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# TOWARDS AN INTEGRATED ASSESSMENT OF SEA-LEVEL OBSERVATIONS ALONG THE U.S. ATLANTIC COAST

by

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A Dissertation Submitted to the Faculty of Old Dominion University in Partial Fulfillment of the Requirements for the Degree of

## DOCTOR OF PHILOSOPHY

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### ABSTRACT

## TOWARDS AN INTEGRATED ASSESSMENT OF SEA-LEVEL OBSERVATIONS ALONG THE U.S. ATLANTIC COAST

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Sea levels are rising globally due to anthropogenic climate change. However, local sea levels that impact coastal ecosystems often differ from the global trend, sometimes by a factor of two or more. Improved understanding of this regional variability provides insights into geophysical processes and has implications for coastal communities developing resilience to ongoing sea-level rise. This dissertation conducts an investigation of sea level and its contributing processes at multiple spatial scales. Focusing on primarily interannual time-scales and data-driven approaches, new data sources and technologies are utilized to reduce current uncertainties.

First, sea-level trends are assessed over the global ocean and at coastlines using data from the recently launched ICESat-2 satellite. These trends agree well with independent measurements, while also filling observational gaps along undersampled coastlines and at high-latitudes. Next, the spatial focus is narrowed to the U.S. East Coast, which is experiencing exceptionally high rates of relative sea-level rise, largely due to land subsidence. By incorporating new state-of-the-art estimates of land-ice melt, an existing Bayesian hierarchical space-time model is expanded to assess the relative contributions of sea surface height and vertical land motion to 20<sup>th</sup> century relative-sea level change. Model results confirm previous findings that identified regional-scale geological processes as the primary driver of spatial variability in East Coast relative sea level. By rigorously quantifying uncertainties, constraints are placed on the current state of knowledge with clear directions for future research.

Finally, small-scale vertical land motion in Hampton Roads, VA is investigated using the remote-sensing technology of Interferometric Synthetic Aperture Radar (InSAR). Two different data sources and processing strategies are implemented which independently reveal substantial rates of vertical land motion that vary over short spatial scales. The results highlight the importance of vertical land motion in exacerbating negative impacts of relative sea-level rise such as flooding and inundation. Overall, this study leverages new spaceborne sensors, an innovative statistical model, and state-of-the-art processing strategies to enhance our understanding of ongoing sea-level change. ©2021, by Brett A. Buzzanga, All Rights Reserved.

This dissertation is dedicated to my Grandmothers.

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I don't think there are many people capable of channeling my particular eccentricities into intentional aspirations. Ben, with incredible patience and care, has turned me from a fledgling master's student into a focused Ph.D. Thank you for believing in me, and for showing me how a collaborative approach allows connections that improve science and society. This is a lesson that, although impossible for anyone to ever fully learn, will always permeate my career and life.

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#### CHAPTER 1

## INTRODUCTION

The North Atlantic Ocean and atmosphere are essential elements of the Earth system. Through transfers of heat and momentum, these components establish the North Atlantic climate, affecting millions of people (e.g *Hurrell*, 1995; *Sutton and Hodson*, 2005; *Lozier*, 2012). Climate changes directly impact the sea surface, defined as the upper boundary of the ocean (*Gregory et al.*, 2019), as heat and mass are exchanged between ocean, atmosphere and land. During the  $20^{\text{th}}$  century, naturally occurring sea-level changes became dominated by an anthropogenically forced upward trend, reflecting primarily thermosteric (volume) expansion of seawater and mass influx from melting land-ice (*IPCC*, 2014; *Dangendorf et al.*, 2015; *Frederikse et al.*, 2020). However, the extent to which sea-level changes affect coastal ecosystems, such as through flooding and habitat loss, is a function of the relative sea-level (RSL) change between the ocean and land surface:

$$RSL(\boldsymbol{r}) = WM(\boldsymbol{r}) + SD(\boldsymbol{r}) + GIA(\boldsymbol{r}) + IB(\boldsymbol{r}) - [VLM(\boldsymbol{r}) - GIA_{VLM}(\boldsymbol{r})]$$
(1)

where WM is the geocentric sea-level change associated with water mass redistribution due to ice mass and terrestrial water storage variations, SD is the sterodynamic component resulting from thermal expansion and ocean dynamics, glacial isostatic adjustment (GIA) is the response to the retreat of ice sheets ~20,000 years ago, vertical land motion (VLM) reflects the changes in elevation of the land surface or ocean bottom, the inverted barometer effect (IB) captures the influence of the atmospheric pressure systems on the sea surface, and all terms are a function of geographical location (r). In that GIA influences the sea surface (through geoid, rotational, and deformation effects) and the land surface ( $GIA_{VLM}$ ), the latter term is removed from VLM in Eq. 1 to prevent double counting this contribution. In that these various contributions are regionally dependent, RSL changes can differ substantially from the global mean (e.g., *Stammer et al.*, 2013). It is thus current and future RSL that are of primary importance for mitigating and adapting to sea-level rise (*Wemelsfelder*, 1970; *Plag*, 2006; *Kirezci et al.*, 2020).

The many geophysical processes impacting sea-level, superimposed upon anthropogenic global-mean sea-level (GMSL) rise, can cause extreme levels which dramatically affect coastal communities (see *Sweet et al.*, 2017, and references therein). Along the relatively low-lying and flat U.S. Atlantic coast, the primary concern is flooding, which ranges from relatively minor flooding from astronomical tides, to event-driven storm surges that cause billions of dollars in damages (e.g., *Ezer and Atkinson*, 2014; *Neumann et al.*, 2015). Such drastic consequences have led to a large body of research investigating the predictability of tropical and extratropical storms, as well as how their characteristics might change in

the coming years due to a more energetic climate (see *Knutson et al.*, 2010; *Shaw et al.*, 2016; *Woollings et al.*, 2018, and references therein). Recent studies are also beginning to place more emphasis on understanding the minor flooding due to astronomical tides, particularly in areas such as Hampton Roads, VA that are experiencing sea-level rise (SLR)  $\sim 3$  times greater than the global average (*Ezer and Atkinson*, 2014; *Sweet et al.*, 2014).

Like high impact events, regular flooding from astronomical tides has also been shown to be increasing and indeed accelerating as SLR reduces the freeboard between the sea and the fixed elevation of coastal infrastructure (e.g., *Ezer and Atkinson*, 2014; *Sweet et al.*, 2014; *Hague and Taylor*, 2021). On the American Atlantic coast, sub-annual variability superimposed on the GMSL rise has been connected to fluctuations in the Florida Current component of the Gulf Stream (*Sweet et al.*, 2009; *Ezer and Atkinson*, 2014). On interannual time-scales, *Sweet and Park* (2014) discovered that the number of days experiencing flooding due to tides in Norfolk for a given year was proportional to the El Niño-Southern Oscillation (ENSO) as characterized by the Oceanic Niño Index. On decadal and longer time scales *Ezer and Atkinson* (2014) also qualitatively identifies an anti-correlation between storm surges and the North Atlantic Oscillation (NAO) index. *Sweet and Park* (2014) additionally identified thresholds of minor flood levels beyond which infrastructure may cease to function as intended, showing they could be reached this decade depending on regional variability.

Quantification of the ocean variability contribution to RSL change enables an improved understanding of both components. This information is essential for developing RSL projections that can foster coastal flood resilience. However local processes, such as waves, currents, and atmospheric pressure systems cause differences in sea level both zonally and parallel along the coast (*Woodworth et al.*, 2019). While tide gauges (TGs) provide invaluable historic records of RSL at a specific location, the spatial variability of coastal processes is often undersampled by the relatively sparse network of TGs. Since 1993, these point source sea level observations have been greatly expanded by satellite radar altimetry measurements, revolutionizing our understanding of the global ocean (see Wunsch and Stammer, 1998). However, these measurements are challenged in the coastal zone - along the continental-shelf and slope - in that estimates derived from them are based on assumptions appropriate for the open ocean (e.g. *Cipollini et al.*, 2017). The recently launched (2018) photon-counting laser altimeter aboard Ice, Cloud, and land Elevation Satellite 2 (ICESat-2) is currently providing high spatial resolution observations in the coastal ocean with the potential to bridge the observational gap between TGs and conventional satellite radar altimetry. This potential has yet to be fully explored.

The breadth of observations and models available for measuring sea level essentially presents an overdetermined problem that allows separate and independent estimates of variability and trends to be compared (e.g., *Church et al.*, 2011). On the global scale, this

has resulted in a near 'closure' of the sea level budget over the altimeter era (*Cazenave* et al., 2019b). However, challenges still exist at the regional scale (5 - 500 km) due to the aforementioned plethora of processes acting on different spatiotemporal timescales. While substantial progress has been made (e.g., *Frederikse et al.*, 2017a; *Piecuch et al.*, 2018; *Dangendorf et al.*, 2021), different methodologies result in different levels of closure, highlighting underlying uncertainties in the source data as well as the assumption of independence between measurements (*Hamlington et al.*, 2020a; *Frederikse et al.*, 2020). A rigorous accounting of these uncertainties within a mathematically coherent framework is essential for understanding current-day and future sea-level change and associated flooding (e.g., *Piecuch et al.*, 2018).

Along the North American Atlantic coast, VLM is a particularly important component of SLR, as the subsidence signal is similar in magnitude to that of the ocean processes, exacerbating the existing flood risk (Engelhart et al., 2009; Eggleston and Pope, 2013; Sweet et al., 2017). VLM on the Eastern seaboard is partly due to ongoing GIA to the retreat of the Laurentide Ice Sheet  $\sim 20,000$  years ago, leading to uplift in the area north of about New York City while the collapsing forebulge to the south is causing  $\sim 1-2$  mm yr<sup>-1</sup> of subsidence (*Peltier*, 2004; *Engelhart et al.*, 2009; *Caron et al.*, 2018). Superimposed on this long-wavelength GIA signal are more localized trends and patterns such as from compaction, dewatering, and fluid extraction (Eqgleston and Pope, 2013; Shirzaei et al., 2021). These local processes are often nonlinear and spatial variability, thus presenting a substantial challenge for the precise understanding of subsidence necessary for mitigating flood risk. While continuous global navigation satellite system (GNSS) stations enable high-resolution temporal sampling of VLM, even dense networks of stations struggle to capture the spatial variability necessary to inform decisions and further scientific investigations (e.g. Brooks et al., 2007; Thompson et al., 2016). However as the volume, quality, and accessibility of remotely sensed SAR data continues to increase, the technique of InSAR can be used to provide spatially dense measurements (~100 pixels  $km^{-2}$ ) of surface ground displacements with millimeter scale precision (*Gabriel et al.*, 1989; Massonnet and Feigl, 1998).

#### 1.1 RESEARCH GOALS

The overall goal of this work is to improve our understanding of the geophysical processes contributing to coastal sea-level trends and variability in an effort to foster resiliency in coastal communities. Here, coastal sea level refers to regional RSL observed by tide gauges that impacts human and natural ecosystems inhabiting coastal lands (e.g., *Ponte*, 2006). Following *Walker and Salt* (2012); *Capra and Luisi* (2014), resilience is an emergent property of a complex system that describes the system's ability to respond to perturbations. The facets of sea-level change investigated in this dissertation are unified through consideration of how the scientific findings can support community efforts to create

resilient social-environmental ecosystems. Beginning with an analysis of global sea-level trends, subsequent chapters narrow the focus to the U.S. East Coast, and Hampton Roads, VA, respectively. A data-driven approach is adopted, that focuses on observations and top-down constraints rather than on dynamical drivers. Three specific research questions are addressed that aim at improving our understanding of sea-level change:

- 1. To what extent can ICESat-2 observations improve our understanding of sea surface height trends and variability?
- 2. What are the relative contributions of GIA and mass redistribution between land and ocean to 20<sup>th</sup>-century U.S. East Coast sea-level change?
- 3. What are the spatiotemporal patterns and trends of vertical land motion in Hampton Roads?

## 1.2 DISSERTATION STRUCTURE

The following document proceeds with a chapter addressing each of the stated research questions. Consideration is first given in Chapter 2 to ICESat-2 measurements of global sea level. All relevant sea level terms and processes are defined and explained, along with their relationship to global change. I describe in detail the current suite of tools used for observing sea-level and discuss their limitations in the coastal zone. Next, the specific analysis used to assess the quality of the ICESat-2 data are detailed. An assessment of linear trend estimates is then presented, demonstrating strong agreement between sea level observations from ICESat-2 and independent sensors. This chapter concludes with a discussion of what this agreement means for ICESat-2 observations plays in communities concerned with developing resilience.

In Chapter 3, the spatial focus narrows from the global to the coastal, and the approach transitions from observation-based to a probabilistic modeling framework. The chapter begins with a review of geophysical processes impacting sea level in the coastal zone and documents recent progress in understanding via 'budgeting' approaches. Next, the particular Bayesian framework adopted here is elaborated on, along with the data sets used to represent the components of sea level along the East Coast of the U.S. Results are presented along with sensitivity experiments aimed at interpreting the findings. The chapter finishes with a discussion of the results and the model sensitivity along with future work in the context of coastal resilience and planning.

Chapter 4 more explicitly considers coastal resilience by quantifying the contribution of VLM to SLR in the metropolitan region of Hampton Roads, Virginia. After a brief introduction to the local drivers of RSL in the region, an extensive review of SAR principles, the InSAR technique, and the state-of-the-art with respect to coastal VLM is provided in Section 4.2. The chapter is then divided into two sections by the type of data and strategy adopted for processing. Section 4.3 utilizes the Persistent Scatterer (PS) approach to quantify VLM from 2007 - 2011 using data from Japan's Advanced Land Observing Satellite (ALOS) satellite. Section 4.4 builds on the results of Section 4.3 by quantifying contemporary VLM (2014 - 2019) using Sentinel-1 SAR images and the Small Baseline Subset (SBAS) processing technique.

Finally, Ch. 5 begins with a restatement of the research goals and how they were accomplished. I discuss the significance of the research, and how it both advances scientific knowledge and can enhance contemporary and near-term coastal resilience. Next, limitations of the analysis are realistically evaluated and the uncertainties and major shortcomings are addressed. I explores how these challenges can be overcome in the coming years with more research, and offer specific avenues for future work.

#### **1.3 PUBLISHED WORKS**

Much of the work contained in this dissertation has been previously published by this author. In Chapter 2, most of Sections 2.3, 2.4 and 2.5 are contained near verbatim in *Buzzanga et al.* (2021). Section 4.3 is composed of work from *Bekaert et al.* (2017). Section 4.4, especially Sections 4.4.2, 4.4.3 and 4.4.4 are reproduced from *Buzzanga et al.* (2020).

#### CHAPTER 2

## AN ASSESSMENT OF REGIONAL ICESAT-2 SEA-LEVEL TRENDS

## 2.1 INTRODUCTION

Global sea-level is one of the best indicators of global climate change, yielding invaluable information about the amplitude and scale of both natural oscillations in the Earth system, and forced trends from anthropogenic warming. As such, it is an essential scientific endeavor to precisely measure and model the ongoing changes. However, global observations at millimeter-scale precision are required for accurate assessments and thus present a formidable challenge. Currently, a suite of both remotely-sensed and *in-situ* observations are used as the foundation of understanding. Despite many strengths, there are nevertheless observational gaps, particularly at the coast and the poles, within the current observational data.

This chapter is an exploration of global sea-level using a dataset of new observations from the Ice, Cloud, and land Elevation Satellite 2 (ICESat-2) satellite. Before detailing the methodology and results of the analysis, a thorough background is given of the geophysical processes that give rise to the spatiotemporal variability of global-mean sea-level (GMSL). All necessary terms are precisely defined, and particular attention is given to the strengths and shortcomings of the current-suite of observational tools used to understand global sea level. In this way, context is provided for the methodology and results detailed in Sections 2.3 and 2.4, respectively. The chapter then concludes with a discussion of the results in relation to Research Question 1: To what extent can ICESat-2 observations improve our understanding of sea surface height trends and variability?

#### 2.2 BACKGROUND

Following *Gregory et al.* (2019), I begin with precise definitions of commonly used terminology. A shown in Figure 1, sea surface height (SSH) is the time varying mean of the ocean surface relative to a reference ellipsoid. A reference ellipsoid is a mathematical approximation of the geoid, which in turn models the shape of the Earth as an equipotential surface. The equipotential surface is chosen such that the volume of water between it and the sea floor is equivalent to the time-mean volume of ocean water (*Gregory et al.*, 2019). The time average of sea surface height (SSH) is then mean sea-level (MSL), where the temporal period used for the averaging depends on the intended use. Mean sea-level (MSL) would be identical to the geoid if not for ocean circulation, which causes a deviation of the local sea from the geoid (after correcting for the inverted barometer effect) referred to as dynamic ocean topography (DOT). Finally, Global-mean sea-level (GMSL) is the heat

content of the Earth system on decadal and longer time scales, thus serving as a powerful indicator of climatic changes (e.g., *Church et al.*, 2013; *Cazenave et al.*, 2018).



Figure 1: Illustration of geodetic surfaces necessary for defining sea level. Here, the vertical coordinate z and gravity (g) are normal to the geoid. H is the distance from the sea surface to the sea floor (F), and  $p'_a$  is the deviation of local atmospheric pressure from the global mean that impacts sea level (source: *Gregory et al.*, 2019).

Theoretically, a detailed understanding of the changes in GMSL enables an assessment of the current rate of global warming, and whether that rate is accelerating. However, the contributions of geophysical processes that determine GMSL can be challenging to understand. Additionally, the realities of existing observations make separating the trend from the background variability a nontrivial task. This section proceeds with a discussion of the processes contributing to GMSL and our current understanding of them. Next, the suite of sea-level observations is explored, with a comparison of the strengths and weaknesses between different tools. I conclude with an update on ongoing developments and the challenges they are designed to meet.

## 2.2.1 CONTRIBUTORS TO GMSL

Increased ocean thermal expansion, land-ice melt, and changes in terrestrial water storage (TWS) are the main contributors to GMSL rise (e.g., *Cazenave et al.*, 2018). On decadal timescales, these contributions result in volume and mass changes of the Earth's oceans and thus GMSL variability. Two different methods can be applied to study these changes: a 'top down' approach, which uses relatively direct observations of sea-level change, or a 'bottom up' approach that seeks to quantify and combine the contributing processes (e.g., *Douglas*, 1991; *Cazenave et al.*, 2009). The two methods serve as important checks on each other, and agreement indicates that the process estimates and measurement assumptions are well-founded. As will be shown, recent advances in space geodesy and autonomous sensors now allow near closure of the budget over the satellite altimetry era (1993 - present) (*Cazenave et al.*, 2018) and since 1900 (*Frederikse et al.*, 2020).

Volume changes in sea level caused by variations in seawater density are known as steric sea-level changes. Making a linear approximation, the relations of temperature ( $\theta$ ) and salinity (S) changes to thermosteric ( $\Delta R_{\theta}$ ) and halosteric ( $\Delta R_S$ ) sea level are respectively:

$$\Delta R_{\theta} = -\frac{1}{\rho_0} \int_F^{\eta} \frac{\partial \rho}{\partial \theta} \Delta \theta(\boldsymbol{r}, z) \, dz \tag{2}$$

$$\Delta R_S = -\frac{1}{\rho_0} \int_F^{\eta} \frac{\partial \rho}{\partial S} \Delta S(\boldsymbol{r}, z) \, dz \tag{3}$$

where F is the ocean floor,  $\eta$  is the sea surface,  $\mathbf{r}$  is region, z is depth and  $\rho_0$  is a constant reference density. Globally averaging  $\Delta R_{\theta}$  then gives the thermosteric contribution to GMSL  $h_{\theta}$  as:

$$h_{\theta} = \frac{1}{A} \int \Delta R_{\theta} \, dA = -\frac{1}{\rho_0 A} \int \int_F^{\eta} \frac{\partial \rho}{\partial \theta} \Delta \theta \, dz \, dA \tag{4}$$

where A is the connected surface area of the oceans (including marginal seas, excluding inland seas) (*Gregory et al.*, 1999). The contribution of  $\Delta R_S$  to GMSL change is negligible as it overwhelmed by changes in mass (*Lowe and Gregory*, 2006).

While records of ocean temperature measurements date back to the late 1700s, only recently have data gathering systems had the spatial coverage and rigorous control to provide unbiased information about the heat content of the upper 2000 m of the oceans (*Abraham et al.*, 2013). Prior to 2002, sporadic expendable bathythermograph measurements (1967) and ship-based observations (especially from the World Ocean Circulation Experiment, 1990-1998) provide the majority of *in-situ* observations. Since 2002, our understanding of the upper ocean has been revolutionized by the the Argo fleet, which is composed of nearly 4000 autonomous floats that vertically sample temperature and salinity to 2000 m depth on ~10 day cycles (*Argo*, 2000). These measurements are an indispensable resource, providing the basis of all global subsurface data products. Using such data products, an international team of ~100 investigators used an ensemble of 11 temperature datasets to calculate an ocean thermal expansion contribution of  $1.3 \pm 0.4$  mm yr<sup>-1</sup> to GMSL between 1993 and 2016 (*WCRP Global Sea Level Budget Group*, 2018).

In addition to volume changes, barystatic GMSL rise  $(h_b)$  occurs due to the transfer

of water mass from land or air to ocean.

$$h_b = \frac{\Delta M}{\rho_f A} \tag{5}$$

where M is mass and  $\rho_f$  is the density of the added water (*Gregory et al.*, 2019). The primary barystatic sources of water are ice, groundwater, and surface water, with lesser contributions from soil moisture and atmospheric water vapor (WCRP Global Sea Level Budget Group, 2018). Land-ice melt can be separated into 3 dominant melt sources: glaciers, the Greenland ice sheet, and the Antarctica ice sheet (neglecting permafrost, which is thought to be inconsequential at this time for SLR, Box and Colgan, 2017). Global glacier mass change have been primarily investigated using data compiled by the World Glacier Monitoring Service<sup>1</sup>. This dataset is mainly composed of *in situ* measurements of front variations (length changes), and estimates of mass-budgets from measures of snow/ice accumulation and ablation (Zemp et al., 2015). Despite a large compilation consisting of  $\sim 40000$  observations of  $\sim 2000$  glaciers, many of the records are subject to uncertainties arising from the transient nature of glaciers and a lack of long-term records (Paul et al., 2004; Bahr and Radić, 2012; Farinotti et al., 2017). However in recent years, observations obtained from modeling studies and remote sensing techniques have begun to improve these uncertainties, especially when used in tandem with sophisticated *in-situ* calculations of glacier-bed topographies (*Marzeion et al.*, 2017, and references therein).

Since 2002, Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) have provided time-varying gravity anomaly measurements that enable the investigation of mass redistribution on a global scale (*Tapley et al.*, 2004). This has provided previously unattainable observations of the glaciers and ice sheets of Greenland and Antarctic which have subsequently been used to construct a variety of datasets quantifying their melt contribution to GMSL rise (e.g. Luthcke et al., 2013; Wiese et al., 2016). The differences in these datasets, while small, stems primarily from the choice of GIA correction, which is a large contributor to the uncertainty of GRACE-derived products (Peltier, 2009; Martín-Español et al., 2015, see Section 4.2.4). Compiling 5, 8 and, 11 existing datasets, the WCRP Global Sea Level Budget Group (2018) determined rates of  $0.74 \pm 0.1 \text{ mm yr}^{-1}$ ,  $0.76 \pm 0.1 \text{ mm yr}^{-1}$ , and  $0.42 \pm 0.1 \text{ mm yr}^{-1}$  for the GMSL contribution from global glaciers, the Greenland ice sheet, and the Antartica ice sheets, respectively, for the period 2005–2015. The combined ice melt contribution to current GMSL rise is then  $1.92 \pm 0.3$  mm yr<sup>-1</sup> and is the largest contributor to current GMSL rise. Similarly, Frederikse et al. (2020) has found ice-melt, mainly of glaciers, has caused twice as much GMSL rise since 1900 as steric changes.

In addition to thermal expansion and land-ice melt, movement of water between the terrestrial and oceanic domains both from natural climate variability and anthropogenic

<sup>&</sup>lt;sup>1</sup>https://wgms.ch/

interventions cause changes in GMSL (e.g., *Milly et al.*, 2003; *Chao*, 1991). More specifically, inter-annual natural variability is dominated by ENSO, the quasi-periodic climate variation with a warm (El Niño) phase that increases precipitation over the oceans to result in higher GMSL (e.g., *Nerem et al.*, 2010; *Gu and Adler*, 2011; *Boening et al.*, 2012; *Cazenave et al.*, 2014). Simultaneously, humans are altering the hydrological cycle by storing water in reservoirs and mining groundwater, which has the potential to decrease and increase GMSL, respectively (*Chao et al.*, 2008; *Gregory et al.*, 2013). Before GRACE, global estimates of TWS relied on modeling studies, which compute time-varying surface water balances from meteorological forcing (e.g. *Humphrey and Gudmundsson*, 2019) Unfortunately these models are highly sensitive to precipitation, resulting in substantial differences in their outputs (*Beck et al.*, 2017; *Felfelani et al.*, 2017).

As with land-ice melt, GRACE has provided an invaluable set of new observations that have been recently used to quantify global TWS changes (e.g., *Reager et al.*, 2016; *Scanlon et al.*, 2018). These studies have concluded that over the GRACE era (2003-present)<sup>2</sup> there was an increase in water stored on land that corresponding to a fall in GMSL (*WCRP Global Sea Level Budget Group*, 2018). However, this may be caused by decadal climate variability which is not resolved in the relatively short GRACE record (*Hamlington et al.*, 2017). A statistical model trained with GRACE and historical data has recently addressed these challenges to reconstruct TWS changes since 1900 (*Humphrey and Gudmundsson*, 2019). With this dataset, *Frederikse et al.* (2020) found TWS to contribute -0.21 ± 0.13 mm yr<sup>-1</sup> to GMSL since 1900, with a contribution of -0.14 mm yr<sup>-1</sup> during 1957-2018 and 0.31 mm yr<sup>-1</sup> since 1993 due to the large-scale impoundment of water in dams during the 20<sup>th</sup> century.

