1.5 Probability distribution function derived from statistical models

A representative surface property - emissivity relationship can be extracted from the conditional distributions. In case of a normal distribution the mean can be considered for deterministic estimates. As shown in the Figure 5.1.6, the correlation coefficient between the emissivity derived from the observed data and the expected emissivity using the soil moisture single-parameter statistical model is above 0.6. However, the correlation coefficients derived with using other single parameter models

are significantly lower. In these cases, the predicted emissivity has a smaller range of variation compared to the observed emissivity.

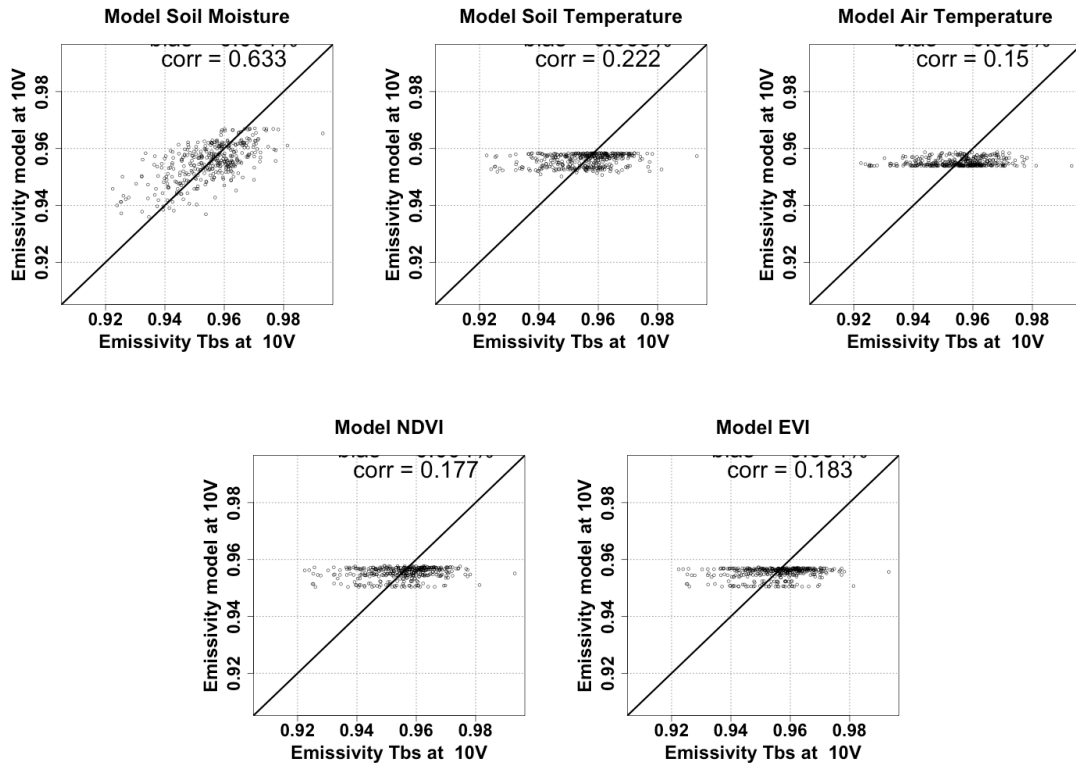


Figure 5.1.6 Scatter plot of emissivity derived from observed data and emissivity predicted using single-parameter statistical model over Abrams grassland station

The statistical models of the emissivity for other channels than 10V-GHz as a function of soil moisture are shown in Figure 5.1.7. First, PMW emissivity behaves differently in the high-frequency channels than the low-frequency channels. Emissivity from channels at 10 GHz, 19 GHz, 23 GHz and 37 GHz exhibits a notable decreasing trend with the soil moisture. The lower the frequency, the more significant the variation of emissivity is found. However, the emissivity at the 89V-GHz channel shows a slight increasing trend and no significant trend at the 89H-GHz channel. It indicates that the

soil moisture conditions to a larger extend the variation of low-frequency channel emissivity but exerts little influence at the high-frequency channels.

Secondly, the emissivity of the horizontally polarized channels demonstrates larger variations than at the vertically polarized channels. Typically, the horizontally polarized channels have emissivity ranging from 0.85 to 0.96 while the vertically polarized channels have emissivity varying from 0.93 to 0.98.

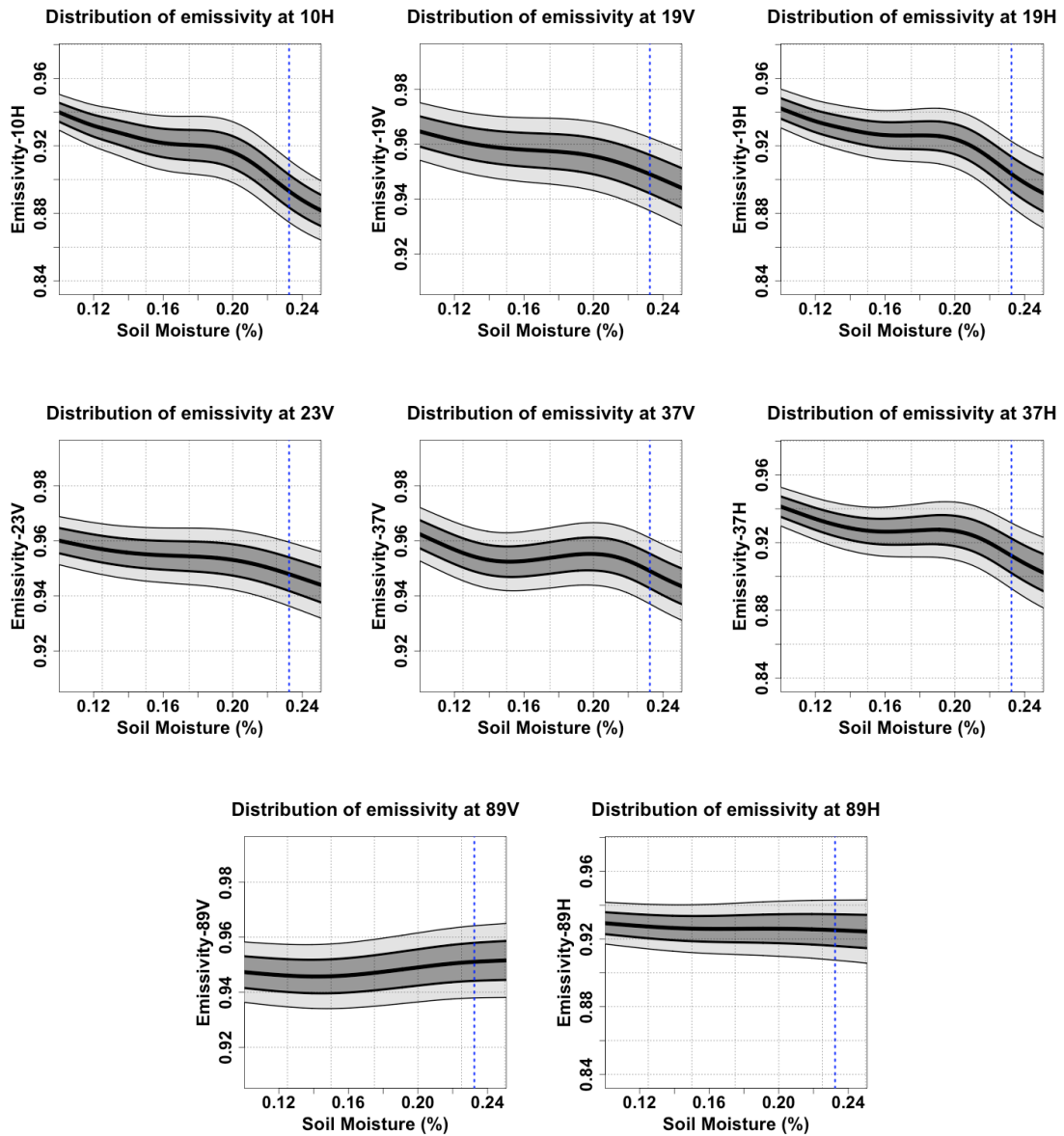


Figure 5.1.7 Statistical modeling of all channel emissivity as a function of soil moisture over Abrams grassland station

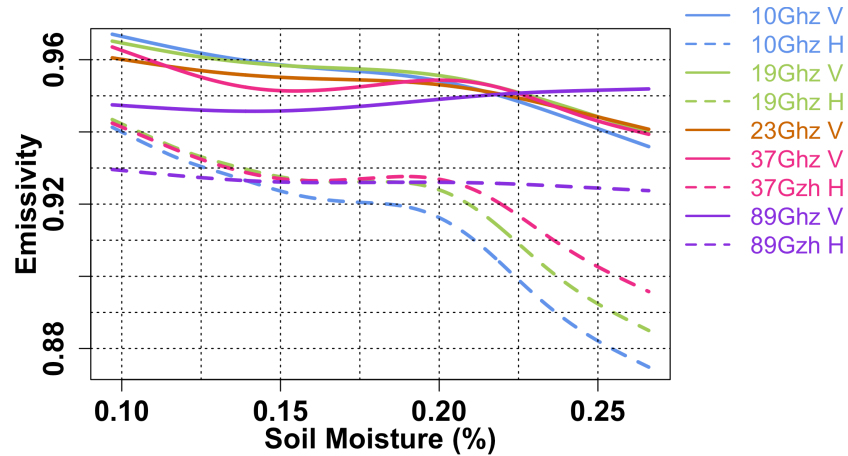


Figure 5.1.8 Statistical model for single-parameter models over different channels

These findings are summarized in Figure 5.1.8 showing the expected emissivity values from the SM-SPM over all the channels. It clearly illustrates that emissivity at both vertically and horizontally polarized channels at 10 GHz, 19 GHz and 37 GHz exhibit a decreasing trend with soil moisture. The decreasing trends of emissivity are more pronounced for the horizontally polarized channels. Emissivity at the 89H-GHz channel does not change obviously with soil moisture while emissivity at 89V-GHz shows a slight increasing trend with the soil moisture.

5.1.2 Multi-parameter modeling

After investigating the individual contributions of each surface property to the PMW emissivity variability over grassland, multi-parameter models are established as shown in Figure 5.1.9.

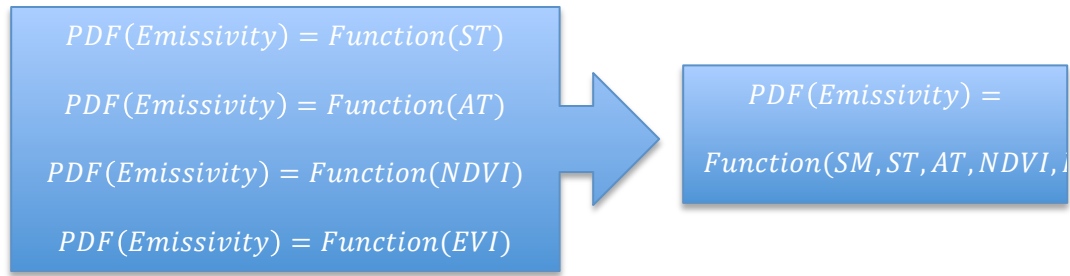


Figure 5.1.9 Framework of the transition from Single-Parameter Modeling to Multi-Parameter Modeling

Various combinations of surface properties that condition the emissivity are tested as shown in Table 5.2. Corresponding models are coded as following: number 1 refers to soil moisture, with number 2 for soil temperature, number 3 for air temperature, number 4 for NDVI and number 5 for EVI. For instance, the SM-SPM is referred as Mod 00001, and the two-parameter model using SM and ST is referred as Mod 00012.

Table 5.2 Different combinations of variables

Single-parameter model	Two-parameter model	Three-parameter model	Five-parameter model
SM—Mod	SM+ST—Mod	SM+ST+NDVI—	SM+ST+AT+

00001	00012	Mod 00124	NDVI+EVI
ST—Mod 00002	SM+AT—Mod 00013	SM+ST+EVI— Mod 00125	—Mod 00124
AT—Mod 00003	SM+NDVI—Mod 00014	SM+AT+NDVI— Mod 00134	
NDVI—Mod 00004	SM+EVI—Mod 00015	SM+AT+EVI— Mod 00135	
EVI – Mod 00005			

The 10V-GHz observed emissivity data are compared with the modeled emissivity from the tested multi-parameter models with correlation coefficients. From Figure 5.1.10, the correlation coefficients of multi-parameter models are higher than single parameter models. The model including all surface properties presents the highest correlation coefficient. Soil moisture contributes significantly to the PMW 10V-GHz emissivity variability for the grassland station and the impact of other surface properties is limited.

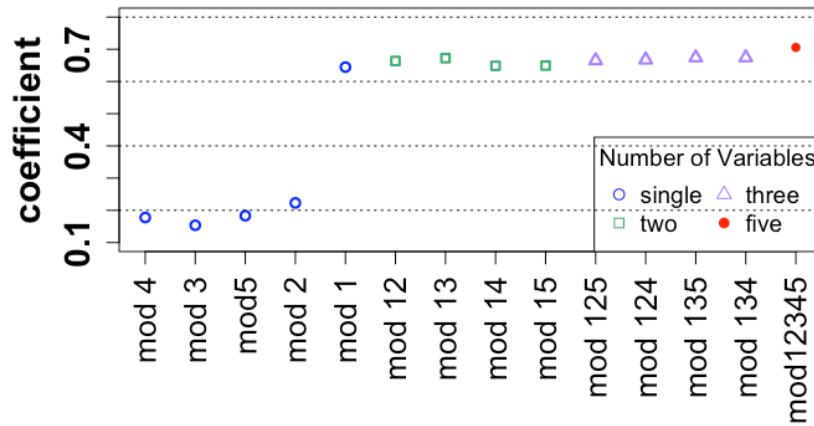


Figure 5.1.10 Correlation coefficients between the 10V-GHz emissivity derived from observed data and 10V-GHz emissivity predicted using single-parameter statistical model over Abrams grassland station

Figure 5.1.11 presents the correlation coefficients for all channels. It reveals that the higher the frequency, the lower the correlation coefficient. It indicates that as expected, the modeling for the Abram grassland station consistently performs better at the low-frequency channels. For example, while correlation coefficients up to 0.8 are found in the lower frequency channels correlation is lower than 0.5 for the high-frequency channel emissivities. Besides, except at 89 GHz, the correlation coefficients from the horizontally polarized channels are higher than those of the vertically polarized channels.

For the single-parameter models and the 10-GHz and 19-GHz channels, the model using soil moisture exhibits a significantly higher correlation coefficient than the models using other parameters. However, for the 37V-GHz channel and 89V-GHz channel the highest correlations are found with using the soil temperature as predictor instead of soil moisture. More analysis is needed to elucidate this behavior.

For the two-parameter models and specifically the 10H-GHz channel, the correlation from models using the combination of soil moisture and soil temperature or the combination of soil moisture and air temperature is higher than that of the models using the combination of soil moisture and vegetation indices. However, for the 37-GHz channels, the combination of soil moisture and soil temperature leads to higher correlation. It indicates that the role of air temperature becomes weaker at high-frequency channel. On the other hand, the model using the combination of NDVI and soil moisture has close correlation coefficient as the model using the combination of EVI and soil moisture. So for the grassland, there is no significant difference between the role of NDVI and EVI in the variation of PMW emissivity.

The correlation is very similar across the three-parameter models at 10-GHz and 19-GHz channels. Regarding the 37-GHz emissivity, the models including only air temperature have lower correlation coefficients than models including only soil temperature. It indicates that two-parameter models that include the soil temperature instead of air temperature achieve a better performance for 37-GHz channel emissivity.

At all channels emissivity models achieve highest correlation with all five-parameters. We might conclude that the more information regarding surface properties, the more accurate the emissivity model can be.

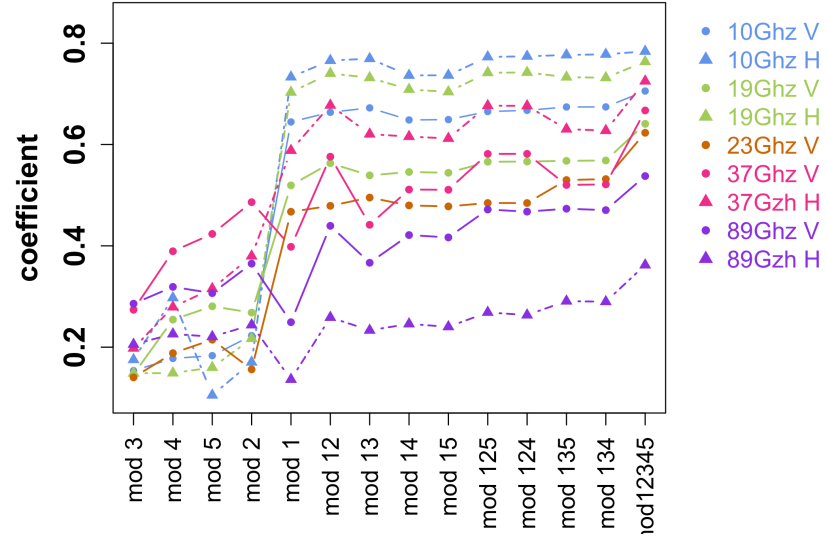


Figure 5.1.11 Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted using single-parameter statistical model over Abrams grassland station

In addition to deterministic predictions, the associated uncertainty can be extracted from the models. Uncertainty can be defined on a basis of the conditional quantiles.

$$\varepsilon = 100\% \times \frac{q_{90} - q_{10}}{q_{50}} \quad (5.7)$$

where, q_{10} , q_{50} and q_{90} represent the 10%, 50% and 90% quantiles derived from PDFs. Cumulative distribution function (CDF) of uncertainty are plotted in the Figure 5.1.12. As expected single-parameter models have larger uncertainty except the model using soil moisture. ST-SPM or AT-SPM exhibits smaller uncertainty than NDVI-SPM or EVI-SPM, confirming the findings using the correlation. For the two-parameter models, the model using the combination of soil moisture and vegetation indices has larger uncertainty than that using soil moisture and soil/air temperature, indicating again

that vegetation is less important than temperature. As expected, the model using all five parameters (SM/ST/AT/NDVI/EVI) has the smallest uncertainty.

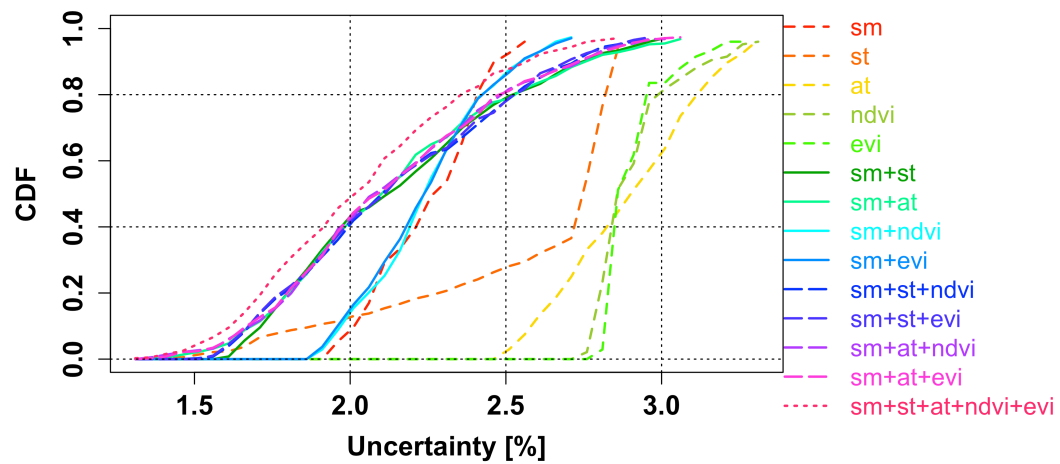


Fig 5.1.12 Cumulative distribution function of uncertainty for 10V GHz emissivity over
Abrams grassland station

The CDFs of uncertainty for other channels are calculated as well. The best models for each channel are indicated in Table 5.3.

Table 5.3. Best model and their correlation coefficient for all the channels for Abrams
grassland station

Channel	Best model	Correlation coefficient
10GHz V	Mod 12345	0.7056
10GHz H	Mod 12345	0.7839
19GHz V	Mod 00012	0.5685
19GHz H	Mod 12345	0.7635

23GHz V	Mod 12345	0.6232
37GHz V	Mod 12345	0.6672
37GHz H	Mod 12345	0.7251
89GHz V	Mod 12345	0.5377
89GHz H	Mod 12345	0.3621

5.1.3 Prediction

Here after we consider the model including all surface variables. Since observations are taken continuously at hourly intervals, time series of emissivity distribution can be generated at the Abrams station. It represents highly complementary information since satellite observations are available only during overpasses separated by lengthy revisit times. Figure 5.1.13 shows the time series of predicted emissivity at the yearly, monthly and daily time scales.

As mentioned in section 5.1.1, supervised extrapolations can be performed outside the range of the predictors in the training dataset. In particular the training is performed under clear air conditions because emissivity is not available when it rains from satellite. The distribution of emissivity is predicted under rainy conditions using the surface conditions sampled by the station sensors.

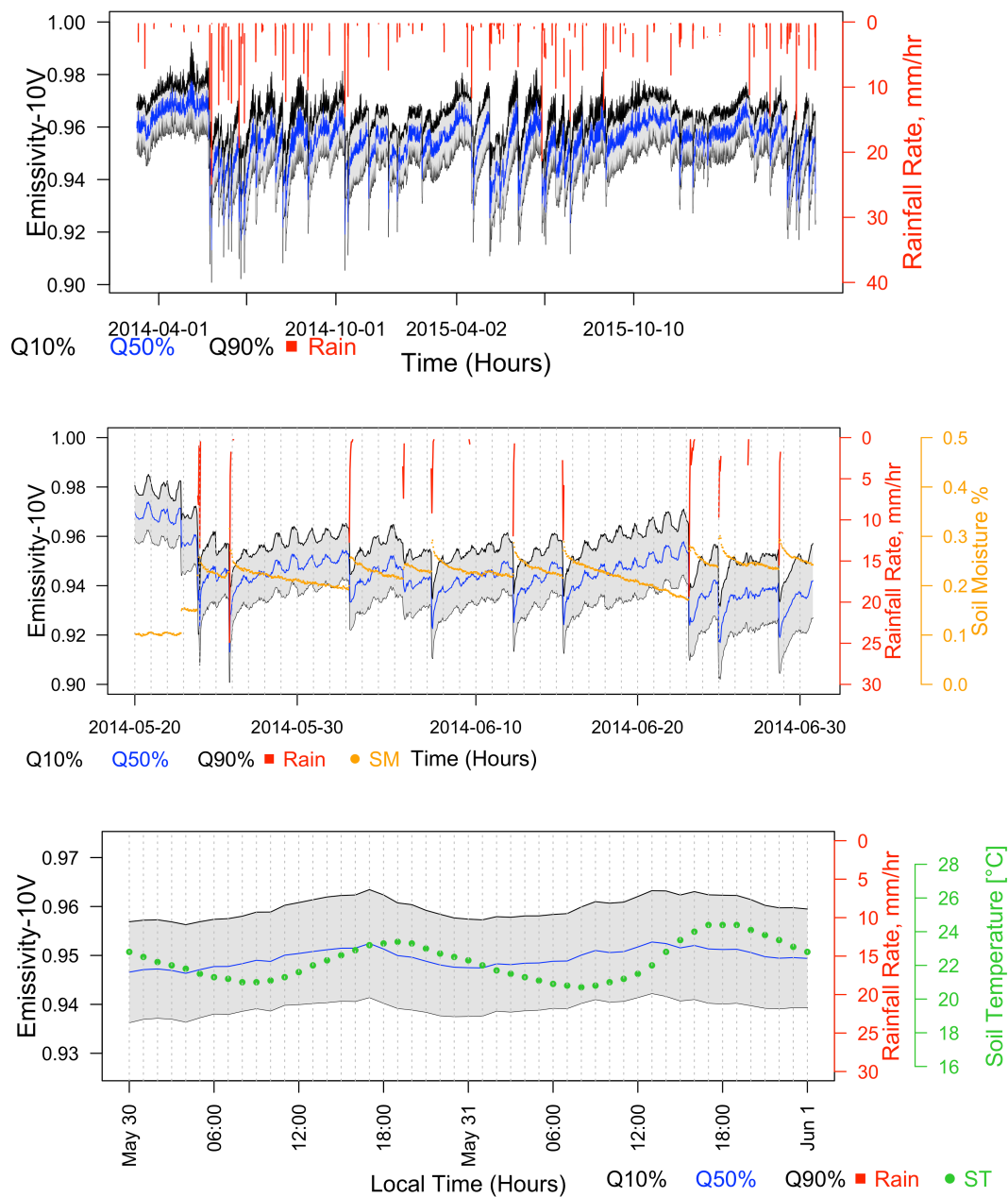


Figure 5.1.3 Prediction of 10V GHz hourly emissivity over Abrams grassland station from 2014, March to Feb 2016 (upper plot), and from May 20, 2014 to June 30, 2014 (middle plot), May 30 00:00 to June 1 00:00 (local time) (bottom plot)

The yearly scale highlights the impact of precipitation on the emissivity. Emissivity decreases rapidly and by a large magnitude during rain events regardless of seasonality. The emissivity gradually returns back to its previous level during the subsequent dry period. The recovery typically takes several days during which it does not rain. Sometimes, before reaching the antecedent level, the emissivity would experience a more rapid decline in case of occurrence of a rain event. At the monthly scale it is apparent that more significant drops are associated to higher rainfall rates. It is expected that the near surface layer becomes more saturated and that the soil moisture increases with higher rainfall rates. As an example rainfall rate on May 26th is higher than on May 24th. Correspondingly, the drop of emissivity on May 26th is larger than on May 24th. The decrease of emissivity also depends on the time interval of two precipitation events.

In addition to precipitation, the diurnal variation of emissivity is illustrated on the middle and bottom plots. In general emissivity increases during daytime then decreases during nighttime, probably with the soil and air temperatures. A combination of physical surface properties, mainly soil moisture and temperature, drives the fluctuations of emissivity at various scales over grassland.

5.1.2 Forest

The distributions of the five surface parameters are shown in Figure 5.2.1. Differing from the Abrams grassland station, the soil moisture has a larger variation ranging from 0.05 to 0.3. As expected the forest station is characterized by higher vegetation indices with NDVI from 0.4 to 0.95 and EVI from 0.15 to 0.75.

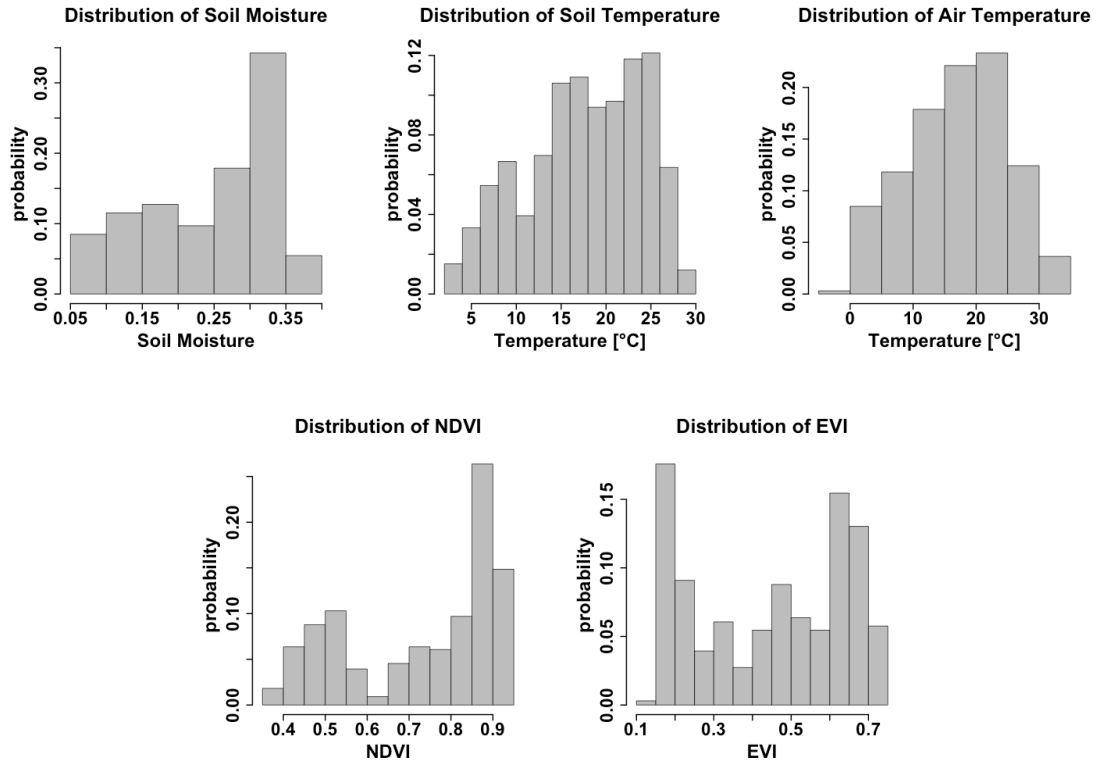


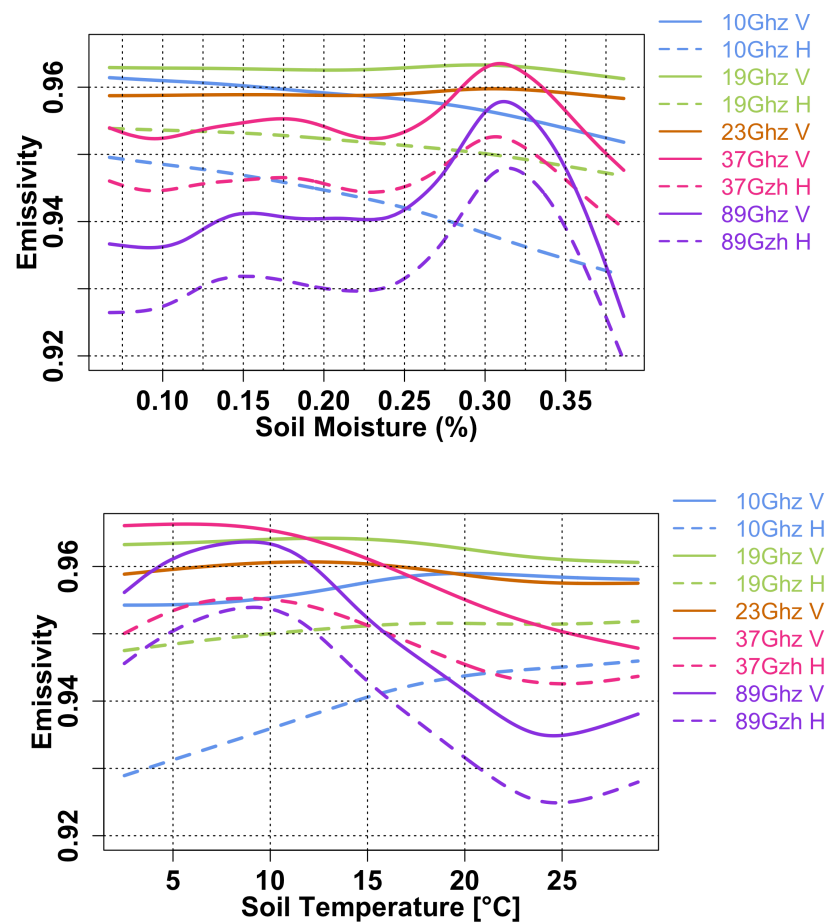
Figure 5.2.1 Distribution of Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) over Mammoth cave forest station

5.2.1 Single parameter modeling

Following a similar analysis to section 5.1 the SM-SPM, ST-SPM, AT-SPM, NDVI-SPM and EVI-SPM models are established for the forest station and presented in the Figure 5.2.2.

For SM-SPM, emissivities of 37 GHz H/V and 89 GHz H/V increase with soil moisture up to 0.3, reaching a peak around 0.325, followed by a rapid decrease. It indicates that a wetter soil tends to be associated with a higher emissivity at high-frequency channels, but a combination of influences not explicitly indicated by the 1D

conditioning may explain this behavior. For the low-frequency horizontally polarized channels such as 10 GHz H and 19 GHz H, the emissivities decrease with soil moisture similar to the Abrams grassland station. However, for the low-frequency vertically polarized channel such as 10 GHz V and 19 GHz V, the emissivities do not change significantly with soil moisture. Emissivities at the high-frequency channels decrease with frequency while the emissivities of the low-frequency channels increase with frequency.



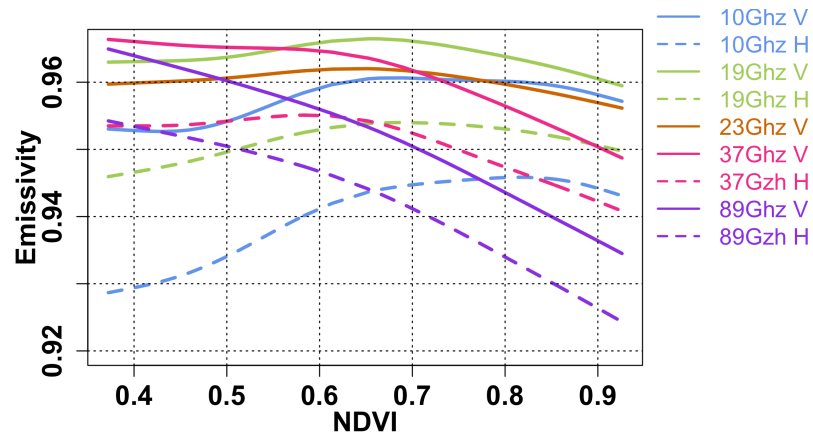


Figure 5.2.2 Statistical model for single-parameter models over different channels for Stovepipewell barren region station; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot) and NDVI single parameter model (bottom plot)

Regarding the ST-SPM model, emissivities at high-frequency channels (37 GHz and 89 GHz) increase with the soil temperature up to approximately 8°C, then decrease with soil temperature until 25°C. In contrast, emissivities at 10-GHz channel increase with soil temperature when soil temperature over the range 0°C to 25°C. The 10H-GHz emissivity experiences a sharper increase than that of 10V-GHz emissivity.

When soil temperature falls to the range 15°C-30°C, the emissivities from both horizontally and vertically polarized channels except 10 GHz decrease with higher frequency while the emissivities at 10-GHz channel are lower than those of 19-GHz channel. When the soil temperature is lower than 15°C, emissivities at 10-GHz channel are lower than those at 19-GHz while emissivity at 89-GHz channel is lower than that of 37-GHz channel.

For the NDVI-SPM model, the emissivities from the 37-GHz and 89-GHz channels decrease with the increasing NDVI, which means that the vegetation effect contributes to the variation of emissivities at the high-frequency channels. Oppositely, 10H-GHz emissivity increases with NDVI, and the 10V-GHz emissivity slightly increases with the NDVI and then slightly decreases. By comparison, we infer that the vegetation indices contribute substantially to the variation of emissivity at the higher frequency channels. Like the SM-SPM model, lower emissivity is found in the 89-GHz channels and 10-GHz channels.

Trends shown by channel-emissivity derived from AT-SPM are similar to ST-SPM and the trends from NDVI-SPM are similar to EVI-SPM.

5.2.2 Multi-parameter modeling

Like for the Abrams station, multi-parameter models are established for Mammoth Cave Forest station as well. They are evaluated through correlation coefficients computed between the observed emissivities and the predictions in Figure 5.2.3. For the single-parameter models and low-frequency channels, NDVI-SPM and EVI-SPM have higher correlation coefficients than the other three SPMs. It confirms the impact of vegetation on the emissivity. Moreover, the correlation coefficient of NDVI-SPM is higher than that of EVI-SPM. However, for the single-parameter models and high-frequency channels, the NDVI-SPM, EVI-SPM and ST-SPM have the higher correlation coefficients. It is noted that AT-SPM does not have correlation coefficient as high as the ST-SPMs. NDVI is a primary factor explaining the variation of emissivities

from high frequency to low frequency channels, while soil temperature contributes to the emissivity of high-frequency channels.

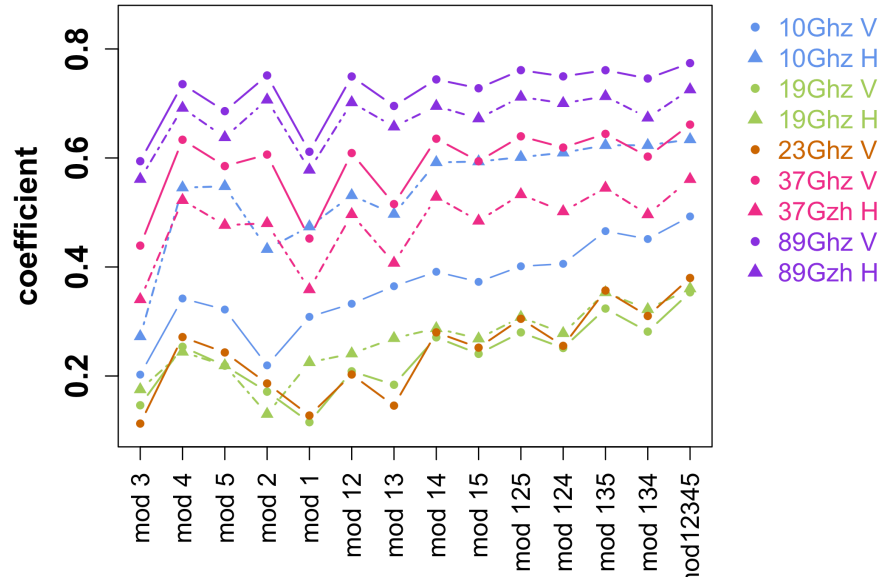


Figure 5.2.3 Correlation coefficients between predicted emissivity using statistical models and the emissivity derived from observation data for all models over all the channels in the Mammoth Cave forest station

For the two-parameter models, the correlation coefficients of the model based on the combination of SM and ST, SM and NDVI, SM and EVI are higher than the model using the combination of SM and AT. It likely indicates that air temperature is not important in the emissivity model over the forest surface. The near surface air temperature is probably more modulated by the vegetation than over grassland.

For the three-parameter models, the models including EVI such as Mod 125 and Mod135 have higher correlation coefficients than models involving NDVI such as Mod 124 and Mod 134. Hence EVI plays a more important role than NDVI. Such conclusion

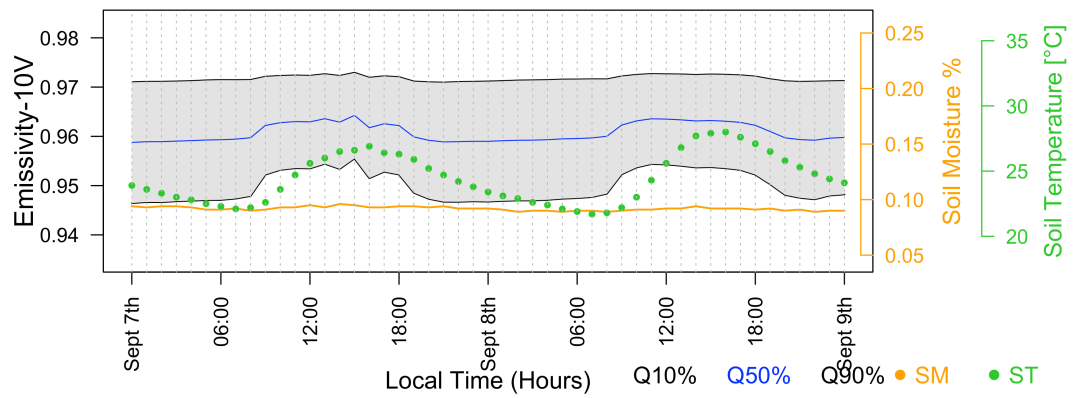
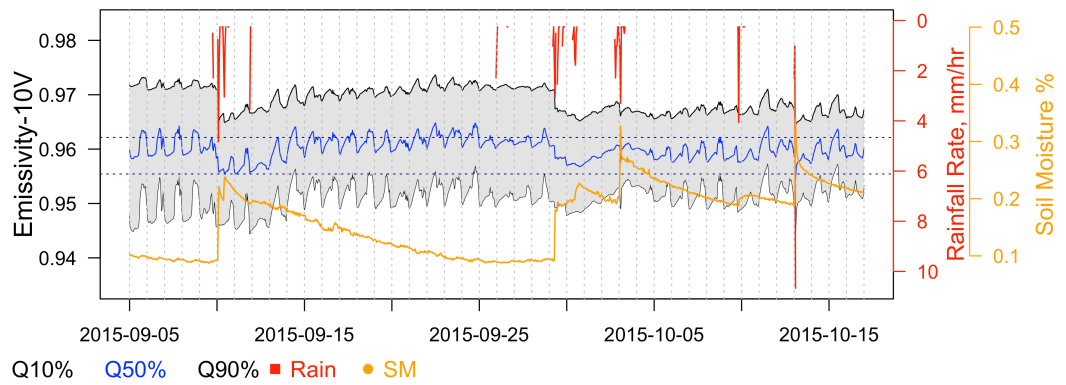
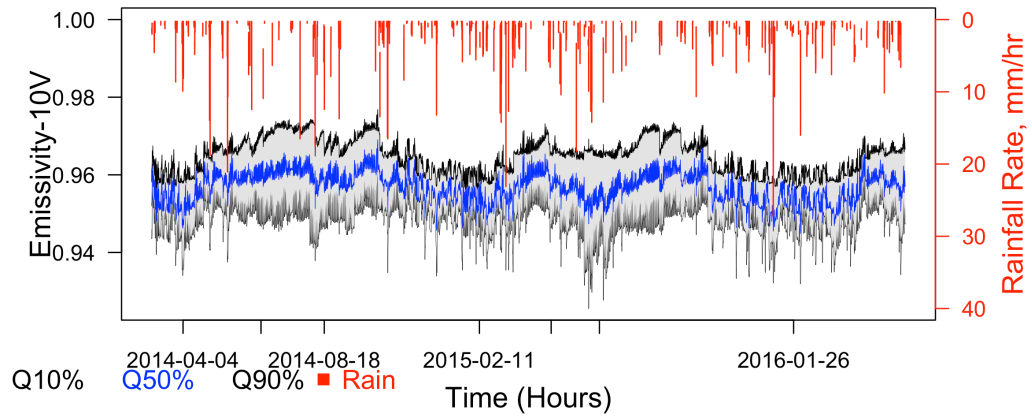
contradicts the conclusion from the single-parameter model, again because a combination of influences is not explicitly shown by the 1D conditioning.

