July 2018

Theory and Application of Geophysical Geodesy for Studying Earth Surface Deformation

Makan A. Karegar

University of South Florida, makan.karegar@gmail.com

Follow this and additional works at: https://digitalcommons.usf.edu/etd

Part of the Climate Commons, Geology Commons, and the Geophysics and Seismology Commons

Scholar Commons Citation


This Dissertation is brought to you for free and open access by the USF Graduate Theses and Dissertations at Digital Commons @ University of South Florida. It has been accepted for inclusion in USF Tampa Graduate Theses and Dissertations by an authorized administrator of Digital Commons @ University of South Florida. For more information, please contact digitalcommons@usf.edu.
Theory and Application of Geophysical Geodesy for Studying Earth Surface Deformation

by

Makan A. Karegar

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
School of Geosciences
College of Arts and Sciences
University of South Florida

Major Professor: Timothy H. Dixon, Ph.D.
Rocco Malservisi, Ph.D.
Jürgen Kusche, Ph.D.
Don Chambers, Ph.D.

Date of Approval:
June 5, 2018

Keywords: GPS, GRACE, Subsidence, Nuisance Flooding, Surface Loading

Copyright © 2018, Makan A. Karegar
Dedication

I dedicate my dissertation to my parents and my family for their endless love,

encouragement and support.
**Acknowledgements**

This dissertation stands on the shoulders of many, and I have had the immense fortune to be supported by many wonderful people. Words here cannot appreciate you all enough, but know that any achievement herein is thanks to all of you.

My time working as a research assistant at The University of South Florida (USF) has taken me through many twists and turns, ups and downs but through it all from the beginning, Tim Dixon has not been just academic advisor to me but has been advisor for all kinds of issues I have faced. His continuous encouragement, patience and guidance have shaped my research and helped me overcome hurdles one after the other. Tim has been unwavering in his optimism and support, always willing to give me absolute freedom to explore new ideas and pave my own path, yet diligent in his guidance. His professionalism and character will no doubt have a significantly beneficial impact on my future career.

I owe a debt of thanks to Jürgen Kusche, for allowing me to come to Germany to work on my research topics with him at the Institute of Geodesy and Geoinformation (IGG), University of Bonn. Throughout my years in Germany, Jürgen provided me with
the unlimited opportunities and support to complete my PhD program. I would like to thank my co-advisor Rocco Malservisi, who always made himself available whenever I needed his inputs and advice – always with a smile. I had the privilege of working with Simon Engelhart of University of Rhode Island over the last three years. I am thankful to him for bringing his invaluable insights into geological data sets. We worked together closely on idea of comparing GPS and geologic rates, although we had not meet each other until a few weeks before my defense. I am also grateful to Don Chambers for being on my dissertation committee and for chairing my defense.

None of the work described here would have been possible without the enormous efforts put in by Mandy Stuck, the Academic Services Administrator of School of Geosciences at USF. She devoted vast amounts of time and energy to advancing my PhD study.

For their invaluable support, professionalism and kindness, I would like to thank Mark Rains, Chair of the School of Geosciences; Jessica Wilson, Academic Program Specialist; Marcia Taylor, Director of USF International Services. I would also like to thank the rest of the academic administration team of the USF for all their help. I would like to give a special note of thanks to Catharina van Eckeren, Office Manager of APMG group (IGG) at University of Bonn, for her prompt and cheerful help every time I had to get administrative works done in Bonn.
I would also like to thank my fellow labmates and friends Denis Voytenko, Nick Voss, Alex Farrell, Surui Xie, Christine Downs, Anita Marshall, Nima Ekhtari, Javad Khazaei, Zohreh Nemati, Iman Nekooeimehr, Sina Izadi at USF (Tampa), and my colleagues at IGG (Bonn), Wolf-Dieter Schuh, Roelof Rietbroek, Jan Martin Brockmann, Anne Springer, Bernd Uebbing, Christina Lück and Michael Schindelegger for many wonderful moments and conversations I have had with them over the past few years. Thank you Mehdi Nikkhoo for your willingness to always support a good cause, and for being a knowledgeable friend I could always rely on.

My parents’ sacrifices, love and complete trust got me to where I am today. I owe them more than I will ever be able to put down in words. I am also privileged and grateful to have two brothers (Salar and Pejman) and sister (Baharak) who never stopped encouraging me.

I also acknowledge the financial support from NASA Fellowship Earth Surface Interior Program grant no. NNX14AQ16G.
Table of contents

List of Tables

List of Figures

Abstract

1. Introduction
   1.1 Research overview
   1.3 Using GPS for monitoring surface deformation associated with CO₂ injection
   1.4 A three-dimensional surface velocity field for the Mississippi Delta
   1.5 Subsidence along the Atlantic Coast of North America
   1.6 Nuisance flooding: the importance of present-day land motion
   1.7 A new hybrid method for estimating hydrologically-induced vertical deformation
   1.8 References

2. GPS-based Monitoring of Surface Deformation Associated with CO₂ Injection at an Enhanced Oil Recovery Site
   2.1 Abstract
   2.2 Introduction
   2.3 Site characteristics
   2.4 Data collection
   2.5 Data analysis
   2.6 Results
### 2.6. Surface deformation
- 2.6.1 Surface deformation 29
- 2.6.2 Model description 35
- 2.6.3 Model solution 38

### 2.7 Discussion 42

### 2.8 Conclusions 47

### 2.9 References 48

### 3. A Three-dimensional Surface Velocity Field for the Mississippi Delta: Implications for Coastal Restoration and Flood Potential 52
- 3.1 Abstract 52
- 3.2 Introduction 53
- 3.3 GPS data and analysis 55
- 3.4 Tide gauge data and analysis 56
- 3.5 Results 58
- 3.6 Discussion 61
- 3.7 Implications for coastal restoration 65
- 3.8 References 67

### 4. Subsidence Along the Atlantic Coast of North America: Insights from GPS and Late Holocene Relative Sea-level Data 70
- 4.1 Abstract 70
- 4.2 Introduction 71
- 4.3 Data and analysis methods 73
  - 4.3.1 GPS 73
  - 4.3.2 Late Holocene relative sea-level database 74
- 4.4 Results 76
- 4.5 Discussion 79
  - 4.5.1 Effects of groundwater withdrawal 82
- 4.6 Conclusions 87
- 4.7 Acknowledgments 88
- 4.8 References 89
5. Nuisance Flooding and Relative Sea-Level Rise: the Importance of Present-day Land Motion

5.1 Abstract
5.2 Introduction
5.3 Data sets and observations
5.4 Methods
5.4.1 Analysis of GRACE data
5.4.2 Modeling the far field effects of water loading from the James Bay Project
5.5 Discussion and conclusions
5.6 Data availability
5.7 References


6.1 Abstract
6.2 Introduction
6.3 A new hybrid method for a spherical non-rotating elastic layered model
6.3.1 Contribution of the computation point and near field from the Green’s function
6.3.2 Contribution of the far field from the spherical harmonic approach
6.4 Study area
6.5 Data processing
6.5.1 GRACE data
6.5.2 Hydrological and land surface models
6.5.3 GPS data
6.6 Evaluation of modeled deformations
6.6.1 Omitting GPS sites responding to non-loading changes
6.6.2 Validating the hybrid approach 151
6.6.3 Modeling the vertical deformation at the GPS sites 154
6.7 Results and discussion 155
  6.7.1 Comparison of the three approaches 155
  6.7.2 Radius of the near field in the hybrid approach at individual GPS sites 158
  6.7.3 Comparison of the hybrid approach with the GRACE-only spherical harmonic approach at individual GPS sites 161
  6.7.4 Contribution of hydrologic loading to the GPS height time series 162
  6.7.5 Sensitivity to different filter intensities in GRACE data 164
6.8 Potential for broader applications 166
6.9 Summary and conclusions 168
6.10 Acknowledgements 169
6.11 References 170

7. Conclusion 179

Appendix A: Supplementary information for Chapter 3 183
Appendix B: Supplementary information for Chapter 4 198
Appendix C: Supplementary information for Chapter 5 209
Appendix D: Supplementary information for Chapter 6 221
Appendix E: References 231
Appendix F: Copyright licenses of previously published works 236
List of tables

Table 2.1 GPS displacements and RMS misfits of the linear fit 34
Table 2.2 Adjustable and fixed parameters in the penny model 37
Table 2.3 Best-fit values and uncertainties for adjustable parameters 41
Table 3.1 Comparison of subsidence rate at tide guages from linear reg and HHT 61
Table A1 GPS site locations, velocities and their uncertainties. 187
Table A2 Average RSLR rates and accelerations from HHT 196
Table A3 GPS site locations, vertical velocities, uncertainties and time series length 208
Table A4 Late Holocene RSLR rates and GPS vertical rates 208
Table A5 Statistics of GRACE TWS trends based on three GRACE solutions 218
Table A6 Characteristics of lakes and annual rate of water-level change 219
List of figures

Figure 1.1  The spatial distribution of permanent GPS stations around the globe 3
Figure 1.2  Histogram showing cumulative number of permanent GPS stations 4
Figure 1.3  Locations of GPS sites in the US and dominant geophysical processes 5
Figure 1.4  Changes in TWS from the GRACE and a test GPS height time series 8
Figure 2.1  Map of the EOR site in southern Texas 19
Figure 2.2  Continuous GPS station TEST-3 at the EOR test site in south Texas 20
Figure 2.3  Pressure changes in northern fault block during the CO2 injection period 21
Figure 2.4  Changes in TWS from the GRACE and TEST-1 GPS time series 23
Figure 2.5  Map of regional GPS stations used in our analysis 25
Figure 2.6  Histogram showing GPS stations with correlation greater than 0.4 26
Figure 2.7  Percentage of PC eigenvalues for the three coordinate components 30
Figure 2.8  Comparison unfiltered and filtered GPS time series 31
Figure 2.9  Filtered GPS time series 33
Figure 2.10 Horizontal displacement vectors of GPS stations and TEST stations 35
Figure 2.11 Cartoon of penny-shaped crack 36
Figure 2.12 Contoured values of chi-square misfit 40
| Figure 2.13 | Predicted and observed GPS displacements | 41 |
| Figure 2.14 | Map of depth of Upper Frio formation as inferred from seismic data | 44 |
| Figure 2.15 | Predicted vertical and radial displacements | 45 |
| Figure 2.16 | Predicted pressure for the first year of GPS observations | 46 |
| Figure 3.1 | Locations of GPS sites and growth fault system in southern Louisiana | 59 |
| Figure 3.2 | Vertical velocities and their standard errors versus latitude | 63 |
| Figure 3.3 | Tide gauge data at Grand Isle referenced to Pensacola | 65 |
| Figure 4.1 | Location of GPS sites and late Holocene RSLR rate data | 77 |
| Figure 4.2 | Vertical motion as a function of latitude from GPS and geologic data | 79 |
| Figure 4.3 | Average trend in groundwater level since 2005 | 84 |
| Figure 4.4 | Vertical motion in south of Chesapeake Bay from GPS stations | 86 |
| Figure 5.1 | Vertical land motion from GPS and geologic data versus latitude | 98 |
| Figure 5.2 | Nuisance flooding level, GPS rate and geological rate versus latitude | 99 |
| Figure 5.3 | Scatter plot of GPS vertical rate compared to nuisance flooding level | 108 |
| Figure 5.4 | Nuisance flooding frequency, rate of RSLR and vertical rate from GPS | 109 |
| Figure 5.5 | GRACE TWS and finite element model prediction | 114 |
| Figure 6.1: | Sketch showing the computation point, near field and far field | 139 |
| Figure 6.2: | RMS scatters of detrended TWS from GRACE, WGHM and |
Figure 6.3: Relationships between loading and foundation depth of GPS sites

Figure 6.4: Mean RMS reduction as a function of spherical cap $\psi$

Figure 6.5: Mean RMS reduction as a function of spherical cap $\psi$

Figure 6.6: Spherical cap size ($\psi_0$) for the maximum RMS reduction

Figure 6.7: Comparison of RMS reduction in GPS time series

Figure 6.8: Comparison of hybrid approach for filter intensities of GRACE

Figure A1: GPS vertical position time series at Cocodrie in south Louisiana

Figure A2: Locations of tide gauges used in this study

Figure A3: Oscillations modes obtained from HHT analysis of tide gauge data

Figure A4: Tide gauge time series for the study area

Figure A5: RSLR with linear and nonlinear trends obtained HHT analysis

Figure A6: Long-term RSL trend obtained from the residual of the HHT analysis

Figure A7: Sea-level trends for Pensacola and Key West

Figure A8: Geoid-height rates predicted from GIA model

Figure A9: Long-term changes in TWS from GRACE

Figure A10: Vertical land motion from GPS and geologic

Figure A11: Map of population density compared to recent subsidence rate

Figure A12: GPS sites superimposed on a map of coastal plain sediment thickness
Figure A13  Locations of GPS sites and geologic rate data  

Figure A14  Comparison of GPS rates, geologic data and GIA model ICE6G-VM5a  

Figure A15  Nuisance flood level as standardized by tidal range versus latitude  

Figure A16  GIA-corrected GPS rate and trend in groundwater-level changes  

Figure A17  Map of Lake-Dam system in Quebec, Canada  

Figure A18  Water-level change from satellite altimetry measurements  

Figure A19  Comparison of trend in TWS from three GRACE solutions  

Figure A20  Sum of groundwater and soil moisture storage trend from WGHM  

Figure A21  RMS scatters of non-tidal ocean loading in CF frame  

Figure A22  Map showing Yellowstone volcanic system and GPS sites  

Figure A23  Locations of GPS sites affected by poroelastic deformation  

Figure A24  Degree variance of TWS from GRACE, WGHM and NLDAS  

Figure A25  RMS scatters of TWS derived different filter intensities of GRACE  

Figure A26  RMS scatters of detrended GPS height time series  

Figure A27  Locations and RMS scatters of GPS stations  

Figure A28  Comparison of RMS reduction in GPS monthly height time series
Abstract

An interdisciplinary approach at the interface between geodesy and geophysics has recently resolved several Earth science problems at regional and global scales. I use the term “geophysical geodesy” to distinguish the technical and theoretical aspect of geodesy from geophysical applications of geodetic techniques. Using a wide range of Earth observation data, I study the spatio-temporal characteristics of Earth surface deformation in the United States associated with several geophysical processes, including natural and anthropogenic subsidence and uplift, regional relative sea-level rise, and continental hydrological loading. The theoretical portion of this dissertation applies loading theory and develops a new hybrid method to improve the estimate of hydrologically-induced vertical deformation at time scales from sub-annual to multi-annual. The application part of this dissertation benefits from GPS and other geodetic and geologic data sets to study and model Earth’s surface uplift due to CO₂ injection at an oil reservoir in coastal Texas, and coastal subsidence and nuisance flooding along the Mississippi River Delta and eastern seaboard of the United States.
1. Introduction

Geodesy is a branch of science that benefits from applied mathematics to study the Earth's gravitational field, including both the dynamic and static fields, and the position and displacement of points on the Earth's surface. The motions can be secular (e.g., plate motion), or periodic, with periods between a few seconds and a few centuries or even longer. Theoretical and technical developments in geodetic science in the 20th and early 21st centuries largely based on the advent of satellite observations have provided highly precise geodetic data that is useful for a variety of Earth Science studies. These advances have greatly expanded the range of geophysical applications of geodesy. An interdisciplinary approach at the interface between geodesy and geophysics has allowed numerous problems in the Earth sciences at regional and global scales to be addressed. I use the term “geophysical geodesy” to distinguish the theoretical science underlying geodesy from the geophysical applications. Such a distinction enables us to include a large number of interdisciplinary applications in geophysics. One of these applications is the use of satellite geodetic observations for studying surface and near-surface processes that cause measurable surface deformation.
In this perspective, Global Position System (GPS) plays an important role by providing increasingly long time series of precise three-dimensional position changes at an increasing number of regional and global permanent stations. Figure 1.1 shows the present spatial distribution of approximately 14,500 permanent GPS stations that is publicly available to the scientific community\(^1\). GPS data at these sites provide good coverage over most of the Europe, Japan and the United States. The availability of continuous GPS observations at an increasing number of regional and global permanent stations (Figure 1.2), improved processing and analysis techniques, longer time spans of data, and better realization of reference frames, provide a means to better study Earth surface deformation.

This dissertation uses a wide range of data to explore the Earth surface deformation in the United States at different time and space scales. The theoretical portion of this dissertation investigates loading deformation and develops a new hybrid method to improve the estimate of hydrological-induced vertical deformation at time scales from sub-annual to multi-annual. The proposed hybrid method provides a mathematical basis for combining global and regional loading data with different spatial resolutions. Our method can be applied to a wide variety of environmental surface loading problems including loading from hydrology, ocean, atmosphere and Greenland and Antarctica ice sheets.

\(^1\) The position time series are available from the Nevada Geodetic Laboratory at http://geodesy.unr.edu/
The application part of this dissertation benefits from GPS and many other geodetic and geologic data sets to study two coastal areas experiencing high rates of coastal subsidence and sea-level rise. The Mississippi Delta and the eastern seaboard of the United States are two impacted regions where several geophysical processes including sediment compaction and loading, Glacial Isostatic Adjustment (GIA), fluid withdrawal and nuisance flooding contribute to relative sea-level rise. In another chapter, I also show that precise GPS measurements can be used to model deformation associated with CO₂ injection and storage at an oil reservoir at depth in coastal Texas. This work is one of the earliest studies applying GPS for monitoring fluid movement within oil reservoirs, and should have future application for monitoring, verification and accounting (MVA) activities if and when Carbon Capture and Storage (CCS) comes into widespread use as a way of reducing CO₂ emissions to the atmosphere.

Figure 1.1: The spatial distribution of permanent GPS stations around the globe.
Figure 1.2: Histogram showing cumulative number of permanent GPS stations as a function of time around the globe (yellow), in the United States (red) and in the central United States (green) including the Mississippi River basin and Texas.

1.1 Research overview

Figure 1.3 shows the main geophysical processes in the United States that cause significant surface deformation. At the continental scale, the dominant deformations are associated with Glacial Isostatic Adjustment (GIA), a viscoelastic response of the Earth’s crust and mantle to retreat of the Laurentide Ice Sheet since the last glacial maximum ~20,000 years ago (e.g., Peltier, 2004). At smaller scales, the dominant deformations are the earthquake and volcanic displacement fields, and subsidence and uplift due to drought and associated water extraction. Other deformation processes have smaller spatial scales but are not necessarily small in amplitude. For example, GPS and InSAR measurements show large ground deformation associated with fluid injection and production at enhanced oil recovery (EOR) fields.
Figure 1.3: Map showing locations of permanent GPS sites (green and red triangles) in the United States and dominant geophysical processes leading to measurable Earth surface deformation. CCS stands for Carbon Capture and Storage and HPA stands for High Plain Aquifer. The white line indicate boundary of river sub-basins in the Central United States. The green triangles are GPS stations inside the Mississippi River basin and Texas. The focus of this dissertation will be on the land surface motion in the Mississippi Delta, subsidence and nuisance flooding along the Atlantic Coast of North America, uplift due to carbon sequestration and storage in the Coastal Texas and hydrological-induced vertical deformation in the Central United States.

Installation and operation of more than 1,000 continuous GPS stations in central and eastern seaboard of United States since 2007 represents a significant improvement in our ability to precisely define the land motions in these regions, improving our ability to better understand the seasonal and long-term deformation pattern associated with different geophysical processes. This dissertation benefits from a wide range of data sets including GPS, satellite gravimetry, hydrological models, tide-gauge records and late-Holocene rate of relative sea-level rise (RSLR) to study local and regional surface deformation. The research includes observing and modeling ground surface
uplift associated with CO\textsubscript{2} injection at an EOR site in coastal Texas, coastal subsidence, RSLR and nuisance flooding along the Atlantic Coast of North America and Mississippi Delta, and hydrological-induced vertical deformation in the Mississippi River basin and Texas.

1.3 Using GPS for monitoring surface deformation associated with CO\textsubscript{2} injection

To date, most studies of surface deformation associated with CO\textsubscript{2} injection have used InSAR (Interferometric Synthetic Aperture Radar) (Mathieson et al., 2009; Klemm et al., 2010; Morris et al., 2011; Shi et al., 2012; Rohmer and Raucoules, 2012; Verdon et al., 2013; Yang et al., 2015). InSAR observations work well in dry areas with little vegetation cover, but may be problematic in areas with variable atmospheric moisture or dense vegetation cover. In these conditions, the radar signal between successive satellite passes may be de-correlated, and the phase change in the radar signal between the passes may be difficult to estimate. Temporal sampling may also be limited; depending on the satellite system used, there may be several days to more than a month between satellite passes. In Chapter 2, precise continuous GPS measurements were used to estimate surface deformation associated with CO\textsubscript{2} injection. GPS is less sensitive to atmospheric water vapor compared to InSAR, is not affected by vegetation, and can be done at relatively low cost. GPS also provides excellent temporal sampling. The reservoir was pressurized with CO\textsubscript{2} for about a year prior to significant extraction of oil,
and the resulting pressure changes were measured with downhole techniques, allowing a quantitative test of the GPS approach. However, the GPS time series show strong seasonal variability, which mainly reflect hydrologic changes. For example, Figure 1.4 shows the vertical component of one of the test GPS sites compared to Total Water Storage (TWS) estimated from the Gravity Recovery and Climate Change (GRACE) mission (Tapley et al., 2004). Recognizing surface deformation related to CO₂ injection in the presence of such dominant hydrological effects is clearly challenging. In Chapter 2, I show that using nearby GPS stations and a Principal Component Analysis (PCA) technique reduces the effects of hydrological loading, allowing us to investigate subtler signals associated with CO₂ injection. Alternatively, the hydrological loading deformation can be modeled using GRACE data and/or hydrological models. However, because the spatial resolution of GRACE measurements (400-500 km) is limited, accurate quantification of hydrological loading in GPS time series is challenging. Given the higher spatial resolution of hydrological models, the accuracy of hydrological loading deformation can be improved when combining with GRACE data. In Chapter 6, I propose a new hybrid method for improving the prediction of the hydrological-induced vertical deformation at individual GPS sites.
Figure 1.4: Changes in total terrestrial water storage (TWS) estimated from the GRACE, and a test GPS height time series in an EOR field. The similarity between the time series implies that the ground surface is strongly affected by regional hydrological signals.

A model assuming uniform pressurization of an infinitely thin horizontal disc-shaped pressure source in an elastic half-space (Fialko et al., 2001) was used in Chapter 2 to predict the three-dimensional GPS deformation data associated with the CO$_2$ injection.

1.4 A three-dimensional surface velocity field for the Mississippi Delta

Parts of coastal Louisiana (the Mississippi Delta) are undergoing accelerated land loss due to the combined effects of sea-level rise and land subsistence (Morton et al., 2009). The subsidence of the land surface reflects natural processes such as sediment compaction and crustal loading, exacerbated by anthropogenic withdrawal of fluids (water, oil, natural gas). Knowledge of current subsidence rates is an important component of long-term planning and mitigation, for example allowing efforts to be focused where current
subsidence rates are low. Unfortunately, despite its obvious importance, the rate of current subsidence in the delta remains unclear. In Chapter 4, a comprehensive three-dimensional surface velocity field is presented for the Mississippi Delta based on a network of 36 high-precision continuous GPS stations. Moreover, new analytical techniques (empirical mode decomposition) allow better extraction of trends from tide-gauge time series with multiple oscillatory modes, allowing a more rigorous comparison of GPS and tide gauge data. The results show that while the majority of the delta is relatively stable, the southern portion continues to experience high rates of subsidence (5-6 mm yr\(^{-1}\)). These results are consistent with long-term tide gauge records at Grand Isle, Louisiana, and several stations in Florida.

1.5 Subsidence along the Atlantic Coast of North America

Eastern North America is a passive continental margin. Most of this margin is experiencing spatially variable, long-term vertical motion due GIA (Peltier, 2004). In Chapter 5, I investigate vertical land motion along the Atlantic Coast of North America, based on 216 continuous GPS sites between New Brunswick, Canada, and southern Florida, United States. These data are compared to high-quality geological rate estimates of late Holocene RSLR describing vertical land motion in the region from 4 ka B.P. to 1900 A.D (Engelhart et al., 2009). I show that for many coastal areas there is no significant difference between these independent data. Exceptions occur in areas of recent excessive groundwater extraction, between Virginia (38°N) and South Carolina (32.5°N). The present-day subsidence rates in these areas are approximately double the long-term geologic rates, which has important implications for flood mitigation. In Chapter 6, I show how these two
data sets (along with other data) can be used to describe the frequency and location of nuisance flooding along the eastern seaboard of North America.

1.6 Nuisance flooding: the importance of present-day land motion

While it is not currently possible to predict the coastal locations that will be flooded by major storms and hurricanes in the future, the timing and location of nuisance flooding (also called sunny-day flooding) can be predicted with some accuracy (Sweet and Park, 2014; Moftakhari et al., 2015; Ray and Foster, 2016; Wdowinski et al., 2016). Timing is a strong function of local tides, while location is determined by places where land elevation is currently close to local sea level, and hence can be temporarily flooded when the sea surface exceeds some threshold elevation. In Chapter 6, the frequency and location of nuisance flooding along the eastern seaboard of North America are investigated, and are compared to various processes affecting relative sea level on different time scales. In addition to the well-known influence of GIA, it is shown that recent anthropogenic activities (e.g., groundwater extraction and surface water storage by dams) and corresponding vertical land motions can also influence whether or not a given area experiences nuisance flooding. These results have implications for flood susceptibility, forecasting and mitigation, including management of groundwater extraction from coastal aquifers.
1.7 A new hybrid method for estimating hydrologically-induced vertical deformation

In Chapter 7, a new method is proposed to combine global and regional loading data with different spatial resolutions to improve the estimate of elastic deformation at GPS sites. The suggested hybrid method incorporates the Green’s function approach and a spherical harmonic approach, allowing the combination of observed and modeled surface mass changes with different accuracies and spatial resolutions. I use the modeled TWS changes from a high resolution global hydrological model (WGHM v2.2b, Döll et al., 2014; Müller Schmied et al., 2014) provided as monthly global 0.5° grid and observed TWS changes from monthly DDK2-filtered Stokes coefficients provided from GRACE (CSR-RL05). GRACE provides accurate mass changes at large scales (at low wavelengths) while hydrological model provides small-scale mass changes (at high wavelengths) with higher accuracy. 762 GPS stations were processed in the Central U.S. using GIPSY-OASIS II (v 6.3) software and state-of-the-art precise point position technique. I show that the proposed hybrid method achieves a better fit to GPS-measured vertical displacement than the widely-used spherical harmonic approach, accounting for local to regional variabilities adjacent to the GPS station. The average amount of improvement is 25% and 35% relative to GRACE- and WGHM-based spherical harmonic solutions, respectively. The hybrid method can be applied to a wide
variety of environmental surface loading problems including loading from hydrology, ocean and atmosphere.

1.8 References


Klemm, H., Quseimi, I., Novali, F., Ferretti, A., & Tamburini, A. (2010). Monitoring horizontal and vertical surface deformation over a hydrocarbon reservoir by PSInSAR. First break, 28(5).


Rohmer, J., & Raucoules, D. (2012). On the applicability of Persistent Scatterers
Interferometry (PSI) analysis for long term CO₂ storage monitoring. Engineering Geology, 147, 137-148.
Sweet, W.V., & Park, J. From the extreme to the mean: Acceleration and tipping points of coastal inundation from sea level rise. Earth’s Future 2, 579-600 (2014).
2. GPS-based Monitoring of Surface Deformation Associated with CO₂ Injection at an Enhanced Oil Recovery Site

2.1 Abstract

High precision GPS measurements have been used to measure surface deformation associated with CO₂ injection at an Enhanced Oil Recovery (EOR) field in South Texas. We describe a filtering procedure to reduce noise associated with seasonal hydrologic effects, achieving post-filter precisions of better than 2 mm and 3 mm in horizontal and vertical components respectively. A model assuming uniform pressurization of a thin horizontal disc-shaped pressure source in an elastic half-space fits the surface deformation data quite well. The model predicts a location of the pressurized source consistent with injection locations, and suggests minimal horizontal migration of the CO₂ fluid during the test period. Our results suggest that a sparse network of dual frequency GPS receivers can be used to augment sub-surface data for Monitoring, Verification and Accounting (MVA) activities associated with Carbon

Capture, Utilization and Storage, deriving independent constraints on pressure changes in the reservoir at depth as well as CO$_2$ plume migration.

2.2 Introduction

An important aspect of large scale Carbon Capture, Utilization and Storage (CCUS) is the ability to assess the fate of injected CO$_2$ and test for containment loss. These so-called Monitoring, Verification and Accounting (MVA) activities typically include active seismic and down-hole geophysical techniques for precise tracking of plume migration, all of which can be expensive. Since the economic viability of CCUS is impacted by the cost of MVA activities, development of lower cost approaches, including surface techniques, is desirable.

Injection of CO$_2$ or other fluid into a reservoir at depth increases fluid pressure in the reservoir, causing deformation in the overlying strata and inducing surface deformation. If the pressure change is large enough, the surface deformation may be measurable. In principle, the measured surface deformation can be inverted to estimate pressure changes at depth. With additional information on geomechanical properties, quantitative information on the mass of injected CO$_2$ as a function of time and its spatial variation can be obtained, allowing assessment of its subsequent fate (successful storage; migration) (e.g., Vasco et al., 2008 & 2010; Rinaldi and Rutqvist, 2013; White et al., 2014). For example, upon initial injection, the surface above the injection point will be uplifted due to the pressure change; subsequent migration of the fluid away from the
initial injection point would result in subsidence at that location unless additional fluid is injected. More generally, defining the time-variable surface deformation field in the vicinity of a reservoir being used for CO₂ storage has the potential to provide a wealth of useful MVA information. Over long periods (decades or centuries), chemical reactions that result in formation of mineral phases will result in pressure and volume reduction and subsidence, and could not be distinguished from migration of the fluid with this technique alone. On the other hand, surface deformation can be measured at relatively low cost, the interpretation is straightforward, and the technique gives useful information in the critical few years immediately following injection.

To date, most studies of surface deformation associated with CO₂ injection have used InSAR (Interferometric Synthetic Aperture Radar) (Mathieson et al., 2009; Klemm et al., 2010; Tamburini et al., 2010; Morris et al., 2011; Shi et al., 2012; Rohmer and Raucoules, 2012; Verdon et al., 2013). This technique works well in dry areas with little vegetation cover, but may be problematic in areas with variable atmospheric moisture or dense vegetation cover. In these conditions, the radar signal between successive satellite passes may be decorrelated and the phase change in the radar signal between the passes (the key observable for the InSAR technique) may be difficult to estimate. Temporal sampling may also be limited; depending on the satellite system used, there may be several days to more than a month between satellite passes.
GPS can be used in a high precision mode to estimate surface deformation. It is less sensitive to atmospheric water vapor compared to InSAR, is not affected by vegetation (assuming the GPS satellites remain visible to the ground antenna), and can be done at relatively low cost. GPS also provides excellent temporal sampling. Although we average our data to once per day, in principle much higher sampling rates are possible. We have tested this concept at an Enhanced Oil Recovery (EOR) site in Texas. Here we report initial results from that experiment. The reservoir was pressurized with CO$_2$ for about a year prior to significant extraction of oil, and the resulting pressure changes were measured with down-hole techniques, allowing a quantitative test of the GPS approach.

### 2.3 Site characteristics

The oilfield for our test is located in southern Texas, and was discovered in the 1930’s. Production peaked in the 1970’s. As of 2011, the field had produced more than 500 million barrels of oil (Davis et al., 2011). Like many oilfields in the region, it represents a structural-stratigraphic trap in the Oligocene-age Frio formation, a high porosity sandstone unit that has been faulted against a deep-seated salt dome. The reservoir includes two sandstone units: the Upper Frio (~60 m thick) and the Lower Frio (~ 200 m thick). The average depth of the reservoir is about 1600 m. Holocene through Miocene age clays, sandstones and shales are present from the surface to approximately
1400 m depth. Below the Miocene, approximately 200 m of Anahuac shale act as impermeable caprock to the Frio reservoir.

The field is divided into several sections by faults (Figure 2.1). These sealing faults are thought to be barriers to CO₂ movement, allowing faster build-up of pressure in the reservoir during EOR-related fluid injection (Davis et al., 2011). One goal of our experiment was to see if the GPS network had sufficient sensitivity to detect fluid migration across one or more of these faults.

