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Junyi Huang

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How the Regional Water Cycle Responds to Recent Climate Change in Northwest Aridzone of China?

HUANG Junyi

A thesis submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy

Principal Supervisor:
Prof. ZHOU Qiming

Hong Kong Baptist University
December 2017
DECLARATION

I hereby declare that this thesis represents my own work which has been done after registration for the degree of PhD at Hong Kong Baptist University, and has not been previously included in a thesis or dissertation submitted to this or any other institution for a degree, diploma or other qualifications.

I have read the University’s current research ethics guidelines, and accept responsibility for the conduct of the procedures in accordance with the University’s Committee on the Use of Human & Animal Subjects in Teaching and Research (HASC). I have attempted to identify all the risks related to this research that may arise in conducting this research, obtained the relevant ethical and/or safety approval, and acknowledged my obligations and the rights of the participants.

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Date: December 2017
Abstract

Climate change has posed significant challenges for the world’s sustainable development, and the water cycle is highly dependent on the climate system. In particular, the arid zone fragile ecosystems in northwest China are highly vulnerable to the sophisticated hydrological variations. While ground-based measurements are less capable for large scale hydrological modelling, remote sensing techniques offer enhanced and effective alternatives for various hydrological states/fluxes. With the advancement of the Gravity Recovery and Climate Experiment (GRACE) satellites, the Terrestrial Water Storage (TWS), an integrative measurement of regional hydro-climatic environment, can now be measured as well for examining the overall hydrological response to recent climate change.

TWS is an essential element of the water cycle and a key state variable for land surface-atmosphere interaction. Investigating the TWS change is important for understanding the response of the water cycle to climate change. In this study, the intra-annual and inter-annual spatio-temporal change pattern of TWS in Xinjiang Uyghur Autonomous Region of China during 2003-2015 are characterized from Gravity Recovery and Climate Experiment (GRACE) Tellus data products. Sub-regional re-analysis reveals that the increasing/decreasing rate in sub-regions, namely, Altay Mountains (ATM), Junggar Basin (JGB), Tianshan
Mountains (TSM), Tarim Basin (TRB) and Kunlun Mountains (KLM), are -3.41mm, -5.82mm, -6.76mm, -2.59mm and +3.05mm per year in unit of equivalent water height (EWH), respectively. The results suggest that TWS variation presents certain spatio-temporal patterns with spatial heterogeneity. The uncertainties from different GRACE products are also assessed.

In conjunction with gridded meteorological data products and land surface model simulations of hydrological variables, the heterogeneous mechanisms of seasonal TWS change are analyzed. The correlation relationship among various hydrologic states/fluxes variables (e.g. snow water, soil water, snow amount) and climatic variables (e.g. temperature and precipitation) with GRACE-derived TWS variation in different sub-regions are investigated. The findings appear to indicate that 1) temperature month-over-month change and temperature anomaly with 4-month time lag, rather than precipitation, are more capable to explain the intra-annual TWS variation; 2) In most part of the study area, the TWS intra-annual change can be primarily attributed to the snow accumulation in winter and melt in spring.

On the other hand, the glacier mass variation, which is particularly sensitive to recent climate change, could be a substantial contributor to inter-annual TWS change. The elevation trends over glaciers are estimated based on ICESat altimetry measurements. Correlation analysis results suggest that, during 2003-2009, the inter-annual TWS loss in Tianshan Mountains (TSM) was tightly associated with glacier mass variation induced by temperature change, particularly
in summer. In contrast, TWS gain in Kunlun Mountains (KLM) can be attributed to glacier mass increase.

By utilizing remote sensing observation techniques/products, this study has characterized the spatio-temporal change pattern of TWS in northwest arid zone of China, as well as the underlying mechanism. It suggests that TWS is an effective indicator of regional climate change. This study contributes to a better understanding of the hydrologic and climatic processes in arid zone water cycle, and could be beneficial for regional water resources management and climate change adaptation effort.

**Keywords:** Water cycle, Terrestrial Water Storage (TWS), Gravity Recovery and Climate Experiment (GRACE), Climate change, Remote sensing, Arid zone
Acknowledgments

This research had been supported by contributions of many peoples and institutions. Support had come in many different ways and each input helped to bring this research to be completed on time.

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<tbody>
<tr>
<td>ATM</td>
<td>Altay Mountains</td>
</tr>
<tr>
<td>AMSR-E</td>
<td>Advanced Microwave Scanning Radiometer–Earth Observing System</td>
</tr>
<tr>
<td>ASTER</td>
<td>Advanced Spaceborne Thermal Emission and Reflection Radiometer</td>
</tr>
<tr>
<td>AVHRR</td>
<td>Advanced Very High Resolution Radiometer</td>
</tr>
<tr>
<td>CSR</td>
<td>Center for Space Research</td>
</tr>
<tr>
<td>CLM</td>
<td>Community Land Model</td>
</tr>
<tr>
<td>CMA</td>
<td>China Meteorological Administration</td>
</tr>
<tr>
<td>DEM</td>
<td>Digital Elevation Model</td>
</tr>
<tr>
<td>EOF</td>
<td>Empirical Orthogonal Function</td>
</tr>
<tr>
<td>ESRI</td>
<td>Environmental Systems Research Institute, Inc.</td>
</tr>
<tr>
<td>ET</td>
<td>Evapotranspiration</td>
</tr>
<tr>
<td>ETM</td>
<td>Enhanced Thematic Mapper</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<tr>
<td>---------</td>
<td>-------------</td>
</tr>
<tr>
<td>GFZ</td>
<td>GeoForschungsZentrum</td>
</tr>
<tr>
<td>GIS</td>
<td>Geographic Information System</td>
</tr>
<tr>
<td>GLAS</td>
<td>Geoscience Laser Altimeter System</td>
</tr>
<tr>
<td>GLDAS</td>
<td>Global Land Data Assimilation System</td>
</tr>
<tr>
<td>GLIMS</td>
<td>Global Land Ice Measurements from Space</td>
</tr>
<tr>
<td>GMSRA</td>
<td>GOES Multispectral Rainfall Algorithm</td>
</tr>
<tr>
<td>GOES</td>
<td>Geostationary Operational Environmental Satellite</td>
</tr>
<tr>
<td>GPI</td>
<td>GEOS Precipitation Index</td>
</tr>
<tr>
<td>GRACE</td>
<td>Gravity Recovery and Climate Experiment</td>
</tr>
<tr>
<td>HDF</td>
<td>Hierarchical Data Format</td>
</tr>
<tr>
<td>ICESat</td>
<td>Ice, Cloud, and land Elevation Satellite</td>
</tr>
<tr>
<td>IPCC</td>
<td>Intergovernmental Panel on Climate Change</td>
</tr>
<tr>
<td>JGB</td>
<td>Junggar Basin</td>
</tr>
<tr>
<td>JPL</td>
<td>Jet Propulsion Laboratory</td>
</tr>
<tr>
<td>KLM</td>
<td>Kunlun Mountains</td>
</tr>
<tr>
<td>LAI</td>
<td>Leaf Area Index</td>
</tr>
<tr>
<td>LiDAR</td>
<td>Light Detection and Ranging</td>
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<tr>
<td>Acronym</td>
<td>Full Form</td>
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<tr>
<td>LSM</td>
<td>Least Square Method</td>
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<td>LST</td>
<td>Land Surface Temperature</td>
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<tr>
<td>MLR</td>
<td>Multiple Linear Regression</td>
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<tr>
<td>MODIS</td>
<td>Moderate-resolution Imaging Spectroradiometer</td>
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<tr>
<td>MSS</td>
<td>Multi-Spectral Scanner</td>
</tr>
<tr>
<td>NASA</td>
<td>The National Aeronautics and Space Administration</td>
</tr>
<tr>
<td>NCC</td>
<td>National Climate Center (China)</td>
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<tr>
<td>NDVI</td>
<td>Normalized Differential Vegetation Index</td>
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<tr>
<td>NetCDF</td>
<td>Network Common Data Format</td>
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<tr>
<td>NOAA</td>
<td>The National Oceanic and Atmospheric Administration</td>
</tr>
<tr>
<td>(N)IR</td>
<td>(Near)-Infrared</td>
</tr>
<tr>
<td>NSIDC</td>
<td>National Snow and Ice Data Center</td>
</tr>
<tr>
<td>R</td>
<td>Surface runoff</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
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<tr>
<td>RS</td>
<td>Remote Sensing</td>
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<tr>
<td>SAR</td>
<td>Synthetic Aperture Radar</td>
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<tr>
<td>SCF</td>
<td>Snow Cover Fraction</td>
</tr>
<tr>
<td>Acronym</td>
<td>Description</td>
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<td>--------------------------------------------------</td>
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<tr>
<td>SEBAL</td>
<td>Surface Energy Balance Algorithm for Land</td>
</tr>
<tr>
<td>SEBS</td>
<td>Surface Energy Balance System</td>
</tr>
<tr>
<td>SM</td>
<td>Soil Moisture</td>
</tr>
<tr>
<td>SMOS</td>
<td>Soil Moisture and Ocean Salinity</td>
</tr>
<tr>
<td>SPOT</td>
<td>Systeme Probatoire d’Observation de la Terre</td>
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<tr>
<td>SPSS</td>
<td>Statistical Package for the Social Sciences</td>
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<tr>
<td>SRTM</td>
<td>Shuttle Radar Topography Mission</td>
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<tr>
<td>SWE</td>
<td>Snow Water Equivalent</td>
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<tr>
<td>TM</td>
<td>Thematic Mapper</td>
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<tr>
<td>TRB</td>
<td>Tarim Basin</td>
</tr>
<tr>
<td>TRMM</td>
<td>The Tropical Rainfall Measuring Mission</td>
</tr>
<tr>
<td>TRMM-TMI</td>
<td>TRMM Microwave Imager</td>
</tr>
<tr>
<td>TSM</td>
<td>Tianshan Mountains (Tienshan Mountains)</td>
</tr>
<tr>
<td>TWS</td>
<td>Terrestrial Water Storage</td>
</tr>
<tr>
<td>TWSC</td>
<td>Terrestrial Water Storage Change (month to month)</td>
</tr>
<tr>
<td>TWSA</td>
<td>Terrestrial Water Storage Anomaly</td>
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<tr>
<td>VIC</td>
<td>Variable Infiltration Capacity</td>
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Chapter 1    Introduction

The substantial impacts of climate change on ecosystems, agriculture, water resources and human well-being can be observed across the globe. While the water system is highly interrelated with the climate system, it is particularly vulnerable to climate variability in arid zone. The advancement of earth observation technology is empowering human beings to tackle those challenges with effective adaptation strategies.

1.1 Background

1.1.1 Water cycle and water resources

Water is an essential element on the Earth, and it is critical resource for sustaining humans and ecosystems. Water on earth is always in movement. The state of water is always changing among three phases: water vapor, liquid water, and solid ice, storing in different reservoirs (oceans, rivers, lakes, glaciers and ice caps, underground aquifers, and the atmosphere). These processes collectively constitute the water cycle, driven by external energy such as solar radiation and earth gravity. According to Figure 1.1, as water goes through its cycle, it can be converted among states (formats of storing) of solid (snow and ice), liquid (surface runoff, groundwater, lake, pond, ocean), or gas (clouds and water vapor)
upon various conditions. These processes are often accompanied by the variation and alteration of hydrological fluxes, including evapotranspiration, infiltration, precipitation and river discharge, due to meteorological/climatic change and human intervention (Oki and Kim 2017). The hydrological cycle has long and primary contribution to the water and energy balance on earth. The research of natural water cycle, also known as the hydrological cycle, investigates the continuous movement and irregular distribution of water on or below the Earth surface.

Figure 1.1 The Earth’s hydrologic cycle and various water states and fluxes
(Houser and Schlosser 2003)

Water resources are sources of water that can readily be used for human, however, 97% of the water on the Earth is saline water and only 2.5% is
freshwater. Despite multiple sources of freshwater are available (e.g. precipitation, surface water, groundwater, frozen water or desalination), they are irregularly distributed in space and time. At present, water resources scarcity is one of the most critical issues challenging the world sustainable development (World Water Assessment Programme (WWAP) 2015). The world is experiencing relentless and increasing pressure from rapid urbanization, growing population, economic development, which is aggravated by the impacts of water pollution, aquifers depletion, regional conflicts and of course, climate change.

1.1.2 Climate change and impacts on hydrological cycle

Climate change has widely been recognized as one of the major and most complicated challenges for the 21st century globally (Huntington 2006). The Intergovernmental Panel on Climate Change (IPCC) recently reported that the linear trend of the globally averaged combined land and ocean temperature shows a warming of 0.85°C (0.65°C to 1.06°C) from 1880 to 2012, according to various independently produced datasets (IPCC 2013). The total increase from the average of the 1850–1900 period to the average of the 2003–2012 period is 0.78°C.

Globally increasing temperature have spurred researches into climate forcing and the responses of Earth systems (Bishop et al. 2014). The water system is highly dependent on the climate system (Chang 2009). The response of water cycle and water resources to climate change is attracting wide concerns among the scientific community and even the general public. It is generally recognized that
climate change intensifies the water cycle, exacerbates intensity and frequency of weather extremes (e.g. drought) and hydrological extremes events (e.g. flooding), and leads to the redistribution of water resources within different time and space scale (Jung et al. 2010; Famiglietti and Rodell 2013; Wang et al. 2014a; Chen et al. 2015b). These meteorological and hydrological variations jointly exert a fundamental influence on terrestrial water storage, which integrates the impacts of natural climate variation and anthropogenic disturbance.

Terrestrial water storage (TWS) is therefore characterized as a key hydrological state variable implying land surface-atmosphere interaction (Creutzfeldt et al. 2012). It is considered as an essential prerequisite for contemporary water management, yet quantifying and interpreting these variations remain a major challenge, partly due to the complexities inherent to their observation, simulation, and attribution on regional and global scales (Fasullo et al. 2016).

1.1.3 Arid zone under climate change

While climate change has been occurring at a global scale, the impacts of climate change will vary by different time and space scale (Chang 2009). Since the end of the Little Ice Age, the climate in northwest China was warm-dry until about 1980, while during the past 20-30 years it has notably transformed to a warm-wet condition (Chen et al. 2007; Shi et al. 2007). It is acknowledged that climate change may have substantial influences on ecosystems, agriculture, water
resources, as well as human well-beings, particularly in Eurasia hinterland (Lioubimtseva and Henebry 2009).

In the arid/semi-arid Asia hinterland, numerous studies have suggested that the hydrological cycle is highly responsive and vulnerable to climate changes, based on both historical records and future climate projections (Immerzeel et al. 2010; Chen et al. 2014c). Nevertheless, the response complexity and vulnerability to regional and global climate change have not yet been fully discovered. Tradition in-situ measurement methods are inadequate for the current and future demands of hydro-climatic monitoring. The remote and challenging geographical condition of arid zone hinders the comprehensive observations for the environment. Remote sensing, which provides the only viable means for many observations, can complement ground-based observations and enhance our capability for understanding such changes.

1.1.4 Hydrology monitoring by remote sensing

Remote sensing technology, with its extensive spatial and temporal coverage advantages, has shown great promise for earth system monitoring where in-situ observation are inadequate (Moradkhani 2008). It has long been a valuable tool as well in water resources monitoring and hydrologic modeling applications, for its capability to provide land/hydrologic models with large-scale surface, near-surface, and below-surface information (Xu et al. 2014b). As the recent and future advancement of earth observation technology, airborne or space-borne sensors, some of them specifically designed for hydrological purposes, will further
enhance our ability of hydrological observations at high spatial and temporal resolutions or for specific hydrological components. This will offer new opportunities for the vibrant hydrological community.

In arid/semi-arid regions in the world, particularly areas with mountainous landscape or often inaccessibly remote location, ground observations are virtually unable to be conducted due to high human and resources cost. Many of the existing approaches and uneven or sparse in-situ records may not be able to meet the requirement for wide geographical and temporal coverage investigations due to the data availability, observation continuity and reliability. There is a strong need for prioritizing the use of remotely-sensed observations techniques for improved estimations.

1.2 Research questions

In the fragile arid/semi-arid ecosystem, water resources are critical for sustaining live and development. The consequences of climatic change can be exerted to many different aspects of the arid zone water cycle and therefore pose significant challenge to regional ecological security. There remain some important open questions, for a better understanding of the hydrological responses to climate change in arid zone:

1) Can remote sensing provide useful data for enhancing regional hydrology change monitoring in space and time?
2) What has been changed in arid zone hydrology under recent climate change?

3) Is terrestrial water storage (TWS) an effective measurement for regional hydro-climatic conditions in arid zone, and providing implications for recent climate change?

1.3 Research objectives and significance

To answer the research questions, this study aims to examining the hydrological response under climate change in northwest arid zone of China, by quantifying the spatio-temporal change of TWS and investigating its attributions. The objectives of this study are:

1) To investigate the methodology of quantifying TWS spatial-temporal variability by remote sensing;

2) To analyze the relationship between the change of TWS and meteorological and hydrological variables;

3) To characterize the hydrological variations in response to recent climate change in arid zone of China.

1.4 Organization of the thesis

This thesis consists of ten chapters, and the organization is outlined as follows:
Chapter 1 presents the research background. The concepts of water resources, water cycle and climate change are firstly introduced. The impacts of climate change on hydrological cycle, particularly in arid zone are discussed. The general use of remote sensing in hydrological studies are summarized which necessitates the need of utilizing advanced earth observation techniques in addressing hydrological problems. Research questions, objectives and thesis structure are presented as well.

Chapter 2 provides a review of the scientific literature on topics of remote sensing hydrological monitoring techniques, TWS monitoring techniques, and the current knowledge of hydrologic changes investigations (especially the TWS) in response to climate change in arid northwest China.

A brief introduction of the study area and the justifications of selecting this particular area as the study object will be presented in Chapter 3. Emphasis will be placed on describing the interactions among topography, hydrology, climate, vegetation and land use of the whole study area, which have caused substantial regional differences and enriched our study.

Chapter 4 and Chapter 5 describe the data acquisition and key methodologies in the study.

Chapter 6 illustrates the pattern of TWS spatio-temporal change. In this chapter, analyses will be conducted in terms of intra-annual change and inter-annual change, for not only the general pattern but the abnormal phenomenon.
This will establish the fact basis of examining the hydrological response to recent climate change.

Chapter 7 examines the mechanisms of TWS intra-annual cyclic change. The analyses will primarily be focusing on correlating the change of TWS with seasonal changes of various climatic and water states/fluxes variables. The deviations among different sub-regions are investigated for a comparative elaboration.

Chapter 8 characterizes the heterogeneous TWS inter-annual change in the study area and reports the core result of this study. Evidence from different sources (glacier elevation change, climatic observation, etc) are compared and examined to characterize and quantify the hydrological response to recent climate change exhibited in TWS.

A discussion section for comparing the result of the current study with similar studies, and acknowledging study limitations (data accuracy or unavailability) can be found in Chapter 9.

The summary of findings and major contributions to knowledge of this study will be wrapped up and highlighted in Chapter 10.