As expected, the model making use of all the surface properties exhibits the highest correlation coefficient for all the channel-emissivity. It can be noted that Mod2 has as high correlation coefficient as MOD12345 for the 89-GHz channel, meaning that the surface temperature is accountable for the most variation of emissivity at 89GHz channel. In contrast, Mod 4 has as high correlation coefficient as Mod 12345 for the 37-GHz channels, which suggests the primary role of NDVI in the variation of emissivity at 37-GHz channel.

Table 5.4 Best models and their correlation coefficient for all the channels over Mammothcave forest station

Channel	Best model	Correlation coefficient
10GHz V	Mod 12345	0.4927
10GHz H	Mod 12345	0.6340
19GHz V	Mod 00134	0.3237
19GHz H	Mod 00134	0.3533
23GHz V	Mod 12345	0.3798
37GHz V	Mod 00014	0.6353
37GHz H	Mod 00134	0.5450
89GHz V	Mod 12345	0.7740
89GHz H	Mod 00124	0.7120

5.2.3 Prediction



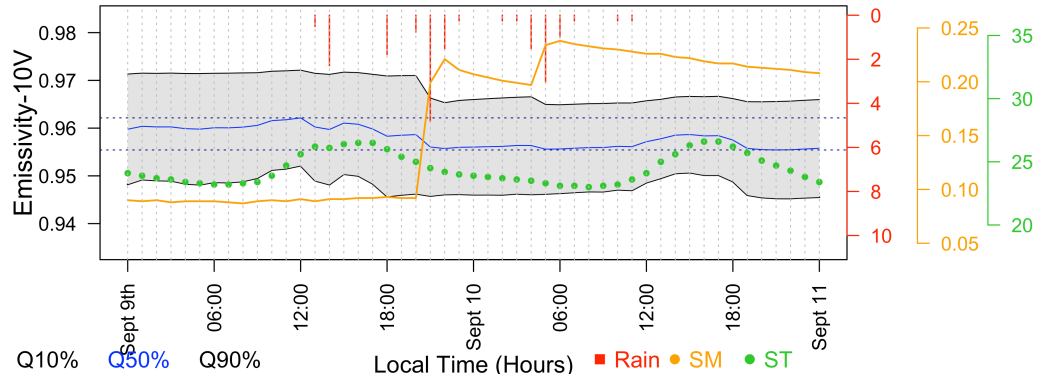


Figure 5.2.4 Prediction of 10GHz V hourly emissivity over MammothCave forest station from 2014, March to Feb 2016(upper plot), and from Sept 5, 2015 to Oct 16, 2015(middle second plot), Sept 7th 00:00 to Sept 9th 00:00 (local time)(middle third plot), Sept 9th 00:00 to Sept 11th 00:00 (local time)(bottom plot)

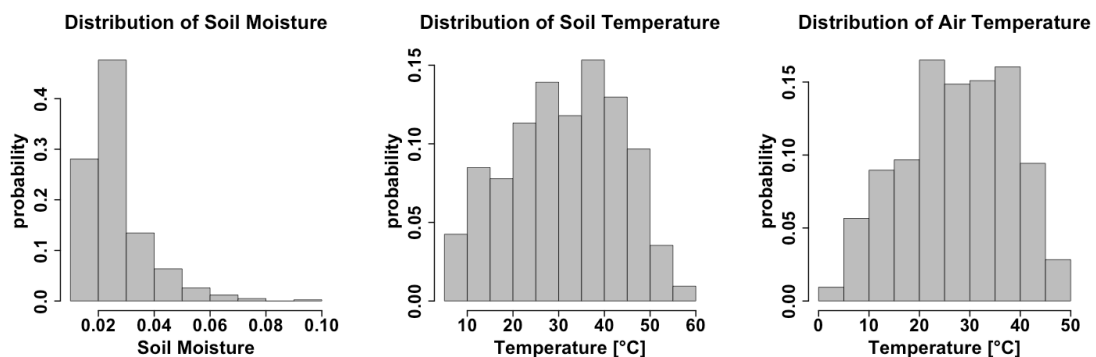
As expected, precipitation occurs over the forest regions. From the long-term perspective (the upper plot in Figure 5.2.4), the emissivity declines every time it rains and a remarkable decline occurs under the condition of heavy precipitation. Emissivity likely decreases when precipitation events are more frequent. The second plot clearly exhibits the diurnal variation of emissivities. When it rains, the soil moisture increases rapidly and then gradually decreases, while the emissivity decreases rapidly and then gradually increases.

The bottom two plots show a non-rainy cases and rainy case, respectively. For the non-rainy case, emissivity increases after the sunrise and decreases after the sunset, which corresponds to the diurnal variation associated to surface soil temperature. For the forest, the soil moisture remains quite stable during the dry period and its effect on emissivity is not significant. In contrast, the diurnal variation of PMW emissivity during

the period undergoing continued precipitation is strongly affected by both soil moisture and soil temperature. For instance, it rained at 2pm on September 9, 2015 on the MammothCave station and the emissivity decreased slightly. It rained again on 9pm and the emissivity decreased again and remained in the lower level compared to the non-rainy value. The diurnal variation of emissivity is controlled by the surface temperature and these rapid changes of emissivity correspond to the rapid changes of soil moisture, which in most cases are caused by the precipitation.

5.3 Barren Region

Discussion on barren region station is presented as follows. From Figure 5.3.1, the soil moisture in Stovepipewell station ranges from 0.01 to 0.04, NDVI narrows around 0.05 and EVI around 0.03. The soil moisture, NDVI and EVI in barren region is nearly one order of magnitude smaller than the forest station.



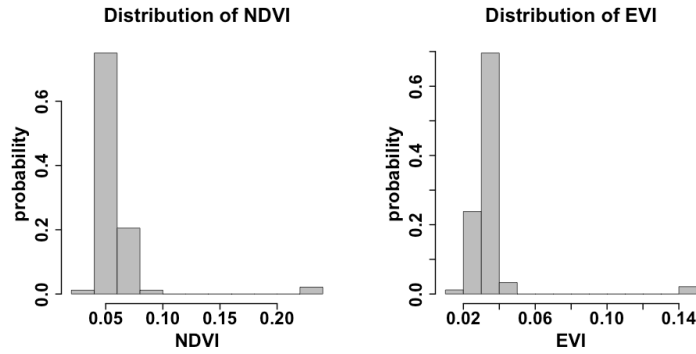


Figure 5.3.1 Distribution of Soil Moisture (SM), Soil Temperature (ST), Air Temperature (AT), Normalized Differential Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) over Stovepipewell barren region station

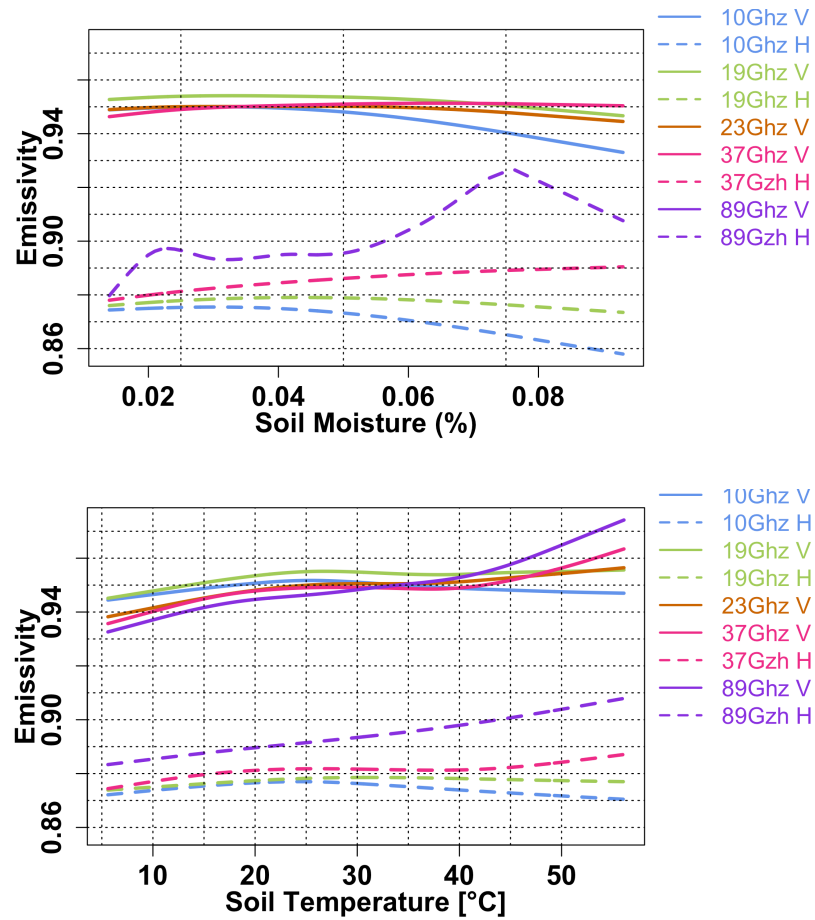
5.3.1 Single parameter modeling

For the barren region, the difference of emissivity between the vertically polarized channels and the horizontally polarized channels is more evident. As opposed to the plots for grassland and forest, there is almost no overlap between the emissivity from the horizontally polarized channels and vertically polarized channels. Typically, emissivities from horizontally polarized channels are around 0.88 while emissivities from vertically polarized channels are around 0.94.

For SM-SPM, the emissivity at 10H-GHz decreases with soil moisture. However given the low and narrow range of soil moisture values, the decreasing trend for 19H-GHz and 37H-GHz is minimal. The emissivity at 89H-GHz channel increases with the soil moisture. Moreover, the horizontally polarized emissivity increases with frequency, so the emissivity at the 89H-GHz channel is greater than at lower-frequency channels. On the other hand, the emissivity from 10V-GHz channel decreases with the

soil moisture, while emissivities from the other three vertically polarized channels are almost overlapped and shows a slight decreasing trend with soil moisture.

For ST-SPM, as for SM-SPM the emissivities from horizontally polarized channels are separated from these of the vertically polarized channels. The high-frequency emissivities derived from ST-SPM generally increase with soil temperature while the emissivities at 10-GHz channel slightly decrease with the soil temperature.



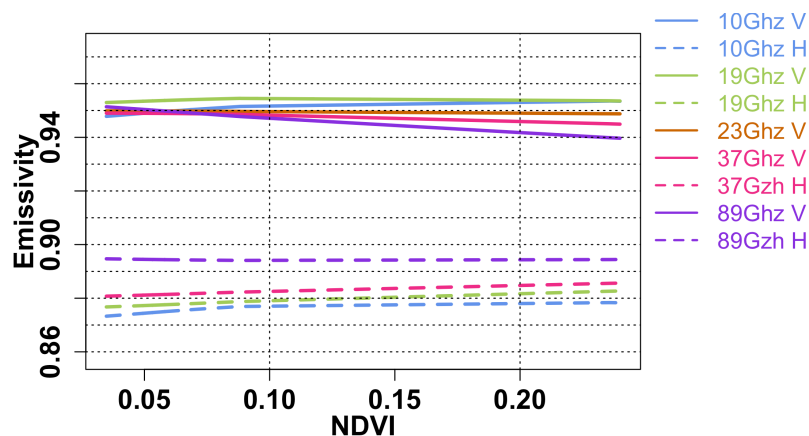


Figure 5.3.2 Statistical model for single-parameter models over different channels; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot) and NDVI single parameter model (bottom plot)

Regarding NDVI-SPM, because of the low and narrow range of NDVI values the emissivities from all the channels do not change significantly with NDVI. It is expected because of the low and narrow range of NDVI values for barren regions.

5.3.2 Multi-parameter Modeling

Evaluation of models with correlation coefficient is illustrated in Figure 5.3.3. For the single parameter models, the correlation coefficients of NDVI-SPM and EVI-SPM are very low due to the lack of vegetation in the barren region. The correlation coefficients of the models including soil temperature are quite similar to those of model including the air temperature. It indicates that the role of soil temperature and air temperature makes little difference in this context.

Similar to the previous discussion, for the low-frequency channels (10-GHz and 19-GHz), the correlation coefficients decrease with higher frequencies, while for the

high-frequency channels (37 GHz and 89 GHz), the correlation coefficients increase with higher frequencies. Surprisingly, the correlation coefficient for 89V-GHz channel emissivity model is near 0.6. The correlation coefficients for the emissivity at the vertical polarized channels are greater than those for the horizontal polarized channels, except the 10-GHz channel.

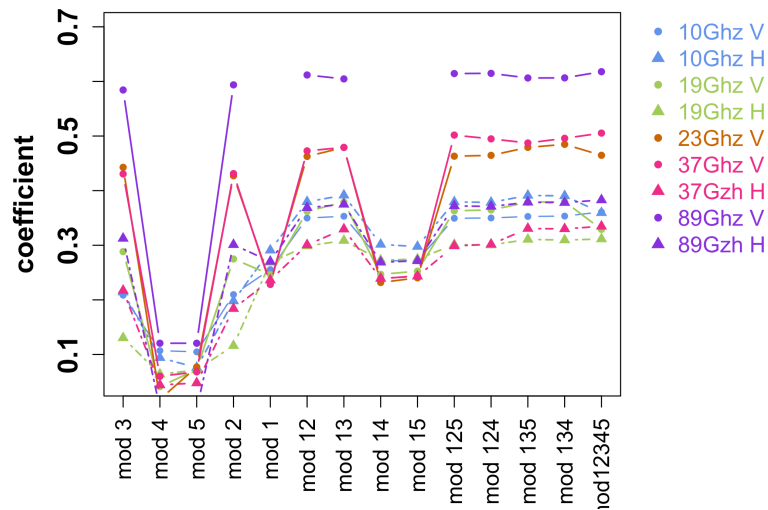


Figure 5.3.3 Correlation coefficient between predicted emissivity and the emissivity derived from observation data for all models over all the channels in the Stovepipewell barren region station

Table 5.5 Best models for all the channels and their correlation coefficients

Channel	Best model	Correlation coefficient
10GHz V	Mod 125	0.351
10GHz H	Mod 135	0.3905

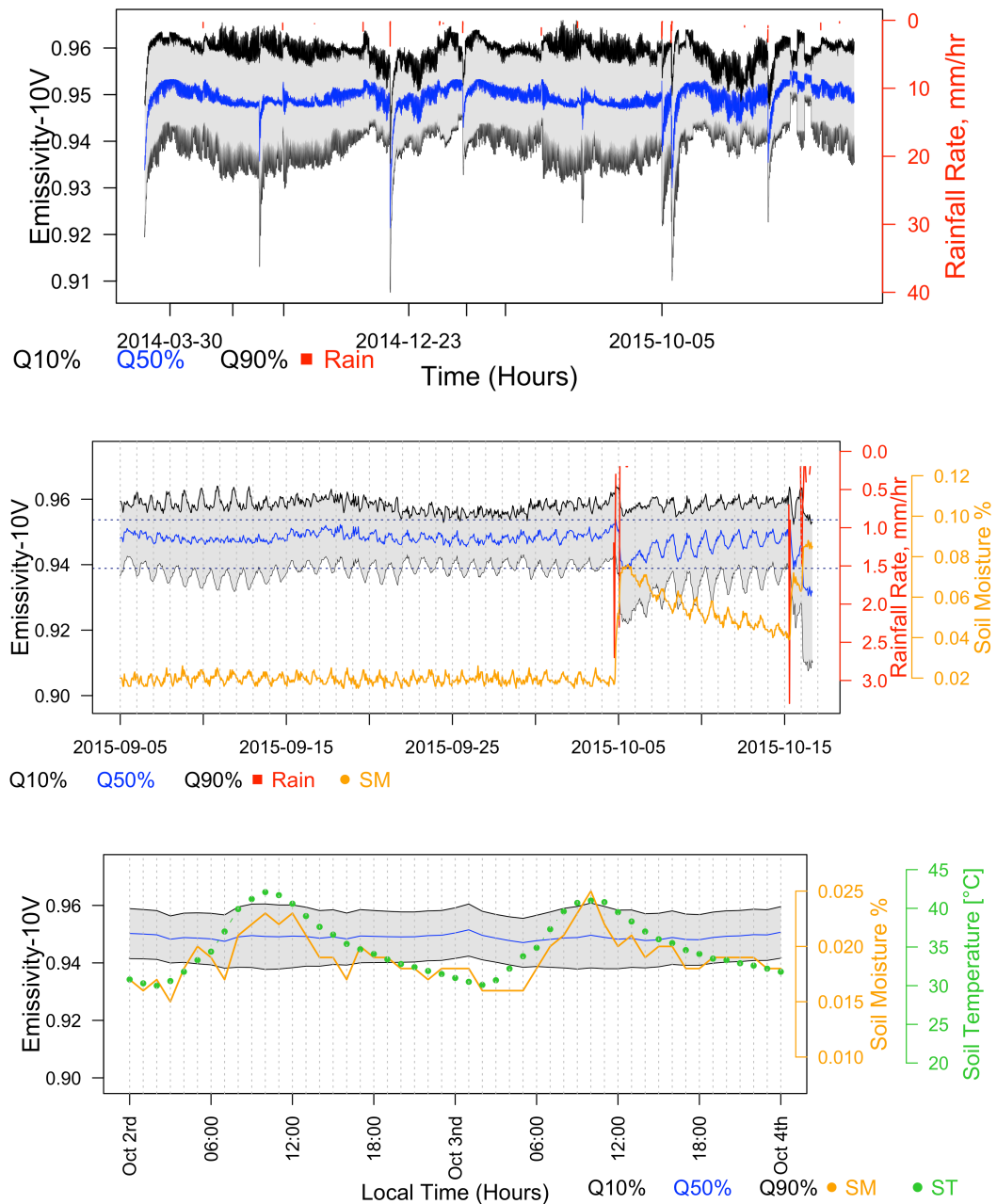
19GHz V	Mod 13	0.3790
19GHz H	Mod 13	0.3086
23GHz V	Mod 13	0.4791
37GHz V	Mod 13	0.4792
37GHz H	Mod 13	0.3295
89GHz V	Mod 13	0.6046
89GHz H	Mod 13	0.3749

5.3.3 Prediction

The prediction of 10V-GHz emissivity using our models is shown below. Precipitation events are rare in the barren region. However, very significant emissivity drops occurred each time when it rains (shown in the upper plot in Figure 5.3.4.). As revealed in the middle second plot, the precipitation event around Oct 5th 2015 generated a drop in the emissivity from 0.9537 to 0.9389, followed by a recovery of emissivity that might last more than a few days.

If we look at the non-rainy period before Oct 2rd, the emissivity along with soil moisture and soil temperature exhibits a diurnal variation. Soil moisture and soil temperature have coincident variations, so do the variations of emissivity. For instance, after sunrise (6am), the soil temperature and soil moisture increase, with emissivity slightly decreasing. It might be concluded that the emissivity is mainly governed by soil moisture and soil temperature for barren region, or vegetation for other kinds of the vegetated surfaces, during the dry period lacking precipitation. If we look at the rainy days from Oct 5th to Oct 7, the precipitation leads to the drastic change of soil moisture

and the diurnal cycle does not dominate any more. As a result, the emissivity exhibits a low value of 0.938 for a long period, compared to the non-rainy emissivity of 0.955. Therefore, it might conclude that, soil moisture, along with soil temperature and resultant emissivity are heavily affected by the precipitation events.



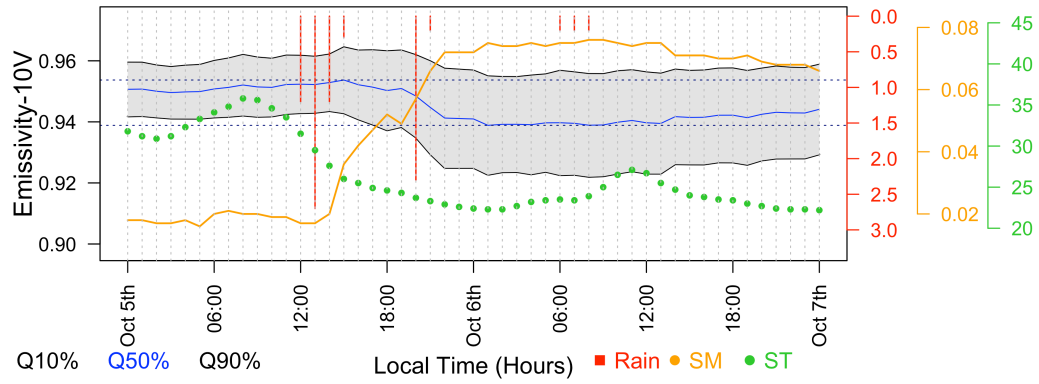


Figure 5.3.4 Prediction of 10V-GHz hourly emissivity over StovepipeWell barren region station from 2014, March to Feb 2016 (upper plot), and from Sept 5, 2015 to Oct 16, 2015 (middle second plot), Oct 2nd 00:00 to Oct 4th 00:00 (local time) (middle third plot), Oct 5th 00:00 to Oct 7th 00:00 (local time) (bottom plot)

5.4 Summary

We established empirical and statistical models of the 9-channel overland passive microwave emissivity derived from GMI brightness temperatures, based on in-situ measurement of surface characteristics over three station located in three different kinds of landcover. The surface parameters include soil moisture, soil temperature and vegetation indices.

For the grassland station, emissivity at all the channels except the 89-GHz decreases with the soil moisture. The decreasing slope diminishes with the frequency. Emissivity at all channels decreases slightly with the soil temperature. Besides, all emissivity channels except 23V-GHz and 89H-GHz channels decrease with air temperature. When it comes to the vegetation, the emissivity also decreases with the

increasing NDVI or EVI, and the decreasing slope is intensified at higher frequencies for the vertically polarized channels.

For the forest station, the emissivity decreases with soil moisture at 10-GHz channels while remains unchanged with soil moisture at 19V-GHz and 23V-GHz channels, and increases with soil moisture at the high-frequency channels. The increasing slope of emissivity is steeper for the 89-GHz channel. The emissivity increases with soil temperature at 10-GHz channel, is constant at 19-GHz and 23V-GHz channels, and decreases with soil temperature for the 37-GHz and 89-GHz channels. Similarly, the decreasing trend is the steepest for the 89-GHz channel. The variation of emissivity with air temperature is almost identical as that of the soil temperature. The emissivity increases with NDVI at the 10GHz channels and decreases at the high-frequency channels. The variation of emissivity with the NDVI is nearly identical as with EVI.

For the barren region station, the emissivity increases with the soil moisture for the 37-GHz channels and is kept unchanged for other channels. Additionally, the emissivity increases with the soil temperature except the low-frequency horizontally polarized channels. Variation of emissivity with air temperature is identical with soil temperature. Emissivity does not change with NDVI/EVI because the vegetation is negligible in the barren regions.

Based on these results, the surface characteristics would play different roles in the variation of emissivity for different channels and types of landcover. Emissivity of horizontally or vertically polarized channels, and high frequency or low frequency channels exhibit different variations. Soil moisture might take the primary role for the

grassland station. The variation of emissivity over forest is more complex and results from a cumulative influence of all the surface parameters. The emissivity over barren regions excludes the influence of vegetation indices.

In addition to the first order trends of variation of emissivity using the surface parameters, various combinations of parameters were tested and compared for different channels and types of landcover. For instance, models for grassland tend to behave best at the low-frequency channels if the model includes all the surface parameters, while the models for forest achieve the best performance at the high-frequency channels if the model includes both information from temperature, vegetation and soil moisture.

The models of emissivity are well responsive to precipitation events especially at low frequency channels and fit quite well with the dynamics variation of surface properties, which can also substantiate our models dynamics to the change of surface properties.

6. A Remote Sensing Perspective

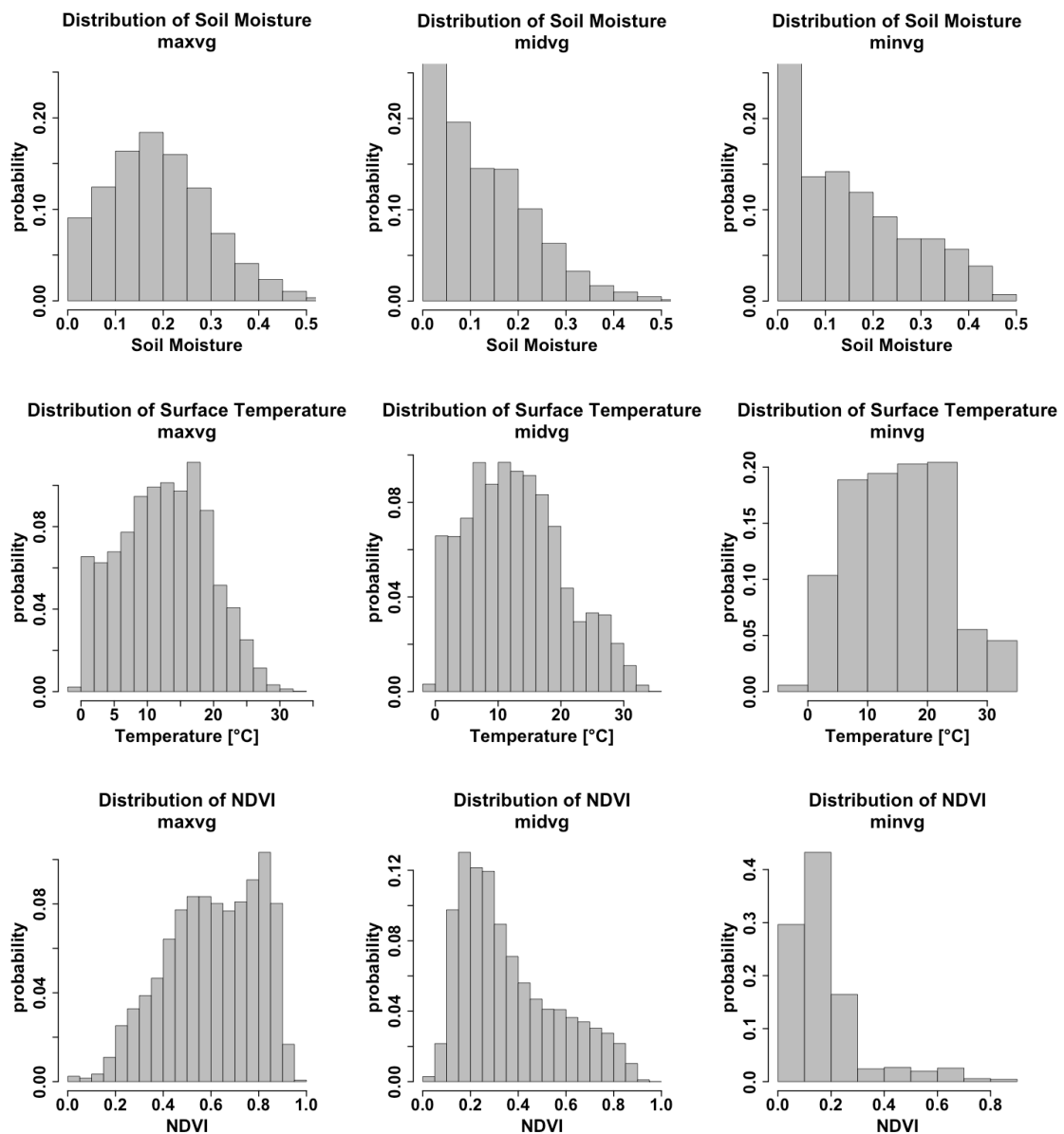
In the previous section, we discussed the procedure of establishing the statistical models, evaluating and comparing the models, and predicting new emissivities datasets based on the surface parameters from in-situ measurement of soil moisture and temperature. This section makes use of the satellite remotely measured soil moisture and temperature to adopt a remote sensing perspective.

The dataset of coincident satellite measurements of surface properties and satellite-derived emissivity are established following the methods discussed in section 4. Note that the resolution of the variables is now at the SMAP footprint scale. The surface type classification in the GMI Level 2 product is used to split the dataset into 5 different categories, which are the maximum vegetated regions, highly vegetated regions, moderate vegetated regions, low vegetated regions and minimal vegetated regions. The sample sizes of these five surface types are shown in the Table 6.1

Table 6.1 Sample sizes of different types of land surface in the remote sensing dataset

Surface type	Index value	Sample Size
Maximum vegetated	3	73681
High vegetated	4	87517
Moderate vegetated	5	34234
Low vegetated	6	3274
Minimal vegetated	7	710

The maximum vegetated regions, the moderate vegetated regions and the minimal vegetated regions are discussed in detail in section 6.1, 6.2 and 6.3, respectively. Other surface parameters from the satellite remote sensing are soil moisture from SMAP, surface temperature from SMAP ancillary dataset, two vegetation indices from MODIS. The distribution of soil moisture, surface temperature, NDVI and EVI over the three surface types are shown as follows.



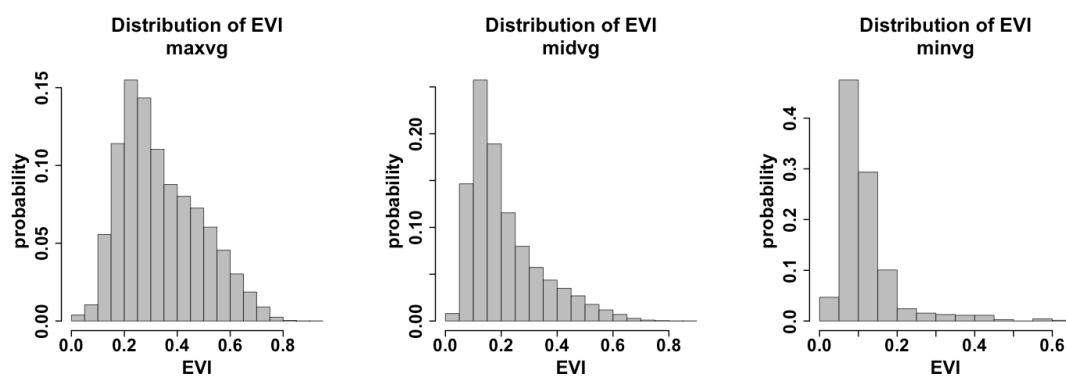


Figure 6.1.1 Distribution of soil moisture, surface temperature, NDVI and EVI over maximum vegetated (maxvg) regions (left column), moderate vegetated (midvg) regions (middle column) and minimal vegetated (minvg) regions (right column)

Table 6.2 Statistics of soil moisture, soil temperature, NDVI and EVI for maximum vegetated regions, moderate vegetated regions and minimal vegetated regions

	Maximum vegetated			Moderate vegetated			Minimal vegetated		
	10%	50%	90%	10%	50%	90%	10%	50%	90%
SM	0.05	0.18	0.33	0.02	0.13	0.27	0.02	0.13	0.35
ST (°C)	3.1	12.6	21.1	2.9	12.8	24	4.9	15.3	25.1
NDVI	0.33	0.61	0.85	0.14	0.36	0.68	0.06	0.14	0.31
EVI	0.17	0.34	0.55	0.09	0.21	0.40	0.06	0.10	0.18

6.1 Minimal Vegetated Regions

6.1.1 Single parameter modeling

Soil moisture over minimal vegetation areas mostly varies from 0.02 to 0.35. From Figure 6.1.2, the modeled emissivity exhibits an apparent decreasing trend when soil moisture is over 0.17. As for the barren station the emissivities from the vertical polarized channels are higher than those from the horizontal polarized channels and the latter ones are characterized with a more substantial decreasing trend. As a result, the emissivity, for example, for the 10H-GHz channel, is as low as 0.75 if the soil moisture is larger than 0.3.

In the minimal vegetated regions, surface temperature ranges from 5°C to 25°C. Emissivities over all the channels exhibit a general increasing trend with the surface temperature. In spite of the different frequencies, modeled vertical polarized channel emissivities report similar and almost identical profiles, while the emissivities of the horizontal polarized channels increase with frequency.

NDVI ranges from 0.06 to 0.3 while most EVI varies from 0.06 to 0.18. If we recall the typical NDVI value ranges for different types of underlying surface, minimal vegetated regions are most likely to be barren soil, grassland or shrubland. The profiles of NDVI-SPM and EVI-SPM are quite similar and thus only discussion of the NDVI-SPM model is covered here. For the range 0.0 to 0.25, emissivities from all the horizontal polarized channels increase with NDVI, while the emissivities from all the vertical polarized channels decrease with NDVI when larger than 0.15. Note that there is a lack of NDVI larger than 0.3 over the minimal vegetated regions. These fluctuating lines for NDVI over 0.3 might be ignored for the minimal vegetated regions.

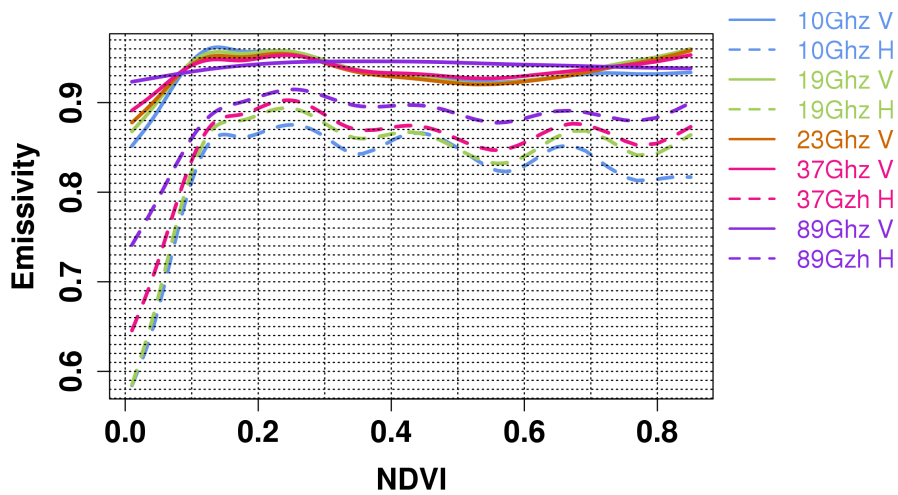
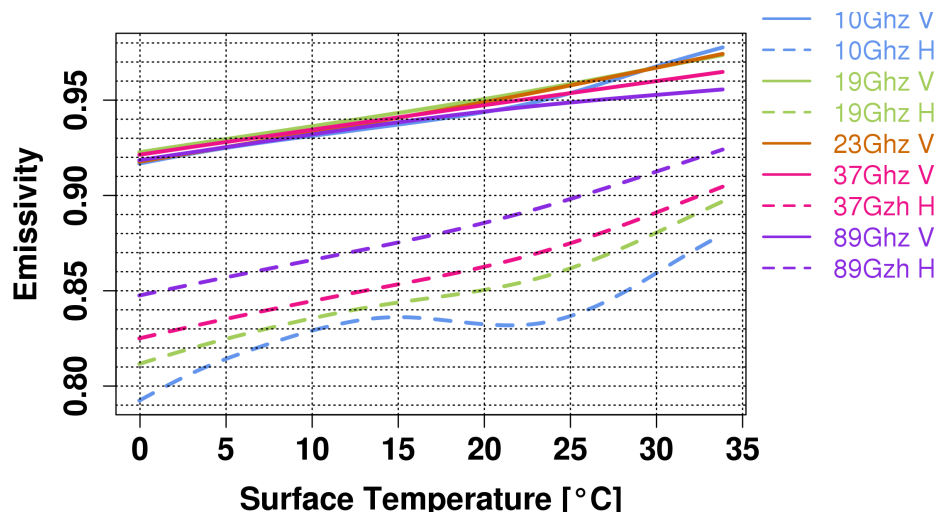
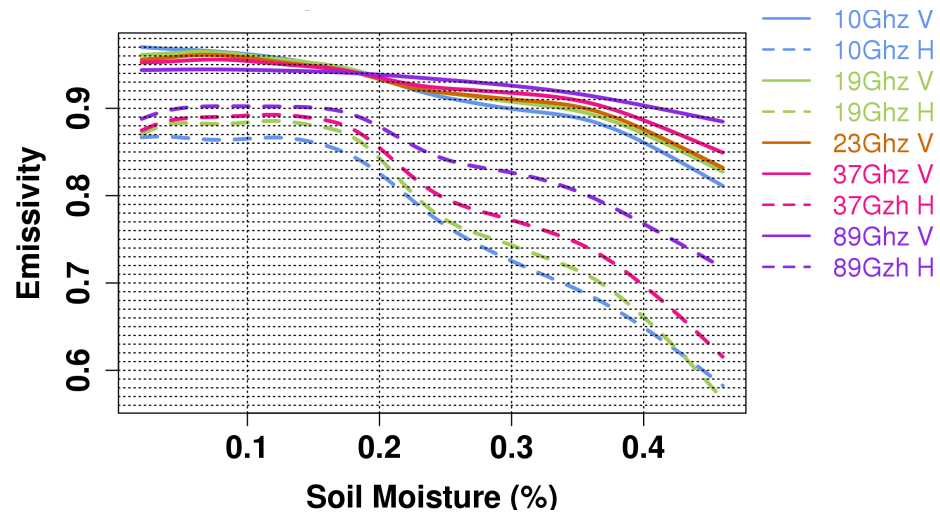


Figure 6.1.2 Single-parameter models over different channels for minimal vegetated region; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot), NDVI single parameter model (bottom plot)

6.1.2 Multi-parameter modeling

The correlation coefficients between the emissivities derived from satellite observation and the emissivities obtained from multi-surface parameter combinations are plotted in Figure 6.1.3.

In general, the lower frequency is, the higher the correlation coefficients can be. For both horizontally and vertically polarized channels, SM-SPM has the highest correlation coefficient compared to other single parameter models. Undoubtedly, the model including all the surface parameters embraces the highest correlation coefficient. However, we find that the model including the soil moisture, surface temperature and NDVI and excluding EVI has as high correlation coefficient as the model that includes all the surface parameters. Therefore we suppose that the effect of EVI overlaps with NDVI and one of the vegetation indices may be neglected in the multi-parameter models.

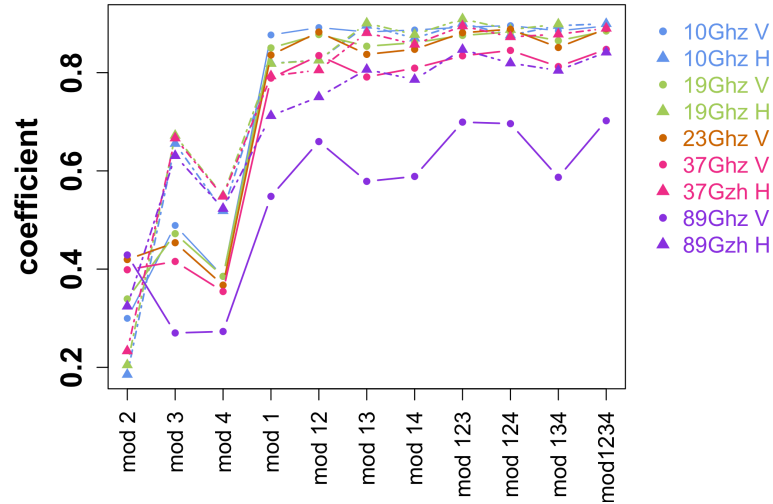


Figure 6.1.3. Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted using single-parameter statistical model over minimal vegetated region

We investigate the relative importance of these surface parameters in the multi-parameter models for different channels. Based on the value of AICs, soil moisture is most important parameter over the minimal vegetated regions and NDVI is more important than surface temperature for low-frequency horizontally polarized channel.

Table 6.3 Rank of importance of different surface parameters in multi-parameter models for all the channels

Channel	1st	2nd	3rd	4th	AICs
10GHz V	SM	ST (minimal)			-3550.6
10GHz H	SM	NDVI	ST	EVI	-2542.6
19GHz V	SM	ST	EVI (minimal)		-3532.1

19GHz H	SM	NDVI	ST (minimal)		-2527.8
23GHz V	SM	ST	EVI		-3677.1
37GHz V	SM	ST	EVI (minimal)		-3713.9
37GHz H	SM	NDVI	ST		-2588.5
89GHz V	SM	ST	NDVI		-3622.9
89GHz H	SM	ST	NDVI	EVI	-2794.8

6.1.3 Prediction

The emissivity is predicted when the surface parameters are given. The prediction of emissivity using two parameter models is shown as follows.

Considering the model using soil moisture and surface temperature (upper left plot), the emissivity at the 10V-GHz channel mainly changes with soil moisture. Lower soil moistures lead to higher emissivity at 10V-GHz channel.

For the model using soil moisture and NDVI (upper middle plot), soil moisture is again responsible for the main variation of emissivities.