WCRP Global Sea Level Budget Group (2018) present several methods of comparing these different contributions to the GMSL rate of  $3.5 \pm 0.2$  mm yr<sup>-1</sup> calculated independently from satellite altimetry observations (see Section 2.2.3). Combining the ensemble mean of the GRACE-based estimates of  $2.3 \pm 0.19$  mm yr<sup>-1</sup> (which includes TWS) with the thermosteric component yields closure of the budget (within uncertainty). However, considering the TWS component as measured by GRACE with the combined independent mass estimates yields a residual of  $0.55 \pm 0.3$  mm yr<sup>-1</sup>. This residual improves to  $0.28 \pm$ 0.2 mm yr<sup>-1</sup> when not considering TWS, leaving a considerable unresolved uncertainty (WCRP Global Sea Level Budget Group, 2018). By leveraging updated datasets and probabilistic methods, Frederikse et al. (2020) minimized this uncertainty, yielding a residual of  $0.19 \pm 0.51$  mm yr<sup>-1</sup> from 1993 - 2018 and  $0.04 \pm 0.37$  mm yr<sup>-1</sup> from 1900 - 2018. Thus, the global sea-level budget can be considered closed, indicating that our scientific understanding of the geophysical processes driving global sea-level change is robust. I now give considerations to the observational tools used in conjunction with the

 $<sup>^2 \</sup>rm While$  the originial GRACE mission ended in October, 2017, GRACE-FO was launched to continue the observations in May of 2018

process estimates.

#### 2.2.2 TIDE GAUGES



Figure 2: Cartoon illustrating coastal observations that facilitate sea-level studies. The difference between the sea surface and Earth's Surface observed by tide gauges is RSL (S). GPS, part of the GNSS constellation, measure the motion of the land with respect to Earth's Center of Mass (U). Satellite altimeters observe the geocentric sea level change (N = S + U). (source: *Wöppelmann and Marcos*, 2016)).

With often multi-decadal records, TGs are one of the most important sources of sea-level information. TGs are physical devices fixed to terrestrial structures which record local sea level relative to the local solid Earth (Fig 2). While historically they measured water levels using analog recording devices, today they use microwave radar sensors that transmit data to receiving stations in near-real time. These data are easily and freely accessible from a number of sources, including the NOAA Center for Operational Oceanographic Products and Services, the University of Hawaii Sea Level Center, and the Permanent Service for Mean Sea Level (PSMSL). Currently, the PSMSL provides a global dataset that contains  $\sim 2000$  TGs with monthly and annual sea level samples (*Holgate et al.*, 2013; *Permanent Service for Mean Sea Level (PSMSL)*, 2021).

There have been a variety of studies to reconstruct historic and project future GMSL using the TG record. Early methods mainly relied on averaging linear trends obtained from TG stations (e.g., *Trupin and Wahr*, 1990; *Mitchum et al.*, 2010), while more recent methods leverage the full sea-level records (e.g., *Dangendorf et al.*, 2017). Sea level estimates are typically obtained from TG stations undergoing minimal or well known VLM. However, this subjectivity led to variable estimates of GMSL change (e.g., *Douglas*, 1991; *Holgate*, 2007; *Jevrejeva et al.*, 2008; *Spada and Galassi*, 2012). Alternatively, larger numbers of TGs can be averaged to create 'virtual stations' (*Jevrejeva et al.*, 2006) which reduces sampling bias in individual TG records , (e.g., *Jevrejeva et al.*, 2014; *Dangendorf et al.*, 2017; *Frederikse et al.*, 2020). Using these various techniques, most studies conclude that GMSL rise was closer to 2 than 1 mm yr<sup>-1</sup> during the 20<sup>th</sup> century, but there is disagreement in the magnitude of the rates which arises from methodology rather than the data itself (*Douglas*, 1997; *Mitchum et al.*, 2010).

Additionally, the TG dataset suffers from several problems that make it challenging to determine GMSL. First, many of the records experienced interruptions due to relocation or replacement and were not rigorously quality controlled. Second, to separate a sea-level trend from background quasi-oscillatory variability, records greater than  $\sim 50$  years should be used (e.g., p. 320, *Pugh*, 1987; *Douglas*, 1991). However, very few TGs meet this requirement, and those that do are not evenly distributed throughout the world (*Thompson et al.*, 2016). Specifically, TG records available before  $\sim 1950$  are biased towards heavily populated areas in the Northern Hemisphere, while the Southern Hemisphere and open ocean are poorly represented.

As further described in Section 4.2.4, VLM from GIA and/or a variety of natural (e.g., tectonic) and anthropogenic (e.g., ground-water (GW) withdrawal) processes manifests in sea-level measurements at many, if not most, TGs (*Emery and Aubrey*, 1991). The amplitude of such VLM is often greater than or comparable to geocentric sea-level change and thus make many TGs unusable for investigations of GMSL (*Peltier and Tushingham*, 1991; *Douglas*, 1991). Additionally, the TG records are referenced to local datums; relating these to one global vertical datum poses another substantial challenge as the relation of the local datum to a precise geoid is often undocumented (e.g., *Church et al.*, 2004; *Holgate and Woodworth*, 2004; *Ray and Douglas*, 2011). For these reasons and others, many investigators have concluded that the existing TG data is insufficient for determining GMSL (*Barnett*, 1984; *Gröger and Plag*, 1993; *Thompson et al.*, 2016) To overcoming theses shortcomings, investigators in recent years have begun incorporating more sophisticated VLM corrections in their analyses (e.g., *Dangendorf et al.*, 2017) and/or leveraging observations from satellite altimetry.

#### 2.2.3 SATELLITE ALTIMETRY

With the launch of the TOPEX/Poseidon (T/P) satellite in late 1992, spaceborne altimeters began reliably observing changes in sea surface height (SSH) (*Fu et al.*, 1994). These observations have continued with the Jason series (NASA/CMES), under the Copernicus program (ESA), and others, which have been merged (after various corrections) into a dataset of sea-level anomaly (SLA), that is the deviation of SSH from a mean sea level (here the mean over 1993-2012 *CNES*, 2018). Covering most of the ice-free oceans ( $\pm 66^{\circ}$ N), satellite altimetry has revolutionized our understanding of the planet, revealing hitherto unobserved mesoscale variability (eddies) and GMSL rise among other substantial advances in knowledge (e.g., *Cheney et al.*, 1983).

Satellite altimeters operate by transmitting microwave pulses towards the Earth and measuring the time delay of the returned echoes (Fig. 2). After correcting these echoes for atmospheric and local surface effects, such as tides and currents, the distance from the satellite to the sea surface is calculated. The satellite's ephemeris is tracked using several on-board devices, which enables the modeling of its position relative to a reference ellipsoid. Subtracting the distance of the satellite to the sea surface from the altitude of the satellite above the ellipsoid results in a measure of SSH. SSH contains both the geoid and the dynamic ocean topography (DOT), while sea surface height anomaly (SSHA) only contains the DOT.

Preliminary attempts at extracting GMSL from T/P observations began soon after its launch in August of 1992 (*Rapp et al.*, 1994; *Nerem*, 1995). Even with such short record lengths, these early studies demonstrated that seasonal and interannual variability - particularly that related to ENSO - were well captured in the T/P dataset (*Hendricks et al.*, 1996; *Nerem et al.*, 1999). With the current altimetry record now approaching 28 years in length, several additional conclusions can be drawn. For one, the GMSL has been rising at rate of  $3.1 \pm 0.4$  mm yr<sup>-1</sup> since 1993 which is approximately twice as large as that of the 20<sup>th</sup> SLR (*Nerem et al.*, 2018; *Cazenave et al.*, 2019a). This difference may be partly explained by the eruption of Mount Pinatubo in 1991, which artificially lowered sea level just before the onset of the altimeter era (*Church et al.*, 2005; *Fasullo et al.*, 2016). Nevertheless, GMSL rise will continue to accelerate beyond that experienced in the previous century due to increased ocean thermal expansion and ice mass loss from anthropogenic climate change (*Church et al.*, 2013). Indeed, adjusting for the Mount Pinatubo eruption, (*Nerem et al.*, 2018) made an effort to determine GMSL acceleration from altimetry data alone, calculating a rate of  $0.084 \pm 0.025$  mm yr<sup>-2</sup>.

Nevertheless, the work by *Nerem et al.* (2018) is only a preliminary effort; while the altimetry record may be just long enough to separate the secular trend from decadal variability, it is not yet long enough to resolve the multi-decadal signals found in many TG records (*Feng et al.*, 2004; *Miller and Douglas*, 2007; *Chambers et al.*, 2012; *Hamlington* 

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et al., 2013, 2020b). Haigh et al. (2014) provide convincing evidence that investigators will need to adequately understand and remove such variability if they are to determine statistically significant acceleration in the near future. The magnitude and acceleration remain a pressing questions for understanding the GMSL and by extension global climate change (*Cazenave et al.*, 2019a).

In addition to difficulties associated with the short temporal record, there are a number of challenges that arise from the altimeter instruments themselves. For example, precisely tracking the ephemerides of the satellites to reduce instrumental bias while maintaining continuity between missions are active areas of research (*Couhert et al.*, 2015; *Quartly* et al., 2017). Further, satellite drift, that is, low frequency trends in the observed data introduced by sensor instabilities (or knowledge of them) must be addressed through calibration (Born et al., 1986; Mitchum, 1994; Chambers et al., 1998). One commonly used method used for calibration is the differencing of an altimetric time series with the closest TG time series (*Mitchum*, 1994, 1998). With a long enough record, the common ocean signals will cancel to result in a measure of altimeter drift and VLM occurring at the TG. While, corrections can be made to minimize the effects of VLM at TGs, (e.g., Mitchum, 2000; Santamaría-Gómez et al., 2012; Dangendorf et al., 2017), this remains a challenge (see Section 4.2.4). Indeed as described in Section 4.2.4, others have utilized independent assessments of altimeter drift (made using well-constrained measures of SSH) and differenced altimeter and TG time series to evaluate VLM (Cazenave et al., 1999; Nerem and Mitchum, 2002; Santamaría-Gómez et al., 2014). These studies represent one of the novel ways in which the TG and altimetry records can be used to supplement one another. Another approach combines the spatial structure of the oceans revealed by satellite altimetry with the temporal records available at TGs to reconstruct historic sea level (Chambers et al., 2002).

## 2.2.4 SEA LEVEL RECONSTRUCTIONS

Sea-level reconstruction techniques have evolved from the empirical orthogonal function (EOF) method formulated by *Preisendorfer* (1988), the projection technique developed by *Smith et al.* (1996), and the reduced space optimal interpolation method devised by *Kaplan et al.* (1997). Satellite altimetry data sets provide the dense spatial data to perform a principal component analysis (PCA) that results in orthogonal functions (EOFs) and principal components. Assuming stationary and orthogonal modes (neither of which is fully true, but are thought to be useful approximations), the EOFs form spatial maps of sea-level variability, and the principal components show how the EOFs vary temporally. The EOFs are then ordered such that first mode corresponds to the greatest variability, and then fit to the TG records using a weighted least squares approach. This results in global sea-level fields for the entire length of the TG records used (e.g. *Chambers et al.*,

2002).

In recent years, a variety of studies have attempted to improve the basic reconstruction technique introduced by *Chambers et al.* (2002) by revising the statistical methods and/or incorporating additional information. For example, Church et al. (2004) introduced an EOF0 to account for a spatially uniform increase in GMSL through time, which more accurately captures the secular trend but impairs the potential for reconstructing past variability (Calafat et al., 2014). Berge-Nguyen et al. (2008) compared reconstructions made using EOFs from thermosteric sea-level data, SSH from the Simple Ocean Data Assimilation (SODA) product, and the T/P altimetry record. They found significant disagreement in the methods, with results being particularly sensitive to the timespan of the data set used to compute the EOFs. Using EOFs from  $\sim 17$  years of T/P and Jason altimeter data, Ray and Douglas (2011) found that while GMSL is relatively insensitive to the length of the EOF series, the reconstruction struggles in capturing ocean variability, especially for the period prior to  $\sim 1950$  when the TG network is sparse. In an effort to overcome reliance on the TG network for historical data, *Hamlington et al.* (2011) used the cyclostationary empirical orthogonal function (CSEOF) technique of Kim and North (1997) to combine sea surface temperature (SST) and TG data with altimetric SSH in a reconstruction that is able to capture climate variability prior to 1950. Seeing no clear best reconstruction at the time, Meyssignac et al. (2012) make a first attempt at a 'mean reconstruction' by averaging three independent reconstructions. Avoiding altimetry data altogether, Hay et al. (2015) leverage a Bayesian approach, which uses all possible combinations of outputs from 161 different Earth rheological models and 6 general circulation models (GCMs) to generate spatial fields of GIA and ocean dynamics, respectively. Similarly, *Dangendorf et al.* (2019) utilize a Kalman Smoother in combination with EOFs and supplement sea level observations with sea surface temperature (SST) and sea-level pressure (SLP) information to show a persistent sea-level acceleration since 1960 linked to an equatorward shift of Southern Hemisphere subtropical westerly winds. While these recent reconstruction attempts are fundamentally limited by the spatial deficiencies in the TG data, temporal deficiencies in the satellite altimetry record, and the assumptions of an EOF (Monahan et al., 2009; Ray and Douglas, 2011), they nevertheless mark substantial advances in the scientific understanding of 20<sup>th</sup> century GMSL.

Indeed, knowledge of the current rate of global SLR is well constrained by both observations and measures of its components (Section 2.2.1; WCRP Global Sea Level Budget Group, 2018; Frederikse et al., 2020). However, regional RSL change results from local conditions superimposed on global trends and deviations of regional RSL from the global mean trend (Section 3.2; Church et al., 2013; Stammer et al., 2013; Woodworth et al., 2019, and references therein). In many locations, regional relative sea-level rise (RSLR) can be greater by a factor of two or more than GMSL rise, leading to negative consequences for affected coastal communities (e.g. Kirezci et al., 2020). Knowledge of

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such regional RSLR is therefore of critical importance for many municipalities developing strategies to mitigate and adapt to ongoing RSLR.

## 2.2.5 COASTAL ALTIMETRY

Currently, TG measurements are the primary data source for stakeholders concerned with RSL change. However, TGs are point-sources, and thus undersample dynamic coastal environments. This limits our ability to fully understand how RSL variability propagates towards and along the coast from TGs. Additionally, local conditions often lead to challenging conditions for altimetric measurements of SSH in the coastal zone (within  $\sim 50$  km from land *Ablain et al.*, 2017; *Cipollini et al.*, 2017). These challenges stem primarily from the presence of land in the altimeter footprint, which decreases the accuracy of the applied geophysical range corrections and the assumptions of the wave model used for estimating SSH (see *Vignudelli et al.*, 2011, and references therein).

Specific strategies have been developed to address these shortcoming, utilizing both sophisticated data processing strategies and/or numerical models. For example, efforts are ongoing to formulate and apply more appropriate waveform models than the Brown model designed for open-ocean echo returns (*Brown*, 1977; *Passaro et al.*, 2014; *Cazenave et al.*, 2019b). Others are developing improved near-shore tropospheric corrections and tidal models (see *Cipollini et al.*, 2017, and references therein). Ocean state estimates such as Estimating the Circulation and Climate of the Ocean (ECCO) (*ECCO Consortium et al.*, 2020), which ingest observational data including those from satellite altimeters, and barotropic models such as those discussed by *Piecuch et al.* (2019a) skillfully reproduce sea level trends and variability as measured at TGs, but are nevertheless unconstrained along the continental shelf and slope.

In addition to improvements in corrections, advancements in altimeter technologies have enabled more precise data returns in the coastal zone. For example, the SARAL/AltiKa mission's Ka-band (36.5 GHz) radar has improved the radar footprint diameter from 20 km (JASON-2) to 8 km, permitting observations within 5 km of the coast. Additionally, higher frequency sampling has considerably reduced white noise, leading to higher spectral contents than conventional Ku-band altimeters, especially at short wavelengths < 70 km (*Bonnefond et al.*, 2018, their Fig. 13). These achievements enable new observations of coastal circulation (*Jebri et al.*, 2016; *Pascual et al.*, 2015) and better retrievals of significant wave heights (*Verron et al.*, 2018). After completing its nominal mission in Spring, 2016, SARAL/AltiKa entered a 'drifting' orbit such that the position of the nadar track is no longer stable. This extended the lifetime of the satellite, enabling import marine geodetic observations and mesoscale ocean sampling (*Dibarboure et al.*, 2018). However, the lack of a consistent repeat track poses challenges for understanding the temporal evolution of the observations, such that data after 2015 are not incorporated in altimetry datasets used for climate studies (e.g., *CNES*, 2018). Another significant step forwards in coastal altimetry is the development of SAR-mode altimeters such as those aboard Cryosat-2 and Sentinel-3. The coherent sensor preserves the phase of the signal return such that the Doppler shift can be exploited to increase the number of looks of the surface scatterers (*Raney*, 1998). By focusing over the illumination period, the along-track resolution is increased by an order of magnitude to the theoretical limit determined by half its antenna length (*Egido and Smith*, 2017, see Section 4.2.1). This leads to a clear improvement in SSH (e.g., *Abulaitijiang et al.*, 2015) and significant wave height (e.g *Nencioli and Quartly*, 2019) retrievals in the coastal zone. However, Cryosat-2 only operates in SAR-mode in a few regions due to on-board data limitations (*Cullen et al.*, 2007). Sentinel-3 is currently operating in SAR mode globally, with ongoing development of retracking algorithms for specific coastlines (e.g., *Dinardo et al.*, 2020).

The wide variety of processes operating in the coastal zone calls for a multi-faceted observational approach to measure and understand the spatiotemporal variability of sea level. Parallel to the progress in coastal altimetry, technological advancements in recent decades have led to the development of spaceborne laser altimeters. In 2018, NASA launched its Advanced Topographic Laser Altimeter System (ATLAS) aboard ICESat-2, which measures ice, ocean and land surface elevations on a 91-day repeat cycle. Advanced Topographic Laser Altimeter System (ATLAS) is a photon-counting lidar with 532 nm wavelength lasers that illuminate three pairs of photon beams. Each pair has a weak (45  $\pm$  5 mJ) and a strong beam (175  $\pm$  17 mJ) that enable multiple lines of scientific inquiry (*Markus et al.*, 2017). The tracks within a pair of beams are each 17 m wide and spaced ~90 m apart, with along-track sampling every 0.7 m, resulting in extremely high-resolution observations (Fig 3). The basic data product consists of geolocated photons of ellipsoidal elevations (ATL03; *Neumann et al.*, 2019).



Figure 3: Cartoon illustrating the ICESat-2 beam pattern. 3 pairs of beams, separated by  $\sim 3$  km, simultaneously collect photons as the satellite transits in the flight direction (source: *Neumann et al.*, 2019).

## 2.2.6 RESEARCH QUESTION 1

While ICESat-2's primary scientific objectives are not centered around ocean elevation observations, there is nevertheless much potential for ICESat-2 to bring new insight into coastal sea-level changes and its underlying dynamics. The original ICESat, which operated sporadically between 2003-2009, demonstrated this potential through validation against TGs and conventional radar altimeters in the open-ocean (*Urban et al.*, 2008). In light of this, an ocean elevation product, ATL12, has been derived from the underlying geolocated photons heights (*Morison et al.*, 2020a). To create the ATL12 product, photons along a 7-km track (or 8000 photons, whichever comes first) are filtered to isolate surface-reflected photons, trimmed by removing a linear trend, and deconvolved with an ATLAS instrument response function to produce a histogram representative of the SSH distribution. The resulting SSH is then fit with a 2-Gaussian mixture model, yielding the mean, standard deviation, skew and kurtosis (see *Morison et al.*, 2020a, for complete details). In addition to these quality assessment statistics, the ATL12 product includes geophysical corrections and a sea-state bias correction to account for the stronger returns from wave troughs than crests.

Despite the potential for ICESat-2 ocean data products to contribute to our existing suite of sea-level observations, they have not yet undergone thorough analysis. For this reason, the remainder of this chapter seeks to answer research question 1: To what extent can ICESat-2 observations improve our understanding of sea surface height trends and variability?

As noted in the Introduction (1.3), much of what follows has been recently published (*Buzzanga et al.*, 2021).

Chapter 2 begin with a description of the data and processing methods, focusing on the first two moments of the SSH distribution, henceforth referring to them as the ATL12 SSH (h) and variance ( $\sigma^2$ ), respectively. I continue with results showing overall comparisons between ATL12 data at TGs, and the radar altimeter Jason-3. Next I present a global view of the sea-level trends estimated from each altimeter. I discuss the basinscale oceanographic patterns that are detectable from the ATL12 record, and potential insights into meso and sub-mesoscale features. Due to the short length of the ICESat-2 observations (2 years), the level of instrumental signal-to-noise ratio currently precludes an investigation of synoptic and climate variability. Using the current uncertainties, we perform a qualitative error analysis to elucidate the timelines for which climate variability may begin to emerge from the higher-frequency noise. I conclude with a discussion of future opportunities, limitations and avenues for further research.

### 2.3 DATA & METHODS

To assess the performance of the ICESat-2 over the global ocean we acquire several data products for comparison that are publicly available. The ICESat-2 ATL12 Ocean Surface Height Version 3 is provided by the National Snow and Ice Data Center, which is updated quarterly in accordance with the 91 day repeat time of the satellite (*Morison et al.*, 2020a). At the time of writing, we use the latest data that spans Oct, 2018 through Nov, 2020. We retrieve the ocean height (h) variable and variance  $(h_{var})$  for each beam.

From the National Center for Environmental Information at the National Ocean and Atmospheric Administration (NOAA), we obtain the Jason-3 Geophysical Data Records that cover the ICESat-2 sensing period (*Lillibridge et al.*, 2019). We extract the SSHA from the data products, containing the SSH relative to the mean sea surface estimated between 1993-2009. We use the ssha\_mle3 variable, which uses the maximum likelihood estimator 3 algorithm for retracking (*Thibaut et al.*, 2010). We explored additional comparisons with the SARAL/ALTIKA dataset, but found the data during the ICESat-2 period to require specialized processing due to its drifting orbit (*Desai*, 2013). All data are obtained as native along-track satellite returns.

In both products, the ocean height variables are provided with geophysical corrections applied. These include tides (ocean and solid-Earth) and the inverted barometer effect (*Morison et al.*, 2020a). After experimenting with different corrections, we found keeping the corrections applied and subtracting the sea-state bias gave the best results (not shown). The ATL12 ocean elevation data are provided relative to the IGS14 reference ellipsoid

and include a geoid estimated from the Earth Gravitational Model 2008. We subtract the geoid at each ATL12 ocean height to yield dynamic ocean topography (DOT; e.g., *Kwok and Morison*, 2011). This enables a more direct comparison to the Jason-3 SSHA, which reflects SSH relative to the mean sea surface estimated between 1993-2009 with the MSS\_CNES-CLS11 model and contains the geoid estimate (*Picot et al.*, 2018).

Water pixels are isolated in the ATL12 product using the Global Self-consistent, Hierarchical, High-resolution Geography Database buffered up to 20 km to include nearshore areas such as low-lying land surface, although this still excluded some coastal data (*Wessel and Smith*, 1996; *Morison et al.*, 2020a). We perform additional masking by excluding samples that do not fall within the ocean polygons available from the Open Street Map project (*OpenStreetMap Contributors*, 2017). We also excluded data acquired during drag make up operations (*Morison et al.*, 2020b). We experimented with removing data acquired during commanded satellite maneuvers performed over the central Pacific ('ocean scans'), but found removal of these data reduced the amount of data for trend computations and thus their quality.

To assess ATL12 DOT data from the global TG network maintained by the Joint Archive for Sea Level (JASL) and accessible through the University of Hawaii Sea Level Center/Joint Institute for Marine and Atmospheric Research. As data from the Research Quality stream is not available after 2019, we use data from the Fast Delivery stream which has records available for most TGs through Aug 2020 (*Caldwell et al.*, 2015).

We compute residuals using linear rates calculated between ATL12 ocean heights that overlap in space and time with the other data sources. We do not account for seasonality in the trends, as the limited data prohibit robust recovery of the annual cycle. The focus on trends as opposed to point estimates circumvents biases induced by the presence of mean dynamic topography in ATL12, which is removed in the SSHA computation of Jason-3, and local datums used for referencing tide-gauges.

For the radar altimetry products, we consider three separate spatial grids with resolution 0.1°, 0.2°, and 0.5°, respectively. In each grid cell, we produce a time series for each sensor (ATL12, Jason-3) by taking an average of the available data. The ATL12 DOT average is weighted by the inverse of the variance ( $\sigma^2$ ) that is provided with the product. For all altimetry datasets, we exclude outliers that lie outside the 99<sup>th</sup> percentile. Only data that overlap in time between sensors are considered. We then difference the linear rates of the ATL12 DOT computed using weighted least squares with linear rates of the Jason-3 computed using ordinary least squares.

Next, we consider TGs in the JASL Fast delivery stream with records that overlap with the ATL12. Within a 0.1°, 0.25°, and 0.5° square centered on each TG we compute an average of the ATL12 data. We treat data that lie beyond  $\sim$ 1 standard deviation of the median as outliers in each ATL12/TG comparison (*Iglewicz and Hoaglin*, 1993). This additional consideration is motivated by the reduced sample size and enhanced

variability of the TG comparisons in the coastal oceans relative to the global oceans. We experimented with additional treatments of outliers, including more liberal median filters, but found negligible differences on the overall results (not shown). We compute the residual between the linear rate for the ATL12 DOT estimated using general least squares and the ordinary least squares linear rate of the TG data. We discard residuals greater than 100 cm for both TG and Jason-3 comparisons, resulting in 104, 194, and 215 ATL12/TG comparisons for 0.1°, 0.25°, and 0.5°, respectively, and greater than 75,000 for all Jason-3 grid sizes.