The oilfield has been re-pressurized with both saline water and CO₂, the latter from both natural and industrial sources. CO₂ injection began in late 2010, and oil production began in early 2012, after approximately 14 months of CO₂ injection. Pressure in the injection interval zone was monitored by a pressure gauge at the bottom of one well. Average reservoir pressure was 2350 psi (pounds per square inch) (16.2 MPa) in December 2010, increasing to a maximum of 2850 psi (19.6 MPa) in March 2012, two months after the beginning of significant oil production. Pore fluid pressure in the injection zone thus increased by about 500 psi (3.5 MPa) after about 14 months of CO₂ injection.
Figure 2.1: Map of the Enhanced Oil Recovery (EOR) site in southern Texas used to test the GPS surface deformation technique. Locations of a well with pressure gauge and CO₂ injectors are shown with red and green circles, respectively. Red triangles indicate location of GPS sites (TEST-1, TEST-2 and TEST-3). The surface projection of major north-northeast striking fault (double black lines) divides the field into west and east parts. Minor east-northeast striking faults separate blocks A, B and C. Contour lines (grey lines) are depth of the top of Upper Frio formation in meters.

2.4 Data collection

Three continuously operating GPS sites (TEST-1, 2 and 3) were installed by the University of South Florida in October 2011, 11 months after CO₂ injection started but 3 months prior to significant oil production (Figure 2.3). TEST-1 and TEST-2 are located in the northern fault block, 728 m apart. TEST-3 is emplaced in a southern fault block, 1879
m from TEST-1 and 1239 m from TEST-2 (Figure 2.1). Each GPS station consists of four components (Figure 2.2): a dual frequency Trimble NetR9 GPS receiver, a stable monument (cement and rebar extending to approximately 1.5 m depth), a GPS antenna (choke-ring design), and a power supply. The latter consists of lead acid batteries recharged with solar panels during daylight hours. The antenna is mounted about 1.7 m above the ground surface in order to minimize multipath noise (Johnson et al., 1995) and is covered with a radome.

![Figure 2.2: Continuous GPS station TEST-3 at the EOR test site in south Texas. The station includes choke ring antenna and radome (on pole in foreground), solar panels, and a white steel box holding the GPS receiver, battery, and power controller. A seismic vault is visible in the background, prior to burial.](image-url)
Figure 2.3: Time series of bore-hole pressure measured in northern fault block during the CO2 injection period. Pressure reached a maximum value 16 months after the beginning of CO2 injection, shortly after the start of oil production. GPS monitoring began approximately 3 months before oil production, and 5 months before peak reservoir pressure was reached. Inset shows the full time series of bore-hole pressure versus oil production expressed in Barrels of oil per day.

2.5 Data analysis

The general characteristics of the GPS system and its use for high precision geophysical applications are described in Dixon (1991). The Precise Point Positioning (PPP) technique uses un-differenced dual frequency pseudo-range and phase measurements from a single GPS receiver, together with external models, to define the position of the ground antenna phase center at the millimeter to centimeter level (Zumberge et al., 1997). The resulting position time series record surface deformation associated with reservoir pressure changes, changes associated with hydrological and
other surficial effects, and variations related to processing artifacts or other noise sources. Here we briefly describe procedures to reduce the effects of hydrological processes and noise in the GPS time series.

GPS raw data are processed using Jet Propulsion Laboratory’s (JPL’s) GIPSY/OASIS II software package (version 6.2) based on the PPP technique. JPL’s precise satellite orbit and clock parameters together with an absolute GPS receiver and satellite antenna phase calibration model (Schmid et al., 2007) are used to generate non-fiducial daily point position solutions. Details on processing are given in Appendix A. The non-fiducial daily position time series are transformed into the IGS (International GNSS Service) 2008 reference frame (Rebischung et al., 2012) using JPL’s X-files, a 7-parameter transformation. The horizontal components of the non-fiducial daily solutions are also transformed into a North American plate-fixed frame (NA12) using a daily 7-parameter transformation calculated according to Blewitt et al. (2013). It is also possible to go directly from non-fiducial positions to NA12. With either approach, the transformed horizontal motions are in general agreement with motions expected for the stable interior of the North America plate, with exceptions noted in the next paragraph.

The resulting GPS time series exhibit strong seasonal changes which mainly reflect hydrological effects. Figure 2.4 shows the vertical component of the TEST-1 site compared to Total Water Storage (TWS) estimated from the Gravity Recovery and Climate Change (GRACE) mission, a satellite project managed by NASA and the
German Aerospace Center (Tapley et al., 2004). The GRACE TWS field has a spatial resolution of ~ 100 km (Landerer and Swenson, 2012) and represents a regional signature of groundwater, surface water and soil moisture changes. The vertical component recorded by our TEST GPS stations and nearby GPS stations (see Figure 2.5) are influenced by this hydrologic signal. Recognizing surface deformation related to CO₂ injection in the presence of such dominant hydrological effects is clearly challenging. Here we describe a procedure for reducing the hydrological effects, in order to investigate subtler signals associated with CO₂ injection.

![Graph](image)

**Figure 2.4:** Relative changes in total terrestrial water storage (TWS) estimated from the GRACE satellite gravity mission, and TEST-1 GPS vertical time series. The similarity between the time series implies that the ground surface is strongly affected by regional hydrological signals.
Consider a regional network of GPS stations within several hundred km of our local network. The position time series for both the regional and local networks record signal as well as noise from a variety of sources with varying amounts of temporal and spatial correlation. A common mode signal across the regional network likely includes regional hydrologic effects. We can therefore use data from the regional network to remove such Common Mode Effects (CME) from our local network, in effect defining a regional reference frame. This approach to regional filtering was first described by Wdowinski et al. (1997). Note that CME can include both common mode signals and common mode errors.

A network of 30 permanent GPS stations covering an area of 400 km × 300 km currently operates near the study area, 24 of which recorded data during our observation period and are available for definition of the regional reference frame (Figure 2.5). The raw GPS data are publicly available through the Continuously Operating Reference System (CORS) website (http://geodesy.noaa.gov/CORS/).
Figure 2.5: Map of regional GPS stations used in our analysis. Black stations are excluded from the definition of the regional filter because their vertical displacement time series includes uncorrelated signal and noise and have site-specific motions (i.e., they are affected by local deformations). Red stations are highly correlated (Figure 2.6) and are used to define the filter for removing common mode effects at the TEST sites (underlined).

One challenge to implementing such a regional filter in this area is that some stations may be also affected by local deformation (site-specific motion unrelated to regional hydrologic effects), for example by water pumping from a local well. To eliminate these stations from the regional reference frame, we performed a correlation analysis for the three components of the GPS displacement time series to find stations whose motions are highly correlated. These stations presumably exhibit CME within the study area, are less affected by local deformation sources (i.e., smaller site-specific motions), and can be used to define and remove CME. Figure 2.6 shows the stations having a correlation coefficient greater than 0.4 in the vertical component. These
stations are used to identify regional CME. Recall that we distinguish common mode error and common mode signal. The common mode signal is mainly related to the response of the lithosphere to continental water storage, which exhibits a strong seasonal cycle, as reflected in the GRACE data. The common mode noise may reflect long wavelength un-modeled (residual) atmospheric effects, reference frame effects, and satellite orbital errors (King et al., 2010). However, the CME may not be spatially uniform. To account for non-uniformity of CME, Dong et al. (2006) developed a spatio-temporal filtering approach based on principal component analysis. This approach has been successfully applied to extract CME in various GPS networks (Savage 1995; Marquez-Azua and DeMets 2004; Tiampo et al., 2004, 2012).

**Figure 2.6:** Histogram showing GPS stations with correlation greater than 0.4. Stations that are correlated with 6 or more other stations (ADKS, ANG5, COH1, TXAG, TXBC, TXED, TXRS and TXWH) were selected for definition of the regional filter.
We used principal component analysis based on the covariance analysis approach (Dong et al., 2006) to spatially filter the CME including hydrological effects and regional noise in the GPS time series. Consider detrended and demeaned GPS time series ordered as columns in a displacement matrix $X$. The rows in $X$ represent displacements of one epoch ($t_i$) for all stations ($n$). $X$ can be decomposed into a linear combination of the principal components (PC) and eigenvectors of the covariance matrix of $X$ as follows:

$$X(t_i, j) = \sum_{k=1}^{n} a_k(t_i) \upsilon_k(j), \quad j = \{1, 2, ..., n\}$$ (2.1)

$$a_k(t_i) = \sum_{j=1}^{n} X(t_i, j) \upsilon_k(j), \quad k = \{1, 2, ..., n\}$$ (2.2)

The elements of the covariance matrix of $X$ are defined as a matrix $B$:

$$B(i, j) = \frac{1}{m-1} \sum_{k=1}^{m} X(t_k, i) X(t_k, j)$$ (2.3)

where $m$ is the number of epochs. $\upsilon_k$ in equations (2.1) and (2.2) is the $k$th eigenvector of $B$ which can be obtained by spectral decomposition:

$$B = V\Lambda V^T$$ (2.4)

where $V$ is an eigenvector matrix with dimension ($n \times n$) and $\Lambda$ is a nonzero diagonal matrix containing eigenvalues $\lambda_k$ (or variances as $B$ is a covariance matrix) arranged in descending order. Each PC ($a_k$) corresponds to the $k$th eigenvalue $\lambda_k$ and can be
determined using equation (2.2). Finally, the filtered displacement matrix $\bar{X}$ can be obtained by using the first $p$ dominant PCs or modes computed from equation (2.1) as follows:

$$\bar{X}(t_i, j) = X(t_i, j) - \sum_{k=1}^{p} a_k(t_i) u_k(j) \quad j = \{1, 2, ..., n\}$$  \hspace{1cm} (2.5)

The second term in equation (2.5) is often called CME. The percent of the variance explained by a particular PC or mode is determined by dividing the corresponding eigenvalues, $\lambda_k$, by the sum of the eigenvalues. The significance of any PC can be tested under the null hypothesis that $k$th modes are not significant from the remaining modes using the F-statistic given by (Smith et al., 2007; Tiampo et al., 2012):

$$F(1, n - k) = \frac{\lambda_k}{\sum_{i=k+1}^{n} \lambda_i / (n-k)}$$  \hspace{1cm} (2.6)

where $\lambda_k$ is the eigenvalues (variances) of covariance matrix $B$ corresponding to the $k$th PC. The above statistic is the ratio of the two variances, that is, the variance of $k$th modes divided by variance of remaining modes. The F-statistic is F-distributed with $(1, n-k)$ degrees of freedom. If the F-statistic is greater than the critical value of the F-distribution for some desired false-rejection probability (e.g., 0.1), then the null hypothesis is not correct and the $k$th mode is dominant.
2.6 Results

2.6.1 Surface deformation

We used stations shown in Figure 2.5 to calculate the eigenvalues and eigenvectors using spectral decomposition of the covariance matrix $B$ (equation 2.4). The percentage of PC eigenvalues is shown in Figure 2.7 for three displacement components. The first PCs explain 49 %, 42 %, and 55 % while the second PCs explain 26 %, 35 % and 18 % of variance for North, East and Up components. We calculate the F-statistic (equation 2.6) for each eigenvalue to determine modes that are significantly different from remaining modes. Our analysis shows that the first two modes are significantly different from the remaining modes at the 90% significance level and represent CME in the vertical component. The first two and three modes are significant for North and East components, respectively. These modes represent common signals (e.g., hydrological loading in the vertical component) at the GPS stations. It should be noted that regional filtering also reduces the amplitudes of common noise, i.e. both the white and colored noise components (Mao et al., 1999; Williams et al., 2004; Hackl et al., 2011; Hackl et al., 2013).
Figure 2.7: Percentage of PC eigenvalues for the three coordinate components.

Figure 2.8 shows the vertical component of TEST-1 and two of the regional stations (ANG5 and COH1) before and after filtering. Stations ANG5 and COH1 are located 32 km and 33 km from TEST-1, respectively, and show 51% and 50% correlation with TEST-1 in the vertical component. The filtered ANG5 and COH1 time series scatters around zero, consistent with random noise. For example, RMS of time series decreases from 6.0 mm and 10.2 mm to 3.0 and 1.5 mm for stations ANG5 and COH1 respectively. In contrast, the filtered TEST-1 data exhibit a clear uplift signal during the CO2 injection period, and also show horizontal motion (to the southeast) that are quite different from other stations in the network (Figure 2.10), presumably reflecting local deformation associated with increased reservoir pressure. While the total uplift over the
initial five-month period is small (8.3 mm) it is clearly resolved with our filtering approach and is significantly different from zero at the 95% confidence level.

**Figure 2.8:** Comparison unfiltered and filtered time series. Upper panel: Unfiltered vertical displacement time series at TEST-1. Middle panel: Unfiltered vertical displacement time series at ANG5 and COH1, 32 km and 33 km from TEST-1, respectively. Bottom panel: Filtered vertical displacement time series at TEST-1, ANG5 and COH1. For the period from the beginning of GPS data collection to 2012.17 (March 1, 2012) ANG5 and COH1 time series show no significant displacement, scattering about zero (blue line) by several mm, whereas TEST-1 exhibits significant uplift, up to about 8 mm.

A least-squares line fit to the north, east and vertical components of the filtered position time series from the beginning of observations (October 11, 2011) to the time of maximum recorded reservoir pressure (March 1, 2012) yields the surface displacements listed in Table 2.1 and shown in Figure 2.9. All three sites within the EOR field have motions distinct from the reference frame sites (Figure 2.10) showing uplift and southeast motion during this period of initial reservoir pressurization. Table 2.1 also
lists the RMS misfits of the linear fit to the displacement time series, presumably reflecting residual noise and un-modeled processes in the filtered position time series. These residuals are quite small: 1.3 mm or less for the horizontal components, and 2.9 mm or less for the vertical component.

We seek to use the behavior of this EOR field as a proxy for the behavior of a reservoir used for long-term storage of CO$_2$, and demonstrate successful MVA techniques based on surface deformation. One difficulty with this approach is that the expected long-term surface deformation for the two types of fields is quite different. For CO$_2$ storage, we expect a long period of injection, during which surface deformation occurs in response to reservoir pressure increases and/or reservoir expansion. In contrast, with EOR, an initial period of injection is generally followed by production. At some point, injection and production more or less balance in the EOR field, at least averaged over long periods. After this point, we do not expect to see significant surface deformation in the EOR field (Figure 2.8).

In our test field, reservoir pressure rises during the initial period of initial CO$_2$ injection, through most of 2011 and early 2012 (Figure 2.3). Shortly after production begins (early 2012) reservoir pressure drops slightly for several months and then stabilizes, presumably because oil production and CO$_2$ injection are in approximate balance, at least in terms of net pressure effects. After this time, we do not expect to see significant deformation.
We therefore focus on deformation data from the beginning of the time series up to the time of maximum reservoir pressure. This gives a time series that is approximately 5 months long, from October 2011 to March 2012. Deformation data during this period should reflect the location, geometry and growth of the reservoir during the initial pressurization phase, and is most representative of the behavior of a reservoir being pressurized for long-term CO₂ storage.

**Figure 2.9:** Filtered time series (North, East and Vertical) of daily position estimates (small black circles) for TEST stations from beginning of data collection to March 1, 2012. Best fit line used to estimate total displacement during this time period is shown in red (Table 2.1). RMS scatter of points about this best fit line (Table 2.1) is one estimate of precision, and is 2.9 mm or less for the vertical component, and 1.3 mm or less for the horizontal components. Note the large vertical displacement at TEST-1 (closer to injection wells) which decreases with distance from the injection wells (see Figure 2.1).
Table 2.1: GPS displacements and RMS misfits of the linear fit to the displacement time series (Figure 2.9).

<table>
<thead>
<tr>
<th>Station</th>
<th>Displacement (mm)</th>
<th>RMS (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>E</td>
</tr>
<tr>
<td>TEST-1</td>
<td>-0.7</td>
<td>+1.5</td>
</tr>
<tr>
<td>TEST-2</td>
<td>-2.8</td>
<td>+2.2</td>
</tr>
<tr>
<td>TEST-3</td>
<td>-1.5</td>
<td>-0.0</td>
</tr>
</tbody>
</table>

The utility of the regional filter is illustrated in Figure 2.10. Figure 2.10a shows horizontal displacement vectors for the 24 CORS stations relative to NA12, i.e., from unfiltered time series, for the time span from October 11, 2011 (beginning of our GPS data) to March 1, 2012. Many of the horizontal vectors exhibit significant common mode displacement (large, cm-level motion to the northeast) which may relate to regional hydrologic loading. Figure 2.10b shows the corresponding filtered displacement, with common mode motion removed. Most stations now show small (less than 1 mm), randomly oriented displacements. In contrast, the three TEST stations in the filtered data show larger (up to 4 mm) southeast displacements, presumably reflecting local deformation associated with the EOR field, and implying a pressure source located northwest of the stations.
Figure 2.10: Horizontal displacement vectors of CORS GPS stations and TEST stations. Vectors represent displacement for the time span from beginning of GPS observations (October 10, 2011) to the time of maximum recorded reservoir pressure (March 1, 2012). For clarity, the location of the three TEST stations is represented by a single triangle. (a) unfiltered time series, referenced to NA12 reference frame. (b) filtered time series.

The relatively large uplift in TEST-1 (8.2 mm) compared to the other two stations implies that the center of the pressurized source is closer to TEST-1 than the other two stations (TEST-2 and TEST-3 experienced ~ 60% and 75% smaller uplift compared to TEST-1). Horizontal motion is largest in TEST-2. The spatial pattern of these displacements implies a pressure source centered close to TEST-1, with a boundary near TEST-2. This is quantified in the next section.

2.6.2 Model description

We model this deformation assuming an infinitely thin horizontal circular disc pressure source (often called a “penny-shaped crack” model; hereafter penny model) in
an elastic half space. The penny model was developed by Fialko et al. (2001a) to describe deformation associated with a sill-like magmatic intrusion, and has been validated with numerical simulations (Fialko et al., 2001b). Several aspects of the volcano deformation problem are analogous to the CO$_2$ storage problem, and we exploit that similarity here.

![Figure 2.11: Cartoon of horizontal crack or “penny” model, with the “penny” defined by radius R and depth H in an elastic half-space. The half space is defined by rheological parameters E (Young’s modulus) and v (Poisson’s ratio). The vertical line labeled H is the axis of symmetry, passing through the center of the disc.](image)

The assumptions and formulation of the penny model are summarized in Figure 2.11 and Table 2.2. We treat the pressurized reservoir as a permeable infinitely thin horizontal circular disc embedded in surrounding impermeable, deformable elastic material. The reservoir and surrounding rocks are assumed homogeneous, with the same, uniform elastic properties. The size (radius R) and depth (H) of the reservoir, its pressure increment (P) and the elastic properties of the surrounding rocks (Young’s modulus E and Poisson’s ratio v) control the surface deformation. The pressure
distribution inside the pressure source is assumed uniform. The model assumes purely elastic behavior, implying that uplift occurs instantaneously from increased reservoir pressure, and is linearly related to pressure. The model therefore does not reflect poroelastic effects, properties of the injected fluids or hydrological parameters such as porosity and permeability of the reservoir or surrounding media.

Table 2.2: Adjustable and fixed parameters in the penny model.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Symbol</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Horizontal position</td>
<td>x,y</td>
<td>adjustable</td>
<td>meter</td>
</tr>
<tr>
<td>Depth</td>
<td>H</td>
<td>1600</td>
<td>meter</td>
</tr>
<tr>
<td>Radius</td>
<td>R</td>
<td>adjustable</td>
<td>meter</td>
</tr>
<tr>
<td>Young’s modulus</td>
<td>E</td>
<td>adjustable</td>
<td>GPa</td>
</tr>
<tr>
<td>Poisson’s ratio</td>
<td>ν</td>
<td>0.25</td>
<td>-</td>
</tr>
<tr>
<td>Reservoir pressure change</td>
<td>ΔP</td>
<td>known, varies</td>
<td>psi</td>
</tr>
</tbody>
</table>

For this model, the vertical displacement $U_z$ and horizontal displacement $U_r$ at the surface are described by:

\[
U_z = 4 \frac{1-(1+\nu)}{\nu} \Delta P \ast R \int_0^1 \left[ S_0^0 + \frac{H}{R} S_0^1 \right] \varphi(t) \, dt + \int_0^1 \left[ C_0^0 - C_0^1 \right] \psi(t) \, dt \quad (2.7)
\]

\[
U_r = 4 \frac{1-(1+\nu)}{\nu} \Delta P \ast R \int_0^1 \left[ S_1^1 - \frac{H}{R} S_0^0 \right] \varphi(t) \, dt - \frac{H}{R} \int_0^1 S_1^1 \psi(t) \, dt \quad (2.8)
\]

where $\psi(t)$ and $\varphi(t)$ are Fredholm integral equations of the second kind.
\[ \phi(t) = -\frac{2}{\pi} + \frac{2}{\pi} \int_0^1 [T_1(r, t)\phi(t) + T_3(r, t)\psi(t)] \, dr \] 
\[ \psi(t) = \frac{2}{\pi} \int_0^1 [T_2(r, t)\psi(t) + T_4(r, t)\phi(t)] \, dr \] 

Variables S, C and kernels T are functions of H/R, r and t and have closed-form expressions (Fialko et al., 2001a). The variable r is the horizontal distance from the center of penny model, readily related to the GPS coordinates, and t is the interval of integration. Equations (2.9) and (2.10) can be solved numerically using iterative techniques (Delves and Mohamed, 1985).

### 2.6.3 Model solution

We calculate the surface deformation associated with the penny model using the time series of reservoir pressure measured at the well shown in Figure 2.1. The unknown parameters estimated in our model are the horizontal position (x,y coordinates) of the center of the penny model, its radius (R), the Young’s modulus (E) and Poisson’s ratio (ν) of the elastic half space. Fixed (known) parameters include the depth (H) of crack, set to 1600 m, the average depth of the Upper Frio at this location based on industry seismic data (Figure 2.1 and Figure 2.14), and the pressure increment, as measured by the down-hole meter. Preliminary modeling suggested minimum sensitivity to Poisson’s ratio, a common result in many Earth deformation problems (e.g., Bevis et al., 2005). We therefore set the value of Poisson’s ratio to 0.25, a value
often used to simulate rock deformation or seismic wave propagation. Table 2.2 summarizes the fixed and adjustable parameters used in our analysis.

A grid search was used to estimate the parameters that best fit the horizontal and vertical motions at the GPS stations. Grid ranges are -3,000 – 2,300 m in the x coordinate of horizontal position, -2,700 – 2,400 m in the y coordinate of horizontal position (both referred to a local coordinate system), 100–1400 m for radius, and 5-155 GPa for Young’s modulus, with search increments 50 m, 100 m and 5 GPa, respectively.

Goodness of fit is assessed using the standard chi-square ($\chi^2$) statistic:

$$
\chi^2 = \sum_{i=1}^{N} \frac{(O_i - C_i)^2}{\sigma_i^2}
$$

where $O_i$ is an observation (data), $C_i$ is the corresponding calculated (model) value, and $\sigma_i$ is the data uncertainty. In its normalized form $\chi^2_{\text{df}}$, $\chi^2$ is divided by the degrees of freedom, $\text{df}=N-u$, where $N$ is the number of observations, equal to 9 (3 GPS stations, each with three components) and $u$ is the number of adjustable parameters, in this case 4. For large data sets characterized by normally distributed, Gaussian uncertainties, values of $\chi^2_{\text{df}}$ close to 1 indicate a good fit of data to model and suggest that uncertainty estimates are reasonable. Our data set is quite small and it is not clear that uncertainties are normally distributed, hence this generalization is a rough guide only. Figure 2.12 displays distribution of $\chi^2$ for various ranges of parameter values, showing trade-offs among the various estimated parameters. For example, larger values of Young’s
modulus require a larger radius for the pressure source. The best fit model (Table 2.3) has $\chi^2=7.1$ corresponding to $\chi^2_{df} = 1.4$. Figure 2.13 shows observed and calculated displacements at the three sites for the best-fit model.

**Figure 2.12:** Contoured values of chi-square misfit between the GPS data and calculated values for the penny model assuming four adjustable parameters. Two parameters were held at their best fit values to calculate misfit for the two indicated parameters. $\chi^2 = 8$ represents approximate 68% confidence level. The region where the best fit solution is located with a confidence better than 68% is indicated by grey shading. Location of injection wells in Figure 2.12a shown with small green circles. Location of GPS stations in Figure 2.12a shown with red triangles. All figures have same contour interval except for Figure 2.12f. Note that all values are well constrained except for Young’s Modulus.
Figure 2.13: Predicted (red) and observed (black) GPS displacements between October 11, 2011 (beginning of GPS data) to March 1, 2012 (time of maximum recorded pressure) for horizontal (13a) and vertical (13b) components. The location of injection wells (small green circles), faults (small squares) and surface projection of best-fit penny model (large gray circle) are also shown. Blue triangles are locations of TEST GPS stations.

Table 2.3: Best-fit values and uncertainties (one standard error) for adjustable parameters based on minimum value for $\chi^2$ (misfit of data versus model, weighted by measurement error).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x$</td>
<td>-250 ± 100 m</td>
</tr>
<tr>
<td>$y$</td>
<td>40 ± 100 m</td>
</tr>
<tr>
<td>Radius $R$</td>
<td>800 + 300/-100 m</td>
</tr>
<tr>
<td>Young’s modulus $E$</td>
<td>55 + 80/-20 GPa</td>
</tr>
</tbody>
</table>
2.7 Discussion

The center location of the circular reservoir in our model is well constrained. The best fit center value is located 250 m and 900 m northwest from TEST-1 and TEST-2 respectively, and 1950 m north from TEST-3. This center is close to the centroid of the multiple CO₂ injector wells (Figures 2.1 and 2.12a). One implication of this observation is that there was limited migration of the CO₂ plume from the injection points during this period. Also, pressure rapidly equilibrated among the various injection wells (at least relative to the resolution of our data) such that a simple, single pressure source adequately fits the data. This is consistent with the high porosity and permeability of the Frio sandstone units.

The source radius is also well constrained, with a best fitting estimate of 800 m and a standard error of +300/-100 m. The asymmetric uncertainty range mainly reflects trade-offs with Young’s modulus. The best fitting estimate of source position and radius places the source and its boundaries within the northern fault block where injection occurred, implying minimal fluid migration and containment within this block (Figures 2.1, 2.12, 2.13, 2.14).

The lower limit of acceptable values for Young’s modulus is well defined, while the upper limit is poorly defined, resulting in an asymmetric uncertainty distribution: 55 GPa (best estimate) with a standard error of +80/-20 GPa. The best estimate and lower limit are typical for sedimentary rocks at relatively shallow crustal levels (e.g.,
Ruiz Penã, 1998), while the upper limit is unrealistically high. To our knowledge, there are currently no publicly available data for the reservoir and caprock properties in our study area for comparison with our results. In a similar geomechanical analysis in Cranfield, Mississippi (Kim and Hosseini, 2014) bottom-hole pressure and temperature monitoring data were available for calibration. Young’s modulus of the confining layer was estimated at 30 GPa, close to our minimum estimate.

Figure 2.12f shows the trade-off between penny model radius and Young’s modulus. For example, increasing Young’s modulus from 30 GPa to 130 GPa would lead to a 30% increase in radius (stiffer elastic material results in a larger radius estimate). However, since we know that higher values of Young’s modulus are physically implausible, the larger radius values are similarly unlikely. Since source location, source radius, and Young’s modulus for the half space are the main physical parameters controlling surface displacement (in addition to the pressure increment, known here), independent constraints on Young’s modulus would be useful in an operational system where GPS was used to estimate reservoir pressure.
Figure 2.14: Map of depth of Upper Frio formation as inferred from seismic data. Dark blue indicates no data. Discontinuities represent normal faults (compare to Figure 2.1). Also shown is the location and size of a thin horizontal disc-shaped pressure source that best fits the GPS data (radius = 800 m shown by arrow). Note that this source does not cross the fault between blocks A and B, implying that the fault represents an impermeable barrier to CO$_2$ fluid during the time period represented by the model (October 11, 2011 to March 1, 2012).

Our GPS stations were installed after the beginning of CO$_2$ injection, and it is interesting to speculate on the maximum signal that might have been observed if data could have been acquired earlier. We predict the horizontal and vertical displacements during the entire CO$_2$ injection period using best fit parameter values in Table 2.3 and observed pressure data (Figure 2.15). After 16 months of CO$_2$ injection (from beginning of CO$_2$ injection to the time of maximum recorded pressure) predicted vertical displacements are as large as 24 mm (at TEST-1), while predicted horizontal...
displacements are as large as 6 mm (at TEST-2). There are respectively 8 times and 5 times higher than the estimated noise level for these components.

Once surface displacements are calibrated against measured reservoir pressure changes (as available here) it is possible to use the observed surface displacement to predict subsequent pressure changes at depth, for independent comparison to the borehole measurements. Figure 2.16 shows a preliminary attempt for the first year of GPS data. This calculation assumes that the source has not moved during this period.

![Figure 2.16](image)

**Figure 2.15:** Predicted vertical and radial displacements (red) assuming best fit parameter values in Table 2.3 and observed pressure data, compared to observed displacements (black) at the three GPS stations (a) TEST-1, (b) TEST-2 and (c) TEST-3.
Figure 2.16: Predicted pressure (black line) for the first year of GPS observations, based on the vertical displacement data at TEST-1 and the penny model described by the best fit parameter values in Table 2.3. Measured borehole pressure (red line) is shown for comparison. Note increasing divergence of measured and predicted values after 2012.6, which may indicate changes in source geometry (probably due to oil production) after that time.

The limited available data are not sufficient to simultaneously estimate reservoir pressure and test for plume migration, both important MVA activities for future Carbon Capture, Utilization and Storage (CCUS). However, we have demonstrated that a sparse network of relatively simple GPS units has the sensitivity to measure surface deformation associated with CO₂ injection at rates likely to be reached in operational CCUS sites. In an operational system, additional (10-20) GPS stations would presumably be available. With a larger GPS network and constraints on the geometry and constitutive properties of the reservoir and caprock (e.g., from seismic, stratigraphic or downhole data) a more sophisticated rheological and deformation model would be
warranted (Vasco et al., 2000; Rutqvist 2011; Rutqvist, 2012). This would allow surface deformation data to better assess plume migration and pressure changes within the reservoir (Newman et al., 2002; Newman et al., 2006; Kim and Hosseini, 2014).

2.8 Conclusions

The GPS system outlined here has demonstrated sensitivity to observe surface demonstration associated with CO\textsubscript{2} injection at depth. We used a principal component analysis to reduce noise associated with seasonal hydrologic effects, achieving post-filter precision of better than 2 mm and 3 mm in horizontal and vertical component respectively. If GPS observations can begin one to two years prior to injection, background deformation associated with other processes, e.g., ground water hydrology can be better resolved.

A model assuming uniform pressurization of an infinitely thin horizontal disc-shaped pressure source in an elastic half-space fits the surface deformation data quite well. The model predicts a location of the pressurized source consistent with injection locations, and suggests minimal horizontal migration of the CO\textsubscript{2} fluid during the test period. Our results suggest that a sparse network of dual frequency GPS receivers can be used to augment sub-surface data for MVA activities associated with Carbon Capture, Utilization and Storage, deriving independent constraints on pressure changes in the reservoir at depth as well as CO\textsubscript{2} plume migration. Future work should include a larger number of stations in order to better describe plume shape and dimensions.
2.9 References


Klemm, H., Quseimi, I., Novali, F., Ferretti, A., & Tamburini, A. (2010). Monitoring horizontal and vertical surface deformation over a hydrocarbon reservoir by PSInSAR. First break, 28(5).


Salah CO₂ storage project. Proceedings of the National Academy of Sciences, 201316465.
3. A Three-dimensional Surface Velocity Field for the Mississippi Delta: Implications for Coastal Restoration and Flood Potential

3.1 Abstract

Accurate estimates of the current rate of subsidence in the Mississippi Delta (southern United States) provide a context for planning of wetland restoration and predictions of storm surge flooding. We present a comprehensive three-dimensional surface velocity field for the Mississippi Delta based on a network of 36 high-precision continuous GPS stations. We show that while the majority of the delta is relatively stable, the southern portion continues to experience high rates of subsidence (5-6 mm yr\(^{-1}\)). Our data are consistent with long-term tide gauge records at Grand Isle, Louisiana, and several stations in Florida. The current relative sea-level rise (combined effect of land subsidence and sea-level rise) along parts of the coastal delta is ~8-9 mm yr\(^{-1}\). Most tide gauge stations have recorded sea-level-rise acceleration after A.D. 1970. These data

\[\text{accuracy estimates of the current rate of subsidence in the Mississippi Delta} \]

\[\text{(southern United States) provide a context for planning of wetland} \]

\[\text{restoration and predictions of storm surge flooding. We present a} \]

\[\text{comprehensive three-dimensional surface velocity field for the} \]

\[\text{Mississippi Delta based on a network of 36 high-precision} \]

\[\text{continuous GPS stations. We show that while the majority of the} \]

\[\text{delta is relatively stable, the southern portion continues to} \]

\[\text{experience high rates of subsidence (5-6 mm} \]

\[\text{yr}^{-1} \]

\[\text{). Our data are consistent with long-term tide gauge} \]

\[\text{records at Grand Isle, Louisiana, and several stations in} \]

\[\text{Florida. The current relative sea-level rise (combined effect of} \]

\[\text{land subsidence and sea-level rise) along parts of the coastal} \]

\[\text{delta is ~8-9 mm yr}^{-1}. \text{Most} \]

\[\text{tide gauge stations have recorded sea-level-rise acceleration} \]

\[\text{after A.D. 1970. These data} \]

---

\[3 \text{ This chapter has been reprinted from Geology with permission as: Karegar, M.A.; Dixon, T.H. \\& Malservisi, R. (2015). A three-dimensional surface velocity field for the Mississippi Delta: Implications for coastal restoration and flood potential. Geology, 43(6), 519-522. Copyright © 2015 Geological Society of America. Published by Geological Society of America. https://doi.org/10.1130/G36598.1} \]
have implications for land reclamation and wetland restoration in the region; parts of the delta may not be viable in the long-term.