1.5 Summary

It has been widely acknowledged that climate change have substantial impacts on ecosystems, agriculture, water resources, as well as human health and
livelihood across the globe, particularly in Eurasia hinterland (Lioubimtseva and Henebry 2009). Arid zone, particularly in northwest China, has long been suffering from water scarcity problem, and this situation is further exacerbated by regional climate change and human activities. Ground observations are yet far from sufficient for water resources monitoring. Remote sensing technology may enhance our capability for monitoring hydrological variation in northwest arid zone of China.
Chapter 2  Literature Review

In this literature review, the arid zone water cycle of northwest China, characterized by its vulnerability to climate change, will be firstly introduced. Second, the technology foundations of remote sensing hydrology monitoring are outlined, with emphasizing the need for a collective hydro-climatic observation in arid zone. Third, evolution of strategies measuring the terrestrial water storage (TWS), and the advantages of GRACE satellite and its applications are illustrated. A review of the current knowledge regarding the hydrological variation in arid northwest China in response to climate change is presented. Research gaps are identified by reviewing the literatures associated with the above discussion.

2.1 Vulnerable water cycle in arid zone

The northwest arid zone of China is located in the hinterland of the Eurasia continent, characterized by a wide-range of temperature, low precipitation, and low humidity (Chen et al. 2014b). In this region, water resources are essential for maintaining the socio-economic development and ecological security. The arid northwest region has distinct features of hydrological processes and spatiotemporal distribution, which are representative of arid regions in the world (Figure 2.1).
Climate change and water resource issues are major constraints of challenging the sustainable development in the northwest arid zone of China and adjacent Central Asia nations (Chen et al. 2016a). Climate and natural environment changes, coupling with the intensive human activities such as irrational farmland expansion (Zhou et al. 2008a, b, 2011; Li and Zhou 2009) and groundwater exploitation, have been altering the arid zone water cycle in many different ways, further deteriorating local water security (Li and Zhou 2009; Sun and Zhou 2016). As population increases and economy develops, the water resource issues facing the arid northwest region are set to worsen and their impact will deepen. This will in turn pose challenges to the ecosystem and social-economic sustainability as well as regional stability.

Ecosystems in arid and semi-arid regions are fragile and sensitive to climate change. It is commonly agreed that the overall climate profile of Xinjiang is
changing from a warm-dry mode to a warmer and humid mode (Li et al. 2012; Fu et al. 2013). Various studies confirm that the temperature of the arid northwest China has significantly increased in recent half century, at a rate of 0.33–0.39°C/10a (Li et al. 2012), higher than the overall rate of China (0.22°C/10a) (Liu et al. 2011) and the global average (0.14°C/10a) (IPCC 2013).

In the past decades, climate warming and intensifying human activities have triggered apparent transition of the hydro-climatic processes, characterized by a continual increase in temperature and precipitation, added river runoff volumes, increased lake water surface elevation and area, and elevated groundwater levels, etc. (Xu et al. 2014a). Annual extreme precipitation events also increased during 1961-2001 in the arid northwest, particularly during summer (Wang and Zhou 2005). A drastic increase in hydrological extreme events (e.g. drought and flooding) is reported from 1901 to 2010, particularly post 1970s (Sun et al. 2014). Li et al. (2014a) analyzed the potential evapotranspiration and the corresponding trend attribution during the past 50 years in northwest China and suggested the occurrence of accelerated or enhanced water cycle under climate change.

In northwest China, water resources predominantly originate from mountain precipitation and snowmelt, which are particularly sensitive to regional climate variability. Greater uncertainty or extreme events of the hydrological cycle and individual components are expected, particularly occurred in the cryosphere. For example, glacier has decreased by 11.5% during 1961-2009 in Tianshan Mountains, accelerated by the climatic trends (Wang et al. 2011). Glacier retreat
in the lower elevation ranges of Tianshan Mountains triggers obvious seasonal changes of run-off in the Tarim Basin (Yang et al. 2015). With the threat of climate change intensifying, greater uncertainty regarding the fluctuation of mountain glaciers, snow patch and their hydrological and ecological consequences have aroused wide concern.

As situated in the Eurasia hinterland, the river systems in the northwest arid zone are predominantly internal drainage with limited precipitation. Water balance are largely controlled by several key climatic and hydrologic variables, such as temperature, snow cover and soil moisture, etc. The northwest arid zone of China, due to the relatively simplicity of hydrological processes, has therefore been an attractive target for hydrological studies.

As arid zone in northwest China is situated in the remote location, despite of the fact that ground measurement network has been established in the region, those in situ measurements are unevenly distributed. Given the spatial heterogeneity and cost (labor and resources), it is extremely difficult to quantify such changes solely by in situ observations. Remote sensing techniques, which enable acquisition of real- or near-real-time data for inaccessible or remote areas within very short span of time, are powerful tool for comprehensive earth observation in this region (Liu et al. 2012).
2.2 Remote sensing for hydrological monitoring

Remote sensing is a major leap in technology that significantly improved the hydrologic simulations, for advantages of wide regional coverage with satisfactory time continuity and data accuracy. Currently, almost all variables in the water balance equation, such as precipitation, evapotranspiration, snow and ice, soil moisture, river discharge, and terrestrial water storage variations, etc., or other auxiliary variables that may contribute to or be affected by hydrological changes, such as land cover/land use, soil salinity, water quality, etc., can be directly or indirectly observable at varying but improving spatial and temporal resolutions and accuracy, either by active, passive, or microgravity sensors. Observational data are utilized for the monitoring or prediction task of single and a combination of hydrological states/fluxes at global, continental or regional level, including soil moisture, sea water/lake levels, snow cover, glacier and ice sheet, rainfall, river discharge, flood inundation or evapotranspiration, or the calibration or the assimilation into hydrodynamics or hydro-meteorological models.

Tang et al. (2009), Kumar and Reshmidevi (2013), and Xu et al. (2014b) have presented a comprehensive review of the common techniques and current research progress in utilizing remote sensing to support hydrological investigations. The following sections will give an overview of the principle strategies of hydrological monitoring by remote sensing, with focusing on several key hydrological variables in northwest arid zone of China.
2.2.1 Rainfall

Rainfall is the most important input of the terrestrial hydrologic system, and it is regarded as the main freshwater sources in most parts of the world. There are three major methodologies for rainfall observation using remote sensing (Schultz and Engman 2000): surface radar, visible (VIS) and infrared (IR) sensors, and active microwave sensors. Despite of the fact that rainfall gauge and ground-based radar networks are well established at local or regional scale, networks are unfortunately sparse in many remote areas (Sorooshian et al. 2011). By detecting the cloud-top temperature and brightness, occurrence and intensity of rainfall can be indirectly measured by geostationary satellite remote sensors, with large geographical coverage and high spatial resolution (~30m). Notable algorithms include: Geostationary Operational Environmental Satellite (GOES) Multispectral Rainfall Algorithm (GMSRA) (Ba and Gruber 2001) and the GOES precipitation index (GPI) using IR measurements (Arkin et al. 1994).

As observations by visible (VIS) and infrared (IR) sensors are less capable with the presence of cloud, microwave sensors, with its capability of all-weather condition operation, are used to improve the retrieval accuracy. On the other hand, passive microwave or space-borne radar sensors are widely utilized for instantaneous precipitation detection for its rapid scanning capability. These observations are based upon the direct physical relations between the radar reflectivity of the cloud and the precipitation rate, and therefore provide an improved precipitation estimate.
Nowadays, gridded precipitation products, with different temporal and spatial resolutions and coverage, are available, with satisfactory level of maturity over the last decade. Tropical Rainfall Measuring Mission (TRMM) multi-satellite precipitation analysis, that have merged precipitation estimates from both in situ gauge and multiple satellites, are among the most widely utilized (Huffman et al. 2007, 2010).

2.2.2 Soil moisture

Soil moisture is an important state variable in land surface hydrology as it modulates the exchange of water among soil infiltration, formation of surface runoff and replenish of water table. Direct observations of soil moisture, which are restricted to specific locations, are inadequate to represent its variability.

Optical remote sensing detects the soil moisture based on the relationship between soil surface reflectance and moisture contents (Lobell and Asner 2002; Wang and Qu 2007). Limitations of optical remote sensing measurements, such as shallow soil penetration and cloud contamination, resulted in the increasing use of thermal (which detects the surface temperature) and microwave for soil moisture detection.

Remote sensing of the soil moisture using the thermal bands can be achieved by thermal inertia method or temperature/vegetation index method, both have clear physical meaning (Wang and Qu 2009). The thermal inertia method generally relates the diurnal amplitude of soil surface temperature surface with soil moisture content (Cai et al. 2007), while the temperature/vegetation index
method usually calculates the Normalized Differential Vegetation Index (NDVI) and land surface temperature (LST) to invert to soil moisture.

Use of passive microwave radiometers and active radar instruments such as SAR are widely believed as the most suitable techniques for monitoring soil moisture. Microwave remote sensing detects the contrast between the dielectric properties of water (~80) and soil particles (<4) leading to soil moisture estimation. Mohanty et al. (2017) has summarized the properties of various microwave platforms and instruments for this task. Passive microwave is considered more suitable for large scale monitoring due to wider swath widths, but has a lower spatial resolution. There is an increasing availability of global soil moisture products from existing space-borne passive microwave sensors, such as Advanced Microwave Scanning Radiometer–Earth Observing System (AMSR-E) and Advanced Microwave Scanning Radiometer-2 (AMSR-2) on Aqua, Soil Moisture and Ocean Salinity (SMOS) and TRMM Microwave Imager (TRMM-TMI). In contrast, active microwave can provide much finer spatial resolution (<100 m with Synthetic Aperture Radar (SAR) instrument), but has low revisit frequency and higher sensitiveness to surface roughness. In addition, it is also suggested that estimates from both passive and active microwave sensors are influenced by vegetation condition and surface roughness (Petropoulos et al. 2015).

A comprehensive overview of soil moisture remote sensing can be found in (Wang and Qu 2009; Lakshmi 2013; Petropoulos et al. 2015; Mohanty et al. 2017)
2.2.3 *Evapotranspiration*

Evapotranspiration (ET) is a collective term that includes two main processes: 1) Transpiration from vegetation or any other moisture-containing living surface and 2) Evaporation from water bodies and soil surface. It is an important controlling factor of water movement and energy transmission among biosphere, atmosphere and hydrosphere.

While the ET still cannot be directly measured by remote sensing, it can be inferred by the empirical relationship with remotely-sensed surface parameters, such as land surface temperature (Jackson et al. 1977) or vegetation indices. The land surface energy balance algorithms, that require input of various remotely-sensed land surface parameters, has also been utilized for ET estimation. In this method, latent heat flux is calculated as a residual of the energy balance, which can be converted into ET. The detail description of residual method of surface energy balance can be found in Gowda et al. (2007) and Li et al. (2009). Land surface parameters input for these algorithms include land surface temperature, air temperature, surface albedo, surface roughness, soil moisture, net radiation, and vegetation parameters (e.g. NDVI, LAI), which can be detected from visible, near infrared and thermal infrared wavebands combined with surface meteorological observation.

Currently, numerous remote sensing models, derived from surface energy balance principle, are available for calculating ET. Many of them have achieved satisfactory ET measurement accuracy. Surface Energy Balance Algorithm for
Land (SEBAL) (Bastiaanssen et al. 1998a, b) and Surface Energy Balance System (SEBS) (Su 2002) are among the most widely utilized worldwide. In arid Central Asia and Xinjiang, China, Chen et al. (2012) investigated the spatio-temporal pattern of ET and developed an improved cloud amount algorithm based on SEBS for arid zone ET inversion. Liou and Kar (2014) have presented the detail description and review of the currently available major algorithms.

Despite the recent advancement of remote sensing technology for evaporation monitoring, there would be a large discrepancy between the actual evapotranspiration (AET) and reference evapotranspiration (also known as potential evapotranspiration, PET) in arid zone, due to limited and highly varied availability of moisture. The ET products in northwest China, therefore, may incur relatively large uncertainty in regional water balance monitoring.

### 2.2.4 Snow cover

Snow cover is one of the most readily identifiable hydrological objectives from satellite imagery. Considerable advances in the recent decade have improved the monitoring in terms of spatial and temporal resolution, as well as observation accuracy. The areal extent of snow cover can generally be detected accurately using common VIS/IR sensors (e.g. Landsat), based on the reflectivity characteristic (higher albedo) in comparison with non-snow-covered areas (Rosenthal and Dozier 1996a; Vikhamar and Solberg 2003). However, due to the lower capturing frequency of Landsat and SPOT, Advanced Very High Resolution Radiometer (AVHRR) on-board National Oceanic and Atmospheric
Administration (NOAA) series satellites, with its twice a day frequent coverage (one daytime pass and one night-time pass) is also utilized for snow mapping (Akyürek and ŞORMAN 2002; Zhao and Fernandes 2008). The major problem of NOAA-AVHRR data is that the resolution of 1km may not be sufficient for small scale monitoring. Data from the Moderate Resolution Imaging Spectroradiometer (MODIS) on-board NASA’s Earth Observing System (EOS) satellites which deliver daily snow cover data at a spatial resolution of 250-1000m have partially alleviated this challenge (Hall et al. 1995, 2002; Hall and Riggs 2007).

To enhance the snow features and simultaneously depress other ground features and cloud, Normalized Difference Snow Index (NDSI) was developed for the auto/semi-auto detection of snow extent. Taking MODIS Terra imagery as an example, the snow mapping algorithm uses bands 4 (0.545-0.565 μm) and 6 (1.628 – 1.652 μm) to calculate the NDSI (Hall et al., 2002), as shown in Equation 2.1 below:

\[ \text{NDSI} = \frac{b_4 - b_6}{b_4 + b_6} \]  

(Eq. 2.1)

Therefore, the estimates of snow cover fraction (SCF) is based on a normalized ratio of visible band to near infrared band, with a threshold value of NDSI ≥ 0.4 indicating snow coverage (Hall et al. 1995). A variety of snow cover products (or snow maps) have been routinely derived from the MODIS observations (Hall et al. 2002; Rittger et al. 2013), provided by the National Snow and Ice Data Center (NSIDC). It is reported that the overall accuracy of daily
MODIS snow maps can achieve an overall accuracy of about 93% under clear-sky conditions, but varies by land-cover type and snow presence (Parajka and Blöschl 2006; Hall and Riggs 2007).

While the snow cover has unique spectral reflectance features, the presence of cloud and mountain shadow are still significant sources of uncertainty, which limits the use of satellite optical sensors (Snehmani et al. 2015). Passive microwave remote sensing, which is more capable to penetrate through cloud and moist precipitation, can perform monitoring under virtually all weather conditions and bad illumination (Chang et al. 1987; Dietz et al. 2012). For example, Kelly et al. (2003) developed global snow area and snow depth algorithms by Advanced Microwave Scanning Radiometer-EOS (AMSR-E) observations aboard the EOS Aqua satellite. Based on the radiative transfer processes within the snowpack, it can improve the estimation of the snow microphysical properties (e.g. grain size) as well. In addition, snow water equivalent (SWE) can also be estimated directly from passive microwave remote sensing data, since the SWE is related to the snow brightness temperature gradient between microwave bands. However, the coarser spatial resolution (typically 25 x 25 km) is a major limitation of the passive microwave application for snow mapping. For northwest arid zone of China, Zhou and Sun (2013) evaluated the accuracy of two passive microwave snow depth product, and raised some concern over the data reliability. Active microwave, such as InSAR (interferometric SAR) and PolSAR (polarimetric SAR), based on backscattering signal difference between snow and bare ground, can provide an improved resolution and precision than passive microwave sensors.
However, its accuracy of estimation particularly for dry snow, still remain as a challenge, which limits the application of active microwave (Snehmani et al. 2015).

Satellite-based snow observations are also integrated to land surface models. Rodell and Houser (2004) assimilated the MODIS-derived snow cover product to the Global Land Data Assimilation System (GLDAS) to provide more accurate SWE estimate. With years of improvement (Zaitchik and Rodell 2009), the GLDAS-derived gridded SWE dataset, which actually quantifies the snowpack with space and time continuity, is now more widely used for water budget studies, compared with traditional snow cover area (SCA) estimation.

A more complete description of remote sensing of snow cover can be found in Dietz et al. (2012).

2.2.5 Glacier

Fluctuations of mountain glaciers and ice caps are considered to be the most visible evidence and reliable indicators of global climate change (Oerlemans 1994; Bishop et al. 2004; Dong et al. 2013). Until early 1970s, aerial photography was the primary remote sensing technique available for observing glacier parameters. New developments in remote sensing technology, in both optical and microwave imaging, have produced revolutionary advances in remote sensing of glaciers. Nowadays, wide range of information for glaciological applications can be obtained from remote sensing, including: glacier area, length, surface elevation, surface flow fields, accumulation/ablation rates, albedo, equilibrium line altitude
(ELA), accumulation area ratio (AAR) (Racoviteanu et al. 2008), which can be directly or directly infer the glacier mass balance. As concluded by Bamber and Rivera (2007), the measurement techniques mainly includes two categories, namely indirect observations and geodetic observations.

Indirect observations primarily refer to detection of glacier areal extent and glaciological parameters from visible remote sensing imageries (such as from Landsat TM/ETM+, SPOT 5, and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)). To provide an accurate and consistency global glacier inventory, the Global Land Ice Measurements from Space (GLIMS) project produced the geospatial glacier database that integrates reliable glacier extent delineation based on Landsat 7 ETM+ and ASTER data (Bishop et al. 2004; Raup et al. 2007a, b). On the other hand, the determination of some key glaciological parameters from, such as transient snowline altitude (SLA) or surface albedo, can provide an indirect estimate of glacier mass balance. The major limitation of the VNIR sensors is the sensitivity to illumination and cloud-presence condition.

Geodetic observations rely on monitoring the change of elevation on glaciers to estimate the mass balance, either by point measurement or raster DEM elevation measurement. Point measurement of glacier elevation can be derived from in situ GPS measurement or airborne/space-borne laser altimetry. Launched in 2002 by NASA, the Ice, Cloud, and land Elevation Satellite (ICESat) made use of the 1064nm laser pulses and have enabled high-resolution multi-temporal
mapping of elevation over glaciers (Schutz et al. 2005), with vertical resolutions of approaching ∼10 cm. Point measurements provide high accuracy estimates (usually in decimeter) but with relatively poor spatial coverage for smaller glaciers (Bamber and Rivera 2007). Raster DEM measurement of glacier mass variation refers to measuring elevation changes over time from various DEMs constructed over the glacier surface. Glacier elevation maps are produced from the subtraction of elevations from older DEMs (e.g. derived from old topographic maps and aerial photography) and more recent, satellite-derived DEMs, either on a pixel-by-pixel basis or as regionally-average elevation change. DEMs can now be derived from satellite imagery or aerial stereo photogrammetry (e.g. ASTER, IKONOS, SPOT5) or interferometric synthetic aperture radar (InSAR) techniques. SAR systems have all-weather and day/night acquisition capabilities, but suffer from severe geometric and radiometric distortions.

A complete review of glacier mass monitoring techniques by remote sensing can be found in Bamber and Rivera (2007).

2.2.6 Arid zone hydro-climatic observation by remote sensing

There have been plenty of literatures regarding the use of remote sensing techniques for quantifying other hydro-climatic indicators in northwest China. For example, Zhang et al. (2016) modelled the enhanced vegetation growth under climate change in northwest China from 1982 to 2011, by Normalized Difference Vegetation Index (NDVI) retrieved from Advanced Very High Resolution Radiometer (AVHRR) observation. By acquiring multi-scale and multi-temporal
remotely-sensed data, including Landsat MSS, TM, ETM and SPOT HRV, temporal trajectory of land-use change in the past 30 years were analyzed by Zhou et al. (2008a) for Tarim River, Xinjiang, China.