For the model using soil moisture and EVI (upper right plot), larger emissivities comes along larger EVI and the lower soil moisture. Emissivity that is higher than 0.925 occurs only when EVI is over 0.7. The variation of emissivity with EVI is nonlinear and a peak is found around EVI equal to 0.55.

For the model using surface temperature and NDVI, emissivity varies mostly with NDVI and the role of surface temperature is minimal. For the model using surface temperature and EVI, lower emissivities occur when the EVI fall into the range 0.4 to 0.7 and the surface temperature is lower than 15 °C. It means that EVI around 0.5

lowers the emissivity. For the model using NDVI and EVI, high emissivity occurs when the EVI varies from 0.2 to 0.4 and NDVI is around 0.2 or 0.8.

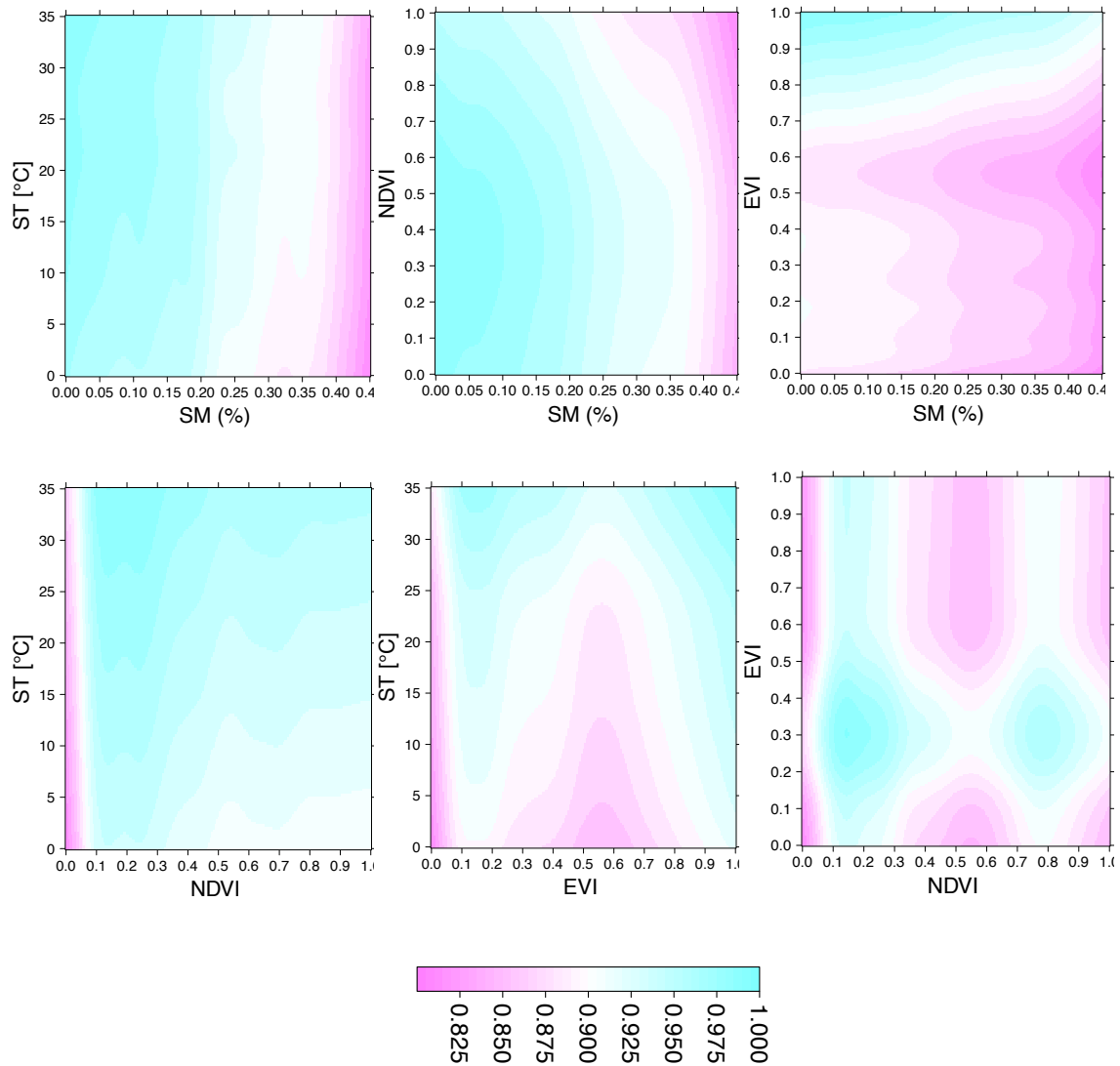


Figure 6.1.4 Prediction of 10GHz V emissivity modeled using two-parameter models over minimal vegetated regions

6.2 Moderate Vegetated Region

6.2.1 Single parameter modeling

The soil moisture over the moderate vegetated region ranges from 0.02 to 0.27. At the vertically polarized channels, the emissivities decrease with soil moisture except the 89V-GHz channel, whose emissivity increases with soil moisture. For the horizontal polarized channels, the variation of emissivity is non-linear as a function of soil moisture.

Surface temperature primarily ranges from 3°C to 24°C. The emissivity over all the channels decreases with temperature and this trend is more apparent for the higher frequency channels. A local minimum is noted around 22°C.

The variation profiles are quite similar for both EVI-SPM and NDVI-SPM. So we only discuss the NDVI-SPM herein. Emissivities from the all horizontally polarized channels and 89V-GHz channels increase with NDVI when larger than 0.07, and remains relatively constant when the NDVI is larger than 0.4. Contrarily, the emissivities from other vertical polarized channels slightly decrease with NDVI when NDVI ranges from 0.2 to 0.5. The emissivity values at vertical polarized channels are quite similar when the NDVI is larger than 0.4. For the horizontal polarized channels, the higher the frequency is, the larger the emissivities are. Besides, the emissivity at 10H-GHz channel is smaller than other horizontally polarized channels.

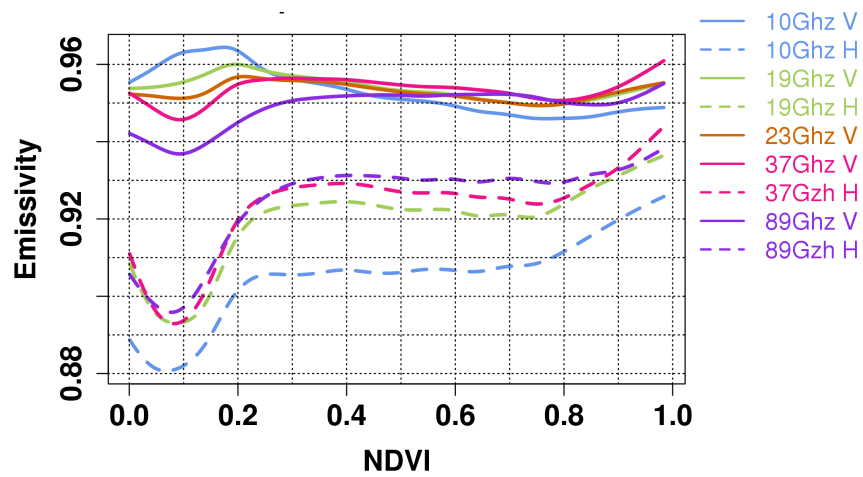
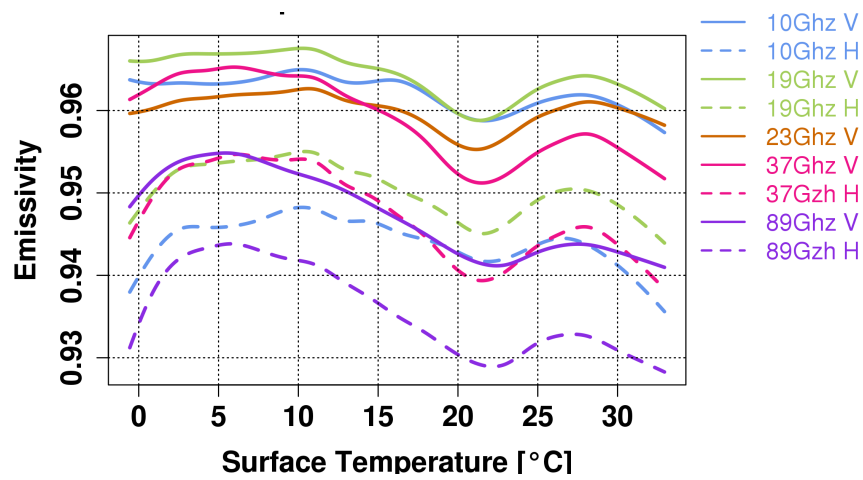
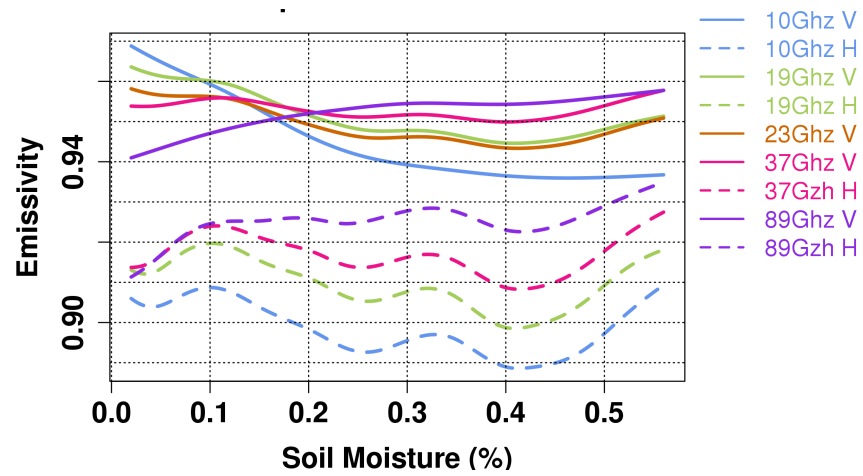


Figure 6.2.1 Statistical model for single-parameter models over different channels for moderate vegetated region; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle plot), NDVI single parameter model (bottom plot)

6.2.2 Multi-parameter modeling

Similar to the section 6.1.2, the correlation coefficients between the emissivity derived from satellite observation and the emissivity calculated with models are presented in the figure below.

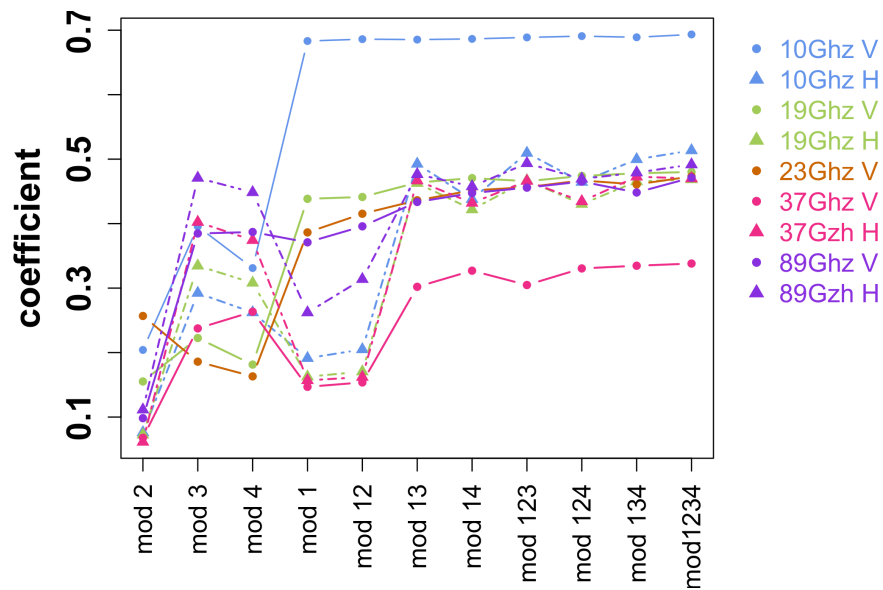


Figure 6.2.2 Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted over moderate vegetated region (number one refers soil moisture, number two refers surface temperature, number 3 and 4 refer vegetation indices)

For the surface type of moderate vegetated regions, most of the multi-parameter models exhibit correlation coefficients around 0.45 except the 37V-GHz and 10V-GHz channels. For the vertically polarized channels other than the 37V-GHz channel, the SM-SPM has the highest correlation coefficient. For 37V-GHz V channel, EVI-SPM has the highest correlation coefficient. A correlation coefficient over 0.65 can be found with SM-SPM for the 10V-GHz channel, which indicates that the soil moisture is a major contributor to the 10V-GHz emissivity.

Similarly, SM-SPM for vertically polarized channels at 19-GHz, 23-GHz and 37GHz has higher correlation coefficients than other single parameter models, which can also substantiate the important role of soil moisture in the emissivities at these frequencies. In contrast, the NDVI-SPM has the highest correlation coefficient among the single parameter models for the horizontal polarized channels. The model including the information of soil moisture, soil temperature and NDVI has the highest correlation coefficient among the multi-parameter models.

Relative importance of these surface parameters in the multi-parameter models for different channel is demonstrated in the Table 6.2. Soil moisture is the primary factor influencing the variation of emissivity except the 37H-GHz and 89H-GHz channels, whereby the NDVI is more important.

Table 6.4 Rank of importance of different surface parameters in multi-parameter models
for all the channels over moderate vegetated regions

Channel	1st	2nd	3rd	4th	AICs
10GHz V	SM	ST	EVI	NDVI	-211976
10GHz H	SM	NDVI	ST	EVI	-160203
19GHz V	SM	EVI	NDVI	ST	-205970
19GHz H	SM	NDVI	EVI	ST	-161243
23GHz V	SM	NDVI	ST		-213356
37GHz V	SM	EVI	NDVI	ST	-210630
37GHz H	NDVI	SM	EVI		-169041
89GHz V	SM	ST	EVI	NDVI	-210761
89GHz H	NDVI	ST	SM	EVI	-179996

6.2.3 Prediction

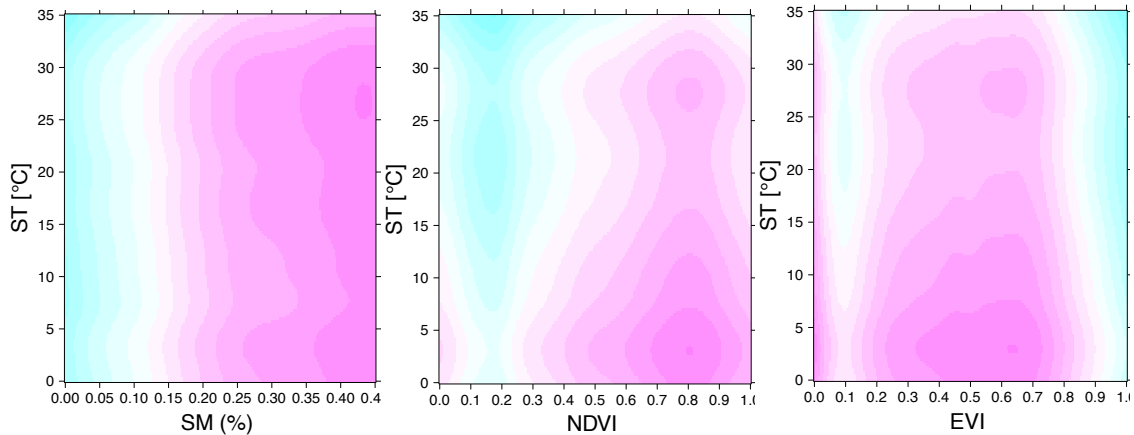
Prediction of emissivity using our statistical models over the moderate vegetated regions is performed herein. Specifically, the predictions using two-parameter models are shown in Figure 6.2.3.

For the model utilizing the soil moisture and surface temperature (upper left plot), the variation of soil moisture governs the variation of emissivity and lower emissivities are found with wetter soil. Soil moisture also plays a primary role in the

variation of emissivity if the emissivity is produced by the models that rely on the combination of soil moisture and NDVI or the combination of soil moisture and EVI.

For the model using the surface temperature and NDVI, low emissivity is obtained when the NDVI is larger than 0.5 and simultaneously the surface temperature is lower than 15°C. Contrarily, high emissivity is produced when the NDVI is lower than 0.3 and the surface temperature is higher than 15°C. For the scenario of high surface temperature, high NDVI or low surface temperature and low NDVI, the emissivity is intermediate. Emissivity predicted using NDVI and EVI (not shown) has similar pattern than the model using surface temperature and NDVI.

For the model using the surface temperature and EVI, low emissivity is found when EVI is roughly 0.5 and surface temperature is lower than 10°C. Generally, the emissivity increases with surface temperature.



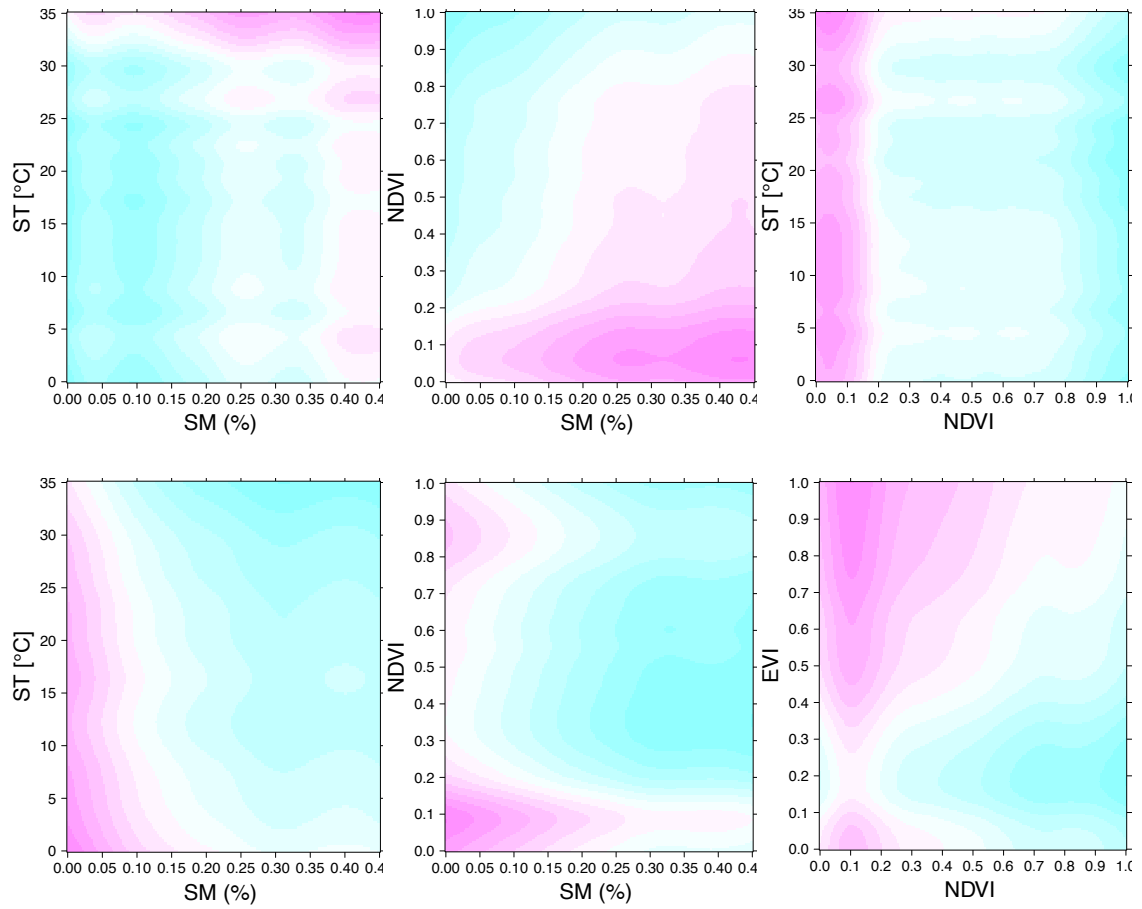


Figure 6.2.3. Prediction of emissivity using two parameter models at 10 GHz V channel (first row) and at 10 GHz H channel (second row), 89 GHz V channel (third row)

Regarding the prediction of emissivity at the horizontally polarized channels such as 10H-GHz channel, for the model based on soil moisture and surface temperature, low emissivity coincides with higher surface temperature and wetter soil, whereby unlike at 10V-GHz channel the soil moisture is not the only contributor to the variation of emissivity. For the model relying on soil moisture and NDVI, the low emissivity happens if NDVI is lower than 0.2, or if NDVI ranges from 0.2 to 0.7 and soil moisture is larger than 0.25. In contrast, NDVI becomes the governing factor

accountable for the variation of emissivity obtained from the model using NDVI and surface temperature, whereby the emissivity increases with NDVI.

The variation of emissivity at 89V-GHz channel computed using two-parameter models behave differently from the 10V-GHz channel. The higher 89V-GHz emissivity comes from the wetter soil. Besides, the increasing surface temperature tends to magnify the emissivity as well. For the model making use of the soil moisture and NDVI, the emissivity increases with the soil moisture and such effect becomes more preeminent when NDVI falls into the range from 0.2 to 0.7, which is usually the typical range for NDVI over the moderate vegetated region. For the modeling utilizing the EVI and surface temperature or NDVI and surface temperature (no shown), the NDVI/EVI is the only factor responsible for the variation of emissivity, whereby the emissivity remains constant with the varying surface temperature. Besides, for the model depending on the NDVI and EVI, low emissivity comes out with the uncommon conditions of low NDVI and high EVI while the high NDVI and low EVI facilitate the high emissivity. For the normal case in which the high NDVI is associated with the high EVI, the increases of NDVI and concurrent EVI do not make a large difference on the variation of emissivity. Accordingly, we guess that the effect of EVI might be same as the effect of NDVI over the moderate vegetated regions.

6.3 Maximum Vegetated Surface

6.3.1 Single parameter modeling

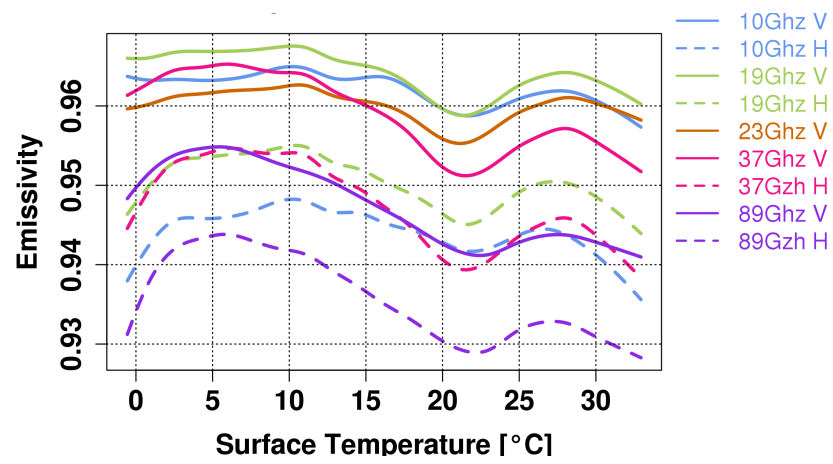
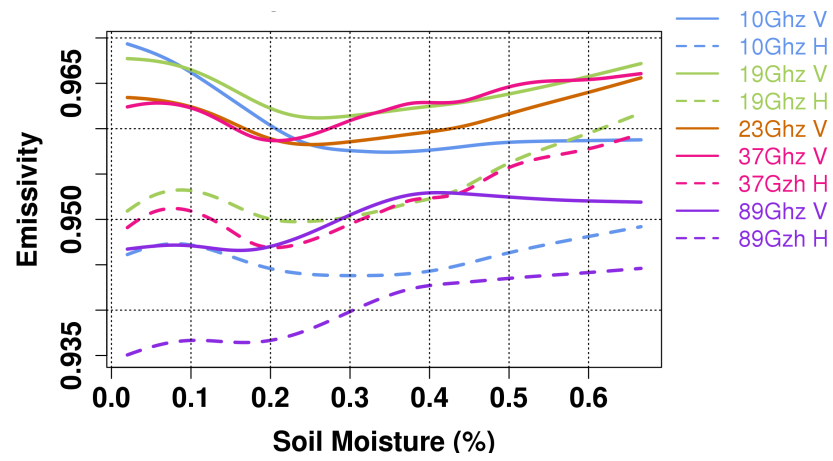
For the maximum-vegetation region, soil moisture ranges from 0.05 to 0.33. Within this range, emissivity at the 10-GHz channels decreases with moisture. The

increasing slope is more obvious when soil moisture is lower than 0.2. However, for the higher frequencies, emissivities at 19-GHz and 37-GHz channels reach a local minimum and increase when the soil moisture is larger than 0.2. Emissivities at 19-GHz remain stable when the soil moisture is between 0.2 to 0.3, while emissivities at 37-GHz increase with soil moisture when soil moisture is larger than 0.2. In contrast, the emissivities at 89-GHz increase with soil moisture and the increasing trend is more evident when soil moisture is within the range 0.2 to 0.4.

For ST-SPM, emissivities for all channels decrease with surface temperature unless the surface temperature is larger than 20°C. The decreasing trend is reversed when the surface temperature is higher than 22°C.

For NDVI-SPM, emissivity at the horizontally polarized channels decrease with NDVI if NDVI is smaller than ~0.15, and then increase with NDVI when from 0.15 to 0.45. Emissivities keep stable when NDVI fall into 0.45 to 0.7. If the NDVI is above 0.7, emissivities decrease with the NDVI. For the vertically polarized channels, emissivities at 10V-GHz and 19V-GHz channels always decrease with NDVI. On the contrary, emissivities at 37V-GHz and 23V-GHz keep stable when NDVI varies from 0.25 to 0.7. Beside, 89V-GHz emissivities increase with NDVI then decreases with NDVI when greater than 0.6.

Regarding EVI-SPM, the emissivities at all the channels increase with EVI when EVI is smaller than 0.2, decrease with EVI when EVI is larger than 0.2. Their profiles exhibit the similar shapes for different channels.



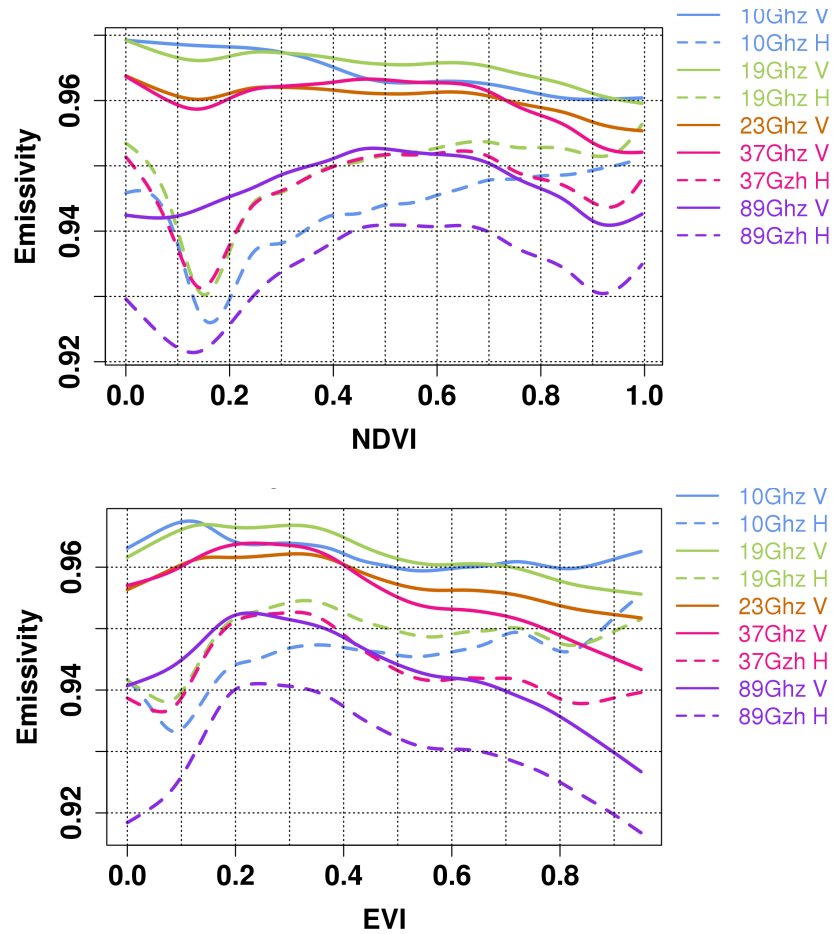


Figure 6.3.1 Statistical model for single-parameter models over different channels for maximum vegetated region; soil moisture single parameter model (upper plot), soil temperature single parameter model (middle second plot), NDVI single parameter model (middle third plot), and EVI single parameter model (bottom plot)

6.3.2 Multi-parameter models

For the inter-comparison between different channels, the emissivity at 89-GHz is lower than at 37-GHz, while emissivity at 10-GHz is lower than at 19-GHz. Besides, the emissivities at horizontally polarized channels are lower than those at vertically polarized channels.

For the 10H-GHz and 19H-GHz channels, NDVI-SPM shows the highest correlation coefficient among the single parameter models. The model making use of soil moisture, surface temperature and NDVI has the highest correlation coefficient among the three-parameter models. For the 37H-GHz channel, the ST-SPM has the highest correlation coefficient among the single parameter models and the model including the information of all the surface parameters leads to a highest correlation coefficient. For 89H-GHz, the EVI-SPM presents the highest correlation coefficient among the single parameter models and the model taking the soil moisture, soil temperature and EVI results in the highest correlation coefficient.

For the vertically polarized channel at 19-GHz, 37-GHz and 89-GHz, ST-SPM has the highest correlation coefficient among the single parameter models and the model taking soil moisture, surface temperature and EVI has the highest correlation coefficient among the multi-parameter models. For the 10V-GHz channel, SM-SPM has the highest correlation coefficient among the single parameter models, the model using soil moisture and surface temperature has the highest correlation coefficient among the two-parameter models.

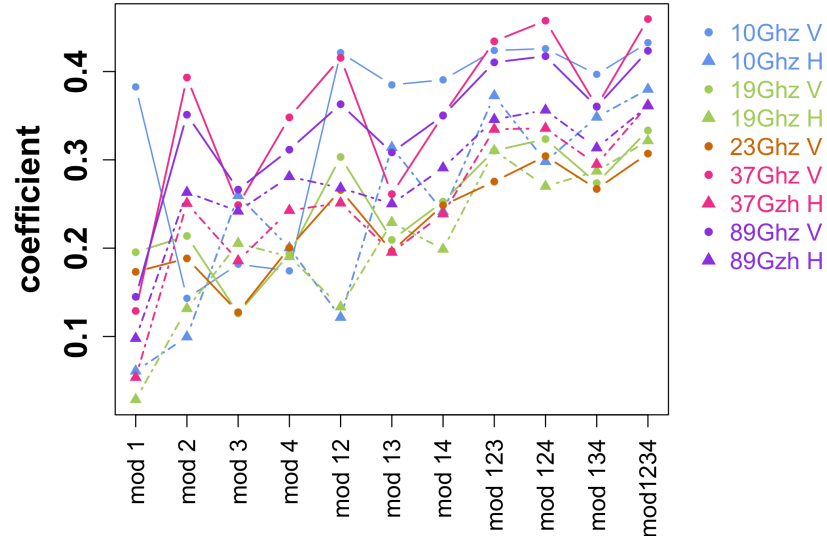


Figure 6.3.2 Correlation coefficients between the all-channel emissivity derived from observed data and all-channel emissivity predicted using single-parameter models over maximum vegetated regions

The importance of each surface parameter on their associated multi-parameter models over the maximum vegetated regions is assessed as shown in Table 6.3. For the low-frequency vertically polarized channels, the variation of emissivity is still primarily determined by soil moisture. Nevertheless, NDVI replaces the roles of soil moisture for the low-frequency horizontally polarized channels and effect of soil moisture is less influential than NDVI. Furthermore, for the high-frequency channels, the most important parameter is the surface temperature.

Table 6.5 Rank of importance of different surface parameters in multi-parameter models
for all the channels over maximum vegetated regions

Channel	1st	2nd	3rd	4th	AICs
10GHz V	SM	ST	NDVI	EVI	-492559
10GHz H	NDVI	SM	ST	EVI	-417118
19GHz V	SM	ST	EVI	NDVI	-475709
19GHz H	NDVI	SM	ST	EVI	-418711
23GHz V	SM	ST	EVI	NDVI	-495624
37GHz V	ST	EVI	SM	NDVI	-482419
37GHz H	ST	NDVI	EVI	SM	-429149
89GHz V	ST	SM	EVI	NDVI	-465904
89GHz H	ST	NDVI	EVI	SM	-426252

6.3.3 Prediction

Our statistical models are adopted to predict the emissivities over the maximum vegetated regions and demonstrate their variation with different surface properties. The following figures show the prediction patterns of the two-parameter models.

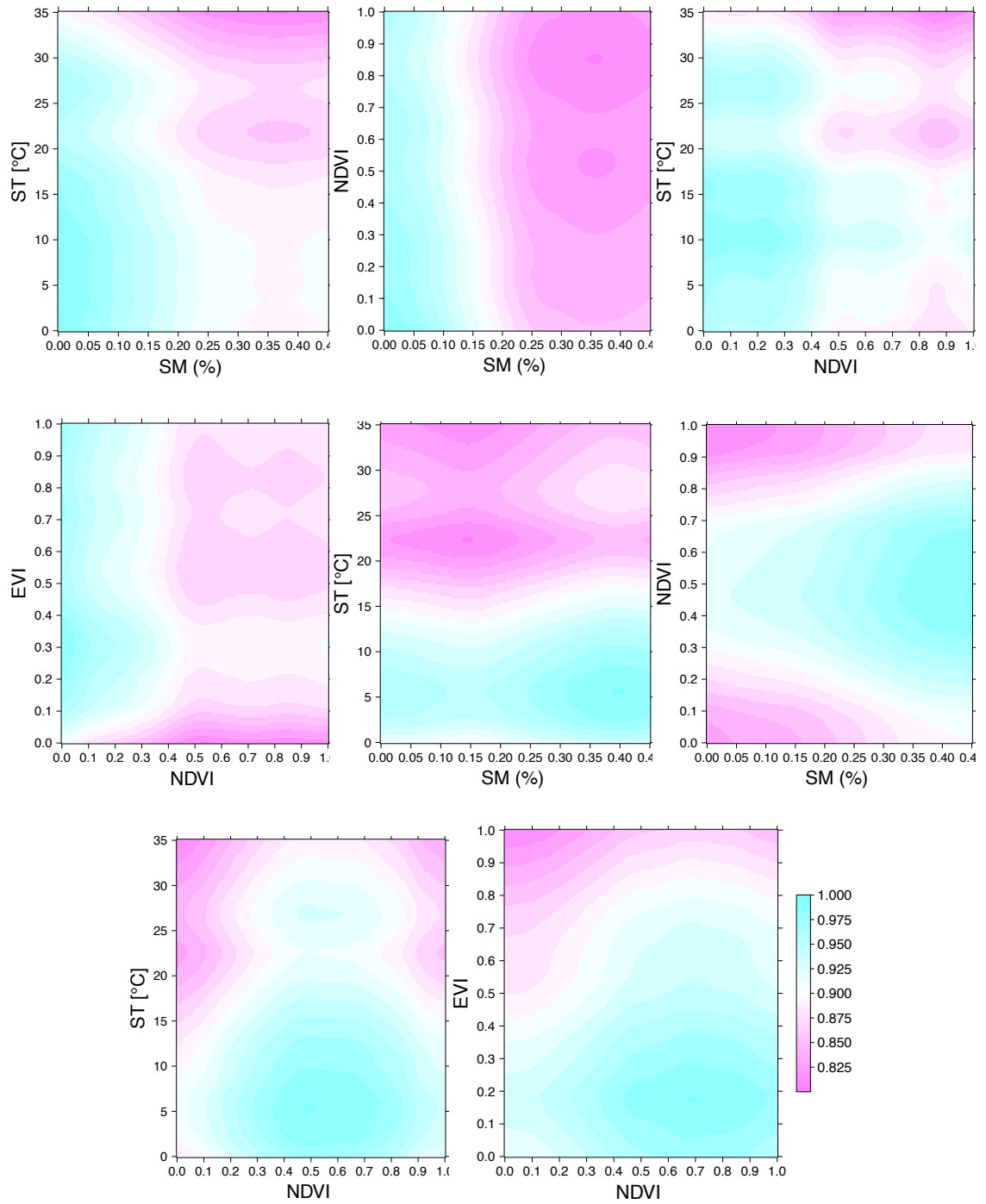


Figure 6.3.3 Prediction of 10GHz V and 89V GHz V emissivity modeled using two-parameter models over maximum vegetated regions

For the model using soil moisture and surface temperature (upper left plot), soil moisture and surface temperature both affect the variation of 10V emissivity. Smaller emissivities occur when the soil moisture is over 0.25 and simultaneously the surface temperature is higher than 18°C. As is demonstrated by the gradient of contours, the variation of emissivity with soil moisture is more apparent when surface temperature is relatively low, while surface temperature plays a more important role when the soil moisture is relatively high. In contrast, for 89V-GHz channel (middle plot in the second row), the emissivity increases with soil moisture except when the soil moisture is lower than 0.1 and surface temperature is lower than 10°C. Such increasing trend is just opposite to that for the 19V-GHz channel.

For the model utilizing soil moisture and NDVI (upper middle plot), the contours are nearly parallel to the y-axis when the soil moisture is less than 0.15, indicating that soil moisture governs the variation of 10V-GHz emissivity for a dry soil surface, compared to the role of NDVI. Moreover, if the soil moisture is higher than 0.25, the lower emissivities are accompanied with the higher NDVI. It indicates that NDVI can help reduce the emissivity for the wet soil surface. In contrast, for 89V-GHz channel, soil moisture increases with soil moisture and NDVI will enhance the emissivity when NDVI ranges from 0.2 to 0.7. Therefore, the peak emissivity is seen when the NDVI falls into the range 0.2 to 0.7 and the soil moisture value is as large as possible.

The plot for the model using the soil moisture and EVI is quite similar to the model using soil moisture and NDVI, so we do not duplicate the discussion herein.

Such similarity, on the other hand, might suggest the similar effect of NDVI and EVI on the emissivity of maximum vegetated region.

For the model using surface temperature and NDVI, the variation of 10V emissivity primarily relies on the NDVI. For NDVI lower than 0.4, the emissivity can get a peak when the surface temperature is around 10°C. Contrarily, when NDVI is higher than 0.4, the low emissivity area can be found when the surface temperature is approximately between 20°C to 25°C, or larger than 30°C. When it comes to 89V-GHz channel, the emissivity decreases with the higher surface temperature, and NDVI increases the emissivity when the NDVI varies from 0.2 to 0.7.

For the model using EVI and NDVI, the increasing EVI generally tends to increase the 10V-GHz emissivity when the NDVI is larger than 0.4. When the NDVI is smaller than 0.4, the 10V-GHz emissivity does not change with the varying EVI. When it comes to 89V-GHz channel, the emissivity generally increases with decreasing EVI and the simultaneous increasing NDVI.

6.4 Summary

In this section, emissivity models were established using surface parameters from the satellite remote sensing observation instead of in-situ measurement. The analysis is primarily performed over maximum vegetated, moderate vegetated and minimal vegetated regions.

The following tables summarize the variation trends of emissivity with soil moisture, soil temperature, NDVI/EVI. Regarding maximum vegetated regions, the emissivity generally decreases with soil moisture and surface temperature. For the

vegetation indices, the decreasing trends at the low frequency reverse to increasing trends at the high frequency. For moderate vegetated regions, the emissivity generally decreases with increasing soil moisture at the low frequency channels and increases with soil moisture at the high frequency channels. Likewise, the emissivity decreases with the NDVI or EVI at the 10-GHz channels but increases with NDVI for other channels. Oppositely, the emissivity increases with surface temperature for the low-frequency channels but is unaffected by the surface temperature at other channels. When it comes to the minimal vegetated regions, the emissivity decreases with increasing soil moisture and increases with surface temperature. Moreover, the decreasing trend with soil moisture generally becomes less steep at low frequency while the increasing trend with surface temperature typically becomes steeper at higher frequency.