3.2 Introduction

Parts of coastal Louisiana (southern United States) are undergoing accelerated land loss due to the combined effects of sea-level rise and land subsidence (Morton et al., 2009). In the case of the Mississippi Delta, where rates of land loss are especially severe, subsidence of the land surface reflects natural processes such as sediment compaction and crustal loading, exacerbated by anthropogenic withdrawal of fluids (water, oil, natural gas). Given stable sea level and sediment deposition, a delta will tend toward an equilibrium state where subsidence is more or less balanced by sediment deposition. In the Mississippi River system, however, a series of dams on various upstream tributaries have reduced sediment supply to the delta (Blum and Roberts, 2012), while levees on the lower part of the river have artificially channelized the flow, forcing sediments to be deposited beyond the delta in the deeper Gulf of Mexico. Mitigation efforts can include river diversion to encourage re-sedimentation, and pumping of offshore sands to restore barrier islands (e.g., CPRA, 2012).

Knowledge of current subsidence rates should be an important component of long-term planning of mitigation, for example allowing efforts to be focused where current subsidence rates are low. Unfortunately, despite its obvious importance, the rate of current subsidence in the delta remains unclear. Dokka (2011) emphasized high rates
of subsidence due to fluid extraction, based on geodetic leveling data. Yu et al. (2012) emphasized low rates of subsidence based on studies of Holocene peat. Both of these studies addressed deeper processes in the Earth’s lithosphere and did not focus on subsidence caused by shallow processes. Morton and Bernier (2010) and Kolker et al. (2011) suggested that high rates of subsidence correlated with periods of on-shore oil production, and that subsidence has declined significantly since the 1990s as oil and gas production moved offshore. State and federal governments are investing significant funds for coastal restoration in the region. Improved knowledge of subsidence could help to better target such efforts.

Part of the problem in quantifying subsidence is that the process may be both temporally variable (Morton and Bernier, 2010; Kolker et al., 2011) and spatially variable. Some of the variability could relate to the technique used (Meckel, 2008). Spot measurements (e.g., tide gauges or sparse GPS measurements) could therefore alias a spatially complex signal. Moreover, some analyses of subsidence rely on tide gauge data, which record temporal variations due to decadal and multi-decadal oceanographic oscillations. Extracting a meaningful subsidence signal in the presence of significant oceanographic and non-oceanographic variations can be challenging.

Dokka et al. (2006) estimated geodetic deformation rates of southeast Louisiana using continuous and episodic GPS data collected between 1995 and 2006 with an average record length of 5 yr. The uncertainties of vertical rates were rather large in that
study (0.8-4.8 mm yr⁻¹, with an average of 2 mm yr⁻¹). New GPS databased on longer time series (average record length of 9 years) and additional stations (18 new sites) are now available, and allow a substantial refinement (See Table A1 in Appendix A) (Figure 3.1A). We present a three-dimensional velocity field based on 36 permanent GPS sites in the lower Mississippi basin using data to June 2014. Moreover, new analytical techniques (see the tide gauge discussion herein, and Appendix A) allow better extraction of trends from tide gauge time series with multiple oscillatory modes, allowing a more rigorous comparison of GPS and tide gauge data.

3.3 GPS data and analysis

The raw GPS data were processed using the software package GIPSY/OASIS II (V. 6.2) of the Jet Propulsion Laboratory (gipsy-oasis.jpl.nasa.gov) and the precise point positioning technique (Appendix A). The stations have nearly continuous observations, ranging from 4 to 18 yr. Half of the stations record data for longer than 10 yr. The non-fiducial daily position time series are transformed into the IGS (International GNSS Service) 2008 reference frame. The horizontal components of the non-fiducial daily solutions are also transformed into a North American plate-fixed frame (NA12).

It has long been recognized that the formal errors of displacement time series based on a white noise approximation underestimate the uncertainty of site velocity (e.g., Hackl et al., 2011). Time-correlated (colored) noise can be estimated using spectral analysis and maximum likelihood estimation. Here, we use the Allan Variance of Rates
(AVR) method (Hackl et al., 2011) which deals with time-correlated noise in a robust manner (Appendix A).

3.4 Tide gauge data and analysis

Tide gauge data have long been used to estimate subsidence of the Mississippi Delta (e.g., Penland and Ramsey, 1990). One challenge is that tide gauges record a combination of land subsidence and sea-level rise, both of which can exhibit variability on a multitude of time and spatial scales, from both natural causes, e.g., decadal and multi-decadal oceanographic oscillations (Chambers et al., 2012), and anthropogenic causes such as global warming and hydrocarbon and groundwater extraction (Morton and Bernier, 2010). Nevertheless, with appropriate analytical techniques, the relative sea-level record from tide gauges can be compared to GPS-derived vertical land motion from nearby stations to provide independent data.

We used tide gauge records from the Permanent Service for Mean Sea Level (PSMSL; www.psmsl.org) database for a station at Grand Isle, Louisiana, and several Florida stations, for comparison to nearby GPS stations (Figure A2 in Appendix A). The tide gauge in Pensacola is located on stable upper Pleistocene sediment. The corresponding GPS station (PCLA) is located 7.5 km away. The PCLA GPS station records vertical land motion of $1.0 \pm 0.2$ mm yr$^{-1}$, similar to $1.1$ mm yr$^{-1}$ estimated at that location from the ICE-5G V1.3 model for Glacial Isostatic Adjustment (GIA) (Peltier, 2004) but $\sim 0.5$ mm yr$^{-1}$ faster subsidence than an estimate of GIA-related subsidence at
the Mississippi delta based on the reconstructed Holocene sea-level record (Yu et al., 2012). The average relative sea-level rise rate from 1924 to 2014 at the corresponding tide gauge at Pensacola, Florida, is $3.1 \pm 0.6$ mm yr$^{-1}$ (Figure A4), suggesting a local sea-level rise (corrected for vertical land motion as measured by GPS) of $2.1$ mm yr$^{-1}$, higher than average global sea-level rise for the past century ($1.7$ mm yr$^{-1}$, Church and White, 2011; $1.2$ mm yr$^{-1}$, Hay et al., 2015). We also use two other tide gauges in Florida to compare results with the tide gauge record at Pensacola, obtaining similar results (Table 3.1).

Differencing of tide gauge data (e.g., Grand Isle relative to Pensacola) has been used to reduce the influence of decadal scale oceanographic effects (e.g., Kolker et al., 2011). When this is done to estimate subsidence rate, it is important to add back the effects of GIA because it is a real physical effect on the land surface that is lost in the differencing approach.

Our analysis of tide gauge data is based on the Hilbert-Huang Transform (HHT) (Huang and Wu, 2008). This method accounts for decadal or multi-decadal effects, extract long-term trends, and distinguishes uniform velocity from records indicating acceleration. The method uses Empirical Mode Decomposition (EMD) and Hilbert spectral analysis to decompose a time series to intrinsic mode functions and a residual with time-dependent amplitudes and frequencies. Numerous studies have documented
its efficacy for extracting longer term trends in the presence of significant shorter term oscillations (see Appendix A).

3.5 Results

GPS results are summarized in Table A1 (Appendix A). With the exception of stations MSHT and LESV, all stations indicate subsidence. The highest subsidence rates are observed at sites near the deltaic shoreline (Figure 3.1A). Subsidence rates of <2 mm yr\(^{-1}\) occur in northern Louisiana, decrease to ~0 in the mid-Louisiana upland, and then increase to 6.5 mm yr\(^{-1}\) in southern Louisiana. Figure 3.2A shows the vertical velocity component as a function of latitude. In southern Louisiana (south of 30.5°N), subsidence rates increase from <2 mm yr\(^{-1}\) north of the Baton Rouge fault zone to 6.5 mm yr\(^{-1}\) in the southern Mississippi Delta, with a north-south gradient of 3.4 mm yr\(^{-1}\) per 100 km.
Figure 3.1: Map showing the locations of GPS sites and growth fault system in southern Louisiana (USA) from Murray (1961). Black stars show locations of major cities. A: Vertical velocities (circles) in IGS08 reference frame (see text). Circle colors indicate value of subsidence. B: Horizontal velocities in North America 2012 frame plotted with 95% error ellipses. Yellow circles show locations of GPS stations.

Table 3.1 also lists the subsidence rates inferred from differencing the tide gauge record at Grand Isle from three different reference tide gauge records along the eastern Gulf of Mexico. The HHT estimates for the three reference tide gauges, correcting for GIA (adding 1 mm yr$^{-1}$) have a very limited range, 6.7–6.8 mm yr$^{-1}$. In contrast, if we use linear regression, the long-term subsidence rate over the same period (1947–2014) for the three reference tide gauges varies between 7.7 and 8.2 mm yr$^{-1}$. Linear regression for
the various sub-periods, also correcting for GIA, yields a subsidence rate for 1947–1959 of <4 mm yr\(^{-1}\), increasing to ~9–10 mm yr\(^{-1}\) for 1959–1994, and decreasing to <5 mm yr\(^{-1}\) from 1994 to 2014.

North of 30.5°N latitude, the horizontal GPS velocities in the NA12 reference frame are <1 mm yr\(^{-1}\), as expected for stable North America (Figure 3.2B). Within the Mississippi Delta, stations show increasing southward motion. This motion may reflect slow downslope movement on a series of listric normal faults due to gravitational sliding (Murray, 1961; Dokka et al., 2006), but could also represent the horizontal component of differential compaction. The boundary between stable sites and southward moving sites corresponds to the Pleistocene-Holocene contact along the southern lower Mississippi valley margins. The new data suggest lower rate of southward displacement than suggested by Dokka et al. (2006). Consequently active faulting, if it occurs, is probably a minor component of subsidence. With the exception of three sites with shorter time series and higher error bars, the new data suggest that southward motion reaches a maximum rate of ~0.5–1.0 mm yr\(^{-1}\) at the southern end of the delta.
**Table 3.1:** Comparison of subsidence rate at Grand Isle relative to three different reference stations from linear regression and Hilbert-Huang transform.

<table>
<thead>
<tr>
<th>Tide Gauge</th>
<th>Rate from linear regression (mm yr$^{-1}$)</th>
<th>Rate from HHT (mm yr$^{-1}$)</th>
<th>Rate from GIA (mm yr$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grand Isle-Pensacola</td>
<td>3.0 ± 1.1</td>
<td>9.7 ± 0.2</td>
<td>3.7 ± 1.1</td>
</tr>
<tr>
<td>Grand Isle-St. Petersburg</td>
<td>1.2 ± 2.9</td>
<td>8.5 ± 0.9</td>
<td>3.5 ± 1.4</td>
</tr>
<tr>
<td>Grand Isle-Key West</td>
<td>1.7 ± 6.7</td>
<td>8.6 ± 0.4</td>
<td>3.9 ± 1.0</td>
</tr>
</tbody>
</table>

*Note:* The subsidence rate (here positive) is calculated by subtracting listed monthly tide gauge record from Grand Isle tide gauge record. The average subsidence rate is computed using linear regression analysis and residual of Hilbert-Huang Transform (HHT) analysis. Uncertainties are 1σ and accounts for colored noise using the Allan Variance of Rates method (Hackl et al., 2011). The Glacial Isostatic Adjustment (GIA)-related subsidence rate is from the model ICE-5G V1.3 (Peltier, 2004).

### 3.6 Discussion

Slow regional subsidence (~1–2 mm yr$^{-1}$) is indicated in northern Louisiana near the cities of Monroe, Shreveport, and Ruston (Figure 3.1A). Total continental water storage estimated from the Gravity Recovery and Climate Change (GRACE) satellite in this region shows decreases of 1–3 cm yr$^{-1}$ in equivalent water thickness for these areas from 2003 to 2012 (Famiglietti and Rodell, 2013). Decline in water storage together with glacial forebulge collapse caused by GIA (Peltier, 2004) likely explains the slow subsidence of these upland areas.

Slow vertical rates of motion (0 ± 0.5 mm yr$^{-1}$) in mid-Louisiana between 30.5°N and 32°N are typical of stable continental interiors. In contrast, areas south of 30.5° N show increasing subsidence, up to 6.5 mm yr$^{-1}$. Two explanations are likely. First, the lower Mississippi Delta is composed of Holocene-age sediments (younger than 12 ka)
underlain by Pleistocene-age sediments. Kulp et al. (2002) showed that the thickness of Holocene strata increases southward. The inset plot in Figure 3.2A shows that subsidence rates in the Mississippi Delta correlate with the thickness of Holocene sediments. This can be explained in terms of faster compaction and expulsion of pore water from younger and thicker saturated sediments (Penland and Ramsey, 1990; Meckel et al., 2006; Törnqvist et al., 2008). Most of the GPS stations in this study are installed on the top of buildings; and so their monuments are actually building foundations that include pilings, vertical structural columns driven to refusal, typically 5–15 m depth. Table DR1 lists the actual foundation depth, where known. Our data therefore do not include the effect of compaction of the uppermost Holocene section, and therefore our subsidence rate estimates for the Mississippi Delta should be considered minimum estimates.

A second possible explanation for subsidence is crustal loading (sedimentary isostatic adjustment, or SIA) where the weight of Holocene sediment causes downward flexure of the crust, with a delayed response due to the visco-elastic nature of Earth’s mantle. Ivins et al. (2007) assumed that SIA is the main process that contributes to delta subsidence. Blum et al. (2008) and Wolstencroft et al. (2014) suggested that SIA-related subsidence is not a dominant process in the Mississippi Delta, contributing <1 mm yr\(^{-1}\). A combination of sediment compaction and SIA is also possible. Meckel et al. (2006)
suggested that subsidence rates >5 mm yr\(^{-1}\) likely reflected processes in addition to compaction.

**Figure 3.2:** A) Vertical velocities and their standard errors versus latitude. Three geomorphic zones are indicated: extension zone (\(\phi \leq 30.5^\circ\)), stable mid-Louisiana (LA) upland (\(30.5^\circ \leq \phi \leq 32^\circ\)), and northern subsidence zone (\(32^\circ < \phi \leq 34^\circ\)). Inset shows vertical velocities (mm yr\(^{-1}\)) versus Holocene sediment thickness (m) from Kulp et al. (2002) with linear regression. The correlation between subsidence rate and sediment thickness is 0.85. B) North-south velocities and their standard errors versus latitude. Color bar shows the length of time series for each station.

As summarized in Table 3.1 and discussed by Kolker et al. (2011) and Morton and Bernier (2010), the high subsidence rates for the period 1959–1994 may correspond to periods of high onshore hydrocarbon production. To investigate this further, and minimize possible effects of sea-level fluctuations, we use three long tide-gauge records along the eastern Gulf of Mexico in stable Florida as reference stations (Table 3.1). The resulting long-term trend from linear regression represents an average rate influenced mainly by episodic high subsidence rates in 1959-1994. This estimate is 2.1–2.6 mm yr\(^{-1}\).
higher than the 5.6 ± 0.2 mm yr$^{-1}$ decadal average subsidence rate obtained from GPS measurement at Grand Isle.

To examine if subsidence rates inferred in the past century from tide gauge data were influenced by multi-decadal oscillations, the trend was also calculated using the HHT, method which filters the effects of oscillatory modes. Our analysis shows that combining the 1947–2014 subsidence rate calculated from tide gauge data using the HHT method with GIA-related subsidence rate (1.0 mm yr$^{-1}$ at Pensacola; somewhat smaller values for more-southern Florida stations) produces results closely comparable to the GPS subsidence rate at Grand Isle (Table 3.1). The residual component in HHT analysis represents a trend after all oscillation modes (such as decadal and multi-decadal variations) are removed (see Figure A3c in Appendix A). In contrast, the trend obtained from simple linear regression may be influenced by decadal or multi-decadal variations and therefore may not accurately reflect long term subsidence associated with sediment compaction, SIA, or other non-anthropogenic processes (Figure 3.3).

The agreement between the subsidence rate obtained from a decade of GPS measurements and those estimated from multi-decadal tide gauge records using the HHT method indicates that continuous GPS measurements adequately measure subsidence of the delta, and also suggests that some prior analyses of subsidence based on tide gauge data may have been overly influenced by multi-decadal oscillations in
either oceanographic effects, subsidence effects, or both (see Figure A3, and the discussion in Appendix A).

![GRIS tide gauge referred to PCLA tide gauge](image)

**Figure 3.3:** Plot of tide gauge data at Grand Isle, Louisiana (GRIS) referenced to Pensacola, Florida (PCLA) (gray dots) and comparison between average long-term subsidence rate (black line) and change of rate (dash line) obtained from linear regression analysis (reg.), compared to Hilbert-Huang Transform (HHT) analysis (blue line).

### 3.7 Implications for coastal restoration

The current subsidence rate of the southern Mississippi delta varies from 5.6 mm yr\(^{-1}\) to 6.5 mm yr\(^{-1}\) based on three southern delta GPS stations. Tide gauge data for the post-1990s suggest subsidence here of at least 4.5 mm yr\(^{-1}\) (adding 3.5 mm yr\(^{-1}\), the minimum rate using St. Petersburg, Florida, tide gauge as a reference and 1.0 mm yr\(^{-1}\)
for the GIA signal). These results do not reconcile with the results of Morton and Bernier (2010) and Kolker et al. (2011), who estimated a current subsidence rate of <2 mm yr\(^{-1}\) since 1990. Assuming 2.1 mm yr\(^{-1}\) for the rate of sea-level rise (the long-term average value at Pensacola), the current rate of relative sea-level rise for the coastal delta is therefore at least 6.6 mm yr\(^{-1}\) using tide gauge data and 7.7 mm yr\(^{-1}\) using the GPS data. Using the higher average rates of sea-level rise since 1990 (e.g., 2.6 mm yr\(^{-1}\) at Pensacola after correcting for GIA; Table A2 in Appendix A) implies total rates of relative sea-level rise for the southern delta are at least 7.1 mm yr\(^{-1}\) (tide gauge) and 8.2 mm yr\(^{-1}\) (GPS). Using the average subsidence rate for the southern delta measured by GPS (5.9 mm yr\(^{-1}\)) and the post-1990 sea-level rate (2.6 mm yr\(^{-1}\)) gives a relative sea-level rise rate of 8.5 mm yr\(^{-1}\). As a check on internal consistency, note that this latter value is similar to the total rate recorded at the GRIS tide gauge since 1990, 9.1 mm yr\(^{-1}\) (Table A2), which presumably records the combined effects of sea-level rise and land subsidence over the same period. We do not know if such elevated rates of sea-level rise will continue in the future, but this seems likely, and prudent planning would dictate that the higher values be used.

Our subsidence rates do not translate directly into rates of surface lowering, as they do not account for loss of organic material by oxidation or compaction in the upper ~5–35 m of Holocene sediment (which would make our rates minimum estimates of the rate of land lowering), or re-sedimentation (which would reduce the effects of
subsidence). Kirwan et al. (2010) noted the adaptability of coastal marshes to relative sea-level rise in the presence of high suspended sediment concentration due to re-sedimentation. However, Blum and Roberts (2012) note that dams on the upper Mississippi have greatly reduced the supply of sediment to the delta. In this context, our new data have important implications for predictions of future land loss and storm surge inundation, as well as land reclamation and wetland restoration efforts. For example, it may be useful to focus such efforts where subsidence rates are lower.

### 3.8 References


CPRA (Coastal Protection and Restoration Authority of Louisiana), 2012: Louisiana’s Comprehensive Master Plan for a Sustainable Coast, Baton Rouge, Louisiana: CPRA, 190p.


Morton, R.A., Bernier, J.C., and Barras, J.A., 2006, Evidence of regional subsidence and associated interior wetland loss induced by hydrocarbon production, Gulf Coast


Penland, S., and Ramsey, K.E., 1990, Relative sea-level rise in Louisiana and the Gulf of Mexico: 1908-1988:


4. Subsidence Along the Atlantic Coast of North America: Insights from GPS and Late Holocene Relative Sea-level Data\(^4\,5\)

4.1 Abstract

The Atlantic Coast of North America is increasingly affected by flooding associated with tropical and extratropical storms, exacerbated by the combined effects of accelerated sea-level rise and land subsidence. The region includes the collapsing forebulge of the Laurentide Ice Sheet. High-quality records of late Holocene relative sea-level (RSL) rise are now available, allowing separation of long-term glacial isostatic adjustment-induced displacement from modern vertical displacement measured by GPS. We compare geological records of late Holocene RSL to present-day vertical rates


from GPS. For many coastal areas there is no significant difference between these independent data. Exceptions occur in areas of recent excessive groundwater extraction, between Virginia (38°N) and South Carolina (32.5°N). The present-day subsidence rates in these areas are approximately double the long-term geologic rates, which has important implications for flood mitigation. Tide gauge records, therefore, should be used with caution for studying sea-level rise in this region

4.2 Introduction

Eastern North America is a passive continental margin. Most of this margin is experiencing spatially variable, long-term vertical motion due to glacial isostatic adjustment (GIA), a viscoelastic response of the Earth’s crust and mantle to retreat of the Laurentide Ice Sheet since the last glacial maximum ~20,000 years ago (e.g., Peltier, 2004). GIA drives land uplift in areas under the former Laurentide Ice Sheet and land subsidence in peripheral areas as the forebulge beyond the former ice sheet margin collapses. Subsidence along parts of the Atlantic Coast constitutes the largest-amplitude proglacial forebulge collapse on Earth. Although GIA is the dominant contributor to vertical land motion in this region, other processes also contribute to crustal movement here. Groundwater withdrawal and recharge induces spatially and temporally variable vertical motion in the Atlantic coastal plain (Depaul et al., 2008; Boon et al., 2010). Sediment loading (Calais et al., 2010), sediment compaction (Miller et al., 2013), topographic relaxation of the slowly eroding Appalachians (Ghosh
et al., 2009), ridge push generated by cooling of the oceanic portion of the North American plate (Zoback, 1992), mantle flow-induced dynamic topography (Rovere et al., 2015), and in-plane stress-induced deformation (Cloetingh et al., 1985; Karner, 1986) are additional active processes that may also contribute to vertical motion in this passive margin environment. Since coastal locations are impacted by flooding from tropical and extratropical storms, the combined effects of accelerating sea-level rise and land subsidence need to be considered in long-term flood mitigation and planning (e.g., Dixon et al., 2006; Ezer and Atkinson, 2014).

Vertical land motion has been measured with continuous GPS stations across the North American plate interior (Sella et al., 2002; Park et al., 2002; Calais et al., 2006; Sella et al., 2007; Argus and Peltier, 2010; Peltier et al., 2015) and along the coastal plain near tide gauges (Snay et al., 2007; Bouin and Wöppelmann, 2010; Santamaría-Gómez et al., 2012). Along the eastern seaboard, these studies have been limited by the number and time span of available data (Peltier et al., 2015). Engelhart et al. (2009) and Kemp et al. (2014) compared late Holocene relative sea level (RSL) data with available GPS vertical rates calculated by Snay et al. (2007) and Sella et al. (2007) and found significant discrepancies. Some of these discrepancies can be attributed to the short GPS time series then available. Other discrepancies may reflect the influence of time-variable groundwater extraction and recharge. New GPS data based on longer time series (average record length of 8.5 years) and additional stations (~190 new sites) are now
available, allowing substantial refinement of the present-day vertical velocity field.

Here we investigate vertical land motion in the central part of eastern coastal North America, based on 216 continuous GPS sites between New Brunswick, Canada, and southern Florida, U.S., using all available data to January 2015. We compare these data to high-quality geological records of Holocene RSL describing vertical land motion in the region from 4 ka B.P. to 1900 A.D. We then discuss the major processes affecting the present-day vertical velocity field.

4.3 Data and analysis methods

4.3.1 GPS

The GPS stations analyzed here have nearly continuous observations, ranging from 4 to 18 years. More than 70 stations have recorded data for longer than 10 years. The raw GPS data were processed using the software package GIPSY/OASIS II (V. 6.2) of the Jet Propulsion Laboratory (JPL) and the precise point positioning technique (see Appendix A). The non-fiducial daily position time series are transformed into the IGb08 reference frame (Rebischung et al., 2012) using JPL’s X files, a seven-parameter transformation.

It has long been recognized that the formal errors of GPS displacement time series based on a white noise approximation underestimate the uncertainty of site velocity (e.g., Mao et al., 1999). Time-correlated (colored) noise can be estimated using spectral analysis and maximum likelihood estimation (Mao et
al., 1999; Williams, 2008; Bos et al., 2008). Here we estimate the vertical rate uncertainties using the Allan variance of rate technique of Hackl et al. (2011) as described in Karegar et al. (2015) and Appendix A.

4.3.2 Late Holocene relative sea-level database

Reconstructions of late Holocene (last 4000 years) RSL have recently been compiled to create a database defining vertical land motion along the Atlantic Coast of the U.S. (Engelhart and Horton, 2012; Kemp et al., 2014; Nikitina et al., 2015). The methodology is described in the Handbook of Sea-Level Research (Shennan et al., 2015) and recent publications (Engelhart et al., 2009; Engelhart and Horton, 2012; Hijma et al., 2015). These data assume that late Holocene ice equivalent meltwater input is minimal from 4 ka B.P. until 1900 A.D.; therefore, RSL trends are an estimate of spatially variable land motion primarily dominated by GIA. A recent study shows global eustatic sea-level rise of ≤1 m from 4.2 ka B.P. to 1900 A.D (Lambeck et al., 2014). Ocean syphoning (migration of water into subsiding peripheral bulges) is also known to affect late Holocene sea-level rise (Mitrovica and Milne, 2002). Late Holocene RSL data suggest a tectonic uplift rate of ∼0.2 ± 0.2 mm yr⁻¹ along the Cape Fear Arch (southeastern United States) (van de Plassche et al., 2014), but along much of the passive Atlantic Coast of North America, the tectonic contribution to RSL data is assumed to be negligible. The effects of natural compaction of Holocene sediment are minimized by using basal peat samples (Engelhart et al., 2009). Compaction of the underlying (pre-
Holocene) strata is believed to occur at low rates (<0.1 mm yr\(^{-1}\)) (Kooi and de Vries, 1998; Kominz et al., 2008; Hayden et al., 2008; Horton et al., 2013; Miller et al., 2013). Engelhart and Horton (2012) recalculated rates of RSL change for 16 regions (from Maine to South Carolina; see Figure 4.1) for the last 4 ka after removing RSL change since 1900 A.D. based on measurements from the nearest reliable tide gauge. These regions are classified based on data availability, distance from the center of the former Laurentide Ice Sheet, and susceptibility to Holocene sediment compaction. We expand/modify the Engelhart et al. (2009) data to reflect the availability of new data and to incorporate data from a site in southern Canada. A RSL history produced for the southern New Brunswick coast (Canada) at Little Dipper Harbour (45.1°N, 66.4°W) shows that late Holocene RSL at this location has been about 1 m/1000 years (Gehrels et al., 2004), i.e., ~1 mm yr\(^{-1}\) subsidence rate. Nikitina et al. (2015) produce a new RSL record covering the last 2200 years in Delaware Bay (39°N, 75°W). They showed that Engelhart et al. (2009) overestimated the late Holocene RSL rate in the inner bay due to tidal range changes. Kemp et al. (2014) provides the RSL data from 2.5 ka to 1800 A.D. from the border of Georgia and northeastern Florida.

Given ongoing mantle relaxation, there is a possibility that late Holocene RSL rates are biased by record length (lower rates for later periods). Engelhart and Horton (2012) compared linear rates of RSL rise from 2 ka B.P. to 1900 A.D. with linear rates from 4 ka B.P. to 1900 A.D. in 11 regions with sufficient data for both time periods.
Within uncertainties, similar rates were obtained for the two periods. Supporting information Text S3 discusses a possible exception.

Uncertainties in the late Holocene RSL rates are derived from propagation of errors and depend on type of coring equipment, techniques of depth measurement, natural compaction of sediment during penetration, and error associated with the leveling of the sample with respect to the North American Vertical Datum of 1988 (see Engelhart et al., 2009; Engelhart and Horton, 2012). Effects of eustatic sea-level rise could also overestimate the vertical land motion from RSL data (<0.2 mm yr\(^{-1}\)) (Lambeck et al., 2014).

4.4 Results

Our GPS analysis gives a present-day snapshot of vertical land motion at 216 sites along the East Coast of North America with an uncertainty of order 0.5 mm yr\(^{-1}\) or better (Figure 4.1 and Table A3 in Appendix B). Subsidence rates of <1 mm yr\(^{-1}\) occur in New Brunswick, Canada, along the shoreline, transitioning to uplift rates of <1 mm yr\(^{-1}\) from Maine (45°N) to New Hampshire (43°N). All stations from New Hampshire to mid-Florida (28°N) show subsidence rates of <3 mm yr\(^{-1}\). The highest subsidence rates concentrate in a coastal region from northern Delaware and Maryland (~40°N) to the northern part of North Carolina (~35°N) (mean ~1.5 mm yr\(^{-1}\), up to ~3 mm yr\(^{-1}\)).
Figure 4.1: Map showing the location of GPS sites used in this study and 18 regions for which the late Holocene relative sea-level rise rate is known. Map showing the location of GPS sites used in this study and 18 regions for which the late Holocene relative sea-level rise rate is known [region 1, Gehrels et al. (2004); regions 2–17, Engelhart et al. (2009), Engelhart and Horton (2012), and Nikitina et al. (2015); region 18, Kemp et al. (2014)]. GPS and geologic rates for each region are detailed in Table A4 in Appendix B. Red line shows the Fall Line, a boundary between compressible coastal plain sediments and incompressible bedrock of the Piedmont Province (Meng and Harsh, 1988). Circle color indicates decadal average vertical land motion in IGb08 reference frame.
The surface vertical velocities defined by GPS are compared to the rates of late Holocene RSL rise in Figure 4.2a and Figure A10a in Appendix B. The pattern of subsidence obtained from the geologic data largely reflects ongoing GIA, including collapse of the proglacial forebulge. The GPS data exhibit a similar pattern, with exceptions discussed below. The GPS and geologic data indicate that the highest rates of subsidence due to forebulge collapse (1.3–1.5 mm yr$^{-1}$) extend from New Jersey (region 9, ~39°N) south to the Chesapeake Bay (region 13, ~37°N). To facilitate comparison, we also average rates from all GPS stations within specific areas where Holocene RSL rise data are available (18 boxes in Figure 4.1; Figure 4.2b; Figure A10b, and Table A4 in Appendix B).
Figure 4.2: (a) Comparison of vertical motion as a function of latitude from GPS and geologic data. Color bar shows the length of time series for individual stations. (b) Spatially averaged GPS, geologic data, and GIA model ICE6G-VM5a (C). The GPS rate is averaged for all stations in the boxes shown in Figure 4.1.

4.5 Discussion

Accurate determination of the forebulge location and amplitude is important for studies of RSL and flood mitigation. Recent findings show accelerated RSL along the coast north of Cape Hatteras (35.2°N), North Carolina, and significant variation of RSL rates along the U.S. eastern seaboard (Boon et al., 2010; Ezer and Corlett, 2012; Sallenger et al., 2012; Kopp, 2013). Slowing of the Atlantic Meridional Overturning Circulation (Sallenger et al., 2012; Yang et al., 2016) and variations in the Gulf Stream location and intensity (Ezer et al., 2013) have recently been identified as possible drivers of accelerated sea-level rise in this region. Our new data will be useful at separating the various contributions influencing present-day tide gauge RSL data, allowing better tests of these hypotheses.

There is a good agreement (within data uncertainty) between estimates of vertical land motion from GPS and geologic data along the Atlantic Coast of North America, except for two regions. Between 38°N and 32.5°N, present-day subsidence rates from GPS are approximately double the long-term geologic rates. In Maine (45°N–43°N), the GPS data show uplift whereas geologic data show subsidence (see Appendix B).
At the regional scale, GPS rates reconcile with geologic rates in much of the mid-Atlantic (regions 1 and 4–12, 45.1°N and 43°N–38°N). The GPS and geologic rates also agree in Georgia and Florida (region 18; 31.5°N–29°N). Note that comparison of GPS and geologic rates is limited to 18 regions where late Holocene RSL data are available (Figure 4.1).