Nevertheless, the techniques and investigations reviewed in the above section were focusing more on specific aspects of the hydro-climatic environment change. The complexity of climate change coupled with the dynamic responses of respective variables tends to exacerbate this problem. To effectively characterize the hydrological response to climate change, an integrative measurement that can collectively characterize the regional hydro-climatic environment change is demanded.

2.3 Terrestrial water storage: An integrative measurement for hydro-climatic environment

Terrestrial water storage (TWS) refers to the vertically integration of all water stored above and below the earth’s surface including surface water, soil moisture, groundwater, vegetation water content, snow, ice and permafrost (Huang et al. 2013). Therefore, the change of TWS (ΔTWS) includes changes of all hydrological states: glacier and perennial snow water equivalent storage (ΔSWE), surface water storage (e.g. lake reservoir storage and streamflow) (ΔSWS), soil moisture (ΔSM) and groundwater storage (ΔGWS). As a unified measurement of all forms of water, TWS assessment is vital to interpret hydrologic and climatic processes controlling its availability. It strongly
influences water, energy, and biogeochemical fluxes, thereby playing a major role not only in the hydrological cycle, but also in the earth’s climate system (Yeh and Famiglietti 2008). According to the terrestrial water balance equation, it can be expressed as follows (Equation 2.2):

\[
\Delta TWS = \Delta SWE + \Delta SWS + \Delta SM + \Delta GWS \quad \text{(Eq. 2.2)}
\]

In terms of water fluxes, this mass conservation equation can be rewritten as Equation 2.3 (Houser 2017; Oki and Kim 2017):

\[
\frac{dS}{dt} = P - E - R \quad \text{(Eq. 2.3)}
\]

Where \( S \) represents the water storage within the area, \( t \) is time, \( dS/dt \) is the change of total water storage with time, \( P \) is precipitation, \( E \) is evapotranspiration, \( R \) is runoff (including both surface and subsurface water flow). All fluxes above are given in the unit volume per time step. If the considered area of water balance is set within an arbitrary boundary, \( R \) could represent the outflow of water from this area (i.e. the total outflow minus total inflow from surrounding areas). Based on Equation 2.2 and Equation 2.3, the total value or the relative change of TWS can be approximated by individual hydrological components and fluxes data.

TWS has not yet been measured with sufficient accuracy for vast area due to the lack of large scale monitoring means (Yang et al. 2015). Traditional methods of approximating and monitoring TWS (e.g. in situ measurements of evapotranspiration, precipitation and soil moisture content) have generally been
inadequate (Famiglietti and Rodell 2013). In-situ sensors, often established as point measurements, are less capable to capture the entire variability in terms of consistency and accuracy. On the other hand, in the remote and mountainous area, the availability of such ground measurements is still scarce, making it difficult to estimate the regional TWS change.

In theory, TWS can be estimated by simply integrating the component measurements (e.g. soil moisture, surface water, groundwater, etc) derived from land surface model. However, it has been pointed out that some of the current generation of global hydrological models have large uncertainties, arising from data deficiencies, error propagation, and overly simplistic descriptions of water cycle processes (van Dijk et al. 2014).

The recent advancement of earth observation technology has greatly improved the human being’s ability to conduct large-scale and accurate measurements on the earth system. Since 2002, the launch of Gravity Recovery and Climate Experiment (GRACE), which performs continuous observations of Earth’s gravity field mission, enables tracking of the mass transport across and underneath the surface of the Earth at an unprecedented resolution. These earth gravity field observations, in form of spherical harmonic coefficients, can be converted to TWS in units of equivalent water height (EWH), by the following equation developed by Wahr et al. (1998):
\[
\Delta \phi (\theta, \phi) = \frac{3 \alpha \rho_w}{\rho_{ave}} \sum_{n=0}^{\infty} \left( \frac{1 + k_n}{2n + 1} \right) \sum_{m=0}^{n} \left\{ [\Delta C_{nm} \cos(m\phi) + \Delta S_{nm} \sin(m\phi)] P_{nm}(\cos \theta) \right\}
\]  
(Eq. 2.4)

Where \( \phi \) is the change in surface mass expressed as equivalent water height, \( \theta \) is the latitude, \( \phi \) is the longitude, \( \alpha \) is the equatorial radius of the Earth, \( \rho_{ave} \) is the mean density of Earth (\( \approx 5517 \text{ kg/m}^3 \)), \( \rho_w \) is the water density (1g/cm\(^3\)), \( k_n \) is the load love number of degree \( n \), \( C_{nm} \) and \( S_{nm} \) are the spherical harmonics coefficients, and \( P_{nm}(\cos \theta) \) is the \( n_{th} \) degree and \( m_{th} \) order (fully-normalized) associated Legendre function.

Based on this conversion, it is now possible to measure the change of TWS (rather than absolute quantity) on the monthly basis with spatial resolution of several hundred kilometers (Chinnasamy et al. 2015). It was confirmed that for regions of 200,000 km\(^2\) or more, GRACE can monitor changes in total water storage with an accuracy of 1.5cm equivalent water thickness (Famiglietti and Rodell 2013). Readers are referred to the NASA’s website for GRACE (www.nasa.gov/mission_pages/Grace/index.html) and Wouters et al. (2014) for a detail history and operations of GRACE satellites.

Early studies have demonstrated that intra-annual and inter-annual change in water storage at the continental-scale and for large river basins can be inferred from GRACE observations with an unprecedented accuracy (Tapley et al. 2004b, a). Since then, longer time collection and improved accuracy of the reprocessed
data products have enabled wider range of analysis and monitoring with significantly higher reliability.

With more than a decade of observation, numerous attempts have been reported on the use of GRACE data to monitor the changing TWS and to explain the underlying causes of such change in various regions, ranging from experimental watersheds to continents. Examples include La Plata basin (Pereira and Pacino 2012), Poyanghu basin of China (Zhou et al. 2016), India (Panda et al. 2016), Qaidam Basin of China (Jiao et al. 2015), source region of Yellow River, China (Xu et al. 2013), northern Iraq (Mulder et al. 2015), Tibetan Plateau (Guo et al. 2016), South Dakota, United States (Proulx et al. 2013), United Arab Emirates (Gonzalez et al. 2016) and West Africa (Ndehedehe et al. 2016). Some of these studies also revealed the high consistency of GRACE-derived TWS change with the results derived from a combination of multiple sources (e.g. land surface models) (Proulx et al. 2013).

In recent years, there has been an increasing interest of applying GRACE data for diverse hydrologic objectives, such as flooding forecast (Chen et al. 2010; Molodtsova et al. 2015; Tangdamrongsub et al. 2016), drought analysis (Chen et al. 2009; Houborg et al. 2012; Thomas et al. 2014; Wang et al. 2014b; Tang et al. 2014; Cao et al. 2015; Kelley et al. 2015; Chao et al. 2016), groundwater depletion (Yeh et al. 2006; Famiglietti et al. 2011; Sun 2013; Chen et al. 2014a, 2015a; Richey et al. 2015; Huang et al. 2015, 2016; Soni and Syed 2015; Liesch and Ohmer 2016), lake level changes ((Singh et al. 2012), glacier and ice sheets
mass loss (Velicogna et al. 2006; Velicogna 2009; Song et al. 2015; Yi et al. 2016), and sea-level variations (Lombard et al. 2007; Ramillien et al. 2008). Jiang et al. (2014), Wouters et al. (2014) and Humphrey et al. (2016) have presented comprehensive reviews for hydrological applications and key features of temporal variability of GRACE data. These studies have confirmed that GRACE data can be a useful tool for identifying impact caused by extreme climate events, or for examining the climate change influence on local water resources. The drastic change of anthropogenic activity in recent decades has brought further demand on understanding the underlying mechanism of TWS variation. TWS observation, combined with other hydrological data derived from various sources, could help us further understand the changes in hydrological cycle.

2.4 TWS change in arid zone: the cryosphere’s response under climate change

TWS change pattern is influenced by different geophysical processes. As a collective reflection of the hydro-climatic environment, TWS could be an attractive study object to examine the hydrological cycle variation and infer the impact of climatic change arid/semi-arid regions. However, the underlying causes of spatial and temporal TWS changes, along with the implications of regional climate change, have received less attention than they deserve, despite numerous attempts to analyze the pattern of TWS change using GRACE data. It can be observed according to the literatures that similar researches mostly done in humid region, amid/semi-arid region have received much less attention. Table 2.1
summarizes relevant literatures for this topic in arid/semi-arid regions worldwide.
Table 2.1 Summary of selected studies associated with GRACE-derived TWS for arid zones of northwest China, Central Asia and around the world

<table>
<thead>
<tr>
<th>Literature</th>
<th>Study area</th>
<th>Major data/model used</th>
<th>Key results and/or conclusions</th>
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</thead>
<tbody>
<tr>
<td>Chen et al.</td>
<td>Xinjiang (and other selected regions</td>
<td>TWS derived by GRACE and GLDAS</td>
<td>TWS has been generally increased significantly in most part of Xinjiang during 1948-2015, while a drastic decrease was observed in the last decade, which is due to climate change.</td>
</tr>
<tr>
<td>(2017)</td>
<td>across China)</td>
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<tr>
<td>Xu (2017)</td>
<td>Tianshan Mountains and Qilian Mountains</td>
<td>GRACE (CSR), precipitation,</td>
<td>The spatial distribution of TWS was more influenced by precipitation in the Tianshan Mountains.</td>
</tr>
<tr>
<td>Literature</td>
<td>Study area</td>
<td>Major data/model used</td>
<td>Key results and/or conclusions</td>
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<tr>
<td>Yang et al. (2017)</td>
<td>Tarim Basin, China</td>
<td>TWS from GRACE and GLDAS, TRMM precipitation data, water level of Bosten Lake</td>
<td>(1) Tarim Basin has experienced TWS decrease at a rate of 1.6±1.1 mm/a;</td>
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<tr>
<td></td>
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<td></td>
<td>(2) Precipitation is the major driver for the TWS changes in the 2005-2010.</td>
</tr>
<tr>
<td>Chen et al. (2016b)</td>
<td>Tianshan Mountains, China</td>
<td>GRACE, climatic data, snow fraction, runoff data</td>
<td>(1) There has been conspicuous warming and fluctuant precipitation change trends;</td>
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<tr>
<td></td>
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<td>(2) TWS has a significant decreasing trend in Middle and East, but a slight decreasing trend in West, which is closely related to changes in runoff, glacier/snow distribution and climatic factors.</td>
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<th>Literature</th>
<th>Study area</th>
<th>Major data/model used</th>
<th>Key results and/or conclusions</th>
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<tbody>
<tr>
<td>Deng and Chen (2016)</td>
<td>Central Asia countries and</td>
<td>GRACE (CSR), GLDAS LSM, climate data</td>
<td>(1) TWS experienced a decreasing trend in Central Asia from 2003 to 2013; (2) TWS decrease in northern Central Asia and Tianshan Mountains was driven by climate factors, but in western Central Asia and northern Tarim River Basin it was driven by human activities.</td>
</tr>
<tr>
<td></td>
<td>Xinjiang, China</td>
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<tr>
<td>Liesch and Ohmer (2016)</td>
<td>Jordan</td>
<td>GRACE (CSR, JPL, GFZ), groundwater data,</td>
<td>(1) GRACE-derived groundwater storage data and in-situ groundwater-level measurements can be correlated with $R^2$ from 0.55 to 0.74; (2) A significant time-lagged cross correlation of the monthly changes in GRACE-derived groundwater storage and precipitation data was found.</td>
</tr>
<tr>
<td></td>
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<td>precipitation data, GLDAS dataset</td>
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<tr>
<td>Literature</td>
<td>Study area</td>
<td>Major data/model used</td>
<td>Key results and/or conclusions</td>
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<tr>
<td>Yi et al. (2016)</td>
<td>Tianshan Mountains, China</td>
<td>GRACE, ICESat, MODIS snow cover product, GLDAS, etc.</td>
<td>Respective changes of mountain glaciers, lake levels and snow coverages.</td>
</tr>
<tr>
<td>Cao et al. (2015)</td>
<td>Xinjiang, Hexi Corridor, Inner Mongolia, China</td>
<td>GRACE (CSR), GLDAS and the Climate Prediction Center (CPC) model, meteorological station data</td>
<td>The GRACE-derived Total Storage Deficit Index (TSDI) is capable for large-scale droughts drought characterization.</td>
</tr>
<tr>
<td>Jiao et al. (2015)</td>
<td>Qaidam Basin, China</td>
<td>GRACE, GLDAS soil moisture, groundwater monitoring wells</td>
<td>There has been a significant increase in the TWS in Qaidam Basin, and groundwater storage accounts for 80.6% of such change.</td>
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<tr>
<td>Literature</td>
<td>Study area</td>
<td>Major data/model used</td>
<td>Key results and/or conclusions</td>
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<tr>
<td>Xu et al. (2015)</td>
<td>Northwestern China (six provinces)</td>
<td>GRACE, GLDAS soil moisture, precipitation data</td>
<td>(1) The TWS estimations from GRACE and GLDAS-Noah model agree well;</td>
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<tr>
<td></td>
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<td>(2) Overall, water storage increased by 0.61 mm/a over northwestern China during the study period. Provincial level differences are also examined;</td>
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<td>(3) Distributions of glaciers and permafrost also affect the spatial distribution of TWS, but evidence is needed for further study.</td>
</tr>
<tr>
<td>Mulder et al. (2015)</td>
<td>northern Iraq</td>
<td>GRACE (CSR), precipitation and temperature, stream flow, lake level, lake area, GLDAS soil moisture</td>
<td>The total mass depletion between 2007 and 2009 can be mainly explained by a lake mass depletion and natural groundwater depletion.</td>
</tr>
<tr>
<td>Literature</td>
<td>Study area</td>
<td>Major data/model used</td>
<td>Key results and/or conclusions</td>
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<tr>
<td>Yang and Chen (2015)</td>
<td>Part of Central Asia</td>
<td>GRACE (CSR) and GLDAS data</td>
<td>(1) Inter-annual and seasonal variability of TWS was modelled;</td>
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<td></td>
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<td></td>
<td>(3) TWS data inverted by GRACE and GLDAS are consistent with significant linear relations.</td>
</tr>
<tr>
<td>Yang et al. (2015)</td>
<td>Tarim Basin, China</td>
<td>GRACE (CSR, GFZ, JPL and GRGS), GLDAS runoff, snow water equivalent and soil moisture, precipitation</td>
<td>(1) An excess of precipitation over evapotranspiration (ET) plus runoff contributes to an increase of TWS in Tarim Basin;</td>
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<td></td>
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<td>(2) There is a recharge process from snowmelt to soil moisture, the phase of soil moisture lags snow water equivalent of 3–4 months;</td>
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<td>(3) Increasing TWS and decreasing SWE resulted in an increase of subsurface water.</td>
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<th>Literature</th>
<th>Study area</th>
<th>Major data/model used</th>
<th>Key results and/or conclusions</th>
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<tbody>
<tr>
<td>Swenson and Wahr (2007)</td>
<td>Caspian Sea</td>
<td>CRACE (CSR), Jason-1 Sea Surface Height, GLDAS-derived TWS, Aqua/MODIS Sea Surface Temperature</td>
<td>(1) The relationship between water storage and surface height variations of the Caspian Sea were examined by three different datasets. The composite time series agree well with each other; (2) An indirect means of validating these data were proposed.</td>
</tr>
<tr>
<td>Literature</td>
<td>Study area</td>
<td>Major data/model used</td>
<td>Key results and/or conclusions</td>
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</table>
| This study | Xinjiang, China  | GRACE (CSR, JPL, GFZ), GLDAS (soil moisture, snow water equivalent, snow precipitation), gridded meteorological data, ICESat land surface altimetry, glacier extent, topography | (1) Sub-regional heterogeneity intra-annual and inter-annual TWS in Xinjiang during 2003-2015: TWS decreases rapidly in Tianshan Mountains and slight increases in Kunlun Mountains;  
(2) The TWS change is highly responsive to changes in cryosphere, which is sensitive to climate change: The seasonal change is primarily controlled by seasonal snow accumulation and melt, while the long-term loss is induced by glacier mass variation;  
(3) The GRACE-derived TWS is an effective indicator for recent climate change. |

*Studies are first listed in reverse chronological order, and then in alphabetical order of lead author’s last name.*
Although these studies cover different time periods and spatial scales, they unequivocally underscore the essential role of TWS in monitoring regional hydro-climatic environment in arid regions. In most arid/semi-arid regions, such as north Africa, middle east, western part of Central Asia, TWS change pattern are primarily controlled by precipitation. Aquifers and reservoirs are recharged seasonally in accordance with the rainy season pattern. Yang et al. (2017) recently analyzed the relationship between TRMM precipitation, GLDAS-derived TWS and GRACE-derived TWS by Empirical Orthogonal Function (EOF) and Multiple Linear Regression (MLR) analysis, and claimed that the surface mass variations in Tarim Basin, China were mostly related with precipitation. Some studies have also highlighted the role of soil moisture as the major water storage component in the hydrologic system of arid/semi-arid regions. In most parts of the world, precipitation is a major controlling factor of the TWS, but a considerable amount of variability in TWS remains unexplained by the precipitation alone. As the average amounts of annual precipitation is extremely low in northwest arid zone of China, it is of little hydrological significance to examine the TWS response to recent climate change (Zwally et al. 2002).

There are a number of studies addressing the techniques of revealing the pattern of TWS changes, correlating and calibrating the GRACE-derived TWS change with land surface model observations (soil moisture, evapotranspiration, etc.) and water balance equation. By calculating the TWS from hydrologic components measurement from GLDAS data, Chen et al. (2017) pointed out that it has been generally increased in Xinjiang and adjacent provinces since 1948. It is
also suggested that the drastic decrease of TWS since 2000 was attributed to climate change. However, the driving factors of recent TWS change, particularly the relationship with changes of cryosphere (glacier and perennial snow) have not yet been sufficiently examined. In a recent study, Deng and Chen (2016) suggested that climate change has affected TWS by influencing changes in mountain glaciers and snow cover in Central Asia. While this assumption may be meaningful, more evidence and analysis on the recent interactions among TWS change, glaciers and snow cover variations, and recent climate change are desired for further elaborations. In the northwest China, the characteristics of water formation, spatial and temporal distribution, and the water supply are very unique which predominantly controlled by the water stored in cryosphere Chen et al. 2015b). In this region, glacier and perennial/seasonal snow cover are dynamic masses that contribute to a considerable portion of fresh water supply for agriculture, energy, and domestic consumption, which is highly vulnerable to even minor climatic fluctuation. Nevertheless, fewer literatures are found quantifying the phenomenon of 1) seasonal conversion of soil moisture, snow pack water and their joint effect on TWS, 2) elevation-dependence phenomenon of TWS change due to the presence of mountain glacier, and 3) synchronous changes of mountain glacier and TWS.