Table 6.6. Variation trends of the emissivity as a function of surface properties for maximum vegetated regions

Maximum Vegetated	SM	ST	NDVI	EVI
10V	Decrease	Flat, then decrease	Decrease	Slightly decrease
19V	Decrease, then flat	Decrease	Flat, then decrease	Slightly decrease
23V	Decrease, then flat	Decrease	Flat and decrease	Slightly decrease

37V	Decrease, then increase	Decrease	Flat and decrease	Slight decrease
89V	Decrease, then increase	Decrease	Flat and decrease	Steeply decrease
10H	Decrease	Flat, decrease	Increase	Flat
19H	Decrease flat	Flat, decrease	Increase then flat	Increase, then decrease
37H	Decrease, increase	Decrease	Increase then decrease	Increase, then decrease
89H	Increase	Decrease	Increase then decrease	Flat, then decrease

Table 6.7. Variation trends of the emissivity as a function of surface properties for
moderate vegetated regions

Moderate vegetated	SM	ST	NDVI	EVI
10V	Decrease	Increase	Decrease	Decrease, then flat

19V	Decrease	Increase	Decrease	Flat
23V	Decrease	Increase	Increase flat	Flat
37V	Flat	Flat	Increase decrease	Increase then flat
89V	Increase	Flat	Increase flat	Increase then flat
10H	Increase then decrease	Flat	Increase then flat	Increase then flat
19H	Increase then decrease	Flat	Increase then flat	Increase then flat
37H	Increase then decrease	Flat	Increase then flat	Increase then flat
89H	Decrease	Flat	Increase then flat	Increase then flat

Table 6.8. Variation trends of the emissivity as a function of surface properties for moderate vegetated regions

Minimal vegetated	SM	ST	NDVI	EVI
10V	Decrease	Increase	Increase than decrease	Increase flat decrease

19V	Decrease	Increase	Increase flat decrease	Increase flat decrease
23V	Decrease	Increase	Increase flat decrease	Increase flat decrease
37V	Decrease	Increase	Increase flat decrease	Increase flat decrease
89V	Decrease	Increase	Increase flat	Flat increase decrease
10H	Decrease	Increase	Increase than slightly decrease	Increase than slightly decrease
19H	Decrease	Increase	Increase than slightly decrease	Increase than slightly decrease
37H	Decrease	Increase	Increase than slightly decrease	Increase than slightly decrease
89H	Decrease	Increase	Increase than slightly decrease	Increase than slightly decrease

The assessment and comparison of the single parameter models and different combination of surface parameters (multi-parameter models) illustrate that soil moisture

is the primary factor to account for the variation of emissivity over minimal vegetated regions. It is noticed that the models of vertically polarized channels perform better than the models for the horizontally polarized channels. In terms of moderate vegetated regions, the most important surface property is soil moisture with the exception of the high-frequency horizontally polarized channels. For the 37H-GHz and 89H-GHz, vegetation indices make the largest contribution to the variation of the emissivity. Again, the models for the vertical polarized channels achieve better performance than the models for the horizontally polarized channels. When it comes to the maximum vegetated regions, the interaction between surface properties is more complex. For the low-frequency vertically polarized channels, soil moisture still governs the variation of emissivity. However, the vegetation becomes more important for the low-frequency horizontally polarized channels. In contrast, the main contributor to the variation of the high-frequency channels is the surface temperature.

7. Comparison

This section focuses on two different comparisons. The first comparison is on the data sources to build the emissivity models, i.e. in-situ measurements and satellite observations respectively. The feasibility of using SMAP and MODIS satellite missions to built emissivity maps will be evaluated. The other comparison focuses on rainy conditions and evaluates the agreement between the GMI-estimated emissivity and the emissivity derived from the statistical models. It will enable to assess the progress and challenges in retrieving surface emissivity in precipitation, which is a major challenge for GPM.

It is important to note that the difference of resolution between in-situ and remote sensing measurement is a crucial issue. However this aspect will require more work and should be addressed in future studies.

7.1 Comparisons between Remote Sensing and In-situ Measurement Perspectives

We separate the in-situ measurements of all the stations according to the Surface Type Index provided by GMI level-2 and obtain five different categories of data stratified by the surface types, (including the maximum vegetated regions, moderate vegetated regions and minimal vegetated regions) similar to section 6. The sample sizes of these in-situ measurements are shown in the Table 7.1. Due to the limited sample for the low vegetated and minimal vegetated regions, the study below will mainly focus on the maximum, high and moderate vegetated regions. Remote sensing data (covered in the section 6) and in-situ measurement differ in that the former uses the soil moisture

and surface temperature data from SMAP while the latter uses in-situ measurements. The statistical analysis developed in previous sections is performed from the two perspectives to explore the differences between the remote sensing observation or in-situ measurements and to investigate how such differences can affect the emissivity models.

The statistics of data for each category of surface types are shown in Table 7.2, except the minimal vegetated region (due to the limited sample size of this category). The discussion of minimal-vegetation region will be ignored in this section.

Similarly, the statistical models are established for each type of surface. For convenience, the models using the data from remote sensing sources are referred as RS, while the models using data from in-situ measurement sources are referred as IS.

Table 7.1 Sample sizes of different surface types in the in-situ measurement datasets

Surface type	Sample Size
Maximum vegetated	22081
High vegetated	31737
Moderate vegetated	14047
Low vegetated	1147
Minimal vegetated	106

Table 7.2 statistics of soil moisture, soil temperature, NDVI and EVI for maximum-vegetation regions, moderate-vegetation regions, low-vegetation regions and minimal-

vegetation regions from the in-situ measurements

	Maximum vegetated			Moderate vegetated		
	10%	50%	90%	10%	50%	90%
SM	0.065	0.19	0.35	0.017	0.09	0.29
ST (°C)	7.3	17.2	26.8	6.4	17.1	32
AT (°C)	4.9	14.5	26.4	4.3	15.8	29.0
NDVI	0.31	0.58	0.83	0.10	0.24	0.56
EVI	0.17	0.36	0.60	0.075	0.14	0.34

	High vegetated			Low vegetated		
	10%	50%	90%	10%	50%	90%
SM	0.047	0.17	0.35	0.04	0.08	0.20
ST (°C)	6.4	16.9	27.0	6.6	18	32
AT (°C)	4.2	15.7	27	4.5	16.3	30
NDVI	0.20	0.43	0.74	0.11	0.15	0.22
EVI	0.12	0.24	0.53	0.068	0.10	0.14

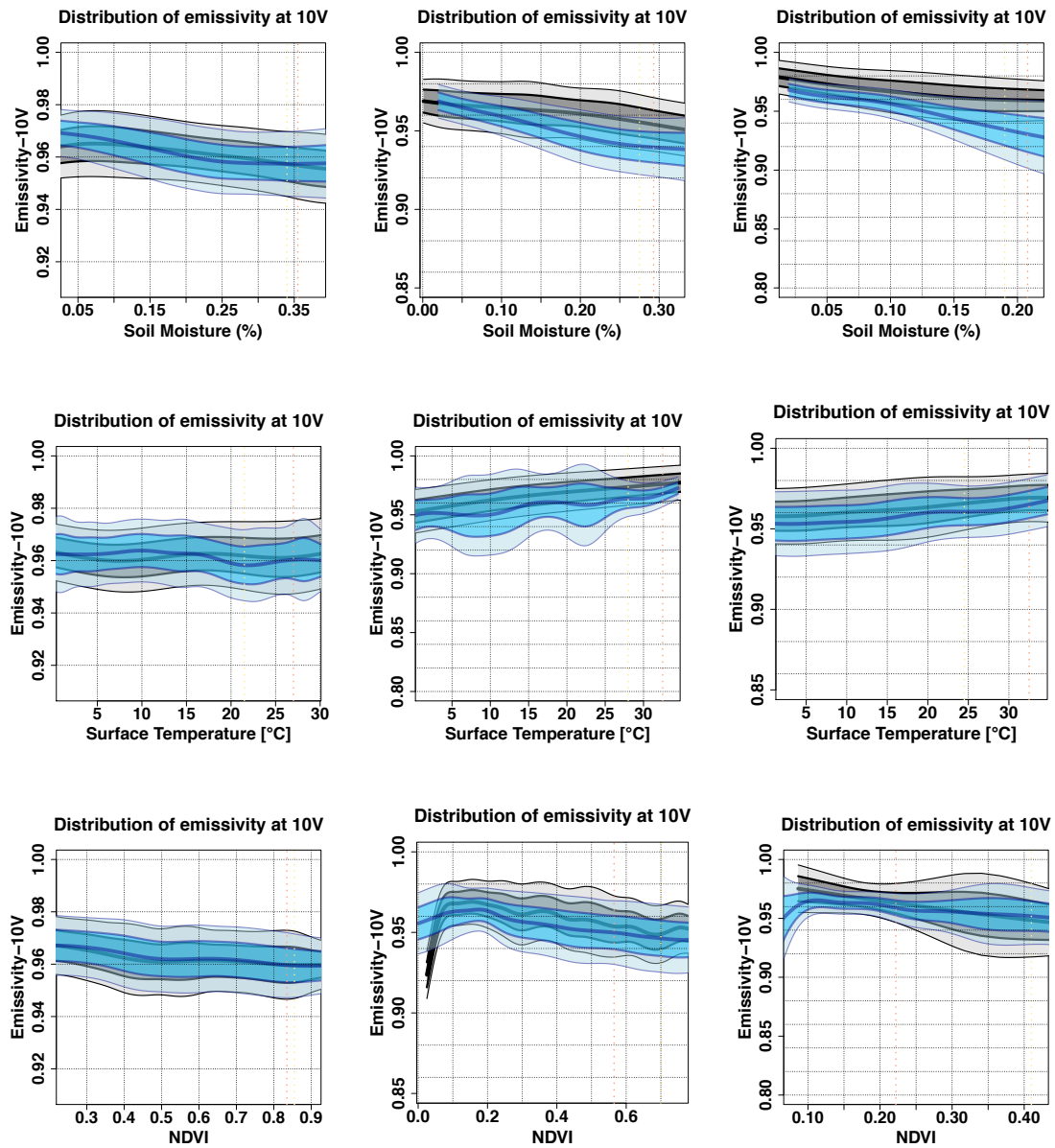
7.1.1 Comparison of single parameter models

As shown in the Figure 7.1.1, the RS and IS conditional probability distribution are similar, particularly for the maximum vegetated regions. For the moderate and low vegetated regions, the emissivity profiles derived from remotely sensed data based models tend to be smaller than the profiles from the in-situ measurements.

The following comparisons focus on SM-SPM, ST-SPM, NDVI-SPM and EVI-SPM respectively. These figures can be found in Appendix B. For the maximum-vegetation regions, in term of SM-SPM, the distribution profiles of SM-SPM-RS and SM-SPM-IS for the 10V-GHz, 19-GHz and 89-GHz channels are virtually identical. Nevertheless, the distribution profiles for the 23V-GHz and 37V-GHz channels from SM-SPM-RS exhibit a narrower shape. This might be attributed to the coarser resolution of the remote sensing information: random variability is smoothed over the SMAP footprint. In contrast, for all the horizontally polarized channels, distribution profiles for the SM-SPM-RS are also very similar to those for SM-SPM-IS but the former ones are marginally higher than the latter ones.

For the moderate vegetated regions, a noticeable similarity between the emissivity obtained from SM-SPM-IS and SM-SPM-RS is found for the 89-GHz channel. Regarding the 10-GHz, 19-GHz and 37-GHz horizontally polarized channels, the emissivity profiles from SM-SPM-IS match quite well with the emissivity profiles from SM-SPM-RS when the soil moisture is lower than 0.15, while the emissivity profiles from SM-SPM-IS are higher than those from SM-SPM-RS, when the soil moisture is larger than 0.15. In contrast, lower emissivity profiles are obtained from

SM-SPM-RS in comparison to SM-SPM-IS, when it comes to the 10-GHz, 19-GHz, 23-GHz and 37-GHz V channels.



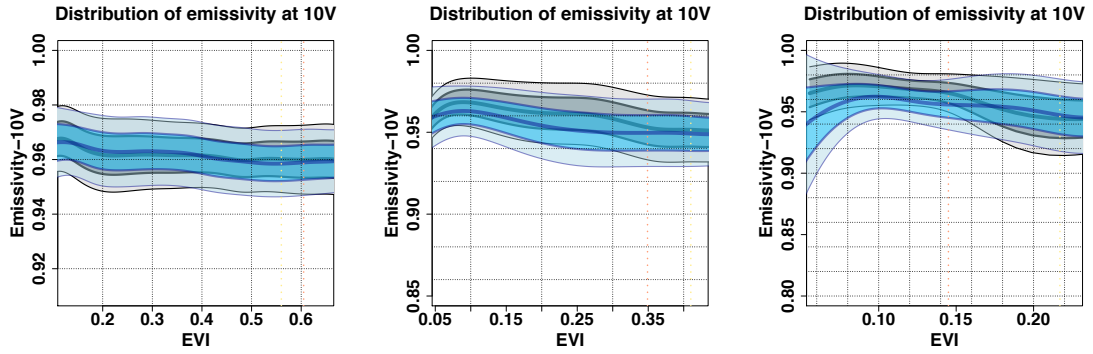


Figure 7.1.1 Comparison of the distribution of emissivity as a function of soil moisture (first row), surface temperature (second row), NDVI (third row) and EVI (fourth row) at 10V-GHz channel from remotely sensed data based-models (blue profiles) and from in situ measurement-based models (grey profiles) over maximum vegetated regions (left), moderate vegetated regions (middle), low vegetated regions (right).

For the low-vegetation regions, the emissivity profiles of vertically polarized channels from SM-SPM-RS are lower than those from SM-SPM-IS, especially for the 10-GHz channel. The difference of emissivity profiles between SM-SPM-RS and SM-SPM-IS diminishes with the increasing frequency. Thus, for the 89-GHz, emissivity profiles from SM-SPM-RS and SM-SPM-IS are much overlapped. For the horizontally polarized channels, the emissivities from SM-SPM-RS have a wider shape and are lower than that from SM-SPM-IS.

As for ST-SPM, the distribution profiles of emissivity at the vertically polarized channels are very similar for the maximum vegetation regions. For the horizontally polarized channels, they are identical at 89H-GHz. However, emissivity derived from ST-SPM-IS at the other three horizontally polarized channels is lower than that of ST-

SPM-RS if the surface or soil temperature is lower than 15°C and verse vice if the surface or soil temperature is higher than 15°C.

For the moderate vegetated regions, the emissivity profiles from ST-SPM-RS and ST-SPM-IS bear close resemblance, for either vertically or horizontally polarized channels, if the wave-shapes for the emissivity profiles from ST-SPM-IS are ignored and only the general trends are taken into account.

For the low vegetation regions, the emissivity profiles of the low-frequency vertically polarized channels from ST-SPM-RS are characterized by a wider shape, especially when the surface temperature is lower than 25°C, while the emissivity profiles from ST-SPM-IS are centralized with a smaller strip. However, with the increasing frequency, emissivity profiles from ST-SPM-IS and ST-SPM-RS become closer, and then can be nearly identical when it comes to the 89GHz channel. For the horizontally polarized channels, the emissivity profiles obtained from ST-SPM-RS are very unstable, fluctuating in wave-like shapes. For instance, the emissivity from ST-SPM-RS might have 10% chance of being as low as 0.85, which is much less likely for the emissivity from ST-SPM-IS. Therefore the profiles from ST-SPM-RS do not fit those from ST-SPM-IS.

Similar discussion for NDVI-SPM is presented as follows. For maximum vegetated regions, the distribution profiles of the emissivity at the vertically polarized channels from the NDVI-SPM-IS are very close to those from NDVI-SPM-RS and the latter ones might be slightly larger than the former ones. However, distributions at the horizontally polarized channels from NDVI-SPM-IS have a wider shape and the associated emissivity profiles are slightly larger than those from NDVI-SPM-RS.

For the moderate vegetated regions, NDVI-SPM-IS shares the almost identical distribution profiles with NDVI-SPM-RS for the 89H-GHz channel. And the very similar distributions between NDVI-SPM-IS and NDVI-SPM-RS exist for the other three horizontally polarized channels regardless of the fluctuating profiles from NDVI-SPM-IS. When considering the vertically polarized channels, the emissivity obtained from NDVI-SPM-RS is smaller than that from NDVI-SPM-IS, except the significant similarity between NDVI-SPM-RS and NDVI-SPM-IS for the 89V-GHz channel.

For the low vegetated regions, NDVI ranges up to 0.2 amid the in-situ measurements while it reaches 0.4 among the satellite observations. Emissivity at the horizontally polarized channels from NDVI-SPM-RS is higher than that of NDVI-SPM-IS if the NDVI is less than 0.26 but both of them exhibit the similar increasing trends. On the contrary, once the NDVI is larger than 0.26, the emissivity from NDVI-SPM-RS increases with NDVI while emissivity from NDVI-SPM-IS decreases with increasing NDVI. When it comes to the vertically polarized channels, the emissivity profiles from NDVI-SPM-IS are more likely to be lower than those from NDVI-SPM-RS when the NDVI is less than 0.26.

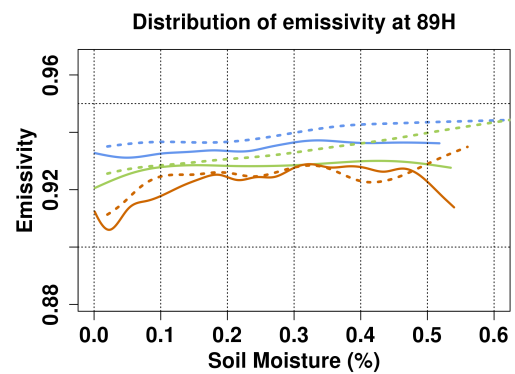
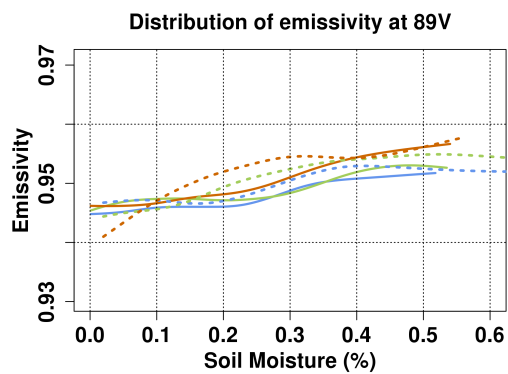
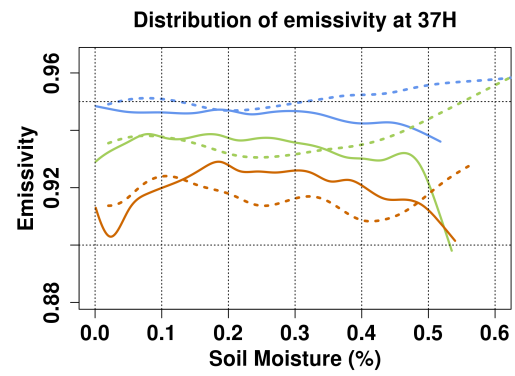
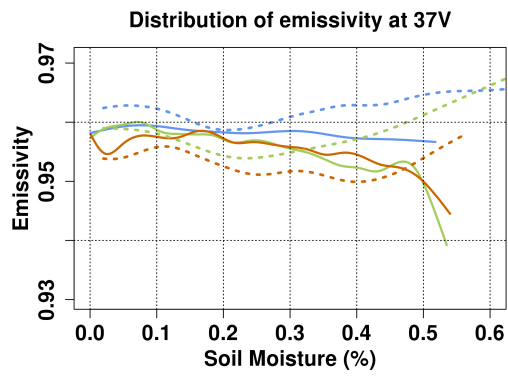
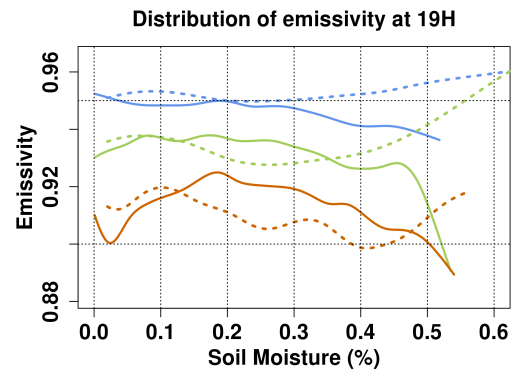
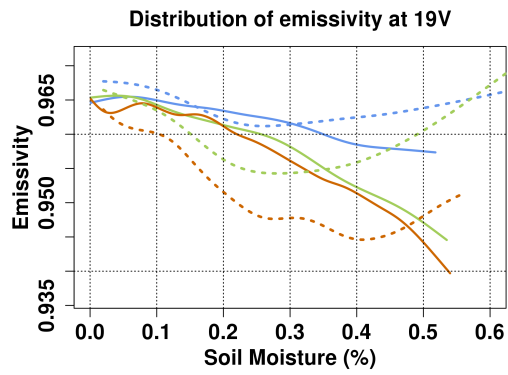
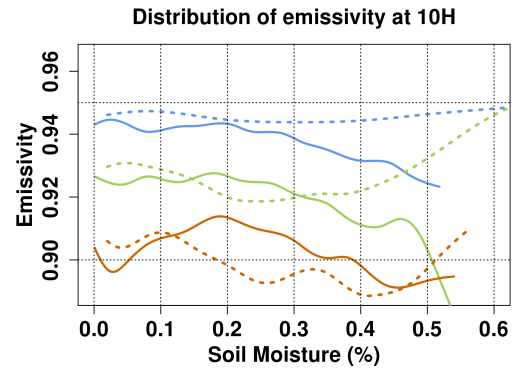
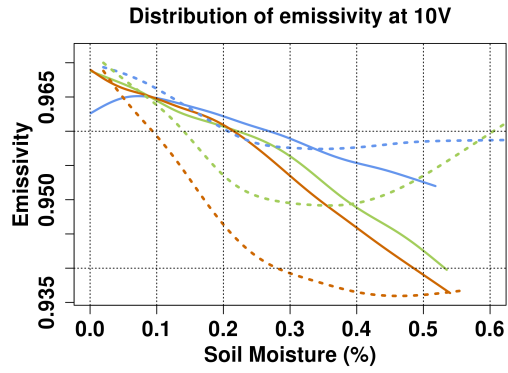
Regarding EVI-SPM, for maximum vegetation, the profiles of distributions of the emissivity from the EVI-SPM-IS and EVI-SPM-RS model are nearly identical for the vertically polarized channels. However, for the horizontally polarized channels, the distribution profiles from the IS model are higher than those from the RS model.

For the moderate vegetated regions, EVI-SPM-IS and EVI-SPM-RS share similar distribution profiles for the horizontally polarized channels. When it comes to the vertically polarized channels, higher emissivities from EVI-SPM-IS can be seen

when compared to the emissivities from NDVI-SPM-RS, with exception of 89V-GHz channel whose emissivity from EVI-SPM-IS and EVI-SPM-RS are extremely similar.

For the low vegetated regions, EVI of the in-situ measurements ranges up to 0.145 while EVI of the satellite observation ranges up to 0.22. Therefore, when EVI is smaller than 0.145, the horizontally polarized emissivity obtained from EVI-SPM-IS is larger than that from EVI-SPM-RS but both of them share the similar trends and shapes. Conversely, when EVI is larger than 0.145, the emissivity profiles from EVI-SPM-IS and EVI-SPM-RS are totally different. Lack of data for the EVI's range from 0.145 to 0.22 might be accountable for such discrepancies. However, no significant deviations are present in the comparison between the EVI-SPM-IS and EVI-SPM-RS for the vertically polarized channels. Specifically, the emissivity from EVI-SPM-IS is slightly higher than that from EVI-SPM-RS if EVI is below 0.15 and verse vice if EVI is above 0.15.

We focus on the median value of the PDFs of the emissivity to compare the models for five types of surfaces. Figure 7.1.2 shows these trends of emissivity as a univariate function of soil moisture at all the channels and over five categories of surface type. The emissivity derived from in-situ measurement and remotely sensing can be compared. Only the maximum vegetated, moderate vegetated and moderate vegetated are discussed in these following figures.



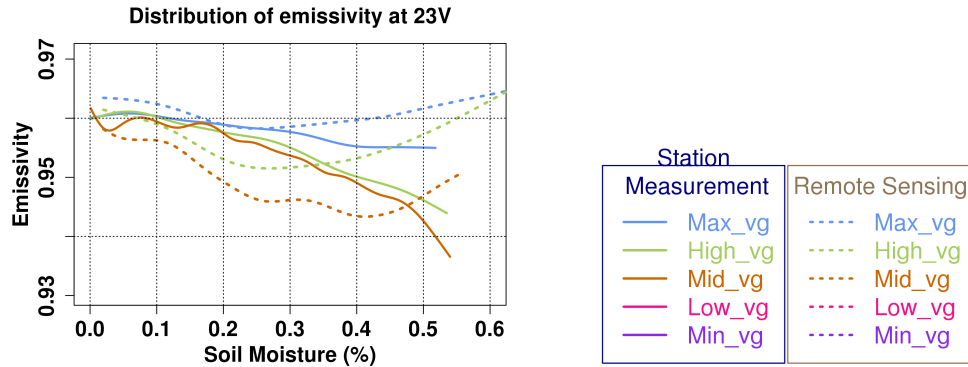


Figure 7.1.2 Comparison of single parameter modeling of emissivity estimated from models based on the remote sensing data and models based on the in-situ measurements over five classifications of surface type for all the channels

For 10V-GHz channel, the model for SM-SPM-RS fits well with that for SM-SPM-IS over the maximum vegetated regions. The typical range of soil moisture over the maximum-vegetation regions is from 0.05 to 0.35. Within this range, the 10V emissivities from both SM-SPM-RS and SM-SPM-IS decrease with soil moisture and the profiles from both of them is almost identical.

For high-and-moderate-vegetation regions, the emissivities from SM-SPM-RS decrease more rapidly than SM-SPM-IS, whereby the difference between SM-SPM-RS and SM-SPM-IS is more notable for moderate vegetation. In other words, given a certain value of soil moisture, the emissivities modeled using SM-SPM-RS are lower than the emissivity modeled from SM-SPM-IS.

When it comes to the higher frequency (37V-GHz and 89V-GHz channels), the discrepancies over moderate-vegetation regions become smaller.

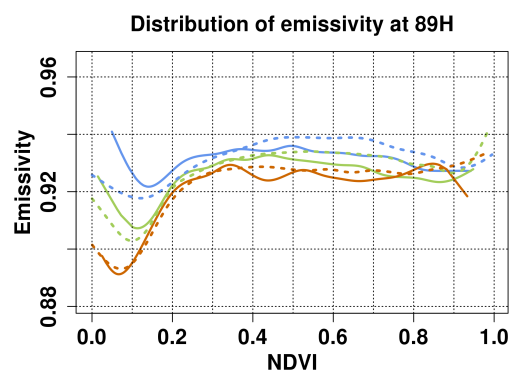
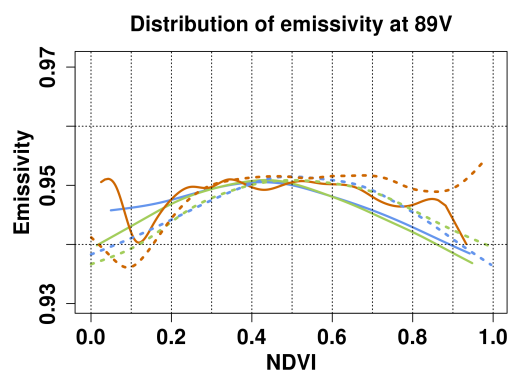
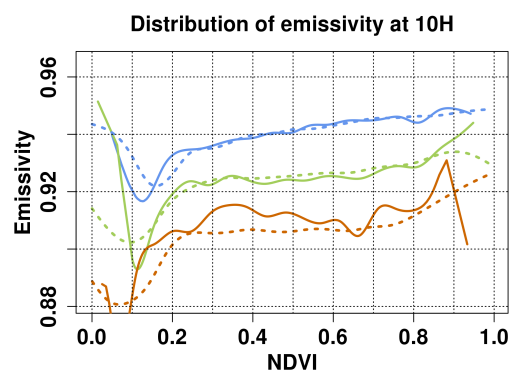
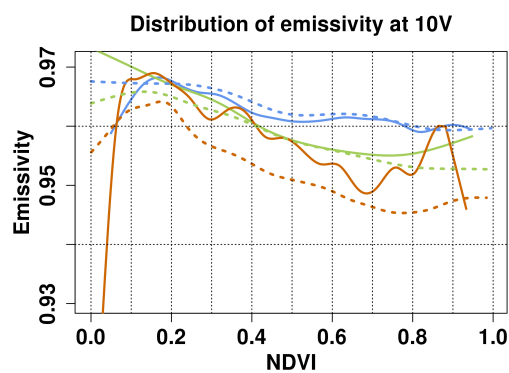
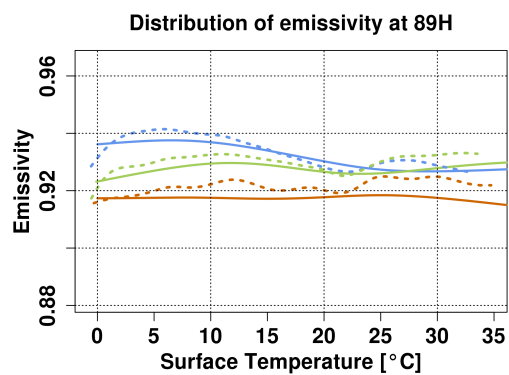
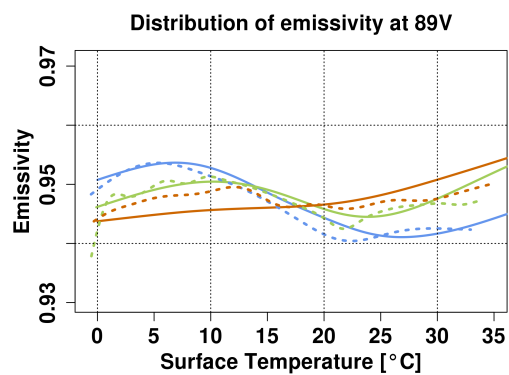
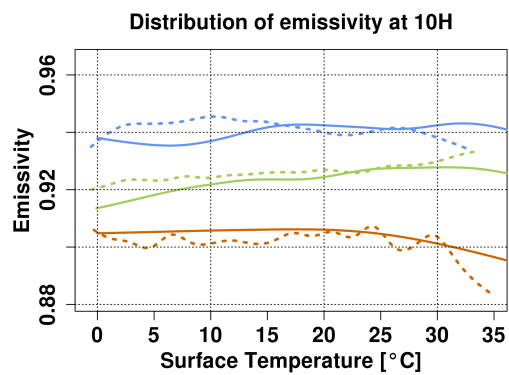
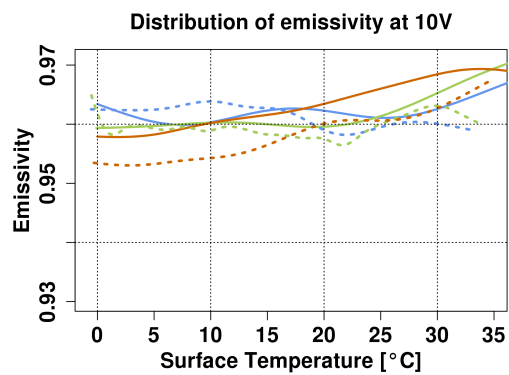
The horizontally polarized channels exhibit similar variations to the vertically polarized channels over the five surface types for SM-SPM-IS and SM-SPM-RS. For the 10H-GHz channel over maximum-and-high-vegetation regions, the emissivities exhibit slightly decreasing trends with soil moisture. For low-vegetation regions, the emissivity modeled from SM-SPM-IS is noisy, probably owing to the small sample size; for the minimum-vegetation regions, in-situ measurements also do not provide sufficient large samples.

The discussion above on the 10H-GHz channel is still valid for the 19H-GHz and 37H-GHz channels. For the 89H-GHz channel, emissivities for maximum-and-high vegetation regions remain rather constant with soil moisture for the typical range from 0.1 to 0.35. Emissivities from SM-SPM-IS and SM-SPM-RS are quite similar across maximum, high and moderate vegetated regions.

When it comes to surface temperature and emissivities at the horizontally polarized channels of 10GHz, 19GHz and 37GHz (not shown), ST-SPM-RS and ST-SPM-IS are very similar over moderate-vegetation regions.

For the low frequency vertically polarized channels, the emissivity profiles derived from ST-SPM-RS are similar to ST-SPM-IS for the high-vegetated regions. Differences noted for the maximum-vegetated and moderate-vegetated regions may arise from the differences between the surface temperature defined for the satellite product and the measured soil temperature.

Regardless of the data sources, the emissivity derived from ST-SPM tends to decrease with the higher frequencies.



Station	
Measurement	Remote Sensing
— Max_vg	----- Max_vg
— High_vg	----- High_vg
— Mid_vg	----- Mid_vg
— Low_vg	----- Low_vg
— Min_vg	----- Min_vg

Figure 7.1.3 Comparison of single parameter modeling (ST and NDVI) of emissivity estimated from models based on the remote sensing data and models based on the in-situ measurements over five classifications of surface type for all the channels

The comparison between NDVI-SPM-IS and NDVI-SPM-RS demonstrates a robust analogy over maximum and high vegetated regions. The emissivities of vertically polarized channels decrease with the higher NDVI as far as NDVI is larger than 0.1 and the decreasing trends are more noticeable over moderate. When it comes to high frequency such as 89 GHz, most emissivity profiles, in spite of the frequency and data sources differences, appear very close to each other.

In general, for the scenarios of the low-vegetated regions, the emissivity derived from NDVI-SPM-RS is higher than that derived from NDVI-SPM-IS when NDVI is larger than 0.3, while it reverses when the NDVI is larger than 0.3. Similar to ST-SPM, the emissivity can be as low as 0.65 for the vertically polarized channels and as low as 0.8 for the horizontally polarized channels for the case of the low and minimal vegetated regions, if the NDVI is smaller than 0.1, which indicates that the underlying surface might be a barren surface with the scarce vegetation coverage.

The comparison for the parameter EVI is quite similar to NDVI and we do not duplicate the discussion herein.

7.2 Comparison of the Rainy Emissivity

The emissivity data we used in this analysis is derived from the GMI brightness temperature for the non-rainy scenes only. However, the emissivity under rainy scenes is very important to analyze because the PMW precipitation retrieval requires the information of the underlying overland surface emissivity.

The rainy emissivity can be obtained through two approaches. One is to search the closest non-rainy satellite overpass back in time and use the emissivity from that overpass for the estimation of the rainy emissivity. We can call this estimate type 1 emissivity. The other approach is to extrapolate the emissivity models discussed in sections 5 and 6 provided that the surface properties are available. Accordingly, the emissivity calculated from the second method is referred as the type 2 rainy emissivity.

We recall that the emissivity models produce a probability distribution function. At a given rainy time over a ISMN station, the deterministic emissivity derived from the first approach can be compared to the distribution of emissivity from the statistical models used as a reference to evaluate the feasibility of estimating the rainy emissivity based on the closest non-rainy emissivity.

Figure 7.2.1 shows the type 2 emissivity quantiles of 10%, 25%, 50%, 75% and 90% as well as the type 1 rainy emissivity over a grassland station named Numm#1 (latitude and longitude are 40.9°N and 104.7°W). The type 1 rainy emissivity might fall into the range that is below 10% quantiles, or between the 25% and 50% quantiles of the distribution of type 2 emissivity.

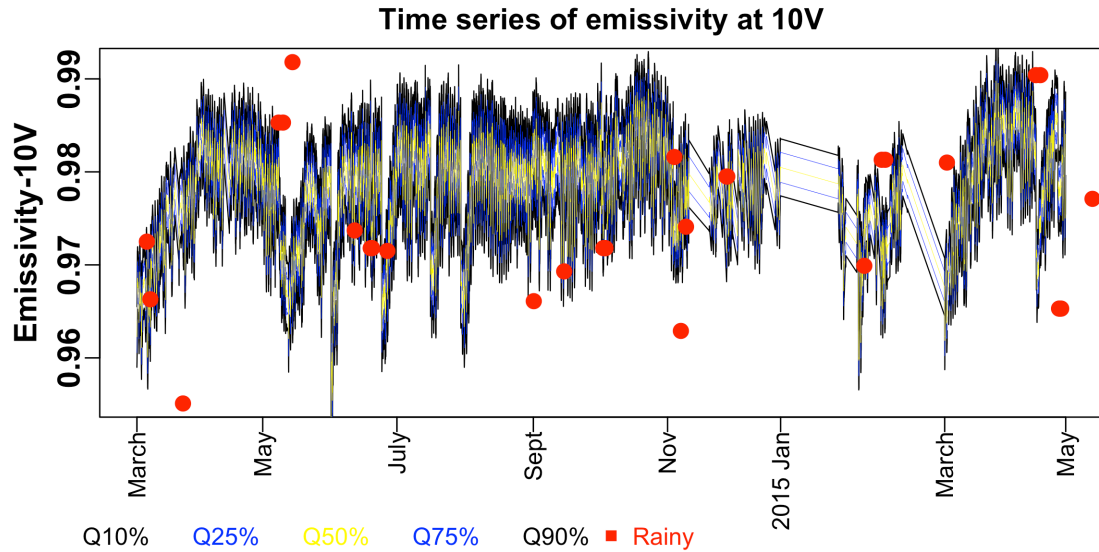


Figure 7.2.1 Time series of emissivity quantiles derived from our statistical models and type 1 rain emissivity over the Numm#1 station

The type 1 emissivity can be converted into a quantile of the distribution of the type 2 rainy emissivity. The statistics of such information are presented in Figure 7.2.2. For the 10V-GHz channel, more than 25% of the type 1 rainy emissivities fall into the range below the quantile 10% of the type 2 rainy emissivity, and around 10% fall into the range above 90% quantile 90%. Similarly the type 1 emissivity is more likely to fall below the quantile 10% for most of the low frequency channels. It indicates that the rainy emissivity based on the closest-time non-rainy emissivity tends to underestimate the surface emissivity at these frequencies. For the 37V-GHz channel, the probabilities associated to the type 1 rainy emissivity are more evenly distributed. For the 89GHz channels, most of the quantiles are above 50%. Therefore, the discrepancy between the type 1 and type 2 rainy emissivity is frequency dependent. More generally it suggests

that the approach of replacing the rainy emissivity using the closest-in-time past non-rainy emissivity is subject to uncertainties.

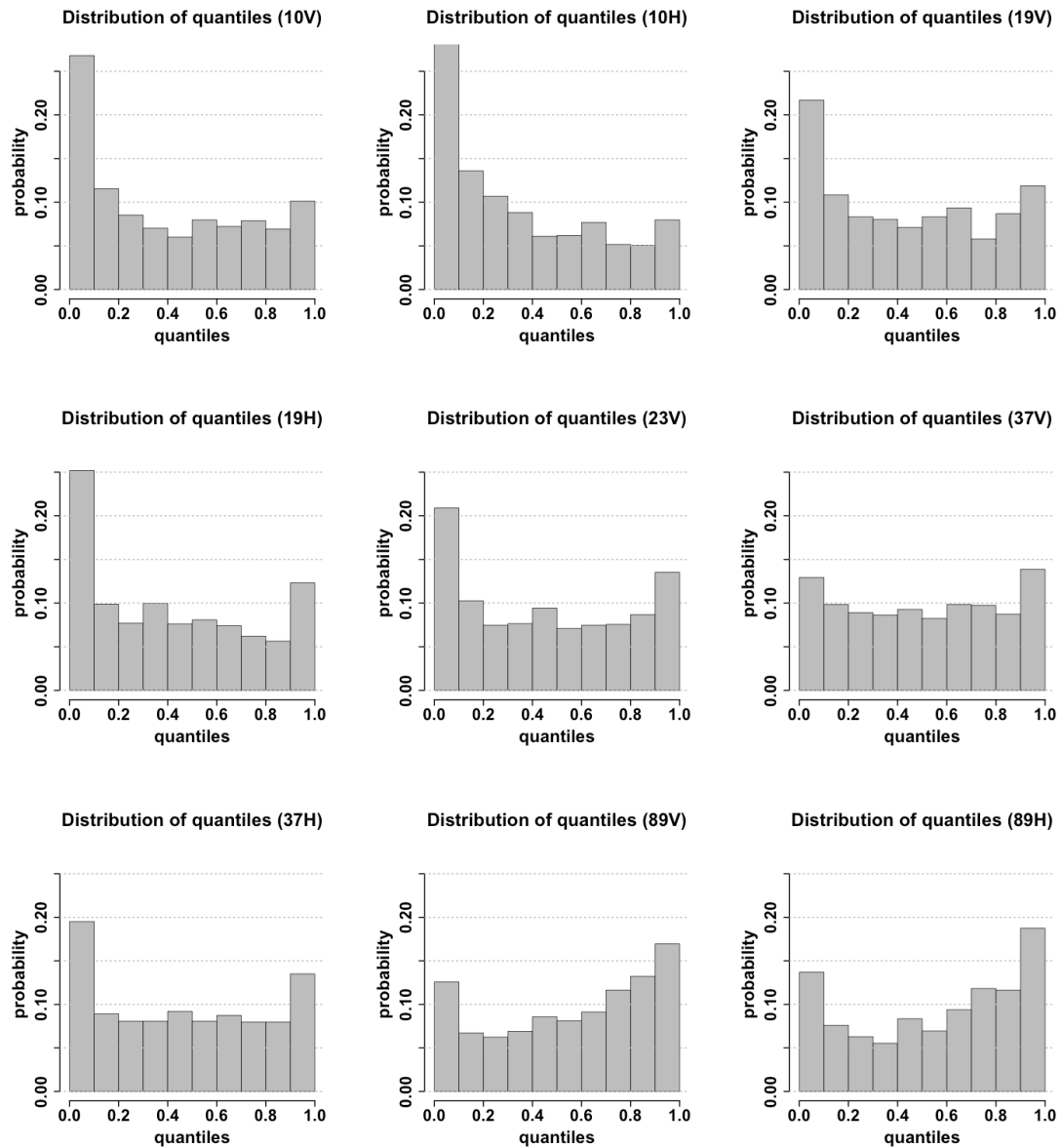


Figure 7.2.2 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the grassland

The discussion above is specific for all the stations across the grassland. However, for other types of landcover (shown in Figure 7.2.3), the situation is found the same. As representative examples, the distribution of probability of the type 1 rainy emissivity falling into different quantiles ranges of the type 2 rainy emissivity is quite even for the 37GHz V channel over cropland, and shifted toward higher quantiles for the 89GHz H channel over the shrubland.