## 2.4 RESULTS

Figure 4 shows an overview of the linear rate comparisons between the ATL12 DOT, JASL hourly fast delivery TG records and Jason-3 along-track altimetry retrievals. The violins combine a boxplot and histogram, with the median and quartile ranges as horizontal dashed lines, and the kernel density estimate of the distribution on the vertical axis. The mean and standard error are marked for each violin. The size of the grid has a clear effect on the ATL12/TG residuals. The extremes and standard errors are inversely correlated to grid size, as larger samples of ATL12 DOT mitigate the impact of outliers. Note that any vertical land motion affecting the TG rate calculations is within the noise of the residuals. The effects of gridding are smaller on the ATL12/Jason-3 residuals, as the open-ocean variability is reduced relative to the coastal waters sampled by TGs and sampling sizes are negligibly different.



Figure 4: Violin plots combining boxplots and histograms for ICESat-2 comparisons. The median and quartiles are marked as horizontal dashed lines, and the width of the violin shows the smoothed kernel density estimate. The underlying distributions are of ATL12 residuals between the Joint Archive of Sea Level hourly fast delivery records (blue), and Jason-3 (teal). Mean and standard error are reported for each comparison.

In Figure 5 we present the ATL12 / JASL TG 0.5° comparison spatially to highlight regional performances. The 0.5° comparison performed markedly better than the smaller grid sizes. There is no global bias to the residuals, and we do not find substantial differences at high latitudes due to orbital convergence near the poles, but some coastlines perform markedly better than others. The Atlantic Coastlines show good agreement, with the exception of a few TGs in high latitudes and the Caribbean Islands. The Pacific residuals are more heterogeneous, with good agreement along the East Asian and Western South American Coasts, but poorer comparisons along Western North America and the Tropical Pacific Islands. The residuals along the Indian and East African Coasts are particularly high, indicating errors in one or both of the data sources along these coasts.



Figure 5: Global comparisons of ATL12 DOT rates in a  $0.5^{\circ}$  box centered on hourly tide gauge data acquired from the Joint Archive of Sea Level at the University of Hawaii. Data exceeding  $\sim 1$  standard deviation of the median is discarded in each time series.

However, over the global oceans, there is remarkable agreement between ATL12 DOT and Jason-3 SSHA (Figure 6). Overall, the two data sources have a mean absolute residual of  $3.60 \pm 0.03$  cm yr<sup>-1</sup> with a standard deviation of 5.94 yr<sup>-1</sup>. There are clear basin scale patterns, especially in the equatorial band of the Pacific. Similarly, the Indian Ocean shows excellent agreement, with elevated rates in the central and Northern regions, and negative rates further south. Very similar regional patterns are also visible in both data sources, such as the sea-level fall in the Red Sea, an absence of sea-level change in the Mediterranean Sea, and high rates of rise in the Baltic Sea. A number of localized features are apparent, including the energetic western boundary currents in the North Hemisphere, and the eddy-driven Antarctic Circumpolar Current. Although particularly noisy ICESat-2 tracks appear as roughly N/S streaks in several places (such as the northern coast of Brazil), these typically arise from data outliers in a single orbit and can be isolated and removed with specialized post-processing.



Figure 6: Global sea-level rates in 1° grids computed from ICESat-2 ATL12 (October 2018 - Nov 2020; top) and Jason-3 (October 14, 2018 - Aug 2020; bottom). Individual ATL12 samples are averaged by hour and then subjected to linear least squares fitting. The two data sources have a mean absolute residual of  $3.60 \pm 0.03$  cm yr<sup>-1</sup> with a standard deviation of 5.94 cm yr<sup>-1</sup>.

Nevertheless, there is still considerable noise associated with the ATL12 trend estimates. Figure 7 captures the substantial amount of spatiotemporal variability in 1.0° grid cells along the U.S. East Coast. While this variability contains climate signals that manifest as mm-scale SSH changes, the observed cm-m scale variations are mainly imparted by instantaneous oceanic and atmospheric conditions. This high-frequency variability is largely uncorrelated in the time domain, and thus will decrease as the ICESat-2 time-series lengthens.



Figure 7: Time-latitude diagram of monthly sea level time series along the East Coast of the United States (left) and the locations of the 1.0° grid cells used in the analysis (right).

Figure 9 presents a qualitative estimate of the effects of further ATL12 samples on uncertainty of the estimated trends. Here we consider 0.25°, 0.5°, and 1.0° grid sizes spanning the global oceans. In each grid cell we construct a single time series  $\langle DOT \rangle$  by averaging N ATL12 samples, weighted by the diagonal covariance matrix Q, that fall within the same hour:

$$\langle \mathbf{DOT} \rangle = (\mathbf{A}^{\mathbf{T}} \mathbf{Q}^{-1} \mathbf{A})^{-1} \mathbf{A}^{\mathbf{T}} \mathbf{Q}^{-1} \cdot \mathbf{DOT}$$
(6)

where  $\boldsymbol{A}$  is an  $N \ge 1$  identity matrix. We then average and propagate the covariance estimate of  $\langle DOT \rangle$  using the variance propagation law to result in  $\hat{\boldsymbol{Q}}$ :

$$\hat{\boldsymbol{Q}} = (\boldsymbol{A}^T \boldsymbol{Q}^{-1} \boldsymbol{A})^{-1} + \frac{1}{N} \sum_{i=1}^N \boldsymbol{Q}_{ii}$$
(7)

Next, we generate a 7 year (~Nov 2018 to Nov 2025) synthetic time series  $\widehat{DOT}_s$ and  $Q_s$  by bootstrapping with replacement. The synthetic time series for each 0.25°, 0.5°, and 1.0° grid in the global oceans have an experimentally determined semimonthly, monthly, and bimonthly sampling interval, respectively (Figure 8). Finally, we estimate linear trends for each successive sample in time of  $\widehat{DOT}_s$  weighted by  $Q_s$  (Figure 9).


Figure 8: Violin showing approximately ATL12 samples per month for the global oceans gridded in 0.25°, 0.5°, and 1.0° square cells. Samples acquired within 2 days are treated as a single sample. The dashed lines at 0.5 sample/month, 1 sample/month, and 2 samples/month correspond to the medians of the 0.25°, 0.5°, and 1.0°, respectively, and are accordingly used as the sampling frequency for generating the synthetic series shown in Figure 9.



Figure 9: Uncertainty reduction through time of synthetic ATL12 data in 0.25°, 0.5°, and 1.0° grid cells spanning the globe. Synthetic data is created by bootstrapping the averaged ATL12 DOT and variance within each grid cell and propagating the uncertainty. The heavy lines show the median estimate, and the shading indicates the 95% confidence interval for each grid size.

While not a rigorous accounting, the standard error of the rate estimate improves considerably for all grid sizes. In one sense these are conservative estimates, given that the temporal correlation of the global sea-level trend is not accounted for and will become more apparent as the time series lengthens. However, lower frequency ocean process variability will also further impact the uncertainty estimates as the time series, obfuscating temporal correlations that would otherwise be apparent. Additionally, there are uncertainties in the geophysical corrections such as sea state bias, the calculation of the geoid used to calculate DOT from ocean elevation, and unaccounted for instrumental uncertainties that require elucidation beyond this analysis.

# 2.5 DISCUSSION

Despite having a short time-series relative to TG and radar altimeter records, ICESat-2 derived products have already been shown to be important observations for a variety of scientific purposes. For example, *Klotz et al.* (2020) map individual waves along the ICESat-2 track and infer wave spectra and wind speed. Others have explored wave detection in sea ice (*Horvat et al.*, 2020), inland water monitoring (*Ryan et al.*, 2020; *Yuan et al.*, 2020), and bathymetry detection (*Albright and Glennie*, 2020; *Armon et al.*, 2020).

By demonstrating general agreement between independent data sources (Figure 4), our analysis indicates an important role for ICESat-2 in observing ongoing sea-level change.

Both along coastlines (Figures 5, 7) and in the open ocean (Figure 6), ICESat-2 observations complement existing measurements by filling in the gaps between TGs and altimeter tracks. The large-scale oceanographic patterns seen in Jason-3 are clearly visible in ATL12 products at much higher resolution (Figure 6). For example, the effects of the 2019 La Niña that dominated tropical Pacific sea-level change during the ICESat-2 sensing period (Oct 2018 - Present) are clearly present. The enhanced easterly trade winds and associated circulation led to anomalously high sea-level rates near Indonesia and lower rates in the central and eastern Pacific (Figure 6). Also clearly evident are the high rates of sea-level change in much of the Indian Ocean, arising from the Indian Ocean Dipole event that occurred in late 2019-2020 (*Lu and Ren*, 2020). Mesoscale eddies are well sampled, and ICESat-2 can contribute to investigations of eddy spatial structure (*Chelton et al.*, 2007) and their role in transporting ocean heat and salinity and kinetic energy (e.g., *Dong et al.*, 2014; *Ezer*, 2015).

However, there are still nonnegligible uncertainties in the ICESat-2 measurements (Figure 9). Recent work has sought to improve the estimation of sea-state bias from laser altimetry (*Morison et al.*, 2018), while ongoing research is targeting the substantial uncertainty caused by large waves (*Morison et al.*, 2020b). Additionally, a monthly mean sea-surface product (ATL19) gridded at 0.25° between  $\pm$  60° and at a 25 km projection at the poles will be released in 2021.

Such improvements will further enhance ICESat-2's role in understanding sea-level change. The excellent agreement with the Jason-3 altimeter data highlights the potential for ICESat-2 to contribute to our existing observations of sea level. Particularly important are coastal and polar oceans, where existing altimetry data is degraded and/or absent (Cf. Fig. 5). These historically undersampled regions are important due to the central role of the polar oceans in the climate system(e.g., *Fyke et al.*, 2018) and the socioeconomic impact of sea-level change at the coast (e.g., *Kirezci et al.*, 2020). Moreover, sea-level variability is often greater along the coast than in the open ocean, due primarily to the impact of bathymetry on dynamic processes (e.g., *Hughes et al.*, 2019).

ICESat-2 offers a new observational tool for understanding coastal sea-level propagation and its physical drivers. No individual sensor by itself can provide a complete sampling of the numerous processes at the coast, necessitating a suite of observational tools. This suite will continue to grow due to the commitment by ESA to support Copernicus through 2030, and the upcoming NASA SWOT and NISAR missions. These instruments will continue to advance our understanding of sea level drivers in the coming years and decade. As tidal flooding and event-driven surges continue to impact coastal communities, this is societally relevant information crucial for fostering mitigation and adaptation to ongoing climate change.

#### CHAPTER 3

# 20<sup>th</sup> CENTURY U.S. EAST COAST SEA-LEVEL CHANGE

### 3.1 INTRODUCTION

Unlike  $20^{\text{th}}$  century GMSL rise, which is dominated by the forced trend from greenhouse gas (GHG) combustion, coastal sea-level as measured by TGs or over continental shelf/slope regions mainly reflects local conditions superimposed on regional climate variability (e.g., *Han et al.*, 2017, and references therein). Understanding and predicting coastal sea-level variability is especially important, as it directly affects human and natural ecosystems (*Kirezci et al.*, 2020; *Hamlington et al.*, 2020c). However, this is a challenging task because coastal sea level consists of both dynamic circulation and static solid Earth processes at a large range of spatial scales superimposed upon GMSL (e.g. *Wunsch*, 1972; Fig. 10). Disentangling the remote (distance scales of tens to thousands of kilometers) from local (distance scales of kilometers or less) influences, and the wind from buoyancy-driven components that manifest in coastal TGs is thus a necessary step in fostering coastal resiliency.

This Chapter begins with a review that provides an overview of the current knowledge of such processes, focusing on the western North Atlantic which is relatively well-observed and of vast societal importance. While the focus is primarily on interannual (1-10 years) and mesoscales (~200 km), this section begins with a summary of processes acting on faster time-scales and how local impacts of the continental shelf and coastal ocean dynamics cause differences in coastal and open-ocean sea level. Next, spatially coherent coastal sea level is discussed as a result of large scale (>1000 km to basin-wide) processes including the Atlantic Meridional Overturning Circulation (AMOC), wind-stress, and the NAO. Finally, the review turns specifically to studies of East Coast sea-level change and highlights recent budgeting efforts that combine knowledge of the processes contributing to sea-level with direct observations from TGs and/or satellite altimeters.

Following the review, Chapter 3 proceeds by answering Research Question 2:

What are the relative contributions of GIA and mass redistribution between land and ocean to 20<sup>th</sup> century sea-level change along the U.S. East Coast?

The modeling approach is detailed and results are presented. A qualitative sensitivity analysis is conducted to support interpretation of the results. The chapter concludes with a discussion of avenues for further inquiry, and implications of the improved understanding for East Coast sea level-projections.



Figure 10: Depiction of some of the many processes affecting coastal sea-level variability and their associated spatiotemporal scales (source: *Woodworth et al.*, 2019)).

### 3.2 BACKGROUND

### 3.2.1 LOCAL PROCESSES

Figure 10 illustrates some of the processes and the spatiotemporal scales at which they affect coastal sea level. On sub-daily timescales, diurnal and/or semi-diurnal astronomical tides are the primary cause of variability in coastal sea level. When the natural frequency of the continental shelf is proportional to the entering tide, tidal resonance occurs which can drastically increase the tidal range, as seen in the Bay of Fundy and Cook Inlet, Alaska (e.g., Gill, 1982; Platzman, 1991; Oey et al., 2007). Storm surge associated with tropical or extra-tropical cyclones also operate on these time scales which can interact with tides to produce extreme coastal sea-level events (e.g., Thompson et al., 2013; Ezer and Atkinson, 2014; Gregory et al., 2019). Superimposed on tides and surges are ocean wind waves, a combination of short-period ( $\sim 1-10$  s), locally sourced energy, and long-period swell ( $\sim 1-25$  s; *LeBlond and Mysak*, 1978). Such wind waves contribute to both high and low frequency sea-level variability, affecting water levels in the near-term and influencing VLM through sediment-transport in the longer-term (Woodworth et al., 2019). When energy from wind or open-ocean forcing (including waves and tides) enters a partially or fully enclosed basin or structure, such as a lake or harbor, oscillations called seiches can occur (e.g., *Forel*, 1876; *Rabinovich*, 2010). Similar to tidal resonance, when the frequency of the oscillation is proportional the natural frequency of the structure, resonance occurs

which can greatly amplify the sea level of the water body.

Additional processes worth noting that particularly affect coastal TGs (but are not restricted to the coastal ocean) are the polar and nodal tides and the 'inverse barometer' effect. At a period of ~ 14 months, ocean and atmospheric circulation excite fluctuations in the position of Earth's rotation axis known as the Chandler Wobble (*Chandler*, 1891; *Gross*, 2000). The Wobble causes the spatially variable pole tide that manifests in TGs measurements at amplitudes up to ~10 mm (*Wahr*, 1985; *Desai*, 2002). On decadal timescales, variability in the Moon's orbital path around Earth causes the 18.61 year lunar nodal tide, which has recently been shown to cause spatially variable fluctuations up to ~ 30 cm in TG measurements (*Kaye and Stuckey*, 1973; *Haigh et al.*, 2011; *Peng et al.*, 2019). The inverse barometer effect is caused by variability in sea surface pressure that causes ~ 1 cm increase in sea level for a 1 mbar drop in air pressure (see *Roden and Rossby*, 1999, and references therein). As storm surges are driven by low-pressure zones, the inverse barometer effect can further amplify the surge in sea level experienced at the coast (*Ponte*, 2006).

Winds associated with local air-pressure gradients impart a force to the sea surface proportional to the square of the wind speed, affecting sea level on hourly to interannual time-scales (Pugh and Woodworth, 2014). On interannual time-scales, coherence in sea level has been demonstrated in TGs located North and South of Cape Hatteras (*Thompson*, 1986) as well as regionally in the southeast Atlantic, mid-Atlantic Bight, and the Gulf of Maine (Maul and Hanson, 1991; Kopp, 2013; Woodworth et al., 2014). Modeling results implicate local along-shelf wind-stress as the primary forcing of this coherence (Woodworth et al., 2014). Particularly north of the wide shelf of the mid-Atlantic Bight (which induces additional dynamics, discussed shortly) observations show significant anti-correlation between along-shore wind-stress and coastal sea level (Andres et al., 2013). Using a barotropic ocean model, *Piecuch et al.* (2016) also find local wind-stress variability forcing causing interannual sea level change. Indeed, they find a proportionality constant of -1  $m^3 N^{-1}$  following Sandstrom (1980) that agrees well with the findings of Andres et al. (2013). Moreover, variability in the winds themselves drives Ekman pumping (the vertical convergence/divergence of the water column, which in turn generates coastal trapped waves (CTWs).

Coastal sea levels differ from nearby open ocean sea level due primarily to topographic and bathymetric influences on dynamical processes (*Huthnance*, 1978). For example, sea level at the coast is partly homogenized by the presence of CTWs. In the northern hemisphere, CTWs propagate cyclonically and thus equatorward along the continental slope (off eastern North America), and are 'trapped' in the coastal ocean by the bottom topography. Such CTWs occur as Kelvin or topographic-Rossby waves, depending on the restoring force as gravity or bathymetry (and thus potential vorticity, see Eq. 14), respectively (*Huthnance*, 1978). In turn, the behavior of a CTW is fundamentally dependent on the geometry of the coastal environment which determines the stratification of the shelf slope, approximately equal to the Burger number:

$$S \equiv \frac{N^2 H^2}{f^2 L^2} \approx \frac{L_d^2}{L^2} \tag{8}$$

$$N^2 = -\frac{g}{\rho_0} \frac{d\rho}{dz} \tag{9}$$

where  $L_d$  is the Rossby radius of deformation, L is the cross-shelf scale of the bathymetry, z is the vertical coordinate (positive upward), g is gravitational acceleration,  $\rho(z)$  is the background potential density and  $\rho_0$  is the reference density (*Hughes et al.*, 2019, e.g.,). When  $S \gg 1$ , the CTW behaves as a baroclinic Kelvin wave with phase speed  $\mathcal{O}(1 \text{ m s}^{-1})$  and a width-scale that decays exponentially in the across-shelf direction. At the other limit of very low stratification ( $S \ll 1$ ) CTWs behave as barotropic topographic Rossby-wave  $\mathcal{O}(10 \text{ m s}^{-1})$  which display a peak over the shelf break. Note that in the real ocean, varying stratification induces CTWs that display behavior between these two extremes. At these speeds, coastal sea-level variability can be transmitted rapidly ( $\mathcal{O}$ days) in the along-shore direction (e.g., *Csanady*, 1978; *Woodworth et al.*, 2012; *Hughes et al.*, 2018)

However, friction damps and spreads the energy transmitted by CTWs on time-scales of days and longer (e.g., *Brink*, 1982). The loss to friction is proportional to the current strength and water-column depth, and results in a decay time-scale of ~ 4 days over a distance of hundreds to thousands of kilometers for long wavelengths (see *Hughes et al.*, 2019). In the across-shelf direction, the transfer of energy can understood using the 'Arrested Topographic Wave Model' (*Csanady*, 1978):

$$\frac{\partial \eta}{\partial y} = -\frac{r}{fs} \frac{\partial^2 \eta}{\partial x^2} \tag{10}$$

where  $\eta$  is the height of the free surface, r is the frictional drag coefficient, f is the coriolis parameter and s is the slope of the continental shelf. This idealized model thus shows that friction diffuses sea-level variability over the continental shelf, homogenizing the signal as it approaches the coast. Moreover, the prominent mesoscale variability of the eddy-filled open ocean is to first order unable to generate the necessary (vertical) velocity required to cross the continental slope due to a vorticity constraint (*Huthnance*, 2004; *Hughes et al.*, 2018). The reduction of variability from open-ocean to coast is well supported by modeling studies (*Zhai et al.*, 2010; *Bingham and Hughes*, 2012; *Hughes et al.*, 2018) and spectral comparisons between altimetric and TG measurements (*Hughes and Williams*, 2010), especially in areas with a wide continental shelf such as the mid-Atlantic Bight (*Higginson et al.*, 2015).

The decoupling of open-ocean mesoscale variability from coastal sea level in the presence

of CTWs implies large-scale (> 1000 km) coherence in along-coast, inverse-barometer corrected sea level (e.g., *Csanady*, 1982; *Thompson*, 1986). *Hughes and Meredith* (2006) showed such correlations globally along continental slopes from satellite altimetry data with no time-lag implicating the barotropic Kelvin mode-0 wave traveling at ~ 200 m s<sup>-1</sup>. High spatial resolution numerical models also highlight the importance of the barotropic topographic-Rossby mode in the North Atlantic, in that the calculated CTW speed is substantially faster than the (internal) Kelvin wave speed in the basin (*Roussenov et al.*, 2008; *Hughes et al.*, 2018). As noted above, mesoscale open-ocean variability is essentially filtered out upon encountering the continental slope and friction dissipates variability generated on the shelf; therefore, the CTW are primarily excited by synoptic scale energies arriving via Rossby waves (*Minobe et al.*, 2017). In turn, low frequency variability recorded by TGs primarily reflect the variability of the large scale processes acting on the North Atlantic (*Huthnance*, 1987, 2004).

## 3.2.2 REGIONAL PROCESSES

On inter-annual to multi-decadal timescales, the regional patterns of sea-level variability are primarily forced by heat and fresh water exchange at the air/sea interface and changes in the wind-driven circulation of the subtropical gyre (*Cazenave et al.*, 2018). Changes in the temperature and salt content at the ocean surface control the seawater density and the resulting buoyancy flux which largely drives the Atlantic Meridional Overturning Circulation (AMOC) (*Little et al.*, 2019) and affects coastal sea level via geostrophy (*Montgomery*, 1941). Simultaneously, changes in regional patterns of openocean atmospheric surface pressure associated with the North Annual Mode (NAM) and its lower-latitude expression the NAO affect coastal sea level through propagation of planetary waves and static effects. Together the AMOC and such remote wind forcing provide mechanisms for the large-scale (>1000 km) coherency in sea-level variability along sections of the U.S. Atlantic and Gulf coasts (e.g., *Häkkinen*, 2000; *Hughes and Meredith*, 2006; *Thompson and Mitchum*, 2014).

The AMOC refers to the aggregated currents of the Atlantic Ocean which transport relatively warm waters in the upper ~ 1000 m northward from the equator via the Gulf Stream (GS), where they cool and sink via convection at North Atlantic Deep Water (NADW) formation sites, and subsequently return southward below the upper flow (e.g., *Bower et al.*, 2019, and reference therein). Transporting over 1 petawatt of heat poleward, the AMOC is a key component of the Earth's climate system (*Trenberth and Caron*, 2001; *Trenberth and Fasullo*, 2017). The AMOC can be modeled as the maximum of the zonally and vertically integrated overturning streamfunction ( $\psi$ ):

$$\psi(y,z,t) = \int_{-z}^{0} \int_{x_{east}(y,z)}^{x_{west}(y,z)} v(x,y,z,t) \, dx \, dz \tag{11}$$

where v is the meridional velocity, x, y, z are spatial coordinates of longitude, latitude, and depth, respectively and  $x_{east(y,z)}$ ,  $x_{west(y,z)}$  are the eastern and western boundaries (*Cunningham and Marsh*, 2010). As this model requires measurements that span the North Atlantic basin both horizontally and vertically (*Bower et al.*, 2019), it is a challenging task to accomplish. Nevertheless, the RAPID/MOCHA/WBTS (hereafter RAPID) array of instruments, which crosses the North Atlantic basin at 26.5°N, has been continuously measuring the AMOC since 2004 and encompasses the Florida Strait, where transport has been calculated from subsurface cable measurements since 1982 (*Baringer and Larsen*, 2001). More recently, the OSNAP array of moorings was established across the subpolar North Atlantic in 2014 to quantify the subpolar AMOC and its variability (*Lozier et al.*, 2017). Despite the short record, these measurements are revolutionizing our understanding of AMOC variability, indicating it is largely wind-forced, rather than reflective of buoyancy changes affecting NADW formation in the Labrador Sea (*Lozier et al.*, 2019). A more in-depth treatment of the drivers of AMOC variability is outside the scope of this review; instead the focus here is on the coherence of AMOC and sea-level variability.

A theoretical diagnostic relationship between the AMOC and coastal sea level is derived from the zonal momentum equation as:

$$H_w = -\frac{Q}{\rho_0} \frac{f}{gH_e} \tag{12}$$

In midlatitudes with  $f \approx 10^{-4} s^{-1}$ , this scaling leads to an increases in coastal sea level  $(H_w)$  of ~ 1.5 cm for ~ 1 Sv decreases in transport  $(Q/\rho_0)$  and is inversely proportional to the layer thickness used to calculate the depth-integrated pressure (proportional to sea level,  $H_e$ ; Little et al., 2019). This relationship has been investigated with numerical models in the context of the predicted slow-down of the AMOC in coming decades due to reduced NADW formation stemming from anthropogenic warming (e.g. *Ezer*, 2001; Yin et al., 2009). While studies focusing on the region north of Cape Hatteras show good agreement with the scaling factor from Eq. 12 (e.g., *Bingham and Hughes*, 2009; Woodworth et al., 2014; Little et al., 2017), there are large deviations from it within a large (25 member) ensemble of Coupled Model Intercomparison Project 5 (CMIP-5) solutions (Little et al., 2019). In addition to the differences in dynamics north and south of Cape Hatteras where the Gulf Stream (GS) separates from the coast, *Little et al.* (2019) also highlights a possible dependence on the time-period analyzed. This agrees with the results of *Lorbacher et al.* (2010) who showed that high-frequency, wind-driven variability superimposed on the AMOC can mask changes in meridionally-coherent coastal SLR driven by a gradual ( $\sim 1 \text{ Sv/decade}$ ) slowdown.