Unlike seasonal snow pack, glacier is made up of fallen snow that compresses into large, persistent body of dense ice over many years. Glacier change, along with its corresponding water cycle variation, can provide important clues to regional climate change or variability, and impacts various aspects of the
environment (Oerlemans 1994; Barry 2006). In northwest arid zone of China, mountain glaciers are important for maintaining ecological health and the sustainable development of industry and agriculture (Wang et al. 2015). It can be served as one of the key variables for early-detection strategy of climate and regional environmental change. Widely used techniques for monitoring glacier mass variation include space imagery, digital elevation models (DEM)s, laser altimetry, and satellite gravimetry (Bamber and Rivera 2007). In the last decades, numerous studies used remote sensing imageries (e.g. Landsat MSS/TM/ETM+) or glacier inventory to examine the areal changes of glaciers (Braithwaite 2002; Ding et al. 2006; Wang et al. 2011; Du et al. 2014). Space-based imagery only constrains the area change in glaciers. However, the retreat and advance of glacier can be occurred in the form(s) of areal extent and/or elevation change. Glacier elevation change is one of the key parameters reflecting glacier change regionally. To further investigate the mechanism of glacier in response to recent climate change, the glacier elevation change, as one of the key parameters reflecting regional cryosphere dynamics, deserves further attention. While serious lack of in-situ measurements in remote mountainous area is hindering our current understanding, the satellite altimetry measurement offers direct indication of mountain glacier elevation change over time. ICESat, a type of laser altimetry, features a smaller footprint (70m) compared with radar altimetry (usually several kilometers), so it is more applicable in the estimation of the glacier mass balance.

On the other hand, snowpack is an important component of the hydrologic cycle and seasonal water supply in many parts of the northern hemisphere
Winter precipitation in the form of snow can be an important water resource for vegetation in arid and semi-arid ecosystems, where spring and early summer runoff may subsequently dominated by the rate snowmelt. The snowmelt runoff is the major supply of water resources that is vital for lives in the harsh environment in northwest China (Zhou and Sun 2013). There are a certain number of studies that relate TWS to snow cover fraction indices, which usually shows the fraction of an area covered by snow on monthly basis. Optical remote sensing is an efficient way to monitor spatial snow cover with high resolution with quantitative output, and measurements were often made by the MODIS sensor on NASA's Terra satellite (Hall et al. 2002). Methodologies and products have been derived from sensors include optical (medium/high resolution VIS/IR sensors such as Moderate Resolution Imaging Spectroradiometer, MODIS (Hall et al. 2002), Advanced Very High Resolution Radiometer, AVHRR (Akyürek and ŞORMAN 2002), and Landsat Thematic Mapper, TM (Rosenthal and Dozier 1996b)) as well as microwave (both passive and active) (Kelly et al. 2003). They all suffer from different limitations such as cloud penetration or lower spatial resolution. As previously introduced, the GLDAS parameterizes, forces, and constrains sophisticated land surface models with ground and satellite products for an improved estimation. To enable direct comparison with TWS change, the snow water equivalent measurement that integrates both snow depth and snow cover is preferred. Therefore, in this study, GLDAS-derived snow water equivalent (SWE) measurement to overcome this problem.
Meanwhile, although the northwest arid zone of China is characterized as an arid environment in general, it features distinct internal differences in terms of geographical characteristics such as climate, terrain setting, land cover, and human settlement. Studying the entire region without considering the regional disagreement would inevitably overgeneralize these differences. While the overall temperature in Xinjiang has been increasing during the last several decades, most of the reported studies are focusing on Tianshan Mountains region. According to our preliminary data analysis, the recent trend of temperature change in the Xinjiang exhibits heterogeneous pattern. It can be observed that temperature in Kunlun Mountains has been oppositely increasing in the last decade. There are important gaps in knowledge of the sub-regional differences of TWS spatio-temporal change patterns due to heterogeneous climate change scenario, thus restricting the planning and implementation of sustainable water management strategies for arid region.

The hydro-climatic environment has experience drastic change in recent decades in northwest China. Snow patch and glacier, as an essential hydrologic component, should be an effective proxy of investigating the influences exerted by recent climate change. The mechanisms of TWS evolutions, as inferred by cryosphere’s response to heterogeneous meteorological and climatic change scenario, remain largely unanswered. In addition, only a limited number of studies currently address the TWS response to recent climate change, with consideration of sub-regional difference.
2.5 Summary

The water cycle processes and the response/feedback mechanism remain as hot topics and key issues in research (Chen et al. 2016a). Recent climate changes in the past decade have had a large impact on regional water cycle in arid northwest China on different hydrological components (Shi et al. 2007). The difficulties of conducting traditional in-situ observations have long been a challenge for hydrological monitoring in remote mountainous area. Remote sensing techniques have generally overcome this challenge, and the launch of GRACE satellite has revolutionized the monitoring the TWS, as the collective reflection of hydro-climatic environment, to an unprecedented level of accuracy and reliability.

Prior to the release of early results from GRACE satellites, TWS was often ignored in water balance studies due to absence of reliable estimates. While GRACE satellites are increasingly being used to monitor TWS changes in northwest China, the spatio-temporal change of TWS in sub-regional level under recent climate change deserves more attention, which could be substantial due to the distinctive geographical differences.

Therefore, in this study, the GRACE satellites observation, in conjunction with multi-platform hydrologic observations such as Global Land Data Assimilation System (GLDAS) products and meteorological record product, were used to analyze TWS variations in a typical hinterland arid zone Xinjiang Uyghur
Autonomous Region of China during 2003-2015. To sum up, according to the literature review and the research gap identified, this study attempts to investigate:

1) Do regional differences exist in northwest arid zone of China (i.e. Xinjiang) in terms of TWS change due to heterogeneous climate change scenario?

2) How can these spatio-temporal differences be attributed to sub-regional hydrological states/fluxes variation and meteorological fluctuation, in terms of seasonally and inter-annually?

3) Does the sensitivity of cryosphere change under different climate change trends related with TWS evolution pattern?

The primary aim of this study is to answer to what extent the TWS variation is consistent with recent trends of climatic change in arid zone. The study also attempts quantify and attribute the observed short-term and long-term variability of TWS. The intra- and inter-annual change patterns of TWS, snow water and soil moisture in various sub-regions are retrieved and analyzed, which may provide proper interpretation about the underlying causes of intra-annual TWS change.
Chapter 3  Study Area

Arid zone covers a large extent of land in the world (approximately 30%), which is generally characterized as limited precipitation, strong evapotranspiration, sparse vegetation and lack of available water resources. Xinjiang Uygur Autonomous Region of China is selected as the study area due to a variety of representative characteristics.

3.1 Location and general geographic characteristics

Xinjiang Uygur Autonomous Region of China, generally confined within 35°-50°N and 70°-100°E, covers an area of 1.66 million km² with a population of 21.81 million. It is characterized as a typical arid and semi-arid area in the hinterland of Eurasian Continent. The study area can be divided into five primary terrain units, as there are three mountain ranges namely Kunlun Mountains (KLM), Tianshan Mountains (TSM), and Altay Mountains (ATM), and two large basins Junggar Basin (JGB), Tarim Basin (TRB) that distributed between those massive mountains. The elevation ranges from 156m below the sea level in Aydingkol Lake near Turpan Depression, and 8611m above sea level in K2 of Karakoram Mountains.
The complex topography differentiates the arid/semi-arid climate, and thereby the underlying surfaces of the sub-regions. The mean annual temperature ranges from -15°C to 19°C in ATM in the north, and -8°C to 26°C in TRB in the south. The annual precipitation ranges from 400-1,000mm, 100-250mm, 100-400mm, and 200-300mm, in ATM, JGB, TSM and KLM, respectively. The annual precipitation in TRB, where features Tarim River and Taklimakan, the largest inland river and desert in China, is typically less than 50 mm. The rivers are predominantly originating from Altay Mountains, Tianshan Mountains, and the Karakorum (Shi et al. 2007), and they primarily form internal drainage systems (e.g. Tarim River), but some, like Irtysh River, are exorheic system that drain towards external water bodies (i.e. Arctic Ocean).

The complex geographical characteristic has led to diverse biomes in the region (Li et al. 2013), but the majority of the area is covered by rangeland and desert vegetation types (Figure 3.2). Grasslands comprise the major seasonal land cover in northern part, while deserts are the dominant land cover in southern part. Glacier and perennial snow patches mostly appear in the high mountains of TSM and KLM.

The study area features Altay Mountains, Tianshan Mountains, and Kunlun Mountains, which are mountainous sub-regions with ample snow and glacier coverage but less direct intervention from human activities. There are distinguishing ecosystems existed due to strong regional differences of climate system as well. Moreover, the water balance model can be simplified as most of
the area is inland river basin. It also has an areal extent that is large enough to be studied by GRACE. Therefore, the selected study area is suitable objectives for modelling the natural sensitivities of hydrological cycle to recent climate change.
Figure 3.1 Location, boundary, topography, river system and sub-regions of the study area
Figure 3.2 Land cover map of study area. The land cover dataset is provided by USGS Land Cover Institute

(http://due.esrin.esa.int/page_globcover.php)
3.2 Interactions of climate, topography hydrology, vegetation and land use

The climate in the study area is deeply affected by the terrain characteristic. Atmospheric water vapor is blocked due to the far distance from oceans and the barriers created by the large mountains ranges. Combined with the effects of westerly circulation and the East Asian monsoon, it creates a unique arid zone climate system featuring three basic ecosystem units, namely mountains, oases and deserts, and produces material migration and energy conversion mainly driven by water cycle (Chen et al. 2016a). Generally, arid zone is usually characterized by a severe lack of available water resources. In the study area, however, much water resources are primarily stored in solid form located in the high altitude mountainous region, namely Tianshan, Kunlun, and Altay Mountains.

Glaciers cover area of over 12,200 km² in Kunlun Mountains and account for 42.5% of the total glaciated area in northwest China; Glaciers in the Tianshan is also covering over 9,200 km² (32% of glaciated land in the northwest China and equivalent to a volume of 1,011 km³ (Shi 2008)), and those in the Altay Mountains cover 296.75 km² (Chen et al. 2014d). Tianshan Mountains are particularly regarded as “Water Tower of Central Asia” which sustaining lives and agriculture that largely depend on meltwater from snow and glaciers (Sorg et al. 2012; Yi et al. 2016). In addition, permafrost is widely distributed in the
southeast of the area (i.e. east Kunlun Mountains), and is regarded as also considerable water storage.

Tarim Basin is the largest endorheic basin in China and situates at the fringe of Taklimakan Desert. The continental arid climate is characterized by extremely poor precipitation and strong evapotranspiration. The desert vegetation and soils under dry and harsh environment represents typical arid zone ecosystem in northwest China (Zhou et al. 2008b).

3.3 Summary

The study area, Xinjiang Uyghur Autonomous Region in northwest arid zone of China, is one of the most representative arid zones in the world. The climate and hydrological features are strongly influenced by the geographic location and topography settings. As there are distinctive differences within the study area, it is further divided into five sub-regions for meaningful investigations and discussions.
Chapter 4  Data Acquisition and Pre-processing

The data utilized in this study will be introduced in this chapter. A variety of remote sensing earth observations, which are enabling wide and constant geographical and temporal coverage, are adopted. They contribute as effective land surface hydrological fluxes/variables observational network in arid zone where in situ measurements are uneven and sparse.

4.1 GRACE-derived terrestrial water storage

The GRACE satellites, launched in 2002, track changes in mass that affect the gravitational pull on the satellites. GRACE consists of twin satellites about 200km apart along identical orbits at 450-500km altitude. The velocities of the satellites respond to the change of the earth’s gravity field. For example, when the twin satellites approach a positive mass anomaly such as mountain ranges, gravitational pull increases and the leading satellite accelerates, increasing the distance between the two, before the second satellite accelerates and catches up (Houborg et al. 2012). Each monthly solution is transformed into an equivalent water layer thickness as a function of latitude and longitude in spherical coordinates according to the method described by (Wahr et al. 1998). In the absence of tectonic movement, mass anomalies are mainly caused by changes of
total water storage (Swenson et al. 2008). Therefore, at the monthly timescale, these mass anomalies are dominated by the redistribution of water (Wahr et al. 1998). The units of the data and error grids are centimeters of equivalent water thickness (cm EWH).

At present, these data were mainly processed and provided by three major data processing centres: Center for Space Research (CSR) at the University of Texas at Austin, USA, the German Research Center for Geosciences (GeoForschungsZentrum, GFZ) at Helmholz Centre Potsdam, and the NASA Jet Propulsion Laboratory (JPL) at the California Institute of Technology. Each uses different data processing and filtering methods to retrieve TWS from the GRACE signal.

It is concluded that TWS variations estimated from different GRACE products are strongly correlated with each other (Yang et al. 2015). Various tests have shown that GRACE Release-05 dataset is more accurate and data from CSR, GFZ and JPL are more consistent with themselves than the previous release-04 data, which minimizes errors due to leakage and measurement errors and improves the spatial resolution. In our study, the GRACE Level-3 product based on Release-05 spherical harmonics released by CSR, JPL and GFZ, from January 2003 to December 2015 was acquired (currently available at the GRACE Tellus website: http://grace.jpl.nasa.gov/). The GRACE gridded product enables the estimation of TWS at 1°×1° resolution. The RL05 L3-land data are based on the RL05 spherical harmonics from the CSR, the Jet Propulsion Laboratory (JPL) and
the German Research Centre for Geosciences (GFZ), and have additional, post-processing steps, summarized on http://grace.jpl.nasa.gov/data/gracemonthlymassgridsland/. It is worth mentioned that the GRACE level-3 data from aforementioned sources already carry corrections and filtering procedures, including atmospheric mass changes removal, glacial isostatic adjustment (GIA) (the solid Earth's response to last deglaciation), truncation of spherical harmonics coefficients at degree 60, and application of destriping filter alongside with a 300-km Gaussian smoother.

4.2 Hydro-climatic variables

Reanalysis flux products, such as Interim Reanalysis Data (ERA-Interim), MERRA (Rienecker et al. 2011), and data assimilation products, such as Global Land Data Assimilation System (GLDAS), simulate the flux, state or associated parameters of the hydrologic and climatic system. These simulations combine the virtues of in situ data, remotely-sensed observations, and modelling (Huang et al. 2013), and therefore have been extensively applied in many hydrological studies (see Section Error! Reference source not found. for detail). In addition, while remotely-sensed data and in situ observations are constrained in certain time coverage or interval, these datasets offer long-term and constant simulations of data, making them suitable for long-term analysis.

Remote sensing observations are merged with land surface models using data assimilation techniques, and generate spatially and temporally complete datasets. For example, Global Land Data Assimilation System (GLDAS) data
products have been extensively applied in hydrological/water resources researches for different parts of the world, at different time scales. It distinguishes itself as a global, high-resolution, near-real time and comprehensive terrestrial modelling framework that incorporates satellite- and ground-based observations in order to produce optimal fields for land surface states/fluxes (Rodell et al. 2004). This project has led to a massive archive of land surface states and fluxes data that have facilitated the hydrological, meteorological and climatically investigations worldwide.

The GLDAS datasets drives four land surface models: Noah, CLM (Community Land Model), VIC (Variable Infiltration Capacity) and MOSAIC, incorporating forcing data from both ground and satellite observations. The goal of GLDAS is to integrate satellite- and ground-based data products, using advanced land surface modelling and data assimilation techniques, to generate optimal fields of land surface states and fluxes (Rodell et al. 2004). In this study, the GLDAS 2.0 monthly 1°×1° datasets from the Noah model were acquired. The dataset is generated through temporal averaging of the reprocessed 3-hourly data, and contains a series of land surface parameters simulated from the Noah Model 3.3 including soil temperature, soil moisture, snowfall rate, runoff, and so on, and are compiled and become available online (http://disc.sci.gsfc.nasa.gov/hydrology/data-holdings). To ensure consistency with the timeline of the GRACE data, anomalies of the GLDAS data relative to the 2003–2013 time-mean baseline were computed. Sub-region level values are
computed using the similar methods as processing GRACE TWS data (Section 4.1).

4.2.1 Precipitation and temperature

In China, gridded precipitation and temperature dataset for recent 50 years are established by interpolating data from 2,400 in situ weather stations across the territory. Monthly precipitation and temperature data from 2003 to 2015 were acquired from 0.5×0.5° gridded daily dataset from National Climate Center (NCC) of the China Meteorological Administration (CMA) (from 2003 to 2012) (available at http://data.cma.cn/) (National Meteorological Information Center 2012) and supplemented by Global Land Data Assimilation System Version 2 (GLDAS-2.0) monthly datasets (total precipitation rate during 2013-2015, in unit of mm converted from kg m⁻² s⁻¹). Monthly CMA precipitation and temperature data were converted from the summation of daily observation. The accuracy of the NMIC dataset has been assessed satisfactory against ground observation data according to Zhao and Zhu (2015). In our study, these data were then resampled to 1×1° grid for further analysis.

4.2.2 Snowfall amount

In the study area, precipitation usually occurs in the form of snowfall from late fall to early spring, and consequently water is temporarily stored as snowpack. In this study, GLDAS-2.0 monthly snow precipitation rate (unit: kg m⁻² s⁻¹) were acquired and converted to monthly snowfall amount (unit: mm).
4.2.3 Snow water equivalent

Snowpack is the storage of water from snowfall, and it is one of the primary fresh water sources in the study area. Snow Water Equivalent (SWE) is a common snowpack measurement that measures the amount of water it contains. It can be considered as the depth of water that would theoretically result if the whole snowpack instantaneously melts.

SWE data retrieved from GLDAS, in the unit of kg/m$^3$, were used in this study to evaluate the change of snow water storage. SWE is the product of snow depth (SD) and snow density ($\rho$) and it represents the resulting water column should a snowpack melt in place (Takala et al. 2011). Sub-regional values are calculated as the weighted arithmetic mean of the covering grids. The units were finally converted to the unit of anomaly (mm) to enable direct comparison with TWS anomaly value.

While ground-observed snow water equivalent (SWE) datasets are useful to validate snowmelt simulations, the in situ SWE datasets are usually rare or confined to limited regions (Niu et al. 2007). In this study area, large scale in situ SWE datasets are currently unavailable for this purpose.

4.2.4 Soil moisture

Soil moisture (SM) is another essential component in water storage. The vertical integrated total soil moisture (SM) was estimated as the sum of all available components including four soil moisture layers in GLDAS at the depth
of 0–10, 10–40, 40–100, and 100–200 cm, in the unit of kg/m$^3$. These data subsets were consequently converted into unit of mm equivalent water height (EWH) relative to the baseline of 2003-2015 that are compatible with the GRACE data.

4.3 Glacier mass variation

Glacier mass variations in the study area are investigated to address the research objectives. In this study, glacier mass variation is measured by laser altimeter (i.e. ICESat), with the delineation of glacier extent according to the GLIMS glacier database.

4.3.1 ICESat laser altimeter

In this study, ICESat land surface altimetry products for land (GLA14) during 2003-2009 were ordered and downloaded from the United States National Snow and Ice Data Center (NSIDC, http://nsidc.org/data/icesat/data.html). The Ice Cloud and Elevation Satellite (ICESat) was launched in January 2003 hosting three laser sensors within the Geoscience Laser Altimeter System (GLAS), provides accurate along-track elevation measurements derived from the two-way travel time of the emitted laser pulse (Kropáček et al. 2014). Elevation data from ICESat have been widely used to detect the inter-annual thickness change of glaciers over 2003-2009, and has proven to be an accurate data source for the regional estimation of glacier elevation changes (Schutz et al. 2005; Kääb et al. 2012). The accuracy of ICESat elevation measurements has been reported on the order of centimeters in case of no cloud cover (Ewert et al., 2012; Shuman et al.,
A detailed description of the GLAS sensor and its measurement concept can be found in Zwally et al. (2002) and Schutz et al. (2005).