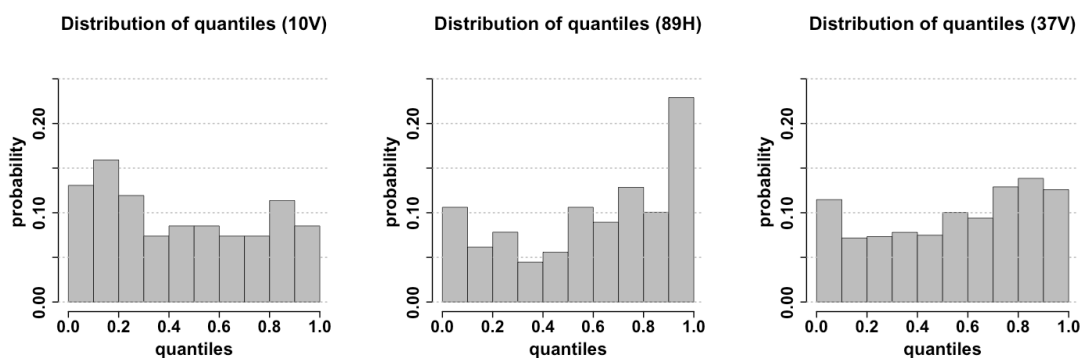


Figure 7.2.3 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations for other types of landcover, such as mixed forest (10 GHz V channel), shrubland (89 GHz H channel) and cropland (37 GHz V channel)

7.3 Summary

Two comparisons are involved in this section. The first comparison is to figure out the difference between emissivity models based on satellite observations and in-situ measurements. The following tables summarize the comparison: “Same” means that the two distributions are nearly identical. “IS Wider” indicates that the distribution of emissivity derived from in-situ measurements has a wider range than the distribution of

emissivity derived from satellite observations. “RS>IS” means that the distribution of the emissivity derived from the satellite observations are shifted positively relative to those derived from the in-situ measurements.

From these tables, it appears that the distributions of emissivity derived from in-situ measurements are similar to the distributions of emissivity derived from satellite observation in many cases. Some discrepancies can arise from the different natures of the measurements and the difference in resolution. These aspects will be addressed in future studies.

Table 7.3 Comparison between distributions of RS and IS emissivities over the maximum vegetated regions

Maximum vegetated	SM	ST	NDVI	EVI
10V	Same	RS>IS, then RS<IS	Same	Same
19V	Same	RS>IS, then RS<IS	Same	Same
23V	IS wider	RS>IS, then RS<IS	Same	Same
37V	IS wider	Same, then RS<IS	Same, then RS>IS	Same
89V	Same	Same, then	Same, then	Same

		RS<IS	RS>IS	
10H	RS>IS	RS>IS, then RS>IS	Similar	RS>IS, then same and IS wider
19H	RS>IS	RS>IS, then RS>IS	IS wider	RS>IS, then same and IS wider
37H	RS>IS	RS>IS, then RS>IS	RS>IS and IS wider	RS>IS, then same and IS wider
89H	RS>IS	Same	RS>IS and IS wider	RS>IS, then same

Table 7.4 Comparison between distributions of RS and IS emissivities over the
moderate vegetated regions

Moderate vegetated	SM	ST	NDVI	EVI
10V	RS<IS	RS<IS	RS<IS	RS<IS
19V	RS<IS	RS<IS	RS<IS	RS<IS
23V	RS<IS	Same	RS<IS	RS<IS
37V	RS<IS	Same	RS<IS	RS<IS
89V	RS<IS, then	Same	Same	Same

	RS>IS			
10H	Same, then RS<IS	Same	RS<IS	RS<IS
19H	Same, then RS<IS	Same	RS<IS, IS wider	RS<IS
37H	Same, then RS<IS	Same	RS<IS	RS<IS
89H	RS>IS	RS<IS	Same	Same

Another comparison addresses the challenge of the rainy emissivity. The rainy emissivity can be obtained by either using the closest past-time non-rainy emissivity or by extrapolating our emissivity models using the continuous measurement of the surface properties at stations. The emissivity obtained by the former method tends to underestimate specifically at low frequency. More analysis is needed to decipher this behavior.

8. Summary

The study addresses the effect of surface properties on the variation of the overland passive microwave (PMW) emissivity. The motivation of our research is presented in section 1. Our research aims at improving the understanding of the emissivity by establishing new emissivity models using surface properties.

We introduce the space missions GPM and SMAP and discuss the current status for the passive microwave precipitation retrievals as well as soil moisture retrievals in section 2. Section 3 details the theoretical basis of PMW emissivity, reviews the current methods for calculating the PMW emissivity and associated primary emissivity products, and discusses the method for the emissivity used in this research. The data of soil moisture, surface temperature, and vegetation indices from both in-situ measurement and remote sensing satellite observation are introduced in section 4.

Results and discussion are presented from section 5 to section 7. In both section 5 and section 6, we show the procedure of establishing empirical and statistical emissivity models, evaluate single-parameter and multi-parameter models, and predict the emissivity. Section 5 focuses on models based on in-situ measurements of soil moisture, soil temperature and air temperature. Section 6 focuses on models based on the satellite remotely sensed soil moisture and surface temperature, leading to a remote sensing perspective of the problem.

Section 5 studies the emissivity model over three stations that are representative of grassland, forest and barren regions. The land cover for these three stations is determined with the MODIS IGBP landcover classification. Section 6 deals with five categories of surface type (the maximum-vegetation, high-vegetation, moderate-

vegetation, low-vegetation and minimal-vegetation regions) based on the GMI level 2 products.

Section 7 addresses the comparison of the emissivity models established in the section 5 and section 6 respectively, compares the robustness and effectiveness of the emissivity models developed using in-situ and remote sensing perspectives. Additionally, section 7 compares the rainy emissivity derived from a satellite-based technique with the rainy emissivity obtained from our emissivity models.

From the results and discussion above we conclude that:

- 1) Soil moisture is a primary factor controlling the variation of emissivity, especially for the surface characterized by little to moderate vegetation at the low vertically polarized channels;
- 2) The effect of vegetation becomes more important at the higher frequency channels for the surface with moderate to high vegetation coverage;
- 3) Soil temperature or air temperature tends to govern the variation of high-frequency emissivity over the barren regions;
- 4) Our model can depict the variation of emissivity at different frequencies and polarizations by including the effect of surface properties. It can be applied over different types of overland surface or landcover;
- 5) A comparison between the in-situ and remote sensing models shows that the emissivities derived from these two different sources bear great resemblance;
- 6) Emissivity decreases with increasing NDVI at the vertically polarized channels, and increases with NDVI at the low-frequency horizontally polarized channels. Emissivity decreases with the EVI at the high frequency horizontally polarized channels;

emissivity at the vertically polarized channels decreases with the vegetation indices over the moderate vegetated regions. Emissivity decreases with the vegetation indices at the low frequency vertically polarized channels, and increases with the increasing NDVI/EVI at other channels for the low vegetated regions.

7) Emissivity decreases with the soil moisture at the low-frequency channels and increases with the soil moisture at the high-frequency channels for the region with maximum to moderate vegetation; emissivity decreases with increasing soil moisture for the low-frequency channel for the low vegetated regions.

8) Emissivity decreases with the surface temperature at the high-frequency channels over maximum-vegetation regions, and increases with the surface temperature at the low frequency vertically polarized channels; emissivity increases with the increasing surface temperature at the vertically polarized channels for the moderate and low vegetated regions.

Through the discussion above, we can estimate or predict the emissivity for the microwave passive precipitation retrievals by applying the emissivity models. This new, dynamic datasets of PMW emissivity can contribute to the improvement of the accuracy of satellite quantitate precipitation estimates.

References

Aires, F., C. Prigent, W. B. Rossow, M. Rothstein, and James E. Hansen. "A new neural network approach including first-guess for retrieval of atmospheric water vapor, cloud liquid water path, surface temperature and emissivities over land from satellite microwave observations." (2000).

Aires, Filipe, Catherine Prigent, Frédéric Bernardo, Carlos Jiménez, Roger Saunders, and Pascal Brunel. "A Tool to Estimate Land-Surface Emissivities at Microwave frequencies (TELSEM) for use in numerical weather prediction." *Quarterly Journal of the Royal Meteorological Society* 137, no. 656 (2011): 690-699.

Albergel, Clement, Patricia De Rosnay, Claire Gruhier, Joaquin Muñoz-Sabater, Stefan Hasenauer, Lars Isaksen, Yann Kerr, and Wolfgang Wagner. "Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations." *Remote Sensing of Environment* 118 (2012): 215-226.

Bartalis, Zoltan, Wolfgang Wagner, Vahid Naeimi, Stefan Hasenauer, Klaus Scipal, Hans Bonekamp, Julia Figa, and Craig Anderson. "Initial soil moisture retrievals from the METOP-A Advanced Scatterometer (ASCAT)." *Geophysical Research Letters* 34, no. 20 (2007).

Bell, Jesse E., Michael A. Palecki, C. Bruce Baker, William G. Collins, Jay H. Lawrimore, Ronald D. Leeper, Mark E. Hall et al. "US Climate Reference Network soil moisture and temperature observations." *Journal of Hydrometeorology* 14, no. 3 (2013): 977-988.

Bellerby, Tim, Martin Todd, Dom Kniveton, and Chris Kidd. "Rainfall estimation from a combination of TRMM precipitation radar and GOES multispectral satellite imagery through the use of an artificial neural network." *Journal of applied Meteorology* 39, no. 12 (2000): 2115-2128.

Bengtsson, Lennart, R. M. Bonnet, M. Calisto, G. Destouni, R. Gurney, J. Johannessen, Y. Kerr, William A. Lahoz, and Michael Rast, eds. *The Earth's Hydrological Cycle*. Springer, 2014.

Beniston, Martin, ed. *Climatic change: implications for the hydrological cycle and for water management*. Kluwer Academic Publishers, 2002.

Berg, Wesley, Tristan L'Ecuyer, and Christian Kummerow. "Rainfall climate regimes: The relationship of regional TRMM rainfall biases to the environment." *Journal of applied meteorology and climatology* 45, no. 3 (2006): 434-454.

Bommarito, Joseph J. "DMSP special sensor microwave imager sounder (SSMIS)." In *Optical Engineering and Photonics in Aerospace Sensing*, pp. 230-238. International Society for Optics and Photonics, 1993.

Boukabara, Sid-Ahmed, Kevin Garrett, Wanchun Chen, Flavio Iturbide-Sanchez, Christopher Grassotti, Cezar Kongoli, Ruiyue Chen et al. "MiRS: An all-weather 1DVAR satellite data assimilation and retrieval system." *IEEE Transactions on Geoscience and Remote Sensing* 49, no. 9 (2011): 3249-3272.

Brandes, Edward A. "Optimizing rainfall estimates with the aid of radar." *Journal of Applied Meteorology* 14, no. 7 (1975): 1339-1345.

Bringi, V. N., and V. Chandrasekar. *Polarimetric Doppler weather radar: principles and applications*. Cambridge University Press, 2001.

Brunfeldt, David R., and Fawwaz T. Ulaby. "Measured microwave emission and scattering in vegetation canopies." *IEEE Transactions on Geoscience and Remote Sensing* 6 (1984): 520-524.

Calvet, Jean-Christophe, Jean-Pierre Wigneron, André Chanzy, and Driss Haboudane. "Retrieval of surface parameters from microwave radiometry over open canopies at high frequencies." *Remote sensing of environment* 53, no. 1 (1995): 46-60.

Calvet, J-C., J-P. Wigneron, Andre Chanzy, Suresh Raju, and Laurent Laguerre. "Microwave dielectric properties of a silt-loam at high frequencies." *IEEE transactions on geoscience and remote sensing* 33, no. 3 (1995): 634-642.

Calvet, Jean-Christophe, Jean-Pierre Wigneron, Jeffrey Walker, Fatima Karbou, André Chanzy, and Clément Albergel. "Sensitivity of passive microwave observations to soil moisture and vegetation water content: L-band to W-band." *IEEE Transactions on Geoscience and Remote Sensing* 49, no. 4 (2011): 1190-1199.

Chahine, Moustafa T. "The hydrological cycle and its influence on climate." *Nature* 359, no. 6394 (1992): 373-380.

Choudhury, B. J., C. J. Tucker, R. E. Golus, and W. W. Newcomb. "Monitoring vegetation using Nimbus-7 scanning multichannel microwave radiometer's data." *International Journal of Remote Sensing* 8, no. 3 (1987): 533-538.

Claassen, J., and A. Fung. "The recovery of polarized apparent temperature distributions of flat scenes from antenna temperature measurements." *IEEE Transactions on Antennas and Propagation* 22, no. 3 (1974): 433-442.

Daly, Edorado, and Amilcare Porporato. "A review of soil moisture dynamics: from rainfall infiltration to ecosystem response." *Environmental engineering science* 22, no. 1 (2005): 9-24.

de Jeu, Richard, Yann Kerr, Jean Pierre Wigneron, Nemesio Rodriguez-Fernandez, Amen Al-Yaari, Robin van der Schalie, Han Dolman, Matthias Drusch, and Susanne Mecklenburg. "The Integration of SMOS Soil Moisture in a Consistent Soil Moisture Climate Record." In EGU General Assembly Conference Abstracts, vol. 17, p. 7286. 2015.

Dobson, Myron C., Fawwaz T. Ulaby, Martti T. Hallikainen, and Mohamed A. El-Rayes. "Microwave dielectric behavior of wet soil—Part II: Dielectric mixing models." IEEE Trans. Geosci. Remote Sens 23, no. 1 (1985): 35-46.

Dorigo, W. A., Wolfgang Wagner, Roland Hohensinn, Sebastian Hahn, Christoph Paulik, Angelika Xaver, Alexander Gruber et al. "The International Soil Moisture Network: a data hosting facility for global in situ soil moisture measurements." Hydrology and Earth System Sciences 15, no. 5 (2011): 1675-1698.

Doviak, Richard J., and Dusan S. Zrnic. Doppler Radar & Weather Observations. Academic press, 2014.

Draper, David W., David A. Newell, Frank J. Wentz, Sergey Krimchansky, and Gail M. Skofronick-Jackson. "The global precipitation measurement (GPM) microwave imager (GMI): Instrument overview and early on-orbit performance." Selected Topics in Applied Earth Observations and Remote Sensing, IEEE Journal of 8, no. 7 (2015): 3452-3462.

Dunbar, S. and S. Chan (2009): SMAP Fixed Earth Grids, SMAP Science Document, May 2009.

Eagleman, Joe R., and Wen C. Lin. "Remote sensing of soil moisture by a 21-cm passive radiometer." Journal of Geophysical Research 81, no. 21 (1976): 3660-3666.

Entekhabi, Dara, Eni G. Njoku, Peggy EO Neill, Kent H. Kellogg, Wade T. Crow, Wendy N. Edelstein, Jared K. Entin et al. "The soil moisture active passive (SMAP) mission." Proceedings of the IEEE 98, no. 5 (2010): 704-716.

Entekhabi, Dara, Simon Yueh, Peggy E. O'Neill, Kent H. Kellogg, Angela Allen, Rajat Bindlish, Molly Brown et al. "SMAP Handbook—Soil Moisture Active Passive: Mapping Soil Moisture and Freeze/Thaw from Space." (2014).

Entekhabi, D., S. Yueh, P. O'Neill, K. Kellogg et al., SMAP Handbook, JPL Publication JPL 400- 1567, Jet Propulsion Laboratory, Pasadena, California, (2014).

Felde, G. W. "The effect of soil moisture on the 37GHz microwave polarization difference index (MPDI)." International Journal of Remote Sensing 19, no. 6 (1998): 1055-1078

Fengqing, Jiang, Zhu Cheng, Mu Guijin, Hu Ruji, and Meng Qingxia. "Magnification of flood disasters and its relation to regional precipitation and local human activities since the 1980s in Xinjiang, Northwestern China." *Natural Hazards* 36, no. 3 (2005): 307-330.

Ferraro, Ralph R. "Special sensor microwave imager derived global rainfall estimates for climatological applications." *Journal of Geophysical Research: Atmospheres* 102, no. D14 (1997): 16715-16735.

Ferraro, Ralph R., Christa D. Peters-Lidard, Cecilia Hernandez, F. Joseph Turk, Filipe Aires, Catherine Prigent, Xin Lin et al. "An evaluation of microwave land surface emissivities over the continental United States to benefit GPM-era precipitation algorithms." *IEEE Transactions on Geoscience and Remote Sensing* 51, no. 1 (2013): 378-398.

Fily, M., A. Royer, K. Goita, and C. Prigent. "A simple retrieval method for land surface temperature and fraction of water surface determination from satellite microwave brightness temperatures in sub-arctic areas." *Remote Sensing of Environment* 85, no. 3 (2003): 328-338.

Ford, Trent W., Anita D. Rapp, Steven M. Quiring, and Jennifer Blake. "Soil moisture–precipitation coupling: observations from the Oklahoma Mesonet and underlying physical mechanisms." *Hydrology and Earth System Sciences* 19, no. 8 (2015): 3617-3631.

Friedl, Mark A., Douglas K. McIver, John CF Hodges, X. Y. Zhang, D. Muchoney, Alan H. Strahler, Curtis E. Woodcock et al. "Global land cover mapping from MODIS: algorithms and early results." *Remote Sensing of Environment* 83, no. 1 (2002): 287-302.

Furuzawa, Fumie A., and Kenji Nakamura. "Differences of rainfall estimates over land by Tropical Rainfall Measuring Mission (TRMM) Precipitation Radar (PR) and TRMM Microwave Imager (TMI)-Dependence on storm height." *Journal of Applied Meteorology* 44, no. 3 (2005): 367-383.

Galantowicz, John F., Jean-Luc Moncet, Pan Liang, Alan E. Lipton, Gennady Uymin, Catherine Prigent, and Christopher Grassotti. "Subsurface emission effects in AMSR-E measurements: Implications for land surface microwave emissivity retrieval." *Journal of Geophysical Research: Atmospheres* 116, no. D17 (2011).

Gao, H., E. F. Wood, T. J. Jackson, M. Drusch, and R. Bindlish. "Using TRMM/TMI to retrieve surface soil moisture over the southern United States from 1998 to 2002." *Journal of Hydrometeorology* 7, no. 1 (2006): 23-38.

Gopalan, Kaushik, Nai-Yu Wang, Ralph Ferraro, and Chuntao Liu. "Status of the TRMM 2A12 land precipitation algorithm." *Journal of Atmospheric and Oceanic Technology* 27, no. 8 (2010): 1343-1354.

Gruber, Alexander, W. A. Dorigo, S. Zwieback, A. Xaver, and W. Wagner. "Characterizing coarse-scale representativeness of in situ soil moisture measurements from the International Soil Moisture Network." *Vadose Zone Journal* 12, no. 2 (2013)

Guedj, Stephanie, Fatima Karbou, Florence Rabier, and Aurelie Bouchard. "Toward a better modeling of surface emissivity to improve AMSU data assimilation over Antarctica." *IEEE Transactions on Geoscience and Remote Sensing* 48, no. 4 (2010): 1976-1985.

Harrison, D. L., S. J. Driscoll, and M. Kitchen. "Improving precipitation estimates from weather radar using quality control and correction techniques." *Meteorological Applications* 7, no. 02 (2000): 135-144.

Harrison, Kenneth W., Yudong Tian, Christa D. Peters-Lidard, Sarah Ringerud, and Sujay V. Kumar. "Calibration to improve forward model simulation of microwave emissivity at GPM frequencies over the US Southern Great Plains." *IEEE Transactions on Geoscience and Remote Sensing* 54, no. 2 (2016): 1103-1117.

Held, Isaac M., and Brian J. Soden. "Robust responses of the hydrological cycle to global warming." *Journal of Climate* 19, no. 21 (2006): 5686-5699.

Hernández, Fidel, Froylán Hernández, Juan A. Arredondo, Fred C. Bryant, Leonard A. Brennan, and Ralph L. Bingham. "Influence of precipitation on demographics of northern bobwhites in southern Texas." *Wildlife Society Bulletin* 33, no. 3 (2005): 1071-1079.

Hewison, Tim J. "Airborne measurements of forest and agricultural land surface emissivity at millimeter wavelengths." *IEEE transactions on geoscience and remote sensing* 39, no. 2 (2001): 393-400.

Hoekstra, P., and Ag Delaney. "Dielectric properties of soils at UHF and microwave frequencies." *Journal of geophysical research* 79, no. 11 (1974): 1699-1708.

Hohenegger, Cathy, Peter Brockhaus, Christopher S. Bretherton, and Christoph Schär. "The soil moisture-precipitation feedback in simulations with explicit and parameterized convection." *Journal of Climate* 22, no. 19 (2009): 5003-5020.

Hou, Arthur Y., Ramesh K. Kakar, Steven Neeck, Ardeshir A. Azarbarzin, Christian D. Kummerow, Masahiro Kojima, Riko Oki, Kenji Nakamura, and Toshio Iguchi. "The global precipitation measurement mission." *Bulletin of the American Meteorological Society* 95, no. 5 (2014): 701-722.

Huete, Alfredo, Chris Justice, and Wim Van Leeuwen. "MODIS vegetation index (MOD13)." Algorithm theoretical basis document 3 (1999): 213.

Huete, Alfredo, Kamel Didan, Tomoaki Miura, E. Patricia Rodriguez, Xiang Gao, and Laerte G. Ferreira. "Overview of the radiometric and biophysical performance of the MODIS vegetation indices." *Remote sensing of environment* 83, no. 1 (2002): 195-213.

Huete, Alfredo R., Kamel Didan, Yosio E. Shimabukuro, Piyachat Ratana, Scott R. Saleska, Lucy R. Hutya, Wenze Yang, Ramakrishna R. Nemani, and Ranga Myneni. "Amazon rainforests green-up with sunlight in dry season." *Geophysical research letters* 33, no. 6 (2006).

Huete, Alfredo R., Karl F. Huemmrich, Tomoaki Miura, Xiangming Xiao, Kamel Didan, Willem van Leeuwen, Forrest Hall, and Compton J. Tucker. "Vegetation Index greenness global data set." NASA ESDR/CDR (2006).

Hunt, E. Raymond, Li Li, M. Tugrul Yilmaz, and Thomas J. Jackson. "Comparison of vegetation water contents derived from shortwave-infrared and passive-microwave sensors over central Iowa." *Remote Sensing of Environment* 115, no. 9 (2011): 2376-2383.

Huffman, George J., Robert F. Adler, David T. Bolvin, and Guojun Gu. "Improving the global precipitation record: GPCP version 2.1." *Geophysical Research Letters* 36, no. 17 (2009).

Isaacs, Ronald G., Y-Q. Jin, Robert D. Worsham, Godelieve Deblonde, and V. J. Falcone. "The RADTRAN microwave surface emission models." *IEEE transactions on geoscience and remote sensing* 27, no. 4 (1989): 433-440.

Jackson, Thomas J., Thomas J. Schmugge, and James R. Wang. "Passive microwave sensing of soil moisture under vegetation canopies." *Water Resources Research* 18, no. 4 (1982): 1137-1142.

Jackson, T. J., and T. J. Schmugge. "Vegetation effects on the microwave emission of soils." *Remote Sensing of Environment* 36, no. 3 (1991): 203-212.

Jackson, Thomas J. "III. Measuring surface soil moisture using passive microwave remote sensing." *Hydrological processes* 7, no. 2 (1993a): 139-152.

Jackson, Thomas J., Peggy E. O'Neill, and Calvin T. Swift. "Passive microwave observation of diurnal surface soil moisture." *IEEE Transactions on Geoscience and Remote Sensing* 35, no. 5 (1997): 1210-1222.

Jackson, Thomas J., and Linda Moy. "Dew effects on passive microwave observations of land surfaces." *Remote sensing of environment* 70, no. 2 (1999): 129-137.

Jackson, T. and J. Kimball, "SMAP Mission Science Issues Associated with Overpass Time," SMAP Science Document No. 003, JPL, 2009.

Jones, Matthew O., Lucas A. Jones, John S. Kimball, and Kyle C. McDonald. "Satellite passive microwave remote sensing for monitoring global land surface phenology." *Remote Sensing of Environment* 115, no. 4 (2011): 1102-1114.

Joyce, Robert J., John E. Janowiak, Phillip A. Arkin, and Pingping Xie. "CMORPH: A method that produces global precipitation estimates from passive microwave and infrared data at high spatial and temporal resolution." *Journal of Hydrometeorology* 5, no. 3 (2004): 487-503.

Justice, Christopher O., Eric Vermote, John RG Townshend, Ruth Defries, David P. Roy, Dorothy K. Hall, Vincent V. Salomonson et al. "The Moderate Resolution Imaging Spectroradiometer (MODIS): Land remote sensing for global change research." *IEEE Transactions on Geoscience and Remote Sensing* 36, no. 4 (1998): 1228-1249.

Justice, C. O., J. R. G. Townshend, E. F. Vermote, E. Masuoka, R. E. Wolfe, N. Saleous, D. P. Roy, and J. T. Morisette. "An overview of MODIS Land data processing and product status." *Remote sensing of Environment* 83, no. 1 (2002): 3-15.

Karbou, Fatima, Catherine Prigent, Laurence Eymard, and Juan R. Pardo. "Microwave land emissivity calculations using AMSU measurements." *Geoscience and Remote Sensing, IEEE Transactions on* 43, no. 5 (2005): 948-959.

Karbou, Fatima, Élisabeth Gérard, and Florence Rabier. "Microwave land emissivity and skin temperature for amsu-A and-B assimilation over land." *Quarterly Journal of the Royal Meteorological Society* 132, no. 620 (2006): 2333-2355.

Kawanishi, Toneo, Toshihiro Sezai, Yasuyuki Ito, Keiji Imaoka, Toshiaki Takeshima, Yoshio Ishido, Akira Shibata, Masaharu Miura, Hiroyuki Inahata, and Roy W. Spencer. "The Advanced Microwave Scanning Radiometer for the Earth Observing System (AMSR-E), NASDA's contribution to the EOS for global energy and water cycle studies." *IEEE Transactions on Geoscience and Remote Sensing* 41, no. 2 (2003): 184-194.

Kerr, Yann H., and Eni G. Njoku. "A semiempirical model for interpreting microwave emission from semiarid land surfaces as seen from space." *IEEE Transactions on Geoscience and Remote Sensing* 28, no. 3 (1990): 384-393.

Kerr, Yann H., Philippe Waldteufel, Jean-Pierre Wigneron, Steven Delwart, François Cabot, Jacqueline Boutin, Maria-Jose Escorihuela et al. "The SMOS mission: New tool for monitoring key elements of the global water cycle." *Proceedings of the IEEE* 98, no. 5 (2010): 666-687.

Kidd, Chris, Dominic R. Kniveton, Martin C. Todd, and Tim J. Bellerby. "Satellite rainfall estimation using combined passive microwave and infrared algorithms." *Journal of Hydrometeorology* 4, no. 6 (2003): 1088-1104.

Kidder, Stanley Q., and Thomas H. Vonder Haar. *Satellite meteorology: an introduction*. Gulf Professional Publishing, 1995.

Kong, Jin Au. "Theory of electromagnetic waves." New York, Wiley-Interscience, 1975. 348 p. 1 (1975).

Koster, Randal D., Max J. Suarez, R. Wayne Higgins, and Huug M. Van den Dool. "Observational evidence that soil moisture variations affect precipitation." *Geophysical Research Letters* 30, no. 5 (2003).

Kozu, Toshiaki, Toneo Kawanishi, Hiroshi Kuroiwa, Masahiro Kojima, Koki Oikawa, Hiroshi Kumagai, Ken'ichi Okamoto, Minoru Okumura, Hirotaka Nakatsuka, and Katsuhiko Nishikawa. "Development of precipitation radar onboard the Tropical Rainfall Measuring Mission (TRMM) satellite." *IEEE transactions on geoscience and remote sensing* 39, no. 1 (2001): 102-116.

Kumar, Sujay V., Christa D. Peters-Lidard, Yudong Tian, Paul R. Houser, James Geiger, S. Olden, L. Lighty et al. "Land information system: An interoperable framework for high resolution land surface modeling." *Environmental modelling & software* 21, no. 10 (2006): 1402-1415.

Kummerow, Christian D., David L. Randel, Mark Kulie, Nai-Yu Wang, Ralph Ferraro, S. Joseph Munchak, and Veljko Petkovic. "The evolution of the Goddard Profiling Algorithm to a fully parametric scheme." *Journal of Atmospheric and Oceanic Technology* 32, no. 12 (2015): 2265-2280.

Le Vine, David M., and Mostafa A. Karam. "Dependence of attenuation in a vegetation canopy on frequency and plant water content." *IEEE Transactions on Geoscience and Remote Sensing* 34, no. 5 (1996): 1090-1096.

Lee, Khil-Ha, and Emmanouil N. Anagnostou. "A combined passive/active microwave remote sensing approach for surface variable retrieval using Tropical Rainfall Measuring Mission observations." *Remote Sensing of Environment* 92, no. 1 (2004): 112-125.

Levizzani, Vincenzo, Peter Bauer, and F. Joseph Turk. *Measuring precipitation from space: EURAINSAT and the future*. Vol. 28. Springer Science & Business Media, 2007.

Li, Li, Peter W. Gaiser, Bo-Cai Gao, Richard M. Bevilacqua, Thomas J. Jackson, Eni G. Njoku, Christoph Rudiger, Jean-Christophe Calvet, and Rajat Bindlish. "WindSat global

soil moisture retrieval and validation." *IEEE Transactions on Geoscience and Remote Sensing* 48, no. 5 (2010): 2224-2241.

Lin, Bing, and Patrick Minnis. "Temporal variations of land surface microwave emissivities over the atmospheric radiation measurement program southern great plains site." *Journal of Applied Meteorology* 39, no. 7 (2000): 1103-1116.

Liu, Yi Y., R. M. Parinussa, Wouter A. Dorigo, Richard AM De Jeu, Wolfgang Wagner, A. I. J. M. Van Dijk, Matthew F. McCabe, and J. P. Evans. "Developing an improved soil moisture dataset by blending passive and active microwave satellite-based retrievals." *Hydrology and Earth System Sciences* 15, no. 2 (2011): 425-436.

Liu, Zhong, D. Ostrenga, B. Vollmer, B. Deshong, K. MacRitchie, M. Greene, and S. Kempler. "Supporting Hydrometeorological Research and Applications with Global Precipitation Measurement (GPM) Products and Services." (2016).

Mecklenburg, Susanne, Matthias Drusch, Yann H. Kerr, Jordi Font, Manuel Martin-Neira, Steven Delwart, Guillermo Buenadicha et al. "ESA's soil moisture and ocean salinity mission: Mission performance and operations." *IEEE Transactions on Geoscience and Remote Sensing* 50, no. 5 (2012): 1354-1366.

Meyers, Patrick C., and Ralph R. Ferraro. "Accounting for surface ice and snow in the goddard profiling algorithm rain rate retrievals." In *2015 IEEE International Geoscience and Remote Sensing Symposium (IGARSS)*, pp. 2619-2621. IEEE, 2015.

Michaelides, Silas C., ed. *Precipitation: advances in measurement, estimation and prediction*. Springer Science & Business Media, 2008.

Middleton, William E. "History of the Theories of Rain and other forms of precipitation." (1966).

Miura, Tomoaki, Hiroki Yoshioka, and Tomoko Suzuki. "Evaluation of spectral vegetation index translation equations for the development of long-term data records." In *IGARSS 2008-2008 IEEE International Geoscience and Remote Sensing Symposium*, vol. 3, pp. III-712. IEEE, 2008.

Mo, T., B. J. Choudhury, T. J. Schmugge, J. R. Wang, and T. J. Jackson. "A model for microwave emission from vegetation-covered fields." *Journal of Geophysical Research: Oceans* 87, no. C13 (1982): 11229-11237.

Moncet, Jean-Luc, Pan Liang, John F. Galantowicz, Alan E. Lipton, Gennady Uymin, Catherine Prigent, and Christopher Grassotti. "Land surface microwave emissivities derived from AMSR-E and MODIS measurements with advanced quality control." *Journal of Geophysical Research: Atmospheres* 116, no. D16 (2011).

Morland, June C., David IF Grimes, and T. J. Hewison. "Satellite observations of the microwave emissivity of a semi-arid land surface." *Remote sensing of environment* 77, no. 2 (2001): 149-164.

Myneni, Ranga B., Forrest G. Hall, Piers J. Sellers, and Alexander L. Marshak. "The interpretation of spectral vegetation indexes." *IEEE Transactions on Geoscience and Remote Sensing* 33, no. 2 (1995): 481-486.

Njoku, Eni G., and Dara Entekhabi. "Passive microwave remote sensing of soil moisture." *Journal of hydrology* 184, no. 1 (1996): 101-129.

Njoku, Eni G., and Li Li. "Retrieval of land surface parameters using passive microwave measurements at 6-18 GHz." *IEEE Transactions on Geoscience and Remote Sensing* 37, no. 1 (1999): 79-93.

Njoku, Eni G., Thomas J. Jackson, Venkat Lakshmi, Tsz K. Chan, and Son V. Nghiem. "Soil moisture retrieval from AMSR-E." *IEEE transactions on Geoscience and remote sensing* 41, no. 2 (2003): 215-229.

Njoku, Eni G., and Steven K. Chan. "Vegetation and surface roughness effects on AMSR-E land observations." *Remote Sensing of environment* 100, no. 2 (2006): 190-199.

Norouzi, Hamidreza, William Rossow, Marouane Temimi, Catherine Prigent, Marzieh Azarderakhsh, Sid Boukabara, and Reza Khanbilvardi. "Using microwave brightness temperature diurnal cycle to improve emissivity retrievals over land." *Remote Sensing of Environment* 123 (2012): 470-482.

Norouzi, H., M. Temimi, C. Prigent, J. Turk, R. Khanbilvardi, Y. Tian, F. A. Furuzawa, and H. Masunaga. "Assessment of the consistency among global microwave land surface emissivity products." *Atmospheric Measurement Techniques* 8, no. 3 (2015): 1197-1205.

Norouzi, H., Temimi, M., Rossow, W. B., and Khanbilvardi, R.: AMSR-E/Aqua Monthly Global Microwave Land Surface Emissivity, Boulder, Colorado USA: NASA National Snow and Ice Data Center Distributed Active Archive Center, available at: <http://nsidc.org/data/nsidc-0543> last access: 27 July 2016, 2013.

Oliver, Howard R., and Sylvia A. Oliver, eds. *The role of water and the hydrological cycle in global change*. Vol. 31. Springer Science & Business Media, 2013.

O'Neill, Peggy. Steven Chan, Eni Njoku, Tom Jackson, Rajat Bindlish, "Algorithm Theoretical Basis Document Level 2 & 3 Soil Moisture (Passive) Data Products". Revision A. Dec 9, 2014

Owe, Manfred, and Adriaan A. Van de Griend. "Comparison of soil moisture penetration depths for several bare soils at two microwave frequencies and implications for remote sensing." *Water resources research* 34, no. 9 (1998): 2319-2327.

Owe, M., R. De Jeu, and J. Walker, "A methodology for surface soil moisture and vegetation optical depth retrieval using the microwave polarization difference index," *IEEE Trans. Geosci. Rem. Sens.*, 39, pp. 1643-1654, 2001.

Owe, M., de Jeu, R., and Holmes, T.: Multisensor historical climatology of satellite-derived global land surface moisture, *J. Geophys. Res.*, 113, F01002, doi:10.1029/2007JF000769, 2008.

Owe, Manfred, Richard de Jeu, and Thomas Holmes. "Multisensor historical climatology of satellite-derived global land surface moisture." *Journal of Geophysical Research: Earth Surface* 113, no. F1 (2008).

Pal, Jeremy S., and Elfatih AB Eltahir. "Pathways relating soil moisture conditions to future summer rainfall within a model of the land-atmosphere system." *Journal of Climate* 14, no. 6 (2001): 1227-1242.

Parinussa, Robert M., Thomas RH Holmes, and Richard AM de Jeu. "Soil moisture retrievals from the WindSat spaceborne polarimetric microwave radiometer." *IEEE Transactions on Geoscience and Remote Sensing* 50, no. 7 (2012): 2683-2694.

Petty, Grant William. *A first course in atmospheric radiation*. Sundog Pub, 2006

Polson, M. T. "SMAP Level 3 Radar Freeze/Thaw Data Product." (2012).

Prigent, Catherine, William B. Rossow, and Elaine Matthews. "Microwave land surface emissivities estimated from SSM/I observations." *Journal of Geophysical Research: Atmospheres* 102, no. D18 (1997): 21867-21890.

Prigent, Catherine, William B. Rossow, and Elaine Matthews. "Global maps of microwave land surface emissivities: Potential for land surface characterization." *Radio Science* 33.3 (1998): 745-751.

Prigent, Catherine, Filipe Aires, William B. Rossow, and Alan Robock. "Sensitivity of satellite microwave and infrared observations to soil moisture at a global scale: Relationship of satellite observations to in situ soil moisture measurements." *Journal of Geophysical Research: Atmospheres* 110, no. D7 (2005).

Prigent, Catherine, Filipe Aires, and William B. Rossow. "Land surface microwave emissivities over the globe for a decade." *Bulletin of the American Meteorological Society* 87, no. 11 (2006): 1573.

Prigent, Catherine, Elodie Jaumouillé, Frédéric Chevallier, and Filipe Aires. "A parameterization of the microwave land surface emissivity between 19 and 100 GHz, anchored to satellite-derived estimates." *Geoscience and Remote Sensing, IEEE Transactions on* 46, no. 2 (2008): 344-352.

Prigent, C., P. Liang, Y. Tian, F. Aires, J-L. Moncet, and S. A. Boukabara. "Evaluation of modeled microwave land surface emissivities with satellite-based estimates." *Journal of Geophysical Research: Atmospheres* 120, no. 7 (2015): 2706-2718.

Pruppacher, Hans R., James D. Klett, and Pao K. Wang. "Microphysics of clouds and precipitation." (1998): 381-382.

Raju, Suresh, André Chanzy, Jean-Pierre Wigneron, Jean-Christophe Calvet, Yann Kerr, and Laurent Laguerre. "Soil moisture and temperature profile effects on microwave emission at low frequencies." *Remote sensing of environment* 54, no. 2 (1995): 85-97.

Reichle, Rolf H., Wade T. Crow, and Christian L. Keppenne. "An adaptive ensemble Kalman filter for soil moisture data assimilation." *Water resources research* 44, no. 3 (2008).

Ringerud, Sarah, Christian Kummerow, Christa Peters-Lidard, Yudong Tian, and Kenneth Harrison. "A comparison of microwave window channel retrieved and forward-modeled emissivities over the US Southern Great Plains." *IEEE Transactions on Geoscience and Remote Sensing* 52, no. 5 (2014): 2395-2412.

Rigby, Robert A., and D. Mikis Stasinopoulos. "Generalized additive models for location, scale and shape." *Journal of the Royal Statistical Society: Series C (Applied Statistics)* 54, no. 3 (2005): 507-554.

Ringerud, Sarah, Christian D. Kummerow, and Christa D. Peters-Lidard. "A semi-empirical model for computing land surface emissivity in the microwave region." *IEEE Transactions on Geoscience and Remote Sensing* 53, no. 4 (2015): 1935-1946.

Robock, Alan, Konstantin Y. Vinnikov, Govindarajalu Srinivasan, and Jared K. Entin. "The global soil moisture data bank." *Bulletin of the American Meteorological Society* 81, no. 6 (2000): 1281.

Rosenzweig, Cynthia, Francesco N. Tubiello, Richard Goldberg, Evan Mills, and Janine Bloomfield. "Increased crop damage in the US from excess precipitation under climate change." *Global Environmental Change* 12, no. 3 (2002): 197-202.

Rouse Jr, J_W, R. H. Haas, J. A. Schell, and D. W. Deering. "Monitoring vegetation systems in the Great Plains with ERTS." *NASA special publication* 351 (1974): 309.

Rosenfeld, Daniel, Meinrat O. Andreae, Ari Asmi, Mian Chin, Gerrit Leeuw, David P. Donovan, Ralph Kahn et al. "Global observations of aerosol-cloud-precipitation-climate interactions." *Reviews of Geophysics* 52, no. 4 (2014): 750-808.

Rossow, William B., and Robert A. Schiffer. "Advances in understanding clouds from ISCCP." *Bulletin of the American Meteorological Society* 80, no. 11 (1999): 2261.

Ruscica, Romina C., Anna A. Sörensson, and Claudio G. Menéndez. "Pathways between soil moisture and precipitation in southeastern South America." *Atmospheric Science Letters* 16, no. 3 (2015): 267-272.

Seneviratne, Sonia I., Thierry Corti, Edouard L. Davin, Martin Hirschi, Eric B. Jaeger, Irene Lehner, Boris Orlowsky, and Adriaan J. Teuling. "Investigating soil moisture–climate interactions in a changing climate: A review." *Earth-Science Reviews* 99, no. 3 (2010): 125-161.

Sibley, Terrell Gene. "Microwave emission and scattering from vegetated terrain." (1973).

Simpson, Joanne, C. Kummerow, W-K. Tao, and Robert F. Adler. "On the tropical rainfall measuring mission (TRMM)." *Meteorology and Atmospheric physics* 60, no. 1-3 (1996): 19-36.

Skofronick-Jackson, Gail M., Min-Jeong Kim, James A. Weinman, and Dong-Eon Chang. "A physical model to determine snowfall over land by microwave radiometry." *IEEE Transactions on Geoscience and Remote Sensing* 42, no. 5 (2004): 1047-1058.

Smith, Eric A., Ghassem Asrar, Yoji Furuhashi, Amnon Ginati, Alberto Mugnai, Kenji Nakamura, Robert F. Adler et al. "International global precipitation measurement (GPM) program and mission: An overview." In *Measuring precipitation from space*, pp. 611-653. Springer Netherlands, 2007.