An alternative approach is to consider separately the variability of the upper (>~1000 m) components of the AMOC: the Florida Current (Gulf Stream), mid-ocean transport, and Ekman transport (e.g., *Blaha*, 1984; *McCarthy et al.*, 2012; *Piecuch et al.*, 2019b).

The Florida Current (the headwaters of the Gulf Stream) transport is measured via the voltage induced by the charged sea-water in submerged telephone line (*Baringer and Larsen*, 2001). Variability in the Florida Current has been shown to be significantly correlated with sea level in TG south of Cape Hatteras (e.g., *Blaha*, 1984; *Park and Sweet*, 2015; *McCarthy et al.*, 2015). Additional results from an innovative Empirical Mode Decomposition (EMD) approach suggest that the Gulf Stream influences interannual and longer-term variability along the entire Atlantic coast (*Ezer et al.*, 2013; *Ezer and Atkinson*, 2017). The principle of geostrophy is invoked to explain these correlations, but the bottom pressure (a measure of total RSL) of the Gulf Stream is also affected by the open-ocean component of the AMOC.

The mid-ocean meridional transport is calculated from vertical density profiles measured by a series of moorings between the Bahamas and Africa to quantify the transport of the southward-flowing upper recirculation of the AMOC. In the winter of 2009-2010 the AMOC experienced ~ 30% reduction in strength due largely to a weakening of this mid-ocean meridional transport (*McCarthy et al.*, 2012; *Caesar et al.*, 2018). Observations from U.S. Atlantic coast TGs show an unprecendented sea level increase over the same period (*Goddard et al.*, 2015), lending support to an AMOC driver of the 'sea-level rise hot spot' in the Mid-atlantic (*Sallenger et al.*, 2012; *Kopp*, 2013). However, ageostrophic wind-stress forcing is also complicit in the observed slowdown (*McCarthy et al.*, 2012).

Ekman transport contributes to the AMOC in the western boundary current via coriolis acting on zonal tradewinds to produce a net northward transport. While this is the typically the smallest component of the transport (~ 3 Sv), it is causes the most subannual variability (*Baringer and Larsen*, 2001). However, *Goddard et al.* (2015) found that the Ekman component can contribute substantially to elevated sea level as in the mid-Alantic during 2009-2010. In some regions, such as along the New England coast, even inter-annual variability is largely due to the Ekman component of the AMOC rather than changes in Gulf Stream or upper mid-ocean transport (*Piecuch et al.*, 2019c). Moroever, the large-scale pressure patterns driving the open-ocean wind anomalies and resulting Ekman transport through the Florida Straits are intricately tied to the subtropical gyre system.

The effect of such open-ocean wind stress  $(\tau)$  on coastal sea-levels (SLs) is reflected by the Sverdrup relation, which relates the curl of the wind-stress forcing  $(\tau)$  to the meridional transport (V):

$$V = \frac{1}{\beta \rho_0} \hat{\boldsymbol{k}} \, \nabla \times \boldsymbol{\tau} \tag{13}$$

where  $\beta$  is rate of change of the coriolis factor,  $\rho_0$  is the reference sea water density, and k is the vertical unit vector (*Sverdrup*, 1947). In an idealized model,  $\hat{k} \nabla \times \tau$  causes the flow to converge in the center of a subtropical gyre which drives downwelling known as 'Ekman pumping'. With no mechanism to change the relative vorticity  $\zeta$  of the compressed fluid

columns, conservation of potential vorticity (PV) demands the fluid moves southward such that the decreasing fluid height (h) is balanced by decreasing planetary vorticity (f):

$$\frac{D}{Dt}(PV) = \frac{D}{Dt}\left(\frac{\zeta + f}{h}\right) = 0 \tag{14}$$

where D/Dt is the material derivative. To maintain conservation of volume, the net southward transport over a zonal range is balanced by return flow in the western boundary current, which as described previously affects coastal sea level.

In that multidecadal time scales are needed for the gyre circulation and wind-forcing of the Sverdrup balance to equilibrate, it is difficult to observe in-phase relationships between the current records of coastal sea level and open-ocean winds (e.g., *Thompson*, 1986). Alternatively, Sturges and Hong (1995) constructed a time-dependent quasi-geostrophic wave model to drive Rossby waves with open ocean wind-stress curl. These Rossby waves manifest as changes in the depth of the thermocline, which explained much of the decadal sea-level variability in Bermuda. They therefore extended the analysis to Atlantic coast sea level by using the same model to calculate zonal transport anomalies into the Gulf Stream which affect the meridional flow speed and resulting geostrophic tilt across the current, finding this relation explained 80 - 90% of the variability south of Cape Hatteras. These results were corroborated by Ezer (1999) with a more sophisticated three-dimensional numerical model, which additionally provided insight into a possible latitudinal dependency of the dominant forcing (i.e., SST may be more important at latitudes north of Cape Hatteras). Indeed, the Rossby mechanism has been implicated in the sea-level 'hot spot' of the mid-Atlantic bight and common decadal mode along the entire Atlantic coast of the North American continent (Ezer et al., 2013; Thompson and Mitchum, 2014). More specifically, Thompson and Mitchum (2014) showed that a net volume transport into the Western Boundary Current (WBC) from the interior ocean directly increases sea level via vertical divergence, rather than affecting the geostrophic tilt of the current (which would cause anti-correlation across Cape Hatteras where the Gulf Stream breaks from the coast).

The large-scale wind fields that drive the North Atlantic WBC are related to the dominant pressure patterns over the basin, such as the NAO, which is particularly relevant for understanding coastal sea level (e.g., *Hurrell*, 1995; *Thompson and Wallace*, 1998; *Han et al.*, 2019). To first order, the NAO index reflects variability in the strength of the permanent low pressure systems over Iceland relative to the strength of the permanent high pressure system of the Azores archipelago near Portugal (*Hurrell*, 1995). Anomalously high sea-level pressure (SLP) over the Azores system occurring with a anomalously low SLP over the Icelandic 'center of action' denotes a positively-phased NAO. Together, these pressure systems impact sea level through fluctuations in the strength and position of the prevailing surface westerly winds over the North Atlantic Ocean (between  $\sim 30^{\circ}$ -60°) N.

The satellite altimetry record reveals broadscale coherence of interannual sea level with the NAO, exhibiting a banded dipole structure with positive correlations south of Cape Hatteras that stretch northeast, separated from the region of negative correlation by the Gulf Stream extension. While long TG records along the coast reflect the regional differences in internnaual variability across Cape Hatteras (Valle-Levinson et al., 2017), the variability is not correlated with NAO. However, strong correlations are shown to exist during different periods of the record that highlight the nonstationarity of the NAO, with a possible regime shift occuring in the mid-1980s (Woolf et al., 2003; Andres et al., 2013; Woodworth et al., 2017; Kenigson et al., 2018; Piecuch et al., 2019b). While these studies point to the influence of the NAO on coastal sea level via local winds, others point to remote effects on the AMOC (e.g. *McCarthy et al.*, 2015; *Ezer*, 2015). A series of studies show that the NAO modifies the buoyancy forcing in the subpolar gyre, affecting the AMOC through the through a reduction of southward flowing NADW which in turn affects coastal sea level via geostrophy (Häkkinen, 2000, 2001; Häkkinen and Rhines, 2004; Delworth et al., 2016). Goddard et al. (2015) presents evidence that remote winds associated with the extreme winter 2010/2011 NAO event forced on-shore volume transport that combined with reduced NADW formation to cause the mid-Atlantic Bight sea-level rise hostpot. The NAO thus reflects a variety of interrelated processes that make attributing dynamical causes of coastal sea-level change nontrivial. Indeed, the NAO is not a unique dynamic mode of the North Atlantic climate due to bias and constraints of the EOF method utilized for analysis (e.g., Monahan et al., 2009; Barrier et al., 2013; Valle-Levinson et al., 2017), and is coupled to the underlying ocean in complex ways (e.g., Häkkinen, 2000; Bryden et al., 2014).

# 3.2.3 REGIONAL RSL BUDGETS

The complexity arising from the interactions of these many dynamic processes in the coastal zone makes constraining the individual contribution of sea-level change an ongoing challenge. Budgeting studies, as introduced in Section 2.2, are a powerful method for combining observations of sea level with knowledge of the contributing processes. However, regional budgets are considerably more difficult to constrain due to the spatially variable nature of the VLM and barystatic processes (*Hamlington et al.*, 2020c). Nevertheless, several recent studies have substantially advanced the state of knowledge by calculating the sea-level budget in the North Atlantic.

In particular *Frederikse et al.* (2016, 2017b) have made significant progress towards quantifying the budget along the Northwestern European Coast and the U.S. Northeast Coast, respectively, over the period ~ 1950-2015. They solve the elastic sea-level equation (*Farrell and Clark*, 1976) for each mass component to account for the barystatic contribution to RSL in each region. GNSS stations are leveraged to quantify VLM,

with an important adjustment to remove the nonlinear solid-Earth deformation (SED) due to contemporary ice-melt (and associated gravitational, rotation, and deformation effects) from the estimation of the long-term trend (*Frederikse et al.*, 2019). The resulting combination of mass and SD changes robustly accounts for the interannual and decadal variability, as well as the trends observed in the TG data.

To expand the budget comparison in space and time along the U.S. East Coast *Piecuch* et al. (2018) developed a formal hierarchical dynamical Bayesian spatiotemporal model (*Cressie and Wikle*, 2015). They model annual  $RSL(\boldsymbol{y})$  as a spatially varying vector of linear trends superimposed on an autoregressive (AR)(1) process. The RSL linear trend field ( $\boldsymbol{b}$ ) is subdivided into SSH and VLM contributions, both of which have a GIA and non-GIA sub-component. Noisy, biased, and gappy observational data from TGs, GNSS stations and RSL index points (*Engelhart and Horton*, 2012), as well as VLM estimates from ice-sheet models are used to constrain the latent RSL process and associated parameters. The joint probability of the RSL process, conditional on the data and parameters, is then inverted using Bayes' Rule:

$$p(\boldsymbol{y}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{\Theta} | \boldsymbol{x}, \boldsymbol{z}, \boldsymbol{Z}, \boldsymbol{S}) \propto p(\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{Z}, \boldsymbol{S} | \boldsymbol{y}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{\Theta}) \times p(\boldsymbol{y}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{\Theta})$$
 (15)

where p is the probability density function,  $\propto$  is proportional to, and | is conditional upon. Therefore, the probability density of the latent RSL process  $\boldsymbol{y}$  and parameters vector  $\boldsymbol{\Theta}$ , conditioned on the imperfect VLM and RSL data vectors ( $\boldsymbol{x}, \boldsymbol{z}$ , respectively), is proportional to the probability of the data vectors given the RSL process and parameters times the prior probability densities. The prior distributions of the parameters and processes are assigned using *apriori* estimates that capture uncertainties in the current state of knowledge.

Leveraging the Metropolis Hasting's algorithm in a Monte-Carlo approach, *Piecuch* et al. (2018) find that RSL is rising fastest in North Carolina or Virginia ( $4.5 \pm 0.7 \text{ mm}$ yr<sup>-1</sup>), coinciding with the highest rate of regional subsidence (averaging  $-1.4 \pm 0.4 \text{ mm}$ yr<sup>-1</sup>). They reveal that the spatial variability of RSL is primarily due to GIA-driven VLM (Fig. 11.)



Figure 11: Geophysical process contributions to relative sea level trends along the East Coast of the U.S. The median estimates are shown as vertical black lines within color shading indicating the quartile range. The extended whiskers mark the 95% credible intervals. A positive (negative) percent variance explained corresponds to a reduction (enhancement) of the spatial variability in the relative sea-level trend field (source: *Piecuch et al.*, 2018)).

Importantly, accounting for the large-scale effects of GIA on RSL change constrains the residual process contributions. However, the residual processes in the non-GIA SSH trend field contains both SD and barystatic contributions that cannot be separated in this analysis. Additionally, the non-GIA VLM rate residual does not account for SED effects due to  $20^{\text{th}}$  century ice-melt. Their linear trend assumption is then likely violated by the non-linear acceleration of SED due to increasing ice-melt rates (*Rignot et al.*, 2011; *Frederikse et al.*, 2017a).

*Frederikse et al.* (2020) have recently attempted to address these shortcomings by including estimates of barystatic sea-level fingerprints in a probabilistic budgeting recon-

struction. In addition to quantifying the global budget (see Section 2.2.1), they also focus their analysis on 6 ocean basins defined using the clustering approach of *Thompson and Merrifield* (2014). They limit the temporal range of their regional study from 1950 to present, in order to use existing *in-situ* salinity estimates in their calculation of SD sea-level change. By perturbing the best estimates of each geophysical process contributing to sea level, *Frederikse et al.* (2020) close the budget within each ocean basin. This demonstrates a robust understanding of  $20^{\text{th}}$  sea-level change by the scientific community.

### 3.2.4 RESEARCH QUESTION 2

However, the regional estimates of *Frederikse et al.* (2020) doesn't fully address coastal sea-level variability, as the tide gauge trends along the coast are averaged with the 'virtual station' methodology to produce a single basin mean estimate (*Jevrejeva et al.*, 2006). Moreover, their statistical methodology leverages a simple perturbation and sampling approach, rather than a Bayesian inversion, in which uncertainties on distributions of parameters are considered as well as the parameters themselves (*Gelman et al.*, 2013).

In the following, the strengths of the approaches of *Frederikse et al.* (2020) and *Piecuch* et al. (2018) are combined to overcome the identified shortcomings and answer:

What are the relative contributions of GIA and mass redistribution between land and ocean to 20<sup>th</sup>-century sea-level change along the East Coast of the United States?

To accomplish this, the Bayesian space-time hierarchical model of U.S. East Coast RSL developed by *Piecuch et al.* (2018) is expanded to incorporate recent estimates of the barystatic contributions to 20<sup>th</sup> century sea-level change. These improvements enable quantification of the barystatic contribution to the non-GIA and non-SSH trend fields. Additionally, this sheds light on the sterodynamic (SD) component RSL change, as all terms in Equation 1 are accounted for (neglecting the inverted-barometer effect, an appropriate assumption on multi-decadal timescales).

This chapter proceeds by detailing the model assumptions and setup, with particular attention paid to the specific expansions of the previously published framework (*Piecuch et al.*, 2018). The data sources used to constrain the process model and parameters are described, as well as the assumptions made in modeling the prior distributions. Next, results from the expanded model are presented and further analyzed to provide insights into East Coast sea-level trends and variability. In the discussion, I identify challenges to the modeling interpretation and propose avenues for future research. I then contemplate the results in relation to projections of future sea-level rise on the East Coast of the United States.

#### 3.3 DATA

The U.S. East Coast is likely the best sampled open-ocean coastline in the world, with a multitude of data available for calculating the coastal sea-level budget. This is a primary motivating factor of a Bayesian approach, which is capable of ingesting these diverse datasets and robustly integrating their respective uncertainties. To model RSL on the East Coast, I leverage, where possible, the datasets previously used in *Piecuch et al.* (2018, see Fig. 12 for locations). These consist of annual RSL observations from 53 TGs obtained from the PSMSL (*Holgate et al.*, 2013; *Permanent Service for Mean Sea Level (PSMSL)*, 2021). Aside from several exceptions in Florida, the included TG records have greater than 25 years of data and 3,248 gauge-years of data between 1900-2017. Three TGs from the southeastern Gulf of Mexico, and three TGs from southwestern Atlantic Canada are included to better resolve the domain boundaries.



Figure 12: Locations of observations included in the Bayesian inference. Blue triangles indicate tide gauges, red inverted triangles show GPS stations, salt marshes are shown as yellow crosses and gray boxes mark the 93 regular  $0.5^{\circ} \ge 0.5^{\circ}$  grid cells.

VLM estimates are obtained for 42 Global Positioning System (GPS) stations on the

US East Coast from the Université de La Rochelle. The 6a data product provides vertical velocities aligned to the 2008 realization of the international terrestrial reference frame (*Altamimi et al.*, 2011) and associated standard errors that account for time-correlated noise (*Santamaria-Gomez et al.*, 2016). The stations have 3–19 years of observations that span 1995–2014 with more than 70% completeness (*Piecuch et al.*, 2018, Supplementary Table 2).

In addition to constraining VLM with GPS data, model estimates for the ongoing GIA to the last glacial maximum are used. More specifically, the output of 216 model runs varied by lithospheric thickness (72 km, 100 km and 125 km), upper-mantle viscosity  $(0.3 \times 10^{21}, \text{ Pa s}, 0.5 \times 10^{21} \text{ Pa s}, 0.8 \times 10^{21} \text{ Pa s}, \text{ and } 1.0 \times 10^{21} \text{ Pa s})$ , lower-mantle viscosity ( $2 \times 10^{21}$  Pa s,  $3 \times 10^{21}$  Pa s,  $5 \times 10^{21}$  Pa s,  $8 \times 10^{21}$  Pa s,  $10 \times 10^{21}$  Pa s and  $20 \times 10^{21}$  Pa s), and ice history (ICE-5G19, ICE-6G20 and ANU21) are used as in *Piecuch et al.* (2018) and described in *Hay et al.* (2015). For sensitivity testing, I also leverage the displacement fields in three additional GIA models: ICE-5G (*Peltier*, 2004), ICE-6G (*Peltier et al.*, 2018), and that of *Caron et al.* (2018).

Proxy RSL reconstructions from radiocarbon-dated saltmarshes are further used to constrain the GIA contribution to East Coast RSL change. That is, due to negligible ice-mass loss and tectonic activity along the U.S. East Coast over 2,000 to 220 years before present GIA was the dominant contributor to RSL trends and can be approximated as a linear trend (*Engelhart et al.*, 2009). Therefore 164 RSL index points from 23 salt marshes are utilized which contain the calibrated age and elevation respective to the midpoints of its range (*Engelhart and Horton*, 2012; *Kemp et al.*, 2014; *Piecuch et al.*, 2018, Supplementary Table 3). Errors associated with the elevation range estimation, radiocarbon dating, and core collection are captured in the provided uncertainties. Only data at sites with at least three index points with median ages 2000-220 years before present are considered in order to minimize nonlinear anthropogenic impacts on RSL change.

As input data for  $20^{\text{th}}$  century mass loss components of sea-level change, I use the result of *Frederikse et al.* (2020) that assimilates a number of available data sources in an ensemble approach. Their approach adopts a Monte Carlo approach to generate 5,000 realizations of observed sea level and its contributing processes. Specifically, this results in global-mean and basin-mean sea level time-series and their processes with all known error sources propagated. Full details can be found in *Frederikse et al.* (2020); here I describe the barystatic datasets which informed the resulting ensembles.

Land-ice melt from Antarctica, primarily from the West Antarctic Ice-Sheet, is assumed to be  $0.05 \pm 0.04 \text{ mm yr}^{-1}$  prior to 1993 (*Adhikari et al.*, 2018). After 1993, satellite altimeter measurements inform surface mass balance models that better constrain the estimate (*Bamber et al.*, 2018; *IMBIE Team*, 2018). To constrain Greenland Ice Sheet mass change, three methods are used: mass-balance approaches that span 1900-2003 (*Kjeldsen*) et al., 2015) and 1972-2003 (Mouginot et al., 2019), and a synthesis of modeling approaches altimetry measurements over 1993-2003 (Bamber et al., 2018). Estimates of glacier mass loss are based on a global glacier model which covers the 20<sup>th</sup> century (Marzeion et al., 2015) and in situ observations since 1961 (Zemp et al., 2019). Missing and/or disappeared glaciers are constrained using the estimates from (Parkes and Marzeion, 2018).

The contribution of TWS over the  $20^{\text{th}}$  century is separated into natural processes associated primarily with large scale climate modes such as ENSO, and anthropogenic dam building and groundwater extraction. The former are represented using the model of *Humphrey and Gudmundsson* (2019). Water impoundment information is derived from a recently updated accounting of global artificial reservoirs (*Chao et al.*, 2008) and the ICOLDS dam database (*Lehner et al.*, 2011). Groundwater extraction information is drawn from *Wada et al.* (2012) and *Wada et al.* (2017), and accounts for the fact that not all extracted groundwater is added to the ocean.

For each of the 5000 realizations, *Frederikse et al.* (2020) solve the sea-level equation (*Farrell and Clark*, 1976) to calculate the geographic location and magnitude of sea-level change associated with these mass source changes. They assume land-mass changes cause an elastic solid-Earth response and express the resulting deformation and geoid changes relative to the center-of-mass reference frame (*Milne and Mitrovica*, 1998). In addition to the locations of the RSL and VLM data, barystatic footprints and GIA model solutions are sampled at 93 regularly spaced  $0.5^{\circ} \times 0.5^{\circ}$  grid cells (gray squares in Fig. 12). Thus in total, the Bayesian inversion estimates a solution at 211 total locations (Fig. 12).

#### 3.4 METHODS

As detailed in *Piecuch et al.* (2017a, 2018), the Bayesian hierarchical spatiotemporal model is composed of process, data, and prior levels. The core principle of the approach is Bayes' Rule, which allows us to represent uncertain observations in the data layer as conditional on the latent (hidden) geophysical processes modeled in the process layer. This results in a joint statistical model composed of a series of simpler conditional probability statements that is inverted using Bayes' Rule to infer the unknown state of the physical process and the governing parameters (see *Gelman et al.*, 2013). In statistical terminology, this is understood as a discrete time, continuous state hidden Markov model (e.g., *Wikle and Berliner*, 2007; *Tingley and Huybers*, 2010)

# 3.4.1 PROCESS LEVEL

Following *Piecuch et al.* (2018) the latent RSL process  $(\boldsymbol{y}_k)$  is modeled simply as a spatially varying vector of linear trends  $(\boldsymbol{b})$  superimposed on the autoregressive (AR) process:

$$\boldsymbol{y}_k = r(\boldsymbol{y}_{k-1} - \boldsymbol{b}t_{k-1}) + \boldsymbol{b}t_k + \boldsymbol{e}_k$$
(16)

with  $t_k$  the time at step k, AR(1) coefficient r, and innovation sequence  $e_k$ . Thus,  $y_k = [y_{1,k}, \ldots, y_{N,k}]$  is the spatiotemporal field of RSL at time steps  $k \in [1, \ldots, K]$  and locations  $n \in [1, \ldots, N]$ . An AR(1) model has been shown to be appropriate for detrended annual and longer sea-level changes by *Bos et al.* (2013). Time steps are centered on zero, and the temporal innovations  $e_k$  are modeled as a zero-mean independent and identically distributed (IID) spatially-correlated vector:

$$\boldsymbol{e}_k \sim \boldsymbol{\mathcal{N}}(\boldsymbol{0}_N, \boldsymbol{\Sigma})$$
 (17)

where  $\mathcal{N}$  is the multivariate normal distribution with a mean vector of 0s and spatial covariance matrix  $\Sigma$ .  $\Sigma$  decays exponentially with distance between locations  $s_{i,j}$ :

$$\boldsymbol{\Sigma} = c_{ij}\sigma^2 \exp(-\phi|\boldsymbol{s}_i - \boldsymbol{s}_j|) \tag{18}$$

with partial sill  $\sigma^2$ , inverse range  $\phi$  and coefficient  $c_{ij} = 1$  if locations i, j are either both North or both South of Cape Hatteras (~35.25 N) and 0 otherwise to reflect the loss of correlation at the Cape.

The RSL trend field  $\boldsymbol{b}$  is separated into contributions from SSH  $(\boldsymbol{w})$  and VLM  $(\boldsymbol{u})$ .

$$\boldsymbol{b} = \boldsymbol{w} - \boldsymbol{u} \tag{19}$$

These in turn are divided by GIA (subscript g), barystatic (subscript m) and non-GIA/barystatic (superscript prime):

$$\boldsymbol{w} = \boldsymbol{w}_q + \boldsymbol{w}_m + \boldsymbol{w}' \tag{20}$$

$$\boldsymbol{u} = \boldsymbol{u}_g + \boldsymbol{u}_m + \boldsymbol{u}' \tag{21}$$

 $\boldsymbol{b}$  and  $\boldsymbol{u}$  are modeled as multivariate normal distributions, thus:

$$\boldsymbol{b} \sim \boldsymbol{\mathcal{N}}(\boldsymbol{w}_g + \boldsymbol{w}_m + \boldsymbol{w}' - \boldsymbol{u}, \boldsymbol{\Pi})$$
 (22)

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{u}_g + \boldsymbol{u}_m + \boldsymbol{u}', \boldsymbol{\Omega})$$
 (23)

with exponential covariance matrices:

$$\mathbf{\Pi} = \pi^2 \exp(-\rho |\mathbf{s}_i - \mathbf{s}_j|) \tag{24}$$

$$\mathbf{\Omega} = \omega^2 \exp(-\lambda |\mathbf{s}_i - \mathbf{s}_j|) \tag{25}$$

The prior distributions that inform these parameters, as well as the large-scale long-period trend fields  $[\boldsymbol{w}_g, \boldsymbol{w}_m, \boldsymbol{w}', \boldsymbol{u}_g, \boldsymbol{u}_m, \boldsymbol{u}']$  are found in Section 3.4.3.

To capture the effects of local VLM, in addition to the regional VLM  $\boldsymbol{u}$ , the full VLM

field (v) is modeled as a spatially uncorrelated Gaussian process about u:

$$\boldsymbol{v} \sim \mathcal{N}(\boldsymbol{u}, \epsilon^2 \boldsymbol{I})$$
 (26)

with  $N \times N$  identity matrix I and a nugget  $\varepsilon^2$  to account for random noise present on short spatial scales (*Banerjee et al.*, 2014).