We use the latest GIA model, ICE6G-VM5a (C) (Peltier et al., 2015), for comparison to the GPS and geologic data (Figure 4.2b). In ICE6G, the mantle viscosity VM5a model (Peltier and Drummond, 2008) is held fixed in the adjustment process, while the glaciation history (ICE5G-VM2) is refined to best fit selected GPS rate data in North America, Northwestern Europe/Eurasia, and Antarctica. We calculated the weighted root-mean-square (WRMS) of residuals (GPS or geologic rate minus the GIA model) to quantify the overall agreement between ICE6G-VM5a (C) and these other data. The WRMS of geologic rates relative to the GIA model (0.15 mm yr⁻¹) is smaller than the WRMS of GPS rates relative to the GIA model (0.66 mm yr⁻¹). The larger discrepancy between GPS and the GIA model may reflect larger uncertainties in GPS rates, inconsistency in the GPS and GIA model reference frames (e.g., Kierulf et al., 2014), inappropriate selection of GPS sites to constrain the ICE6G-VM5a (C) GIA model, and non-GIA signals in our GPS data, e.g., signals related to groundwater fluctuations. Here we focus on this latter explanation.
The GPS subsidence rates decrease with distance away from the coastal plain and toward the center of mass loading of the Laurentide Ice Sheet (Figure 4.1). The geomorphic boundary (Fall Line, see Figure 4.1 and Figure A12a in appendix B) that separates compressible coastal plain sediments (Cretaceous to Holocene unconsolidated sediments) and incompressible bedrock of the Piedmont Province closely corresponds to the boundary separating high subsidence rates (2–3 mm yr\(^{-1}\)) and low subsidence rates (<1 mm yr\(^{-1}\)). Subsidence of stations east of the Fall Line is also more variable than those of bedrock sites. Stations east of the Fall Line are likely affected by both groundwater fluctuations and natural sediment compaction. Groundwater extraction in excess of recharge reduces pore fluid pressure, leading to aquifer-related compaction and surface subsidence. Conversely, net groundwater recharge increases pore fluid pressure and can lead to uplift.

As noted earlier, the influence of shallow sediment compaction on Holocene RSL data is minimized through the use of basal peats. The agreement between GPS and Holocene RSL data in regions 9–12 (New Jersey to Virginia, 40°N–38°N, an area underlain by unconsolidated sediments) therefore implies that subsidence due to shallow sediment compactions is very small in the GPS data. This makes sense, because most of the GPS stations used in this study are installed on the top of buildings. Their monuments are building foundations that usually include concrete pilings, vertical structural columns driven to refusal, typically several meters or more in depth.
Therefore, our GPS subsidence rates are not sensitive to compaction in the upper few meters of Holocene sediment. For purposes of flood mitigation and planning, the GPS rates should be considered minimum rates.

4.5.1 Effects of groundwater withdrawal

The GPS data reflect a combination of long-term deformation (e.g., from GIA, deep sediment compaction, and sedimentary isostatic adjustment) and short-term deformation (e.g., from groundwater withdrawal). The geologic rates of RSL (indicating long-term deformation) can be used to correct the GPS data to investigate recent changes to the vertical velocity field. This information may be useful to understand and predict future wetland loss and storm surge inundation, particularly in areas (e.g., north of Cape Hatteras) where accelerated sea-level rise has been observed and is associated with increased flooding (Ezer and Atkinson, 2014).

Figure 4.3a shows the distribution of coastal groundwater monitoring wells with depth > 100 m. We calculated the average trend in groundwater level since 2005, corresponding to the time span of most of the GPS observations. These data and other studies (e.g., Konikow, 2013; Russo et al., 2015) demonstrate that the central and southern Atlantic coastal plain (Virginia and the Carolinas) are experiencing groundwater declines. We can test whether areas experiencing rapid modern subsidence correlate with areas of intense groundwater extraction, as follows. We subtract the geologic subsidence rate (which includes the GIA component) from the
average GPS rate calculated for each box shown in Figure 4.1 to derive a residual rate (“GPS minus Holocene RSL” in Figure 4.3a and 4.3b). We then compare these residual rates with the average trend of groundwater level as a function of latitude (Figure 4.3b). In the central and southern Atlantic coastal plains (38°N–32°N), we observe a correlation between rapid subsidence and groundwater depletion, consistent with the idea that excessive groundwater extraction is driving rapid land subsidence in these regions. The short-term GPS subsidence rates are double the long-term geologic subsidence rates.

The Atlantic coastal plain is composed of a multilayered aquifer system underlain by a wedge of unconsolidated to semiconsolidated sedimentary rocks. The sedimentary wedge thickens eastward beneath the continental shelf, ranging from a featheredge near the Fall Line to about 3000 m at Cape Hatteras (35.2°N), North Carolina (Figure A12a in Appendix B). The relatively weak correlation between local GPS subsidence and local coastal plain thickness (ρ=0.40; supporting information Figure A12) implies that subsidence due to natural compaction of deep sediment and sedimentary isostatic loading, while present, is not the major process affecting these data. Both GPS and geologic subsidence rates include the effects of natural compaction of deep strata and sedimentary isostatic loading as well as GIA. These long-term effects are presumably eliminated from the GPS rates by subtracting the corresponding geologic rates. Figure 4.3c shows these “corrected” GPS subsidence rates, which better
correlate with the thickness of underlying coastal plain sediments \( (\rho = 0.54; \text{Figure A12c in Appendix B}) \). A possible explanation is that regions underlain by thicker sediments are more susceptible to faster recent subsidence, perhaps due to groundwater extraction and aquifer compaction. Figure A11 in Appendix B discusses possible correlations with population density and other indirect indicators of groundwater extraction rates.

**Figure 4.3:** (a) Average trend in groundwater level since 2005. (b) GPS vertical velocities corrected for GIA and other long-term geologic effects (GPS rate minus late Holocene RSL rate calculated for each box shown in Figure 4.1) (red dots) and average trend in groundwater level changes (gray dots, east of Fall Line) versus latitude. (c) Corrected GPS vertical velocities (red dots) and sediment thickness (Trapp and Meisler, 1992) (black dots for each box) versus latitude.
The groundwater level in most of the southern Chesapeake Bay region (south of Virginia) declined from the early 1970s until the late 2000s in response to excessive withdrawal. However, from the late 2000s until the present (2015), the trend reversed, indicating groundwater recharge (Figure 4.4). In unconsolidated sediments, aquifer recharge increases pore fluid pressure and results in surface uplift. The longest GPS time series in the southern Chesapeake Bay region spans September 1999 to January 2015 at site DRV1 (DRV5 after June 2006). Figure 4.4c shows vertical displacement at this site, where land subsided at 2.6 mm yr\(^{-1}\) from 1999 to 2010 and at 1.3 mm yr\(^{-1}\) (essentially the GIA rate) from 2010 to 2015. The observed displacements correlate with the abrupt increase in groundwater levels at nearby wells after about 2010 (Figure 4.4). The subsidence rate of 1.3 mm yr\(^{-1}\) for the period 2010–2015 at DRV1(5) agrees with subsidence rates observed at nearby GPS stations with shorter observational period (2009–2015) and the long-term geologic rate of 1.3 mm yr\(^{-1}\) for region 12. Subsidence prior to 2010 in southern Chesapeake Bay was double the geologic rate, while subsidence after 2010 occurred at the geologic rate. Tide gauge records here will need to be corrected for these effects in order to investigate recent sea-level changes. Our result also suggests that recent changes in groundwater management have been effective at reducing aquifer compaction. In summary, for the region from Virginia to South Carolina (38°N to 32.5°N) approximately 50% of present-
day land subsidence is related to groundwater depletion and consequent aquifer compaction.

Figure 4.4: Vertical motion in south of Chesapeake Bay, Virginia, from GPS stations: (a) LOY2, (b) LOYZ, (c) DRV1 (5), and (d) time series of groundwater level change in south of Chesapeake Bay. (e) Location of groundwater monitoring wells (squares and circles) and GPS sites (black triangles) in southern Chesapeake Bay. Square colors indicate groundwater level decrease (1970 to 2010), while circle colors indicate groundwater level increase from 2010 to 2015.
4.6 Conclusions

Installation and operation of more than 130 continuous GPS stations in eastern coastal North America since 2006 represents a significant improvement in our ability to precisely define present-day vertical land motions in this region, improving our ability to understand and predict RSL variations and long-term flood hazard (e.g., Bouin and Wöppelmann, 2010).

Comparison of present-day vertical land motions estimated from GPS with rates of late Holocene RSL rise determined geologically indicates substantial agreement in most areas.

The geologic rate of RSL change provides an independent constraint to separate the long-term GIA-induced displacement (average motion over the past 2–4 ka) from the GPS vertical displacement (average over one to two decades). The present-day subsidence rates measured by GPS between Virginia (38°N) and South Carolina (32.5°N) are approximately double the long-term geologic rates, most likely reflecting recent groundwater depletion. Differences between the geologic and geodetic data are useful for understanding some of the human impacts in the coastal plain and for flood mitigation. For example, parts of the coastal plain (north of Cape Hatteras, North Carolina, 35.2°N) are susceptible to frequent minor to moderate storm-related flooding due to the combined effects of accelerated sea-level rise and land subsidence.
Knowledge of present-day subsidence can help mitigate coastal land loss and predict future storm surge inundation.

4.7 Acknowledgments

This work was supported by NASA grant NNX14AQ16G to T.H.D. and M.A.K., NSF grant OCE-1458903, the U.S. Department of Agriculture National Institute of Food and Agriculture, Hatch funding, and the Rhode Island Agricultural Experiment Station grant RI0015 H104 contribution 5442 to S.E.E. The GPS data used in this study are archived at CORS (http://www.ngs.noaa.gov/CORS/), SOPAC (https://igscb.jpl.nasa.gov/components/dcnav/sopac_rinex.html), UNAVCO (https://www.unavco.org/data/gps-gnss/ftp/ftp.html), and Maine Technical Source (http://www.mainetechnical.com/c6/gps-data-post-processing-c7.html). The groundwater level data are available from the U.S. Geological Survey groundwater information page (http://waterdata.usgs.gov/nwis), North Carolina Division of Water Source (http://www.ncwater.org/?page=20), and South Carolina Department of Natural Resources (http://www.dnr.sc.gov/water/hydro/groundwater/groundwater.html). The GIA model ICE6G-VM5a (C) is available from the University of Toronto database (http://www.atmosp.physics.utoronto.ca/~peltier/data.php). We thank Torbjörn E. Törnqvist and Michael S. Steckler, whose thoughtful comments greatly improved the manuscript. We thank Torbjörn E. Törnqvist and Mead A. Allison for bringing the
authors together at a stimulating workshop on coastal subsidence. This paper is a contribution to IGCP Project 639.

4.8 References


Kopp, R. E. (2013), Does the mid-Atlantic United States sea level acceleration hot spot


5. Nuisance Flooding and Relative Sea-Level Rise: the Importance of Present-day Land Motion\textsuperscript{6,7}

5.1 Abstract

Sea-level rise is beginning to cause increased inundation of many low-lying coastal areas. While most of Earth’s coastal areas are at risk, areas that will be affected first are characterized by several additional factors. These include regional oceanographic and meteorological effects and/or land subsidence that cause relative sea level to rise faster than the global average. For catastrophic coastal flooding, when wind-driven storm surge inundates large areas, the relative contribution of sea-level rise to the frequency of these events is difficult to evaluate. For small scale “nuisance flooding,” often associated with high tides, recent increases in frequency are more clearly linked to sea-level rise and global warming. While both types of flooding are


\textsuperscript{7} This chapter is featured in my interview with Earth and Space Sciences News (Eos) of American Geophysical Union in an article by: Cartier, K.M.S. (2017). Playing with water: Humans are altering risk of nuisance floods, Eos, 98, https://doi.org/10.1029/2017EO083271. Published on 28 September 2017.
likely to increase in the future, only nuisance flooding is an early indicator of areas that will eventually experience increased catastrophic flooding and land loss. Here we assess the frequency and location of nuisance flooding along the eastern seaboard of North America. We show that vertical land motion induced by recent anthropogenic activity and glacial isostatic adjustment are contributing factors for increased nuisance flooding. Our results have implications for flood susceptibility, forecasting and mitigation, including management of groundwater extraction from coastal aquifers.

5.2 Introduction

While it is not currently possible to predict the coastal locations that will be flooded by major storms and hurricanes in the future, the timing and location of nuisance flooding can be predicted with some accuracy (Sweet and Park, 2014; Moftakhari et al., 2015; Ray and Foster, 2016; Wdowinski et al., 2016). Timing is a strong function of local tides, while location is determined by places where land elevation is currently close to local sea level, and hence can be temporarily flooded when the sea surface exceeds some threshold elevation (termed the nuisance flood level). Even moderate amounts of relative sea-level rise (RSLR; the combination of land motion and absolute sea-level rise) can affect this threshold, and hence the nuisance flood frequency.
We investigate the frequency and location of nuisance flooding along the eastern seaboard of North America, and compare these to various processes affecting relative sea level on different time scales. We use rates of vertical land motion measured by Global Positioning System (GPS), rates of recent (1990 - present) RSLR from tide gauges, groundwater-level change from monitoring wells, water storage from the GRACE satellite gravity mission, the geologic rate of RSLR, and Glacial Isostatic Adjustment (GIA) models. We use these diverse data to assess the various factors that influence nuisance-flooding events. In addition to the well-known influence of GIA (described below) we show that recent anthropogenic activities (e.g., groundwater extraction and surface water storage by dams) and corresponding vertical land motions can also influence whether or not a given area experiences nuisance flooding. Parts of the Atlantic coast of North America may also be experiencing sea-level changes in response to large-scale changes in North Atlantic circulation (Boon, 2012; Sallenger et al., 2012; Ezer and Corlett, 2012; Ezer, 2013; Ezer et al., 2013; Kopp, 2013; Andres, 2016; Yang et al., 2016). Since tide gauges measure the combined effect of water-level change and vertical land motion, an accurate description and understanding of relevant land motions is important if we hope to use tide-gauge data to describe and understand recent inter-annual to decadal-scale oceanographic changes (Frederikse et al., 2017).
5.3 Data sets and observations

We use GPS data spanning the last one to two decades to estimate recent vertical land motions over this period (see Chapter 4 and Karegar et al., 2016). These data can be compared to longer term geological data based on radiocarbon dating of basal peat deposits, which define rates of RSLR averaged over the late Holocene period (Engelhart et al., 2009). These data assume that late Holocene glacier meltwater input is minimal from 4 ka B.P. until 1900 A.D., and hence provide estimates of spatially variable vertical land motion dominated by GIA over this time frame. Melting of the polar ice sheets could affect RSLS rates inferred from the geological data. For example, Antarctic effects across the US Atlantic coast have been estimated at $1.3 \times$ the eustatic melt signal (Mitrovica et al., 2009). However, recent research suggests melting from Antarctica ceased or slowed substantially approximately 4000 years ago (Cofaigh et al., 2014; Yokoyama et al., 2016), and similar timing probably applies to Greenland. While eustatic effects could lead to over- or under-estimation of the vertical land motion with the geological approach, several studies suggests that these effects are small ($< 0.2 \text{ mm yr}^{-1}$) (Lambeck et al., 2014; Ullman et al., 2016). The good agreement between our GPS rates and the geological estimates over a substantial fraction of the east coast of North America confirms this (see Chapter 4 and Karegar et al., 2016) (see also Figure 5.1). Details concerning assumptions and uncertainties in the Holocene RSLR database can be found in Engelhart et al. (2009), Karegar et al. (2016) and Chapter 4. The current
database consists of eighteen coastal sites in the US and southern Canada (see Chapter 4 and Karegar et al., 2016).

Vertical land motions averaged over the two time scales are shown in Figure 5.1. To facilitate comparison, we also average rates from all GPS stations within specific regions where Holocene RSL rise data are available (18 boxes in Figure A13). As shown in Figures 5.1 and 5.2, the two data sets are in broad agreement. Both show the expected subsidence maxima centered near Chesapeake Bay (39° North), in agreement with GIA models (Figure A14). These models describe the delayed response of the lithosphere to mass unloading associated with retreat of the Laurentide ice sheet starting about 20,000 years ago (Peltier et al., 2015). The subsidence maximum reflects the collapse of a peripheral bulge, which occurs just south of maximum glacier extent. The bulge is a typical mechanical response to loading and subsequent isostatic adjustment of a rigid or semi-rigid plate over a viscous or inviscid fluid substrate (Walcott, 1972; Peltier 1974; Mitrovica and Peltier, 1991a). Its subsequent collapse leads to long-term subsidence (Mitrovica and Peltier, 1991b) and explains one of the areas experiencing a low threshold for nuisance flooding (Figures 5.2 and A15). The recent increase in flooding rate here reflects this susceptibility, combined with recent SLR.

There are two areas where the GPS (decadal) and geological (late Holocene) data show different rates. We call these areas the southern and northern anomalies, respectively. The southern anomaly is a broad region from 32.5°-37.5° North (Virginia,
North and South Carolina), with substantial scatter in the GPS data. While some GPS sites agree with the geological data, other show high subsidence rates, at roughly twice the geological rate (Figures 5.1, 5.2 and A14). Parts of this area are also experiencing an increase in the frequency of nuisance flooding.

The northern anomaly is from 43-45° North (the states of Maine and New Hampshire) where the GPS data show uniformly slow uplift, in contrast to the geological data, which indicate slow subsidence. This area is not experiencing an increase in the frequency of nuisance flooding.

**Figure 5.1:** Comparison of vertical land motion from GPS (triangles) and late Holocene RSL data (circles) as a function of latitude. The green solid curve is 4th-order polynomial fit to the geologic rates and shows the general pattern of GIA-induced subsidence along the Atlantic Coast of North America. Error bars are 1σ. The GPS rate uncertainties account for time-correlated noise using the Allan Variance of rates method.
Uncertainties in the late Holocene RSL rates are derived from propagation of errors (Engelhart et al., 2009). There is a good agreement (within data uncertainty) between estimates of vertical land motion from GPS and geologic data, except for two regions. Between 37.5°N and 32.5°N (southern anomaly) the GPS data show present-day subsidence rates that are approximately double the long-term geologic rates (see also Figure A14). In Maine, between 45°N-43°N (northern anomaly), the GPS data show uplift whereas geologic data show subsidence. “max. GIA” indicates the maximum subsidence due to collapse of the peripheral bulge associated with the Laurentide ice sheet.

Figure 5.2: Comparison of nuisance flooding level (red circles), GPS vertical rate (blue triangles) and geological vertical rate (green circles) as a function of latitude along the US eastern seaboard. Shaded error bar is 1σ. The GPS rates and nuisance flooding level data are averaged for all stations and tide gauges in areas where geologic rate data are available (boxes in Figure A13). Nuisance flood level is defined by NOAA as threshold flood elevation (a fixed height) above the 1983-2001 Mean Higher High Water (MHHW) tidal datum. Nuisance flooding is thus more frequent where nuisance flood level is lower. Dashed red line marks arbitrary 0.5 m nuisance flood level. Areas lower than this threshold (parts of our southern anomaly, and areas affected by GIA-induced subsidence) experience significant nuisance flooding, and are at greater risk of catastrophic flooding from storm surge. Possible effects of tidal range variations can be isolated by dividing the nuisance flood level by tidal range (Figure A15).
5.4 Methods

5.4.1 Analysis of GRACE data

Monthly total water storage (TWS) estimates were produced based on post-processing the Stokes coefficients (RL05) provided by the Center for Space Research (CSR), the Jet Propulsion Laboratory (JPL) and the GeoForschungsZentrum Potsdam (GFZ) for the period 2002 - present. We post-processed the non-isotropic filtered Stokes coefficients (Kusche. 2007) provided by ICGEM (http://icgem.gfzpotsdam.de/ICGEM/TimeSeries.html) as is typical, replacing zonal degree 2 Stokes coefficients ($C_{20}$) with the more reliable solution from analysis of Satellite Laser Ranging (SLR) measurements (Cheng et al., 2013) and adding degree 1 Stokes coefficients ($C_{10}$, $C_{11}$ and $S_{11}$) obtained from oceanic models (Swenson et al., 2008) available at the NASA-JPL Tellus website (ftp://podaac.jpl.nasa.gov/allData/tellus/L2/degree_1/). The spherical harmonic expansion was truncated at degree and order 60. These coefficients are non-isotropic filtered Stokes coefficients (DDK2) where the isotropic part resembles a Gaussian filter with a half width of 340 km (Kusche et al., 2009), corresponding approximately to the isotropic filter used in producing the NASA-JPL Tellus gridded GRACE TWS data.
We also used post-processed gridded TWS data provided by the NASA-JPL Tellus website (https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/) to compare the magnitudes of TWS trends with those estimated using the DDK2 filter. Recent studies have used the Tellus GRACE TWS products in hydrology (Reager et al., 2014; Famiglietti, 2014; Thomas, et al., 2014; Wu et al., 2015; Fu et al., 2015; Scanlon et al., 2015; Humphrey et al., 2016; ). The Stokes coefficients are smoothed using de-striping filter (Swenson and Wahr, 2006) and a 300 km wide isotropic Gaussian filter (Wahr et al., 1998). The post-processing algorithms are detailed in the literature (Swenson and Wahr, 2006; Landerer and Swenson, 2012). The Tellus gridded GRACE TWS data are corrected for GIA effects based on a model (Geruo et al., 2013), which uses ICE-5G (Peltier, 2004) for ice loading history and a compressible Earth model. We smoothed the GIA model using the DDK2 filter and corrected the DDK2-derived GRACE TWS trend.

The trend estimates based on DDK2-filtered Stokes coefficients and the Tellus gridded GRACE TWS data from three processing centers (CSR, GFZ and JPL) are compared in eastern Canada (Figure A19 and Table A5). Although the processing centers use different algorithms to produce Stokes coefficients, the TWS trends from all three processing centers are very similar over eastern Canada. The trends based on DDK2 Stokes coefficients show a similarity in shape but are slightly larger (3-4 mm yr\(^{-1}\)) relative to trends estimated from the Tellus gridded GRACE TWS data.
The loading signal from a single water reservoir typically has a wavelength much shorter than the GRACE spatial resolution. Loads from dams are often modeled as point sources, especially in high relief terrain where the reservoir is spatially compact. In this case the transfer function from water storage to radial displacement has little power (Chanard et al., 2014). However, the James Bay project consists of multiple dams and reservoirs on a broad Precambrian peneplain, covering thousands of square kilometers. The total rate of mass increase from just the nine reservoirs shown in Figure A17 where altimetry is available is about 1.7 km$^3$ yr$^{-1}$, explaining about 30% - 40% of TWS changes trend observed by GRACE. The excess mass observed in Quebec with GRACE has a radius of ~ 500 km (the dark blue region in Figure 5.5a). This includes real mass increases due to increased groundwater and soil moisture in areas surrounding the reservoirs, but also includes some leakage effects due to filtering and truncating Stokes coefficients. We therefore model the excess mass as a uniform flat disc load (simulated as a uniform pressure) with a smaller radius, 400 km (white circle in Figure 5.5a and Figure A19) to account for the leakage effect. Given the low pass filtering behavior of an elastic lithosphere, the details of the load geometry are not important, and this approach is probably adequate.

The TWS observed with GRACE includes the sum of soil moisture, groundwater and surface water (including rivers, dams, lakes and snow). Surface water is probably the main contributor, and its relative contribution be estimated by looking at
hydrological models for the other components. Figure A20 shows the sum of soil moisture and groundwater trends estimated from the WaterGap Global Hydrological Model (WGHM, version 2.2b) (Döll et al., 2014; Müller Schmied et al., 2014). These components of water storage show a small trend, ranging from -1.7 to 1.7 mm yr\(^{-1}\) over the James Bay hydroelectric project and its adjacent areas. Thus, the excess mass observed with GRACE is primarily stored as surface water in rivers, dams and lakes.

5.4.2 Modeling the far field effects of water loading from the James Bay Project

Construction of the James Bay project began in the mid-1970’s and was largely complete by the late-1990’s. The project had two main phases, Phase 1 from the mid-1970s to the mid-1980’s, and Phase 2 from the late 1980’s to 1996. Filling of the reservoir with surface water continued into the early or mid-2000’s, but increases in groundwater would likely continue for a much longer period given the low permeability of Precambrian Shield rocks. GRACE began to collect data in 2002, and hence covers the later phases of reservoir filling and groundwater increase. This likely explains slightly negative acceleration in TWS data observed in Quebec (Eicker et al., 2016). Our modeling uses the observed rate of mass change as measured by GRACE, and hence predicts current rates of surface deformation, assuming elastic deformation. The load is centered in the middle of the excess mass observed by GRACE (blue region in Figure
5.5a) southeast of James Bay – Hudson Bay dams, the region of maximum flooding, i.e., upstream from these dams.

We present a numerical solution for the deformation of a thin elastic plate of uniform or tapering thickness overlying an inviscid dense substratum (a fluid with zero viscosity) with a density of \( \rho_s = 3300 \text{ kg/m}^3 \). The condition of static force equilibrium (i.e., between the surface load \( P \), the elastic response of the plate and the response of the fluid substratum on the base of the plate) for a thin plate on a fluid substrate results in a fourth-order differential equation (Jeffreys, 1959; Watts, 2001):

\[
\rho_s g w(r) + D \Delta w(x,y) = P
\]  

(5.1)

where \( \Delta \) is the Laplacian operator, \( w(r) \) is the vertical deflection of the plate at a distance \( r \) from centre of load and \( D \) is a plate flexural rigidity which depends on the elastic rigidity \( \mu \), plate thickness \( h \) and the Poisson’s ratio \( \nu \):

\[
D = \frac{\mu h^3}{6(1 - \nu)}
\]  

(5.2)

The load \( P \) is approximated with a disc of height \( d \):

\[
P = \rho_w g d
\]  

(5.3)

where \( \rho_w = 1000 \text{ kg m}^3 \) is the water density and \( g = 9.8 \text{ m s}^2 \) is the gravitational acceleration. Our solution is based on numerical evaluation of equation (5.1) using the Finite Element Modeling (FEM) code GTecton (Govers and Wortel, 2005) in the axisymmetric version (George et al., 2016). The response of the fluid substratum at the
The base of the plate (the term $\rho gw$) is assumed to be Winkler type in equation (5.1), thus the isostatic adjustment is estimated through the use of Winkler restoring forces (Williams and Richardson, 1991). The shear modulus and Poisson’s ratio are taken as $\mu = 30$ GPa and $\nu = 0.3$ respectively, and we let the plate thickness vary. We tested thicknesses between 50 and 120 km (Audet and Mareschal, 2004; Tesauro et al., 2005) compatible with the elastic thickness estimated for the Appalachians (the smaller number) or the Canadian Shield (the larger number), as well as a transitional model, tapering between the two thicknesses. As mention earlier, we model the excess mass observed in Quebec as a disc-shape constant load with radius 400 km and a mean thickness rate $\dot{d} = 18$ mm yr$^{-1}$.

Although our model of a thin elastic lithosphere over an inviscid mantle and its response to GRACE-derived loading can explain the location of uplift along the Maine shoreline, there is an inherent inconsistency in our approach. In calculating TWS from GRACE Stokes coefficients (conversion from potential anomaly to surface mass anomaly), a series of dimensionless load Love’s numbers (LLNs) are used to account for the effects of solid earth deformation (Wahr et al., 1998). The LLNs represents the static deformation of a spherically-symmetric non-rotating elastic isotropic Earth model such as the Preliminary Reference Earth Model (PREM) (Dziewonski and Anderson, 1981). The PREM model assumes an elastic crust and mantle with radial variations of elastic parameters and density based on a linear Maxwell solid rheology. Thus, there is
an inconsistency in the rheological assumptions used in the calculation of TWS from GRACE Stokes coefficients compared to the rheological assumptions used in our modeled response to surface loading, which includes a thin lithosphere over an inviscid mantle. While our approach provides a first-order approximation of lithospheric peripheral bulge effects associated with recent loading by dams in northern Quebec, Canada, a more detailed model, and a more consistent approach between GRACE-derived data and deformation model, is warranted.

5.5 Discussion and conclusions

Figure 5.2 compares GPS-derived rates of land motion to the nuisance flooding level. The latter is defined as a fixed height threshold elevation above the 1983 – 2001 MHHW (Mean Higher High Water) tidal datum at a given location, above which a rise in water level begins to impact lives, property, or commerce (Sweet et al., 2014). Thus, lower nuisance flood levels indicate a higher likelihood of flooding - the low elevation threshold is easily exceeded by even moderate flood events. The GPS and nuisance flood level data sets show moderate positive correlation (see also Figure A15) with a Pearson correlation coefficient of 0.54 (P-value 0.02). We used a non-parametric bootstrap calculation to assess the influence of data uncertainty on the estimate of correlation coefficient, and to rigorously estimate the standard error and confidence interval of this estimate. We generate data subsets by random sampling from normal
distributions with means equal to GPS rates and standard deviations equal to the rate uncertainty. We repeatedly estimate the Pearson correlation coefficient based on $10^7$ bootstrap resamples of the data points. The resulting distribution of correlation coefficient defines the 95% bootstrap confidence interval (Figure 5.3b). The bootstrap estimated Pearson correlation coefficient (the mean of bootstrapped sampling distributions) is 0.52 with estimated bias of -0.05 and standard error of 0.21. These parameters are used to form the bias-corrected and accelerated (BCa) confidence interval (DiCiccio and Efron, 1996) to adjust for both bias (the skewness in the bootstrap sampling distribution) and non-normality of the sampling distribution. The BCa 95% confidence interval is 0.10 to 0.84. Even the lowest value of correlation coefficient at the 95% significance level is positive. Hence there is a likely connection between subsidence and nuisance flooding. The nuisance flooding database shows a local minimum in nuisance flooding level (i.e., lowest threshold elevation, highest likelihood of flooding) near the maximum subsidence rate associated with the collapse of the peripheral bulge. Recent increases in flood frequency are focused here (Figures 5.2, 5.4 and Figure A15). This should not be surprising - much of the eastern seaboard is a low-slope coastal plain. Coastal settlements here were established close to sea level, hence even small increases in relative sea level will have a significant impact on flood frequency.
Figure 5.3: Scatter plot of GPS-derived vertical rate compared to nuisance flooding level. (a) The simple Pearson correlation coefficient and the bootstrap-estimated Pearson correlation coefficient (accounting for uncertainty in GPS rates) are 0.54 and 0.52, respectively. The red shaded area is 95% confidence interval for the regression line. Error bar are 1.96σ. The bootstrap estimated slop and 95% confidence interval is significantly different from zero. (b) Histogram showing bootstrap result for correlation coefficients. The red line represents the mean of the population (0.52) and the green lines bracket 95% of the estimates (0.10 – 0.84).
Figure 5.4: Nuisance flooding frequency versus time for various latitudes, rate of relative sea-level rise for 1990-present from tide gauges, and vertical rate from GPS. The flood frequency is defined as the number of days per year above a threshold flood level (nuisance flood level), for 34 tide gauges from St John’s in eastern Canada to Mayport, Florida. “max. GIA” refers to maximum subsidence due to the collapse of a peripheral bulge as observed by geologic data and GPS measurements. The southern anomaly refers to groundwater-induced subsidence as shown in Figures 5.2, A15 and A16.

Although the peak subsidence rate from GIA (1.5 mm yr\(^{-1}\)) is only half the current rate of global sea-level rise estimated from satellite altimetry (Nerem et al., 2010), it is the dominant factor in east coast nuisance flooding because it has been operating much longer, and thus has had the largest impact on changes in relative sea
level. Many coastal towns in the region were established in the late 1600’s and early 1700’s. Those established near the GIA subsidence maximum have experienced approximately 0.45 meters of land subsidence from GIA (1.5 mm yr\(^{-1}\) × 300 years). Combined with 1.2 mm yr\(^{-1}\) of global sea-level rise for 90 years (1901-1990) (Hay et al., 2015) (assumed insignificant prior to 1900) and the effects of recently accelerated global sea-level rise (ranging from 2.5 mm yr\(^{-1}\) to 3.4 mm yr\(^{-1}\)) over the past two and a half decades, these urban centers have experienced a total of approximately 0.6 meters of RSLR since their establishment, with 75% of it due to GIA. This area may also be experiencing recent accelerated sea-level rise due to ocean dynamics and ice-mass loss from Greenland (Davis and Vinogradova, 2017). Increased frequency of nuisance flooding here (Figure 5.4) is thus easy to understand. The combination of factors contributing to RSLR here also puts the region at greater risk from catastrophic flooding during storm surge events.