Spencer, Michael, Kevin Wheeler, Chris White, Richard West, Jeffrey Piepmeier, Derek Hudson, and James Medeiros. "The Soil Moisture Active Passive (SMAP) mission L-band radar/radiometer instrument." In *Geoscience and Remote Sensing Symposium (IGARSS), 2010 IEEE International*, pp. 3240-3243. IEEE, 2010.

Sorooshian, Soroosh, Kuo-lin Hsu, Erika Coppola, Barbara Tomassetti, Marco Verdecchia, and Guido Visconti, eds. *Hydrological modelling and the water cycle: coupling the atmospheric and hydrological models*. Vol. 63. Springer Science & Business Media, 2008.

Stasinopoulos, D. Mikis, and Robert A. Rigby. "Generalized additive models for location scale and shape (GAMLSS) in R." *Journal of Statistical Software* 23, no. 7 (2007): 1-46.

Strangeways, Ian. Precipitation: theory, measurement and distribution. Cambridge University Press, 2006.

Tian, Yudong, Christa D. Peters-Lidard, Kenneth W. Harrison, Catherine Prigent, Hamidreza Norouzi, Filipe Aires, Sid-Ahmed Boukabara, Fumie A. Furuzawa, and Hirohiko Masunaga. "Quantifying uncertainties in land-surface microwave emissivity retrievals." *Geoscience and Remote Sensing, IEEE Transactions on* 52, no. 2 (2014): 829-840.

Thenkabail, Prasad S., ed. *Remotely Sensed Data Characterization, Classification, and Accuracies*. CRC Press, 2015.

Tian, Yudong, Christa D. Peters-Lidard, Kenneth W. Harrison, Catherine Prigent, Hamidreza Norouzi, Filipe Aires, Sid-Ahmed Boukabara, Fumie A. Furuzawa, and Hirohiko Masunaga. "Quantifying uncertainties in land-surface microwave emissivity retrievals." *IEEE Transactions on Geoscience and Remote Sensing* 52, no. 2 (2014): 829-840.

Trenberth, Kevin E. "Changes in precipitation with climate change." *Climate Research* 47, no. 1-2 (2011): 123-138.

Turk, F. Joseph, L. Li, and Z. S. Haddad. "Physical modeling of microwave surface emissivity from passive microwave satellite observations." In *Preprints, 18th Conf. on Satellite Meteorology, Oceanography and Climatology*, New Orleans, LA, Amer. Meteor. Soc. J, vol. 5. 2012.

Turk, Francis Joseph, Li Li, and Ziad S. Haddad. "A physically based soil moisture and microwave emissivity data set for Global Precipitation Measurement (GPM) applications." *IEEE Transactions on Geoscience and Remote Sensing* 52, no. 12 (2014): 7637-7650.

Turk, F. Joseph, Ziad S. Haddad, and Yalei You. "Principal components of multifrequency microwave land surface emissivities. Part I: Estimation under clear and precipitating conditions." *Journal of Hydrometeorology* 15, no. 1 (2014): 3-19.

Tucker, Ch J., J. H. Elgin, Je E. McMurtrey, and C. J. Fan. "Monitoring corn and soybean crop development with hand-held radiometer spectral data." *Remote Sensing of Environment* 8, no. 3 (1979): 237-248.

Ulaby, Fawwaz T., Richard K. Moore, and Adrian K. Fung. "Microwave remote sensing: Active and passive. volume 1-microwave remote sensing fundamentals and radiometry." (1981)

Ulaby, Fawwaz T., Richard K. Moore, and Adrian K. Fung. "Microwave remote sensing active and passive-volume III: from theory to applications." (1986).

Ushio, Tomoo, Ken'ichi Okamoto, Toshio Iguchi, Nobuhiro Takahashi, Koyuru Iwanami, Kazumasa Aonashi, Shoichi Shige, Hiroshi Hashizume, Takuji Kubota, and Toshiro Inoue. "The global satellite mapping of precipitation (GSMaP) project." *Aqua (AMSR-E) 2004* (2003).

van den Hurk, Bart, Francisco Doblas-Reyes, Gianpaolo Balsamo, Randal D. Koster, Sonia I. Seneviratne, and Helio Camargo Jr. "Soil moisture effects on seasonal temperature and precipitation forecast scores in Europe." *Climate dynamics* 38, no. 1-2 (2012): 349-362.

Villarini, Gabriele, and Witold F. Krajewski. "Review of the different sources of uncertainty in single polarization radar-based estimates of rainfall." *Surveys in Geophysics* 31, no. 1 (2010): 107-129.

Wang, J. R., and B. J. Choudhury. "Passive microwave radiation from soil: Examples of emission models and observations". *Passive Microwave Remote Sensing of Land-Atmosphere Interactions*, B. J. Choudhury et al., Eds., (1995): VSP Publishing, Utrecht., 423-460.

Weng, Fuzhong, Banghua Yan, and Norman C. Grody. "A microwave land emissivity model." *Journal of Geophysical Research: Atmospheres* 106, no. D17 (2001): 20115-20123.

Weng, Fuzhong, Limin Zhao, Ralph R. Ferraro, Gene Poe, Xiaofan Li, and Norman C. Grody. "Advanced microwave sounding unit cloud and precipitation algorithms." *Radio Science* 38, no. 4 (2003).

Weng, Fuzhong, and Quanhua Liu. "Satellite data assimilation in numerical weather prediction models. Part I: Forward radiative transfer and Jacobian modeling in cloudy atmospheres." *Journal of the atmospheric sciences* 60, no. 21 (2003): 2633-2646.

Wigneron, Jean-Pierre, André Chanzy, Jean-Christophe Calvet, and Nadine Bruguier. "A simple algorithm to retrieve soil moisture and vegetation biomass using passive microwave measurements over crop fields." *Remote Sensing of Environment* 51, no. 3 (1995): 331-341.

Wigneron, Jean-Pierre, Dominique Guyon, Jean-Christophe Calvet, Gaston Courier, and Nadine Bruguier. "Monitoring coniferous forest characteristics using a multifrequency (5-90 GHz) microwave radiometer." *Remote sensing of environment* 60, no. 3 (1997): 299-310.

Yang, Hu, and Fuzhong Weng. "Error sources in remote sensing of microwave land surface emissivity." *IEEE Transactions on Geoscience and Remote Sensing* 49, no. 9 (2011): 3437-3442.

Yau, Man Kong, and R. R. Rogers. *A short course in cloud physics*. Elsevier, 1996.

Yeh, T. C., R. T. Wetherald, and S. Manabe. "The effect of soil moisture on the short-term climate and hydrology change-A numerical experiment." *Monthly Weather Review* 112, no. 3 (1984): 474-490.

Zhang, Jian, et al. "National Mosaic and Multi-Sensor QPE (NMQ) system: Description, results, and future plans." *Bulletin of the American Meteorological Society* 92.10 (2011): 1321.

Appendices

Appendix A: Distribution of Emissivity for In-situ Measurement from Three Stations

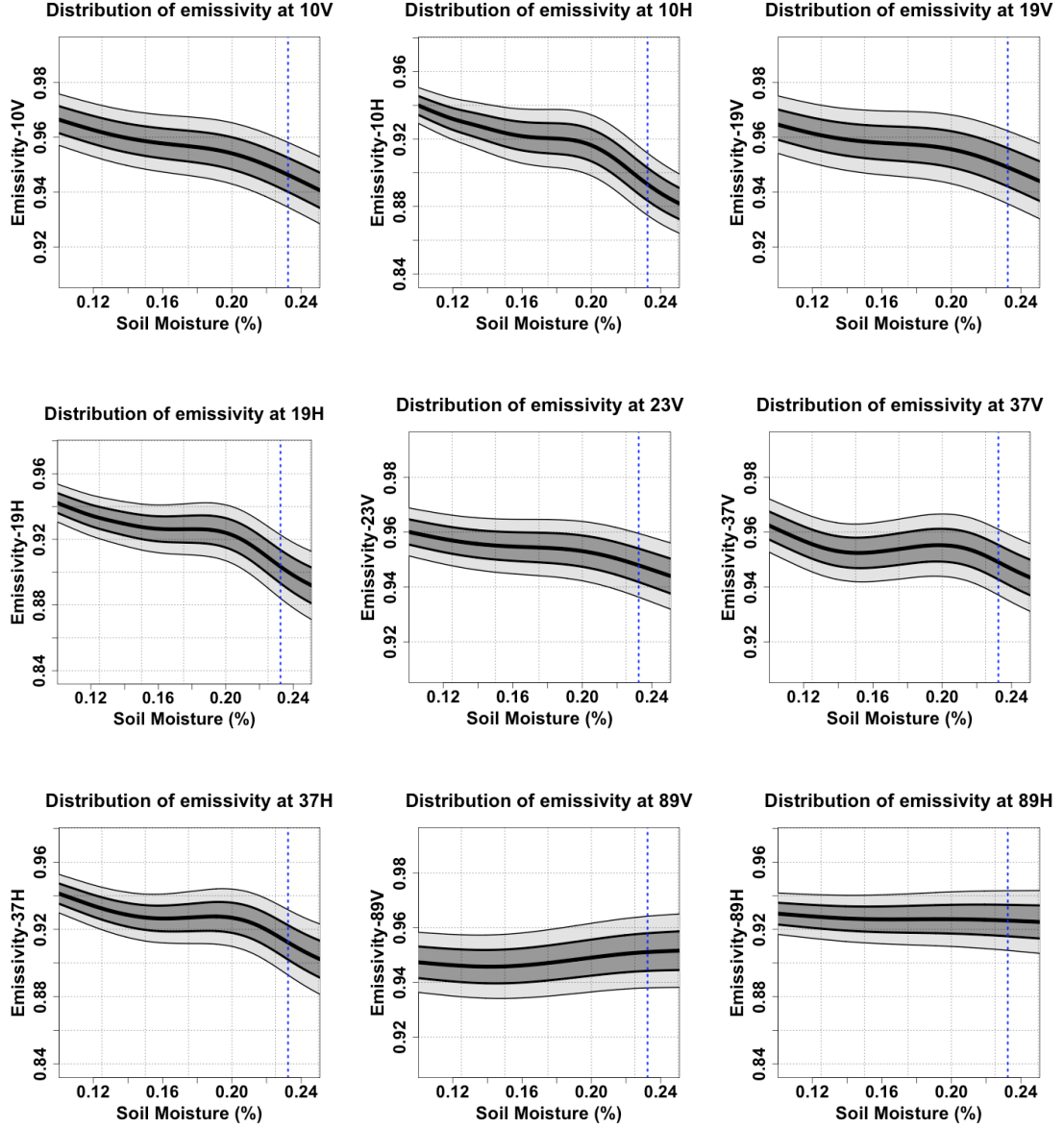


Figure A.1.1 Distribution of emissivity from the soil moisture single parameter model
for Abrams grassland station

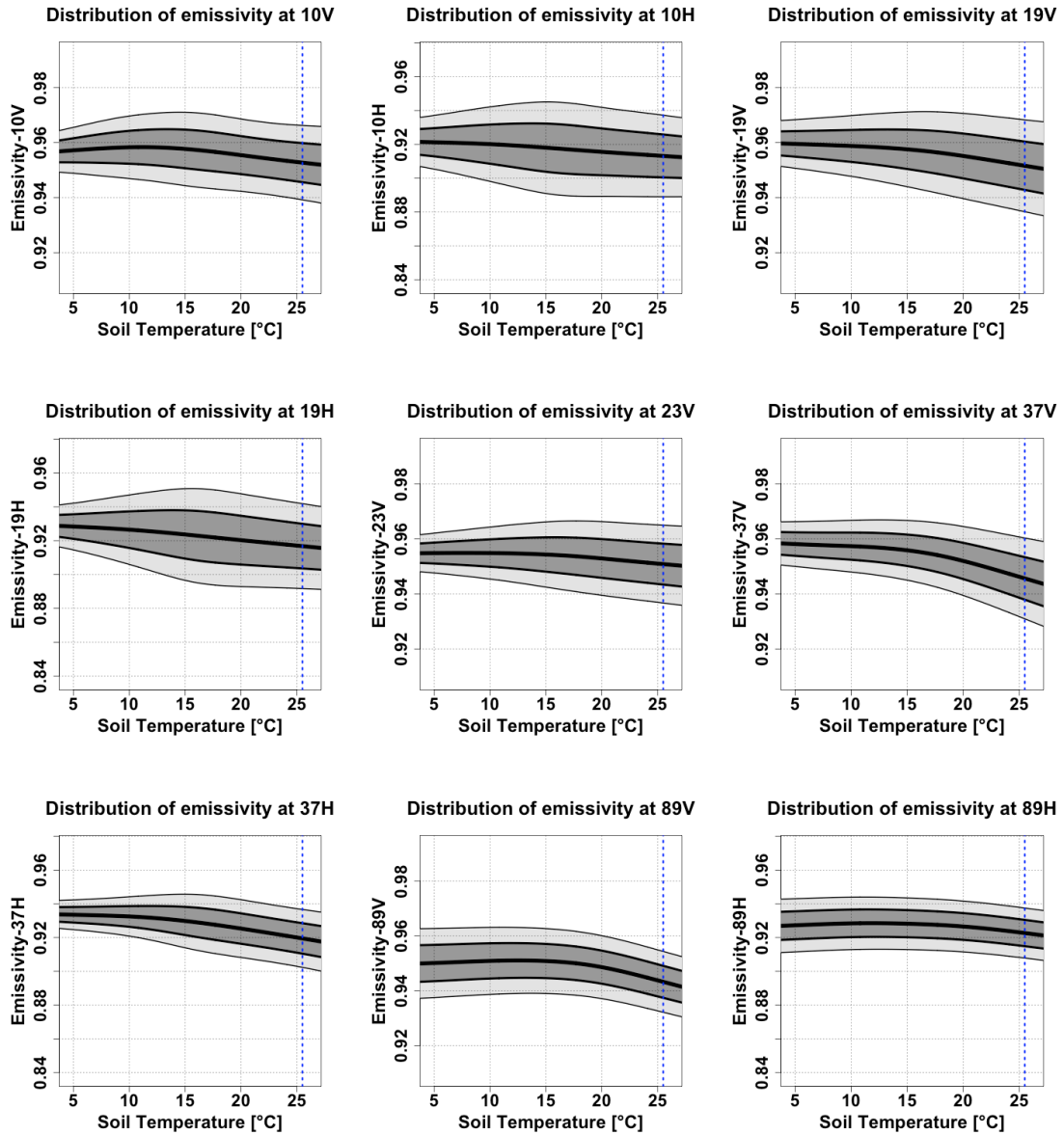


Figure A.1.2 Distribution of emissivity from the soil temperature single parameter model
for Abrams grassland station

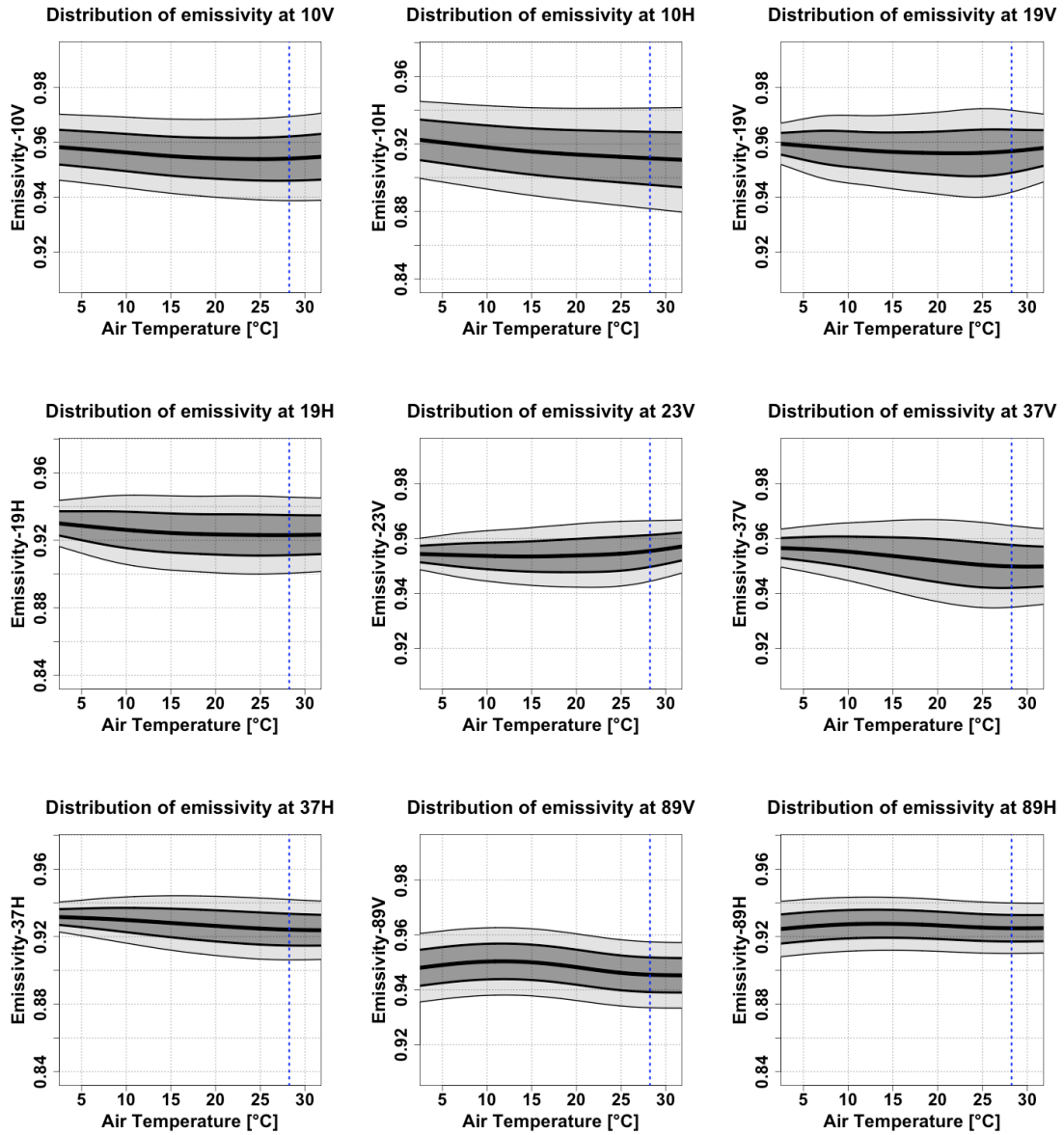


Figure A.1.3 Distribution of emissivity from the air temperature single parameter model
for Abrams grassland station

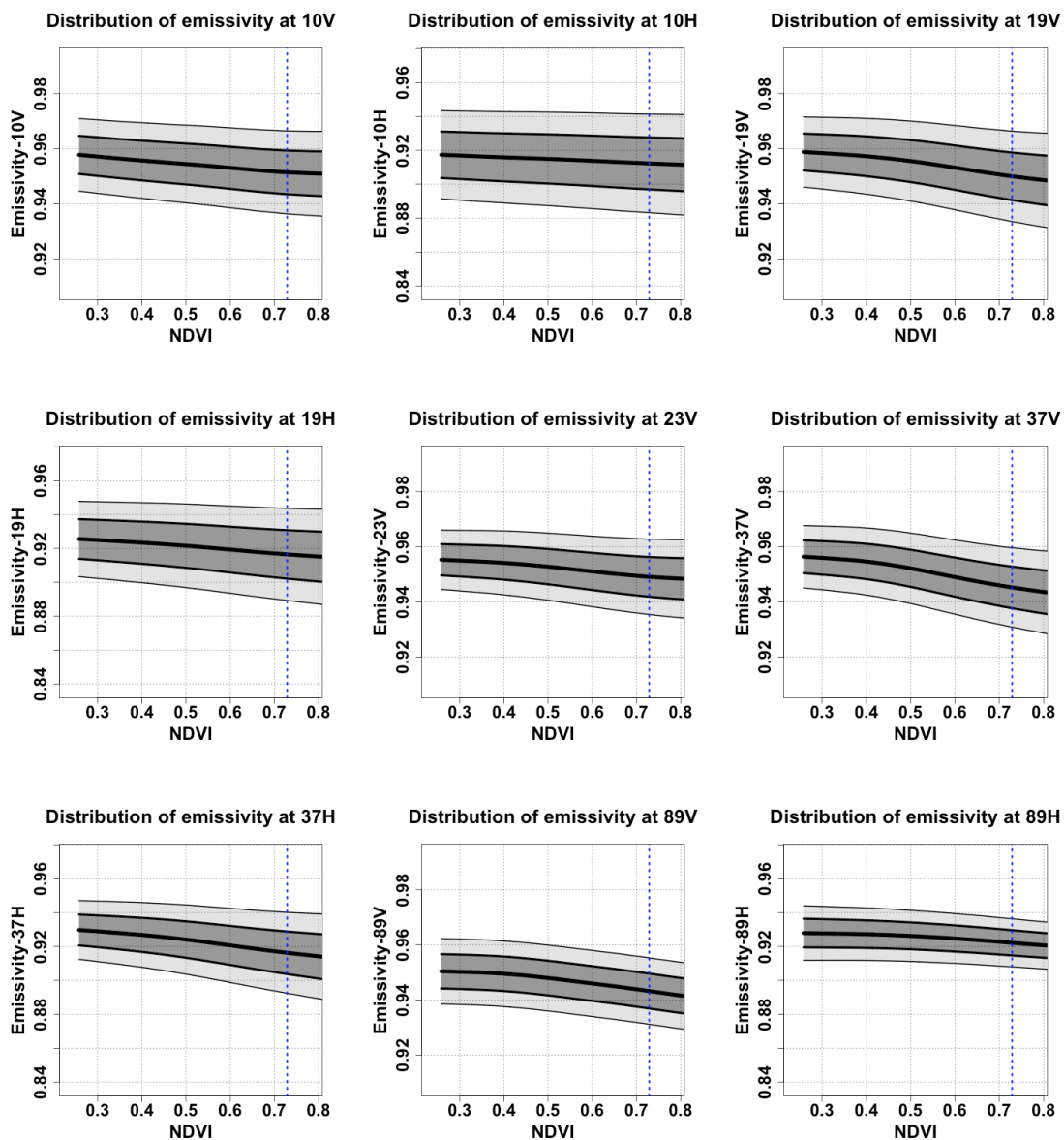


Figure A.1.4 Distribution of emissivity from the NDVI single parameter model for

Abrams grassland station

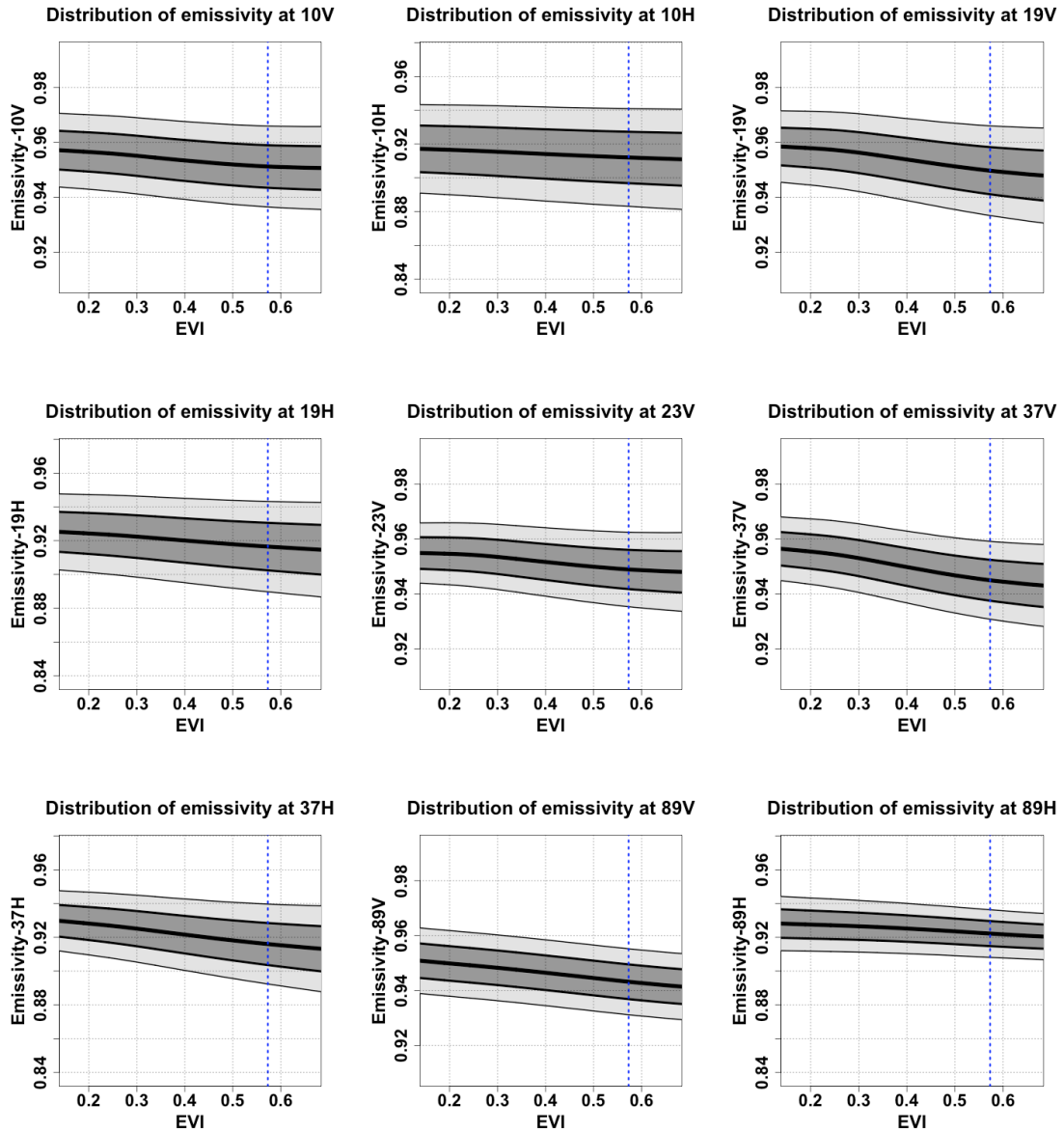


Figure A.1.5 Distribution of emissivity from the EVI single parameter model for Abrams grassland station

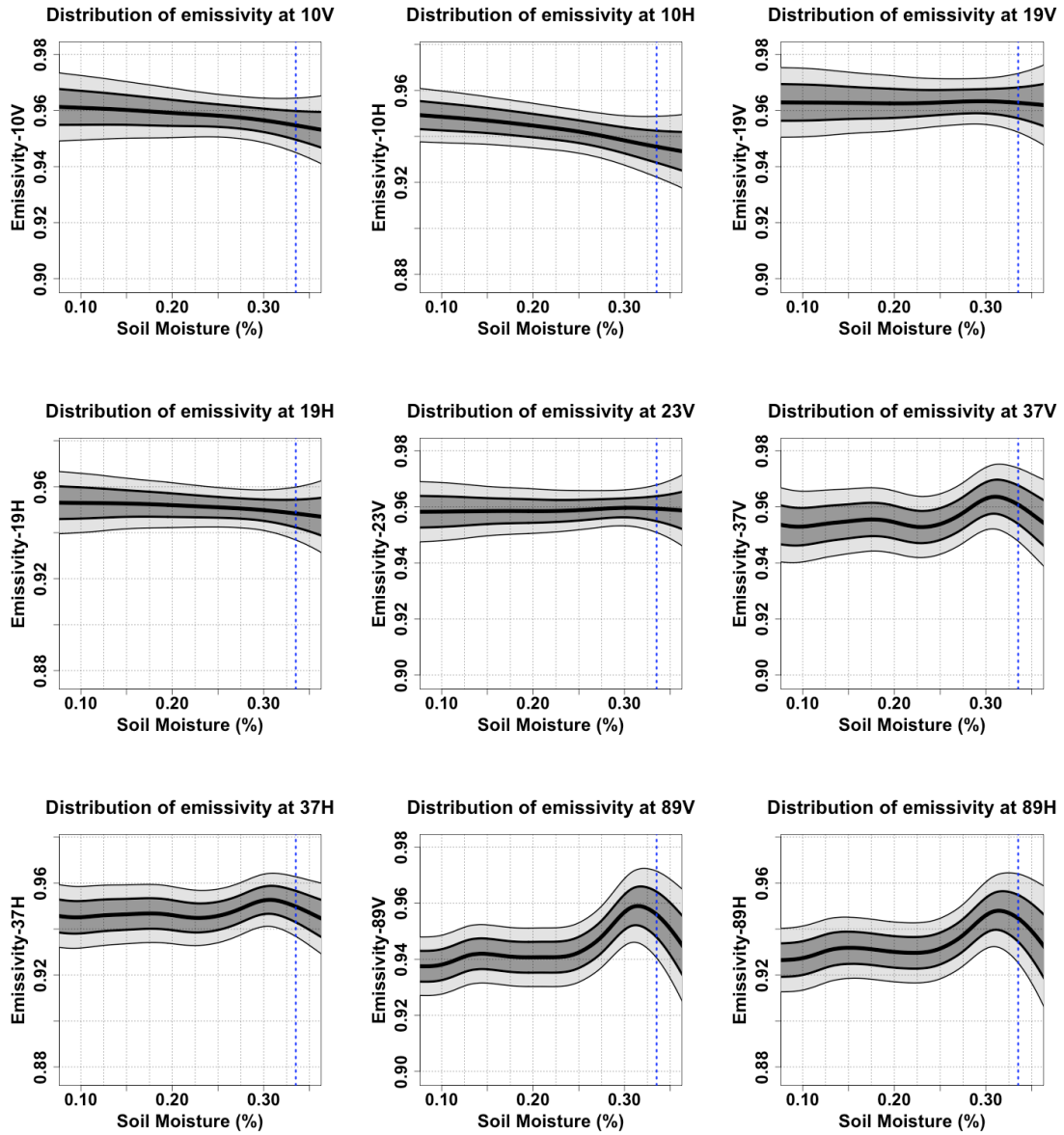


Figure A.1.6 Distribution of emissivity from the soil moisture single parameter model
for Mammothcave forest station

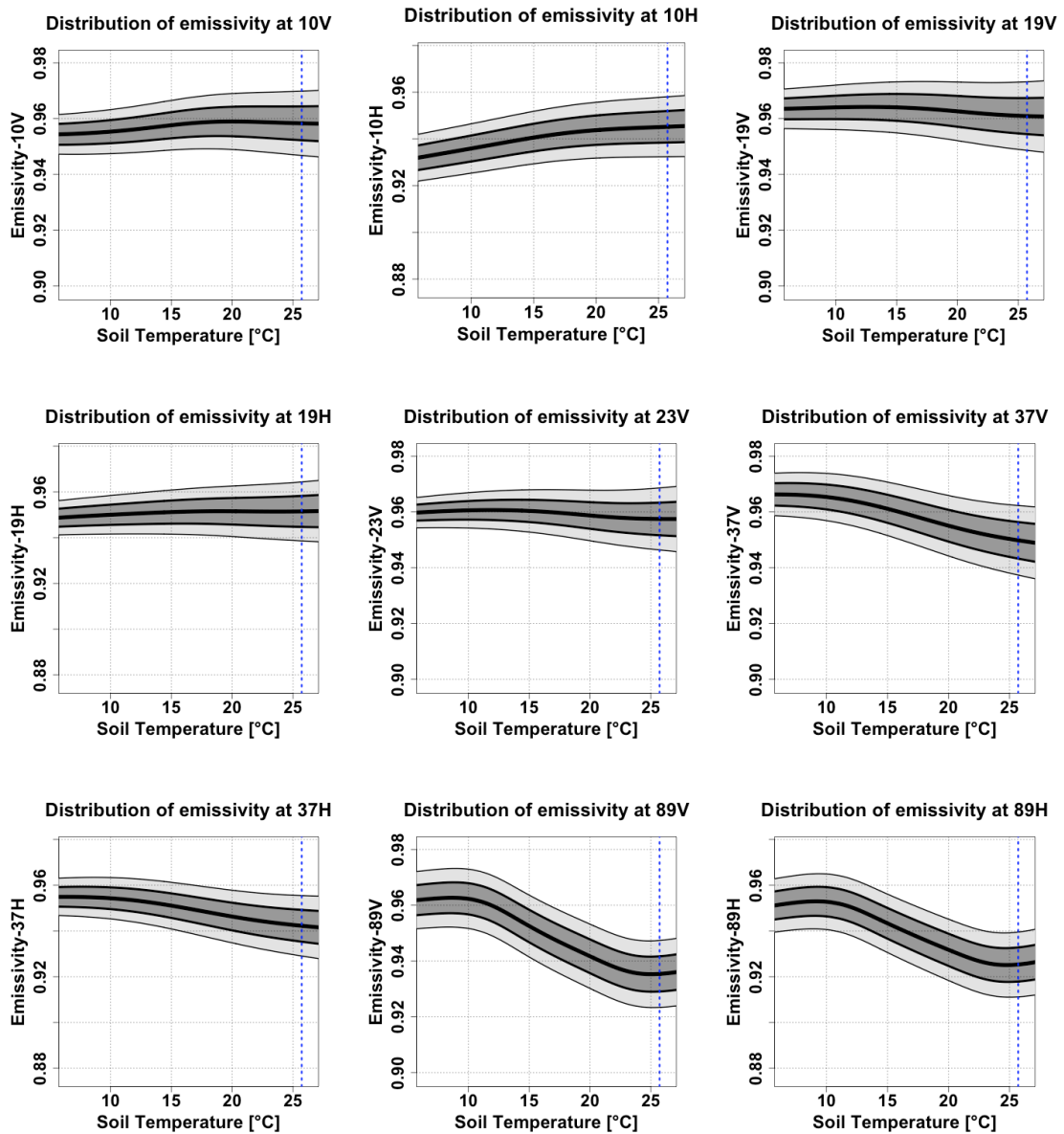


Figure A.1.7 Distribution of emissivity from the soil temperature single parameter model
for Mammothcave forest station

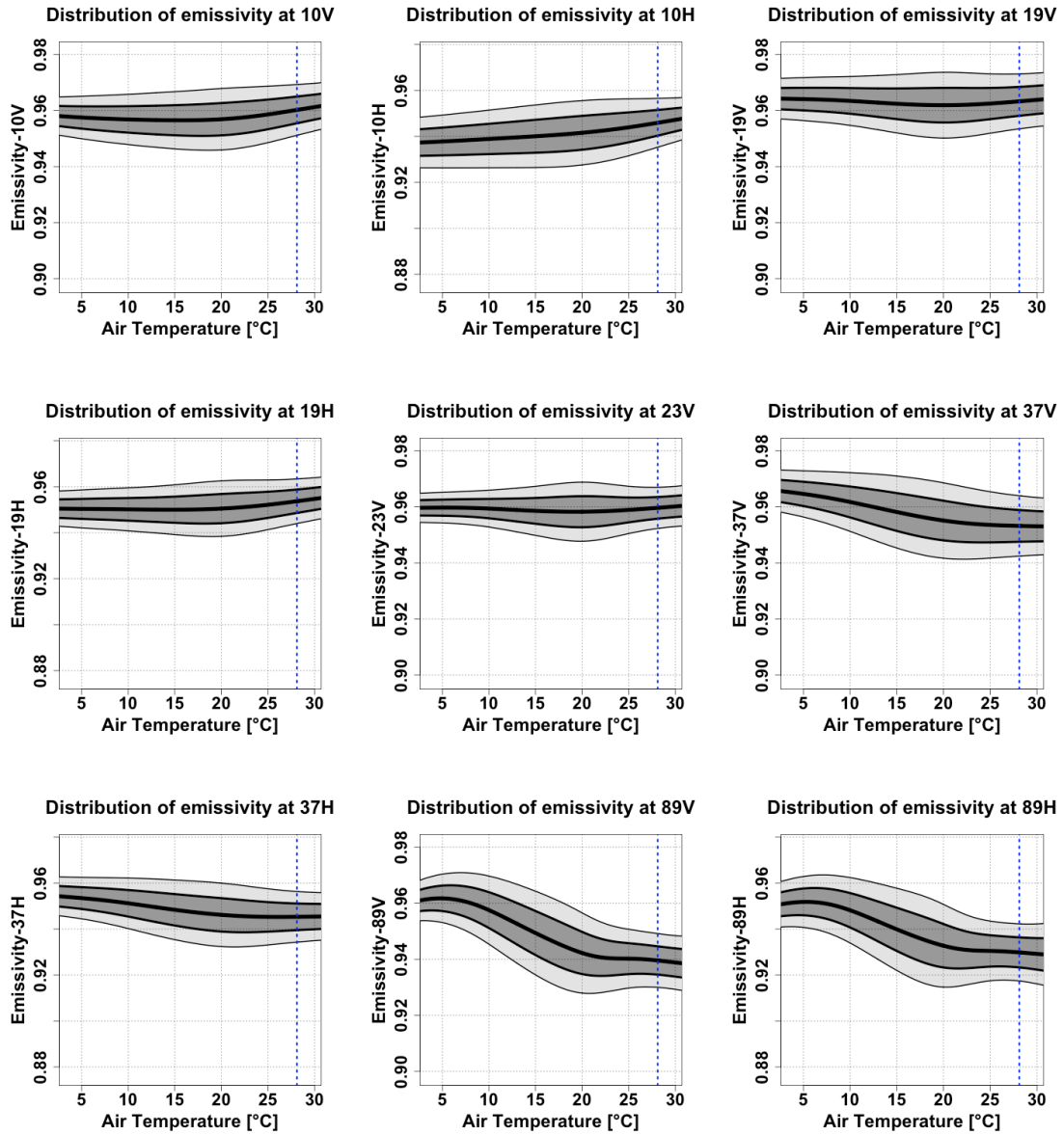


Figure A.1.8 Distribution of emissivity from the air temperature single parameter model
for Mammothcave forest station