As an additional constraint on the long term GIA contribution to SSH  $(\boldsymbol{w}_g)$  and VLM  $(\boldsymbol{u}_g)$ , we utilize the available proxy record  $N_d$  spacetime points at times  $\boldsymbol{T} = [T_1, \ldots, T_{N_d}]^T$ :

$$\boldsymbol{Y} = \left[\sum_{i=1}^{N_d} \boldsymbol{e}_i \boldsymbol{e}_i^T \mathbf{G} (\boldsymbol{w}_g - \boldsymbol{u}_g) \boldsymbol{e}_i^T\right] \boldsymbol{T} + \mathbf{D}\boldsymbol{\iota} + \boldsymbol{f}$$
(27)

Where  $\mathbf{Y} = [Y_1, \ldots, Y_{N_D}]$  is the spatiotemporal pre-industrial RSL process,  $\boldsymbol{\iota}$  contains the offset at the salt-marsh sites where the index points are collected, and  $\boldsymbol{f}$  is the IID residual spacetime process.  $\boldsymbol{\iota}$  is modeled as spatially uncorrelated normal field about a mean vector that varies spatially across the salt-marsh locations  $(N_s)$  with variance  $\kappa^2$ :

$$\boldsymbol{\iota} \sim \boldsymbol{\mathcal{N}}(\beta \mathbf{1}_{N_s}, \kappa^2 \boldsymbol{I}_{N_s}) \tag{28}$$

 $\boldsymbol{f}$  is modeled as a normally distributed zero-mean vector with variance  $\epsilon^2$ :

$$\boldsymbol{f} \sim \boldsymbol{\mathcal{N}}(\boldsymbol{0}_{N_d}, \epsilon^2 \boldsymbol{I}_{N_d}) \tag{29}$$

e are the standard basis functions of  $\mathbb{R}^{N_d}$  which are used with design matrices  $\mathbf{G}$  and  $\mathbf{D}$  to select the RSL trend due to GIA  $(\boldsymbol{w}_g - \boldsymbol{u}_g)$  at the appropriate inference location. Note that pre-industrial RSL  $(\boldsymbol{Y})$  is not modeled as an AR process as the index points are widely separated in time (decades-centuries). Thus the auto correlation is assumed negligible, and justified in residual experiments included in the supplementary material to *Piecuch et al.* (2018).

#### 3.4.2 DATA LEVEL

The instrumental data recorded at TG are considered noisy, gappy, and biased representations of the underlying RSL process. TG data  $(\boldsymbol{z}_k = \boldsymbol{z}_{1,k}, \dots, \boldsymbol{z}_{M_k,k}]^T)$  at  $M_k$  TGs locations and timestep k are represented as:

$$\boldsymbol{z}_{k} = \boldsymbol{\mathrm{H}}_{k}\boldsymbol{y}_{k} + \boldsymbol{d}_{k} + \boldsymbol{\mathrm{F}}_{k}(\boldsymbol{a}t_{k} + \boldsymbol{l})$$

$$(30)$$

Spatially uncorrelated, temporally IID random errors are contained in  $d_k \sim \mathcal{N}(\mathbf{0}_{M_k}, \delta^2 \mathbf{I}_{M_k})$ , with variance parameter  $\delta^2$ . Similarly, spatially independent gaussian data error trends are modeled as  $\boldsymbol{a} \sim \mathcal{N}(\mathbf{0}_{M_k}, \gamma^2 \mathbf{I}_{M_k})$  with variance parameter  $\gamma^2$ . The bias of the trend estimate at each TG location is represented as a spatially uncorrelated normal field with mean  $\nu$  and variance  $\tau^2$ ,  $\boldsymbol{l} \sim \mathcal{N}(\nu \mathbf{1}_M, \tau^2 \mathbf{I}_M)$ , where M is the total number of TG stations (59).  $\mathbf{H}_k$  and  $\mathbf{F}_k$  are design matrices which select the associated RSL process  $(\boldsymbol{y}_k)$  and data bias and error trend vectors at each time step.

Unlike the (mainly) multidecadal TG records used here, records from East Coast GPS stations are much shorter, at best starting at 1994. The common approximation that the VLM process is linear over the last century is adopted such that the rates observed at GPS stations are regarded as long-term rates (*Wöppelmann and Marcos*, 2016). This is justified by the small (on the order of 0.5 mm yr<sup>-1</sup>) standard errors observed at GPS stations with 5 year-long records or more (*Santamaría-Gómez and Mémin*, 2015). Further, the model is designed such that GPS stations represent steady trends over large spatial scales  $\boldsymbol{u}$ , while spatially uncorrelated higher frequency noise is captured in the residual  $\boldsymbol{\nu} - \boldsymbol{u}$ .

Specifically, data from GPS stations  $(\boldsymbol{x}_k = \boldsymbol{x}_{1,k}, \dots, \boldsymbol{x}_{M_k,k}]^T)$  at locations L are cast as a gappy and noisy representation of the underlying VLM process:

$$\boldsymbol{x} \sim \mathcal{N}(\mathbf{E}\boldsymbol{\nu}, \boldsymbol{\Delta})$$
 (31)

with selection and covariance matrices  $\mathbf{E}$  and  $\Delta$ , respectively. Diagonal  $\Delta$  contains the uncorrelated standard errors of the vertical velocities within the Université de La Rochelle 6a dataset (*Santamaría-Gómez and Mémin*, 2015). While  $\Delta$  does not contain the uncertainty associated with the realization of the International Terrestrial Reference Frame, *Piecuch et al.* (2018) performed additional experiments using different combinations of GPS datasets to ascertain the realization's impact. These experiments revealed that estimations of the quantities of interest (such as the origin of spatial variation in East Coast RSL rates) are robust. The instrumental data recorded at TG and GPS stations are considered noisy, gappy, and biased representations of the underlying RSL and VLM processes, respectively.

Each RSL index point contains a height and age estimate, which are modelled as noisy representations of the true RSL height and age. The heights,  $\boldsymbol{Z} = [Z_1, \ldots, Z_{N_d}]^T$ , are thus  $\boldsymbol{Z} \sim \mathcal{N}(\boldsymbol{Y}, \boldsymbol{\Gamma})$ , with  $\boldsymbol{\Gamma}$  the diagonal covariance matrix of formal uncertainties available with the Holocene RSL Database (*Engelhart and Horton*, 2012; *Kemp et al.*, 2014). Similarly, the  $\boldsymbol{S} = [S_1, \ldots, S_{N_d}]^T$ , are thus  $\boldsymbol{S} \sim \mathcal{N}(\boldsymbol{T}, \boldsymbol{\Xi})$  with  $\boldsymbol{\Xi}$  the diagonal covariance matrix of formal uncertainties available with the Holocene RSL Database (*Engelhart and Horton*, 2012; *Kemp et al.*, 2014).

To capture the gravitation, rotation and deformation (GRD) effects of mass exchange, I subsample the barystatic fingerprints of ice mass loss from Antarctica, the Greenland Ice Sheet, and glaciers from *Frederikse et al.* (2020) at each inference location. I use the median of the ensemble and assume that the fingerprint patterns associated with the  $20^{\text{th}}$  trends are time invariant and known with negligible uncertainty. The uncertainty associated with the magnitude of the mass-change trend is captured in the prior level.

# 3.4.3 PRIOR LEVEL

The final layer of the Bayesian hierarchical model is composed of priors distributions, which reflect aprior knowledge of all parameters. Except for the inverse range parameters  $\lambda, \rho, \phi$ , conjugate priors are chosen to improve the efficiency of the model (*Gelman et al.*, 2013). The priors are generally non-informative, such that the data more strongly control the posterior. In other words, non-informative priors enable the model to 'learn' from the data. More informative priors constrain the GIA and barystatic vectors, as well as the inverse range parameters, which are detailed below.

Following *Piecuch et al.* (2018), multivariate normal priors are placed on GIA-driven SSH  $w_g \sim \mathcal{N}(\tilde{\eta}_{w_g}, \tilde{\mathbf{Z}}_{w_g})$  and VLM  $u_g \sim \mathcal{N}(\tilde{\eta}_{u_g}, \tilde{\mathbf{Z}}_{u_g})$  priors with mean vectors and covariance matrices estimated from the 216 GIA model predictions. Mean vectors and covariance matrices are not defined directly at the target locations as the distance between locations is small compared to the spatial scale of the GIA process and thus results in nearly singular matrices. Instead, a parametric approach is adopted to express the model predictions for  $w_g$  and  $u_g$  at each inference location with truncated Legendre polynomial expansions as a function of latitude. A degree 2 (6) polynomial expansion for  $w_g$  ( $u_g$ ) captures >95% of the variance across the SSH (VLM) GIA model predictions and results in accurate representations of the full GIA model predictions while remaining well-conditioned and invertible (see *Piecuch et al.*, 2018, Figs. S7, S8).

I inform the barystatic estimate of ice-mass change with priors based on the ensemble results of (*Frederikse et al.*, 2020). Specifically, I use the mean of the ensemble trends (weighted by the likelihood of the underlying GIA model of *Caron et al.* (2018)) and variance for each ice-melt component (expressed in sea-level equivalent), *viz.*,

$$\boldsymbol{M} \sim \boldsymbol{\mathcal{N}}(\boldsymbol{\tilde{\eta}}_M, \mathbf{Z}_M)$$
 (32)

$$\tilde{\boldsymbol{\eta}}_M = [8 \times 10^{-5}, 4.4 \times 10^{-4}, 7.0 \times 10^{-4}]^T \quad m \ yr^{-1}$$
 (33)

$$\tilde{\mathbf{Z}}_{M} = \begin{pmatrix} 1.38 \times 10^{-9} & 0 & 0\\ 0 & 1.70 \times 10^{-9} & 0\\ 0 & 0 & 9.08 \times 10^{-9} \end{pmatrix} \qquad (m \ yr^{-1})^{2} \qquad (34)$$

Here,  $\tilde{\boldsymbol{\eta}}_M$  contains the mass loss trend from the Antarctic Ice Sheet, Greenland Ice Sheet, and glaciers, respectively. With time-invariant ice-mass fingerprints of SSH  $(\boldsymbol{W}_m)$  and



Figure 13: Unitless barystatic fingerprints creating by scaling the ensemble of fingerprints in *Frederikse et al.* (2020) by the mean linear trend ice melt for each process.

VLM  $(U_m)$  are scaled by  $\tilde{\eta}_M$ :

$$\boldsymbol{w}_m = \boldsymbol{M}\hat{\boldsymbol{w}}_m = \boldsymbol{M} \times \frac{\boldsymbol{W}_m}{\tilde{\boldsymbol{\eta}}_m}$$
 (35)

$$\boldsymbol{u}_m = \boldsymbol{M}\hat{\boldsymbol{u}}_m = \boldsymbol{M} imes rac{\boldsymbol{U}_m}{\tilde{\boldsymbol{\eta}}_m}$$
(36)

where  $\boldsymbol{w}_m$  and  $\boldsymbol{u}_m$  comprise the barystatic ice-melt contribution to the process level (Equations 22 and 23, respectively). The time-invariant 20<sup>th</sup> century unitless fingerprints are shown in Fig. 13. This separation of an uncertain mass change component from the assumed static fingerprint enables a more efficient modeling framework without sacrificing a robust result.

For TWS, a different approach is adopted because the spatial fingerprints, as well as the magnitude of  $20^{\text{th}}$  TWS is more uncertain than cryosphere change. To model this I implement an empirical Bayes approach, utilizing the entire ensemble of TWS mass change from (*Frederikse et al.*, 2020). At each iteration of the sampling, a random ensemble member is used to represent TWS at the target locations. In this way, the uncertainty in both the spatial location and magnitude of TWS changes are captured.

Informative priors are also placed on the inverse range parameters  $\varphi$ ,  $\lambda$ ,  $\rho$ , which control

the magnitude of the spatial covariance in the RSL innovations  $(e_k)$ , VLM unrelated to GIA or GRD (u') and SSH unrelated to GIA or GRD processes (w'), respectively. Priors on these parameters are chosen such that there is 95% prior probability that the length scale is between ~500 km and 2,000 km, which reflect the interest here in understanding the large scale impacts of climate and geology. However, additional data assimilation experiments showed that the module is robust to both narrower and wider specifications of this length scale (*Piecuch et al.*, 2018).

# 3.4.4 POSTERIOR DISTRIBUTION

The three levels (data, process, prior) are jointly inverted using Bayes' rule as:

$$p(\boldsymbol{y}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{\Theta} | \boldsymbol{x}, \boldsymbol{z}, \boldsymbol{Z}, \boldsymbol{S}) \propto p(\boldsymbol{x}, \boldsymbol{z}, \boldsymbol{Z}, \boldsymbol{S} | \boldsymbol{y}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{\Theta}) \times p(\boldsymbol{y}, \boldsymbol{Y}, \boldsymbol{T}, \boldsymbol{\Theta}) =$$

$$p(\boldsymbol{y}_{0}) \times p(r) \times p(\sigma^{2}) \times p(\phi) \times p(\mu) \times p(\pi^{2}) \times p(\lambda) \times p(\alpha) \times p(\omega^{2}) \times p(\rho) \times$$

$$p(\varepsilon^{2}) \times p(\delta^{2}) \times p(\nu) \times p(\tau^{2}) \times p(\gamma^{2}) \times p(B) \times p(\kappa^{2}) \times p(\varepsilon^{2}) \times p(\boldsymbol{w}_{g}) \times p(\boldsymbol{u}_{g}) \times$$

$$p(\boldsymbol{b} | \boldsymbol{u}, \boldsymbol{w}_{g}, \boldsymbol{M}, \boldsymbol{\mu}, \pi^{2}, \lambda) \times p(\boldsymbol{u} | \boldsymbol{u}_{g}, \boldsymbol{M}, \boldsymbol{\alpha}, \omega^{2}, \rho) \times p(\boldsymbol{\nu}, | \boldsymbol{u}, \epsilon^{2}) \times p(\boldsymbol{l} | \boldsymbol{\nu}, \tau^{2})$$

$$\times p(\boldsymbol{a} | \gamma^{2}) \times p(\boldsymbol{x} | \boldsymbol{\nu}) \times p(\boldsymbol{\iota} | \boldsymbol{\beta}, \kappa^{2}) \times p(\boldsymbol{Y} | \boldsymbol{u}_{g}, \boldsymbol{w}_{g}, \boldsymbol{T}, \boldsymbol{\iota}, \epsilon^{2}), \times p(\boldsymbol{Z} | \boldsymbol{Y}) \times p(\boldsymbol{S} | \boldsymbol{T}) \times$$

$$\prod_{k=1}^{K} [p(\boldsymbol{z}_{k} | \boldsymbol{y}_{k}, \delta^{2}, \boldsymbol{l}, \boldsymbol{a}) \times p(\boldsymbol{y}_{k} | \boldsymbol{y}_{k-1}, \boldsymbol{b}, r, \sigma^{2}, \varphi)]$$
(37)

The data are assumed conditionally independent from the process and parameters and samples are drawn from the posterior using Markov chain Monte Carlo (MCMC) methods as in *Piecuch et al.* (2017b). A Gibbs sampler, implemented in Matlab, simply draws samples for parameters whose posteriors are conjugate. For the inverse range parameters (which are not conjugate, and thus do not have a known distribution to draw from), the Metropolis-Hasting algorithm is used.

A normal proposal distribution centered on the parameter in question and with a standard deviation of 0.05 m/y provides the foundation for the Metropolis-Hasting approach. The posterior is then evaluated for both the current value of parameter (e.g.,  $\rho$ ) and a proposed new value (e.g.,  $\rho^*$ ; see example Appendix B, Eq. 130). If the  $R_{M-H} = \rho^*/\rho > 1$ , the proposal is accepted. Otherwise, the proposal  $\rho^*$  is accepted based on the magnitude of  $R_{M-H}$ . That is, a sample w is first drawn from a uniform distribution between 0 and 1. If the draw  $w < R_{M-H}$ , the proposal is accepted and  $\rho$ is set to  $\rho^*$ . With enough samples, the conditional posterior converges to a stationary distribution such that the long-term probability of  $\rho$  is proportional to target probability density (*Gelman et al.*, 2013).

500000 MCMC iterations are run to achieve convergence, with initial process values set to 0 and initial parameter values drawn from their respective priors. The first half (250000) samples are discarded to minimize initialization impacts. Only one of every 250 samples is kept to minimize correlation between iterations. To test for model convergence, the convergence monitor factor ( $\hat{R}$ ; Gelman et al., 2013; Vehtari et al., 2021) is used to assess the variability between and within separate model experiments (known as chains). More specifically,  $\hat{R}$  estimates the impact of further simulations on the inter and intra-chain variability, approaching unity as the number of simulations  $\rightarrow \infty$ . Thus, convergence is typically indicated by  $0.9 < \hat{R} < 1.1$  (Gelman et al., 2013).

# 3.5 RESULTS

### 3.5.1 BAYES RSL

The overall spatial pattern of 20<sup>th</sup> century East Coast RSL is shown in Figure 14a. Elevated rates in the mid-Atlantic ( $\sim 35-45^{\circ}$ N) are primarily driven by total VLM (Fig. 14b). Melt rates from the Greenland Ice Sheet and Arctic glaciers are greater than those from the Antarctic Ice Sheet (*Frederikse et al.*, 2020). The loss of this mass results in elastic rebound, which in turn manifests as an uplift (positive VLM trend from South to North 14h). The median total SSH contribution (Fig. 14c) is relatively constant along the coast, with a slight linear spatial trend from South to North of 0.03 mm/yr. The spatial trend arises from GIA (Fig. 14f), which exhibits a median alongshore rise of 0.05 mm/yr, as the ongoing flow of mantle material causes GRD effects (*Piecuch et al.*, 2018). Conversely, the median spatial trend in Fig. 14i is -0.02 mm/yr from South to North. Again, this change is driven by GRD effects, with relatively faster rates of positive SSH farther from the Greenland Ice Sheet and Arctic glaciers. Due to the use of an informative prior on the barystatic contributions to East Coast RSL, their uncertainties are well constrained and the model doesn't learn from the instrumental data (TGs and GPS stations), as shown by essentially unchanged prior/posterior distributions (Fig 15; full comparisons of prior and posterior distributions can be found in Appendix C). Nevertheless, the Bayesian inference provides important constraints on the uncertainties of coastal sea-level change.

The results shown in Figure 14 confirm the main finding of *Piecuch et al.* (2018): that large-scale VLM drives the along-shore variation in centennial RSL rates on the U.S. East Coast. More specifically, the percentage of variance that each component contributes to along-shore variance in total RSL is shown in Fig. 16. That is, the percentage of variance explained E(y) in the total spatial field x by y is calculated according to:

$$E(y) = 100 \times \frac{\operatorname{var}(x) - \operatorname{var}(x - Sy)}{\operatorname{var}(x)}$$
(38)

where var is the variance operator and S = -1 when considering VLM fields to account for the inverse relationship with RSL and S = 1 otherwise. Fig. 16 shows that ~ 73% of the alongshore spatial variance in RSL is due to regional-scale VLM, with only ~ 2% arising from SSH. Further analyzing the specific component contributions reveals ~ 61%



Figure 14: Posterior median (thick line) and 95% credible interval of regional trends for: RSL (**a**); VLM (**b**); SSH (**c**); GIA-driven RSL (**d**); GIA-driven VLM (**e**); GIA-driven SSH (**f**); Mass-driven RSL (**g**); Mass-driven VLM (**h**); Mass-driven SSH (**i**); RSL unrelated to GIA/Mass (**j**); VLM unrelated to GIA/Mass (**k**); and SSH due to sterodynamics (SD; **l**). Results are shown at the 93 regularly spaced grid cells and averaged by latitude.



Figure 15: Violin plot that combines a boxplot and histogram for each prior and posterior barystatic ice-melt term expressed in sea-level equivalent global trends. The median and quartiles of the respective distribution are marked on the interior of each violin as horizontal dashed lines. The width of the violin shows the smoothed kernel density estimate of the underlying distribution. The similarity shows that the model does not learn further information about the ice-melt contributions from the instrumental records (tide gauges and GPS), but rather relies on the *aprior* best estimate.

of the variance results from GIA, with the next largest process contribution from VLM unrelated to the GIA and mass terms ( $\sim 17\%$ ). Note that a negative percent variance indicates that removal of the trend, for example the regional SSH due to GIA trend, increases the variance in total RSL.



Figure 16: Percent of alongshore variance in total RSL (Fig. 14a) explained by VLM or SSH related processes. Black vertical lines indicate the model median, the interquartile range is shown by the colored shading, and the whiskers represent the posterior 95% credible interval.

# 3.5.2 BAYES RESIDUAL SSH

Beyond identifying the large scale contributions of total VLM and SSH to RSL, an important outcome of incorporating the barystatic terms into the model construction is to constrain the residual components of VLM and SSH to gain insight into large scale SD (Fig. 14j-l). These residual terms are loosely specified in the model design with uninformative priors, such that they capture variance in the data unexplained by the other parameters. In other words, by specifying all components in Eq. 1 *except* SD, this component should dominate residual SSH (Fig. 14l). The SD component is subjected to further analysis by calculating and removing its spatial median (Fig. 17a-c). In effect, the spatial mean represents the thermosteric component (which is assumed to be consistent across the basin over the 20<sup>th</sup> century) and large regional-scale ocean dynamics, while the remaining signal is representative of locally variable ocean dynamics.



Figure 17: Bayes residual trends in RSL after quantifying GIA and barystatic sea-level change. The total trends  $(\mathbf{a}, \mathbf{d})$  replicates Fig. 14**k**, **l** and are modeled here as a spatially variable component superimposed on a spatially constant median. The constant median is removed to show the spatially variable component alone in panels **b** (SSH) and **e** (VLM). In the bottom row, the posterior median total trend and regional trends (which correspond to the medians in the upper two rows) are shown together with the spatial median and its uncertainty (dashed-black line  $\pm$  gray shading).

Figure 17c shows that the basin mean (primarily thermosteric) of 0.51 [-0.81, 1.62] mm/yr dominates SD. This finding agrees well with an independent estimate of  $20^{\text{th}}$  century global thermosteric trend of 0.52 [0.35, 0.69] mm/yr from *Frederikse et al.* (2020). However, uncertainties are high relative to *Frederikse et al.* (2020) for the SD component, precluding more robust conclusions without further analysis.

#### 3.5.3 BAYES RESIDUAL VLM

While the uncertainty in SD mainly reflects uncertainties present in the TG records, it is coupled to the uncertainty in VLM unrelated to GIA/Mass (Fig 18; Appendix Eq. 70). Thus, constraining VLM uncertainty is imperative for a confident interpretation of SSH due to SD. Fig. 17f shows a clear bias in the residual term, in the form of a spatially



Figure 18: Comparison of parameters controlling the residual (unrelated to GIA/Mass) VLM and SSH vector fields. Each point is a posterior sample. The linear dependence indicates coupling between the two quantities, as specified in Appendix Eq. 70.

consistent trend of  $\sim -1$  mm/yr dominating the VLM residual field. While this residual was also found by *Piecuch et al.* (2018, albeit smaller:  $\sim -0.6$  mm/yr), their focus on the spatial variability of the trends rather than the central estimate precluded in-depth analysis.

Here, an attempt was made to provide more insight into the cause of this bias in the VLM residual. First, the impacts of using different GPS solutions was investigated by performing the Bayesian assimilation with GPS velocities obtained from the University of Nevada, Reno (UNR) database (*Blewitt et al.*, 2018), rather than those from the ULR-6a (*Santamaria-Gomez et al.*, 2016). Locations were kept constant, with the exception that

three stations in ULR-6a that didn't exist in UNR were excluded. Fig. 19 shows that the large-scale bias is also found using the UNR stations in the Bayesian solution, indicative that the model is largely insensitive to the differences in GPS processing performed to create the two data products (full results of the sensitivity experiments can be found in the Appendix C).



Figure 19: Comparison of residual bias in Bayesian solutions between GPS solutions in the ULR-6a database (*Santamaria-Gomez et al.*, 2016) (top) and by the UNR Geodetic Lab (*Blewitt et al.*, 2018).

Next, a series of offline (i.e. separate from the Bayesian model) were performed to probe the GPS solutions in conjunction with a suite of GIA modeling outputs. Fig 20 shows GPS data for both the ULR-6a and UNR solutions with GIA estimates from four separate sources: Mitrovica (as used here and in *Piecuch et al.* (2018); henceforth referred to as the baseline experiment), ICE-5G (*Peltier*, 2004), ICE-6G (*Peltier et al.*, 2018), and Caron *Caron et al.* (2018). Note that there is not an uncertainty quantification provided with ICE-5G/6G, so separate experiments are made using both the Mitrovica and Caron

uncertainty estimates, with the latter shown here (full results in Appendix C). The relative impacts of the magnitude and uncertainties of the stations can be qualitatively seen in the Bayes VLM estimate (red) associated with the Mitrovica model (Fig 20 **a**,**b**).



Figure 20: VLM estimates at each GPS location from GPS solutions, GIA model estimates, and the Bayesian model. Columns display two set of GPS solutions (left: ULR-6a, right: UNR), while different GIA model estimates are shown in row **a-d**. **a**: Mitrovica, as used in *Piecuch et al.* (2018) (baseline experiment); **b** ICE-5G (*Peltier*, 2004); **c**: ICE6G (*Peltier et al.*, 2018); **d**: Caron *Caron et al.* (2018).