Nuisance flooding frequency shows a second maxima centered near 34° North, close to the southern anomaly defined by our GPS data (Figures 5.1 and 5.4). A recent study by Davis and Vinogradova (2017) suggests ice-mass loss from Greenland, ocean dynamics and the inverted barometer effect explains accelerated sea-level rise along much of the East Coast of North America. However, this model produces a poor fit (see Figure 4 in Davis and Vinogradova, 2017) along our southern anomaly. Figures 5.1, 5.2 and 5.4 show that the GPS-measured subsidence rates, while variable, can be as high or
higher here as they are in the “max GIA” anomaly. We suggest that the recent increased rate of RSLR here includes a contribution from subsidence of the land surface associated with recent groundwater loss, where pumping rates have exceeded the rate of natural recharge for a number of years (Karegar et al., 2016 and Chapter 4). The resulting loss of pore fluid pressure in the aquifer leads to compaction, loss of porosity, and surface subsidence. A database showing changes in groundwater level (Figure A16) shows a large degree of spatial variability (aquifers tend to be locally managed) but also exhibits a broad minima (extreme drop in groundwater level) near 34° North, similar to the GPS-geological rate. This is encouraging for short-term (next few decades) mitigation, since groundwater management practices can be modified, reducing induced subsidence, and perhaps even promoting moderate uplift via groundwater recharge (Galloway et al., 1999).

In the area between 36° North and 38° North (south of Chesapeake Bay, Virginia) despite the higher rate of RSLR (tide gauge) and vertical land motion (GPS), the nuisance flooding frequency data show only a small increase (Figure 5.4). Perhaps GPS-measured subsidence is sufficiently recent to have only a marginal effect on elevation. Our previous study (Karegar et al., 2016 and Chapter 4) shows that groundwater levels in most of the southern Chesapeake Bay region (south of Virginia) declined from the early 1970s until the late 2000s in response to excessive withdrawal but reversed from the late 2000s until 2015, indicating groundwater recharge (Figure 4.4 in Chapter 4 or
Figure 4 in Karegar et al, 2016). This indicates that groundwater-related subsidence can be a short-term phenomenon, and suggests that recent groundwater management efforts have been effective at reducing aquifer compaction and subsequent land subsidence in this area.

The northern anomaly is positive (GPS indicates slow uplift, differing by about 1 mm yr$^{-1}$ from the geologic rate, which indicate slow subsidence) and does not appear to be related to recent changes in groundwater usage. The northern anomaly might reflect a modern peripheral bulge associated with recent loading by dams in northern Quebec, Canada (Karegar et al., 2016). The James Bay Project is a massive hydro-electric project involving construction of many dams on rivers draining into James Bay, Hudson Bay, and the Gulf of St Lawrence, constructed between the mid-1970’s and the late 1990s. Here we explore a quantitative test of this hypothesis.

Figure 5.5a shows the recent (2002-2015) change in Total Water Storage (TWS) in Quebec using data from the GRACE satellite gravity mission (Tapley et al., 2004). These data define the magnitude and approximate location of recent changes to water load, in this case concentrated southeast (upstream) from dams draining into James and Hudson Bay, and northwest of dams draining into the Gulf of St Lawrence. TWS is an estimate of total surface and near surface water stored on the continent, including groundwater, soil moisture, surface water, snow, ice, and biomass. Details of the GRACE processing and the TWS estimation are described in the Methods section.
Although dam construction was completed prior to the start of the GRACE mission, reservoir filling continued for some time. To verify this, we also used satellite altimetry estimates for nine large lakes and reservoirs in the area (Figure 5.5a and A17). Time series of water-level changes here during part of the GRACE mission show significant positive trends, consistent with the GRACE observations (Figures A17, A18 and Table A6). While the main effect of this excess mass in the immediate area of the James Bay project is subsidence, distal areas experience uplift due to the peripheral bulge effect.

Figure 5.5b shows the modeled response of the lithosphere to this recent load, including the far field response along the coast of Maine. The model simulates the elastic (short-term) response of the lithosphere (an elastic plate with thicknesses between 50 and 100 km) (Audet and Mareschal, 2004; Tesauro et al., 2015) overlying a dense inviscid substratum. Details of the modeling procedure are described in the Methods section. The coast of Maine is ~ 780 - 880 km from the load maximum, close to the region of maximum uplift associated with the peripheral bulge predicted by the model, assuming elastic thickness transitioning from 100 km (elastic thickness for the Canadian Shield) (Audet and Mareschal, 2004) to 50 km (elastic thickness for the Appalachians) (Tesauro et al., 2015).
Figure 5.5: GRACE TWS and finite element model prediction. **A.** Trend in total water storage (in equivalent water height) for eastern North America estimated from GRACE DDK2-filtered Stokes coefficients (corrected for GIA model, Geruo et al., 2013). The data represent an average for the period 2002 – 2015. The location of active major dams (red dots) and formal boundaries for the James Bay hydroelectric project (yellow line) are also shown. The white dashed circle with radius 400 km approximates the excess mass observed with GRACE. The mass anomaly is centered southeast of dams on rivers running northwest into James and Hudson Bay, and northwest of dams on rivers running southeast into the Gulf of St Lawrence. **B.** Axisymmetric finite element model results for the peripheral bulge uplift rate in the vicinity of the northern anomaly induced by a load comparable to the total water storage estimated by GRACE for the James Bay Hydro-Electric Project in Quebec. The gray band shows distance of coast of Maine from the load centre. Triangles with error bar represent GIA-corrected vertical rate (GPS rate – geologic rate) for two regions where GPS and geologic rates are available\(^{13}\). Black line and dashed gray lines represent the average vertical rate (mean of two rates) and its uncertainty (1-σ error) along the northern anomaly. Dashed green line corresponds to a model where the elastic thickness \(h\) transitions from 100 km (elastic thickness for the Canadian Shield) for distances closer than 500 km, to 50 km (elastic thickness for the Appalachians) for distances farther than 780 km. Map is generated using GMT software version 5.1.0 (http://gmt.soest.hawaii.edu/) (Wessel et al., 2013).
While the model correctly predicts the location of anomalous uplift, it underpredicts the amplitude by ~0.5 mm yr\(^{-1}\). This may be related to the uncertainty of GIA models used to correct GRACE TWS data (Guo et al., 2012) (a range of 20% is often assumed for GIA models) and the greater uncertainty associated with geologic rates along the southern coast of Maine (±0.5 mm yr\(^{-1}\)), but we cannot preclude the possibility of additional or alternate processes. Better understanding of these processes will be important for interpreting tide-gauge data in terms of future oceanographic changes. For example, rates of RSLR are lower in the northern anomaly than surrounding areas (Figure 5.4).

Both nuisance flooding associated with periods of high tide, and catastrophic flooding associated with tropical storms and hurricanes, are increasing due to sea-level rise. While the latter cannot yet be predicted with any certainty, both the timing and location of nuisance flooding can in principle be predicted. In the short term, such predictions are useful in several ways. First, they can assist municipalities in mitigating the worst effects of flooding through improved infrastructure. Second, better management practices for extraction of groundwater from coastal aquifers can reduce nuisance flooding, by reducing or eliminating the coastal subsidence associated with over-extraction, temporarily reducing the rate of RSLR. On longer time scales however, many areas currently affected by nuisance flooding can expect to experience loss of
coastal land unless significant infrastructure investments are made. Recognition of this fact can assist municipalities in making the necessary long-term plans and investments.

5.6 Data availability

Late Holocene RSL data and GPS data on the rates of vertical land motion are publicly available (Engelhart et al., 2009; Karegar et al., 2016). Data describing nuisance flooding level and nuisance flooding frequency are available from NOAA National Weather Service (http://water.weather.gov/ahps/) and other studies (Moftakhari et al., 2015). Changes in local groundwater levels are available as well data from the U.S. Geological Survey groundwater information page (https://waterdata.usgs.gov/nwis), the North Carolina Division of Water Source (http://www.ncwater.org/?page=343), and the South Carolina Department of Natural Resources (http://www.dnr.sc.gov/water/hydro/groundwater/groundwater.html). Tide-gauge data were obtained from NOAA (http://tidesandcurrents.noaa.gov/).

5.7 References


Chanard, K., Avouac, J.P., Ramillien, G., & Genrich, J. Modeling deformation induced


Cofaigh, Colm Ó. et al. Reconstruction of ice-sheet changes in the Antarctic Peninsula since the Last Glacial Maximum. *Quaternary Science Reviews*, 100, 87-110 (2014).


Karegar, M.A., Dixon, T.H., & Engelhart, S.E. Subsidence along the Atlantic Coast of


6. A New Hybrid Method for Estimating Hydrologically-induced Vertical Deformation from GRACE and a Hydrological Model: An Example from Central North America\textsuperscript{8,9}

6.1 Abstract

Hydrologically-induced deformation of Earth’s surface can be measured with high precision geodetic techniques, which in turn can be used to study the underlying hydrologic process. For geodetic study of other Earth processes such as tectonic and volcanic deformation, or coastal subsidence and its relation to relative sea-level rise and flood risk, hydrological loading may be a source of systematic error, requiring accurate correction. Accurate estimation of the hydrologic loading deformation may require consideration of local as well as regional loading effects. We present a new hybrid


approach to this problem, providing a mathematical basis for combining local (near field) and regional to global (far field) loading data with different accuracies and spatial resolutions. We use a high-resolution hydrological model (WGHM) for the near field and GRACE data for the far field. The near field is defined as a spherical cap and its contribution is calculated using numerical evaluation of Green’s functions. The far field covers the entire Earth, excluding only the near field cap. The far field contribution is calculated using a modified spherical harmonic approach. We test our method with a large GPS data set from central North America. Our new hybrid approach improves fits to GPS-measured vertical displacements, with 25% and 35% average improvement relative to GRACE-only or WGHM-only spherical harmonic solutions. Our hybrid approach can be applied to a wide variety of environmental surface loading problems.

6.2 Introduction

Earth’s surface experiences dynamic loading on a wide variety of temporal and spatial scales. In addition to solid Earth processes such as earthquakes and volcanoes, mass distribution throughout Earth’s outer fluid envelope, including its atmosphere, ocean and cryosphere, as well as groundwater movements in the porous uppermost continental crust, occurs with significant seasonal to decadal variability. Loading of the solid Earth displaces the ground surface and changes the gravitational potential. Loading usually causes an elastic response (horizontal and vertical surface displacements), depending on the temporal and spatial scales of the load, and the
mechanical properties of the solid Earth. Gravity changes can be divided into the direct effect, related to the gravitational attraction of the load itself, and the indirect effect resulting from Earth deformation.

For more than two decades, continuously operating geodetic networks (e.g., GPS, VLBI, SLR) and satellite InSAR (Interferometric Synthetic Aperture Radar) have provided essentially global observations, and corresponding opportunities to study the elastic response to surface loading. These techniques are also useful for measuring poroelastic and unrecoverable (inelastic) deformation associated with hydrologic phenomena. While loading theory cannot be used to study the porous response of Earth’s surface to groundwater discharge and recharge (typically a short spatial wavelength effect; see section 5.1 and Argus et al., 2014), correct calculation of the loading response (typically a long spatial wavelength effect) may be important when using geodetic data to investigate hydrologic processes, since the space geodetic data incorporate both short and long wavelength effects.

The elastic response of the Earth’s crust to an arbitrary surface load distribution can be estimated through spatial convolution of appropriate Green’s function with a surface mass loading field. The Green’s functions describe the deformation of the Earth under action of a unit surface point mass through the three dimensionless load Love numbers for a spherical non-rotating elastic layered Earth model (Longman, 1963; Farrell, 1972) or through the elastic moduli (Poisson’s ratio and
Young’s modulus) for a layered elastic half-space model (Farrell, 1972). The half-space model provides a useful analytical solution when the load extends over a small area and Earth’s curvature can be neglected (e.g., for volcanic deformation, for smaller earthquakes, and for smaller aquifers and lakes). For larger areas, the amplitude and phase of the vertical and horizontal components of the deformation are better explained with a spherical non-rotating elastic layered Earth model (Chanard et al., 2014). In addition, if the spatial extent of the load is large, the Young’s modulus may have to be unrealistically increased to include more distant loads in the computation (e.g., Fu and Freymueller, 2012; Karegar et al., 2014; Chanard et al., 2014).

The convolution integral of Green’s functions with a surface mass loading field for a spherical non-rotating elastic layered Earth model can be analytically expressed in terms of spherical harmonics (e.g., Mitrovica et al., 1994; Le Meur and Hindmarsh, 2000). The spherical harmonic approach is commonly used to model Earth’s surface elastic response to environmental loading (e.g., Blewitt, 2003; Davis et al., 2004; Kusche and Schrama, 2005; van Dam et al., 2007; Fu and Freymueller, 2012; Wahr et al., 2013; Chanard et al., 2014; Zou et al., 2014). This approach requires as input the spherical harmonic coefficients of the geoid changes (Stokes coefficients) and the load Love numbers. The major advantage of the spherical harmonic approach is that spectral analyses such as analysis of degree variance spectrum and degree correlations can be readily implemented (e.g., Yan et al., 2016). Furthermore, the same filtering and
smoothing procedures that are used for satellite observations (e.g. GRACE) can be applied to the modeled deformation when using hydrological models (e.g., Döll et al., 2014). The spherical harmonic approach is particularly suitable when the modeling spans a large part or all of Earth’s surface so that most of the load energy is concentrated in the low-degree spherical harmonics. But, it does require an accurate prediction of far-field contributions (e.g., Glacial Isostatic Adjustment or global sea-level rise). However, the spatial resolution of modeled deformation is independent of position. For example, high spatial resolution in one region requires the same resolution for other regions, which increases processing time (Mitrovica et al., 1994). Furthermore, to properly represent the geometrical properties of the surface mass load, the correct choice of truncation of the spherical harmonic expansion (cut-off value) can be challenging (Le Meur and Hindmarsh, 2000; Yan et al., 2016). The convolution integral can alternatively be computed by numerical techniques in the space domain (often called the Green’s function approach). The Green’s function approach is suitable for regional and basin-scale studies where mass changes adjacent to the location of geodetic sites have the largest influence on the displacements. However, this approach is sensitive to the total number of terms used to calculate the Green’s functions. In practice, the convergence problem can be overcome by taking into account the asymptotic expressions of the load Love numbers and Kummer’s transformation (see section 6.2).
The Green’s function approach and the spherical harmonic approach have been widely used to model the effect of hydrological loading on geodetic position or displacement time series. Among the various types of geophysical fluid loads (atmosphere, ocean and cryosphere) hydrological loading often represents the dominant signal in the vertical component, especially at multi-annual and shorter periods (e.g., Fritsche et al., 2012; Jiang et al., 2013). Accurate modeling of these effects in position time series is therefore beneficial for reliable long-term surface velocity estimates (Santamaria-Gomez and Memin, 2015; Klos et al., 2017) and noise analysis (Santamaría-Gómez et al., 2011; Davis et al., 2012; Bogusz and Klos, 2016), as well as studies of tectonic processes (Blewitt and Lavallée, 2002; Bennett, 2008; Bos et al., 2010; Vergnolle et al., 2010), volcanic processes (Henderson and Pritchard, 2017), geodynamics (Chanard et al., 2018; Clarke, 2018), sea-level rise (Santamaría-Gómez et al., 2017), geo-mechanics (Karegar et al., 2015b) and reference frame definition (Collilieux et al., 2012; Krásná et al., 2015).

Since 2002, the Gravity Recovery and Climate Experiment (GRACE) satellite mission has described monthly changes in Earth’s gravitational potential, reflecting mass redistribution close to the Earth’s surface (Tapley et al., 2004). The raw GRACE data (Level-1) are processed by different research centers, and the time-variable gravitational field is determined either in the form of spherical harmonics, or as mascons (mass concentrations). Noise is removed through filtering the Stokes
coefficients during post-processing or through the introduction of *a priori* information (geophysical models) in the mascon solution. Although these filters are quite effective, they damp geophysical signals and limit GRACE resolution at spatial scales smaller than the native resolution (300 km). Hence, a rigorous comparison of observed deformation (for example from GPS) and GRACE-based modeled deformation should be based on a regionally coherent deformation signal among neighboring sites rather than on individual deformation signals at single sites. One could spatially filter the GPS time series in a way that is similar to the GRACE products, estimating deformation caused only by those components of the mass distribution that have scales similar to GRACE products (~ 400 - 500 km), but this results in information loss, i.e., local hydrological deformation with spatial scales smaller that 400 - 500 km.

So far, modeling the effects of hydrological loading on geodetic position time series has been limited to water storage data sets from GRACE or hydrological models. In this chapter, we describe and evaluate a new hybrid approach for more accurate estimation of the Earth’s elastic response to hydrological loading. We combine water storage data from GRACE with limited spatial resolution, and a hydrological model with more detailed spatial resolution. Our proposed hybrid approach combines the spherical harmonic approach and the Green’s function approach, providing a flexible way that benefits from each method’s strengths. We use this hybrid approach to investigate vertical crustal changes in the continental interior of North America, a
region that is undergoing spatially variable water stress. We show that our proposed approach results in a solution with a better fit to the observed deformation at individual GPS sites. The key advantage to our hybrid approach is that it provides a mathematical basis for combining global and regional loading data with different spatial resolutions for regions closer and regions farther away from the point of computation (e.g., geodetic sites). Such a combination is useful for loading studies, as the larger impact of small-scale mass changes in the near field makes it important to include higher resolution dataset, while not neglecting effect of large-scale mass changes in the far field (Dill and Dobslaw, 2013). The method can be applied to a wide variety of environmental surface loading problems including hydrologic, ice, ocean and atmospheric loads.

The remainder of this chapter is organized as follows. In section 6.3, we derive a hybrid formula to model observed vertical surface displacement based on a combination of the Green’s function approach to describe near-field deformation, and the spherical harmonic approach for far-field deformation. In section 6.4, we describe the study region. In section 6.5, we describe the GPS, GRACE and hydrological model data sets and their respective processing. In section 6.6, we describe the model calculations. Section 6.7 presents results, section 6.8 briefly describes potential applications, and section 6.9 summarizes the conclusions.
6.3 A new hybrid method for a spherical non-rotating elastic layered Earth model

The Green’s function approach establishes a convolution integral relationship between the surface mass density variations $\Delta \sigma(\theta', \lambda', t)$, that is available at integration point $(\theta', \lambda')$ at time $t$ over a certain integration domain, and vertical displacement $v(\theta, \lambda, t)$ at a computation point $(\theta, \lambda)$ (Mitrovica et al., 1994; Eq. 23):

$$v(\theta, \lambda, t) = a^2 \int_{\sigma} \Delta \sigma(\theta', \lambda', t) G(\psi) d\sigma$$  \hspace{1cm} (6.1)

where $a$ is the mean Earth’s radius, $\sigma$ is the integration domain which is the surface of a whole sphere and $d\sigma$ are infinitesimally small surface compartments. The quantity $G(\psi)$ denotes the vertical Green’s function, which is a function of the angular distance $\psi$ between the computation point and the integration point. The need for performing the integration over the entire surface of the Earth in the Green’s function approach makes this method computationally very expensive. Therefore, the integration is generally performed over a limited area or truncated spherical cap. Neglecting loading data outside the spherical cap results in errors which might adversely affect the predicted deformation. We divide the integration domain into a spherical cap with certain radius $\psi_0$ around each computation point and the remainder of the sphere. The contribution of loading within the spherical cap $\psi_0$ is evaluated using discrete numerical integration of Green’s functions and the gridded water storage data from a hydrological model (see
section 6.3.1). This term is called contribution of the near field \( (v_{nf}) \). The contribution of the distant load (the far field, \( v_{ff} \)) for the region outside the spherical cap is computed using the spherical harmonic approach. Our approach is similar to that of Molodenskii (1962), who used for the geoid determination to calculate the contribution of the far field. The vertical deformation can be then written as a sum:

\[
v(\theta, \lambda, t) = v_{nf}(\theta, \lambda, t) + v_{ff}(\theta, \lambda, t)
\]

(6.2)

where each term will be formulated for the point-load type of the vertical Green’s functions.

The point-load Green’s function \( G(\psi) \) for computation of vertical displacement in Eq. (6.1) is given in terms of load Love numbers \( h_n \) and the Legendre polynomials of degree \( n, P_n(\cos \psi) \) (Farrell, 1972):

\[
G(\psi) = \frac{a}{m_e} \sum_{n=0}^{\infty} h_n P_n(\cos \psi)
\]

(6.3)

where \( m_e \) is the total mass of the Earth. The Green’s function (6.3) is truncated at a cut-off value \( N_{max} \), causing oscillations whose wavelengths are controlled by the cut-off (knows as Gibbs phenomena) and results in an incorrect response (e.g., Le Meur and Hindmarsh, 2000). The load Love numbers \( h_n \) reach an asymptotic non-zero value (denoted with \( h_{\infty} \)) when \( n \) gets large. Thus, the Green’s function does not converge, particularly when the angular distance \( \psi \) is very small, i.e., for \( \psi=0, P_n(\cos \psi) = 1, \forall n \). To avoid the Gibbs effect and speed up converging series (6.3), Kummer’s transformation
is used. This consists of adding and subtracting the asymptotic value $h_\infty$ from series (6.3) (Farrell, 1972; Le Meur and Hindmarsh, 2000):

$$G(\psi) = \frac{a}{m_v} \frac{h_\infty}{2 \sin \frac{\psi}{2}} + \frac{a}{m_v} \sum_{n=0}^{\infty} (h_n - h_\infty) P_n(\cos \psi)$$  \hfill (6.4)

where the first term represents the infinite sum of the Legendre polynomials $P_n$. Several load Love numbers have been computed for a spherical non-rotating elastic layered Earth model based on seismic wave travel times. Here, we use a set of high-degree load Love numbers produced in the CE frame (a frame whose origin is fixed to the center of mass of the solid Earth) and extended to degree 45,000 determined by Wang et al., (2012) for the PREM (Preliminary Reference Earth Model) (Dziewonski and Anderson, 1981).

6.3.1 Contribution of the computation point and near field from the Green’s function

The point-load Green’s function is singular for angular distance $\psi=0$. Therefore, an appropriate treatment should be chosen when evaluating the convolution integral (6.1) at the computation point. We use a similar approach to that of Novák et al. (2001) who treat the singularity of Stokes integral for the geoid determination. We add and subtract the surface mass density at the computation point $\Delta \sigma_P = \Delta \sigma (\theta, \lambda, t)$ in Eq. (6.1) as:
\[ v_{nf}(\theta, \lambda, t) = a^2 \int_{\alpha=0}^{\alpha=2\pi} \int_{\psi=0}^{\psi=\psi_0} \{ \Delta \sigma_p \ G(\psi) + [\Delta \sigma(\theta', \lambda', t) - \Delta \sigma_p] \ G(\psi) \} \, d\psi \, d\alpha \]  

(6.5)

Note that the integration in Eq. (6.5) is performed over a limited spherical cap \( \psi_0 \). Eq. (6.5) is split into two integrals:

\[ v_{cp}(\theta, \lambda, t) = a^2 \int_{\alpha=0}^{\alpha=2\pi} \int_{\psi=0}^{\psi=\psi_0} \Delta \sigma_p \ G(\psi) \, d\psi \, d\alpha \]  

(6.6)

which is the contribution of the computation point and

\[ v_{rc}(\theta, \lambda, t) = a^2 \int_{\alpha=0}^{\alpha=2\pi} \int_{\psi=0}^{\psi=\psi_0} [\Delta \sigma(\theta', \lambda', t) - \Delta \sigma_p] \ G(\psi) \, d\psi \, d\alpha \]  

(6.7)

which is the contribution of rest of the spherical cap near the surface load. Eq. (6.7) is no longer singular at the angular distance \( \psi=0 \) since \( \Delta \sigma(\theta', \lambda', t) = \Delta \sigma_p \) at the computation point and the value of the integral equals zero. To compute the contribution of the computation point we use the analytical formalism below:

\[ v_{cp}(\theta, \lambda, t) = 2\pi a^2 \Delta \sigma_p \int_{\psi=0}^{\psi=\psi_0} G(\psi) \sin \psi \, d\psi \]  

(6.8)

The integral of Green’s function over the spherical cap \( \psi_0 \) can be written as the difference between integral over the whole sphere (\( 0 \leq \psi \leq \pi \)) and integral over the area outside the spherical cap (\( \psi_0 \leq \psi \leq \pi \))

\[ \int_{\psi=0}^{\psi=\psi_0} G(\psi) \sin \psi \, d\psi = \int_{\psi=0}^{\psi=\pi} G(\psi) \sin \psi \, d\psi - \int_{\psi=\psi_0}^{\psi=\pi} G(\psi) \sin \psi \, d\psi \]  

(6.9)
from the orthogonality of the Legendre polynomials over the sphere (Heiskanen and Moritz, 1967; section 1-13):

\[
\int_{\psi=0}^{\pi} G(\psi) \sin \psi \, d\psi = \frac{a}{m_e} \sum_{n=0}^{\infty} \int_{\psi=0}^{\pi} h_n P_n(\cos \psi) \sin \psi \, d\psi = \begin{cases} 2h_0 & n = 0 \\ 0 & n \geq 1 \end{cases} \quad (6.10)
\]

Degree-zero load Love number \( (h_0) \) equals zero to ensure the Earth’s total mass to be conserved. Thus,

\[
\int_{\psi=0}^{\psi_0} G(\psi) \sin \psi \, d\psi = - \int_{\psi_0}^{\pi} G(\psi) \sin \psi \, d\psi \quad (6.11)
\]

The integral on the right-hand side of Eq. (6.11) is then of the form:

\[
Q_0(\psi_0) = \int_{\psi=\psi_0}^{\pi} G(\psi) \sin \psi \, d\psi \quad (6.12)
\]

which has an analytical derivation (see section 6.3.2, Eq. 6.23). Finally the contribution of the surface mass density at the computation point to the vertical deformation is given by:

\[
v_{cp}(\theta, \lambda, t) = -2\pi a^2 \Delta \sigma_p Q_0(\psi_0) \quad (6.13)
\]

The convolution integral (6.1) is generally discretized and numerically evaluated by means of summation of the products \( \Delta \sigma(\theta', \lambda', t)G(\psi) \) over \( j \) compartments within the spherical cap \( \psi_0 \) (e.g., Heiskanen and Moritz, 1981). After accounting for contribution of computation point, the contribution of the rest of cap is:

\[
v_{rc}(\theta, \lambda, t) = \sum_{k} [\Delta \sigma_k - \Delta \sigma_p] G(\psi_k) A_k \quad (6.14)
\]
where $\Delta \sigma_k$ and $A_k$ are the mass density anomaly and the area of $k$-th compartment, respectively. $G(\psi_k)$ is the value of Green’s function at the center of $k$-th compartment which approximates the mean value of Green’s function across the compartment. Finally, the contribution of near zone is a sum:

$$v_{nf}(\theta, \lambda, t) = v_{cp}(\theta, \lambda, t) + v_{rc}(\theta, \lambda, t) \quad (6.15)$$

6.3.2 Contribution of the far field from the spherical harmonic approach

In this section we find a spectral formalism based on spherical harmonics for the contribution of surface mass density outside the integration domain $\psi_0$. As mentioned earlier, within the spherical cap $\psi_0$ we use the Green’s function approach to estimate the vertical deformation. This leads to an error due to neglecting the contribution of loading outside the spherical cap $\psi_0$ (the contribution of far field $v_{ff}$):

$$v_{ff}(\theta, \lambda, t) = a^2 \int_{\alpha=0}^{\alpha=2\pi} \int_{\psi=\psi_0}^{\psi=\pi} \Delta \sigma(\theta', \lambda', t) G(\psi) \, d\psi \, d\alpha \quad (6.16)$$

which may be expressed over the whole sphere by:

$$v(\theta, \lambda, t) = a^2 \int_{\alpha=0}^{\alpha=2\pi} \int_{\psi=0}^{\psi=\pi} \Delta \sigma(\theta', \lambda', t) \, \tilde{G}(\psi) \, d\psi \, d\alpha \quad (6.17)$$

upon the introduction of the truncated Green’s function $\tilde{G}(\psi)$ defined by:

$$\tilde{G}(\psi) = \begin{cases} 
0 & 0 \leq \psi \leq \psi_0 \\
G(\psi) & \psi_0 < \psi \leq \pi 
\end{cases} \quad (6.18)$$
which is complementary to the integration kernel in Eq. (6.5). The truncated Green’s function \( \tilde{G}(\psi) \) in now expanded in series of orthogonal Legendre polynomial basis functions:

\[
\tilde{G}(\psi) = \frac{a}{m_e} \sum_{n=0}^{\infty} \frac{2n + 1}{2} Q_n(\psi_0) P_n(cos\psi)
\]  

(6.19)

where the expansion (truncation) coefficients \( Q_n(\psi_0) \) are derived using properties of series expansions in terms of orthogonal polynomials, analogous to a Fourier series (e.g., Gottlieb and Orszag, 1977):

\[
Q_n(\psi_0) = \frac{m_e}{a} \int_{\psi=0}^{\psi=\pi} \tilde{G}(\psi) P_n(cos\psi) sin\psi d\psi = \frac{m_e}{a} \int_{\psi=\psi_0}^{\psi=\pi} G(\psi) P_n(cos\psi) sin\psi d\psi
\]  

(6.20)

which follow from the orthogonality relationships for Legendre polynomials. The surface mass density at the computation point \( \Delta \sigma(\theta, \lambda, t) \) is given by infinite series of surface spherical harmonics (e.g., Wahr et al., 1998):

\[
\Delta \sigma(\theta, \lambda, t) = a \rho_w \sum_{n=0}^{\infty} \sigma_n(\theta, \lambda, t)
\]

\[
= a \rho_w \sum_{n=0}^{\infty} \sum_{m=0}^{n} (\Delta \hat{C}_{nm} \cos m\lambda + \Delta \hat{S}_{nm} \sin m\lambda) \bar{P}_{nm}(\cos \theta)
\]  

(6.21)

where \( \sigma_n \) is the \( n \)-th degree surface spherical harmonic of surface mass density, \( \rho_w \) is the density of water (~1000 kg/m\(^3\)), \( \Delta \hat{C}_{nm} \) and \( \Delta \hat{S}_{nm} \) are dimensionless spherical harmonic coefficients of surface mass density at time \( t \) which can be related to the GRACE stokes coefficients (e.g., Wahr et al., 1998, Eq. 13). \( \bar{P}_{nm} \) is a fully-normalized associated
Legendre function of degree \( n \) and order \( m \). Using the two series, Eqs. (6.21) and (6.19), in Eq. (6.17), and performing the integrations over the sphere, after some simplification (e.g., Mitrovica et al., 1994) we arrive at the following spectral representation:

\[
\nu_{ff}(\theta, \lambda, t) = \frac{a \rho_w}{2 \rho_{avg}} \sum_{n=0}^{\infty} Q_n(\psi_0) \sigma_n(\theta, \lambda, t)
\] (6.22)

where \( \rho_{avg} = m_e/4\pi a^3 \) is the average density of the Earth (\( \sim 5517 \text{ kg/m}^3 \)). Eq. (6.22) is used to replace the integral (6.17), which yields a series expansion of the contribution of the far field in terms of the surface spherical harmonics of the surface mass density. It shows that the contribution of the far field is a function of the truncation coefficients \( Q_n(\psi_0) \). By inserting Eq. (6.4) into Eq. (6.20) and interchanging the order of summation and integration, we obtain:

\[
Q_n(\psi_0) = h_\infty \int_{\psi=\psi_0}^{\psi=\pi} \frac{\sin \psi}{2 \sin \frac{\psi}{2}} P_n(\cos \psi) d\psi
\]

\[
+ \sum_{k=0}^{\infty} (h_k - h_\infty) \int_{\psi=\psi_0}^{\psi=\pi} P_k(\cos \psi) P_n(\cos \psi) \sin \psi \, d\psi
\] (6.23)

we then can derive the following expression for \( Q_n(\psi_0) \):

\[
Q_n(\psi_0) = h_\infty b_n + (h_n - h_\infty) R_{n,n}(\psi_0) + \sum_{k=0}^{\infty} (h_k - h_\infty) R_{n,k}(\psi_0)
\] (6.24)

where the coefficients \( b_n \) are:

\[
b_n = \int_{\psi=\psi_0}^{\psi=\pi} \frac{\sin \psi}{2 \sin \frac{\psi}{2}} P_n(\cos \psi) \, d\psi
\] (6.25)
which can be computed using the recursive algorithms of Meissl (1971) given in Appendix D. The coefficients $R_{n,k}(\psi_0)$ are:

$$
R_{n,k}(\psi_0) = \int_{\psi=\psi_0}^{\psi=\pi} P_k(\cos\psi) P_n(\cos\psi) \sin\psi d\psi
$$

(6.26)

which can be evaluated using the recursive algorithms of Paul (1973) given in Appendix B. The truncation coefficients $Q_n(\psi_0)$ as a function of spherical cap ($\psi_0$, integration domain) is an important parameter that controls the contribution of the far field to the vertical displacement. For example, when the integration domain spans the whole sphere, i.e., $\psi_0=0$, $R_{n,k}(0) = 0$ due to orthogonality of Legendre polynomials and $R_{n,n}(0) = \frac{2}{2n+1}$ (Heiskanen and Moritz, 1967), therefore $Q_n(0) = \frac{2h_n}{2n+1}$ and $\bar{G}(\psi) \equiv G(\psi)$.