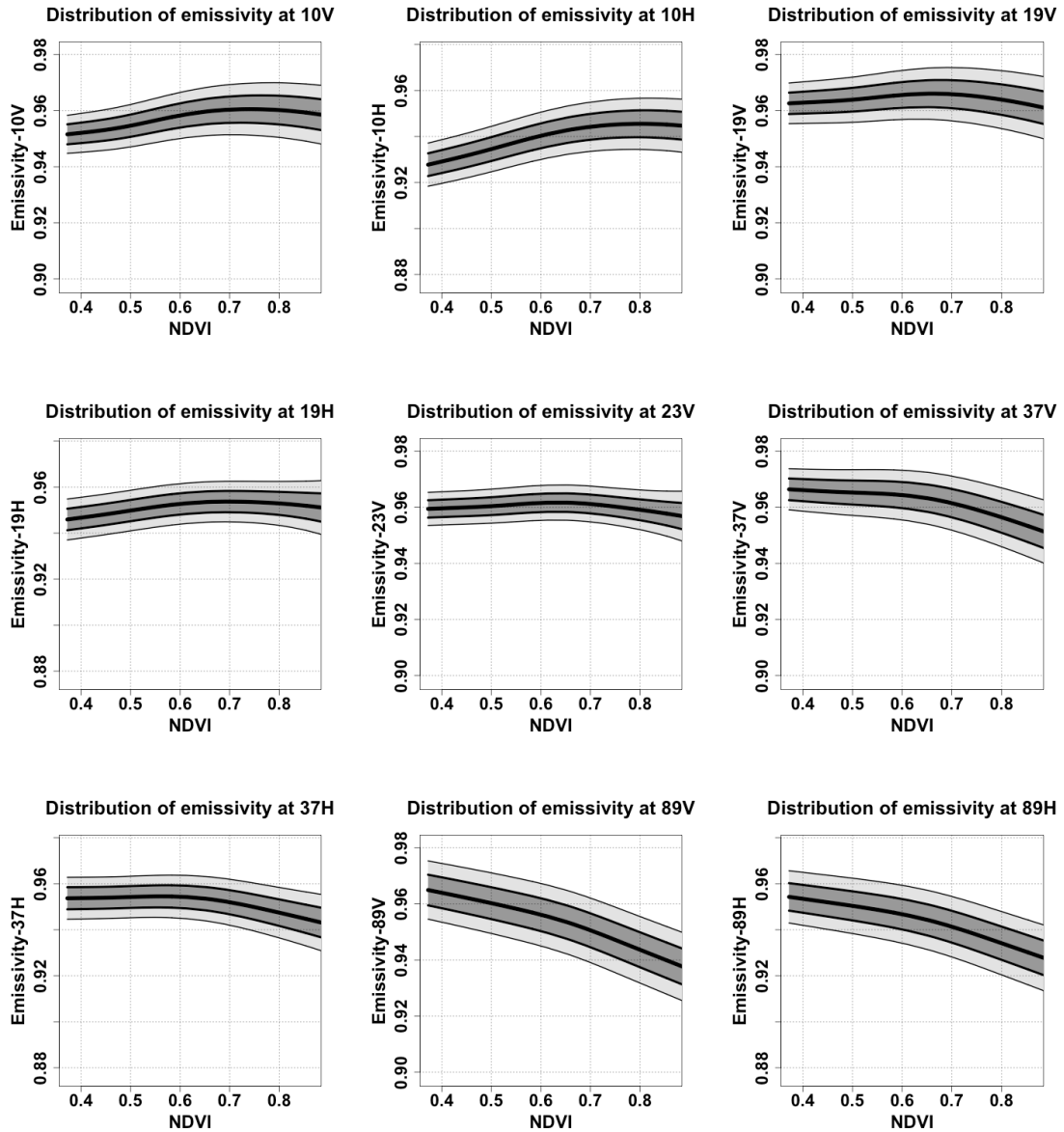


Figure A.1.9 Distribution of emissivity from the NDVI single parameter model for

Mammothcave forest station

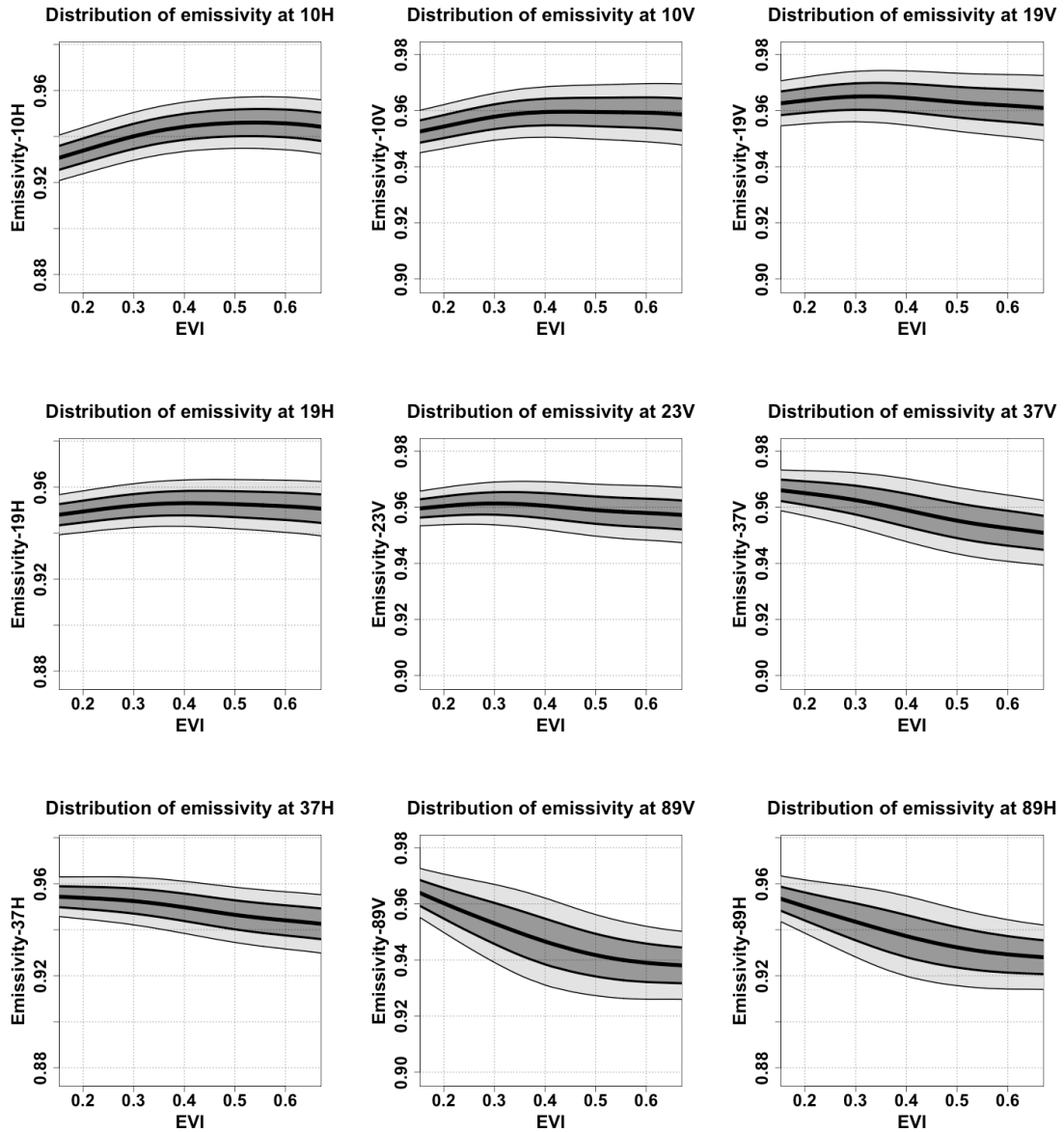


Figure A.1.10 Distribution of emissivity from the EVI single parameter model for

Mammothcave forest station

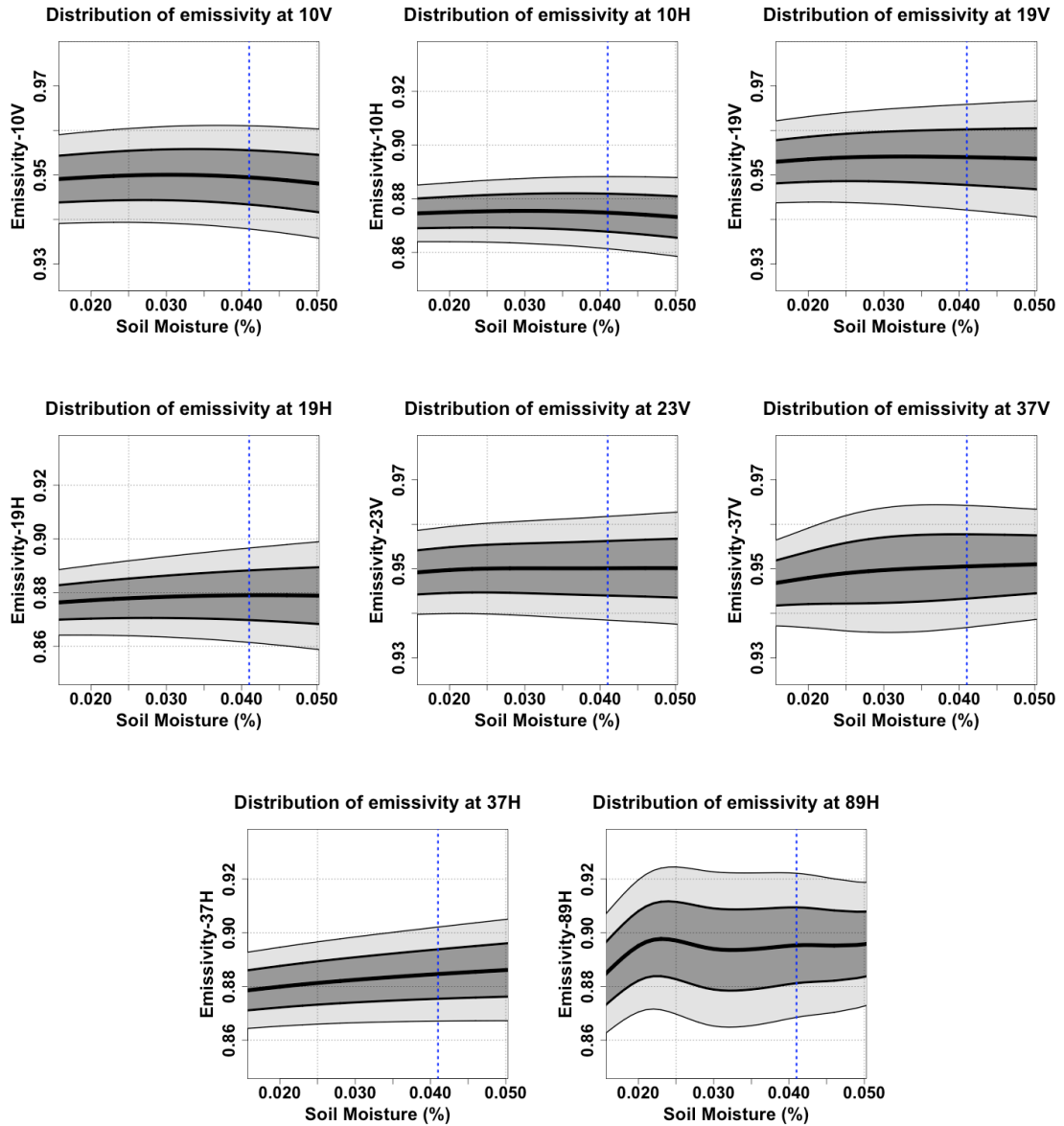


Figure A.1.11 Distribution of emissivity from the soil moisture single parameter model
for Stovepipewell barren region station

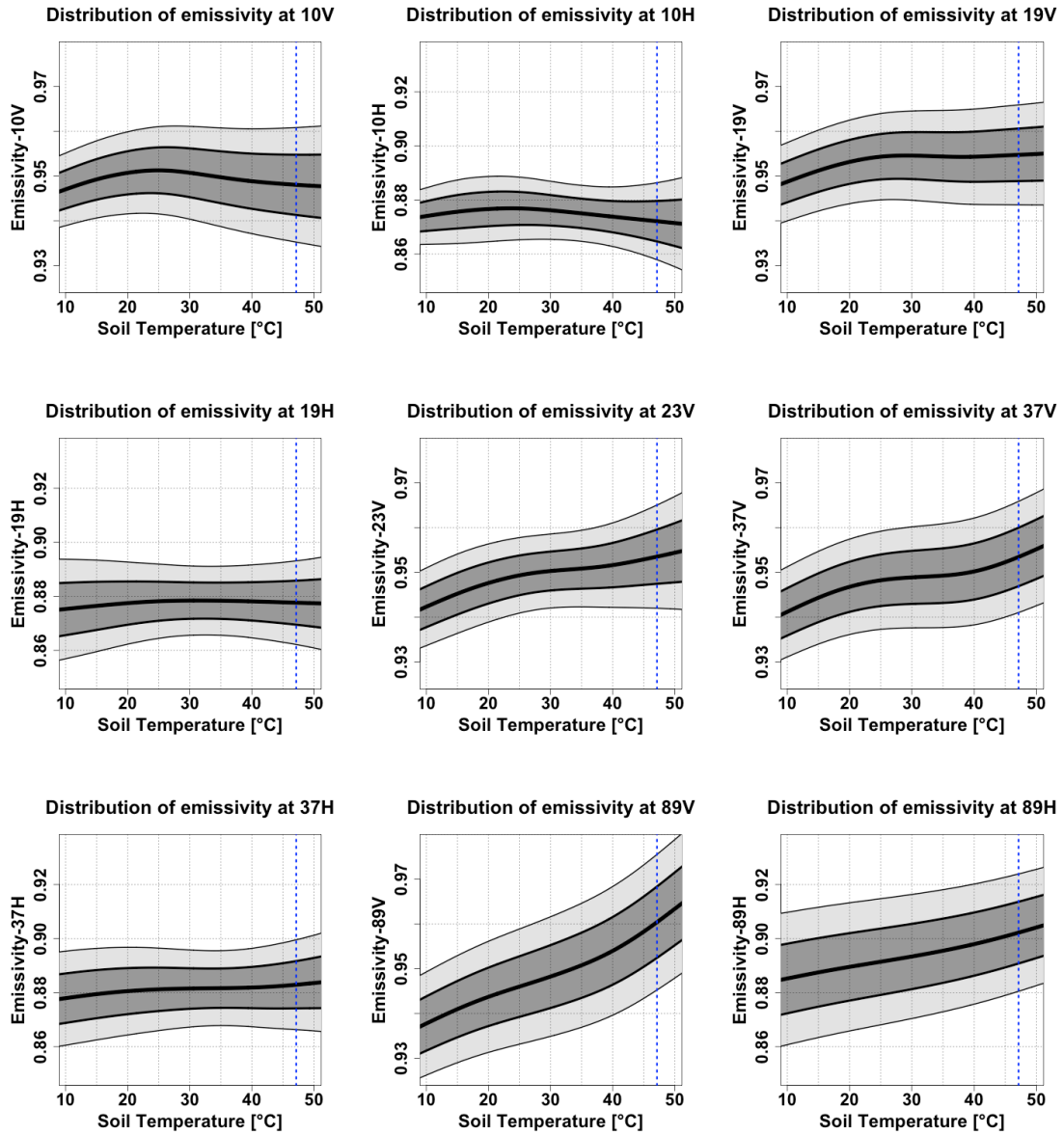


Figure A.1.12 Distribution of emissivity from the soil temperature single parameter model for Stovepipewell barren region station

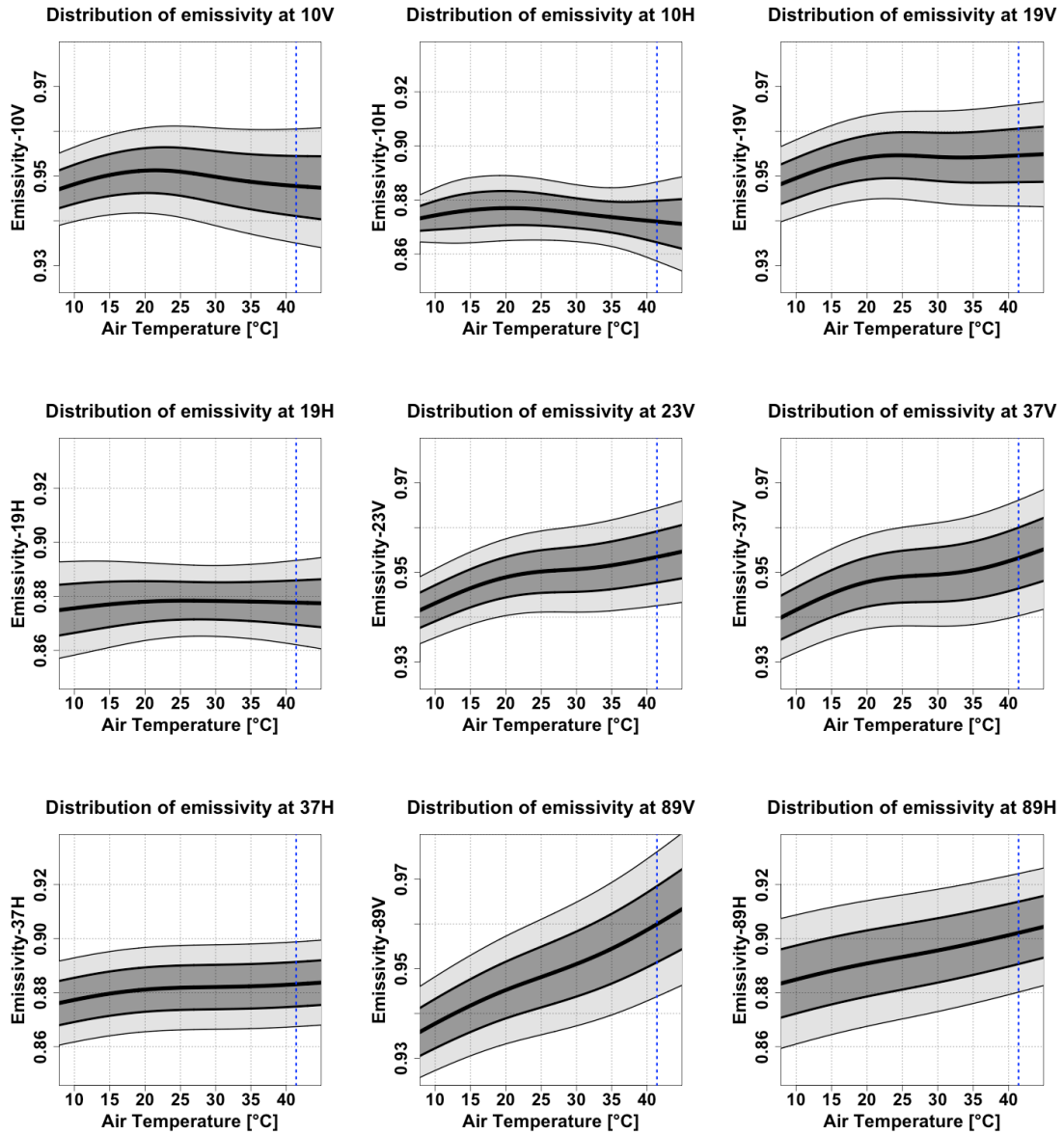


Figure A.1.13 Distribution of emissivity from the air temperature single parameter model for Stovepipewell barren region station

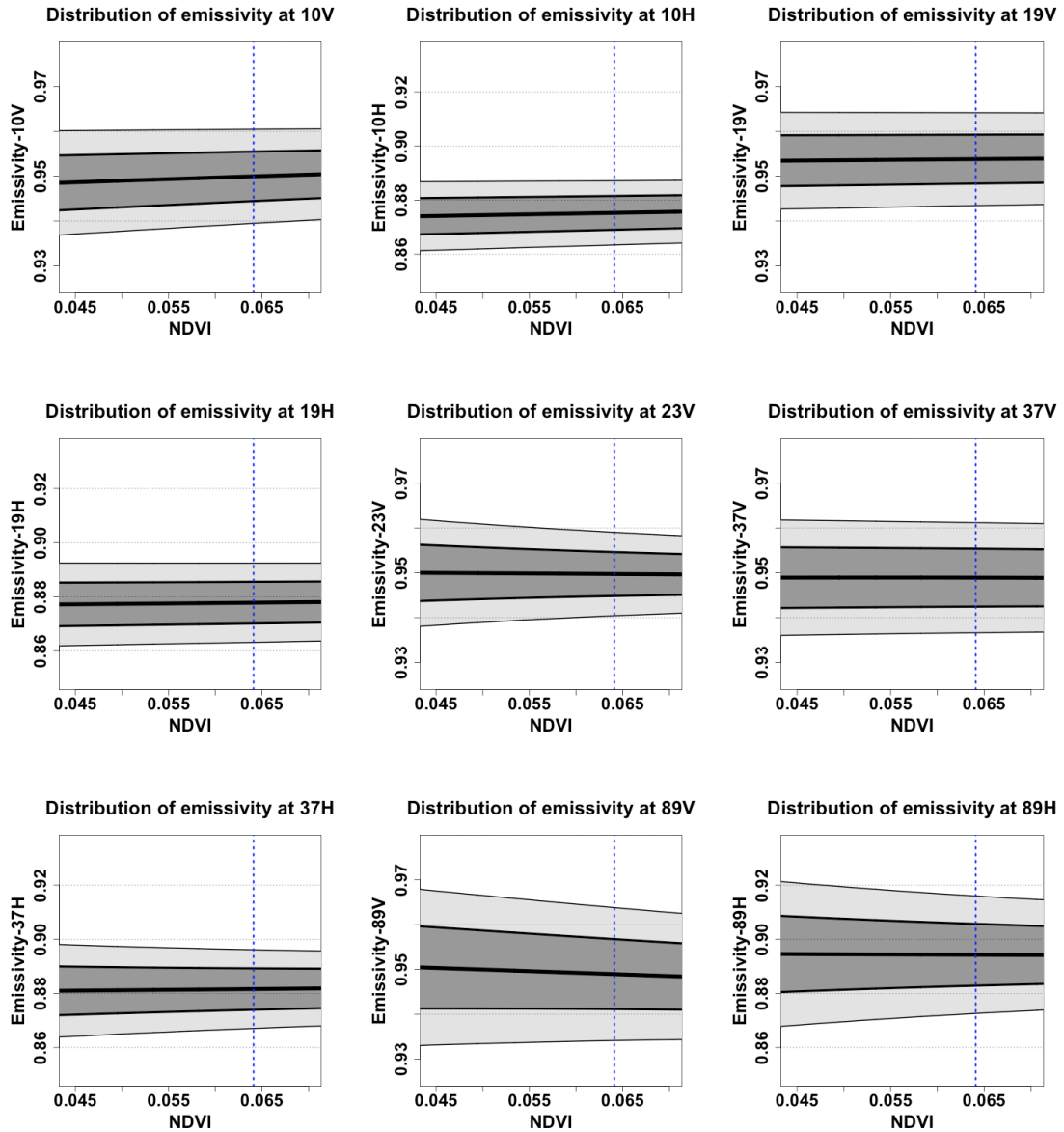


Figure A.1.14 Distribution of emissivity from the NDVI single parameter model for Stovepipewell barren region station

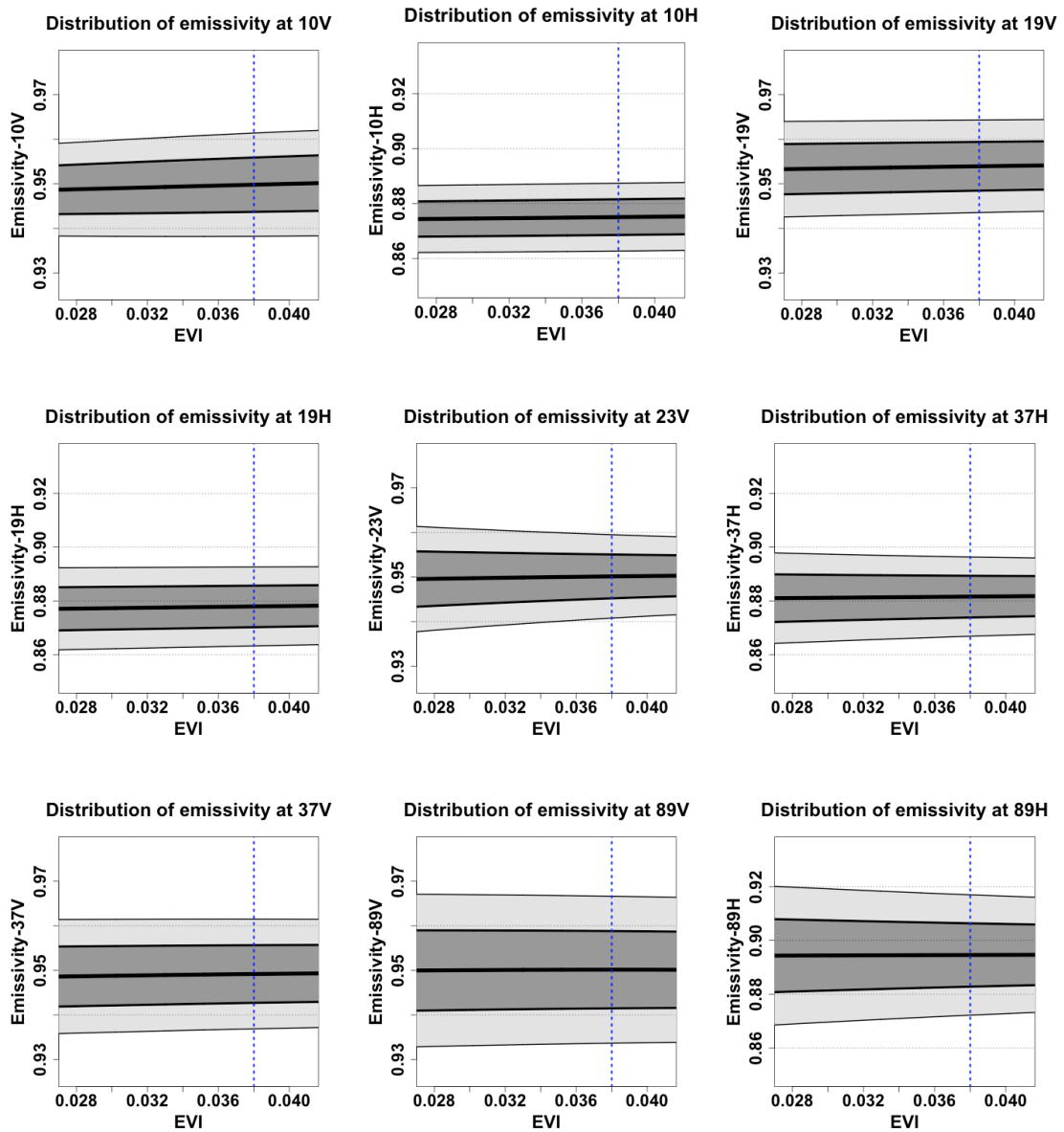


Figure A.1.15 Distribution of emissivity from the EVI single parameter model for Stovepipewell barren region station

Appendix B: Comparison of the Distribution of Emissivity from In-situ Measurement and Satellite Observation

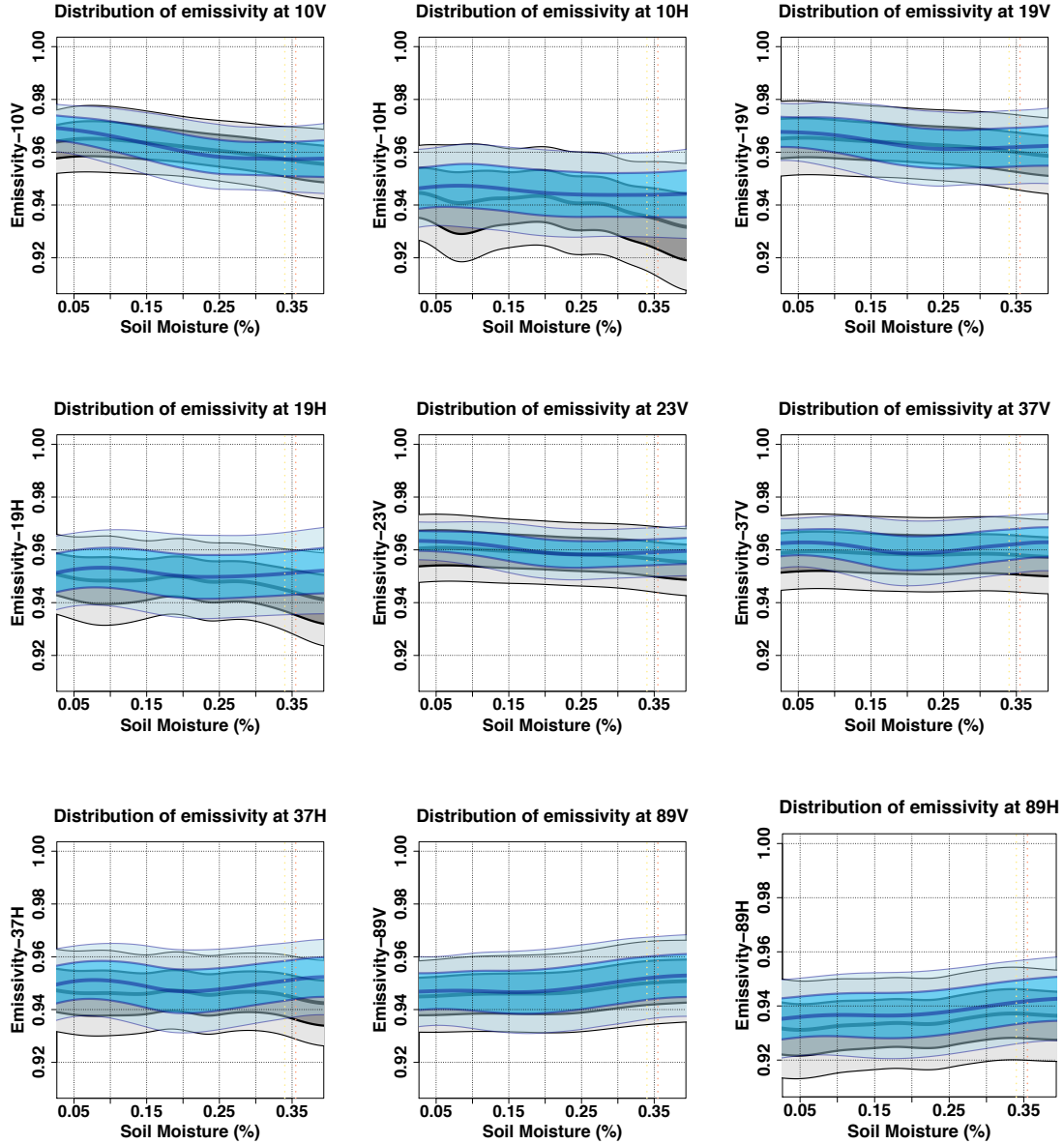


Fig B.1.1 Comparison of distribution of the emissivity from the soil moisture single parameter models based on the satellite remotely sensed data and the emissivity from the soil moisture single parameter models based on in-situ measurements over the maximum vegetated regions

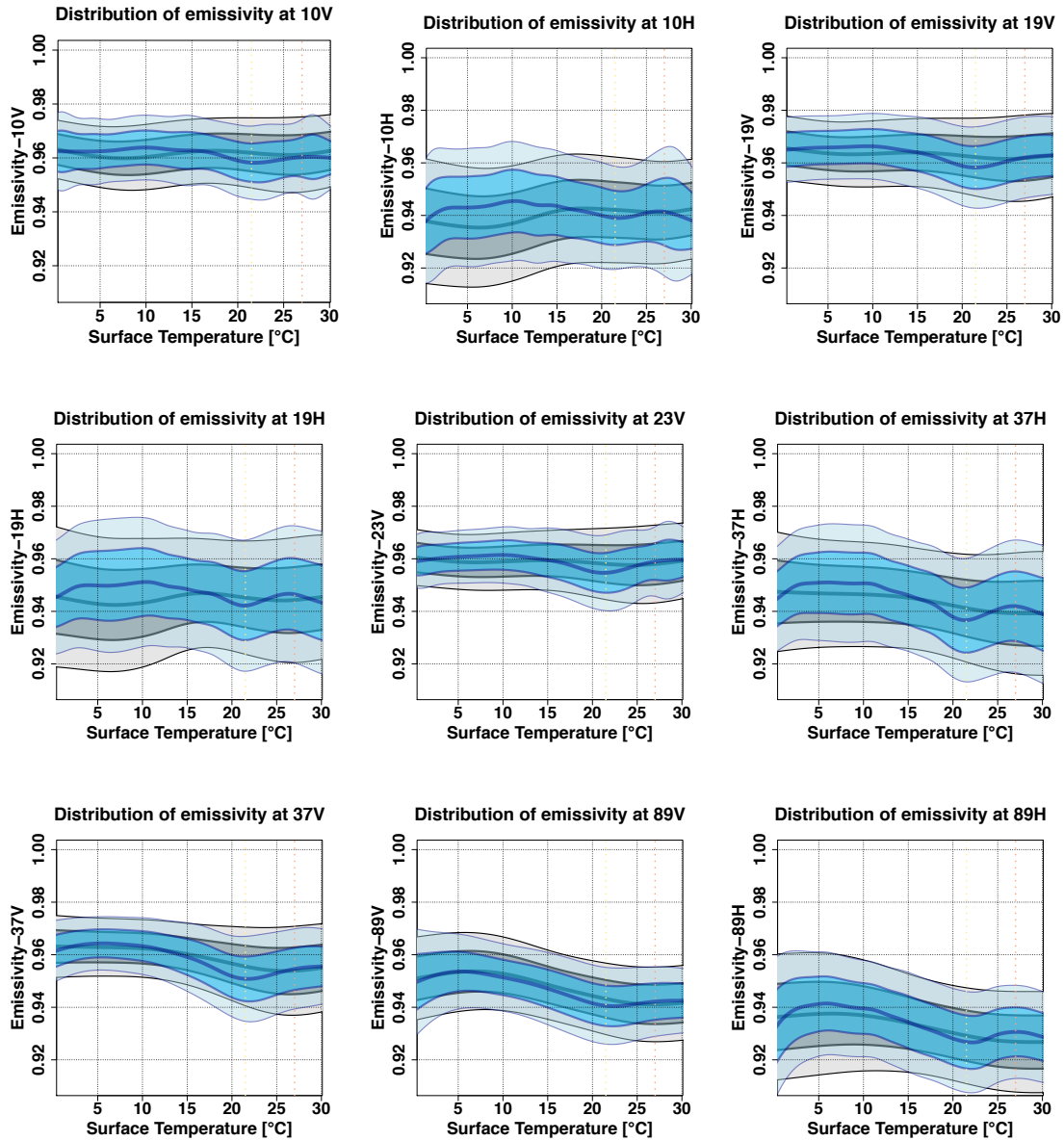


Figure B.1.2 Comparison of distribution of the emissivity from the surface temperature single parameter models based on the satellite remotely sensed data and the emissivity from the soil temperature single parameter models based on in-situ measurements over the maximum vegetated regions

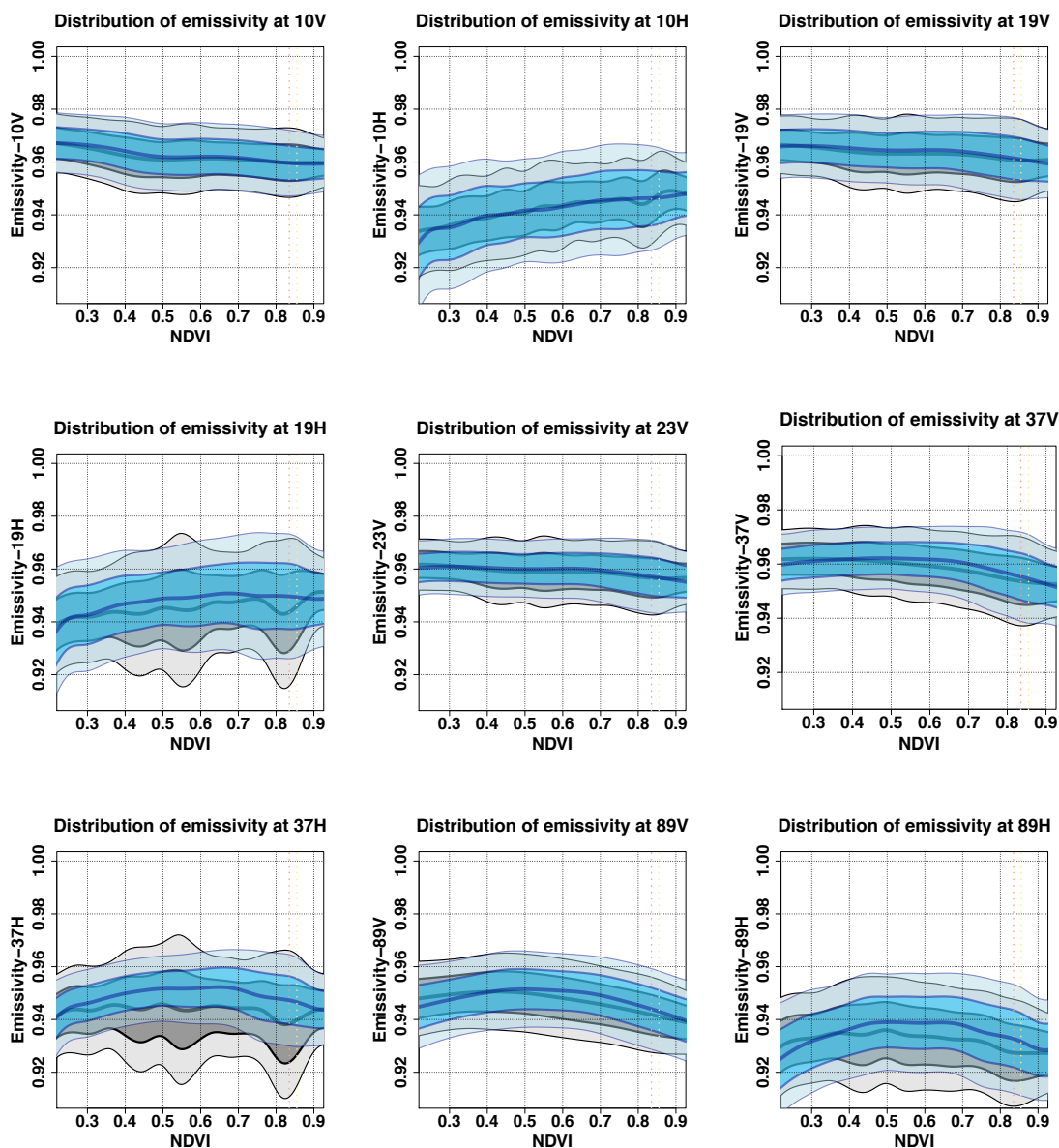


Figure B.1.3 Comparison of distribution of the emissivity from the NDVI single parameter models based on the satellite remotely sensed data and the emissivity from the NDVI single parameter models based on in-situ measurements over the maximum vegetated regions

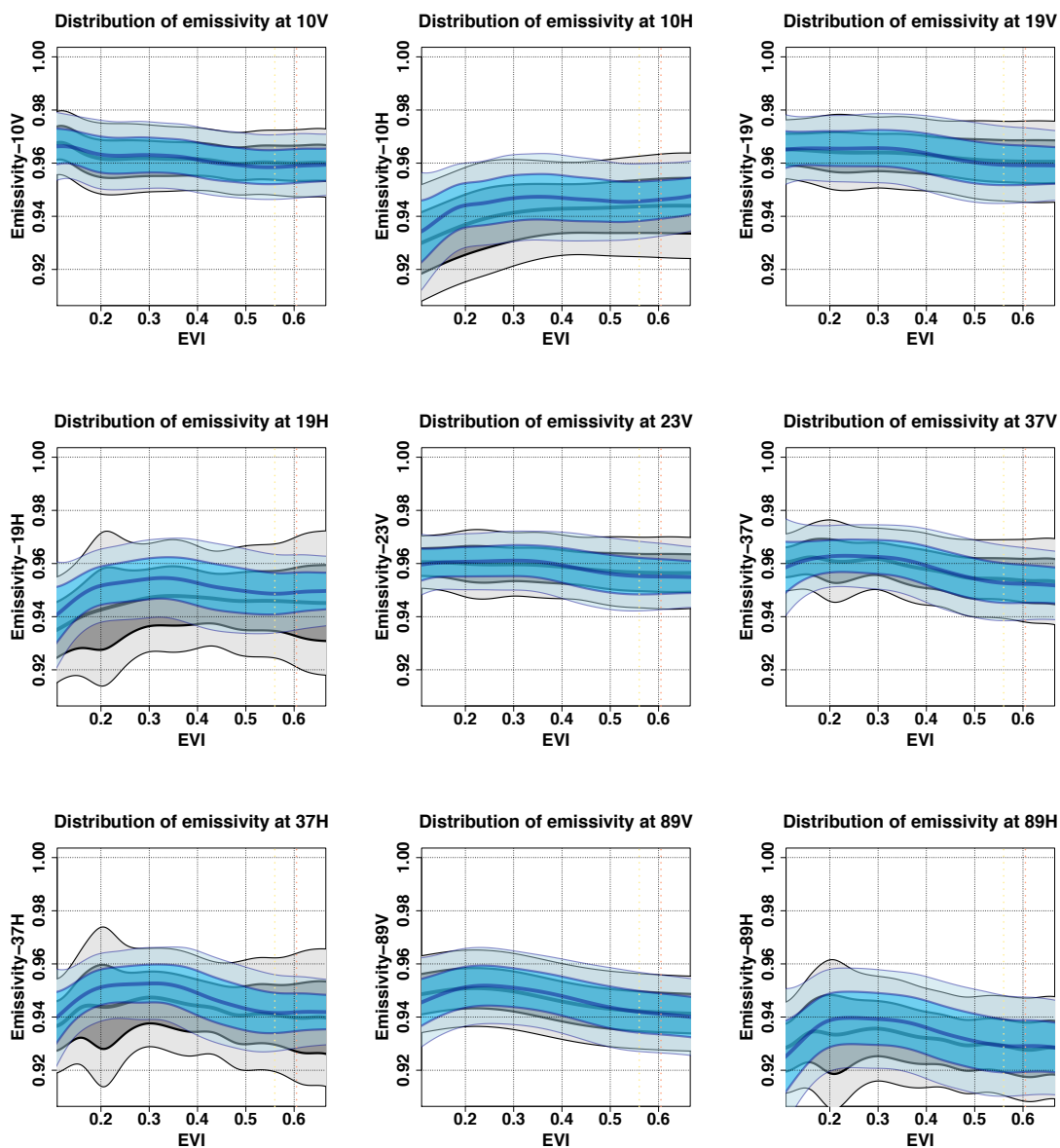


Figure B.1.4 Comparison of distribution of the emissivity from the EVI single parameter models based on the satellite remotely sensed data and the emissivity from the EVI single parameter models based on in-situ measurements over the maximum vegetated regions