This study used level-2 ICESat Global Land Surface Altimetry Data product-GLA14 of release 34 provided by the National Snow and Ice Data Center (Zwally et al. 2002). The GLA14 dataset includes date, location, corrected surface ellipsoidal heights, geoid heights (referred to Earth Gravity Model (EGM) 2008), saturation flags (for correction purpose) and other information of individual footprint. Correction for atmospheric delay effects have been performed by the instrument.

The laser channels for surface altimetry operated at a wavelength of 1064nm to measure elevations over the footprints with a diameter of 70m and spaced at about 172m along the track. As a type of laser altimetry, it has a smaller footprint diameter of 70 m compared with radar altimetry (several kilometers), so it is applicable in the estimation of the glacier mass balance (Yi et al. 2016). Elevation data were collected every 3 to 6 months during the total 18 ICESat laser periods (each lasting between 12 and 55 days), from February 2003 to November 2009. The detail procedure of retrieving glacier elevation change data will be described in Section 5.2.

4.3.2 Glacier extent

The extent of glaciers for mass variation analysis is based on the Global Land Ice Measurements from Space (GLIMS) glacier database (Raup et al. 2007a, b). GLIMS is a collaboration project among approximately 40 international
institutions. This project also implements guidelines and rules to ensure the consistency of glacier inventories prepared by different institutions worldwide. The goal of this project is to build a spatio-temporal database storing glacier outlines and related attributes, derived primarily from satellite imagery, such as from ASTER and Landsat, and therefore enabling the assessment of current world glacier extent and change. As of August 2011, the database, located at the National Snow and Ice Data Center (NSIDC), contains delineation result for approximately 95,000 glaciers, covering 290,000 km².

4.3.3 Topography

The Shuttle Radar Topography Mission (SRTM) Digital Elevation Database v4.1 (Jarvis et al. 2008) was used for the analysis of elevation dependency of TWS change (data available at: http://srtm.csi.cgiar.org/SELECTION/inputCoord.asp). SRTM is an InSAR mission specifically designed for topography mapping of land surfaces in 2000. The SRTM-derived DEM products provide unprecedented and consistent accuracy for topography dataset, with a resolution 90m (30m in USA) and with a vertical accuracy of better than 16 m (Bamler 1999; Rabus et al. 2003; Bhang et al. 2007).

4.4 Summary

To address the research questions, gridded climatic data (i.e. temperature and precipitation) based on ground station monitoring and interpolation, as well as
land surface model simulation data are acquired. They are used to examine the correlation relationship between climatic/hydrologic variables and GRACE terrestrial water storage change (TWSC). The elevation trends over glaciers are to be estimated based on ICESat and SRTM elevation measurements, according to the extent of glaciers database.
Chapter 5  Methodology

This chapter illustrates the methodology used to address the research objectives, including detail processing steps of GRACE TWS products as well as error correction and uncertainty assessment, glacier elevation change assessment, and statistical and spatial analyst methods for climatic and hydrological variables. All statistical analyses were performed by using Statistical Package for the Social Sciences (SPSS) software and Microsoft Office Excel. Geospatial relevant analyses were conducted mainly in ESRI ArcGIS 10.4 package.

5.1 GRACE-derived TWS calculation and analysis

The GRACE Level 3 gridded data products were obtained from JPL, GFZ and CSR for the period January 2003 to December 2015. The data were in NetCDF format and processed in ArcGIS 10.4 software to produce gridded data in geographic coordinate system (using WGS 84 datum).

5.1.1 Leakage error correction

Leakage error of GRACE observation refers to the error or discrepancy induced by the truncation, destriping and Gaussian smoothing processes for producing gridded dataset (Swenson and Wahr 2006). Leakage error correction is
required to compensate bias and leakage and restore much of the lost energy, and therefore ensuring meaning calculation and analysis of TWS time series.

The scaling factor (or gain factor) approach is the most widely used method that has been applied to individual basins or regions globally (Long et al. 2015). The scaling factor is the multiplicative factor that can minimize the difference between the filtered and unfiltered modelled TWS values at a certain geographic location. The corresponding scaling factors for individual grid are computed by applying the same filters that have been applied to the GRACE data to a numerical land-hydrology model. In this study, the factors are calculated based on National Center for Atmospheric Research Community Land Model (CLM4.0) (Landerer and Swenson 2012), and are available from the data distribution platform. TWS grids are multiplied by these 1°×1° grids of scaling coefficients to mitigate the attenuation and leakage errors and obtain the true TWS values. The average scaling factor in the study area is 1.1257.

On the other hand, recent studies suggested that the ensemble mean (the arithmetic mean of JPL, CSR, GFZ fields) are effective in reducing the noise in the gravity field solutions (Sakumura et al. 2014). In this study, therefore, we use the ensemble mean (arithmetic average) of the three solutions from CSR, JPL and GFZ provided in the GRACE Tellus dataset for noise reduction. Therefore, if not mentioned otherwise, the value of TWS in the following chapters would refer to the ensemble mean of three GRACE gridded products (CSR, JPL, GFZ).
5.1.2 TWS time-series calculation and analysis

According to the data description, each monthly GRACE Tellus grid represents the surface mass deviation for that month relative to the baseline average over Jan 2004 to Dec 2009, in the unit of equivalent water height (cm). In this study, the baselines of the grid values are adjusted accordingly. The anomalies refer to the deviation from the mean value averaging over certain period of time. Therefore, each GRCAE 1.0°x1.0° monthly grid \( i \) can represent the gravity field anomaly (TWSA), which refers to the difference between the gravity for that month (\( TWS_i \)) and the average gravity (\( \overline{TWS} \)) during a designated reference period (i.e. January 2003 to December 2015 in our study). This can be expressed as:

\[
TWSA_i = TWS_i - \overline{TWS} \quad \text{(Eq. 5.1)}
\]

According to Equation 5.1, positive and negative values indicate higher or lower water storage mass than the long-term average, respectively. Missing GRACE data due to battery maintenance (June 2003, January and June 2011) were remedied by linear interpolation to maintain the average seasonal cycle well.

The TWS month-over-month change refers to the difference of GRACE TWSA in two successive months, which can be calculated as:

\[
TWSC = TWSA_i - TWSA_{i-1} \quad \text{(Eq. 5.2)}
\]
Where $TWSA$ is terrestrial water storage anomaly and $i$ indicates the GRACE measurement period or month.

Sub-regional TWS values are calculated as the weighted arithmetic mean of the covering grids. Equation 5.3 and Equation 5.4 were used to assign the weight and estimate the mean monthly GRACE TWS anomaly value for the respective sub-regions.

\[ W_i = \frac{a_i}{A_s} \quad \text{(Eq. 5.3)} \]

\[ TWSA_S = \sum_{i=1}^{n} (TWSA_i \times W_i) \quad \text{(Eq. 5.4)} \]

In Equation 5.3, $W_i$ is the weight of grid $i$, $a_i$ is the area of the grid that belongs to respective sub-region, $A_s$ is the total area of the sub-region. Thereby, the sum of $W_i$ should be equal to 1. In Equation 5.4, $TWSA_i$ is the TWS anomaly value of the grid $i$, $n$ is the number of grids in the sub-region, $TWSA_S$ is the sub-region level monthly TWS anomaly which equals to the sum of areal weighted $TWSA$.

5.1.3 Uncertainty assessment

Errors in estimated TWS variations mainly include measurement errors and leakage errors (residual errors after filtering and rescaling), which are provided in the GRACE Tellus website (https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/) along with the pseudo-code for processing. The regional-scale
total error included both regional-scale measurement error and regional-scale leakage error. The total errors of each grid are estimated by Equation 5.5 (Landerer and Swenson 2012).

\[ E_{total} = \sqrt{L_e^2 + M_e^2} \]  

(Eq. 5.5)

Where \( E_{total} \) is the total errors of each grid cell, and \( L_e \) and \( M_e \) are the leakage errors and measurement errors of each grid cell, respectively. Early analysis suggested that the TWS variations could be distinguished from GRACE monthly data over regions larger than 200,000km\(^2\), with an accuracy of 1.5cm equivalent water thickness (Famiglietti and Rodell 2013). The larger the spatial scale of the research area is, the higher the accuracy the results could achieve (Mo et al. 2015). As shown in Figure and Table 6.2, the average uncertainty value is approximately ±0.69 cm.

5.2 Glacier elevation change

In the study area, mountain glacier primary distributes in Kunlun Mountains sub-region (KLM) and Tianshan Mountains sub-region (TSM). To analyze the glacier elevation change for these two sub-regions, elevations derived from ICESat glacier altimetry were compared with corresponding SRTM DEM elevation (as reference surface). ICESat global land surface altimetry products (GLA14) release-34 data are downloaded from National Snow and Ice Data Center (NSIDC) and processed. Based on the data availability, ICESat data were acquired between 2003 and 2009, in several 33 to 56-day campaigns each year.
The raw data were retrieved and converted into glacier surface elevations using HDFView 3.0 software (http://nsidc.org/data/icesat/tool.html). Saturation corrections are then conducted to remove invalid elevation data and ensure meaningful analysis of relative surface elevations, according to the value of Saturation Correction Flag value \(d_{satElevCorr}\) provided along with the data.

In this study, the calculation of elevation difference is achieved by combining two elevation data sets, the sparse laser measurements from ICESat over 2003–09 and the corresponding Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission (SRTM) of February 2000 (Kääb et al. 2012). The difference of elevation (\(\Delta H\)) between ICESat-derived glacier orthometric height (\(H_{ortho}\)) and the corresponding SRTM DEM height (\(H_{srtm}\)) are calculated using Equation 5.6.

\[
\Delta H = H_{ortho} - H_{srtm}
\]  

(Eq. 5.6)

As the ICESat GLA14 altimetry elevation data has not been adjusted to geoid and is relative to the ellipsoid as the TOPEX/Poseidon satellite, the conversion from ellipsoid height (\(H^{ICESat}\)) provided in the GLA14 to orthometric (\(H_{ortho}\)) height as the same reference of SRTM DEM (referred to WGS84 Ellipsoid and EGM96 Geoid) are required, by using Equation 5.7 below:

\[
H_{ortho} = H^{ICESat} - H_{geoid} - 0.7
\]

(Eq. 5.7)

where \(H_{ortho}\) is ICESat-derived glacier orthometric height, and \(H^{ICESat}\) is the ellipsoid height provided as \(d_{elev}\) value in GLA14, \(H_{geoid}\) is the EGM96
geoid height referred to WGS84 Ellipsoid estimated at the location of the footprint according to the model provided by NGA/NASA (http://earth-info.nga.mil/GandG/wgs84/gravitymod/egm96/egm96.html) (Ke et al. 2015). The offset 0.7m is a rough estimate of the vertical difference between WGS84 ellipsoid and TOPEX/POSEIDON ellipsoid (Bhang et al. 2007).

Similar to previous studies, a threshold of 150m is set to filter obvious errors of elevation difference value due to cloud cover and atmospheric noise (Kääb et al. 2012; Neckel et al. 2014; Ke et al. 2015). If this value exceeds the 150m threshold, this data would be excluded from further analysis. The subsequent statistical analyses are based on 30,552 shots for both KLM and TSM sub-regions, which were retained after the pre-processing and filtering procedure described above.

Trends of elevation changes are estimated through robust regression for $\Delta H$ values for all over-glacier ICESat footprints (with geographic coordinates $d_{lat}$ and $d_{long}$ indicating latitude and longitude value) identified from GLIMS glacier database. As individual ICESat tracks do not exactly match, but can be horizontally separated by several hundred meters, the trend of elevation change is analyzed on different averaging scales (overall, sub-regions, and $1^\circ \times 1^\circ$ area-averaged) with a sufficient number of measurements to derive robust statistical analysis.
5.3 Trend analysis with Mann–Kendall test for significance

Trend analyses include linear regression and the non-parametric Mann-Kendall (MK) test. The inter-annual and intra-annual trends of the meteorological and hydrological time series were investigated by linear regression. The trend and magnitude of variables are be characterized by the trend coefficient. Let \( x_i \) be a given variable with sample size \( n \) and \( t_i \) be the corresponding time of \( x_i \). The linear regression equation between \( x_i \) and \( t_i \) can be expressed as \( X_i = a + bt_i \). The magnitude of trend in the respective time series is characterized by the linear regression coefficient \( b \). A positive (negative) value of slope indicates increasing (decreasing) trend in the respective estimates.

The nonparametric Mann-Kendall method, established by Mann (1945) and Kendall (1948), is commonly used to assess the significance of monotonic trends in climatic and hydrologic time series (Burn and Hag Elnur 2002). It is simple in computation and does not require the data to comply with a certain statistical distribution (Kahya and Kalayci 2004). In this study, it was applied to test the significances of trend for TWS and various hydrological and meteorological parameters. According to this test, the null hypothesis \( H_0 \) assumes that there is no trend (the data is independent and randomly ordered) and this is tested against the alternative hypothesis \( H_1 \), the data follow a monotonic trend. The Mann-Kendal test was performed on time series data at a 95% confidence level. Trends with \( p < 0.05 \) are considered significant.
In this study, the seasons are defined as: spring (March-May), summer (June-August), autumn (September-November) and winter (December-February). In this way, the intra- and inter-annual trends of different variables are analysed.

5.4 Correlation analysis

The correlation analysis method is applied to detect the relationship between different hydrologic and climatic variables with GRACE-derived TWS change. Pearson’s correlation coefficient to detect the association between two variables, which are commonly measured by the correlation coefficient \( r \) as calculated below:

\[
 r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}
\]  
(Eq. 5.8)

Where \( x_i \) and \( y_i \) denote value of respective variable during the \( i \)th year or month, and \( \bar{x} \) and \( \bar{y} \) denote the mean value accordingly. The correlation coefficient \( r \) ranges between \(-1 \leq r \leq +1\). When the correlation coefficient is positive, it indicates a positive correlation between two variables; when the correlation coefficient is negative, it indicates a negative correlation between two variables. Larger absolute value of the correlation coefficient \(|r|\) indicates closer degree of correlation between two variables. To determine if the relationship is significant, results are tested for statistical validity at 95% confidence level (\( p < 0.05 \)).
5.5 Summary

GRACE gridded TWS time series are analyzed after leakage correction, data uncertainty is assessed accordingly. Topography altimetry data and glacier inventory data are employed to examine the recent glacier change. Trend analyses of are conducted to identify the changing trend of TWS and hydro-climate variables, which provides supports for examining their change in response to seasonal weather and recent climate change. Correlation and regression analysis was carried out to relate these variabilities. Significance of trends was tested using the non-parametric Mann–Kendall test. In general, hydrological model combined with statistic methods has been a prevalent and useful tool for hydro-climatic phenomenon investigation for various time and space scale (He et al. 2013).
Chapter 6  TWS Spatio-temporal Change Pattern: A Sub-regional Level Analysis for Heterogeneity

This chapter reports the findings from (1) detecting the spatio-temporal trend of TWS over different sub-regions of Xinjiang, and (2) analyzing the major characteristics of the change pattern in different sub-regions, in terms of seasonally and intra-annually. It should be noted that, if not mentioned otherwise, the value of TWS in the following sections would refer to the ensemble mean of three GRACE gridded products (i.e. CSR, JPL, GFZ).

6.1 Intra-annual change

The intra-annual variability refers to the change of yearly average, which primarily reflects its intra-annual pattern, in regardless of the long-term growth or decline. As shown in Figure 6.1, TWSA results in different sub-regions are generally consistent with each other, especially in terms of phase. A cyclic pattern of one year (12 months) can be observed, which is a shared feature of all sub-regions. In general, TWS is in surplus status (TWSA>0) from January/February to July, and in deficit level (TWSA<0) from July to January/February in the next year.
Figure 6.1 Average monthly GRACE terrestrial water storage anomaly (TWSA) during 2003-2015

All sub-regions share a similar trend pattern in a year but have their individual specific characteristics. In ATM, JGB and KLM, the highest level of TWS appears around April, while the lowest level appears around October. However, the TWS in TRB and KLM, which situate in the south of the study area, remain at a relatively high level (around +18mm) during April and July, and start to decrease in July. In TRB, which is an extreme dry basin with very limited precipitation and strong evapotranspiration, the amplitude of TWS is the lowest (35mm). In summer (May to July), while all other sub-regions exhibit increasing water storage loss, the TWS changes in TRB and KLM are very limited (<±5mm). As water may lose through stronger evapotranspiration in summer, the relatively stable total water storage may due to the remedial effect from increase runoff,
water originating from melted mountain glacier (Peng and Xu 2010; Ling et al. 2013; Chen et al. 2014b).

There are also explicit temporal differences in TWS variations in Xinjiang in terms of change amplitude. Annual amplitude of TWS anomaly refers to the magnitude of the difference between the highest and the lowest TWS anomaly within a change cycle (one year). According to Figure 6.1, the average annual amplitudes of all sub-regions around 51mm. ATM, where situates in the north, has significantly larger amplitude of approximately 60mm. In summer and winter, the TWS also changes most rapidly among all sub-regions. This pattern might due to the largest amount of snowfall it receives annually, which constitutes the major water storage component in ATM. The subsequent snow melting process facilitates the most rapid water loss rate in spring and summer.

![Figure 6.2 Average monthly GRACE terrestrial water storage change (TWSC) during 2003-2015](image.png)

TWSC refers to the net increase/decrease of TWS compared with the previous month, and Figure 6.2 presents the yearly average TWSC. According to
Figure 6.2, a cyclic pattern of one year (12 months) can be observed for TWSC, which is also a shared feature of all sub-regions. In general, TWS increases (TWSC>0) from fall (November) to spring (April) in the next year, and decreases (TWSC<0) from late spring (May) to early fall (October). These patterns correspond to the major climatic pattern in the study area.
Table 6.1 Seasonal TWS anomalies (TWSA) (unit: mm EWH), intra-annual TWS changes (TWSC) (unit: mm EWH/season) and TWSA annual amplitudes (unit: mm EWH) in different sub-regions during 2003–2015

<table>
<thead>
<tr>
<th></th>
<th>Spring (3-5)</th>
<th>Summer (6-8)</th>
<th>Fall (9-11)</th>
<th>Winter (12-1)</th>
<th>TWSA Annual Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TWSC</td>
<td>TWSA</td>
<td>TWSC</td>
<td>TWSA</td>
<td>TWSC</td>
</tr>
<tr>
<td>ATM</td>
<td>22.82</td>
<td>28.73↑</td>
<td>-30.02↓</td>
<td>-1.29↓</td>
<td>-32.51</td>
</tr>
<tr>
<td>JGB</td>
<td>18.83↓</td>
<td>19.40</td>
<td>-14.21</td>
<td>5.19</td>
<td>-30.67</td>
</tr>
<tr>
<td>TSM</td>
<td>24.24</td>
<td>23.10</td>
<td>-17.83</td>
<td>5.27</td>
<td>-32.81</td>
</tr>
<tr>
<td>TRB</td>
<td>20.34</td>
<td>13.35↓</td>
<td>-3.04↑</td>
<td>10.31</td>
<td>-27.28↑</td>
</tr>
</tbody>
</table>
(Continued)

<table>
<thead>
<tr>
<th></th>
<th>Spring (3-5)</th>
<th>Summer (6-8)</th>
<th>Fall (9-11)</th>
<th>Winter (12-1)</th>
<th>TWSA Annual Amplitude</th>
</tr>
</thead>
<tbody>
<tr>
<td>TWSC</td>
<td>TWSA</td>
<td>TWSC</td>
<td>TWSA</td>
<td>TWSC</td>
<td>TWSA</td>
</tr>
<tr>
<td>KLM</td>
<td>26.96↑</td>
<td>17.10</td>
<td>-5.22</td>
<td>11.88↑</td>
<td>9.52↓ -9.87↓</td>
</tr>
<tr>
<td>Mean</td>
<td>22.64</td>
<td>20.33</td>
<td>-14.06</td>
<td>6.27</td>
<td>-30.91 -24.63 22.33 -2.31</td>
</tr>
</tbody>
</table>

**Note:** Significantly high/low TWSC, TWSA and annual amplitude value (with one standard deviation higher/lower from the corresponding mean value) value are illustrated as bold numbers. The ↑ and ↓ symbols indicate the abnormally high or low values, respectively.
Sub-regions with significant higher/lower annual TWSC amplitude or TWSC/TWSA values in different seasons, compared with other sub-regions at the same season, are summarized in Table 6.1, which are defined as one standard deviation higher/lower than the corresponding mean value.