To further analyze these data, a large scale residual VLM field is computed from each GPS/GIA configuration (Fig. 21). Specifically, the residual field is:

$$VLM_{resid_{Ng}} = VLM_{GPS_{Ng}} - (VLM_{GIA_{Ng}} + VLM_{AIS_{Ng}} + VLM_{GrIS_{Ng}} + VLM_{glac_{Ng}})$$
(39)

Where  $Ng \in [1, L]$  with L the number of GPS station locations,  $VLM_{GPS}$  is the vertical rate measured by GPS from either the ULR-6a or UNR solutions,  $VLM_{GIA}$  corresponds to



Figure 21: Residuals between GPS (ULR-6a and UNR solutions) and GIA (Mitrovica, ICE5G, ICE6G, and Caron models) at each GPS station location computed according to Eq. 39. The median is shown as a horizontal vertical line and the color shading indices the interquartile range. With the exception of the Mitrovica model, the median is  $\sim 0$  mm/yr.

# 3.6 DISCUSSION

The discrepancies in GIA estimates between the Mitrovica estimate and ICE-5G/6G and Caron highlight the challenges in understanding large scale 20<sup>th</sup> century VLM (Fig. 21). To shed light on the extent to which the GIA uncertainty impacts the the Bayesian solution, additional full assimilations were run using GIA priors from ICE-6G (*Peltier et al.*, 2018) *Caron et al.* (2018) (specifically replacing  $\tilde{\eta}_{\omega_q}$  and  $\tilde{\eta}_{u_q}$ , Section 3.4.3). In that no uncertainties are provided with ICE-6G, two experiments are run using the radial displacement field from ICE-6G as the prior mean: 1) using the GIA prior covariance  $(\tilde{Z}_{\omega_g}, \tilde{Z}_{u_g})$  associated with the Mitrovica model, and 2) creating a diagonal covariance matrix with uncertainty estimates from *Caron et al.* (2018) model.

Overall these sensitivity experiments reinforce the findings of *Piecuch et al.* (2018): that GIA drives the large scale along-shore spatial variation in RSL. Fig. 22 shows the gradients of the GIA fields for the four experiments.



Figure 22: Spatial derivative of the different model experiments for ULR-6a GPS stations. The posterior median (95% credible interval) of the baseline experiment with results from the Mitrovica GIA is shown in black (gray shading). The posterior medians of the other sensitivity experiments fall within the uncertainty of the baseline assimilation, lending support to the finding that GIA drives the spatial variation in the SSH and VLM trend fields.

Figures showing the full posterior trend fields and percent variance in total RSL are shown in Appendix C.

While the spatial variability agrees well between experiments, the posterior median contributions of VLM and SSH due to GIA are qualitatively different than the baseline experiment. This is most clearly seen in VLM due to GIA (Fig. AA62e): using GIA from ICE-6G causes the latitude of maximum subsidence (minimum VLM) to shift northward 2.5° from Hampton Roads Virginia to Central New Jersey. Additionally, the Mitrovica estimates in the baseline experiment lead to uplift outside of the Mid-Atlantic (south of 29.5°N, north of 43.5°N), while the ICE-6G prior results in subsidence over the entire coastline, with no VLM due to GIA rates greater than -0.84 mm/yr.

There is also a clear impact on the residual terms VLM unrelated to GIA/Mass and SSH due to SD (Fig. 23). Taking the ICE6G with Mitrovica uncertainties as a representative case, is it evident that the median residual VLM field is no longer biased about a trend of -1 mm/yr trend (23,  $3^{rd}$  pair of boxplots), instead it is centered on a positive spatial median trend of +0.36 [-0.27, 0.68] mm/yr. This is expected given the reduction in bias shown in Fig. 21.



Figure 23: Spatial residual trend (SSH and VLM) fields of sensitivity experiments. Mit: Baseline experiment with Mitrovica GIA estimates; Caron: *Caron et al.* (2018); ICE6G (Mit) *Peltier et al.* (2018) with covariance matrix from Mitrovica estimates; ICE6G (Car) *Peltier et al.* (2018) with diagonal covariance matrix from *Caron et al.* (2018) uncertainties.

However, there is still a large scale  $\sim 1 \text{ mm/yr}$  residual trend bias in the ICE-6G result, but now it manifests as a 1.70 [1.47, 2.01] mm/yr trend in the SSH due to SD field. In other words, the model framework has elucidated an underlying  $\sim 1 \text{ mm/yr}$  bias in the geophysical data and/or GIA model output.

Further research is needed to discover the source of the spatial bias. The robustness of the large scale gradient (Fig. 22, as well as independent analysis of TG records (*Bos et al.*, 2013) provide evidence that the process level RSL model (Eq. 16) is unbiased. Further credence is given to the process level equations through residual analysis (*Cryer and Chan*, 2008), which verifies the IID assumption of the RSL innovations  $e_k$  and data errors  $d_k$  in Equations 16 and 30, respectively (not shown). This evidence suggests that the spatial trend bias lies in the data itself. Given the analysis performed in Section 3.5, the next most likely candidate for a large scale bias is the RSL index points. This analysis will be conducted in future research.

This Chapter set out to quantify relative contributions of GIA and mass redistribution between land and ocean to  $20^{\text{th}}$ -century sea-level change along the East Coast of the United States. By expanding the Bayesian assimilation of *Piecuch et al.* (2018), the contributions of mass redistribution are well constrained. The spatial gradients of sensitivity experiments agree well with the baseline model, reinforcing the conclusion of *Piecuch et al.* (2018) that GIA drives along-shore variance in  $20^{\text{th}}$  century East Coast RSL.

While the magnitude and exact locations of VLM and SSH due to GIA are more sensitive to the specific model input data, there are nevertheless conclusions that can be inferred. The highest rates of subsidence due to GIA are found in the mid-Atlantic, consistent with independent estimates (e.g., *Engelhart et al.*, 2009; *Karegar et al.*, 2016). Additionally, SSH due to GIA exhibits an upward linear gradient from south to north, indicative of the GRD effects associated with the ongoing viscoelastic response to the last glacial maximum.

RSL is a primary challenge to coastal communities responding to past and present climate change. Accurate projections of regional RSL changes are imperative for developing and implementing successful adaptation strategies (*Kopp et al.*, 2019). Similar to the findings of *Piecuch et al.* (2018), the results here can provide basic insights into future projections. Due to the long temporal time-scales over which GIA occurs indicates that the resulting spatial pattern of rates of RSL can be considered to continue into the future. Conversely, the magnitude of RSL cannot be considered linear due to accelerating ice-melt (*Bamber et al.*, 2018), large decadal and longer variability in TWS (*Reager et al.*, 2016), and large uncertainties in melt-rates of Antarctica Ice Sheets. (e.g., *Edwards et al.*, 2021). Nevertheless, the spatial pattern of VLM and SSH due to mass change is likely to remain the same on centennial timescales, contributing to a relatively smaller range of uncertainty (tenths of mm/yr) than that due to GIA and unrelated to GIA/mass (mm/yr). Continuing to narrow the uncertainties on GIA and non-GIA/Mass components of coastal RSL, as well
as understanding more localized VLM patterns, is a primary consideration for constraining the decision space of stakeholders in the coastal zone (e.g., *Sobel*, 2021).

#### CHAPTER 4

# OBSERVING VLM IN HAMPTON ROADS WITH SAR

### 4.1 INTRODUCTION

Having now conducted an analysis of both global and regional sea-level processes, the extent of the investigation is further narrowed to the metropolitan region of Hampton Roads and the vertical land motion (VLM) component of relative sea-level (RSL) change. Hampton Roads is a region of southeastern Virginia (Fig. 30), composed of urban and suburban areas, agricultural lands, and coastal wetlands. As mentioned in Section 1, it is experiencing one of the highest rates of RSLR on the Atlantic coast of the United States due to a combination of land subsidence and ocean variability (*Sweet and Park*, 2014; *Zervas*, 2009). This has driven the substantial increase in coastal flooding observed over the last century (Fig. 24; *Ezer and Atkinson*, 2014).



Figure 24: Hours per year of water-levels exceeding 30 cm above mean higher high water at the Sewell's Point tide gauge. Mean higher high water is a proxy beyond which 'nuisance' flooding occurs, which is not life threatening but leads to road closures and disruptions to ordinary operations (modified from: *Atkinson et al.*, 2012).

The remote-sensing technique of InSAR has matured in recent years such that measurements of VLM with mm-scale precision can be obtained from historic and ongoing satellite missions (e.g., *Brooks et al.*, 2007; *Palanisamy Vadivel et al.*, 2021; *Shirzaei et al.*, 2021). This chapter begins with a detailed overview of InSAR, from basic principles and practical processing considerations to state-of-the-art time series analysis methods. I consider the most problematic error sources and the fundamentally relative nature of InSAR measurements in relation to geophysical interpretation of the data. I conclude the background section with a review of a number of recent efforts that have used InSAR measurements to increase understanding of VLM in relation to coastal sea level.

Following the review, I turn to Hampton Roads and the specific research that has been carried out to answer Research Question 3:

What are the spatiotemporal patterns and trends of VLM in Hampton Roads?

I first detail the data and methods of our study using historic ALOS-1 data acquired between 2007-2011, previously published as *Bekaert, Hamlington, Buzzanga, and Jones* (2017). I present our findings and discuss how the results pertain to the challenges of RSLR driven flooding in Hampton Roads. However, the high uncertainties of the results and the historical data limit their usefulness in informing planning efforts in the region.

To overcome these challenges, Section 4.4 presents findings from an additional investigation of VLM in Hampton Roads using higher quality and current satellite observations from the Sentinel-1 satellite. A robust approach is presented that can be routinely updated and is applicable to additional studies areas. With much improved uncertainties relative to the ALOS-1 study, I conduct an initial assessment of an ongoing infrastructure project aimed in part at reducing regional subsidence and associated flooding. Much of the content is reproduced from work previously published as *Buzzanga, Bekaert, Hamlington, and Sangha* (2020).

### 4.2 BACKGROUND

## 4.2.1 SAR FUNDAMENTALS

Radar is a system which generates an electromagnetic signal in the radio or microwave frequency range and records the echo of scattered pulses. The signal penetrates clouds and darkness, precipitation and many kinds of vegetation, and thus can be used to reveal a vast amount of information about planetary surfaces. Radar remote sensing systems are mounted on moving platforms, typically airplanes or satellites, travel along the flight path or 'azimuth' direction, and emit a train of pulses off-nadir in the 'range' or line-of-sight (LoS) direction (Fig. 25). In the range direction, the ground resolution, or the smallest distinguishable distance between ground scatters, is simply a function of distance from the sensor to the target. However, the resolution in the azimuth direction  $R_a$ , is additionally dependent on the aperture of the radar antenna (which is proportional to its size):

$$R_a = \frac{\lambda}{L_a} r \tag{40}$$

where  $\lambda$  is the wavelength of the electromagnetic pulses,  $L_a$  is the aperture, r is the distance in the range direction from the antenna to a point scatterer, and  $R_a = \mathcal{O}(km)$ 

The principle of Synthetic Aperture Radar (SAR) arose as a method for improve the resolution of  $R_a$  while avoiding the practical limitations of a large antenna array.

As shown in Fig. 25, a side-looking Synthetic Aperture Radar (SAR) senses ground resolution cell Q at multiple time intervals, effectively creating a 'synthetic' antenna size of  $L_S = 2\pi r/L_a$ , which implies that  $R_a$  for a SAR system is independent of height and increases with smaller antennae:

$$R_a = \frac{L_a}{2} \tag{41}$$

For context, the C-band radar mounted on Sentinel-1 has a wavelength of  $\lambda \sim 5.66$  cm, and the range and azimuth resolution for the base products produced by the European Space Agency (ESA) are ~ 5 m and ~ 20 m, respectively.



Figure 25: Basic SAR principles. The radar antenna of size  $L_a$  moves at velocity V in the azimuth direction from  $P_1$  to  $P_2$ . Ground resolution element Q is sensed from multiple locations at the off-nadir look angle  $\theta$  to form synthetic aperture  $L_s$  (Modified from: Usai et al., 1999).

In addition to measurements of backscatter, SAR systems are coherent, meaning that the phase ( $\psi$ ) of the emitted pulses is measured upon generation and return. However, the wavelengths used in SAR typically operate at  $\lambda \sim 3$  (X-band),  $\lambda \sim 5.6$  (C-band), or  $\lambda \sim 23.5$  (L-band) cm, and thus they do not capture the reflected energy of the much smaller individual point scatters. Rather, the phase of the ground resolution cell, or posting, reflecting the summation of the many scatterers it contains. The scatterers are uncorrelated, creating a random phase that is nevertheless deterministic in that it is dependent on the summed backscattering properties of all the scatterers and the range of the posting to the antenna. This leads to the technique of Interferometric Synthetic Aperture Radar (InSAR), in which the differencing of two or more resolution cells acquired from either a different viewing geometry or a different time effectively eliminates the random component and reveals information about the distance of the sensor to the cell between images.

Perhaps the most notable example of across-track InSAR was the Shuttle Radar Topography mission in 2000, in which two SAR antennae were attached to the Space Shuttle Endeavor and produced a near-global scale digital elevation model (DEM) (*Farr et al.*, 2007). Considering the phase differences of a single sensor through time is referred to as Differential InSAR, or simply InSAR, which will be used henceforth.

## 4.2.2 INSAR PROCESSING

While it is possible to begin interferometric processing from the raw SAR data, these data, especially those captured via satellites, are commonly pre-processed by the respective operating facilities (e.g. ESA for the Sentinel-1 satellites). This pre-processing step is mainly concerned with compressing the energy spread in range and azimuth of a point scatter into a single pixel. The raw image is subject to 'migration' in the range direction and 'focusing' in the azimuth direction, in which a matched filter derived from the SAR characteristics and Doppler principles is convolved with the returned signal that consolidates the radar pulse energy around its peak value (*Hanssen*, 2001). The range-Doppler algorithms that implement these techniques are phase-preserving, thus resulting in a 2-D array of complex valued pixels known as a single look complex (SLC) image (*Cumming and Bennett*, 1979). The processing steps described in the following begin with SLC products derived from spaceborne SAR acquisitions, which are the focus of the analysis in the chapters 3 and 4.

To begin interferometric processing, the two SAR SLCs, referred to as reference and secondary<sup>3</sup>, must be aligned to the same geometry in a 'co-registration' step. Geometric co-registration has been shown to be robust, in which offsets between the reference and secondary image image are estimated using *apriori* knowledge of the orbital state vectors and an external DEM (*Hanssen*, 2001; *Sansosti et al.*, 2006; *Nitti et al.*, 2011). The offsets are then used to fit a warp function which maps the secondary to the reference. The secondary image is then resampled to the reference geometry. Co-registration is

<sup>&</sup>lt;sup>3</sup>historically referred to as master and slave

computationally expensive, and thus typically separated into a 'coarse' step which aligns the images to within a few pixels, and a 'fine' step that that oversamples the SLCs such that matching is achieved at the subpixel level (*Hanssen*, 2001). The degree of subpixel alignment is sensor dependent; while alignment within ~0.1 pixel is considered sufficient for older sensors, the rotation of the sensor aboard Sentinel-1 requires more sophisticated algorithms that exploit the overlap in the azimuthal footprint to increase alignment to within the required ~0.001 pixels (*Scheiber and Moreira*, 2000; *Prats-Iraola et al.*, 2012; *De Zan et al.*, 2014)

With the aligned reference and secondary SLCs (subscripts 1 and 2, respectively), an interferogram is then produced from complex multiplication performed on a pixel-by-pixel basis:

$$I = S_1 S_2^* = |S_1| |S_2| e^{i(\psi_1 - \psi_2)} = |S_1| S_2| e^{i\Delta\psi}$$
(42)

where  $S_n = |\hat{S}_n| e^{i\psi_n}$ , and '\*' indicates the complex conjugate operator.  $\Delta \psi$  is the lumped interferometric phase:

$$\Delta \psi = \psi_1 - \psi_2 = \psi_D + \psi_{orbit} + \psi_{atm} + \psi_{scat} + \psi_{noise}$$

$$\psi_D = \psi_d + \psi_{flat} + \psi_{topo}$$

$$\psi_{atm} = \psi_{tropo} + \psi_{iono}$$
(43)

 $\psi_d$  is the ground displacement signal sought in most differential InSAR applications, including the studies considered here.  $\psi_{flat}$  arises from the shape of the Earth, and  $\psi_{topo}$ from topography which, along with  $\psi_d$ , stem from the range difference equation between subsequent SLC acquisitions (*Bamler and Hartl*, 1998):

$$\psi_D = -\frac{4\pi\Delta r}{\lambda} \tag{44}$$

Using Eq. 44,  $\psi_{flat}$  is simulated and removed using precise information of the difference between satellite orbits and a reference geoid such as WGS 84.  $\psi_{topo}$  is similarly removed using satellite state vectors and an external DEM. The uncertainty in satellite state vectors (small in newer satellites, approximated by a linear ramp in older) is reflected in the  $\psi_{orbits}$  term, and instrument noise in  $\psi_{noise}$ .

 $\psi_{scat}$  is known as temporal decorrelation, and reflects the change in the summation of the point scatterers within a ground resolution cell between acquisitions (e.g. Zebker and Villasenor, 1992). Substantial intra-annual temporal decorrelation can occur due to seasonal changes such as vegetation cover and snowfall (*Rosen et al.*, 2000). Atmospheric noise ( $\psi_{atm}$ ), commonly referred to as the atmospheric phase screen (APS), consists of delays in phase as the radar signal encounters temperature, pressure, and relative humidity variability in the troposphere, and free electrons in the ionosphere. Tropospheric noise ( $\psi_{tropo}$ ) can be estimated using a variety of methods, including multi-spectral observations co-located in time, weather-models, and phase-based empirical corrections (see *Bekaert* et al., 2015a, and references therein). The effectiveness of such methods is regionally dependent on a combination of the transient tropospheric conditions and topographic features. Ionospheric noise ( $\psi_{iono}$ ) can be estimated using 'split-spectrum' methods, in which the spectrum of the radar signal is separated into two sub-bands, from which two interferograms are formed (*Rosen et al.*, 2010). The non-dispersive and dispersive components of the phase are then calculated, the latter of which is the ionospheric contribution. Split-spectrum methods have been demonstrated to be applicable for modern sensors (e.g. *Gomba et al.*, 2017), although errors still arise due to temporal decorrelation which can conspire to mask slower deformation signals such as subsidence or slow-slip processes in the Earthquake cycle (e.g. *Goldstein*, 1995; *Hooper and Zebker*, 2007; *Bekaert et al.*, 2015b). Further consideration of current methods for reduction that rely on time-series analysis is given in Section 4.2.3.

Coherence, statistically defined as the amplitude of the cross-correlation factor of an interferometric pair, is used as a measure of temporal decorrelation. Practically, it is approximated using a summation of the pixels within a window of size n as  $\gamma$ :

$$\hat{\gamma} = \frac{\sum_{n} S_1 S_2^*}{\sqrt{\sum_{n} |S_1|^2 \sum_{n} |S_2|^2}} \tag{45}$$

where  $\psi_{flat}$  and  $\psi_{topo}$  have been removed from the phase of SLC acquisitions  $S_{1,2}$ . The magnitude of  $|\hat{\gamma}|$  then ranges from 0 to 1 and functions as measure of similarity between the acquisitions. In Section 4.2.3 I will show that coherence is a useful metric for selecting interferograms to subject to Multi-temporal InSAR (MT-InSAR) processing. Window size depends in part on the desired output resolution, which can be subjected to filtering and multilooking (the averaging of neighboring pixels) to increase the signal-to-noise ratio.

Even with a perfect representation of all the components comprising the interferometric phase (Eq. 43), it is still inherently ambiguous by integer multiples of  $2\pi$ . An intuitive description is provided by *Osmanoğlu et al.* (2016), which considers a SAR system as an analog watch with only a second hand. At any point, the number of seconds is accurately known, but nothing is recording the integer multiples of rotations, i.e. minutes and hours. Similarly, a SAR measures very accurately the phase, i.e. the position of the wave at generation and receipt, but not the number of integer wavelengths it has cycled through during transit. The problem of recovering the absolute phase difference  $\varphi$  can be posed as:

$$\psi = W\{\varphi\} = \operatorname{mod}\{\varphi + \pi, 2\pi\} - \pi \qquad \in [-\pi, \pi)$$
(46)

$$\varphi = 2\varphi k + \varphi_N \tag{47}$$

where  $W(\cdot)$  is a wrapping operator, k is the integer ambiguity and  $\varphi_N$  captures the phase noise (e.g. *Ghiglia and Pritt*, 1998; *Hanssen*, 2001). The process of 'unwrapping' is

concerned with finding an estimate  $\hat{\varphi}$  of  $\varphi$ , by assuming that the gradient of the wrapped phase reflects the gradient of the absolute phase:  $\nabla \psi \sim \nabla \hat{\varphi} = \nabla \varphi + n_{\nabla}$ . The observed phase gradients capture the absolute phase gradient plus noise, and for N > 1 dimensions must be integrated over domain C between  $L_0$  and L to obtain  $\varphi$ :

$$\varphi(\boldsymbol{L}) = \varphi(\boldsymbol{L}_0) + \int_C \nabla \hat{\varphi} \cdot \boldsymbol{dL}$$
(48)

where the phase of the reference point at  $L_0$  is known aprior. However, the phase gradient error  $(n_{\nabla})$  can introduce discontinuities that cause the unwrapping procedure to fail, i.e. rendering it non-conservative:

$$\nabla \times \nabla \hat{\varphi}(\boldsymbol{L}) = \nabla \times \boldsymbol{n}_{\nabla} \neq 0 \tag{49}$$

using the fact that the true absolute phase gradient is conservative and thus  $\nabla \times \nabla \varphi \equiv 0$ .

Therefore, unwrapping (Eq. 48) is dependent on the path of integration and implies an infinite amount of possible  $\varphi$  values (*Bamler and Hartl*, 1998). The main approaches for overcoming this difficulty are 'path-following' algorithms which exploit the assumption of smooth phase gradient between adjacent pixels ( $-\pi \leq \nabla \varphi < \pi$ ), or 'path-independent' schemes which focus on minimizing the error between  $n_{\nabla}$ .

While a variety of path-following algorithms exist, they all are essentially concerned with implementing Eq. 48 by performing a summation of the phase differences between neighboring pixels over some closed loop (*Ghiglia and Pritt*, 1998; *Osmanoğlu et al.*, 2016, and references therein). 'Residues' exist where the summation is nonzero, local errors caused by noise (*Goldstein et al.*, 1988). The foundational algorithm developed by *Goldstein et al.* (1988) follows a path pixel-by-pixel using the location of identified residues to place 'branch-cuts' which serve as barriers for an unwrapping path, thus ensuring a unique solution. Subsequent work has developed numerous techniques for choosing the placement of the branch-cuts, as well as sophisticated methods that use cost functions to optimize starting points and unwrapping paths (e.g. *Flynn*, 1997; *Gutmann and Weber*, 2000; *Hooper and Zebker*, 2007).

Path-independent algorithms operate globally on an entire interferogram, thus avoiding the problem of path-selection. They seek to minimize the small error  $n_{\nabla}$  between the absolute  $\nabla \varphi$  and wrapped phase  $\nabla \psi$  gradients (*Ghiglia and Romero*, 1996):

$$|n_{\nabla}|^{p} = \sum_{k=1}^{N} |(\hat{\varphi}_{k} - \hat{\varphi}_{k} - 1) - \arg(\psi_{k}\psi_{k-1}^{*})|^{P}$$
(50)

where N is the total number of pixels in the interferogram and p is the degree of the norm. Using a Helmholtz decomposition, Eq. 50 is transformed into a Poisson equation relating the estimated absolute phase to the observed wrapped phase:

$$\nabla^2 \hat{\varphi} = \nabla^2 \psi \tag{51}$$

While several mechanisms are available to solve Eq. 51 (e.g. *Ghiglia and Romero*, 1996; *Pritt and Shipman*, 1994), Eq. 50 will underestimate  $n_{\nabla}$  in the presence of residues since the curl of the vector field is not conservative (see Eq. 49). To account for this bias, techniques from graph and network theory can be adopted, such as in the widely used Statistical-cost, Network-flow Algorithm for Phase Unwrapping (SNAHPU) algorithm (*Chen and Zebker*, 2000).

In addition to the main processing steps outlined here - co-registration, interferogram formation and coherence computation, range difference corrections, and phase unwrapping - interferograms are commonly subject to spatial and temporal filtering and geocoded. Filtering enhances the signal-to-noise ratio (SNR) ratio, while geocoding converts the image from radar coordinates (azimuth, range) to geographic coordinates (lat, lon). While many of these topics remain under investigation, the rapidly increasing volume of SAR data has driven research towards the development of time series approaches to interferometry.

### 4.2.3 MULTI-TEMPORAL INSAR

Repeat images from SAR platforms with well-known orbits enables the time series approach to interferometry known as Multi-temporal InSAR (MT-InSAR). There are two main families of methods, SBAS and PS which both aim to reduce temporal decorrelation  $(\psi_{scat})$  but leverage different kinds of scatterer information, namely distributed and persistent, respectively (Fig. 26). The SBAS algorithm relies on 'stacking' numerous interferograms separated by small differences in acquisition times and orbital geometry to average out differences in distributed pixels in time (e.g. *Lundgren et al.*, 2001; *Berardino et al.*, 2002). Alternatively, PS algorithms focus on pixels with a dominant scatterer, i.e. a pixel that has stable amplitude or phase characteristics through time (e.g. *Ferretti et al.*, 2000; *Hooper et al.*, 2004)).

In addition to adding a time-dimension which can improve phase unwrapping (e.g. *Hooper and Zebker*, 2007), MT-InSAR effectively reduces atmospheric interference and temporal decorrelation, the primary noise sources of interferometric phase (Eq. 43). This sub-section describes the essential components of the PS and SBAS methodologies. I present three software packages: Generic InSAR Analysis Toolbox (GIAnT), Miami InSAR Time-series software in Python (MintPy) and Stanford Method for Persistent Scatterers (StaMPS). All three are capable of SBAS MT-InSAR, but only StaMPS additionally performs PS InSAR.