Thus, the convolution integral (6.1) and Eq. (6.22) reduce to the spherical harmonic representation of the vertical deformation (the spherical harmonic approach). The validity of truncation coefficients can be further verified by varying the angular distance from zero to $\pi$. Figure 6.1b shows that the values of truncation coefficients are diminished with increasing integration domain ($\psi_0$). Truncation coefficients at higher degrees ($n$) decay faster than those at lower degrees, emphasizing the relative importance of the nearby mass load.
Figure 6.1: a) Sketch showing the computation point, near field and far field on a sphere. b) Truncation coefficients for point-load vertical Green’s functions for $n = 5, 15, 25, 35$ as a function of angular distance ($\psi_\theta$, integration cap).

6.4 Study area

GRACE observations have been extensively used to model hydrological loading in geodetic position time series at global and regional scales. A number of studies have emphasized the significance of GRACE-derived hydrological loading signals in global GPS networks (Kusche and Schrama, 2005; King et al., 2006; Tregoning et al., 2009, Horwath et al., 2010; Tesmer et al., 2011, Rietbroek et al., 2012, 2014; Döll et al., 2014; Yan et al., 2016). Consistency between GPS and GRACE-derived deformation have been observed in large drainage basins where seasonal changes are significant, including Africa (Nahmani et al., 2012; Birhanu and Bendick, 2015), the Amazon River Basin and South America (Davis et al., 2004, 2008; Fu et al., 2013), Europe (van Dam et al., 2007; Valty et al., 2013), the Himalayan region (Steckler et al., 2010; Fu and
Southern Alaska (Fu et al., 2012), the Western United States (Argus et al., 2014, 2017; Fu et al., 2015), Australia (Han, 2017) and near the Greenland Ice Sheet (Liu et al., 2017).

Here we compare GPS and GRACE-derived vertical deformation for a large region in the interior of North America, including the Mississippi River basin and Texas. The Mississippi River basin is the fifth largest in the world in terms of water discharge. It drains ~40 percent of the contiguous U.S., discharging a yearly average of about 1.5 km$^3$/day into the Gulf of Mexico. It is also fifth in drainage basin size, with a drainage area of 4.76 $\times 10^6$ km$^2$. The basin spans three different climate regimes: cold in the north, subtropical in the southeast, and dry in the southwest. The basin is divided into five main sub-basins (Figure 6.2): 1) the Missouri River basin, 2) the upper-Mississippi River basin, 3) the Ohio and Tennessee River basin 4) the Arkansas and Red River basin, and 5) the lower-Mississippi River basin. Most of Texas is hydrologically isolated from the Mississippi Basin, with climate that varies from humid in the east (maximum annual precipitation 140 cm) to arid in the west (maximum annual precipitation 30 cm). Groundwater management is critical in west Texas because of diminishing water supplies and frequent droughts, while flood management is critical along the Gulf Coast from both hurricane storm surge and high rainfall events (Karegar et al., 2015a). The Mississippi basin and Texas include extensively irrigated regions and some of the world’s significant aquifer systems: the High Plains aquifer, Atlantic and
Gulf Coastal Plains Aquifer, and Cambro-Ordovician Aquifer System (WHYMAP and Margat, 2008).

GRACE-based studies indicate that soil moisture and groundwater changes comprise the majority of total water storage (TWS) changes in the Mississippi basin and Texas region (Rodell et al., 2007; Kim et al., 2009; Long et al., 2013; Freedman et al., 2014). However, river and snow loads are still of important components of TWS variability in the Mississippi basin. For example Kim et al. (2009) showed that rivers and snow contribute up to 28% of TWS variability. The TWS changes in the southeast Mississippi basin (Ohio and Tennessee River basin and the lower Mississippi River basin) shows a strong seasonal cycle (Figure 6.2) with maximum loading and storage in spring and early summer, and minimum loading in late fall and early winter (see Figure 9 in Humphrey et al., 2016). The area is characterized by long humid summers and relatively short, mild winters. Annual precipitation averages about 100-150 cm but exceeds 150 cm near the coastline.

6.5 Data processing

6.5.1 GRACE data

We produce monthly TWS and surface mass density ($\Delta\sigma$) estimates based on post-processing the GRACE Stokes coefficients (RL05) provided by the Center for Space Research (CSR) at the University of Texas for the period 2002 - 2015. The GRACE Stokes coefficients describe changes in the geoid surface. We post-processed the non-isotropic
filtered Stokes coefficients (Kusche, 2007) provided by ICGEM (http://icgem.gfz-potsdam.de/ICGEM/TimeSeries.html) by replacing zonal degree 2 Stokes coefficients ($C_{20}$) with the more reliable solution from analysis of Satellite Laser Ranging (SLR) measurements and adding degree 1 Stokes coefficients ($C_{10}$, $C_{11}$ and $S_{11}$) obtained from oceanic models available at the NASA-JPL Tellus website (ftp://podaac.jpl.nasa.gov/allData/tellus/L2/degree_1/) (Swenson et al., 2008). The spherical harmonic expansion was truncated at degree and order 90. These coefficients are non-isotropic filtered Stokes coefficients (DDK2) where the isotropic part resembles a Gaussian filter with a half width of 340 km (Kusche et al., 2009). The filtered Stokes coefficients are used in Eq. (6.21) to calculate the surface spherical harmonic of surface mass density ($\sigma_n$), which is then applied in Eq. (6.22) to estimate the contribution of the far field in our hybrid approach.

6.5.2 Hydrological and land surface models

We use monthly terrestrial water storage estimate from two high spatial resolution models: (1) the WaterGap Global Hydrological Model (WGHM) (Döll et al., 2003) and (2) the North American Land Data Assimilation System (NLDAS-Noah) (Mitchell et al., 2004). WGHM is a global hydrological model with 0.5° spatial resolution accounting for all main compartments of continental total water storage including groundwater but excluding the polar ice sheets and glaciers. The model has been calibrated by observed long-term average river discharge at river gauges. We use the
latest version of WGHM (version 2.2b, Müller Schmied et al., 2014) calibrated for monthly time series of observed precipitation WFDEI (Watch Forcing Data based on ERA-Interim) and GPCC (Global Precipitation Climatology Center) data. WGHM has been widely used for estimating global and regional hydrological flux and storage (e.g., Scanlon et al., 2018), and loading deformation at global scale (e.g., Fritsche et al., 2012; Döll et al., 2014). NLDAS-Noah is a land surface model that provides monthly changes in soil moisture, snow equivalent water height and canopy surface water over the U.S. with 0.125° spatial resolution. Unlike WGHM, NLDAS does not explicitly represent groundwater and surface water storage. We chose the NLDAS model for comparison to the WGHM model because it has the highest spatial resolution of the modeled water storage datasets available at continental scale. In addition, the NLDAS model is a physically-based land surface model that integrates more observations at the surface while the WGHM model is a conceptual model with very simplified realization of physical processes of hydrosphere that is only calibrated and validated by river discharge measurements. We use the NLDAS-2 Noah version (Xia et al., 2012) with improved accuracy and consistency of climate data and with upgraded model parameters compared to the first version of NLDAS (NLDAS-1) (Mitchell et al., 2004). TWS changes from hydrological models and land surface models compared with GRACE TWS observations have shown the limitations of models for resolving large-scale TWS changes (section 6.6 and Figure A24) due to errors in climate data and
uncertainty in the model structure and hydrologic process representation (e.g., Eicker et al., 2014; Scanlon et al., 2018).

Water storage changes from the models are detrended and are used in Eq. (6.15) to compute the contribution of the near field in the hybrid approach. Note that the aim of this study is not to assess performance of different hydrological and land surface models. Rather, comparison of results from two different models provides information on the reliability and evaluation of our hybrid approach.

6.5.3 GPS data

We use publicly available data from continuous GPS sites. Data from a total of 762 GPS sites with nearly continuous observations is available, with durations ranging from 4 to 20 years. The raw GPS data were processed using the software package GIPSY/OASIS II (Release 6.3) of JPL and the precise point positioning technique using 24 hour data batches. JPL’s reprocessed precise satellite orbit and clock parameters (Repro 2.1, Desai et al., 2014) together with the absolute GPS receiver and satellite antenna phase calibration model igs08.atx (Schmid et al., 2016) are used to generate non-fiducial daily point position time series. Since the GPS satellites orbit are expressed in Center of Mass (CM) of the Earth’s system (solid Earth and its fluid envelope), the non-fiducial position time series are calculated in the CM frame. We applied the same processing strategy used in JPL’s reanalysis of orbit and clock products (Repro 2.1) to our GPS raw data to isolate effects of inconsistency between orbits/clocks and our
solutions. The first-order effects of the ionosphere are corrected using the dual-frequency approach and a linear combination of carrier phase measurements. The second-order effects are corrected using the JPL IONEX model for the data after 1999 and the IGS IRI2012 model for the data prior to 1999. Tropospheric effects are modeled using the troposphere mapping function GPT2 (Lagler et al., 2013) which maps the zenith troposphere delay to the elevation of each observation. A priori zenith tropospheric delays are estimated from GPT2. The elevation cut-off angle is fixed to 7°, a compromise to better constrain tropospheric effects but minimize multipath errors. The single station ambiguity resolution algorithm of Bertiger et al. (2010) is adopted to solve integer ambiguities for each station. The effects of solid Earth tides, solid Earth and ocean pole tides were corrected following the IERS 2010 conventions (Petit and Luzum, 2010). These models are consistent with the background models used in raw GRACE data processing (e.g., Watkins et al., 2015; Wiese, 2015).

The effects of atmospheric and oceanic mass changes should be removed from the GPS time series to be consistent with modeled deformation from GRACE and WGHM. Tidal contributions of ocean loading, which can reach several mm in the vertical component for near-coastal sites, are corrected using 11 tidal constituents from the latest version of Ray’s (1999) global ocean tide model GOT4.8 in the CM frame. The current version of GIPSY software does not incorporate the total effects of atmospheric (tidal + non-tidal) and non-tidal oceanic mass loading at the observation level.
However, these effects are removed at a post-processing step using $1^\circ \times 1^\circ$ global daily displacement models provided by GeoForschungsZentrum Potsdam (GFZ). These displacement fields are produced using the same global ocean bottom pressure data (MPIOM) and atmospheric surface pressure data (ECMWF) as applied to remove the relevant effects (AOD1B) from GRACE gravity field. We first detrended the loading displacement field (Jiang et al., 2013) and then subtracted the detrended daily time series (in the CM frame) from our GPS non-fiducial displacement time series. In our study area the non-tidal ocean loading effect is small compared to hydrological loading effects but its amplitude reaches 1.5 mm (Figure A21) along the Gulf of Mexico and hence is non-negligible for stations near the coastline.

Degree 1 Stokes coefficients represent the geocenter motion (the relative motion between CE and CM). Similar to GPS satellites, GRACE satellite orbit are expressed in the inertial CM frame and are thus insensitive to geocenter displacement. Therefore, the GRACE satellites do not deliver degree 1 Stokes coefficients. However, in calculating TWS, degree 1 stokes coefficients have been added from the combination of GRACE data and ocean models. The Green’s function used here is specified in the CE frame which is consistent with GRACE TWS data. For an appropriate comparison with GPS time series, the non-fiducial daily position time series are transformed into the IGb08 reference frame (Rebischung et al., 2012) using JPL’s X-files, a 7-parameter transformation. The GPS time series transformed into the IGb08 are in a frame defined
by the center of surface figure of the Earth (CF) which differs from the CE frame. We therefore transferred degree 1 load love number \( (l_1) \) from the CE frame to CF frame using the formula given in Blewitt (2003, Eq. 6.23). In this way, the predicted vertical displacements will be in a consistent frame (CF) with the GPS height time series.

### Figure 6.2: RMS scatters of detrended total water storage (2002-2015) from a) GRACE DDK2-filtered Stokes coefficients (CSR-RL05) b) WaterGap Global Hydrological Model (WGHM, version 2.2b). c) North American Land Data Assimilation System (NLDAS2-Noah). The red dots represent the location of GPS stations used in this study. Also shown are the seven sub-basins: 1) the Missouri River basin, 2) the upper-Mississippi River basin, 3) the Ohio and Tennessee River basin 4) the Arkansas and Red River basin, 5) the lower-Mississippi River basin, 6) the Rio Grande basin and 7) the Texas and Gulf basin.

#### 6.6 Evaluation of modeled deformations

The daily GPS height time series were detrended and averaged to monthly intervals to be consistent with the temporal resolution of the GRACE and WGHM data sets. The quality of the modeled deformation was estimated by calculating the RMS scatter of GPS monthly height time series \( (u_{GPS}) \) before and after removing the detrended modeled vertical deformation \( (u_{model}) \). The reduction in RMS is a common
statistic to quantitatively compare the observed and modeled deformation and assess the impact of hydrological loading in GPS height time series (e.g., Dixon 1991; van Dam et al., 2007; Tregoning et al., 2009; Tesmer et al., 2011; Fu et al., 2012). The RMS reduction in percentage is defined as:

\[
RMS_{\text{red}} = \frac{\text{rms}(u_{GPS}) - \text{rms}(u_{GPS} - u_{model})}{\text{rms}(u_{GPS})} \times 100
\]  

(6.27)

representing the average contribution of the hydrological loading estimated from the hydrological data sets in the GPS height time series.

### 6.6.1 Omitting GPS sites responding to non-loading changes

Four GPS stations located inside the Yellowstone Caldera in the Missouri River basin were removed from the data set as they are strongly influenced by volcanic and hydrothermal activity (Figure A22). Unlike the Plate Boundary Observatory (PBO) GPS network in the Western U.S. designed for Earth science studies, the GPS stations in the central U.S. are operated by several agencies and organizations and are not necessarily focused on Earth science applications. The optimum (low noise) PBO style GPS monument (a deep-drilled and braced design) is limited in this area (< 20 stations). 233 stations have shallow-drilled braced monuments or concrete pillars and masts for monuments, while 257 stations are building roof installations. The remaining stations have unknown monument types description. The diversity of monument types leads to colored noise in the displacement time series that is site-dependent. Of the 762 GPS
stations used in this study, only 210 stations have a known foundation depth, at least as described in the publicly available meta-data. Figure 6.3 compares the RMS reduction (e.g., using hybrid solution) in GPS height time series and the foundation depth of GPS monuments where this is known. For stations with foundation depths shallower than 3 m, we found a moderate correlation ($\rho = 0.55$). The hydrological loading in GPS stations with deeper foundation depth is more significant relative to stations anchored at shallower depth. We interpret this as follows. GPS stations with shallower foundation depths experience additional processes besides mass loading. Local soil expansion and compaction due to shallow water table-level fluctuations can cause shallow poroelastic deformation, a sponge-like behavior of ground, i.e., increase in water table-level causes uplift, while subsequent drying causes subsidence (Argus et al., 2014). These effects can be large and can dominate other signals. For example, GPS stations in Houston, Texas, show poroelastic deformation in response to shallow groundwater changes and heavy municipal and industrial pumpage (Figure A23) (Bawden et al., 2012). The elastic mass loading theory cannot be applied to estimate shallow hydrological deformation at GPS sites affected by such poroelastic effects. We thus excluded these sites from our study.

Thermoelastic deformation due to surface temperature variation is another process that influences GPS stations, in particular, those with shallow foundation depth. Thermal expansion of GPS monument (structure supporting the antenna and structure supporting the foundation) and thermal expansion of the ground surface through heat
conduction into nearby bedrock are two major components that contribute to thermoelastic deformation (Dong et al., 2002; Yan et al., 2009). There is a one-to-one correspondence between thermoelasticity and poroelasticity (e.g., Tsai, 2011; Fang et al., 2014) which differs from elastic mass loading theory. However, the heat conduction from the ground surface to the depth decreases exponentially, hence stations with shallower foundation depth are more likely to be affected. GPS stations with deeper foundation depth are less likely to be affected by thermal expansion, hence elastic mass loading theory and mass changes from GRACE and hydrological models are more likely to fit the observed deformation. As a result of these considerations, of the total 762 processed GPS stations, 36 were eliminated from our database, either because of volcanic deformation, or poroelastic or thermo-elastic effects associated with shallow monuments.
Figure 6.3: The relationships between significance of hydrological loading in GPS height time series and foundation depth of GPS monuments that are shallower than 3 m. The correlation coefficient $\rho$ between RMS reduction and foundation depth is 0.55.

6.6.2 Validating the hybrid approach

We validate our hybrid approach by using GRACE data in both near and far field in the following steps. In this case, the hybrid approach should produce a solution equal to the spherical harmonic approach.

1. We use the filtered Stokes coefficients in Eq. (6.21) to generate the surface mass density ($\Delta \sigma$) on $1^\circ \times 1^\circ$ grid. The gridded surface mass density is then used to calculate the contribution of the near field using the Green’s function approach (Eqs. 6.13 - 6.15), for the spherical cap with radius $\psi_0$ varying from $1^\circ$ to $20^\circ$ in steps of $1^\circ$. 
2. We use the filtered Stokes coefficients to calculate the surface spherical harmonic of surface mass density ($\sigma_n$), which is then applied in Eq. (6.22) to estimate the contribution of the far field for the spherical cap with radius $\psi_0$ varying from 0° to 20° in steps of 1°. As mentioned earlier, the truncation coefficients at $\psi_0 = 0$ are $Q_n(0) = \frac{2h_n}{2n+1}$, thus, Eq. (6.22) reduces to the spherical harmonic representation of the vertical deformation (the spherical harmonic approach).

3. We then calculate the hybrid solution by adding the contribution of the near field from step 1 to the contribution of the far field from step 2.

4. The mean GPS and model misfit for each aforementioned step is computed by averaging RMS reductions for all of 736 GPS stations.

When our modeling of the vertical deformation is limited to the effect of the near field (blue circles in Figure 6.4a), the mean RMS reduction increases with increasing radius of the integration cap, reaching a maximum value at $\psi_0 \approx 5°$ (except at $\psi_0 = 180°$ which reproduces spherical harmonic approach) and then drops slightly. Note that at $\psi_0 = 5°$ the overall fit to GPS height time series is slightly better relative to the spherical harmonic approach (red dashed line in Figure 4a). This is primarily due to including a larger number of load Love numbers in the Green’s function approach (Eq. 6.4). Here we chose the upper limit of the Green’s function expansion to be 1500, while in the spherical harmonic approach the series expansion is limited to the spatial resolution of load, typically maximum degree expansion 90 for GRACE data and 180 for
When summing up the contributions of the far field and near field with the hybrid approach, the mean RMS reduction becomes independent of the radius of the integration cap (cyan triangles in Figure 6.4a), reproducing the spherical harmonic approach (red dashed line) and validating our formulation of the hybrid approach.

**Figure 6.4:** Mean RMS reduction as a function of spherical cap $\psi_0$. The mean RMS reductions were computed by averaging RMS reductions for all 736 GPS stations shown in Figure 6.2 (GPS stations affected by volcanic deformation and poroelastic deformation were excluded). a) GRACE data were used in both near field and far field for validating the hybrid approach. Blue circles are the Green’s function solution (the contribution of the near field, Eqs. 6.13 – 6.15), cyan stars are the contribution of the far field (Eq. 6.22) and cyan triangles are the hybrid solution (the contributions of the near and far field). Note that the hybrid approach reproduces the spherical harmonic solution (red dashed line), which is independent of integration cap. At zero cap size ($\psi_0 = 0$), Eq. (6.22) reproduces the spherical harmonic solution (cyan star at $\psi_0 = 0$). b) Comparison of solutions from the Green’s function approach (near field contribution) for GRACE, WGHM and NLDAS data. Circles in Figure 6.4b are mean RMS reduction for GPS height time series (original GPS) while squares are mean RMS reduction for residual GPS height time series (residual GPS). The residual time series were calculated by removing the contribution of loading data outside the spherical cap $\psi_0$ (the contribution of the far field) from GPS height time series using processed GRACE Stokes coefficients (Eq. 6.22).
6.6.3 Modeling the vertical deformation at the GPS sites

We produce three sets of solutions using the following three approaches: (1) Green’s function approach (2) spherical harmonic approach; and (3) the hybrid approach. For the Green’s function approach (near field contribution), we use the detrended surface mass density changes from hydrological models and GRACE in Eqs. (6.13 - 6.15) to estimate vertical displacements at GPS sites. We estimate the vertical deformation for spherical caps with radius $\psi_0$ varying from $1^\circ$ to $20^\circ$. For the spherical harmonic approach, we converted the monthly detrended TWS changes from WGHM and NLDAS to the surface mass density changes ($\Delta \sigma = \frac{\rho_w}{\Delta t_{w_s}}$) and then to spherical harmonic coefficients (e.g., Eq. 1.76 in Heiskanen and Moritz, 1967; Eshagh and Karegar, 2010) of surface mass density. The processed GRACE Stokes coefficients (section 6.4.1) and the WGHM and NLDAS spherical harmonic coefficients are then used in Eq. (6.22) with $\psi_0 = 0$ and $Q_n(0) = \frac{2h_n}{2n+1}$ to estimate vertical displacement at GPS sites. For the hybrid approach, we use the processed GRACE Stokes coefficients to calculate the contribution of the far field at various spherical caps. We then add the contribution of the near field estimated from WGHM and NLDAS TWS data (using the Green’s function approach) to the contribution of the far field computed from GRACE. The GPS and model misfit for each approach is computed by averaging RMS reductions for all GPS stations.
6.7 Results and discussion

6.7.1 Comparison of the three approaches

Estimates of vertical crustal deformation based on GRACE data in both the spherical harmonic approach (Figure 6.5, dashed lines) and Green’s function approach (Figure 6.4b, circles) provide a better fit to GPS height time series than the WGHM and NLDAS models. However, combining WGHM and NLDAS TWS data with GRACE data through the hybrid approach results in the greatest mean RMS reduction (triangles in Figure 6.5). The hybrid approach (combining GRACE and WGHM) improves the fit to GPS time series by an average of 25% and 35% relative to respectively, the GRACE-only and WGHM-only spherical harmonic solutions (Figure 6.5). The hybrid approach (combining GRACE and NLDAS) improves the fit to GPS time series by an average of 10% and 25% relative to, respectively, the GRACE-only and NLDAS-only spherical harmonic solutions.

When comparing the Green’s function approach (circles in Figure 6.4b), at the spherical cap \( \psi_0 = 4^\circ \) (~ 450 km from GPS sites) GRACE provides a maximum mean RMS reduction 15.1%, while WGHM and NLDAS models lead to 11.7% and 12.7% RMS reduction. This implies that GRACE can better describe the loading changes adjacent to the GPS stations. As we stated earlier, GRACE data are by-products of filtering processes which damp TWS changes. The GRACE water storage variability is smoother than WGHM and NLDAS models in Central North America (Figure 6.2). How does the
combination of TWS data from hydrological models in the near field with TWS data from GRACE in the far field lead to a better fit to GPS height time series? To assess which data set better models deformation in the near field at GPS sites we should remove the effect of the far field from GPS time series and then compare the solution from the Green’s function approach for each data set. First, we calculate the contribution of the far field using processed GRACE Stokes coefficients (Eq. 6.22). Second, residual GPS time series are calculated by subtracting the far field contribution for varying spherical cap sizes from the GPS time series. We attribute displacement in residual GPS time series to near field deformation. Third, the fit of Green’s function approach (near field contribution using GRACE and hydrological models) to the residual GPS height time series is calculated. We find that WGHM and NLDAS (red and green squares in Figure 6.4b) significantly better model deformation in the residual GPS height time series compared to GRACE (blue squares). These results are consistent with the known spatial resolution of GRACE TWS data (~500 km). While GRACE accounts for large scale variabilities (> 500 km due to filtering and smoothing), WGHM and NLDAS models incorporate higher spatial variability in TWS, better explaining the small-scale deformation near GPS stations.

For spherical integration caps smaller than 7°, the hybrid solutions (combining GRACE with WGHM; or GRACE with NLDAS) is better than the GRACE-only spherical harmonic approach (Figure 6.5). For caps with radii larger than 7° the hybrid
approach does not improve the estimate relative to GRACE and the mean RMS reduction decreases. The rapid drop in mean RMS reduction for the hybrid solution indicates that hydrological models cannot resolve the large-scale deformation in comparison to GRACE. Therefore, hydrological and land surface models alone are not sufficient to characterize the hydrological deformation at geodetic sites. This result can be further investigated by calculating the degree variance spectrum of the TWS data. The degree variance spectrum gives an indication of the power in the TWS data as a function of spherical harmonic degree. The WGHM and NLDAS models deliver higher power than GRACE in higher spectral degrees (larger than 30 - 40), i.e., short wavelength signals in the models are contained in higher degrees, as expected (Figure A24). However, the WGHM TWS data indicate higher power than NLDAS for degrees larger than 30 (Figure A24b). This suggests that the WGHM hydrological model better determines hydrological loading deformation relative to the NLDAS land surface model (Figure 6.4b and Figure 6.5). This is consistent with results in Argus et al. (2014, 2017) and Fu et al., (2015) that suggest that the NLDAS model underestimates snow equivalent height in the western United States. Moreover, groundwater and surface water are not explicitly represented in the NLDAS model, which are two important components of TWS changes in the Mississippi River basin and Texas. These comparisons provide some characterization of the uncertainties inherent in the WGHM and NLDAS models, reflecting the spatial heterogeneity of the region, non-linear
processes, and complex interactions and feedbacks between surface and subsurface water cycles that are not fully captured by the models. In the remaining discussion, we adopt the WGHM model to evaluate the hybrid approach and hydrological loading in the GPS height time series.

![Figure 6.5: Mean RMS reduction as a function of spherical cap $\psi_0$. The solutions of the spherical harmonic approach (dashed lines) and the hybrid approach (triangles) are compared.](image)

6.7.2 Radius of the near field in the hybrid approach at individual GPS sites

We use the maximum RMS reduction to find the corresponding radius of the near field for individual GPS stations in the hybrid approach (GRACE + WGHM) (Figure 6.6). Integrations caps with sizes between $1^\circ$ and $3^\circ$ result in the highest RMS
reduction at more than 95% of GPS stations (inset histogram in Figure 6.6). Given the spatial resolution of the GRACE TWS data (a few degrees), WGHM model adds the surface mass loading at higher spectrum, making the optimum predication of vertical deformation limited to integration caps between 1° and 3°. Stations with cap size larger than 3° are primarily concentrated in arid regions, including the Rio Grande basin and southwest area of the Arkansas and red River basin. In these regions, GPS data indicate relatively small deformation, i.e., RMS scatters of detrended time series are smaller than 3 mm (Figure A26a).

The hybrid approach provides a fast and flexible way of combining two loading data sets, minimizing the difference between observed and modeled deformation at individual geodetic sites when the size of the spherical cap (the boundary between the near and far field) is optimized. This will be useful in geophysical studies where accurate characterization of deformation due to hydrological loading in geodetic position or displacement time series is required.
Figure 6.6: Spherical cap size ($\psi_0$, radius of the near field) for the maximum RMS reduction in GPS monthly height time series. Color circles show the values of maximum RMS reduction and the size of circles represent the size of corresponding integration caps. Black circles indicate that RMS reduction is negative. Lower-right inset is a histogram of the size of integration caps. At 95% of GPS stations, spherical caps smaller than $3^\circ$ achieve the maximum RMS reduction. Upper-right inset shows RMS reduction at GPS stations as a function of distance from the coastline. The red line is linear regression fit. For distances shorter than 300 km the correlation coefficient between RMS reduction and distance from the coast is 0.40.
6.7.3 Comparison of the hybrid approach with the GRACE-only spherical harmonic approach at individual GPS Sites

We show the performance of hybrid approach at individual GPS stations by comparing the maximum RMS reduction from the hybrid solution with those from the GRACE-based spherical harmonic solution (Figure 6.7). Note that stations with RMS reduction larger than 10% (from the hybrid approach) were included (80% of stations). The hybrid solution substantially improves the scatter of observed vertical displacements compared to GRACE-based spherical harmonic results. Almost half of the GPS stations show an improvement greater than 30% in RMS reduction, and 35% of stations show an improvement larger than 50%. Most significant improvements are in areas where the WGHM model provides small-scale variabilities that are not resolved by GRACE. These areas also include coastal regions where GRACE data are affected by spatial leakage error.

15% of stations show no improvement with the hybrid approach. These stations are mainly located near riverbanks (Figure 6.7 and Figure A28). One possible explanation is the rather conceptual representation of groundwater and river storage in the hydrological model, which may break down in these areas of high water flux, high temporal variability, and feedback with local groundwater.
Figure 6.7: Comparison of RMS reduction in GPS monthly height time series between GRACE-based spherical harmonic solution and hybrid solution (GRACE + WGHM). Stations with RMS reduction larger than 10% (from the hybrid approach) are shown. The light to dark blue circles indicate sites where the RMS reduction has increased; the light to dark red, where the RMS reduction has decreased.

6.7.4 Contribution of hydrologic loading to the GPS height time series

The RMS scatters of 94% of the GPS stations are reduced after removing the hydrological loading model using the hybrid approach (Figures 6.6 and S6b). 80% of these stations have a RMS decrease greater than 10%. Stations with the greatest RMS decrease (e.g., larger than 30%) are primarily located in the centre of the Mississippi River, regions where GRACE and WGHM TWS data indicate higher variability (Figure
6.2). Application of the hydrologic loading correction to the height time series increases RMS scatter in 6% of studied stations (47 stations). Most of these stations (black circles in Figure 6.6) exhibit only small deformation, i.e., RMS scatters of displacement time series are smaller than 3 mm (Figure A27). A few exceptions (RMS scatters significantly larger than nearby stations; Figure A27) may be affected by local processes such that loading theory is not applicable.

For stations close to the Gulf coast and Great Lakes, there is less improvement than for stations at larger distances from these coasts (Figure 6.6). The level of agreement is positively correlated (ρ = 0.40) with station’s proximity (up to 300 km) to the coastline, i.e. stations farther form the coast have larger RMS reductions (upper-right inset plot in Figure 6.6). The RMS scatter of non-tidal ocean loading displacements reach 1.5 mm at these coastal sites (Figure A21) comparable to RMS scatters of GPS height time series (corrected for ocean loading) (Figure A26a). Perhaps small-scale coastal ocean or lake dynamics not resolvable in current models is affecting the vertical displacement of the nearby land stations. Spurious long-period displacements have been shown to arise from mismodeling of tidal ocean loading at sub-daily periods (e.g., Penna et al., 2007; van Dam et al., 2007). Also, required post-processing of GRACE level-2 data (filtering and truncating) can lead to leakage of water mass variabilities in the ocean and Great lakes to neighboring land areas, contaminating the estimate of
hydrologic loading displacement. The hybrid approach described here actually reduces this effect (see Figure 6.7 and section 6.3).

6.7.5 Sensitivity to different filter intensities in GRACE data

We assess the sensitivity of different filter intensities in the GRACE data using different versions of the decorrelation DDK filter developed by Kusche (2007). These coefficients are non-isotropic filtered Stokes coefficients with various degree of smoothing from DDK1 to DDK8, with DDK1 having the strongest smoothing and DDK8 the weakest. The RMS of total water storage shows significant variability among different filter intensities (Figure A25). Since the optimal signal to noise ratio of GRACE data is unknown, we test the performance of different filters in the hybrid approach. First, we use WGHM TWS data to calculate the contribution of the near field using the Green’s function approach (Eq. 6.15), for a spherical cap with radius $\psi_0$ varying from 1° to 20°. Second, we use DDK-filtered stokes coefficients (DDK1 to DKK8) to calculate the contribution of the far field using Eq. (6.22), for the same spherical cap size. Third, we compute the mean GPS and model misfit for a given solution by averaging RMS reductions for all of the GPS stations. Figure 6.8 plots the mean RMS reduction as a function of spherical cap size for the various filters.
Figure 6.8: Mean RMS reduction versus spherical cap size ($\psi_0$). Solutions of the hybrid approach are compared for different filter intensities of GRACE Stokes coefficients. WGHM is used to calculate the near field contribution. The x-axis scale is logarithmic. Differences appear at small radii.

Different filter intensities cause different GRACE error reduction and leakage effects in TWS changes (Figure A25). However, the effects of different filters on the estimated deformation are controlled by the size of the spherical cap in the hybrid approach (Figure 6.8). For spherical caps larger than 6° ($> 600 - 700$ km), different GRACE filter intensities do not alter the estimated deformation, as WGHM TWS data are used for larger areas. Larger differences occur for smaller spherical caps, since GRACE TWS data are used in a larger fraction of the test area. The greatest mean RMS reduction occurs at spherical cap $\psi_0 = 2°$ ($\sim 220$ km) for all tested solutions. The filter
with the most smoothing (DDK1) generates TWS data that greatly damps estimated deformation at the GPS sites. The filter with the least smoothing (DDK8) leads to erroneous TWS data and deformation estimates. Among other applied filters (DDK2 – DDK7), no significant differences are observed at $\psi_0 = 2^\circ$. This analysis suggests that when GRACE TWS data are combined with WGHM TWS data using our the hybrid approach, the deformation estimates are relatively insensitive to moderate filter strengths (DDK2 – DDK7) for spherical caps with sizes larger than $\sim 2^\circ – 3^\circ$. We chose the DDK2-filtered Stokes coefficients to calculate the far field signal in the hybrid approach.