Figure 6.3 Spatio-temporal pattern of intra-annual GRACE-derived TWS anomaly
Spatially, there are explicit different pattern of intra-annual TWSA variations in Xinjiang as well. According to Figure 6.3, while the TWS generally reaches to the highest during April in the study area, area with higher TWSA is observed in the southwest, or the west KLM region (around +60mm), followed by the northwest, or the east TSM and east ATM region (around +40mm). On the other hand, while the TWS generally reaches to the lowest during October, area with lower TWSA is observed also in the southwest, or the west KLM region (around -60mm), followed by the northwest, or the east TSM and east ATM region (around -40mm). Apart from these regions, the TWS remains relatively stable. It is observed that from west to east of the study area, the annual amplitude evolves from larger to smaller. Seasonal climatic variables are assumed as the major influencing factors for this pattern. The detail mechanism of TWS intra-annual change will be further examined in Chapter 7.

6.2 Inter-annual change

The inter-annual variability refers to the long-term TWS change, in regardless of the seasonal cyclic growth/decline. In this section, the inter-annual TWS change based on different solutions in different sub-regions are analyzed based on trend and seasonal contribution analysis. The detail mechanism of TWS inter-annual change will be further examined in Chapter 8.
6.2.1 Inter-annual change pattern of different sub-regions

Figure 6.4(a-d) illustrates the inter-annual TWSA change trend with significant test result at 1-degree gridded level, derived from GRACE CSR, GFZ, JPL products and their ensemble mean (arithmetic average), respectively. While different GRACE products are processed by different solutions of gravity field for final users, the spatial patterns of trend distributions of TWS anomaly from CSR, GFZ, and JPL are highly consistent with each other, except some minor deviations. It is suggested that the minor differences of spatio-temporal pattern among various GRACE products may be introduced by the processing methodologies, the tuning parameters, and the error patterns in the GRACE Science Data System (Sakumura et al. 2014). Our discussion will be primarily based on the ensemble mean shown in Figure 6.4(d).

According to the result Figure 6.4(d), virtually all ensemble mean GRACE-derived TWS increase/decrease trends are statistically significant ($p<0.05$, under the Mann–Kendall test). Spatially, TWS decreased by 70.5% (134/190) of the whole study area, and 63.2% (120/190) of the whole study area showed significant decreases ($p<0.05$), including JGB, TSM, south part of ATM and north part of TRB, with a peak decrease rate of approximately 11mm/a occurred in central and west TSM. Stronger decrease of TWS can be found across TSM, particularly in mountainous glaciated area.

The TWS increase area accounts for 29.5% (56/190) of the whole study area, and 23.7% (45/190) regions exhibited significant increases ($p<0.05$), including
TSM, north rim of ATM and south part of TRB, with a peak increase rate of approximately 7mm/a occurred in east TSM. To sum up, during 2003-2015, TWS have significantly increased in the north part of Xinjiang, while a substantial increase of TWS is exhibited in the south (particularly the southeast).
Figure 6.4 GRACE-derived TWS change rate from 2003-2015
Figure 6.5 Temporal change of TWS anomaly during 2003-2015 of (a) ATM, (b) JGB, (c) TSM, (d) TRB, and (e) KLM, derived from GFZ, JPL and CSR GRACE products, ensemble mean (blue line) with corresponding error and 12-month moving average (black line).
Figure 6.5 Temporal change of TWS anomaly during 2003-2015 of different sub-regions, derived from GFZ, JPL and CSR GRACE products, ensemble mean (blue line) with corresponding error and 12-month moving average (black line) (continued).
Figure 6.5 Temporal change of TWS anomaly during 2003-2015 of different sub-regions, derived from GFZ, JPL and CSR GRACE products, ensemble mean (blue line) with corresponding error and 12-month moving average (black line) (continued).

Figure 6.6 Monthly time series (with 12-month moving average filter) of TWS anomaly in TSM, KLM and the entire study area
Figure (a-e) depicts the respective sub-region weighted averaged TWS anomaly change curves during 2003-2015, with the respective monthly value derived from CSR, JPL and GFZ solutions, and the ensemble mean (shown as blue line). To highlight the inter-annual variability and remove the effect of seasonal cycle, the curves (shown as black line) are result after applying a centred 12-month moving smoothing average filter to all ensemble mean time series, along with the corresponding uncertainty estimates (shown as error bar). To further examine the TWS linear trend in specific time span during 2003-2015, superimposed is the partial linear trend lines estimated from least-squares-fit of the time series, indicating increase (green) or decrease (red) during specific years.

According to the result, the inter-annual trends derived from CSR, GFZ and JPL are also highly consistent for respective sub-region. There has been a general decreasing trend of TWS, with some fluctuation, during 2003-2015, which may primarily be attributed to the recent climate change pattern or anthropogenic influences. They generally agree well among all sub-regions in terms of timing but may largely disagree in terms of the amplitude of each change. For the whole study area, the maximum surplus of TWS was around 35mm and occurred in spring 2005, while the minimum deficit anomaly of about -40mm occurred during fall 2014. The inter-annual variability is found to be associated with the extreme climate events, as reported in local news and annual meteorological extreme events report. For instance, TWS in all sub-regions exhibit a strong rebound in 2010, an extreme wet year as reported. During the winter season from December 2009 to February 2010, it was also reported by the Meteorological
Bureau of Xinjiang that it has experienced a severe snow season. The total snow precipitation was 1.5 times higher than normal years and reached the historical extreme. In south Xinjiang, the annual rainfall in 2010 was 90% higher than normal years.

Despite some shared trend characteristics exist among sub-regions, there have been certain differences in terms spatially and temporally. As summarized in Table 6.2, during 2003-2015, TWS have been decreasing at a rate of -3.41mm, -5.82mm, -6.76mm, and -2.59mm of equivalent water height (EWH) annually in ATM, JGB, TSM and TRB sub-regions, respectively, which are equivalent to a water storage net loss of around -5.56×10^8, -10.48×10^8, -20.52×10^8, -16.47×10^8 m^3/year, respectively. However, it is worth noted that TWS has increased by 3.05mm of EWH annually in KLM, which equivalents to a water storage net increase of 11.16×10^8 m^3/year. Figure 6.6 highlights the particularly drastic TWS increase/decrease change trends in TSM and KLM, with respect to the mean value of the whole study area.

Rapid and continuous trend, even occurred in relatively short term (i.e. a couple of years), can contribute significantly to the overall trend during 2003-2015. In ATM and JGB sub-regions, partial linear fit identifies two obvious downward trends during 2006-2009 and 2010-2013, the periods that primary contribute to the overall downward trend of TWS. However, no significant yearly upward trend is found, except a very short term rebound during 2009-2010. In
TSM, where the TWS has experience the most rapid decline among all sub-regions, the yearly downward trends (2005-2009, 2011-2015) were also longer than other sub-regions. A two-year upward (2009-2011) was nevertheless occurred, at the time it received substantial and record amount of snowfall during winter. On the other hand, a five-year (2008-2013) significant upward trend is identified in KLM, while the TWS have remained generally stable or slightly fluctuation in other years. The detail mechanism of TWS inter-annual change will be further examined in Chapter 8, by considering the corresponding variations of climatic and hydrologic parameters.
<table>
<thead>
<tr>
<th>Sub-region</th>
<th>Area (1,000 km²)</th>
<th>Average GRACE TWS error (mm EWH)</th>
<th>TWS inter-annual change trend (mm/a) (p&lt;0.05)</th>
<th>Estimated water net gain/loss (m³/a)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Altai Mountains (ATM)</td>
<td>163</td>
<td>8.43</td>
<td>-3.41±2.77</td>
<td>-5.56×10⁸</td>
</tr>
<tr>
<td>Junggar Basin (JGB)</td>
<td>180</td>
<td>8.13</td>
<td>-5.82±2.47</td>
<td>-10.48×10⁸</td>
</tr>
<tr>
<td>Tianshan Mountains (TSM)</td>
<td>308</td>
<td>7.39</td>
<td>-6.76±2.81</td>
<td>-20.82×10⁸</td>
</tr>
<tr>
<td>Tarim Basin (TRM)</td>
<td>636</td>
<td>4.24</td>
<td>-2.59±1.69</td>
<td>-16.47×10⁸</td>
</tr>
<tr>
<td>Kunlun Mountains (KLM)</td>
<td>366</td>
<td>6.25</td>
<td>+3.05±2.19</td>
<td>11.16×10⁸</td>
</tr>
</tbody>
</table>
6.2.2 Seasonal TWSC contribution to inter-annual trend

To examine if certain seasons played a greater role than others in the TWS inter-annual trend, the contribution of seasonal TWSC (i.e. change during the season) are calculated at 1-degree gridded cell level. The contribution of the TWS change during respective seasons (defined as the average difference between TWSA at the ending month of the season, and the TWSA at the starting month of the season) to the inter-annual TWS trend is quantified as its proportion to the accumulated TWS change during 2003-2015 (calculated as the sum of all monthly TWSC value). The process can be expressed as follows:

\[
a = \frac{(TWSA_{t_{s,n}} - TWSA_{t_{s,n}'})}{\sum_{1}^{n} TWSC_{t,n}} \quad \text{(Eq. 6.1)}
\]

\[
C_{s,n} = \left\{ \begin{array}{ll} 
\frac{TWSA_{t_{s,n}} - TWSA_{t_{s,n}'}}{\sum_{1}^{n} TWSC_{t,n}} \times 100, & a > 0 \\
0, & a < 0 
\end{array} \right. \quad \text{(Eq. 6.2)}
\]

First, Equation 6.1 is to determine whether, at the nth grid cell, TWSC during the specific season \( s \in \{spring, summer, fall, winter\} \) contributes positively for the overall trend. In this study, the seasons are defined as: spring (March-May), summer (June-August), fall (September-November) and winter (December-February). Correspondingly at the nth grid cell, when \( s \) represents spring, summer, fall or winter, \( TWSA_{t_{s,n}} \) refers to the multi-year average TWSA value in June \( (t'_{spring}) \), September \( (t'_{summer}) \), December \( (t'_{fall}) \) or March \( (t'_{winter}) \), while \( TWSA_{t_{s,n}'} \) refers to the multi-year average TWSA value in March \( (t_{spring}) \), June...
September \( (t_{\text{fall}}) \) or December \( (t_{\text{winter}}) \), respectively. \( \sum_{t}^{156} TWSC_{tn} \) refers to the sum of the TWSC value of all \( t \) \( (t=156) \) months at the \( nth \) grid cell. Therefore, for individual season, if \( a > 0 \), it indicates that this season has contributed positively in the inter-annual trend, otherwise, \( a < 0 \) indicates a reverse trend and thereby considered as no contribution. Finally, Equation 6.2 calculates the proportion \( (\%) \) of seasonal trend to the accumulated TWS change, and determines the contribution \( (C_{s,n}) \) from each season \( s \) at the \( nth \) grid cell.

Figure 6.7 Contribution of different season to TWS inter-annual increase/decrease from 2003 to 2015
Figure 6.7 illustrates the major contributing season with its contribution (%) to the inter-annual TWS pattern, and Table 6.3 summarizes the average seasonal contribution in each sub-region. During 2003-2015, TWS losses during summer have contributed substantially in most part of north Xinjiang, particularly in JGB (81.7%) and TSM (79.9%). On the other hand, TWS gain in KLM was mostly occurred during winter (62.7%). Increased glacier melting triggered by recent climate change, as demonstrated in various studies, may have incurred water storage loss in summer. Further analysis will be demonstrated in the following chapters.

Surprisingly, in the east KLM region, where the TWS has drastically increased, the trend was largely attributed to TWS increase in summer. This phenomenon could be associated with increased water availability in permafrost aquifer system. Several studies have reported the enhanced permafrost melting or degradation triggered by warming climate in this region (Jiao et al. 2015).
Table 6.3 Seasonal contributions toward inter-annual increase/decrease of different sub-regions

<table>
<thead>
<tr>
<th></th>
<th>Spring</th>
<th>Summer</th>
<th>Fall</th>
<th>Winter</th>
<th>2013-2015 accumulated TWS gain/loss (mm EWH)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATM</td>
<td>0.0%</td>
<td>76.4%</td>
<td>2.3%</td>
<td>0.0%</td>
<td>-19.86</td>
</tr>
<tr>
<td>JGB</td>
<td>0.0%</td>
<td>81.7%</td>
<td>4.9%</td>
<td>0.0%</td>
<td>-62.68</td>
</tr>
<tr>
<td>TSM</td>
<td>0.0%</td>
<td>79.9%</td>
<td>2.4%</td>
<td>0.0%</td>
<td>-80.34</td>
</tr>
<tr>
<td>TRB</td>
<td>0.5%</td>
<td>53.5%</td>
<td>7.6%</td>
<td>19.9%</td>
<td>-23.63</td>
</tr>
<tr>
<td>KLM</td>
<td>1.6%</td>
<td>22.1%</td>
<td>0.8%</td>
<td>62.7%</td>
<td>46.73</td>
</tr>
</tbody>
</table>

6.3 Summary

TWS signal is a synthesis of signals with different periods. A sub-regional reanalysis for TWS spatial and temporal pattern reveals several key characteristics of regional differences in terms of 1) intra-annual change amplitude, 2) inter-annual trend pattern (particularly between TSM and KLM) and 3) seasonal contribution to inter-annual trend. In addition, according to the result, only limited
discrepancy can be observed among different GRACE products. Similar as common hydrological cycle, TWS cycles may also be forced by the intra-annual cycle of solar radiation, atmospheric circulation and precipitation, while inter-annual trend was controlled by mid to long term climatic change.
Chapter 7  TWS Intra-annual Change: Relationship with Seasonal Climate and Hydrologic Cycle

As a collective reflection of the regional hydro-climatic environment, the terrestrial water storage presents regular and cyclic change pattern within a year, which may correspond to the seasonal meteorological and hydrological pattern of a particular region. In this chapter, based on the result presented in last chapter, the underlying mechanism of TWS intra-annual change will be investigated. Thus, the primary influencing factors for the TWS intra-annual change are identified, which lays a foundation for the analysis of TWS inter-annual change.
7.1 Correlation relations between TWS intra-annual anomaly and climatic factors

Figure 7.1 Pearson’s correlation coefficient $R$ between TWS anomaly and (a) temperature anomaly, (b) temperature month-over-month change (c) temperature anomaly with 4-month time lag, and (d) precipitation anomaly

To identify the primary controlling factor of TWS intra-annual change, correlation relationships are investigated between TWS anomaly and various climatic factors. Figure 7.1(a-d) illustrates the respective correlation coefficients $R$ between monthly TWS anomaly and temperature anomaly, temperature month-
over-month change, temperature anomaly with 4-month time lag and precipitation anomaly within a year. The black dots represent significant correlations at levels of \( p < 0.05 \). The corresponding average coefficients for respective sub-regions are also summarized in Table 7.1.

Table 7.1 Correlation coefficient (R) between GRACE derived TWSA and various forms of climatic factors in different sub-regions

<table>
<thead>
<tr>
<th>Correlation</th>
<th>ATM</th>
<th>JGB</th>
<th>TSM</th>
<th>TRB</th>
<th>KLM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature anomaly</td>
<td>-0.057</td>
<td>0.108</td>
<td>0.090</td>
<td>0.302*</td>
<td>0.267*</td>
</tr>
<tr>
<td>Temperature month-over-month change</td>
<td>0.598*</td>
<td>0.457*</td>
<td>0.418*</td>
<td>0.369*</td>
<td>0.349*</td>
</tr>
<tr>
<td>Temperature anomaly with 4-month lag</td>
<td>-0.582*</td>
<td>-0.460*</td>
<td>-0.420*</td>
<td>-0.455*</td>
<td>-0.424*</td>
</tr>
<tr>
<td>Precipitation anomaly</td>
<td>0.074</td>
<td>0.172</td>
<td>0.222</td>
<td>0.202</td>
<td>0.254</td>
</tr>
</tbody>
</table>

Superscripts in this table indicate significance:

* Significant at 95 % confidence level

According to Figure 7.1(a), it can be observed that the TWS only presents a moderate positive correlation relationship with temperature. In the area (mostly extremely arid basin) with higher positive correlation coefficient (+0.4, \( p < 0.05 \)),
TWS increase can be primarily attributed to the intra-annual surface runoff originated from glacier melts in mountains.

Temperature generally increases most rapidly in spring and reaches the highest in summer. In the study area, therefore, the pattern of temperature month-over-month change (i.e. the difference between two consecutive months) is similar to the value of temperature anomaly with 4-month time-lag. Figure 7.1(b) and Figure 7.1(c) thereby both present similarly strong correlation relationship, particularly in area with abundant snow accumulation (northwest and southwest Xinjiang, around 0.7, p<0.05), which confirms our suggestion that intra-annual TWS variability of primarily controlled by intra-annual snow accumulation and melt.

Figure 7.1(d) suggests that TWS change in Xinjiang has insignificant relationship (around +0.1) with seasonal precipitation, due to limited rainfall and strong evapotranspiration in arid and semi-arid region.
Figure 7.2 Adjusted correlation between TWS anomaly and temperature anomaly (0-6 months lag) and month-over-month change) in different sub-regions

Shown in Figure 7.2 are the correlations between monthly TWS anomaly, temperature month-over-month change and temperature anomaly with 0-6 month(s) time-lag. In general, TWS anomalies are best correlated with each of the temperature anomaly with a certain time lag (R= -0.63 in ATM), the TWS peaks about 3-4 months later than the corresponding through of temperature. One of the primary reasons behind the 3 to 4 months lagged response is that snow normally begins to melt in April-May while the temperature reaches to lowest in January. The relationship between intra-annual snow accumulation/melt and TWS anomaly is sustained by the high coefficients between TWS and temperature month-over-change (R=0.56 in ATM). The loss rate of water in spring is primarily attributed to the temperature increase speed in spring.

While spatially monthly changes in TWS are moderately correlated with temperature anomaly as shown in Figure 7.1(a), their change phase are
significantly different. According Figure 7.3, monthly TWS anomaly can be negatively correlated with temperature anomaly with a time lag of 3-4 months. More importantly, the TWS anomaly is strongly correlated with temperature month-over-month change. Their concurrence might due to seasonal snow accumulation in winter and melting in spring, which is considered as the major hydrological state/flux process in the region.