Pioneered by *Berardino et al.* (2002) the SBAS technique relies on using the information in a variety of interferograms with small spatial separations in orbital geometry (specifically



Figure 26: Illustration depicting phase characteristics of a pixel with distributed scatterers (a) and a persistent scatterer (b) (source: *Hooper et al.*, 2007).

the perpendicular baseline) and in time interval (referred to as temporal baseline) to minimize temporal decorrelation (Fig. 27b). SBAS algorithms typically utilize a set of unwrapped multi-looked interferograms ( $\Gamma \in 1, ..., M$ ) that are aligned to the same grid via coregistration to the same radar geometry or by geocoding to a geocentric coordinate system (*Berardino et al.*, 2002; *Lanari et al.*, 2007). Multi-looking increases coherence (at the expense of resolution) which is used to exclude from analysis pixels which decorrelate through time; together this substantially reduces  $\psi_n$  The algorithm operates pixel-by-pixel, such that a time series of the mean velocity (v) between SAR acquisitions at times t = 1, ..., N is formed according to: (*Berardino et al.*, 2002):

$$Bv = \Delta \psi \tag{52}$$

$$v = \left[v_1 = \frac{\psi(t_1)}{t_1 - t_0}, \quad \dots, \quad v_N = \frac{\psi(t_N) - \psi(t_{N-1})}{t_N - t_{N-1}}\right]$$
(53)

where B is an  $M \times N - 1$  design matrix that relates the SAR acquisitions to the interferometric pair they compose. B is rank-deficient when the interferogram network is composed of disconnected subsets, such that the minimum-norm Least Squares solution is found using the singular value decomposition (SVD) method; otherwise the classic linear algebra solution  $v = (B^T * Q^{-1}B)^{-1} * B^{-1}\Delta\psi$ , where Q is the covariance matrix, can be leveraged (*Strang*, 2006).

Recalling that  $\Delta \psi$  includes a topographic ( $\Delta \psi_{topo}$ ) and atmospheric component ( $\Delta \psi_{atm}$ )



Figure 27: Example perpendicular baseline plots for (a) a single-reference stack, as used by Persistent Scatterer (PS) algorithms and (b) a network of interferograms, as used by the Small Baseline Subset (SBAS) approach. The blue lines show the interferograms formed from the individual SAR acquisitions (red circles; source: *Hooper et al.*, 2012).

that obscure the deformation signal, these should be estimated and removed.  $\Delta \psi_{topo}$  is proportional to the perpendicular baseline and is thus calculated from the orbital state vectors using an apriori selected reference point. Since  $\Delta \psi_{atm}$  is correlated in space but not in time, a spatio-temporal filter is used to extract the deformation signal (*Ferretti et al.*, 2000). The overall SBAS algorithm (Fig. 28) results in a time-series of displacement history at each coherent pixel (*Lanari et al.*, 2007).



Figure 28: The Small Baseline Subset (SBAS) processing algorithm (source: *Lanari et al.*, 2007).

GIAnT is a MT-InSAR toolbox developed primarily at the NASA Jet Propulsion Laboratory (JPL). It contains implementations in the Python programming language of four time-series methods: SBAS, New Small Baseline Subset (NSBAS), Multiscale Interferometric TimeSeries (MInTS), and Temporally Parameterized Inversion (TimeFun) (*Agram et al.*, 2013). The GIAnT-SBAS and GIAnT-NSBAS implement the inversion described in Eq. 52. GIAnT-NSBAS has the additional capability of linking interferograms with disconnected networks and/or pixels that are not coherent in all interferograms<sup>4</sup> with a user-defined deformation model.

The MInTS approach differs from those previously described in that it transforms the interferometric phase into the wavelet domain before temporally inverting it (Agram et al., 2012). The main rationalization behind this is to overcome the errors that arise due to the spatial covariances in InSAR phase measurements (Hetland et al., 2012). MInTS is also more flexible than the other methods outlined since it allows the description of each pixel's phase evolution by incorporating a number of temporal models, such as spline functions for characterizing unknown processes, and/or sinusoids for known seasonal oscillations (Agram et al., 2013). TimeFun is essentially MInTS implemented in the data domain (rather than the wavelet domain) and uses a very similar inversion scheme.

The recently released MintPy software is now the de-facto MT-InSAR SBAS processing tool (*Zhang et al.*, 2019). The complete workflow proceeds from an unwrapped stack of interferograms to a displacement time series (Fig. 29). Some notable advances over GIAnT include a network inversion that utilizes the coherence information as weights, external atmospheric corrections, and unwrapping error corrections. The unwrapping error corrections can be implemented in the space domain via 'bridging', which utilizes a tree searching algorithm to minimize phase offsets between neighboring regions already identified as error free by an unwrapping algorithm. Alternatively (or in combination) unwrapping error corrections can be implemented in the time domain via 'phase closure', which sweeps the network and determines the phase closure  $C^{lmo}$  of each pixel:

$$C^{lmn} = \Delta \psi^{lm} + \Delta \psi^{mn} - \Delta \psi^{ln} \tag{54}$$

$$C_{int}^{lmn} = (C^{lmn} - W\{C^{lmn}\})/2\pi$$
(55)

where  $\Delta \psi^{lm}$ ,  $\Delta \psi^{mn}$ , and  $\Delta \psi^{ln}$  are the unwrapped interferometric phases formed from SAR images acquired at times  $t_l$ ,  $t_m$ , and  $t_n$ . When  $C_{int}^{lmn} \equiv 0$ , the phase is correctly unwrapped, which is then used to automatically identify and minimize unwrapping errors by using the  $L^1$ -norm regularized least squares optimization (Andersen et al., 2011; Zhang et al., 2019).

Rather than dealing with a network of multi-looked interferograms separated by short temporal and spatial (baseline) separation, PS algorithms operate on a stack of coregistered SLC images at full spatial resolution (Fig. 27). The goal of such algorithms is to find

 $<sup>^4</sup>$ Because the inversion is solved on a pixel-by-pixel basis, there may be some pixels that decorrelate and thus form a disconnected network, while others remain connected



Figure 29: Miami InSAR Time-series software in Python (MintPy) workflow. The blue (green) ovals represent steps in the interferogram (time-series) domain, while white (green) rectangles indicate input (output) data. Dashed boundaries represent optional steps/data (source: *Zhang et al.*, 2019).

resolution cells with the lowest phase noise  $(\psi_{scat})$ , which indicates a persistent scatterer within the posting. In general, the algorithms make an initial selection PS candidates from the single-reference stack based on their amplitude dispersion, a proxy for the relative strength of scatterers within a resolution cell :  $D_a = \sigma_A/\mu_A$ , where  $\sigma_A$  and  $\mu_A$  are the standard deviation and mean of the amplitude values, respectively (*Ferretti et al.*, 2001). Next, the reference topographic component and APS, present in all interferograms due to the co-registration are estimated and removed via the techniques described previously. The decorrelation noise of the PS candidates is then estimated as the residual between the data and 1) a model fit to 'double differenced' adjacent pixels (which further minimizes  $\psi_{topo}$  and  $\psi_{atm}$ ) or 2) phase with the spatially correlated components removed (which includes  $\psi_{topo}$ ,  $\psi_{atm}$ , and  $\psi_d$ ) (*Hooper et al.*, 2012). Both approaches agree well and serve to increase the quality of the deformation history by reducing the number of PS candidates (an thus overall data density) to those with high SNR ratios.

The Stanford Method for Persistent Scatterers (StaMPS) extends the general PS amplitude-dispersion approach of *Ferretti et al.* (2001) and *Colesanti et al.* (2003) by leveraging a pixel's phase stability to choose PS, and applying a full-resolution SBAS

approach (*Hooper et al.*, 2004; *Hooper*, 2008). These extensions increase the spatial sampling of the interferogram stack, which mitigates the major shortcomings of the earlier methods; namely, an increased number of PS reduces the likelihood of phase unwrapping errors while allowing an estimate of the spatially correlated nature of deformation, used in place of an *apriori* model to separate deformation from noise (see Eq. 43). StaMPS requires slight differences in interferogram formation to facilitate an estimation of the phase stability and subsequent PS selection. The displacement signal can then be estimated via unwrapping and removal of the noise terms.

The main considerations for interferogram processing for PS analysis in StaMPS are related to resolution and coregistration. To avoid dampening the PS signal, no multi-looking or spatial filtering should be applied during interferogram formation which introduces additional squint angle (formed between the azimuth and range direction) and look angle ( $\theta$ ; Fig. 25) errors. The squint angle error is mitigated in conventional InSAR by transforming to a common squint but is not done for PS processing as this coarsens azimuthal resolution. Look angle error, primarily composed of errors in the DEM, is also increased due to the difference in the PS position form the (assumed) center of the resolution cell. These errors only reduce the positional accuracy by a few meters and are thus negligible for most crustal deformation studies with ground resolutions  $\mathcal{O}(10)$  m (as opposed to infrastructure monitoring) (*Hooper et al.*, 2007). Since the interferogram stack may possess SAR acquisitions with long temporal or spatial baselines, a custom coregistration algorithm is implemented that derives a mapping function from well correlated interferogram pairs and applies it in a least squares sense to each reference - secondary pair in the stack (*Hooper et al.*, 2007).

After an initial selection of PS candidates using the amplitude dispersion method described above, an iterative process is used to estimate the phase noise  $\psi_{scat}$  for each candidate. First, pixels are weighted by their SNR, estimated first using the amplitude dispersion. Next, the weighted pixels are convert to the frequency domain and filtered with a moving window with a size based on the expected spatial correlation distance. The filter is adaptive, determining the correlated frequencies (pass band) from the frequencies present in the local window and smoothed using a low-pass Butterworth filter. This yields an estimate of the spatially correlated components of phase,  $\psi_{topo}$ ,  $\psi_{atm}$ , and  $\psi_d$ , which is subtracted from  $\psi$  to given an estimate of the phase noise  $\psi_{scat}$  and a residual phase. The cycle then repeats with a new calculation of the SNR using  $\psi_{scat}$  until several user controlled criteria, such as the spatial pixel density and the variation of the residual phase, are met. PS are then chosen from the candidates based on a probability. Full details on the probability density construction can be found in (*Hooper et al.*, 2007).

To recover the displacement from the wrapped phase, the phase must be unwrapped and the errors estimated and removed, similar to SBAS processing. In addition to incorporating 2-D unwrapping algorithms, StaMPS provides an option for 3-D unwrapping algorithm which leverages the time dimension in addition to the two space dimensions (*Hooper*, 2008). The contributions of the spatially correlated reference  $\psi_{atm}$  and  $\psi_{orbit}$ , and spatially uncorrelated secondary  $\psi_{atm}$  and  $\psi_{orbit}$  are estimated using a combination of low, high, and gaussian filters and removed (*Hooper and Zebker*, 2007).

A final extension of StaMPS over the traditional PS methodologies is the capability to complement PS processing with SBAS-like processing (*Hooper*, 2008). Similar to the typical SBAS approach, StaMPS-SBAS relies on a network of interferograms with small temporal and spatial and temporal baselines. It then differs by operating at full resolution and identifying slowly-decorrelated filtered phase (SDFP) pixels using the same methodology outlined above for PS pixels to identify stable pixels within the small baseline interferogram stack. Separately applying a PS approach results in a two potentially overlapping datasets of PS and SDFP pixels. The datasets are then combined and subjected to phase unwrapping, which results in reduced errors compared to either method alone due to the increased spatial density of the combined data. The typical filtering is applied to remove the unwanted components and the network inverted as in the typical SBAS algorithm (*Berardino et al.*, 2002; *Hooper*, 2008).

The power of MT-InSAR will continue to grow in the coming years with the commitment by the ESA to support the Sentinel-1 mission through 2030, the upcoming NASA-ISRO SAR (NISAR) mission, and others similarly providing high quality repeat pass SAR data free of charge. However, new InSAR processing methods are required to deal with such a volume of data, as the computation cost of the interferogram formation is already proving prohibitive. The National Aeronautics and Space Administration (NASA) JPL, in collaboration with California Institute of Technology (CalTech) has begun to address this issue through its Advanced Rapid Imaging and Analysis (ARIA) Project, which is automatically generating interferograms in near-real time over an expanding selection of Sentinel-1 tracks. In addition to urgent-response products, ARIA is forming standard displacment products suitable for a wide range of deformation purposes, such as Earthquake and subsidence monitoring via time-series analysis (*Bekaert et al.*, 2019a). Where available, these products are informing stakeholders and decision makers in a variety of fields, and enabling scientific investigation of processes on unprecedented spatial and temporal scales.

## 4.2.4 APPLICATIONS FOR SEA LEVEL

Many coastal communities are sinking as a response to both natural and anthropogenic activities, such as GIA and groundwater extraction, respectively (e.g. *Wöppelmann and Marcos*, 2016). A precise understanding of this subsidence is important both for coastal communities, as it enhances flood risk, and sea level studies, which rely in part on tide

gauge (TG) information (a more detailed description of TGs is provided in Section 2.2.2). While GNSS allow precise temporal sampling in some locations, even with dense networks they are not able to capture the spatial variability necessary to inform decisions and scientific investigations (e.g *Brooks et al.*, 2007). However, researchers have begun to explore new ways that the increasing volume, quality, and accessibility of SAR data can be combined with GNSS data to answer pressing questions related to current and future SLR. This section will review such efforts, detailing the current state of the science and proposing questions necessary for advancing our knowledge.

In that TGs are fixed to the land, they record both land and ocean signals, the former of which is commonly referred to as vertical land motion (VLM) (Fig. 2). The unwanted VLM component cannot be considered negligible due to the mm-scale climate signal sought in the SL information (*Emery and Aubrey*, 1991). Indeed, in many polar locations linear VLM from GIA is greater than the ocean component of the recorded SL and should be modeled and removed (*Peltier and Tushingham*, 1989; *Peltier*, 2004). However, nonlinear deformation, such as that resulting from tectonics, is much more difficult to constrain due to data deficiencies and the sub-millimeter precision necessary for quantifying the mm-scale climate signals in SL (*Blewitt et al.*, 2010; *Wöppelmann and Marcos*, 2016). Nevertheless, several methods exist for estimating VLM at TGs using external data from mainly continuous GNSS, satellite altimetry, and/or MT-InSAR.

Recent studies have shown that the statistical uncertainties of the vertical rate of the continuous GNSS solutions are now small enough to reduce the dispersion in SL trends (*Wöppelmann et al.*, 2007; *Santamaría-Gómez et al.*, 2012; *Wöppelmann et al.*, 2014). To achieve such accuracy, GNSS stations should be 'colocated' with TGs such that such that the antennae is placed directly on (or within several meters of) a structurally sound TG (*Intergovernmental Oceanographic Commission*, 2012). While there is a current push to colocate newly installed TGs with GNSS antennae and retrofit existing TGs (*Heitsenrether et al.*, 2019; *Thompson et al.*, 2019), the reality is that the majority ( $\sim 60\%$ ) of existing tide gauges do not have a station within a kilometer radius (*Gravelle et al.*, 2015; *Hamlington et al.*, 2016).

An alternative approach to understand VLM at TGs is to compare the TG measurement to the nearby open ocean SL as sensed by satellite altimetry (Fig. 2; a more detailed description of satellite altimetry is provided in Section 2.2.3). When the appropriate atmospheric and ocean corrections are applied, the difference in the two measurements can be considered the VLM occurring at the TG (*Cazenave et al.*, 1999). A global analysis by *Wöppelmann and Marcos* (2016) demonstrates considerable agreement in VLM calculated from this altimetry-TG differencing with VLM from TGs colocated with GNSS. Indeed, the median of the two velocity datasets differs by only 0.25 mm and agrees well with *Watson et al.* (2015), who used a different GNSS dataset. Moreover, this rate falls within the uncertainty of the terrestrial reference frame realization of  $\sim 0.5$  mm, which is a major limiting factor of SL studies (*Collilieux et al.*, 2014; *Wöppelmann and Marcos*, 2016). Additional errors can arise from coastal processes that affect SL at tide gauges but don't necessarily manifest in the the altimetry data used for the differencing, which is not directly adjacent to the TG, since land corrupts the altimetry-derived SL measurement (*Cazenave et al.*, 2019b).

Even in an ideal situation with VLM known at a TG, this point source cannot capture the spatial variability observed in coastal settings (*Brooks et al.*, 2007). However InSAR has this capability, and when combined with GNSS measurements to tie the relative InSAR rates to a geodetic reference frame, can be provide useful information on impacts from coastal SL change. Since the pioneering work of *Brooks et al.* (2007) developed this technique to study coastal VLM in Los Angeles, CA, a number of studies have refined and applied it to coastal locations around the world. Wöppelmann et al. (2013) used it to investigate Alexandria, Egypt, finding reduced VLM relative to previous studies and good agreement with VLM at a TG measured using the altimetry-TG method described above. Raucoules et al. (2013) showed high (15 cm/yr), nonlinear subsidence throughout Manila, Phillipines, as a result of anthropogenic groundwater withdrawal that affected the stability of sensors including a TG and GNSS station, calling into question the usefulness of the TG for SL studies. In contrast, *Cozannet et al.* (2015) showed regional stability in Dakar, Senegal, highlighting the importance of the 100+ year TG record recently re-discovered there. To compute high-resolution relative SL along the coast of northwestern France, *Poitevin et al.* (2019) subtracted MT-InSAR-derived VLM rates from satellite altimetry derived SL, showing overall ground stability and good agreement with the TG at Brest. Alternatively, *Filmer et al.* (2019) evaluated the potential of MT-InSAR to be used in calculating the offset between a TG and a nearby GNSS. Such a 'geodetic-tie' compared well in Western Australia to a differential leveling study in that both had a precision within  $\pm 0.4 \text{ mm/yr}$  to  $\pm 0.5 \text{ mm/yr}$ .

Despite the encouraging results from such investigations, VLM as derived from both GNSS and MT-InSAR suffers from a lack of historic data. At best, the two datasets have 10-20 year records which is insufficient for capturing and thus projecting nonlinear VLM into the past and future. Indeed, only since the launch of Sentinel-1 in 2014 have high quality SAR data been acquired regularly, which pales in comparison to the multidecadal climate signals sought in long TG (e.g. *Thompson et al.*, 2016). Nevertheless, with a SAR record approaching 6 years providing sub-millimeter precision, VLM trends can be distinguished from the annual cycle and inform near-term ( $\sim < 10$  years) SL studies with the assumption that the dominant driver of nonlinear VLM, that is groundwater pumping, will remain unchanged over this time period (*Blewitt and Lavallée*, 2002; *Colesanti et al.*, 2003; *Blewitt et al.*, 2010).

#### 4.2.5 RESEARCH QUESTION 3

Despite a wide geographical range encompassing a diverse array of geophysical processes, the previously described case studies all find considerable spatial heterogeneity in VLM throughout their study areas. Hampton Roads, a large metropolis in coastal Virginia, is experiencing the fastest RSLR on the U.S. East Coast in large part due to VLM (*Zervas*, 2009; *Eggleston and Pope*, 2013). However, it is not known whether VLM is spatially variable or dominated by long-wavelength GIA and thus homogeneous. Thus, research question 3 sought to determine:

What are the spatiotemporal patterns and trends of VLM in Hampton Roads?

This chapter proceeds towards answering this question by further describing the study area of Hampton Roads and the ongoing challenge of RSLR-driven flooding (Section 4.3). Next, VLM research leveraging historic ALOS data is documented. The specific InSAR approach is detailed, and findings presented and discussed. Attention then turns to the potential for ongoing VLM monitoring by using regularly acquired Sentinel-1 data (Section 4.4). These data are automatically processed with the ARIA system and then analyzed using the state-of-the-art time-series MintPy software. These steps are elaborated upon, and results are presented and qualitatively compared with those from the historic analysis (Section 4.3). The findings are placed in the context of regional efforts to enhance resiliency, and used as an initial assessment of a specific infrastructure project. As noted in the Introduction (Section 1), much of Section 4.3 has been published in *Bekaert, Hamlington, Buzzanga, and Jones* (2017). Similarly, most of Section 4.4 has been published in *Buzzanga, Bekaert, Hamlington, and Sangha* (2020).

## 4.3 HISTORIC VLM FROM PS MULTITEMPORAL INSAR

# 4.3.1 INTRODUCTION

Hampton Roads in southeast Virginia is home to the largest naval base in the world (Naval Station Norfolk), so mitigating and adapting to future RSLR is an issue of critical importance and national security. As such, planning efforts are underway to address the RSLR and increasing levels of coastal flooding in the region (e.g., *McFarlane*, 2012; *City of Norfolk*, 2015). Despite these efforts, information regarding the land contribution to the RSLR is lacking. The most comprehensive VLM measurements for the area cover the time period from 1940 to 1971, and although local rates of VLM can be inferred from a combination of these historic measurements and sparsely located *in-situ* observations (e.g., continuous GPS stations), current VLM estimates are insufficient – both in terms of accuracy and spatial resolution - for federal, state, regional and local governing bodies to develop locally precise adaptation and mitigation strategies to RSLR (*Eggleston and Pope*, 2013). In planning efforts, it has generally been assumed that subsidence across

the region is relatively constant spatially and consistent with the rates measured from 1940 to 1971, varying only within a couple mm/yr over Hampton Roads. In part, this assumption is made because of the lack of higher-resolution information on VLM.



Figure 30: Area of study covering Hampton Roads, showing available GPS stations. Green triangles represent stations used for the GPS reference frame tie-in, while yellow triangles represent stations used only for independent comparison. SRTM topography varies from -55 m tot 15 m. The ALOS-1 track used in this study is shown with the dashed line.

InSAR has proven to be a powerful technique to study VLM (*Hooper et al.*, 2012). However, measurement of VLM using InSAR in agricultural areas is notoriously difficult because of temporal decorrelation, which causes loss of signal coherence over time (Zebker and Villasenor, 1992). It is much easier to measure VLM in urban settings because hard targets provide consistent, coherent targets that can be processed using MT-InSAR, which have been used successfully in similar settings to the Hampton Roads area and with similar required precision (1–4 mm/yr Dixon et al., 2006; Brooks et al., 2007). Although the larger goal of this work is to quantify VLM and RSLR rates throughout the Hampton Roads area, both urban and agricultural, the primary focus here is on determining local VLM rates in the populous areas and at the facilities in Norfolk, Virginia Beach, Portsmouth, Hampton and Newport News that are critical to national security, particularly ship yards, military installations, power facilities, and water treatment facilities. Thus, this study seeks to resolve the gaps in our current state of knowledge by providing the first horizontal high-resolution (20–30 m) estimates of VLM in the Hampton Roads region based on analysis of historic satellite SAR data using state-of-the-art time-series InSAR methods. Maps of the spatial variation of vertical land motion across the region with associated uncertainties are generated and used to identify the areas experiencing high rates of subsidence that will consequently be under the greatest threat from future RSLR. The limitations of the historic SAR dataset over Hampton Roads are discussed, and suggestions made for future work that is necessary to improve knowledge of VLM in the region.



Figure 31: ALOS-1 small-baseline plot showing the perpendicular baseline for the 12 acquisitions (red circles) of the time series. Green lines indicate the interferograms that were used in the time-series analysis.

We used available historic satellite SAR data acquired from the Japanese ALOS-1 satellite between 2007 and 2011 (Fig. 31). This data is freely available through the Alaska Satellite Facility. Figure 31 shows the available ALOS-1 data acquired during the period of study (2007–2011). A minimum of 10–12 acquisitions is recommended for time-series processing (*Hooper et al.*, 2012), and met for the study area by the two scenes bisecting Norfolk, VA, on track 137 (shown as a dashed outline in Fig. 30). These two scenes cover a range of land types, both urban and vegetated, allowing for a determination of the suitability of the applied analysis across the entirety of Hampton Roads. Figure 31 shows the distribution of the 12 acquisitions across the time series, and shows a notable increase in acquisition frequency during 2010 and 2011. The considered interferogram pairs along with relevant baselines are also shown in Fig. 31 and summarized in Table 1. Note that interferograms 2, 4, 7, 9, 19, 21, and 23 were removed from the processing due to large perpendicular baselines (> 1000 km) and the presence of large ionospheric path delay errors, which were identified by visual inspection.

Table 1: Perpendicular and temporal baseline information of the interferograms used in the time-series InSAR. Interferograms 2, 4, 7, 9, 19, 21 and 23 were dropped during processing.

Interferogram	Time Period	Days Covered	Baseline (m)
1	20070924-20080626	276	-604
2	20070924-20080926	368	-2745
3	20070924-20100401	920	586
4	20080626-20080926	92	-2140
5	20080626-20090814	414	-532
6	20080626-20100401	644	1190
7	20080926-20090814	322	1680
8	20090814-20100401	230	1723
9	20090814-20101117	460	2333
10	20100401-20100517	46	204
11	20100401-20101117	230	611
12	20100517-20100702	46	261
13	20100517-20101117	184	406
14	20100702-20100817	46	213
15	20100702-20101117	138	146
16	20100817-20101002	46	300
17	20100817 - 20101117	92	-67
18	20101002-20101117	46	-367
19	20101002-20110102	92	319
20	20101002-20110217	138	971
21	20101117-20110102	46	686
22	20101117-20110217	92	1338
23	20110102-20110217	46	652

The relative subsidence map derived from InSAR is combined with GPS rates (NA12 plate reference) generated at the University of Reno (*Hammond et al.*, 2012; *Blewitt et al.*, 2016) in order to tie the InSAR rates to an absolute GPS reference frame. We performed a visual inspection of individual GPS time-series using the online portal (http://geodesy.unr.edu/) to make sure the rates can be assumed stable in time and to also confirm the automated system captured any cabling and antenna changes correctly. In the area of study, there are eight available GPS stations (Fig. 30). The measured

vertical rates and associated time periods for each GPS station are shown in Table 2. Six of the GPS stations were used to tie the InSAR rates with the reference frame. One of the stations provided measurements that did not overlap our study time period, and another was located in an area with relatively few valid InSAR measurements. Both of these GPS stations were omitted from the process of transferring the InSAR rates into an absolute GPS reference frame, but were used as independent points of comparison.