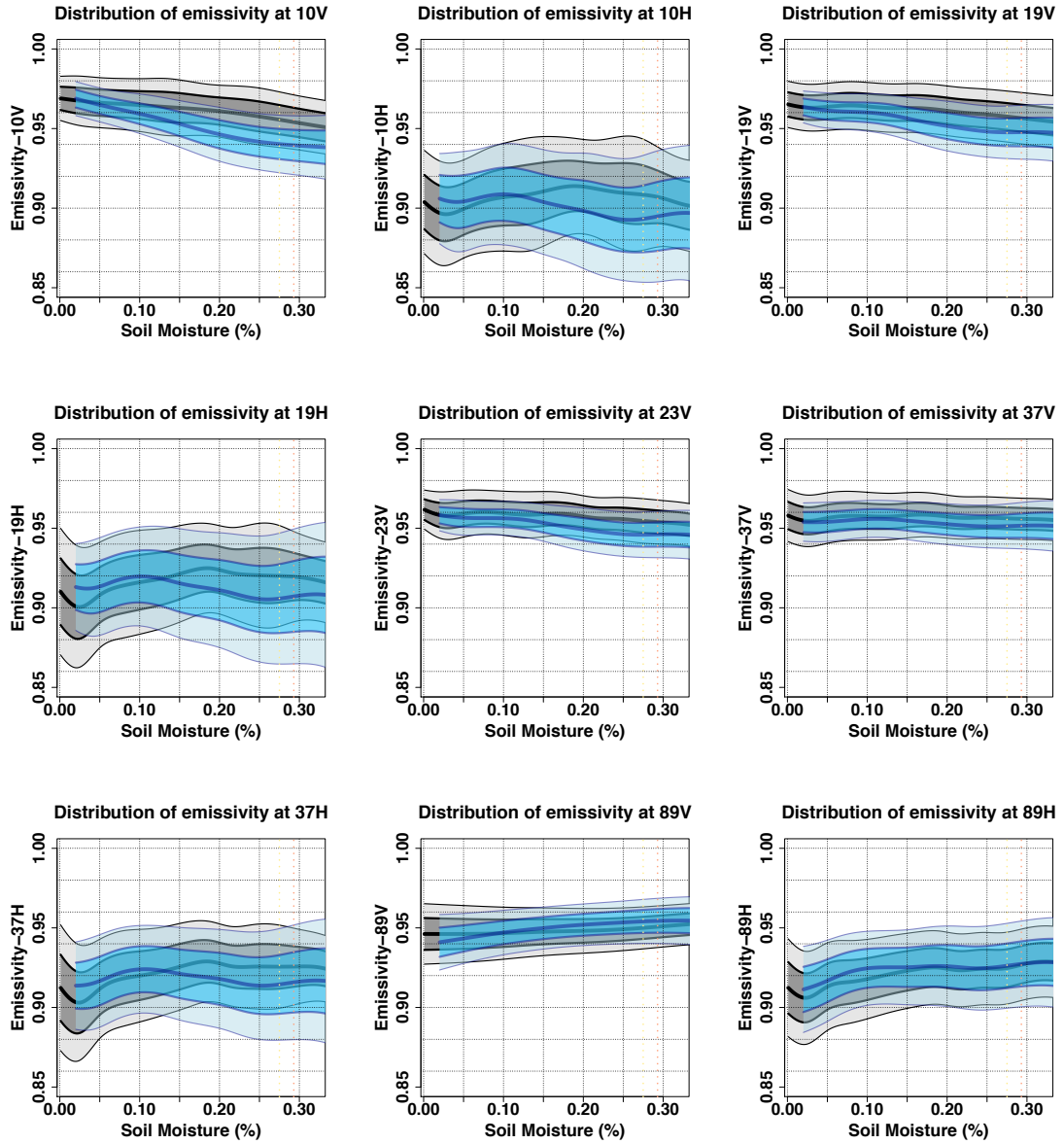


Figure B.1.5 Comparison of distribution of the emissivity from the soil moisture single parameter models based on the satellite remotely sensed data and the emissivity from the soil moisture single parameter models based on in-situ measurements over the moderate vegetated regions

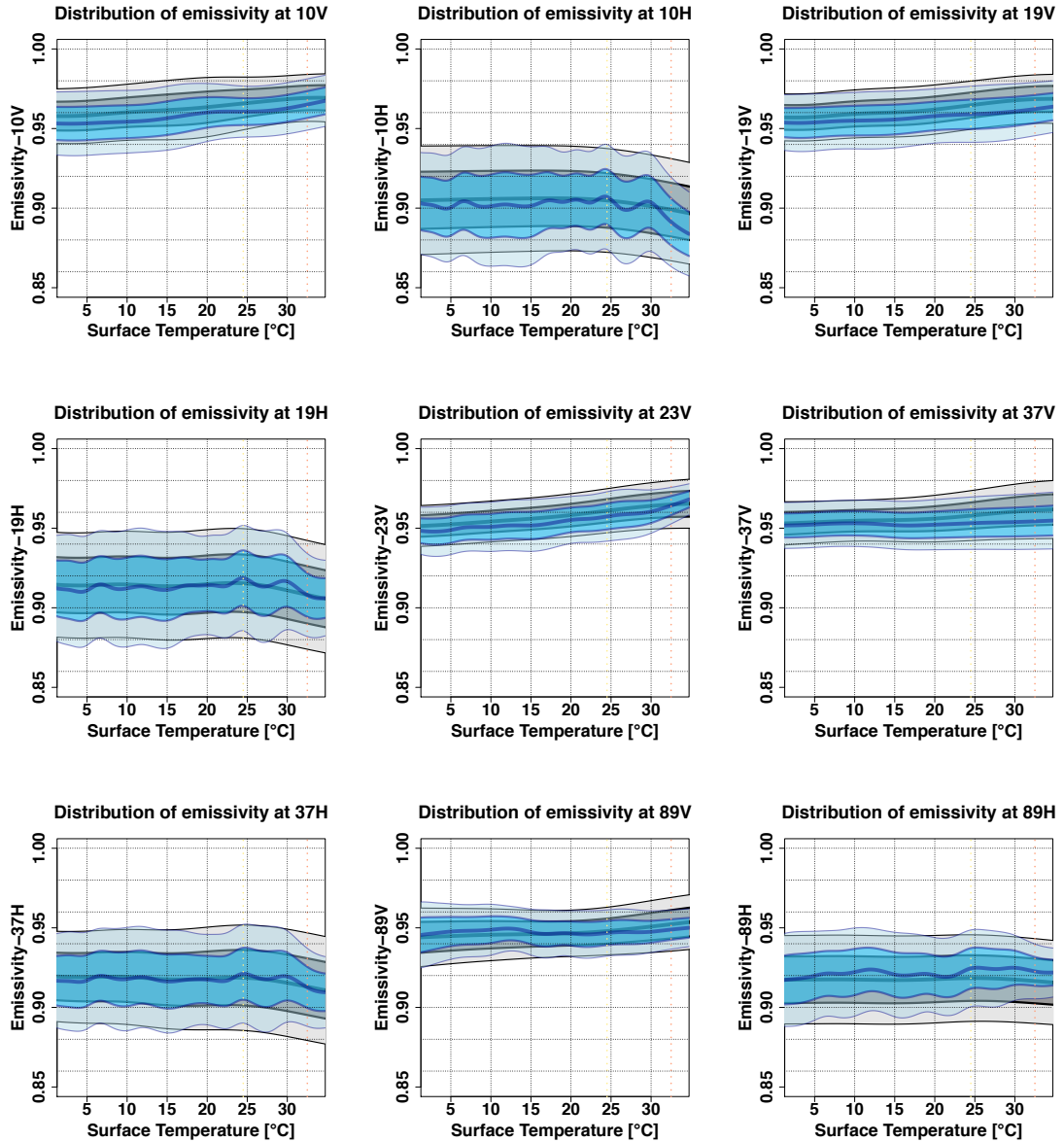


Figure B.1.6 Comparison of distribution of the emissivity from the surface temperature single parameter models based on the satellite remotely sensed data and the emissivity from the soil temperature single parameter models based on in-situ measurements over the moderate vegetated regions

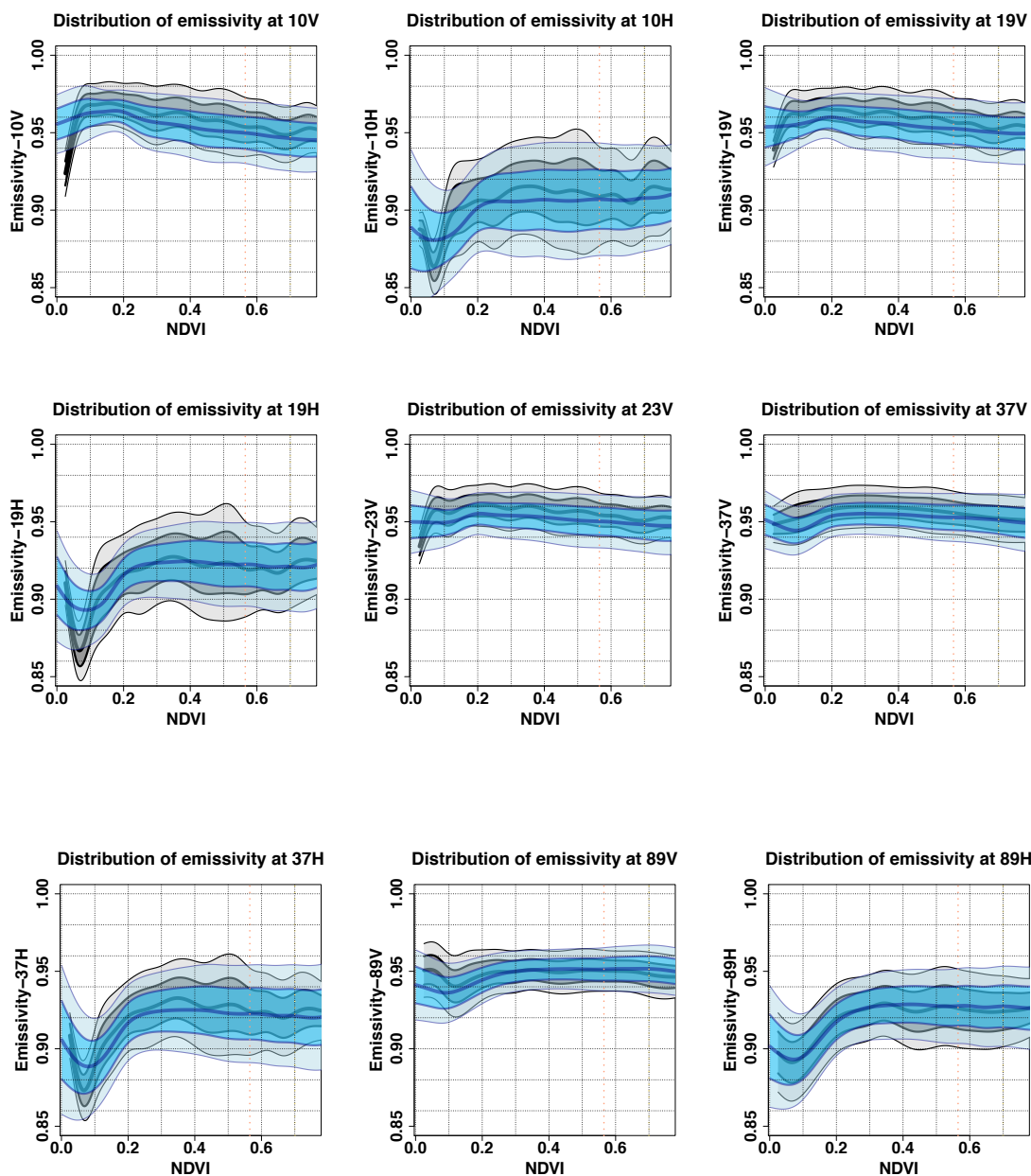


Figure B.1.7 Comparison of distribution of the emissivity from the NDVI single parameter models based on the satellite remotely sensed data and the emissivity from the NDVI single parameter models based on in-situ measurements over the moderate vegetated regions

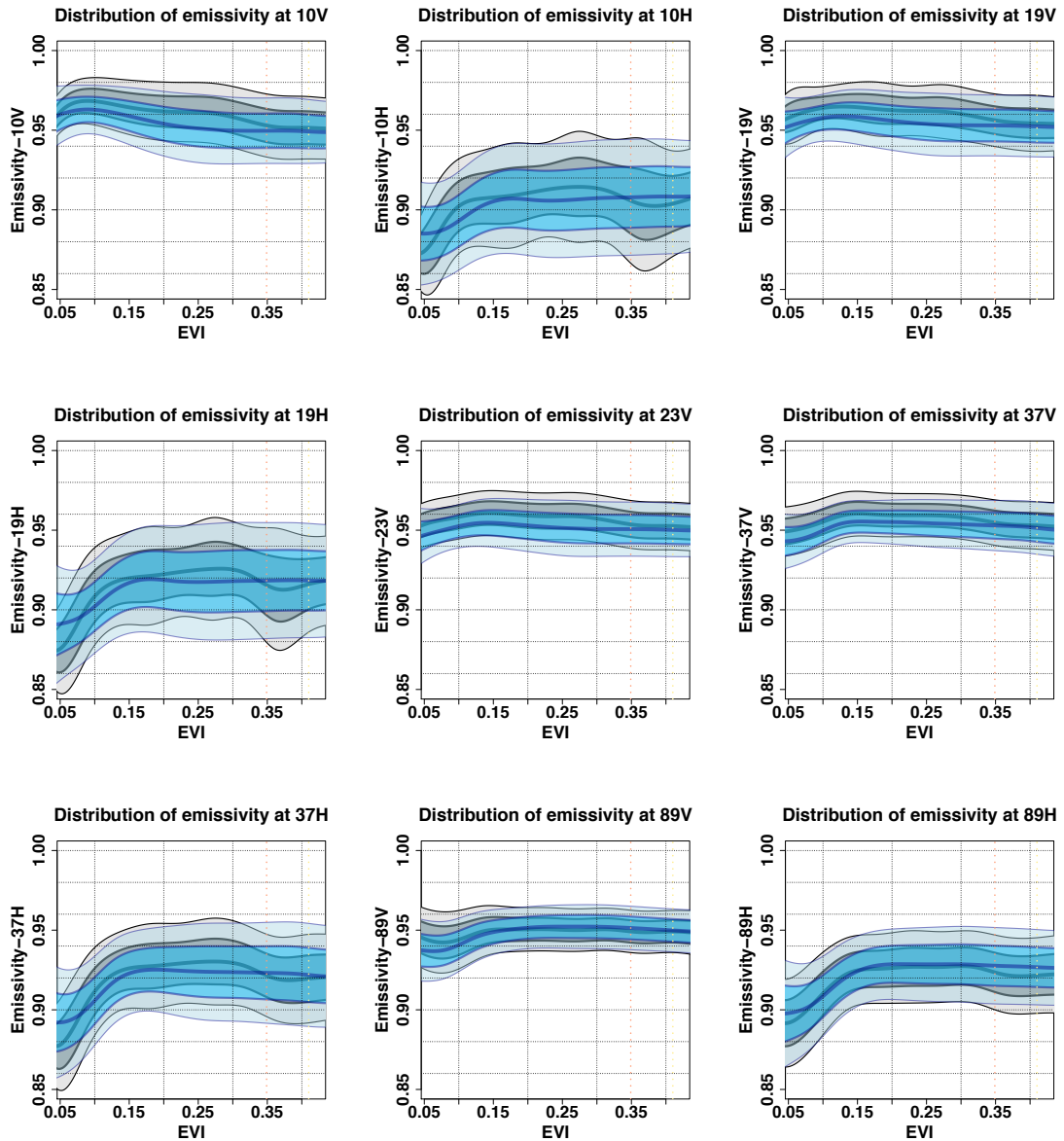


Figure B.1.8 Comparison of distribution of the emissivity from the EVI single parameter models based on the satellite remotely sensed data and the emissivity from the EVI single parameter models based on in-situ measurements over the moderate vegetated regions

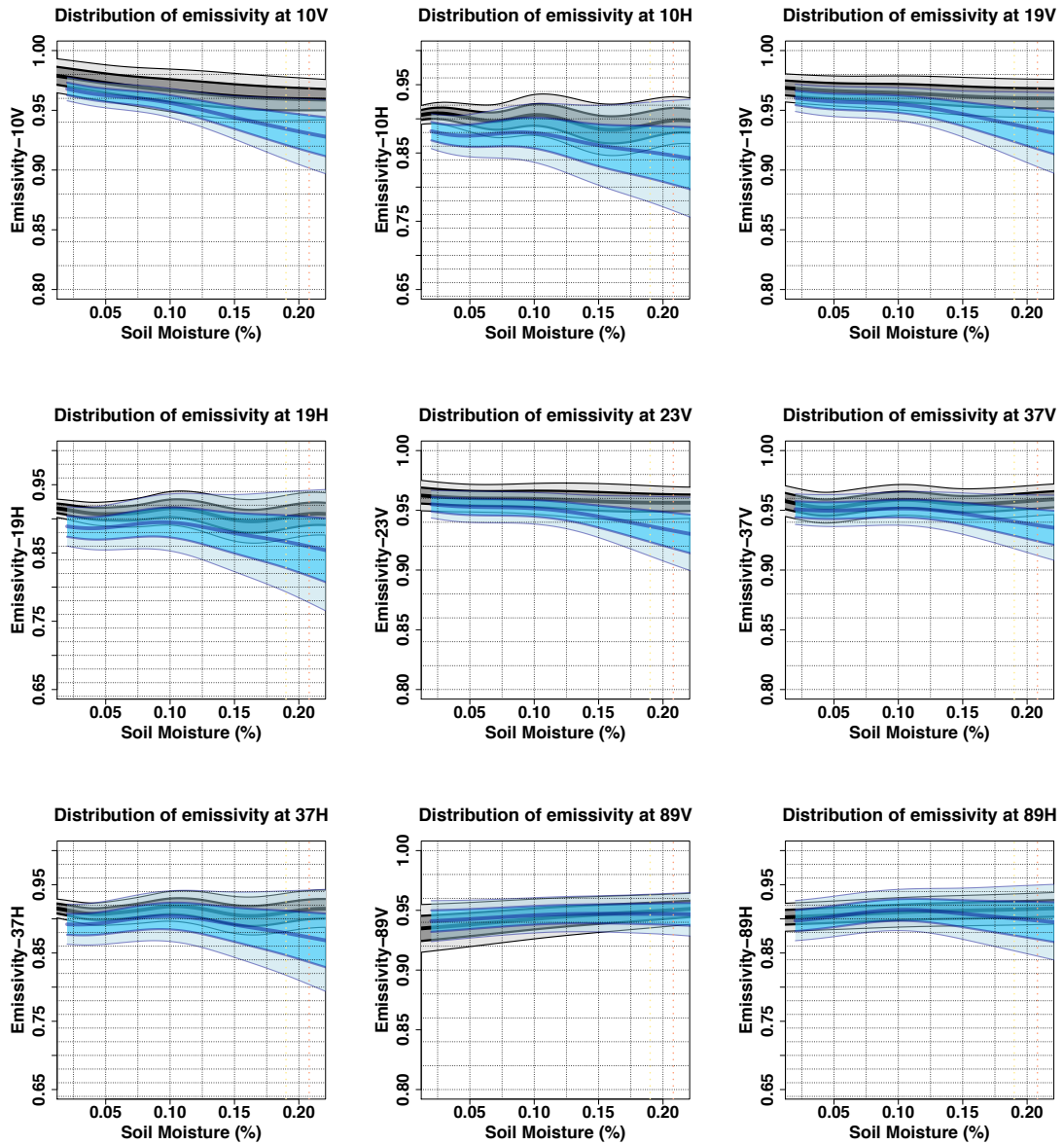


Figure B.1.9 Comparison of distribution of the emissivity from the soil moisture single parameter models based on the satellite remotely sensed data and the emissivity from the soil moisture single parameter models based on in-situ measurements over the low vegetated regions

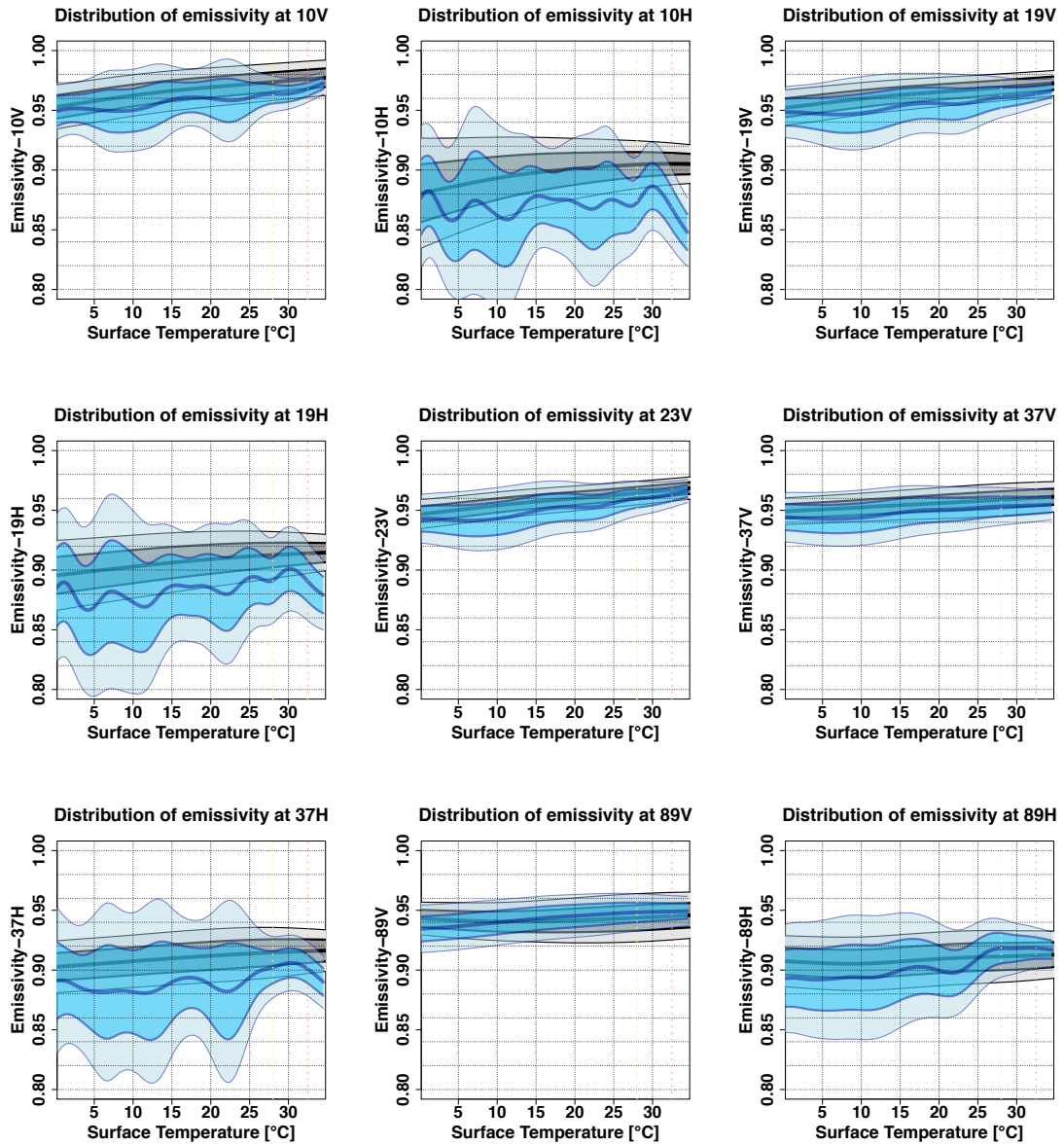


Figure B.1.10 Comparison of distribution of the emissivity from the surface temperature single parameter models based on the satellite remotely sensed data and the emissivity from the soil temperature single parameter models based on in-situ measurements over the low vegetated regions

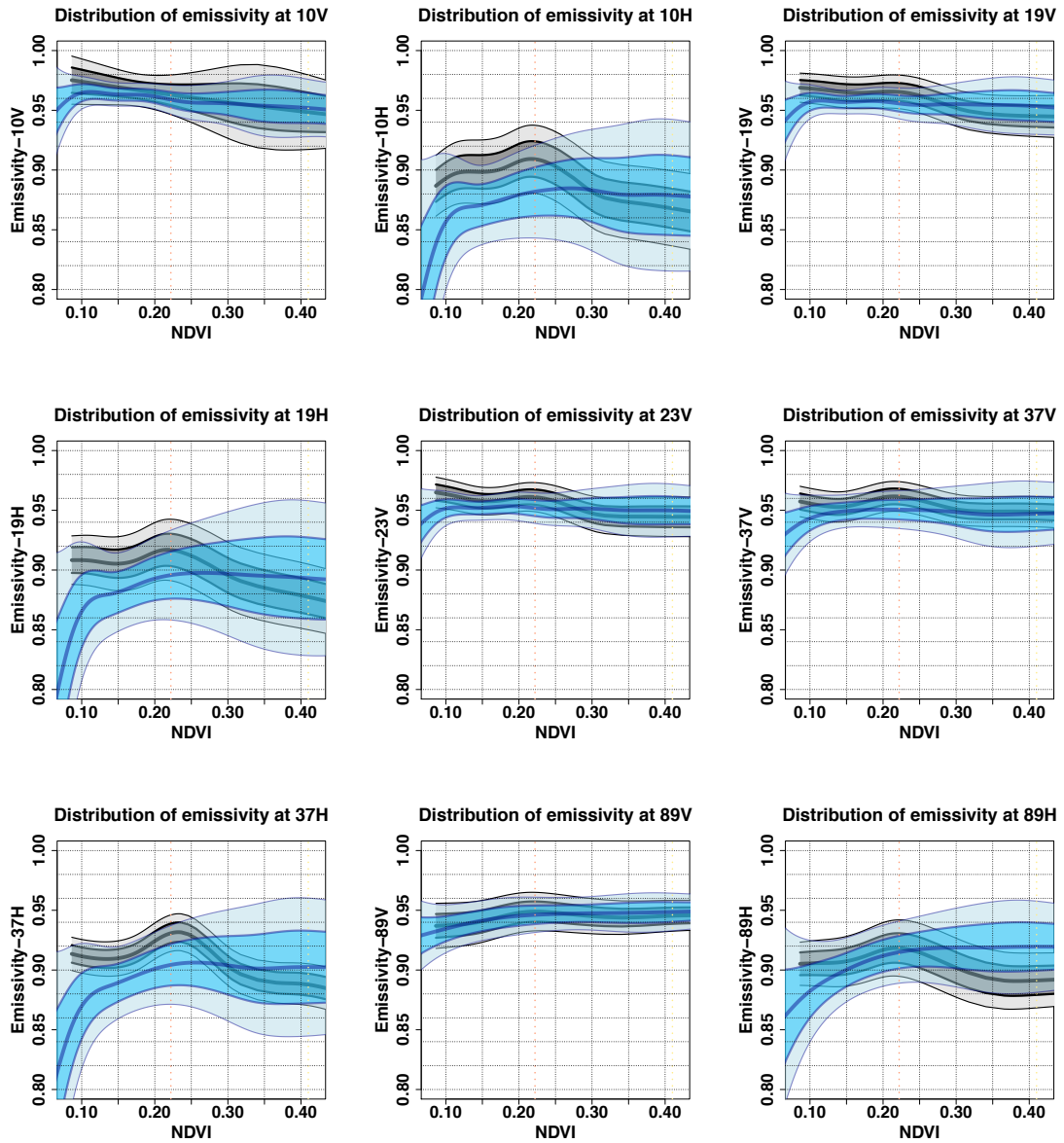


Figure B.1.11 Comparison of distribution of the emissivity from the NDVI single parameter models based on the satellite remotely sensed data and the emissivity from the NDVI single parameter models based on in-situ measurements over the low vegetated regions

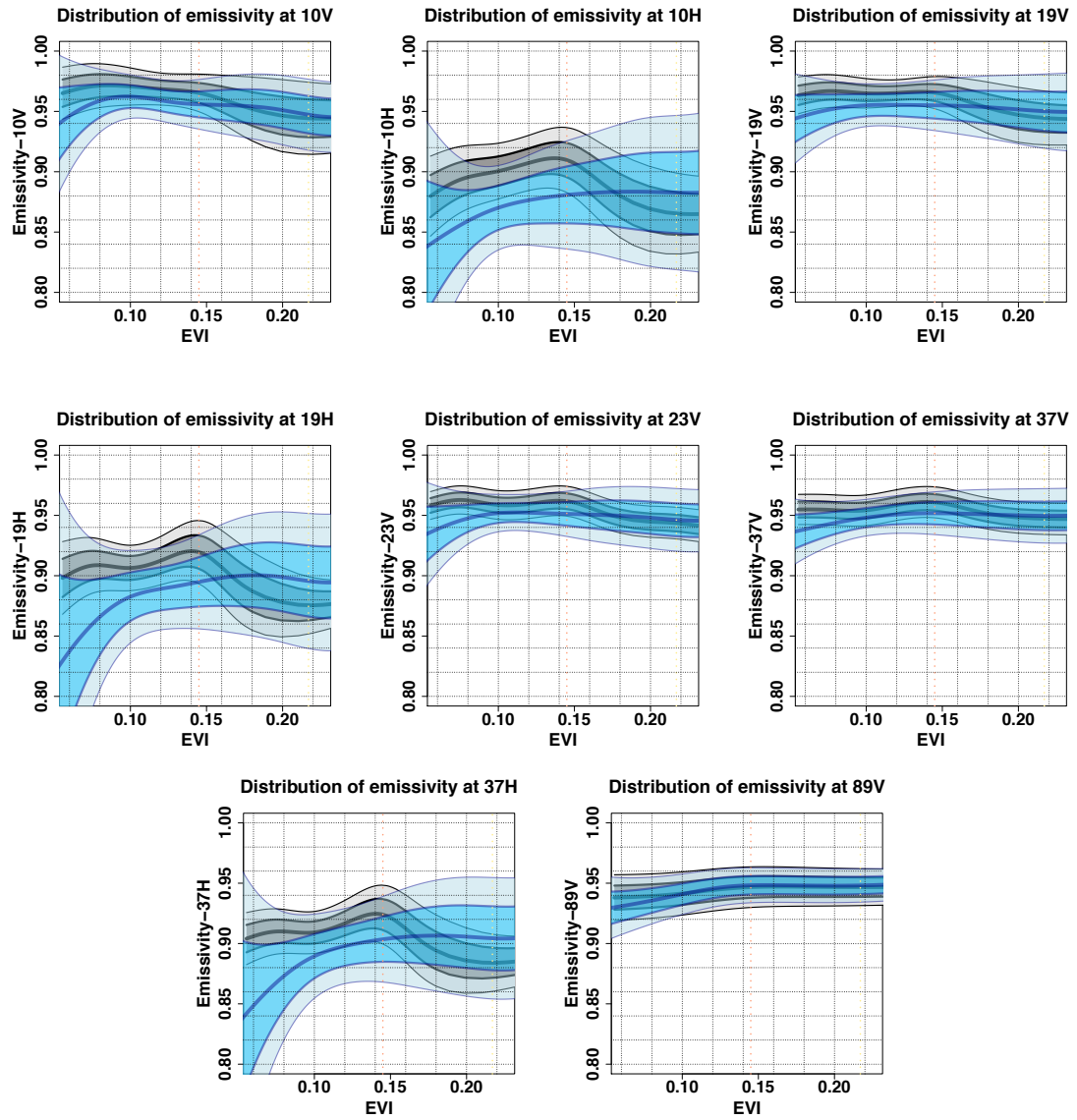


Figure B.1.12 Comparison of distribution of the emissivity from the EVI single parameter models based on the satellite remotely sensed data and the emissivity from the EVI single parameter models based on in-situ measurements over the low vegetated regions

Appendix C: Comparison of the Rainy Emissivity from Model and from Satellite

Retrievals

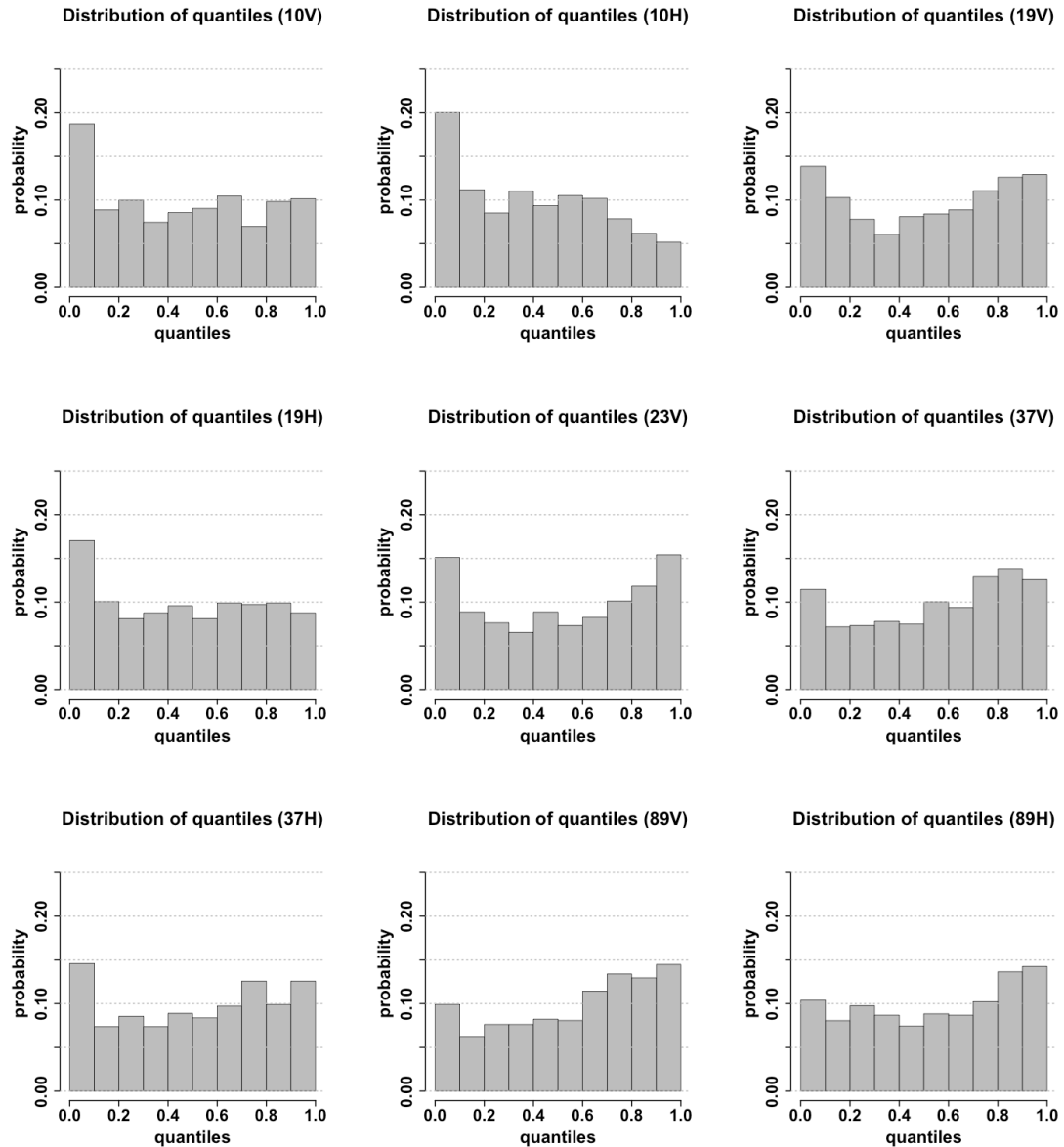


Figure C.1.1 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the mixed forest

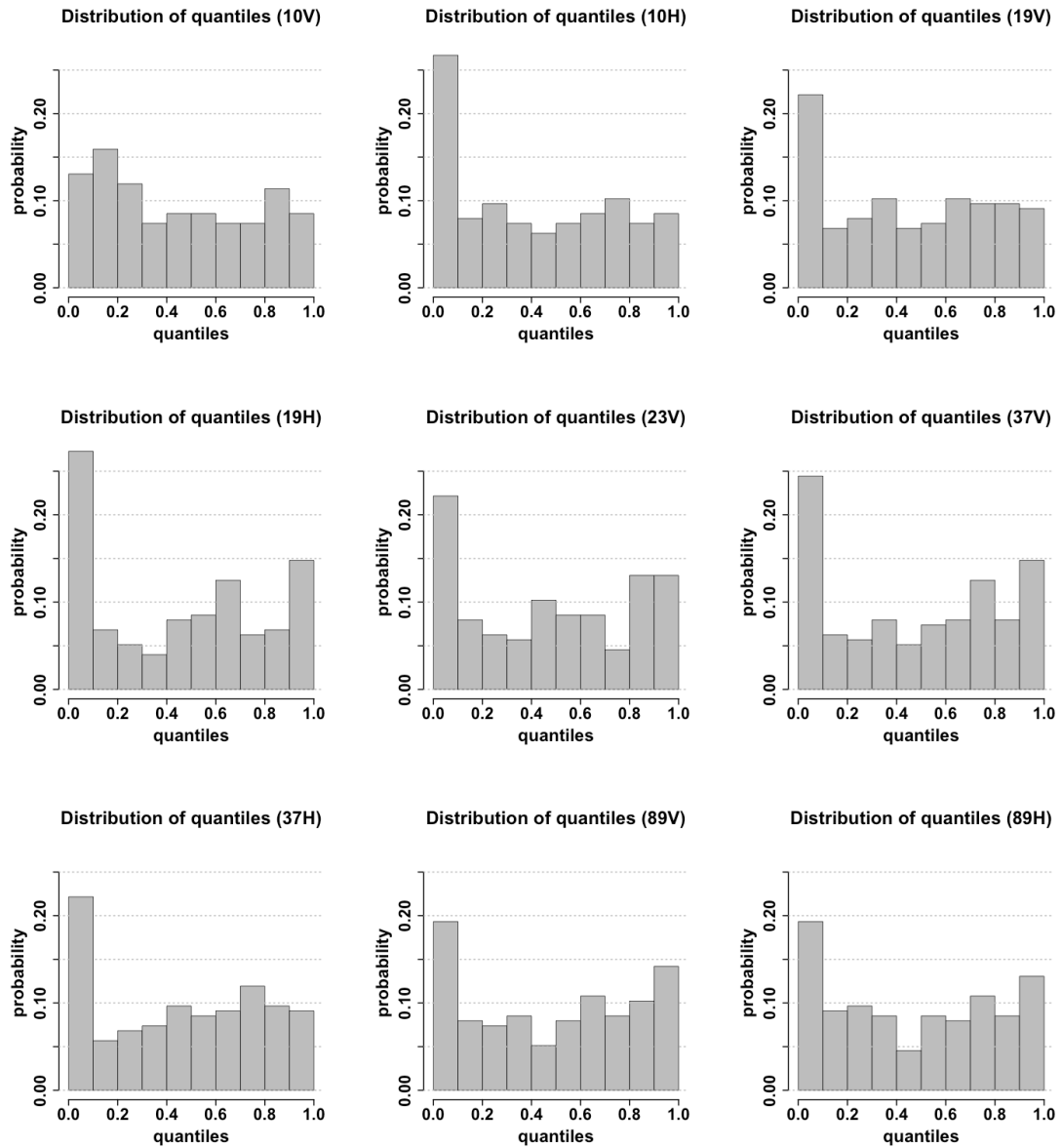


Figure C.1.2 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the cropland

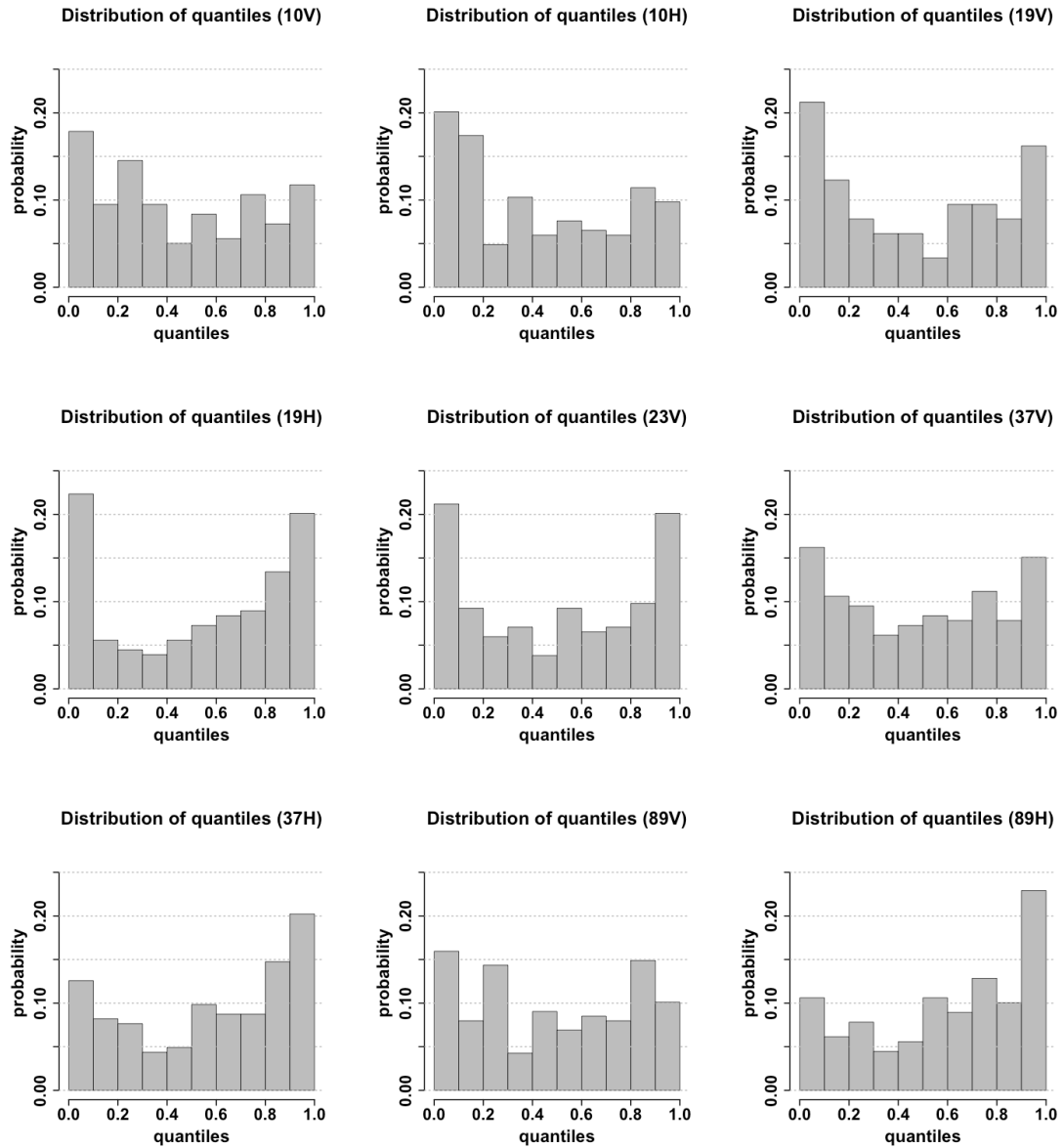


Figure C.1.3 Quantile information of the type 1 rainy emissivity in the distribution of the type 2 rainy emissivity for all the stations over the shrubland