Among all sub-regions, ATM, which receives the strongest snowfall annually, is the most representative example as shown in Figure 7.3.

Figure 7.3 Intra-annual change pattern of TWS and temperature in Altay Mountains (ATM) sub-region

To sum up, the TWS intra-annual change is closely associated with temperature change, particularly the temperature month-over-month change, in
most part of the study area. The pattern of temperature month-over-month change might be indicative to seasonal snow accumulation and melting.

### 7.2 The spatial correlation relation between TWS anomaly and annual snowfall

![Map showing spatial distribution](image)

Figure 7.4 Annual average snowfall and TWS amplitude during 2003-2015

Figure 7.4 illustrates the spatial distribution of average intra-annual TWS change amplitude (which refers to the difference between the average highest and the average lowest TWS anomaly within a change cycle, i.e. one year) at 1-degree gridded level. It can be observed that the snowfall primarily occurs northwest and
southwest of the study area (ATM and west KLM, TSM and JGB). Areas with larger annual amplitude of TWS anomaly (>70 mm) distribute mainly in the northwest and southwest region, which is spatially corresponding to the areas with high average annual snowfall (>70mm).

Figure 7.5 The relationship between TWS anomaly annual amplitude and annual snowfall for different sub-regions

Figure 7.5 further presents the scatter plot of TWS anomaly annual amplitude and annual snowfall at 1-degree level, which are classified as different sub-regions and summarized in Table 7.2. The linear/non-linear fitted trends further suggest that higher annual snowfall appeared have caused greater fluctuation of TWS within a year, which are particularly evident in TSM, by a
logarithmic correlation with $R^2 = 0.68$, and KLM, by linear correlation with $R^2 = 0.65$, both at 95% confidence level. In mountainous sub-regions, i.e. ATM, KLM and TSM, water stored as seasonal snow pack constitutes a large proportion of water storage. As snowfall amounts are considerably much higher than they are in basin sub-regions, i.e. JGB and TRB, TWS volume usually varies significantly within a year. It also suggests that snowfall plays more important roles for seasonal TWS dynamics in mountainous sub-regions.

Table 7.2 Statistical relations between TWS annual amplitude and annual snowfall

<table>
<thead>
<tr>
<th>Sub-region</th>
<th>Average annual amplitude of TWS (mm)</th>
<th>Average annual snowfall (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ATM</td>
<td>71.12</td>
<td>81.57</td>
</tr>
<tr>
<td>JGB</td>
<td>50.22</td>
<td>39.47</td>
</tr>
<tr>
<td>TSM</td>
<td>57.08</td>
<td>53.10</td>
</tr>
<tr>
<td>TRB</td>
<td>35.89</td>
<td>9.52</td>
</tr>
<tr>
<td>KLM</td>
<td>43.99</td>
<td>89.43</td>
</tr>
</tbody>
</table>
7.3 Conversion from seasonal snow pack to soil moisture

Snow is an appreciable fraction of soil water recharge in the middle and high latitude areas (Wang et al. 2014c). As described in the previous chapters, the study area is characterized as a unique arid zone in the world, in terms of water formation, spatial and temporal distribution, which predominantly controlled by the water stored in cryosphere (Chen et al. 2015b). Therefore, water fluxes into and out of the cryosphere are the most essential hydrologic processes. Snow precipitation can be an important water resource for arid and semi-arid ecosystems as it melts in the spring, and subsequently improves soil moisture conditions and offsets water loss through evapotranspiration in summer (Barnett et al. 2005). The seasonal conversion processes (rate and response time) between snow water and soil moisture may have primarily facilitated the intra-annual change of regional TWS.
Figure 7.6 Intra-annual anomaly of SM, SWE and TWS in mountainous sub-regions (ATM, TSM and KLM)
Figure 7.6 (a-c) presents the average monthly change the SM, SWE and TWS anomaly in three mountainous sub-regions (ATM, TSM and KLM). The grey columns, green curves and brown curves represent the TWS anomaly, soil moisture (SM) anomaly, and snow water equivalent (SWE) anomaly within a year. It can be observed that, generally, snow starts melting during spring, the snowmelt water consequently infiltrates into soil profile and converted as soil moisture (SM), showing increasing SM while maintaining the TWS. On the other hand, snowmelt water may also be converted to surface runoff water (R), which may flow out of the region and thereby reduce the TWS. Evapotranspiration effect is considered limited due to lower temperature in mountainous area. During snow ablation seasons (spring and summer), the change pattern of TWS, which can be regarded as the total amount of water that remains in the region, should be equivalent to the sum of SWE net decrease and SM net increase, and minus the surface runoff (R), which can be express as:

$$\triangle \text{TWS} = \triangle \text{SWE} + \triangle \text{SM} - \triangle \text{R} \quad \text{(Eq. 7.1)}$$

According to Figure 7.6, SWE reaches to its highest level at late February and March (when snowfall gets less and melting starts) in all sub-regions, while TSM has different temporal patterns in different sub-regions. Infiltration is the process by which water on the ground surface enters the soil. There is an obvious time lag between the phase of soil moisture (SM) and snow water equivalent (SWE), for about three months in ATM and TSM, and about five months in TSM, indicating different recharge rates from SWE to SM. The change of TWS seems
to be primarily influenced by the conversion from SWE to SM, and is generally fall between the peak of SWE and SM. It is also affected by the amount of outflow (R).

Figure 7.7 Soil moisture infiltration rate and snow melt rate

Figure 7.7 illustrates the relationship of soil moisture infiltration/evaporation rate, snow melt rate and TWS anomaly change rate during spring and summer in ATM, TSM and KLM sub-regions. Soil moisture infiltration/evaporation rate and snow melt rate refers to the differences between SM/SWE of current month and the previous month. It can be observed that for individual sub-regions, snow melt rates and soil water infiltration rates generally agree well with each other. The soil moisture infiltration rate increases with the snow melt rate. The monthly TWS reaches to its highest level at the time the snow melt rate and soil moisture infiltration rate reach to their maximum. However, certain differences in terms of change rate and phase among sub-regions exist:
(1) In ATM sub-region, SWE converts to SM rapidly in spring as temperature increases most rapidly. Outflow through the exorheic Irtyshev River reduces the TWS at the same time. As temperature increased rapidly in summer, water stored in soil evaporated, TWS in ATM region reaches to deficit status (<0) earlier than other sub-regions (June-July);

(2) In TSM sub-region, SWE converts to SM at a lower speed in spring due to lower temperature at high elevation. A large proportion of snow pack is not melted until summer, as reflected by the relatively smooth curve of TWS;

(3) In KLM sub-region, the peak of TWS anomaly occurs in June, significantly later than it is in ATM or TSM. This phenomenon might be due to much lower temperature and thereby slower snowmelt.

Intra-annual changes of TWS in those regions are primarily controlled by intra-annual snow accumulation and ablation. TWS normally starts to decrease around May in ATM and TSM, while the loss of TWS becomes visible two month later in KLM, where the temperature is much lower because of the high altitude. This can be explained as well by TWS sensitivity to temperature month-over-month change, which has strong influences on the rate of melting, as illustrated in Section 7.2. In fall to winter, as snow falls, water storage starts to increase in October-November in most sub-regions, which are a shared feature of all three sub-regions.

These conversion processes suggest that the difference of intra-annual TWS change pattern, demonstrated by the spatio-temporal redistribution of water,
appear to be caused by the difference of seasonal temperature change among sub-regions.

7.4 Summary

This chapter reports the analyses, from various aspects by combining the climatic factors observations (precipitation and temperature) and LSM outputs (snow water equivalent and soil moisture, snow precipitation rate), for the mechanism of intra-annual TWS change and its relationship with seasonal weather and hydrological states/fluxes dynamics. The findings appear to indicate that 1) temperature month-over-month change and temperature anomaly with 4 months lag, rather than precipitation, are more capable to explain the intra-annual TWS variation; 2) In most part of the northwest arid zone of China, the TWS intra-annual change can be primarily attributed to the snow accumulation in winter and melt in spring, with minor pattern differences exist among sub-regions.

Climate change and its impact on mountain hydrology that is characterized by the snow-melting streamflow have direct implications on freshwater supply for living and irrigation agriculture. The snow cover and its melt tend to dominate regional hydrology over study area. Based on the above analysis, it can be concluded clearly that TWS in Xinjiang is highly sensitive to the variation of cryosphere.
Chapter 8  TWS Inter-annual Change: Implications of Recent Climate Change

The primary objective of this study will be addressed in this chapter. The response of inter-annual TWS change to recent climate change will be examined. As glacier is the most vulnerable and dynamic changing hydrologic component under climate change, this chapter will focus on investigating the feedback mechanism between water storage fluctuation and glacier mass variation in mountainous sub-regions.

8.1 Recent temperature and precipitation change: Dissimilar influences on TWS

As the major climatic factors which play important roles in sustaining arid zone ecosystem, the temperature and precipitation change trends in northwest China have been thoroughly investigated. Many researchers have recognized and agreed on the change from a warm-dry to a warm-wet climate in Xinjiang (Li et al. 2011). Chen et al. (2014c) have also revealed that over the past 50 years, the temperature in the arid region of Northwest China has shown a significant increasing trend ($p<0.01$), at a rate of 0.343 °C/10a. However, due to its large
extent and complex terrain, heterogeneous responses of TWS variation to dissimilar climatic change patterns should be expected.

Figure 8.1 Temperature change trend during 2003-2015

Dissimilar trend of temperature exists in terms of time and space. Various studies have confirmed that there is a general trend of warming during the last century in northwest China (Li et al. 2011; Hu et al. 2014; Bai et al. 2015). During the past decade, however, a more conspicuous warming trend was shown. Regionally, temperature increase pattern has exhibited strong regional differences. Generally, TSM and KLM, two mountainous sub-regions with vast amount the water stored as seasonal snow pack or glacier, have experienced more drastic while dissimilar temperature change in the past decade. A greater warming trend
is particularly evident in the TSM, where the temperature rising rate reached 1.94°C/10a (Figure 8.1). In contrast, an obvious cooling trend, especially in winter, was observed in the KLM, where the intra-annual snow cover and glacier are mainly distributed (Figure 8.1). During the past decade, certain seasons have contributed more significantly in the overall trend. Figure 8.2 also shows that the temperature in summer season has risen most rapidly compared with other seasons.

![Figure 8.2 Seasonal temperature change rate during 2003-2015](image)

A general increasing trend in the annual precipitation was found in Xinjiang during 1951-2013 (Hu et al. 2017). However, the trend is not obvious during the study period. Spatially, the mountain ranges show increasing precipitation, while the most the west TSM sub-region has the most decrease of precipitation (Figure 8.3). In the whole area, however, the annual change rate varies only within ±1% of annual precipitation, which may not be a major contributor of TWS change. By analysing time series datasets from 1961 to 2005 at 65 meteorological stations in Xinjiang, Li et al. (2011) also acknowledged that the increase in temperature is more obvious than that of precipitation. However, despite of the fact that the
average levels of precipitation have remained stable, the precipitation variability has increased. Similar conclusions were explicitly drawn by Lioubimtseva and Henebry (2009), who suggested that while the warming trend in Central Asia during the past century are supported by most ground station datasets, the precipitation trends are highly variable.

![Map of precipitation change percentage during 2003-2015](image)

Figure 8.3 Precipitation change percentage during 2003-2015

This negligible change of mean precipitation, in all sub-regions, suggests that the inter-annual TWS change may not be associated with additional water flux input from precipitation.

As suggested from the analysis in Section 8.1, summer temperature increase appears to be more conspicuous compared with other seasons in TSM, while there
has been a general decrease trend of temperature in KLM, which is particularly evident in winter and spring. These changes may have exerted strong yet heterogeneous influences in the glacier mass variation in mountainous sub-regions.

The response of TWS inter-annual variability to climate variability in summer is specifically examined. As illustrated in Figure 8.4 and Figure 8.5, the summer temperature in TSM (shown as solid red curve) has been increased around 2°C since 2003, while it has remained stable in other mountainous sub-regions (i.e. ATM and KLM, shown as blue and green dotted curves). In TSM, this trend was accompanied by a substantial water storage loss in TSM during summer. Since summer season of 2003, the average TWS anomaly has decreased from approximate +50mm to -39mm in summer season of 2015. It is apparent that rapid warming in TSM since 2003 has accelerated glacier shrinkage and melting of perennial snow, led to significant reduction in total water storage. The severe loss of TWS in KLM also suggests that the slightly increasing precipitation (+0.6% during 2003-2015) has not been able to compensate for the loss of water resulting from the warming.
Illustrated as time series scatter point diagram, Figure 8.5 further highlights the trend co-occurrence of TWS lost and summer temperature increase in TSM (shown as blue dashed line). A negative linear trend between TWS anomaly and summer temperature can be observed in TSM. During 2003-2015, the trend developed from wet-cold condition to dry-hot condition, which was primarily occurred in summer. The minor fluctuation of TWS during 2008-2012 corresponds well with the similarly fluctuated temperature change. In contrast, the relationships are unclear for both ATM and KLM. The temperature seemed to be fluctuating within a certain range of the time mean value. There has also been a generally increasing trend of TWS in KLM. The relatively stable summer temperature in KLM, however, suggests that it is unlikely to be the major attribution of this phenomenon.
Figure 8.5 Change of summer temperature and summer TWS anomaly of TSM

8.2 TWS response to climate change: Evidence from glacier mass variation

To signify and quantify the response senility of TWS to recent climate change, investigations to where and which hydrological component have the TWS variation occurred are needed. Climatic differences between low and high altitudes involve important issues relating to warming, examining the elevation dependency of TWS variation may further corroborate our assumptions. In this study, average annual TWS change trend (mm/a) for different ranges of elevation (grouped as 500m interval) are calculated for three mountainous sub-regions (ATM, TSM and KLM), and presented in Figure 8.6. The grey columns denote the area proportion of individual elevation range to the total area of the sub-region.
According to Figure 8.6(a), there has been a rapid decline of TWS in high elevation range in TSM, which spatially correspond to the distribution of glaciated area. The decreasing rate in TSM at 3000m-5000m elevation was -8.21 mm/a, significantly faster than that at its lower elevation (-7.61 mm/a) or at same elevation of ATM (-1.51 mm/a) and KLM (+1.77 mm/a). As water storage at this elevation range is predominantly in the form of glacier, this dramatic loss of TWS would primarily be in the form by glacier melting.
Figure 8.6 TWS change by elevation in TSM(a) and KLM(b)

On the other hand, opposite trend is observed in KLM. According to Figure 8.6(b), while there has been a general increase of TWS during 2003-2015, the increase rates differ by elevation. In higher elevation area (from 4000m and above) where glaciers mainly distributed, the average TWS increase rate is +1.86mm/a. As mountainous glaciers tend to be increasingly occurred in higher elevation, the
positive trend of TWS increase may suggest that glacier mass increase is the major attribution of overall mass variation during 2003-2015.

To sum up, strong negative/positive correlation relationships between TWS variations and elevation tend to suggest that long term water storage loss/gain were more apparent at high elevation glaciated area. These observations reinforce our assumption that the inter-annual TWS loss was primarily driven by non-seasonal glacier melt which is closely associated with recent climate change.
Figure 8.7 ICESat tracks in TSM and KLM sub-regions
The monitoring of glacier mass balance (annual mass gain or loss at the surface) is probably the most effective way to infer climatic change with glaciers (Oerlemans 1994). Therefore, glacier changes within two mountainous sub-regions with large extent glacier distribution (i.e. TSM and KLM), will be analyzed based on the ICESat data. Based on the retrieval result, we try to relate the recent glacier elevation change to the changes of GRACE-derived TWS observations, and discuss the glacier-climate-TWS interaction over different regions during 2003-2009. The detail methodology of extracting the calculating glacier elevation change from altimetry data is described in Section 5.2. Figure 8.7 provides an overview of the study region, with presenting the distribution of glacier and all ICESat tracks within both regions. Only ICESat footprints over glaciers are indicated. To provide a clear picture of how ICESat footprint distributes in smaller scale, two sample areas selected from KLM (Figure 8.8(a)) and TSM (Figure 8.8(b)), with the on-glacier ICESat footprints grouped according to laser campaigned are presented. White polygons correspond to the glacier outlines according to GLIMS Glacier Database. As summarized in Table 8.1, the analyses are based on 10,005 and 20,547 shots for TSM and KLM sub-regions, respectively, which were retained after the pre-processing and filtering procedure described in Section 5.2.
Figure 8.8 Sample glacier area with ICESat multi-year footprint
Table 8.1 ICESat campaign operation dates and footprints

<table>
<thead>
<tr>
<th>Campaign</th>
<th>Operation start date</th>
<th>Operation end date</th>
<th>Duration (days)</th>
<th>Available footprints in study area (Xinjiang)</th>
<th>TSM glaciers</th>
<th>KLM glaciers</th>
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<td>TSM glaciers</td>
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<td>34</td>
<td>206,190</td>
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<tr>
<td>Campaign</td>
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<td>Operation end date</td>
<td>Duration (days)</td>
<td>Available footprints in study area (Xinjiang)</td>
<td>TSM glaciers</td>
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<td>232,369</td>
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<td>922</td>
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<td>Duration (days)</td>
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<td>579</td>
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According to Figure 8.9, ICESat measurement reveal drastic surface lowering (-0.68±0.27 m/a) over the glaciers in the TSM, and slight elevation increase (+0.18±0.13 m/a) over the KLM region, during 2003 and 2009. In general, there is a very good agreement between the curve of glacier elevation change and terrestrial water storage anomaly. Close correlation is found associating the elevation change and TWS anomaly in TSM (correlation coefficients +0.66). Striking warming trend (over 0.40°C per decade) in the TSM over 2003-2015 was especially unfavorable for the maintenance of glacier mass, which explained the severe glacier shrinkage as measured by ICESat. In TSM, the ICESat-SRTM elevation difference started further increase since early 2007, indicating an accelerating glacier melt. The deteriorating situation of glacier shrinkage under warming temperature, as evidenced by substantial TWS lost in
TSM, highlights the negative effects of climate change on vulnerable ecology in arid region.

Figure 8.10 Time series of glacier elevation change by ICESat by different seasons and TWS anomaly during 2003-2009 in TSM

To further characterize the seasonal contribution of glacier shrinkage to overall TWS loss in TSM, the ICESat observation time series data are fitted according to different seasons. As shown in Figure 8.10, general decrease trends of glacier elevation can be observed in spring and fall seasons, which have also shown co-occurrence relationship with TWS anomaly during 2003-2009. The change trend is -0.71m/a in spring and -0.65m/a in fall. It should be noted that there are only three samples of summer for analysis, which precludes our analysis for the pattern in summer. The observations revealed that the impact of recent climate change is most severe in TSM sub-region. While the ICESat data is not yet available for years after 2009, we may assume that the glacier shrinkage
phenomenon has been further deteriorating by increasing warming rate of temperature.
Figure 8.11 Trends of elevation change in TSM and KLM
As individual ICESat track do not repeat exactly and could not be directly compared, on-glacier footprints data within a specific 1-degree grid are grouped and averaged for calculation. Figure 8.11 demonstrates the trends of elevation difference at 1-degree gridded scale in TSM and KLM. White polygons correspond to the glacier outlines according to GLIMS Glacier Database. For glaciers in each grid, blue color arrows stand for increasing trend, while red color arrows stand for decreasing trend. The size of the arrow denotes the trend of elevation difference. Grids with less than 150 ICESat footprint or insignificant trends ($p<0.05$) are excluded in this analysis.