6.8 Potential for broader applications

Our hybrid solution can be applied to a wide variety of environmental surface loading problems. For example, in situations where it is desirable to measure vertical coastal motions, a global ocean circulation model along with a high resolution local tide model and storm surge model can be used to improve estimates of tidal and non-tidal ocean loading coastal deformation, so that residual signals (e.g., due to local subsidence or isostatic adjustment) are clear. This is particularly important for GPS sites co-located with tide gauges along the coast, where GPS data are used to study sea-level change. Similarly, global and local models of atmospheric surface pressure can be used with our method to better predict the atmospheric pressure loading, and high-
resolution regional coupled land-surface-groundwater models may be employed for the near field. Our approach also allows the optimal combination of GRACE data with Surface Mass Balance models in Greenland and Antarctica to model annual and inter-annual deformation due to ice mass changes near individual GPS sites. It can be used to effectively separate ice and non-ice loading sources (e.g., Lui et al., 2017). Our approach also has implications for tectonic and volcanic deformation, as the accurate determination of secular rates, post-seismic deformation, and detection of slow slip transient deformation requires proper modeling of nontectonic sources of surface deformation. Recent studies typically use statistical signal separation techniques to identify signals of interest in GPS time series (e.g., Bird and Carafa, 2016; Crowell et al., 2016; Walwer et al., 2016; Voss et al., 2017). These methods divide the displacement time series into different modes (or channels) to separate tectonic signal from other sources (e.g., anthropogenic water extraction or drought). However, these techniques do not provide any information about the physical processes governing specific deformation modes. This could lead to misinterpretation of the extracted signal. For example, Karegar et al. (2015b) showed that three GPS sites exhibit surface uplift associated with CO₂ injection and storage in an oil reservoir at depth in coastal Texas, where the timing and magnitude of uplift were also influenced by hydrological seasonal deformation. A principal component analysis was applied to a network of nearby GPS sites to detect and remove the hydrological loading signal. However, a portion of the uplift signal in
the excluded principal components was likely related to hydrological loading, affecting the interpretation. The hybrid approach provides tools for investigating the interplay of elastic deformation produced by near-field and far field mass changes. This could be beneficial for definition of terrestrial reference frame parameters, for example reducing aliasing of load-related deformation into reference frame estimation, and understanding the effects of elastic displacement due to nearby surface loads on the geocenter. Finally, the hybrid approach can be used to assess the quality of hydrological models as well as GRACE and GRACE-Follow products.

6.9 Summary and conclusions

We develop a hybrid approach to exploit loading data with different accuracies and spatial resolutions, combining near field and far field contributions for hydrologic loading calculations. The hybrid approach consists of two steps: (1) the contribution of the near field (2) the contribution of the far field. Using Green’s functions and mass changes from high-resolution hydrological models, contributions to the near field can be estimated at the location of geodetic sites. To properly treat the singularity of Green’s function at the computation point, the near field is split into the contribution at the computation point and the contributions from the rest of a spherical cap. We then derive a formula based on spherical harmonics to account for far field contributions using filtered GRACE Stokes coefficients. This effect is added to the near field effect to calculate total displacement. Monthly modeled mass changes from two
high-resolution hydrological models were compared to estimate the near field information, while mass changes from GRACE contribute far field information.

Data from 762 high precision GPS stations in the Central U.S. were processed and corrected for tidal and non-tidal atmospheric and ocean loading effects, using parameters consistent with GRACE processing, and used to validate the model. Our new hybrid approach achieves a better fit to GPS-measured vertical displacement than the widely-used spherical harmonic approach, accounting for local to regional variabilities adjacent to the GPS station. We tested two high-resolution hydrological models and several different GRACE DDK-filtered Stokes coefficients. The WGHM model better resolves smaller scale and local mass variability compared to the NLDAS model. Combining the WGHM model with GRACE DDK filtered data (DDK2 - DDK7) through the hybrid approach results in the highest RMS reduction in GPS height time series in Central North America. The estimated deformations are insensitive to the filter strength (DDK2 - DDK7) for spherical caps larger than ~ 2°-3°.

6.10 Acknowledgements

This work was supported by NASA grant NNX14AQ16G to T.H.D. and M.A.K. The GPS RINEX data (up to mid-2015) were obtained from the CORS (https://www.ngs.noaa.gov/CORS/data.shtml), UNAVCO


(https://igsorb.jpl.nasa.gov/components/dcnave/sopac_rinex.html) and several other
archives (States Department of Transportation). The tidal and non-tidal atmospheric and non-tidal ocean loading displacement fields are available through GFZ’s website (ftp://ig2-dmz.gfz-potsdam.de/LOADING/). The GRACE DDK-filtered Stokes coefficients (CSR-RL05) are available at ICGEM (http://icgem.gfz-potsdam.de/series/99_non-iso/CSR%20Release%2005). We thank Donald Argus, Paul Dirmeyer and an anonymous reviewer, whose thoughtful comments greatly improved the manuscript.

6.11 References


7. Conclusion

This dissertation uses a wide range of data sets to explore the Earth surface deformation in the United States at different spatio-temporal scales. The main conclusions from five studies are summarized here.

In Chapter 2, it was shown that GPS has sensitivity to observe surface demonstration associated with CO$_2$ injection at depth. I used a principal component analysis to reduce noise associated with seasonal hydrologic effects, achieving post-filter precision of better than 2 mm and 3 mm in horizontal and vertical component respectively. A model assuming uniform pressurization of an infinitely thin horizontal disc-shaped pressure source in an elastic half-space fits the surface deformation data quite well. The model predicts a location of the pressurized source consistent with injection locations, and suggests minimal horizontal migration of the CO$_2$ fluid during the test period. Our results suggest that a sparse network of dual frequency GPS receivers can be used to augment sub-surface data for MVA activities associated with Carbon Capture, Utilization and Storage, deriving independent constraints on pressure changes in the reservoir at depth as well as CO$_2$ plume migration.
In Chapter 3, I present a comprehensive three-dimensional surface velocity field for the Mississippi Delta based on a network of 36 high-precision continuous GPS stations. I show that while the majority of the delta is relatively stable, the southern portion continues to experience high rates of subsidence (5-6 mm yr\(^{-1}\)). These data are consistent with long-term tide gauge records at Grand Isle, Louisiana, and several stations in Florida. The current relative sea-level rise along parts of the coastal delta is ~8-9 mm yr\(^{-1}\). Most tide gauge stations have recorded sea-level-rise acceleration after A.D. 1970. These data have implications for land reclamation and wetland restoration in the region; parts of the delta may not be viable in the long-term.

In chapter 4, I compared the present-day vertical land motions estimated from GPS with rates of late Holocene RSL rise along the eastern seaboard of United States. For many coastal areas there is no significant difference between these independent data. I showed that the geologic rate of RSL change provides an independent constraint to separate the long-term GIA-induced displacement from the GPS vertical displacement. The present-day subsidence rates measured by GPS between Virginia (38°N) and South Carolina (32.5°N) are approximately double the long-term geologic rates, most likely reflecting recent groundwater depletion. Differences between the geologic and geodetic data are useful for understanding some of the human impacts in the coastal plain and for flood mitigation.
In Chapter 5, it was shown that vertical land motion induced by recent anthropogenic activity and GIA discussed in Chapter 4 are contributing factors for increased nuisance flooding. These results have implications for flood susceptibility, forecasting and mitigation, including management of groundwater extraction from coastal aquifers.

In Chapter 6, I presented a mathematical basis for combining global and regional loading data with different spatial resolutions to improve the estimate of elastic deformation. The proposed hybrid method incorporates the Green’s function approach and spherical harmonic approach, allowing combining observed and modeled surface mass changes with different accuracy and spatial resolutions. Given the higher spatial resolution of hydrological models, the accuracy of hydrological loading deformation can be improved when combining with GRACE data. I processed more than 700 GPS stations in Central North America using state-of-the-art precise point position techniques, and showed that the new hybrid approach improves fits to GPS-measured vertical displacement, with 25% to 35% average improvement, respectively relative to pure GRACE or pure hydrological model-based spherical harmonic solutions. The proposed hybrid approach can be applied to a wide variety of environmental surface loading problems including assessing the quality of GRACE and GRACE-Follow products and validating hydrological models.
Appendices
Appendix A: Supplementary information for Chapter 3

GPS time series analysis

The raw GPS data were processed using JPL’s GIPSY/OASIS II software package (V. 6.2) and the precise point positioning technique (Zumberge et al., 1997). JPL’s precise satellite orbit and clock parameters together with an absolute GPS receiver and satellite antenna phase calibration model igs05.atx (Schmid et al., 2007) are used to generate daily position time series. The first-order effects of the ionosphere are corrected using the dual-frequency approach and a linear combination of the carrier phase measurements. Higher-order ionospheric effects are not considered here, as Hernandez-Pajares et al. (2007) and Petrie et al. (2010) showed that these effects are less than 1 mm. Tropospheric effects are modeled using the Global Mapping Function model of Böhm et al. (2006) which maps the zenith troposphere delay to the elevation of each observation. A priori zenith tropospheric delays are estimated from a Global Pressure and Temperature model (Böhm et al., 2007). The elevation cut-off angle is fixed to 7°, a compromise to better constrain tropospheric effects but minimize multipath errors. Tidal and non-tidal atmospheric loading effects are believed to have a 1 to 2 mm level impact on the vertical component (Tregoning and Watson, 2009). These effects are removed using a global 2.5 degree displacement field computed from a model provided by the National Center for Environmental Protection. The effects of ocean loading, which can reach several mm in the vertical component for near-coastal sites, are
corrected using the FES2004 model (Lyard et al., 2006). The single station ambiguity resolution algorithm of Bertiger et al. (2010) is adopted to solve integer ambiguities for each station. The non-fiducial daily position time series generated by these procedures are transformed into the IGb08 reference frame (Rebischung et al., 2012) using JPL’s X-files, a 7-parameter transformation.

Outliers were eliminated from the daily GPS position time series, as follows: 1) a data point with error larger than 3 times the root mean square (RMS) scatter of the time series; or 2) a data point that differs from the mean of the series by more than 3 times the RMS scatter.

We use a least squares model fit to the GPS daily position time series, with parameters that include a constant initial offset \(a\), a constant velocity \(v\), annual and semi-annual variations, and, in the case of equipment changes, one or more offset parameters \(n_c\). The daily position of each site in each direction component can hence be written as:

\[
y(t_i) = a + vt_i + c \sin(2\pi t_i) + d \cos(2\pi t_i) + e \sin(4\pi t_i) + f \cos(4\pi t_i) + \sum_{j=1}^{n_c} g_j (t_i - T_j) + \epsilon(t_i)
\]

(A1)

where \(t_i\) is the epoch of observation \(i\) in decimal year, \(c\) and \(d\) are the coefficients of annual periodic motion, \(e\) and \(f\) are the coefficients of semi-annual periodic motion, \(g\) and \(T\) are magnitude and epoch of offset, \(H\) is heavy site step function, and \(\epsilon\) is observational error.
We use the Allan Variance of Rate (AVR) method to estimate the velocity uncertainty in our GPS data and tide gauge records. This method deals with time-correlated noise in a robust manner (Hackl et al., 2011). The AVR is defined as one half the average of the squared differences between consecutive readings of the observable sampled over a certain interval $\tau$,

$$\sigma^2(\tau) = \frac{1}{2(n-1)} \sum^n_l [v_{i+1}(\tau) - v_i(\tau)]^2$$  \hspace{1cm} (A2)

where $n$ is the number of bins with length $\tau$ and $v_i(\tau)$ is the velocity of the position time series in the $i$th bin. The rate uncertainty corresponding to the full length of the time series $T$ is calculated by fitting an error model to the AVR and extrapolating to the full length of the time series. White noise, flicker noise, random walk and power law noise can be fitted to the AVR time series. Based on tests with selected time series we chose a power law noise model to fit the AVR time series as a function of the entire length of the time series $T$ (Hackl et al., 2011):

$$\sigma_0^2(T) = \alpha T^{-(\mu+3)}$$  \hspace{1cm} (A3)

where $\mu$ is the spectral index and $\alpha$ is a coefficient specifying amplitude of noise. These parameters are determined using a least squares fit to the AVR time series (Figure A1). Table A1 summarizes the GPS sites velocity and their standard error. An example daily position time series for the vertical component at station Cocodrie in south Louisiana is shown in Figure A1.
**Figure A1:** (a) GPS vertical position time series at Cocodrie in south Louisiana. (b) The corresponding AVR time series (grey line) and power law noise model (red line). The blue square indicates the variance of the velocity extrapolated to the entire length of the time series $T$; the corresponding standard deviation is 0.1 mm yr$^{-1}$. The best fit parameters for the noise model are: $\alpha = 657.49$ and $\mu = -2.79$. 


<table>
<thead>
<tr>
<th>Station</th>
<th>Lat. (deg.)</th>
<th>Lon. (deg.)</th>
<th>length (year)</th>
<th>&quot;Comp.&quot;</th>
<th>$V_{north}$ (mmyr$^{-1}$)</th>
<th>$V_{east}$ (mmyr$^{-1}$)</th>
<th>$V_{up}$ (mmyr$^{-1}$)</th>
<th>&quot;Foundation depth (m)&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARCM</td>
<td>-92.88</td>
<td>33.54</td>
<td>8.96</td>
<td>0.94</td>
<td>0.5±0.0</td>
<td>-0.2±0.0</td>
<td>-1.4±0.2</td>
<td>unknown</td>
</tr>
<tr>
<td>AWES</td>
<td>-90.98</td>
<td>30.10</td>
<td>4.19</td>
<td>0.96</td>
<td>0.1±0.1</td>
<td>0.1±0.1</td>
<td>-4.0±0.4</td>
<td>1</td>
</tr>
<tr>
<td>BVHS</td>
<td>-89.41</td>
<td>29.34</td>
<td>11.93</td>
<td>0.68</td>
<td>-1.0±0.0</td>
<td>0.1±0.0</td>
<td>-5.7±0.1</td>
<td>&gt;20</td>
</tr>
<tr>
<td>CAMR</td>
<td>-93.33</td>
<td>29.80</td>
<td>6.38</td>
<td>0.59</td>
<td>0.1±0.0</td>
<td>1.0±0.0</td>
<td>-2.4±0.1</td>
<td>unknown</td>
</tr>
<tr>
<td>COVG</td>
<td>-90.10</td>
<td>30.48</td>
<td>10.02</td>
<td>0.95</td>
<td>0.3±0.0</td>
<td>0.1±0.0</td>
<td>-0.8±0.2</td>
<td>&gt;15</td>
</tr>
<tr>
<td>DSTR</td>
<td>-90.38</td>
<td>29.96</td>
<td>8.38</td>
<td>0.89</td>
<td>-0.3±0.0</td>
<td>0.2±0.0</td>
<td>-2.0±0.2</td>
<td>unknown</td>
</tr>
<tr>
<td>DQCY</td>
<td>-93.45</td>
<td>30.45</td>
<td>4.53</td>
<td>0.87</td>
<td>0.9±0.0</td>
<td>0.1±0.1</td>
<td>-1.6±0.3</td>
<td>1</td>
</tr>
<tr>
<td>ENGI</td>
<td>-89.94</td>
<td>29.88</td>
<td>18.54</td>
<td>0.81</td>
<td>-0.1±0.2</td>
<td>0.2±0.1</td>
<td>-2.3±0.1</td>
<td>~3</td>
</tr>
<tr>
<td>FSHS</td>
<td>-91.50</td>
<td>29.81</td>
<td>4.20</td>
<td>0.95</td>
<td>-2.5±0.1</td>
<td>0.9±0.0</td>
<td>-3.4±0.4</td>
<td>1</td>
</tr>
<tr>
<td>GRIS</td>
<td>-89.96</td>
<td>29.27</td>
<td>8.89</td>
<td>0.78</td>
<td>-0.5±0.0</td>
<td>-0.2±0.0</td>
<td>-5.6±0.2</td>
<td>unknown</td>
</tr>
<tr>
<td>GVMS</td>
<td>-90.90</td>
<td>30.31</td>
<td>4.19</td>
<td>0.94</td>
<td>0.2±0.0</td>
<td>0.2±0.0</td>
<td>-2.5±0.3</td>
<td>1</td>
</tr>
<tr>
<td>HAMM</td>
<td>-90.47</td>
<td>30.51</td>
<td>13.45</td>
<td>0.86</td>
<td>-0.0±0.0</td>
<td>0.2±0.0</td>
<td>-1.0±0.1</td>
<td>&gt;15</td>
</tr>
<tr>
<td>HOUM</td>
<td>-90.72</td>
<td>29.59</td>
<td>10.67</td>
<td>0.83</td>
<td>-0.7±0.0</td>
<td>-0.0±0.0</td>
<td>-3.9±0.1</td>
<td>&gt;15</td>
</tr>
<tr>
<td>LALA</td>
<td>-92.05</td>
<td>30.22</td>
<td>2.16</td>
<td>0.91</td>
<td>-1.9±0.2</td>
<td>-0.6±0.1</td>
<td>-3.4±1.0</td>
<td>unknown</td>
</tr>
<tr>
<td>LAFR</td>
<td>-91.50</td>
<td>29.79</td>
<td>2.16</td>
<td>0.96</td>
<td>-3.2±1.0</td>
<td>0.5±0.1</td>
<td>-3.2±0.7</td>
<td>unknown</td>
</tr>
<tr>
<td>LESV</td>
<td>-93.27</td>
<td>31.14</td>
<td>11.18</td>
<td>0.90</td>
<td>-0.0±0.0</td>
<td>-0.0±0.0</td>
<td>0.3±0.1</td>
<td>&lt;15</td>
</tr>
<tr>
<td>LMPCN</td>
<td>-90.66</td>
<td>29.25</td>
<td>11.26</td>
<td>0.94</td>
<td>-0.6±0.0</td>
<td>0.7±0.0</td>
<td>-6.5±0.1</td>
<td>36.5</td>
</tr>
<tr>
<td>LSUA</td>
<td>-92.41</td>
<td>31.18</td>
<td>10.90</td>
<td>0.86</td>
<td>0.2±0.0</td>
<td>0.1±0.0</td>
<td>-0.3±0.1</td>
<td>10-15</td>
</tr>
<tr>
<td>LTEC</td>
<td>-92.65</td>
<td>32.52</td>
<td>4.19</td>
<td>0.96</td>
<td>0.3±0.1</td>
<td>0.3±0.0</td>
<td>-2.0±0.3</td>
<td>unknown</td>
</tr>
<tr>
<td>LWES</td>
<td>-90.35</td>
<td>29.90</td>
<td>6.67</td>
<td>0.74</td>
<td>0.2±0.0</td>
<td>0.4±0.0</td>
<td>-2.7±0.3</td>
<td>unknown</td>
</tr>
<tr>
<td>MCNE</td>
<td>-93.22</td>
<td>30.18</td>
<td>11.93</td>
<td>0.82</td>
<td>-0.7±0.0</td>
<td>0.7±0.0</td>
<td>-0.2±0.1</td>
<td>&gt;15</td>
</tr>
<tr>
<td>MSHT</td>
<td>-89.34</td>
<td>31.33</td>
<td>6.53</td>
<td>0.88</td>
<td>0.0±0.0</td>
<td>-0.3±0.0</td>
<td>0.0±0.2</td>
<td>unknown</td>
</tr>
<tr>
<td>MSPTK</td>
<td>-89.14</td>
<td>30.78</td>
<td>5.19</td>
<td>0.95</td>
<td>0.0±0.0</td>
<td>-0.1±0.0</td>
<td>-0.6±0.3</td>
<td>unknown</td>
</tr>
<tr>
<td>MSSC</td>
<td>-89.61</td>
<td>30.38</td>
<td>9.23</td>
<td>0.94</td>
<td>0.0±0.0</td>
<td>0.6±0.0</td>
<td>-1.5±0.1</td>
<td>unknown</td>
</tr>
<tr>
<td>NDBC</td>
<td>-89.61</td>
<td>30.36</td>
<td>13.18</td>
<td>0.86</td>
<td>-0.2±0.0</td>
<td>0.2±0.0</td>
<td>-1.3±0.1</td>
<td>unknown</td>
</tr>
<tr>
<td>OAKH</td>
<td>-92.66</td>
<td>30.82</td>
<td>10.30</td>
<td>0.84</td>
<td>0.0±0.0</td>
<td>0.1±0.0</td>
<td>-0.7±0.1</td>
<td>unknown</td>
</tr>
<tr>
<td>SIHS</td>
<td>-91.66</td>
<td>31.84</td>
<td>11.12</td>
<td>0.92</td>
<td>0.2±0.0</td>
<td>-0.2±0.0</td>
<td>-0.8±0.1</td>
<td>&lt;15</td>
</tr>
<tr>
<td>SHRV</td>
<td>-93.70</td>
<td>32.43</td>
<td>9.94</td>
<td>0.85</td>
<td>0.1±0.0</td>
<td>0.6±0.0</td>
<td>-1.6±0.2</td>
<td>&lt;15</td>
</tr>
<tr>
<td>SJB1</td>
<td>-91.11</td>
<td>30.40</td>
<td>5.36</td>
<td>0.85</td>
<td>-0.5±0.1</td>
<td>0.2±0.3</td>
<td>-1.5±0.3</td>
<td>unknown</td>
</tr>
<tr>
<td>TALL</td>
<td>-91.18</td>
<td>32.40</td>
<td>10.49</td>
<td>0.66</td>
<td>-0.1±0.1</td>
<td>-0.0±0.0</td>
<td>-0.9±0.4</td>
<td>unknown</td>
</tr>
<tr>
<td>THHR</td>
<td>-92.08</td>
<td>30.53</td>
<td>4.19</td>
<td>0.93</td>
<td>0.3±0.0</td>
<td>0.4±0.1</td>
<td>-3.7±0.6</td>
<td>1</td>
</tr>
<tr>
<td>TONY</td>
<td>-92.05</td>
<td>30.22</td>
<td>4.28</td>
<td>0.97</td>
<td>-1.9±0.0</td>
<td>-0.9±0.1</td>
<td>-2.3±0.4</td>
<td>1</td>
</tr>
<tr>
<td>WNFL</td>
<td>-92.78</td>
<td>31.90</td>
<td>13.19</td>
<td>0.91</td>
<td>-0.2±0.0</td>
<td>0.6±0.0</td>
<td>-0.6±0.1</td>
<td>~2</td>
</tr>
<tr>
<td>1NSU</td>
<td>-93.10</td>
<td>31.75</td>
<td>10.52</td>
<td>0.87</td>
<td>1.3±0.0</td>
<td>-0.3±0.0</td>
<td>-0.8±0.2</td>
<td>&lt;15</td>
</tr>
<tr>
<td>1LSU</td>
<td>-91.18</td>
<td>30.41</td>
<td>11.21</td>
<td>0.87</td>
<td>-0.1±0.1</td>
<td>0.3±0.3</td>
<td>-2.9±0.1</td>
<td>&lt;15</td>
</tr>
</tbody>
</table>
The horizontal velocities are in the NA12 reference frame. Vertical velocities are in IGS2008 reference frame. Uncertainties are quoted at the 1σ level. “Comp” indicates the completeness of time series, defined as the fraction (available days of data) / (total days since observation start). “Foundation depth” is the approximate depth of foundation of building or driven rod, from Dokka et al. (2006) and GPS log files provided by the National Geodetic Survey database.

Tide gauge time series analysis

We identified 8 tide gauges in Louisiana and Florida with monthly records of relative mean sea level along the eastern Gulf of Mexico in the Permanent Service for Mean Sea Level (PSMSL) database. Only 5 tide gauges are located at or near permanent GPS stations (Table A2 and Figure A2). As discussed in the earlier here, we use three long-record tide gauges at Pensacola (PCLA), St. Petersburg (SPBG) and Key West (KYWS) as reference stations to estimate the subsidence rate at Grand Isle (GRIS).

Figure A2: Location of tide gauges used in this study.
We use the Hilbert-Huang Transform (HHT) for analyzing tide gauge data. The method uses empirical mode decomposition and Hilbert spectral analysis to decompose a time series \( x(t) \) with \( N \) data points to intrinsic mode functions \( c_j(t) \) and a residual \( r(t) \) with time-dependent amplitudes and frequencies (Huang et al., 1998):

\[
x(t) = \sum_{i=1}^{M} c_i(t) + r(t),
\]

where \( M \) is the total number of modes equal to the integer value of \( \log_2 N \). The residual in Eq. (A4) represents a trend in the time series which could be a time-dependent function with one extrema indicating uniformly increasing or decreasing rate (uniform acceleration), or a steady state function indicating a constant rate.

The idea of HHT is to analyze time series with non-stationary and non-linear processes (e.g., tide gauge data at Grand Isle) and separate the oscillatory modes (e.g., semi-annual to multi-decadal oceanographic effects; time-variable subsidence) from the long-term trend (e.g., Ezer and Corlett, 2012; Ezer, 2013). Monthly tide gauge time series with a typical length of 70-80 years are decomposed into 8 modes, where modes 1-4 indicate seasonal and inter-annual variations, modes 5-6 indicate decadal variations, and mode 7-8 indicates multi-decadal oscillations. The residual produces the long-term relative sea-level trend and acceleration (if present), comparable to estimates of linear trend and acceleration using least square methods. The mean rate is estimated by integrating the slope of \( r \) over the entire time series \( T \):
We used this approach for several reasons. First, it is a non-parametric model and does not impose a pre-defined functional form (e.g. standard least squares methods) to the analysis of tide gauge records. Using the standard least squares methods, selected oscillations (e.g. annual to decadal variations) are usually eliminated using low-pass filters, and a trend is estimated which can be contaminated by the filtering process. Second, the oscillating modes in the HHT method may represent oceanographic and non-oceanographic signals on different time scales, including long term cycles with periods close to or longer than the record itself, e.g., the 60-year cycle discussed by Chambers et al. (2012). The residual represents a trend that is separated from the oscillatory modes. Therefore, the HHT trend is less contaminated by longer term oscillations compared to standard least squares methods. Third, using standard methods, at least 60 years of data are required to obtain an uncertainty of ±0.5 mm/yr at 95% confidence interval (Douglas, 2001). Ezer (2013) demonstrated that HHT analysis obtains similar accuracy for shorter intervals of data.

For clarity, we plot all modes of HHT analysis for three tide gauges: GRIS, PCLA and KYWS. Mode 6 represents decadal variability, mode 7 represents multi-decadal variability and mode 8 represents longer variability that seems to show a 60-year cycle. While the other two tide gauges show similar multi-decadal variability, the tide gauge record at Grand Isle (mode 7) is affected by variations that may represent high
hydrocarbon extraction rates between 1960 and 1990. The HHT analysis removes this variability from the trend, thus providing better assessment of subsidence at Grand Isle, allowing direct comparison to the GPS rate. Rate differences between the two methods at Pensacola (Figure A3c) can be explained in terms of a long-term trend from the HHT analysis that less influenced by decadal and multi-decadal variability.

**Figure A3**: Oscillations modes obtained from HHT analysis of tide gauge data a) Pensacola b) Key West c) Grand Isle.
Figure A4 shows the relative mean sea-level rise at Grand Isle and Pensacola with estimated trends using linear regression and HHT methods. Subsidence at Grand Isle is determined by differencing this record from the Pensacola record (to minimize oceanographic effects) and adding back the differential GIA component. GPS vertical position time series at these stations are also shown.

**Figure A4:** Tide gauge time series for a) Grand Isle and c) Pensacola. GPS time series for b) Grand Isle and d) Pensacola. e) Tide gauge time series at Grand Isle referred to Pensacola. Note that the subsidence rates are estimated using linear regression (see Figure 3.3 in chapter 3 for HHT rate) corrected for GIA (~1 mm yr$^{-1}$ from GPS at Pensacola). f) GPS time series at Grand Isle referred to Pensacola. Note that sea-level trends are estimated from both linear regression (black) and residual of HHT analysis (blue). Uncertainties are the standard error estimated using the AVR method.

We further analyze all relative sea-level rise records along the eastern Gulf using the HHT method. Two examples of the HHT analysis are shown in Figure A5. For the Fort Meyer (FRMY) record, the sea-level trend is nonlinear (only one extrema) and sea
level rise is increasing at a constant rate. The acceleration is therefore positive constant.

In contrast, the sea-level trend at Key West is linear (no extrema), thus the rate is constant and the acceleration is zero when the entire record is used.
Figure A5: Two examples of relative sea-level rise with linear and nonlinear trends obtained from the residual of HHT analysis of tide gauge records at a) Fort Myers; and b) Key West. The sea level is relative to the level of January 2014.

The results of HHT analysis are summarized in Table A2. With the exception of Grand Isle, the long-term relative sea-level rise rate along the west coast of Florida varies between 2.2-4.1 mm yr\(^{-1}\). The rate increases southward in a region between Apalachee to Naples. Assuming that GPS velocities are representative of the long-
term vertical land motion sensed by the tide gauge, the relative sea levels can be corrected for vertical land motion. For those stations lacking GPS data, the vertical land motion is estimated using a GIA model (ICE-5G V1.3, Peltier, 2004). The sea-level rise rate (the relative sea-level rate corrected for vertical land motion) varies within a limited range, 2.1-2.3 mm yr\(^{-1}\) with exception for Apalachicola, Cedar Key and Key West which show 1 mm yr\(^{-1}\) lower rate.

The relative sea-level rise at Grand Isle, Cedar Key, St. Petersburg, Fort Myers and Naples show a positive acceleration consistent with an increasing rate after 1990 (0.005-0.021 mm yr\(^{-2}\)) close to global acceleration of 0.009 mm yr\(^{-2}\) (e.g., Church and White, 2011). However, the longer time series at Pensacola and Key West show no acceleration. We split these time series into two segments to examine if the zero acceleration inferred from our HHT analysis might be related to record length. The relative sea-level rise acceleration is calculated using two segments of 40 years. The accelerations for both stations for the period 1970-2013 are distinctly positive and close to recent records (e.g., sea level at Fort Myers) suggesting that recent sea-level rise is in fact accelerating, and that this trend can be missed in the HHT analysis when long time series such as Key West are analyzed.
Table A2: Average relative sea-level rise rates and accelerations from HHT.

<table>
<thead>
<tr>
<th>tide gauge stations</th>
<th>length (year)</th>
<th>(^a)mean RSL rate (mm yr(^{-1}))</th>
<th>(^b)mean RSL rate after 1990 (mm yr(^{-1}))</th>
<th>(^c)mean RSL acceleration (mm yr(^{-2}))</th>
<th>(^d)vertical displacement (mm yr(^{-1}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grand Isle (GRIS)</td>
<td>66.9</td>
<td>7.3±0.4</td>
<td>9.1±1.2</td>
<td>0.007</td>
<td>-5.6±0.2 (GPS)</td>
</tr>
<tr>
<td>Pensacola (PCLA)</td>
<td>90.5</td>
<td>3.1±0.6</td>
<td>3.6±3.1</td>
<td>0.001</td>
<td>-1.0±0.2 (GPS)</td>
</tr>
<tr>
<td>Apalachicola (APCA)</td>
<td>46.5</td>
<td>2.2±1.1</td>
<td>2.3±1.2</td>
<td>0.000</td>
<td>-1.1 (GIA)</td>
</tr>
<tr>
<td>Cedar Key (CDKY)</td>
<td>75.1</td>
<td>2.5±0.3</td>
<td>4.0±3.4</td>
<td>0.005</td>
<td>-0.9 (GIA)</td>
</tr>
<tr>
<td>St. Petersburg (SPBG)</td>
<td>66.9</td>
<td>3.2±0.6</td>
<td>4.6±2.2</td>
<td>0.005</td>
<td>-0.9 (GIA)</td>
</tr>
<tr>
<td>Fort Myers (FRMY)</td>
<td>48.6</td>
<td>3.4±0.7</td>
<td>6.0±3.2</td>
<td>0.021</td>
<td>-1.1±0.1 (GPS)</td>
</tr>
<tr>
<td>Naples (NAPL)</td>
<td>48.7</td>
<td>4.1±0.6</td>
<td>5.2±1.1</td>
<td>0.008</td>
<td>-1.9±0.1 (GPS)</td>
</tr>
<tr>
<td>Key West (KYWS)</td>
<td>100.9</td>
<td>2.4±0.7</td>
<td>2.4±1.2</td>
<td>0.000</td>
<td>-1.1±0.1 (GPS)</td>
</tr>
</tbody>
</table>

Note. \(^a\) Average relative sea-level rise rates over entire period. \(^b\) Average relative sea-level rise rates after 1990. \(^c\) Average relative sea-level rise acceleration over entire period. \(^d\) Land vertical motion from continuous GPS measurements at nearby station or GIA model. Note that the relative sea-level rates and accelerations are obtained from the trend (\(r\)) of HHT analysis (Figure B5).
**Figure A6:** Long-term relative sea-level trend referred to the level of January 2014, obtained from the residual of the HHT analysis. The relative sea-level rise rates in Table B1 are calculated from the slope of these trends (equation A5).