The TSM sub-region has most developed glaciers. The number, area and volume of glaciers in middle TSM region account for 41.9%, 59.3% and 74.9%, respectively, of all glaciers in TSM region (Chen et al. 2016b). According to Figure 8.11, most glaciers in TSM showed decreasing trends of surface elevation, except some in the southwest. The decrease trend was particularly obvious in the east TSM, where more significant temperature increase was reported. As shown in Figure 8.1, temperature in TSM, especially in the east, has experienced a rapid increase. Stronger evapotranspiration caused by rapid increase of temperature may overwhelm the effect of precipitation fluctuation. In west TSM, despite the fact that the elevation decrease was not as dramatic as it was in the east, the large extent of glacier distribution led to a severe net loss of water storage (over -7mm/a). Therefore, the pattern of glacier elevation change seems to be corresponding well with the TWS inter-annual change.
These results are in broad agreement with many glacier mass retreat monitoring and investigation in the study area. It is reported that there was negative glacier mass balance in Tianshan Mountains from 2003 to 2009, with a retreat rate of $-6.6\pm4$ Gt/a (Farinotti et al. 2015), partly due to remarkable rising trend of the summer $0^\circ$C level height (FLH) on the northern slopes of TSM (Chen et al. 2016c). Observation site data also indicated that more than 80% of the mountainous glaciers in western China are currently in a state of retreat, with those in east TSM region among the most rapid (Piao et al. 2010).

Water from melted glaciers may recharge soil water and groundwater, or be transferred to other places through runoff and evaporation, causing reduced mass around the glacier region (Zhang et al. 2016). It was calculated that as temperature increased, glaciers melting accelerated and the meltwater runoff has increased to over $200 \times 10^8$ m$^3$, accounting for more than 25% of the quantity of surface water $789 \times 10^8$ m$^3$ in Xinjiang (Li et al. 2014b). Similar conclusions were explicitly drawn in TSM by Zhang et al. (2016) as well, who suggested that the annual runoff from glacial melt in the TSM increased 84% from 1958–1985 to 1985–2001. It also appeared that river basins with a higher fraction of glacierized area mainly showed increasing runoff trends, while those with less or no glacierization exhibited larger variations in the observed runoff (Jiao et al. 2015; Chen et al. 2016b).

While the deteriorating situation of glacier retreat under warming temperature in the study area is commonly acknowledged among many studies,
opposite pattern was identified in KLM in the most recent decade, which have resulted in a heterogeneous TWS inter-annual change pattern. According to Figure 8.11, most of the glaciers in KLM has experienced certain elevation increased during 2003-2009, with a mean increase rate of +0.33m/a. In the western KLM, also known as Karakoram region, glaciers have exhibited mass stability or even expansion at a rate of +0.45m/a. Similarly, the pattern of glacier elevation increase in KLM corresponds to the pattern of TWS change as well.

It was suggested that the summer 0°C level height in the northern slope of the KLM has been decreasing with the speed of 2.33m/a in recent years (Chen et al. 2016c), leading to weakening glacial melt and increasing TWS. There has also been a slight increase of precipitation. It was pointed out in an earlier study that glaciers in KLM have generally retreated during the past four decades (Ding et al. 2006). However, our results disagree with this and suggest that the glaciers in KLM may generally remain stable after 2003. In addition, there has been an obvious increase of TWS in east KLM, known as the Qaidam Basin, which is partly due to the degradation of permafrost.

Glaciers are one of the most important freshwater resource in northwest China, where many large river systems have their sources in glacierized regions (Ding et al. 2006). Our study confirms that glacial melting in the Tianshan Mountains is among the most rapid in northwest arid zone of China due to climate warming. However, the spatial distribution of elevation changes is far from homogeneous in TSM and KLM. With the threat of climate change intensifying,
greater uncertainty regarding the fluctuation of mountain glaciers are expected, which may eventually affect the distribution of terrestrial water storage.

### 8.3 Summary

Heterogeneous responses of hydrological cycle to dissimilar patterns of recent climatic change, as reflected by the intra-annual terrestrial water storage, are discovered and analysed in the study area. These phenomena are primarily evidenced by the glacier mass variation during 2003-2012.

Our study results reveal that terrestrial water storage is sensitive to regional climate change. Significant glacier retreat driven by drastic recent temperature increase in Tianshan Mountains sub-region contribute to the severe TWS loss, while moderate TWS gain in Kunlun Mountains is also facilitated by the expansion of glacier volume.
Chapter 9  Discussion

This chapter discusses and provides further interpretation for the major findings in the study. Results are also compared with other similar studies. Several key issues and limitations related to the overall study outcome are stated as well.

9.1 Comparison with other studies

This study has revealed a severe TWS in Xinjiang, particularly in TSM sub-region. The TWS lost pattern according to the study result generally agree with various similar studies (Yang and Chen 2015; Yang et al. 2015). The results also indicate that intra-annual TWS change can be mainly attributed to intra-annual snow accumulation and ablation, while inter-annual is primarily associated to glacier retreat. Different from the similar studies in the past, this study attempts to identify the attribution of severe inter-annual TWS loss not only by recent temperature change data, but also the glacier mass variation measured by ICESat laser altimetry. This study, as a further step, performed sub-regional level re-analyses for the TWS spatial-temporal pattern. The comparison among sub-regions revealed that there has been distinctive regional difference in terms of the TWS trend in Xinjiang. On the other hand, despite different trends of TWS were identified in different sub-regions, the result confirms that the TWS pattern was
highly responsive to recent climate change, as evidenced by the heterogeneous ICESat-derived glacier mass variation pattern exhibited in Tianshan Mountains and Kunlun Mountains.

The major findings presented in this thesis regarding the glacier mass variations are collaborated by many other literatures from various aspects. As suggested by Shi et al. (2007), the north Xinjiang (TSM, JGB and ATM) has experienced notable climate change while the south part of Xinjiang (KLM and south part of TRB) has experienced slight change, which is coincide with our modelling result of intra-annual TWS. Similar studies conducted by Yang and Chen (2015), Xu (2017), Chen et al. (2017), Cao et al. (2015), Deng and Chen (2016) and Chen et al. (2016c) unequivocally confirmed the drastic TWS loss occurred in TSM sub-region.

Similar conclusions were drawn in recent investigations for specific glaciated river basin and peak. For example, between 1989 and 2012, the area of a glacier in the Karatal river basin in the western Tianshan Mountains shrank from 142.8 km$^2$ to 109.3 km$^2$, with a mean annual retreat rate of 1.02%, which was much higher than other areas of the Tianshan Mountains (Kaldybayev et al. 2016). The north TSM and Bogda Peak in the eastern part of the Tianshan Mountains exhibited accelerated glacier retreat rates of -13.8% and -7.45%, respectively (Chen et al. 2016b). Increasing glacier degradation rates were found for more recent decade compared to the mid-20th century.
On the other hand, it is concluded the cryosphere also exhibited response to recent climate change in KLM, which have led to an increase of TWS. As observed by the ICESat altimetry, the glacier mass in KLM have generally remained stable during the past decade, with considerable increase in some area. Similar conclusions were also reported in recent investigations for specific glaciated regions. Neckel et al. (2014) specified that the western KLM are characterized by a heterogeneous behaviour of glacier elevation changes, with a significant surface lowering in the accumulation areas of some glaciers, and a simultaneous elevation increase in ablation areas, indicating the occurrence of glacier surges in this sub-region. There are several studies trying to relate the recent glacier surges in KLM to atmospheric interactions. Researches have indicated that the seasonal cycle in Karakorum (along with adjacent glaciers), situated at west Kunlun Mountains, is dominated by non-monsoonal winter precipitation, which uniquely protects it from reductions in annual snowfall under climate warming over the twenty-first century (Gardelle et al. 2012; Kapnick et al. 2014). Yao et al. (2012) also reported that due to different atmospheric circulations, there was a positive mass balance increase in the Muztag Ata Glacier (38°14’N, 75°03’ E) in the western Kunlun Mountains at an average of +250mm/a during 2002–2010, which consequently also contributed to an increase in TWS in the southern TRB.

As concluded by Shi et al. (2007), essential indicators of climate change in northwest China may include: increasing air temperature, increase of precipitation, melting of glaciers and increase of glacial melt water, increase of river runoff,
water level rise, area expansion of the inland lakes, increasing frequency of flood disasters, increase of vegetation cover, reduction of sand-dust storm days. This study suggests that TWS can be an effective indicator of recent climate change as well.

To sum up, this study has extended the current understanding of spatio-temporal variation of TWS change on sub-region level in northwest arid zone of China, and the interactions between climate change, snow/ice variation, and corresponding TWS changes.

9.2 Additional factors influencing TWS changes

Irrigation is another important process in Xinjiang that may reduce the TWS by groundwater pumping and evapotranspiration (Zhang et al. 2016). The region of highest TWS deficit spatially corresponds to the region with highest population density, which implies heavier groundwater exploitation and land use expansion. However, these factors are a minor effect compared to glacier retreat as it occurs in relatively small area.

Similarly in Tarim Basin, Zhang et al. (2015) suggested that increasing population and arable land increased the exploitation of water resources and shrinking water supplies, which have intensified the drought vulnerability. The changes of TWS in TRB might be linked to excessive exploitation of water resources, increased population, and shrinking water supplies, which would have impact on the water level of the lakes or reservoir (Yang et al. 2017).
In east KLM region where permafrost persists, significant TWS increase was observed during 2003-2015. Increasing temperature not only accelerates the melting of glaciers and perennial snow cover, but also triggers permafrost degradation (Jiao et al. 2015). The increase and thickening of the active layer of permafrost could lead to more infiltration of surface water into the groundwater, which result in increasing water storage and changes in the regional water balance (Xu 2017).

9.3 Data uncertainty

The accuracy of GRACE-derived TWS determined the quality and liability of the study result. While the GRACE data has been well validated against in situ, modelled and remotely sensed data, the errors in GRACE data can be induced by measurement and leakage errors. In this study, the average uncertainty value of monthly TWS anomaly is approximately ±0.69cm.

Despite that the accuracy of the GRACE-retrieved TWS has been verified in different basins around the world, it remains difficult to validate due to its integrative nature, and can only be approximated from other datasets. To validate the GRACE estimations, many studies have used the GLDAS land surface model data to indirectly validate the GRACE estimations in the study area, and have generally found a very high agreement level. The reliability of GRACE and GLDAS to reveal large scale TWS change have been demonstrated in several regions where intense surface water, soil moisture and groundwater measurements exist (Yang et al. 2015; Soni and Syed 2015). In general, GRACE-derived storage
changes are in good agreement with those obtained from land surface model (LSM) simulations (Güntner 2008; Syed et al. 2009; Singh et al. 2017) and in situ observations (Swenson and Wahr 2006; Yeh et al. 2006; Rodell et al. 2007). Variability in the outputs of different products can provide an estimate of the uncertainties in the magnitudes of TWS trends (Scanlon et al. 2015). However, Eicker et al. (2016) recently reported that global reanalyses data (ERA-Interim and MERRA-Land) perform well at reproducing short-term GRACE TWSA rates beyond the annual and semi-annual signals, yet distinctive disagreements are found with the corresponding GRACE flux trends.

Despite remarkably high agreement with GLDAS (Global Land Data Assimilation System) terrestrial hydrological assimilation data, challenges remain to understand the uncertainty of TWS due to the lack of ground observation data. Nevertheless, the coherence among different GLDAS simulations and various GRACE products in the study area makes the analytical results more acceptable in relative and comparative measures (Yang et al. 2015).

In addition, since no published error estimates for the monthly 1°×1° GLDAS Noah model datasets were available, as well as no other models in this resolution for comparison (Famiglietti et al. 2011; Liesch and Ohmer 2016), uncertainties of data utilized in this study from the land surface model has not yet been examined. While GLDAS-derived TWS has widely been used to evaluate the performance of different GRACE products and processing methods, or use a priori information to correct the leakage errors, GRACE data has recently been
used to benchmark the accuracy of hydrological model simulations (Felfelani et al. 2017).

To provide glacier elevation change estimation in Xinjiang, geodetics (altimetry) method are utilized. The major limitation of ICESat for detecting mountain glacier changes lies in the relatively sparse sampling over the glacier surface and therefore sufficient number of repeated measurements are demanded for robust statistical analysis. This approach also relies on the assumption that a change of elevation over time can be regarded as a change in mass (Bamber and Rivera 2007), given that (1) there is no change in elevation of the bedrock due to tectonic activity or post glacial rebound; and (2) the density of the ice mass has not changed. As it is believed that the magnitudes of these changes are much smaller than the glacier itself, the measurements of these uncertainties are not discussed in detail for this study. Future glacier surface elevation measurements can be extended from the new satellite altimetry missions such as the ICESat-2 and the CryoSat-2 mission.

9.4 Other limitations

As the hydrology system in the study area involves a large number of transboundary watersheds, the runoff/discharge data with sufficient observation accuracy and consistency are limited and sometimes unavailable for scientific purpose. Therefore, river runoff/discharge data are not yet utilized in this study which may potentially hinder a straightforward interpretation of hydrological
cycles. However, it is indicated that the amount of water stored in rivers is rather tiny compared to other reserves at any time (Oki and Kim 2017).

Partitioning of these TWS values into individual or smaller storage components would enhance the potential of GRACE applications (Andrew et al. 2017). In this study, however, due to the lack of in situ measurement or modeled data of several key hydrological variable (e.g. river discharge), the decomposition of TWS variability was not included in the research scope.

In addition, even though the data currently available is relatively short and in lower resolution, GRACE has provided new source of information that would lead to better approximation of long-term water cycle evolution (Eicker et al. 2016). With the launch of GRACE follow-on mission (in 2017), the earth’s mass variation would able to be captured at an up to five times higher spatial resolution than it is in the currently available products.
Chapter 10 Conclusion

This chapter concludes the entire thesis by summarizing the research findings and spelling out the major contribution of knowledge. Potential areas of research are also suggested.

10.1 Summary of research

This thesis has demonstrated the use of remote sensing techniques for regional hydrological investigations, and analyzed the variability of terrestrial water storage (TWS) change over northwest arid zone of China in response of recent climate change. By combining with observations made by various remote sensing such as GRACE satellites and ICESat laser altimetry, as well as GLDAS Noah land surface model and ground data products, the spatial-temporal variation of TWS and its driving factors are examined. The analyses results indicate that:

(1) The intra-annual TWS change in all sub-regions presents a similar half-year cyclic pattern, which the peaks normally occur around spring and the valleys normally occurs around fall. This change is primarily controlled by the intra-annual snow accumulation and melt. In each cycle, the TWS normally starts to increase since October as snow accumulates and it starts to decrease since April as snow melts. The
Altay Mountains (ATM) exhibits the largest amplitude due to largest amount of annual snowfall it receives. This intra-annual change can be well explained by month-over-month (MoM) temperature change as temperature increases most rapidly in spring, which causes snowmelt.

(2) Besides a pronounced annual cycle, the GRACE signal also indicates significantly decreasing TWS in most sub-regions. During 2003-2015, TWS have been decreasing at a rate of -3.41mm, -5.82mm, -6.76mm, and -2.59mm of equivalent water height (EWH) annually in ATM, JGB, TSM and TRB sub-regions, respectively, which are equivalent to a water storage net loss of around -5.56×10⁸, -10.48×10⁸, -20.52×10⁸, -16.47×10⁸ m³/year, respectively. However, TWS has increased by 3.05mm of EWH annually in KLM, which equivalents to a water storage net increase of 11.16×10⁸ m³/year. Among two mountainous sub-regions with extensive glacier distribution (i.e. Tianshan Mountains and Kunlun Mountains): (a) TWS has decreased in Tianshan Mountains rapidly while the summer temperature increased dramatically; (b) TWS has decreased more rapidly in high elevation area, where water is stored as glacier format. This trend is evidenced by the ICESat laser altimetry quantifying the glacier elevation change. Correlation analyses results suggest that the spatiotemporal evolution of TWS is tightly related to temperature change, which have triggered mass variation in cryosphere in the study area. These patterns suggest that the decline of TWS in Tianshan Mountains can mainly be attributed to glacier retreat.
Nevertheless, TWS in Kunlun Mountains has been increasing along with the decrease temperature.

TWS is a key state variable for land surface-atmosphere interaction, and heterogeneous climate variability, in turn, is an important factor affecting TWS regional difference. This study has clearly revealed the heterogeneous TWS inter-annual change pattern in Tianshan Mountains and Kunlun Mountains. The substantial TWS lost in Tianshan Mountains during last decade, as evidenced by deteriorating situation glacier elevation decrease in response of recent climate change, highlights the negative effects of climate change on vulnerable ecology in the region. It can be concluded that TWS change is a key state variable in the regional water cycle modelling, and it is highly responsive to regional climate change in Xinjiang. Such a huge decrease in TWS will have profound impacts both locally and globally.

Remote sensing techniques have greatly improved our ability for earth environmental change observation. The invent of GRACE offers an alternative and independent pathway to examine the hydrological cycle as a complement to in situ hydro-meteorological observations, and therefore has provided a valuable tool for the comprehensive observation of hydrological variation at regional or continental scale under global change scenario.
10.2 Major contribution of knowledge

First, in light of the significant regional difference in northwest arid zone of China, this study has improved the current understanding by characterizing the sub-regional level TWS change and heterogeneous trends are identified despite of the geographical proximity. On the other hand, as the distinguish geographical and hydrological characteristics in arid region, this study also contributes to the existing literatures that mostly focus in humid regions gloabally.

Second, this study concludes that the terrestrial water storage, in terms of form and amount, is closely associated with snow melt processes and glacier mass variation in arid zone of China, rather than precipitation. Based on the spatial-temporal pattern of TWS and laser altimetry observation, the co-occurrence relationships with sub-regional glacier mass variation were examined. It is to be hoped to contribute to literature of the hydrological response mechanism to climate change.

Finally, this study confirms that TWS can be a key diagnostic criterion of climate change effect in northwest arid zone of China. Investigating the variability of TWS in the vulnerable ecosystem of northwest China will be of practical merit for effective adaption to the consequences of future climate change.. Consistency between hydrological variation and climatic change, in terms of space and time among indicator variables would greatly strengthen our confidence in projections of the potential consequences of water resources that could be caused by future climate change.
10.3 Recommendation and future work

The long-term change of TWS will have profound impacts both locally and globally. The time availability of GRACE data (only after 2002) limits its applicability for investigating the temporal characteristics of water storage variation over a long period. With longer time series observations from GRACE are made available, better interpretation of mass variation and further elaboration for various hydrological objectives can be achieved.

On the other hand, with the advancement of earth observation techniques and the enhancing ground surface monitoring network, the improving completeness and accuracy of hydrological variable data would further enable vertical disaggregation of the TWS signal, to understand the dynamics of individual hydrological components (e.g. groundwater).

Monitoring the TWS could be a feasible complementary approach to understand current and project future climate change. It is necessary to conduct advanced planning for effective adaptation of the possible impacts of climate change, to ensure sustainable development and ecological safety in the northwest arid area (Chen et al. 2015b).
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Netherlands, Dordrecht, pp 359–404


Major Publications and Awards

Publication of the thesis author, Mr. HUANG Junyi:


Award received by the thesis author, Mr. HUANG Junyi:

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