**Figure A7:** Sea-level trends for Pensacola and Key West. a) for period 1930-1970 b) for period 1970-2014. Note that for both time series, the more recent period exhibits positive (upward) acceleration in the rate of relative sea-level rise.
Appendix B: Supplementary information for Chapter 4

Correction for GIA Geoid-height Changes

GIA causes temporal changes of the Earth’s surface and its gravitational field. The present-day deformational effects include uplift near the location of former Laurentide Ice Sheet and subsidence around the peripheral bulges. The gravitational effects can be described as changes to an equipotential surface of the Earth’s gravitational field, the geoid. The Holocene RSL data contain the combined GIA effects of vertical land motions and geoid-height changes. The latter effect includes the return of glacial melt water to the oceans, redistribution due to surface mass changes (e.g., ice sheet decrease) and deeper seated mass redistribution related to mantle motions. GPS only measure the vertical land motion (deformational GIA effects) and is not sensitive to geoid-height changes (gravitational GIA effects). Geruo et al. (2013) recently developed a 3-D finite-element model of viscoelastic response of Earth’s gravity to the past ice sheets. We use this model to estimate the approximate magnitude of geoid-height changes along the eastern seaboard of North America. We compare the
differences between GPS and geologic observed rates with geoid-height predicted rates (Figure A8). The results show that differences between GPS and geologic rates are very close to geoid-height changes in an area between New Hampshire (43° N) and Delaware (38.4° N) where other processes (e.g., groundwater extraction, sediment compaction) have minimal effects on both data sets.

![Figure A8: Comparison of present-day GIA geoid-height rates predicted from GIA model of Geruo et al. (2013) and differences between GPS vertical rates and late Holocene RSL rise rates. The GIA model is available through JPL's ftp (ftp://podaac-ftp.jpl.nasa.gov/GeodeticsGravity/tellus/L3/pgr/).](image)

**Figure A8:** Comparison of present-day GIA geoid-height rates predicted from GIA model of Geruo et al. (2013) and differences between GPS vertical rates and late Holocene RSL rise rates. The GIA model is available through JPL’s ftp (ftp://podaac-ftp.jpl.nasa.gov/GeodeticsGravity/tellus/L3/pgr/).

**Discrepancy in Maine (45° N-43° N)**

The GPS data suggest slow uplift (< 0.5 mm yr$^{-1}$) along the Maine shoreline, which disagrees with the geologically defined subsidence rate of ~ 0.7 mm yr$^{-1}$. Tide gauge data here show trends in the rate of 20$^{th}$ century RSL that are consistent with the
geologic data (Zervas, 2009; Boon, 2012; Kopp, 2013). Perhaps a very recent (last one or two decades) process is causing uplift over the period measured by GPS. For example, GRACE satellite measurements indicate positive trends (up to 14 mm yr\(^{-1}\)) in water storage for the period 2002-2015 north of the St. Lawrence River basin, Canada (Figure A9 and Wang et al., 2013; Reager et al., 2016). The current GPS vertical rates in Maine could be influenced by the long-distance response of this surface mass increase.

Fluid injection into deep reservoirs can also cause uplift of several mm yr\(^{-1}\) or more (e.g., Karegar et al., 2014, 2015; Yang et al., 2015). However, we are not aware of nearby fluid injection at the scale necessary to explain the discrepancy.

Since GIA is a non-linear process, it is possible that the record length of the geologic data contributes to the discrepancy. The rate of RSL rise from 2 ka B.P. to 1900 A.D. (0.5 mm yr\(^{-1}\)) is 0.2 mm yr\(^{-1}\) lower than the rate from 4 ka B.P. to 1900 A.D. (0.7 mm yr\(^{-1}\)) (Engelhart and Horton, 2012). The difference is in the right direction but too small to explain the discrepancy. Other possible sources of error in Holocene RSL observations include effects of eustatic sea-level rise, sediment compaction (e.g., Horton and Shennan, 2009), tidal range variations (e.g., Nikitina et al., 2015) and tectonics. For example, the impact of compaction on sea-level index points is not accounted for, although our analysis does not incorporate samples most likely to show significant compaction (e.g., Engelhart and Horton, 2012) and this effect is likely small for late Holocene data (e.g., Brain et al., 2015).
It is interesting to note that the discrepancy occurs at the location where GIA vertical motion changes from subsidence to uplift. Perhaps rheological changes in the mantle flow field accommodating GIA produces a time-dependent shift of the boundary between uplift and subsidence (Engelhart et al., 2011). Alternately, geoidal effects (Figure A8) may be more important at this boundary than elsewhere.

Figure A10 is an alternative plot to Figure 4.2. The GPS and geologic rates are plotted as a function of distance from the center of the former ice sheet in Hudson Bay, Canada. We chose a tide gauge at Churchill (58.76° N, 94.18° W) from the PSMSL (Permanent Service for Mean Sea Level) database as a reference point. The vertical deformation rates in both data sets decrease with distance from the center of the former ice mass. The maximum subsidence occurs from ~ 2500 km (New Jersey, ~ 39° N) to ~ 2700 km (Chesapeake Bay, ~ 37° N) from the center, clearly showing the fore bulge collapse.
Figure A9: Long-term changes in water storage (2002-2015) based on monthly 1° gridded GRACE products (CSR-RL05) provided by NASA JPL TELLUS website (http://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/). Details of gridded GRACE products can be found in Landerer and Swenson (2012). The large anomaly corresponds approximately to the location of the James Bay Hydro-Electric Project in Quebec, where a series of large dams began to hold back water beginning in the mid-2000’s. The uplift anomaly we observed in Maine may relate to peripheral bulge effects from this load.
Figure A10: a) Comparison of vertical land motion from GPS and geologic data as a function of distance from a tide gauge at Churchill, Canada (58.76° N, 94.18° W). Color bar shows the length of time series for individual stations. b) Spatially averaged GPS and geologic data. The GPS rates are averaged for all stations in the boxes shown in Figure 4.1.

GPS subsidence rate and population density

In some cases groundwater use can correlate with population density (areas of heavy agricultural use are an obvious exception). Figure A11 shows population density in the central and southern Atlantic coastal plain for comparison to GPS subsidence
rates. The nature of water-use varies across this region (Masterson et al., 2013). To the north (Long Island in New York, New Jersey, southern Pennsylvania and Maryland), the most densely populated areas, groundwater is used mainly for public and domestic supply. Subsidence rates due to groundwater extraction are likely influenced by population density. However, the subsidence rates here are generally lower than those in southern states where compressible aquifers are more widespread. In Delaware, Virginia and North Carolina, large scale groundwater withdrawal occurs for agricultural and industrial uses. For example, in 2005, groundwater withdrawal for industrial use in North Carolina accounted for about 68 percent of total groundwater use (sum of public/domestic, agricultural and industrial groundwater use) (Kenny et al., 2009). In Virginia groundwater extraction is used for a combination of industrial uses and public/domestic supply. In Delaware agriculture is the major user of groundwater, accounting for about 47 percent of total groundwater withdrawal in 2005, and 56 percent in 2010 (Kenny et al., 2009 and Maupin et al., 2014).
Figure A11: Map of population density based on the 2010 census, compared to recent subsidence rate. Circle colors indicate GPS rate of vertical land motion in IGb08 reference frame.
Figure A12: a) Location of GPS sites superimposed on a map of coastal plain sediment thickness (modified from Trapp and Meisler, 1992). Circle colors indicate GPS rate of vertical land motion in IGB08 reference frame. Contours (blue lines) are sediment thickness in meters. b) GPS subsidence rates versus local sediment thickness with linear regression. The correlation between subsidence rate and sediment thickness is 0.40. c) GPS subsidence rates corrected for GIA-related subsidence for boxes shown in Figure 1 (GPS rate - late Holocene RSL rate) compared to regional sediment thickness with linear regression. The correlation between subsidence rate and sediment thickness is 0.54. For (c), regional sediment thickness is an average at all GPS stations within specific boxes.
**Table A3:** GPS site locations, vertical velocities, 1-σ uncertainties, time series length, time series completeness and number of outliers eliminated from the individual time series. This table is available at:


**Table A4:** Late Holocene RSL rise rates and GPS vertical rates listed for each region shown in Figure 4.1. This table is available at:

http://onlinelibrary.wiley.com/store/10.1002/2016GL068015/asset/supinfo/grl54201-sup-0003-2016GL068015-s03.xlsx?v=1&s=7c1942a324445df7b7d539faf4389d1c894e7fc6
Appendix C: Supplementary information for Chapter 5

Figure A13: Map showing the location of GPS sites and 18 regions (boxes) for which the geologic rate is known. Circle color indicates decadal average vertical land motion in IGb08 reference frame. Black triangles are locations of tide gauges for which nuisance flooding level data and nuisance flooding frequency are available. The GPS rates and nuisance flooding level data shown in Figure 5.2 and Figure A14-A17 are average values for all stations in the boxes. Map is generated using GMT software version 5.1.0 (http://gmt.soest.hawaii.edu/) (Wessel et al. 2013). Modified from Karegar et al. (2016).
Figure A14: Comparison of spatially averaged GPS (gray triangles), geologic data (red circles), and GIA model ICE6G-VM5a (green circles) for eighteen coastal sites in the US and southern Canada (Figure A13). Error bars are 1σ.
**Figure A15**: Comparison of nuisance flood level (red circles) as standardized by tidal range (MHHW- MLLW), GPS rate (blue triangles) and geologic rate (green circles) as a function of latitude along the US eastern seaboard. Figure A15 is an alternative plot to Figure 5.2. Here the possible effects of tidal range variations are isolated by dividing the nuisance flood level (measured from MHHW) and tidal range. As in Figure 5.2, the same relationships are seen between nuisance flood level and GPS rate. Note that the GPS rates and standardized nuisance flooding level data are averaged for all stations and tide gauges in the boxes shown in Figure A13 where geologic data are available.
Figure A16: Comparison of GIA-corrected GPS-derived vertical rate (red dots) and average trend in groundwater-level changes (gray dots). The black and red solid curves are quadratic polynomials fit to the groundwater and vertical rate data, respectively.
Figure A.17: Map of Lake-Dam system in Quebec, Canada. Lakes with water-level data (virtual gauges) are numbered. For time series see Figure A18. Lake area and annual rate of water-level change are listed in Table A6. Map is generated using GMT software version 5.1.0 (http://gmt.soest.hawaii.edu/) (Wessel et al. 2013).
Figure A18: Time series of water-level change from satellite altimetry measurements produced by different processing centers. Lake level products are courtesy of (a) USDA/NASA G-REALM. (b) database for Hydrological Time Series of Inland
Waters (DAHITI) (c) HYDROWEB database from Legos and THEIA platform. A least squares model fit was used to define the rate. Model parameters include an initial offset, a constant rate and fixed amplitude annual variation.

**Figure A19:** Comparison of trend in total water storage (in equivalent water height) from three GRACE solutions: The University of Texas Center for Space Research (CSR), Geoforschungszentrum (GFZ), and NASA Jet Propulsion Lab (JPL) (Top panel) GRACE Stokes coefficients were smoothed by applying the non-isotropic filter DDK2 (Kusche, 2007). (Bottom panel) Post-processed gridded monthly TWS data provided by NASA JPL Tellus were used. Trend is corrected for the GIA model of Geruo et al. (2013). The location of active major dams (red dots) and formal boundaries for the James Bay hydroelectric project (yellow line) are also shown. The white dashed circle with radius
400 km approximates the excess mass observed in Quebec with GRACE. Map is generated using GMT software version 5.1.0 (http://gmt.soest.hawaii.edu/) (Wessel et al. 2013).

**Figure A20:** Sum of groundwater and soil moisture storage trend (in equivalent water height) from WaterGap Global Hydrological Model (WGHM, version 2.2b) (Döll et al. 2014; Müller Schmied et al. 2014). Map is generated using GMT software version 5.1.0 (http://gmt.soest.hawaii.edu/) (Wessel et al. 2013).
Table A5: Statistics of GRACE TWS trends (in equivalent water height) based on three GRACE solutions (CSR, GFZ, and JPL) and two post-processing products including Tellus gridded GRACE TWS data (isotropic filter: Gaussian + de-stripping filters) and non-isotropic filter (DDK2 filter). Unit: mm yr$^{-1}$.

<table>
<thead>
<tr>
<th>Solution (G+De/D2K2)</th>
<th>Min.</th>
<th>Max.</th>
<th>Mean</th>
<th>RMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>CSR</td>
<td>-6.7/-9.9</td>
<td>13.1/17.9</td>
<td>4.3/6.1</td>
<td>6.0/8.5</td>
</tr>
<tr>
<td>GFZ</td>
<td>-6.6/-11.0</td>
<td>13.9/18.5</td>
<td>4.7/6.3</td>
<td>6.4/8.8</td>
</tr>
<tr>
<td>JPL</td>
<td>-6.2/-10.8</td>
<td>12.0/17.5</td>
<td>4.7/6.1</td>
<td>6.3/8.5</td>
</tr>
</tbody>
</table>

$^1$ G: Gaussian filter, De: de-stripping filter
Table A6: Characteristics of lakes and annual rate of water-level change from different satellite altimetry missions and processing centers. The non-parametric Mann-Kendall trend test was applied to the water-level change time series. The P-value of the two-tailed test at the significance level of 0.05 is listed. The trends are considered statistically significant when the p value falls below a critical value (P < 0.05). It is sufficient to conclude that there is a positive trend in the water-level variations for different periods. The total rate of change of water volume from the nine reservoirs listed in Table A6 is about 1.7 km$^3$ yr$^{-1}$ which is ~ 30% - 40% of TWS changes observed by GRACE. Columns 6 and 7 are rate of water-level change and rate of volume change, respectively.

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Area (km$^2$)</th>
<th>Altimetry data period</th>
<th>Satellite mission</th>
<th>Rate (m yr$^{-1}$)</th>
<th>Rate (km$^3$ yr$^{-1}$)</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>La Grande$^1$</td>
<td>78</td>
<td>2009 - 2017</td>
<td>Jason 2 &amp; 3</td>
<td>0.05</td>
<td>0.004</td>
<td>0.01</td>
</tr>
<tr>
<td>2</td>
<td>Robert Bourassa$^1$</td>
<td>2,900</td>
<td>2008 - 2017</td>
<td>Jason 2 &amp; 3</td>
<td>0.05</td>
<td>0.15</td>
<td>0.03</td>
</tr>
<tr>
<td>2</td>
<td>Robert Bourassa$^3$</td>
<td>2,900</td>
<td>2002 - 2011</td>
<td>Envisat</td>
<td>0.06</td>
<td>0.17</td>
<td>0.06</td>
</tr>
<tr>
<td>3</td>
<td>La Grande$^2$</td>
<td>2,500</td>
<td>1992 - 2017</td>
<td>T/P, Envisat, GFO, Jason 2 &amp; 3</td>
<td>0.19</td>
<td>0.47</td>
<td>0</td>
</tr>
<tr>
<td>3</td>
<td>La Grande$^3$</td>
<td>2,500</td>
<td>2002 - 2014</td>
<td>Jason 1 &amp; 2</td>
<td>0.30</td>
<td>0.74</td>
<td>0</td>
</tr>
<tr>
<td>4</td>
<td>Opinaca$^2$</td>
<td>1,100</td>
<td>1992 - 2017</td>
<td>T/P, Envisat, Jason 2 &amp; 3</td>
<td>0.13</td>
<td>0.12</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>Low Lake$^1$</td>
<td>200</td>
<td>2008 - 2017</td>
<td>Jason 2 &amp; 3</td>
<td>0.27</td>
<td>0.06</td>
<td>0</td>
</tr>
<tr>
<td>6</td>
<td>Manicouagan$^1$</td>
<td>1,950</td>
<td>2008 - 2017</td>
<td>Jason 2 &amp; 3</td>
<td>0.07</td>
<td>0.14</td>
<td>0.02</td>
</tr>
<tr>
<td>7</td>
<td>Pipmuacan$^1$</td>
<td>980</td>
<td>2008 - 2017</td>
<td>Jason 2 &amp; 3</td>
<td>0.24</td>
<td>0.24</td>
<td>1.7E-04</td>
</tr>
<tr>
<td>8</td>
<td>Lake Saint Jean$^2$</td>
<td>1,053</td>
<td>1992 - 2014</td>
<td>T/P, Envisat, GFO, Jason 2</td>
<td>0.05</td>
<td>0.05</td>
<td>9.3E-10</td>
</tr>
<tr>
<td>9</td>
<td>Gouin$^1$</td>
<td>1,600</td>
<td>2008 - 2017</td>
<td>Jason 2 &amp; 3</td>
<td>0.08</td>
<td>0.13</td>
<td>2.3E-08</td>
</tr>
</tbody>
</table>

Lake level products are from 1. USDA/NASA G-REALM program (https://www.pecad.fas.usda.gov/cropexplorer/global_reservoir/); 2. database for...
Hydrological Time Series of Inland Waters (DAHITI) developed by the Deutsches Geodätisches Forschungsinstitut der Technischen Universität München (DGFI-TUM) (http://dahiti.dgfi.tum.de/en/map/) (Schwatke et al. 2015); and 3. HYDROWEB database from Legos and THEIA platform (http://hydroweb.theia-land.fr/) (Crétaux et al. 2011).
Appendix D: Supplementary information for Chapter 6

Recursive algorithm for coefficients $b_n$ (Eq. 6.25)

Meissl (1971, P. 45) derives a recursive algorithm for the integral:

$$b_n^* = - \int_{\psi=\psi_0}^{\psi=\pi} \frac{\sin\psi}{\sqrt{2}\sin\frac{\psi}{2}} P_n(cos\psi) \, d\psi$$

(Integral (A6))

Integral (6.25) can be written in terms of $b_n^*$, as follows:

$$b_n = \frac{\sqrt{2}}{2} b_n^*$$

where

$$b_n^* = \frac{P_{n-2}(cos\psi_0) - P_n(cos\psi_0)}{n + \frac{1}{2}} \sqrt{1 - \cos(\psi_0)} + \frac{2(n - \frac{1}{2})}{n + \frac{1}{2}} b_{n-1}^* - \frac{n - \frac{3}{2}}{n + \frac{1}{2}} b_{n-2}^*$$

(A8)

with the initial values:

$$b_0^* = -2\sqrt{1 - \cos(\psi_0)} + 2\sqrt{2}$$

(A9)

$$b_1^* = -\frac{2\sqrt{[1 - \cos(\psi_0)]^3}}{3} - 2\sqrt{1 - \cos(\psi_0)} + \frac{2\sqrt{2}}{3}$$

(A10)

Recursive algorithm for coefficients $r_{n,k}(\psi_0)$ (Eq. 6.26)

Paul (1973) presents recursive algorithms for integral (6.26) which is used for computing truncation coefficients $Q_n(\psi_0)$. For $k \neq n$:

$$R_{n,k}(\psi_0) = \int_{\psi=\psi_0}^{\psi=\pi} P_k(cos\psi) P_n(cos\psi) \sin\psi \, d\psi$$

(A11)
\[ R_{n,k}(\psi_0) = \frac{n(n + 1)}{2n + 1} P_k (P_{n+1} - P_{n-1}) - \frac{k(k + 1)}{2k + 1} P_n (P_{k+1} - P_{k-1}) \]
\[ \frac{1}{(n - k)(n + k + 1)} \]

(A12)

where \( P_j = P_j(\cos \psi_0) \); and for \( k = n \):

\[
R_{n,n}(\psi_0) = \int_{\psi=\psi_0}^{\psi=\pi} P_n(\cos \psi)^2 \sin \psi \, d\psi
\]

\[ R_{n,n}(\psi_0) = \frac{(n + 1)(2n - 1)}{n(2n + 1)} R_{n+1,n-1}(\psi_0) - \frac{n - 1}{n} R_{n,n-2}(\psi_0) + \frac{2n - 1}{2n + 1} R_{n-1,n-1}(\psi_0) \]

(A13)

with the initial values,

\[ R_{0,0}(\psi_0) = \cos \psi_0 + 1 \]

(A14)

\[ R_{1,1}(\psi_0) = \frac{(\cos \psi_0)^3 + 1}{3} \]

(A15)
Figure A21: RMS (root mean squares) scatters of non-tidal ocean loading in CF frame (available at GFZ’s ftp: ftp://ig2-dmz.gfz-potsdam.de/LOADING/NTOL/).
Figure A22: a) Map showing the boundary of Yellowstone volcanic system and locations of GPS sites. Circle color indicates GPS vertical velocity in IGb08 reference frame. Time series are vertical displacements in vicinity of the Yellowstone volcanic system from GPS stations: (b) inside the caldera, (c) outside the caldera. Stations inside the caldera were excluded from our study.
Figure A23: Map showing locations of GPS sites affected by poroelastic deformation in response to shallow groundwater changes and heavy municipal and industrial pumpage. These sites were excluded from our study. Time series are daily GPS height displacements (black dots). Error bars are 3σ. The red lines are monthly average of daily GPS height time series. The blue lines are modeled deformation using hybrid approach.
Figure A24: Comparison of monthly degree variance (2002 - 2015) of total water storage (TWS) in equivalent water height (EVH) from a) GRACE and WGHM b) GRACE, WGHM and NLDAS. In Figure A24a, for GRACE TWS data, all ocean and large lakes areas were assigned to zero values, allowing a correct comparison of degree variances with those from WGHM model. In Figure A24b, for GRACE and WGHM TWS data, area outside the United States (the coverage area of NLDAS model) were assigned to zero values, allowing a correct comparison of degree variances with those from NLDAS model.
Figure A25: RMS scatters of detrended total water storage (2002-2015) derived from different GRACE DDK-filtered Stokes coefficients. The black dots represent the location of GPS stations.
Figure A26: RMS (root-mean-squares) scatters of detrended a) GPS monthly height time series b) residual GPS monthly height time series (GPS – hybrid model). Triangles (circles) are stations with RMS scatters smaller (larger) than 3 mm. Inset shows a histogram of the RMS scatters of GPS time series.
Figure A27: Locations and RMS scatters of GPS stations (triangles: RMS scatters smaller than 3 mm; circles: RMS scatters greater than 3 mm) for which applying hydrological loading correction (using the hybrid solution) to the GPS height time series increases the RMS scatter. Half of these stations have small deformation, i.e., RMS scatters of observed displacement time series are smaller than 3 mm (triangles). There are some stations that have RMS scatters significantly larger than the nearby stations (e.g., 1LSU, HGMA, PINR, P777, P778, SG20, Vcio, TXTI, TXAN, JTNT). These stations are also shown in Figure A26a, and are most likely affected by local processes such that the loading theory is not applicable.
Figure A28: Locations and RMS scatters of GPS stations (triangles: RMS scatters smaller than 3 mm; circles: RMS scatters greater than 3 mm) for which applying hydrological loading correction (using the hybrid solution) to the GPS height time series increases the RMS scatter. Half of these stations have small deformation, i.e., RMS scatters of observed displacement time series are smaller than 3 mm (triangles). There are some stations that have RMS scatters significantly larger than the nearby stations (e.g., 1LSU, HGMA, PINR, P777, P778, SG20, VCIO, TXTI, TXAN, JTNT). These stations are also shown in Figure A26a, and are most likely affected by local processes such that the loading theory is not applicable.
Appendix E: References


Appendix F: Copyright licenses of previously published works

Title: GPS-based monitoring of surface deformation associated with CO2 injection at an enhanced oil recovery site
Author: Makan A. Karegar, Timothy H. Dixon, Rocco Malservisi, Qian Yang, Seyyed A. Hosseini, Susan D. Hovorka
Publication: International Journal of Greenhouse Gas Control
Publisher: Elsevier
Date: October 2015
Copyright © 2015 Elsevier Ltd. Published by Elsevier B.V. All rights reserved.

Please note that, as the author of this Elsevier article, you retain the right to include it in a thesis or dissertation, provided it is not published commercially. Permission is not required, but please ensure that you reference the journal as the original source. For more information on this and on your other retained rights, please visit: https://www.elsevier.com/about/our-business/policies/copyright#Author-rights
Step 3: Order Confirmation

Thank you for your order! A confirmation for your order will be sent to your account email address. If you have questions about your order, you can call us 24 hrs/day, M-F at +1.855.239.3415 Toll Free, or write to us at info@copyright.com. This is not an invoice.

Confirmation Number: 11727836
Order Date: 07/02/2018
If you paid by credit card, your order will be finalized and your card will be charged within 24 hours. If you choose to be invoiced, you can change or cancel your order until the invoice is generated.

Payment Information

Makan A. Karegar
University of South Florida
makan.karegar@gmail.com
Payment Method: n/a

Order Details

Geology

- Order detail ID: 71278069
- Order License Id: 4380751133887
- ISSN: 1943-2682
- Publication Type: e-Journal
- Volume:
- Issue:
- Start page:
- Publisher: Geological Society of America
- Author/Editor: Geological Society of America
- Permission Status: Granted
- Permission type: Republish or display content
- Type of use: Republish in a thesis/dissertation

Requestor type: Academic institution
<table>
<thead>
<tr>
<th><strong>Format</strong></th>
<th>Electronic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Portion</strong></td>
<td>chapter/article</td>
</tr>
<tr>
<td><strong>The requesting person/organization</strong></td>
<td>Makan A. Karegar</td>
</tr>
<tr>
<td><strong>Title or numeric reference of the portion(s)</strong></td>
<td>A three-dimensional surface velocity field for the Mississippi Delta: Implications for coastal restoration and flood potential</td>
</tr>
<tr>
<td><strong>Title of the article or chapter the portion is from</strong></td>
<td>A three-dimensional surface velocity field for the Mississippi Delta: Implications for coastal restoration and flood potential</td>
</tr>
<tr>
<td><strong>Editor of portion(s)</strong></td>
<td>N/A</td>
</tr>
<tr>
<td><strong>Author of portion(s)</strong></td>
<td>Makan A. Karegar, Timothy H. Dixon, Rocco Malservisi</td>
</tr>
<tr>
<td><strong>Volume of serial or monograph</strong></td>
<td>43</td>
</tr>
<tr>
<td><strong>Issue, if republishing an article from a serial</strong></td>
<td>6</td>
</tr>
<tr>
<td><strong>Page range of portion</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Publication date of portion</strong></td>
<td>JUNE 01, 2015</td>
</tr>
<tr>
<td><strong>Rights for</strong></td>
<td>Main product</td>
</tr>
<tr>
<td><strong>Duration of use</strong></td>
<td>Life of current and all future editions</td>
</tr>
<tr>
<td><strong>Creation of copies for the disabled</strong></td>
<td>no</td>
</tr>
<tr>
<td><strong>With minor editing privileges</strong></td>
<td>no</td>
</tr>
<tr>
<td><strong>For distribution to</strong></td>
<td>Worldwide</td>
</tr>
<tr>
<td><strong>In the following language(s)</strong></td>
<td>Original language of publication</td>
</tr>
<tr>
<td><strong>With incidental</strong></td>
<td>no</td>
</tr>
</tbody>
</table>
promotional use

**Lifetime unit quantity**  Up to 9,999
of new product

**Title**  
Theory and Application of Geophysical Geodesy for Studying Earth Surface Deformation

**Instructor name**  n/a

**Institution name**  n/a

**Expected presentation date**  Jul 2018

**Note:** This item will be invoiced or charged separately through CCC's RightsLink service.  

Confirmation Number: 11727836

Special Rightsholder Terms & Conditions

The following terms & conditions apply to the specific publication under which they are listed

**Geology**

**Permission type:**  Republish or display content

**Type of use:**  Republish in a thesis/dissertation
This Agreement between University of South Florida -- Makan A. Karegar ("You") and John Wiley and Sons ("John Wiley and Sons") consists of your license details and the terms and conditions provided by John Wiley and Sons and Copyright Clearance Center.

<table>
<thead>
<tr>
<th>License Number</th>
<th>4380700221513</th>
</tr>
</thead>
<tbody>
<tr>
<td>License date</td>
<td>Jul 02, 2018</td>
</tr>
<tr>
<td>Licensed Content</td>
<td>John Wiley and Sons</td>
</tr>
<tr>
<td>Publisher</td>
<td></td>
</tr>
<tr>
<td>Publication</td>
<td>Geophysical Research Letters</td>
</tr>
<tr>
<td>Licensed Content Title</td>
<td>Subsidence along the Atlantic Coast of North America: Insights from GPS and late Holocene relative sea level data</td>
</tr>
<tr>
<td>Author</td>
<td>Makan A. Karegar, Timothy H. Dixon, Simon E. Engelhart</td>
</tr>
<tr>
<td>Licensed Content Date</td>
<td>Apr 2, 2016</td>
</tr>
<tr>
<td>Licensed Content Volume</td>
<td>43</td>
</tr>
<tr>
<td>Licensed Content Issue</td>
<td>7</td>
</tr>
<tr>
<td>Licensed Content Pages</td>
<td>8</td>
</tr>
<tr>
<td>Type of use</td>
<td>Dissertation/Thesis</td>
</tr>
<tr>
<td>Requestor type</td>
<td>Author of this Wiley article</td>
</tr>
<tr>
<td>Format</td>
<td>Electronic</td>
</tr>
<tr>
<td>Portion</td>
<td>Full article</td>
</tr>
<tr>
<td>Will you be translating?</td>
<td>No</td>
</tr>
<tr>
<td>Title of your thesis / dissertation</td>
<td>Theory and Application of Geophysical Geodesy for Studying Earth Surface Deformation</td>
</tr>
<tr>
<td>Expected completion date</td>
<td>Jul 2018</td>
</tr>
<tr>
<td>Expected size (number of pages)</td>
<td>300</td>
</tr>
<tr>
<td>Requestor Location</td>
<td>University of South Florida, 4202 E. Fowler Avenue, NES 107, TAMPA, FL 33620, USA.</td>
</tr>
<tr>
<td>Publisher Tax ID</td>
<td>EU826007151</td>
</tr>
<tr>
<td>Total</td>
<td>0.00 USD</td>
</tr>
</tbody>
</table>
This Agreement between University of South Florida -- Makan A. Karegar ("You") and John and Sons ("John Wiley and Sons") consists of your license details and the terms and conditions provided by John Wiley and Sons and Copyright Clearance Center.

<table>
<thead>
<tr>
<th>License Number</th>
<th>4380700495691</th>
</tr>
</thead>
<tbody>
<tr>
<td>License date</td>
<td>Jul 02, 2018</td>
</tr>
<tr>
<td>Licensed Content</td>
<td>John Wiley and Sons</td>
</tr>
<tr>
<td>Publisher</td>
<td></td>
</tr>
<tr>
<td>Licensed Content</td>
<td>Journal of Advances in Modeling Earth Systems</td>
</tr>
<tr>
<td>Publication</td>
<td></td>
</tr>
<tr>
<td>Licensed Content Title</td>
<td>A New Hybrid Method for Estimating Hydrologically Induced Vertical Deformation From GRACE and a Hydrological Model: An Example From Central North America</td>
</tr>
<tr>
<td>Licensed Content Author</td>
<td>Makan A. Karegar, Timothy H. Dixon, Jürgen Kusche, Don P. Chambers</td>
</tr>
<tr>
<td>Licensed Content Date</td>
<td>May 22, 2018</td>
</tr>
<tr>
<td>Licensed Content Volume</td>
<td>10</td>
</tr>
<tr>
<td>Licensed Content Issue</td>
<td>5</td>
</tr>
<tr>
<td>Licensed Content Pages</td>
<td>22</td>
</tr>
<tr>
<td>Type of use</td>
<td>Dissertation/Thesis</td>
</tr>
<tr>
<td>Requestor type</td>
<td>Author of this Wiley article</td>
</tr>
<tr>
<td>Format</td>
<td>Electronic</td>
</tr>
<tr>
<td>Portion</td>
<td>Full article</td>
</tr>
<tr>
<td>Will you be translating?</td>
<td>No</td>
</tr>
<tr>
<td>Title of your thesis / dissertation</td>
<td>Theory and Application of Geophysical Geodesy for Studying Earth Surface Deformation</td>
</tr>
<tr>
<td>Expected completion date</td>
<td>Jul 2018</td>
</tr>
<tr>
<td>Expected size (number of pages)</td>
<td>300</td>
</tr>
<tr>
<td>Requestor Location</td>
<td>University of South Florida, 4202 E. Fowler Avenue, NES 107, TAMPA, FL 33620, USA.</td>
</tr>
<tr>
<td>Publisher Tax ID</td>
<td>EU826007151</td>
</tr>
<tr>
<td>Total</td>
<td>0.00 USD</td>
</tr>
</tbody>
</table>
Rights and permissions

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license, and indicate if changes were made. The images or other third party material in this article are included in the article’s Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the article’s Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this license, visit http://creativecommons.org/licenses/by/4.0/.