Table 2: Station name and calculated horizontal and vertical linear GPS rates with corresponding 1-sigma uncertainties for the vertical rate. Subscripts E, N, and U correspond to east, north, and up directions, respectively. The time period of each GPS record is shown in addition to whether it was used in the reference frame correction. For stations within a 250 m radius a weighted average rate and uncertainty was calculated.

Station	$V_U (mm/yr)$	$V_U$ std. (mm/yr)	Time Period	Ref?
LOYX	-1.89	0.93	20090509-20170408	Yes
VAGP	-2.24	1.21	20071010-20160409	Yes
LOY1	-2.42	1.45	20090206-20120321	Yes
DRV5/07	-1.86	0.48	20060310-20160818	Yes
LOYZ	-1.80	0.82	20090220-20170408	No
LOY2	-1.77	0.86	20090206-20170408	Yes
LS03	-0.98	0.90	20090225-20170408	Yes
CHR1	1.40	1.53	19960114-19990618	No

### 4.3.3 METHODS

As described in Section 4.2, InSAR refers to the phase difference between two SAR images acquired over the same location. Interferograms are generated from two SAR images that need to be aligned correctly, and the contribution of flat Earth and topography removed (*Hooper et al.*, 2012; *Hanssen*, 2001). Further processing is required to reduce: (1) decorrelation noise introduced by a change in the satellite acquisition geometry and surface scattering properties (*Zebker and Villasenor*, 1992), and (2) atmospheric noise from the ionosphere and troposphere (*Hanssen*, 2001; *Bekaert et al.*, 2015a). We reduce the problem of decorrelation noise by applying advanced time-series InSAR processing using the StaMPS software (*Hooper et al.*, 2012). This method selects only those pixels that remain stable over time, which substantially decreases the noise level (see Section 4.2). After time-series processing, we find interferograms with an average phase (scattering and thermal) noise of 25 degrees equivalent to an ~0.85 cm average precision for each

interferogram. For unwrapping we use the iterative approach as proposed in *Hussain et al.* (2016). Prior to time-series processing using StaMPS, we perform the interferometric processing using the JPL InSAR Scientific Computing Environment software (*Rosen et al.*, 2000) and the SRTM DEM in our processing (*Farr et al.*, 2007).

The atmospheric noise can be split into ionospheric and tropospheric components (*Bekaert et al.*, 2015a). The ionospheric noise is typically of a long spatial wavelength (>100 km) and, being a dispersive process, manifests more strongly in long wavelength SAR systems such as the L-band sensor aboard ALOS-1 (Hanssen, 2001). The magnitude of the tropospheric InSAR noise is independent of the SAR wavelength, and becomes even more apparent for larger study areas (e.g., >20 km) and in the presence of topographic relief (>100's m). It is mainly spatial and temporal variations of pressure, temperature, and relative humidity in the lower part of the troposphere which lead to a spatially variable tropospheric signal in InSAR(*Bekaert et al.*, 2015b). Over our study area tropospheric topography-correlated noise is expected to be small as topography varies smoothly from -55 m to 15 m (SRTM WGS84 heights). We correct InSAR with GPS to account for residual long-wavelength errors such as orbit errors and residual atmospheric noise. By limiting to relatively small study areas, the ionosphere manifests as a long-wavelength signal which can generally be removed by setting a local reference area. For those study areas that exhibit strong ionospheric noise, contaminated SAR acquisitions are rejected. The tropospheric noise is further reduced through time-series processing, as temporally uncorrelated noise gets averaged over time.

After time-series InSAR processing, a map of average radar LoS surface velocities is obtained. The subsidence map follows from projecting the LoS rates into the vertical and referencing to local GPS stations while propagating full uncertainties. We therefore assume negligible horizontal motion for InSAR. The impact of this assumption is expected small as the horizontal unit vectors have a smaller contribution when projecting into the radar LoS than the vertical and with horizontal rates that are on average an order of magnitude smaller than the vertical rate (see Table 2). Linear rates were computed for each GPS station and then used in the analysis. Atmospheric InSAR noise becomes more apparent with distance from a reference point, with maximum uncertainties at 20 km distance of 1 cm/yr.

Common practice is to reference InSAR observations to GPS by fitting a plane and minimizing the residuals (*Hooper et al.*, 2012; *Hussain et al.*, 2016; *Bekaert et al.*, 2015c). However, we found a simple planar fitting insufficient to account for the variability of the ionospheric noise and had too few GPS stations to constrain a higher degree plane. We address this problem by utilizing only InSAR observations within a 20 km radius of a GPS station, allowing us to limit the impact of longer-wavelength atmospheric InSAR noise. Given the local InSAR thermal and scattering noise, we average InSAR rates within a 500 m radius of the GPS site when referencing all InSAR observations within 20 km of that station. We require at least 50 InSAR observations (stable and well-sampled) to justify using the station in the GPS reference frame tie-in. The associated uncertainty of the InSAR rate tied to the local GPS site follows by propagating the GPS and InSAR uncertainty, with the InSAR uncertainty estimated through bootstrapping the InSAR time-series (*Efron and Tibshirani*, 1986) while defining the GPS station location as a stable or reference point. By repeating this for all GPS stations, we obtain a locally-tied InSAR rate map with corresponding uncertainty for each station. Next, we compute the weighted average of the the locally tied rate maps and propagate the associated uncertainty to obtain the rate and uncertainty map tied to the complete GPS network. Locations in the vicinity of multiple GPS stations (where circles overlap) will have the smallest rate uncertainties. Given the precision and atmospheric noise of individual interferograms in combination with the ALOS acquisition sampling and uncertainty of the GPS vertical rates, we find at best an uncertainty of 3–4 mm/yr for the derived subsidence map.

#### 4.3.4 RESULTS



Figure 32: Subsidence rate-map (left) and corresponding uncertainties (right) as estimated from historic (Sept 2007-Feb 2011) ALOS SAR data referenced to a GPS reference frame. Left, due to longer wavelength spatial variation (>20 km) of ionospheric InSAR noise, only InSAR subsidence rates within a 20 km radius of a GPS site (dashed circles) are use to locally reference InSAR to the vertical GPS rate. A weighed average is performed in the circle overlap regions to integrate the local referenced InSAR subsidence in a regional map. Right, propagated uncertainties shows the uncertainty grows with distance from a GPS station due to atmospheric noise, and areas falling within multiple circles to have a smaller uncertainty due to noise averaging. GPS measured rates are shown in square and circular markers on the subsidence rate map, with the square markers representing the stations used for the GPS referencing and the circular markers stations used for comparison only.

After processing the ALOS-1 data, a VLM rate map for Hampton Roads over the time period from 2007 to 2011 is obtained (Fig. 32, left) along with the associated uncertainty in the rate (Fig. 32, right). The available GPS-measured rates are also shown for comparison (square markers are used for GPS stations used to tie into GPS NA12 plate reference frame), showing good agreement with the underlying InSAR-generated

rate map. As detailed in the methods, using the InSAR data to constrain the short spatial scales and the GPS data to constrain subsidence across longer spatial scales allows us to mitigate long-wavelength errors introduced by atmospheric (ionosphere and troposphere) noise in the InSAR data. As a result of this procedure, locations near to a GPS station have reduced uncertainty when compared to areas without a nearby GPS station.

Although in many areas the uncertainty is large and the estimated rates are not significant at either the one- or two-sigma levels, there is still important information that can be withdrawn. From a broad perspective, significant spatial variability in rates of VLM exists around the region. Contrary to commonly thought, there are a number of areas experiencing positive displacement over the time period, particularly in the vicinity of Poquoson and York County (north of LOY1), and in Cape Henry (near CHR1). Further focusing on the area of low uncertainty around Hampton and Newport News, there are relatively large changes in VLM over short spatial scales. Indeed, over a  $\sim 20$  km range extending west to east through Hampton, there is a shift from negative to positive displacement. Along the shore of Virginia Beach, a gradual change from positive to negative displacement, (north to south) is observed, with these rates confirmed by the two available GPS stations in the vicinity and indicating potential impacts of beach nourishment.

This apparent spatial variability in the vertical rates likely precludes a "one size fits all" approach to planning for subsidence in the region. The associated uncertainty estimates (Fig. 32, right) also demonstrate the importance of *in situ* observations in the form of continuous GPS measurements. InSAR-measured rates in the vicinity of a GPS station have significantly lower uncertainty than those further afield of GPS. This is particularly notable for northern Norfolk, which contains the Naval Station and urban center, and has rate uncertainties on the order of 1 cm/yr and few GPS stations.

As an additional method of viewing the spatial variability of VLM and uncertainty in the region, three profiles are drawn, transecting the region of study (Fig. 33, left). Profile A-A' begins on the shore of Virginia Beach and ends in the northwest portion of the region. The large uncertainty for much of the region is clear (indicated by the gray-shaded error bars), but a number of features stand out with exceptional rates of VLM including subsidence signals in the Norfolk Naval Shipyard and Craney Island land reclamation project. To the north (end of A-A' profile), further subsidence is found, including near the closed landfill in Epes, Newport News. The rates at the GPS stations along the profile are shown in red and green and demonstrate good agreement with the underlying InSAR map. Two further profiles are drawn, one from Cape Henry to Chesapeake/Suffolk (B-B') showing a transition from an area of uplift to an area of subsidence, and one starting from Smithfield/Isle of Wight (C-C') and showing agreement with several of the available GPS stations in the area.



Figure 33: Profiles drawn across the VLM map (left) showing change in rates along each transect (right). Uncertainty is shown across each profile, with dark gray showing the one-sigma uncertainty, and lighter gray representing the two-sigma level. Each measurement along the profile is obtained by including the InSAR rates within a 500 m radius about the point along the profile. Rates measured at the GPS stations that are found along the profiles are shown in red (if used in inversion) and light-blue with 2-sigma uncertainties, and labeled with the station name.

Two primary benefits of the approach used here are the representation of subsidence on small spatial scales and the ability to analyze the time series of vertical land motion at each location. In order to identify areas that are experiencing large rates of subsidence, we focus on a region centered on Norfolk and encompassing Hampton, Virginia Beach (among other areas; box shown in Fig. 32A, zoomed in area shown in Fig. 34, top). Differencing the time series of two nearby locations has the benefit of reducing the atmospheric error, which generally varies over longer spatial scales. Here, we select several points and difference the InSAR measured time series relative to the InSAR measurements surrounding a nearby GPS station. It should be noted that this difference is built upon the assumptions that the respective time series are linear and that the InSAR observations near the GPS stations are accurate and agree with the GPS measured rates.

Seven separate points are selected for time series analysis: (A) southern Newport News, (B) the Island where Monitor Merrimack bridge connects to a tunnel, (C) Craney Island, (D) Old Dominion University in Norfolk, (E) Norfolk Naval Shipyard, (F) southeast Virginia Beach, and (G) the Kings Grant area of Virginia Beach. The time series for each point relative to the nearest GPS station are shown in the bottom panels of Fig. 34. Significant rates of subsidence exceeding the two-sigma level are found at Craney Island, and exceeding the one-sigma level at the Naval Shipyard, while a significant rate of uplift is found on the bridge (one-sigma). These rates are consistent with a time-series InSAR study over the bridge using RADARSAT-1 data (*Hoppe et al.*, 2015). During the study time period (2007–2011), Craney Island was expanded eastward through a land-reclamation project. This expansion is being accomplished through the disposal of dredged material that is then contained by the surrounding dikes. This additional loading appears to be causing subsidence in the dikes that is occurring at a higher rate than the addition of dredged material, which has been monitored with *in situ* measurements and is a design feature of the site. The cause of the subsidence at the Norfolk Naval Shipyard was unknown at the time of the study, but has since been identified as loading from construction. Although the other selected locations do not individually show statistically significant rates given the uncertainty, the observed rates do highlight the spatial variability of VLM across the area of study.



Figure 34: VLM rate map focused on the area centered on Norfolk (box shown in Fig. 32). Bottom panels show differenced time series for seven locations relative to the nearest GPS station.

#### 4.3.5 DISCUSSION

As discussed above, the Hampton Roads coastlines are experiencing exceptionally high rates of RSLR, owing to both the steady increase of sea level and the long-term subsidence of the land. The rate of GMSL over the past century is approximately 1.5 mm/yr. On the other hand, the relative average RSLR measured at Sewell's Point gauge in the Hampton Roads region from 1950 through the present is on the order of 4 mm/yr. While some of this increased rate is likely ocean-related, these first order data imply a significant level of subsidence in the region contributes to this RSLR. Specific – albeit sparse – previous measurements of subsidence, indicate a broad range of subsidence that could be even greater in some localities. Subsidence measurements based on geodetic surveys made from 1940 to 1971 indicated an average subsidence rate of 2.2 mm/yr with a range of 1.1 to 4.8 mm/yr across the region (Holdahl and Morrison, 1974). These data were updated with GPS measurements taken between 2006 and 2011 that showed an average subsidence rate of 3.1 mm/yr at three GPS stations (VAGP, DRV6 and VIMS) in the region (*Snay and Soler*, 2008). These stations are shown in Fig. 32, except for VIMS which is outside our study area. The stations, inland at Franklin, Virginia, and closer to the Hampton Roads littoral at Suffolk, Virginia, showed subsidence rates of 1.5 and 3.7 mm/yr respectively, based on groundwater extensioneter measurements taken between 1979 and 1995 (*Pope and Burbey*, 2004). While the Suffolk station is within the ALOS frame boundary, there are no collocated InSAR measurements. In short, there is evidence of high rates of subsidence that appear to vary considerably across the region.

To date, little has been done to improve upon this spatially sparse information and satellite observations have been a heretofore-untapped resource. The results presented here represent a first attempt at filling a gap in current knowledge regarding the threat of future RSLR that is needed for developing resilience in the Hampton Roads region. While the available historic ALOS SAR data is limited (Fig. 4), there are clear indications of spatial variability in VLM with some areas experiencing high rates of local subsidence. Given the costly infrastructure in Hampton Roads, identifying these areas has important implications for future planning efforts.

There are a number of issues with the historical SAR data and the results presented here that limit their implementation as the basis for planning efforts. First, the estimated rates reflect only the VLM from 2007 to 2011, which is assumed to be linear. Whether or not these can be extrapolated into the future depends on the geophysical causes of the surface VLM rates and whether land use remains consistent in time. In addition, uncertainties would also scale over time. If loading in Craney Island were to cease, for example, there would be an expected associated change in the VLM rate. Second, the observations provided by the ALOS-1 satellite limit the quality of the VLM rate information that can be extracted. The L-band measurements are particularly sensitive to the ionosphere, leading to increased uncertainty from that source of atmospheric noise (*Hanssen*, 2001). The number and intermittent nature of the available acquisitions are also less than ideal for estimating linear VLM rates (*Hooper et al.*, 2012). These inherent challenges underscore the need for further analysis. Given the thermal and scattering noise of the sensor in combination with the data sampling and atmospheric noise we find at best an uncertainty of 3-4 mm/yr for the derived rates.

Since 2015, the Sentinel-1 satellite has been acquiring data over the Hampton Roads region every 12 days. Additionally, the Sentinel-1 satellite samples in the C-band, leading to a dramatic reduction in the uncertainty associated with the ionosphere. Importantly, the European Union Commission has committed to continuing and augmenting the Sentinel constellation until at least 2030, ensuring the ability to monitor subsidence over Hampton Roads and leading to substantially reduced uncertainties as the time series gets longer. In summary, while analysis of the Sentinel-1 data should eventually provide the decision-making quality VLM maps that are needed for Hampton Roads, the results presented here motivate and demonstrate the need to improve the understanding of the VLM in the region.

## 4.4 CONTEMPORARY VLM FROM SBAS MULTITEMPORAL INSAR

## 4.4.1 INTRODUCTION

As demonstrated in Section 4.3, Hampton Roads in southeastern Virgina (Fig. 35) is undergoing significant RSLR due to both the long-term rise in GMSL associated with anthropogenic global warming and substantial regional subsidence. The regional subsidence is attributed largely to aquifer compaction resulting from groundwater extraction of ~150 Million Gallons per Day (MGD) and the impacts of GIA, which together contribute more than half of the RSLR (*Engelhart et al.*, 2009; *Eggleston and Pope*, 2013; *Karegar et al.*, 2016). While a constant rate of regional land subsidence caused by GIA (-1.3  $\pm$  0.2 mm/yr; *Engelhart et al.*, 2009) has been assumed (*Eggleston and Pope*, 2013), Section 4.3 showed that the spatial variability of land surface subsidence due to anthropogenic activities should be considered in planning. Neglecting such localized subsidence could have negative consequences in mitigation and adaptation activities, particularly as efforts are already underway to address future RSLR in the region.

One such effort to mitigate the consequences of RSLR, headed by the Hampton Roads Sanitation District, is the "Sustainable Water Initiative for Tomorrow" (SWIFT; http://swiftva.com; Holloway et al., 2017), which aims to inject 90% (i.e. 135 MGD) of reclaimed wastewater - treated to potable quality - directly into the Potomac aquifer instead of releasing it downstream by 2030. This project aims to (1) increase the fresh groundwater availability, (2) reduce or reverse saltwater intrusion, and (3) contribute to a partial elastic rebound of the aquifer, reducing the rate of land subsidence and thus the

rate of RSLR. Since May 18th, 2018, SWIFT has been injecting 1 MGD in a pilot well as an initial experiment; the construction of the first of 5 full-scale facilities begins in 2020, increasing the rate of injection to 135 MGD by 2030 (*SWIFT*, 2019). To monitor the local effects of the SWIFT project, an extensometer was installed at the pilot well site which measures the change through time of aquifer thickness (see Fig. 35 for location; data available at: https://waterdata.usgs.gov/va/nwis/dv?referred\_module=sw&site\_ no=365337076251606&format=gif\_mult\_sites&PARAmeter\_cd=50012&period=365).



Figure 35: Overview of our Hampton Roads study area (dotted inner outline), located in Virginia, USA. Land subsidence accounts for more than half of the RSLR, primarily due to aquifer compaction resulting from groundwater withdrawal (*Eggleston and Pope*, 2013). The Sustainable Water Initiative for Tomorrow (SWIFT) project aims to reinject 90% of reclaimed wastewater into the Potomac aquifer to increase water availability and alleviate coastal challenges. Initial injection at 1 MGD started on May 18<sup>th</sup>, 2018 and is monitored using an *in-situ* extensometer (triangle marked EXT) measuring aquifer compaction Here, we use GPS (colored markers; blue are used for the geodetic tie-in while gold are used as in independent-check) and InSAR from Sentinel-1 (Track 4; dashed outline) to measure VLM especially in response to the injection.

Figure 36 shows the aquifer thickness (which is proportional to uplift) time-series of the extensometer, which is still too short to resolve the annual cycle but does show the effects of specific events. The thickness of the aquifer increased following the pilot injection start until August 18 when a relatively large amount (~1.5 mm) of aquifer compaction (proportional to subsidence) occurred. Between August 3 and August 22, injection at the well ceased and was replaced by a groundwater withdrawal (26.6 MG total) in response to the detection of unsafe levels of nitrate in previously injected water (*SWIFT*, 2018).

While the extensioneter provides valuable information about aquifer thickness and thus the VLM at the pilot well, it does not provide information about regional subsidence, at locations particularly vulnerable to RSLR. Although GPS stations are available and provide high-precision and high-temporal sampling of VLM in the region (e.g., *Hammond et al.*, 2012; *Blewitt et al.*, 2016; *Argus et al.*, 2017), they are spaced about 30 km apart so cannot resolve horizontal variability of VLM at finer scales.

InSAR can provide VLM measurements up to a few meters' spatial resolution (e.g., Sneed et al., 2003; Hooper et al., 2012; Jones et al., 2016; Shirzaei and Bürgmann, 2018) and thus allows for capturing the spatial variability of the subsidence over Hampton Roads (Section 4.3). The volume of SAR data has been increasing rapidly with the launch of Sentinel-1 in 2014 and will continue to increase with future launches, such as the upcoming NISAR mission. These data can be processed rapidly with state-of-the-art InSAR techniques, enabling sustained monitoring over large spatial scales. Such ongoing monitoring is particularly important in subsiding coastal regions such as Hampton Roads where flooding continues to worsen with RSLR. Additionally, sustained InSAR analysis of the SWIFT project may provide unique insights into nonlocal effects of groundwater injection on VLM through time.

In this study, we combine observations from GPS and Sentinel-1 InSAR to map VLM across the Hampton Roads region at 90 m spatial resolution and quantify its corresponding uncertainties. By utilizing InSAR and GPS we combine the strengths of both data sources and can convert the relative LoS InSAR displacement rates into a geodetic reference frame. We investigate locations experiencing high rates of subsidence, which are thus particularly vulnerable to RSLR. We provide an analysis of the region around the SWIFT injection site in an attempt to determine the impact on local VLM. In highlighting the SWIFT project, we provide a specific instance of how ongoing monitoring of VLM can be used for developing targeted mitigation and adaptation approaches addressing RSLR.



Figure 36: Aquifer thickness time-series of the extensometer located at the SWIFT pilot well reinjection site (Location EXT on Fig. 35). The start of the reinjection period is indicated by the dotted green line. While too short to resolve the annual cycle over the duration of our study (ending in May, 2019), specific events such as groundwater extraction (shaded gray region) can be observed (data available at: https://waterdata.usgs.gov/va/nwis/dv?referred\_module=sw&site\_no= 365337076251606&format=gif\_mult\_sites&PARAmeter\_cd=50012&period=365.)

#### 4.4.2 DATA

To generate a subsidence map from InSAR, we use Sentinel-1 data acquired by the European Space Agency provided free of charge under the Copernicus program. With a commitment by the European Commission to support the Sentinel-1 constellation at least until 2030, Sentinel-1 is an attractive sensor for sustained monitoring. Over Hampton Roads, Sentinel-1 has acquired data consistently on a 12-day interval since July 2016, leading to 75 acquisitions up to June 2019. The ARIA Center for Natural Hazards project (*Bekaert et al.*, 2019b) provides open and free access to an operational archive of standard Sentinel-1 UNWrapped Geocoded interferogram (GUNW) products, enabling rapid ingestion into post-processing algorithms. These InSAR derived surface displacement products are provided as native Sentinel-1 frames and processed at 90 m spatial resolution with interferometric pairs generated between the nearest two acquisitions, leading to

temporal baselines of 12 and 24 days over Norfolk. The ARIA project provided additional annual interferogram pairs spanning October and May each year.



Figure 37: **a)** Sentinel-1 small-baseline plot showing the perpendicular baseline and average spatial coherence of each interferogram in the time series. The circles are individual acquisitions and the lines are interferograms. The coherence can be used as a quality marker, ranging between 0 and 1, with 0 indicating a complete loss of the signal, i.e. noise. **b)** Temporally averaged map of coherence. The urban centers of Norfolk, Hampton, and Virginia Beach have higher coherence compared to vegetated regions which will decorrelate more rapidly in time.

In our analysis, we use a fully connected network of 163 Sentinel-1 interferograms (equivalent to 163 GUNW products) spanning March 2015 to July 2019 (Fig. 37a). Coherence, ranging between 0 and 1, is a proxy for the interferogram quality and guided our interferogram selection such that we excluded interferograms with a spatial average land coherence < 0.525. Nearest annual pairs excluded summer months, which suffered from decorrelation due to changing vegetation and humidity. We focused our study area on the urban centers of Hampton Roads, which maintained their coherence longer than periphery rural regions (Fig. 37b).

We combine the high spatial resolution of the InSAR observations with highly accurate, but sparsely distributed (average station spacing of 30 km), GPS observations (see Fig. 35 for station locations). GPS provides an important constraint as it allows us to tie the relative InSAR displacement rates into a geodetic reference frame (e.g., *Bekaert et al.*, 2017; *Pritchard et al.*, 2002; *Bock et al.*, 2012; *Hammond et al.*, 2012; *Zerbini et al.*, 2017). We use the Median Interannual Difference Adjusted for Skewness (MIDAS) east/north/up land surface displacement rates and formal uncertainties provided in the IGS14 reference frame by the Nevada Geodetic Laboratory (Table 3; http://geodesy.unr.edu; *Blewitt et al.*, 2018).
Table 3: Station name, longitude and latitude coordinates, observational period, vertical MIDAS displacement rate and corresponding 1-sigma uncertainties for each GPS station (*Blewitt et al.*, 2016). An asterisk next to the station name indicates it was used for the reference frame tie-in. The last column shows the residual between the InSAR pixels in a 300 m radius around the GPS station after tying InSAR to the GPS IGS14 reference frame computed from a 300 m radius around the GPS station.

Station	Latitude	Longitude	Start	End	$V_{up} (\mathrm{mm/yr})$	$\sigma_{up} \ (\mathrm{mm/yr})$	Residual (mm)
DRV5/6	36.959	-76.557	1999-07-17	2019-09-03	-2.6	0.5	0.2
LNG4	37.103	-76.383	2015-11-07	2019-02-10	-2.6	2.9	0.3
LOY2	36.764	-76.238	2009-02-06	2020-05-02	-2.3	0.4	1.0
LOYZ	36.864	-76.574	2009-02-20	2020-05-02	-1.3	0.6	2.0
LS03	36.789	-75.959	2009-02-25	2020-05-02	-2.7	0.6	0.5
SPVA	36.943	-76.329	2015-04-30	2020-04-21	-0.7	2.3	2.0
VAHP	37.062	-76.403	2009-02-06	2015-09-28	-1.2	1.0	0.2

## 4.4.3 METHODS

We use InSAR surface displacement products (GUNW products) generated by the ARIA project, which has been automatically generating SAR-derived data products using the JPL ISCE software (*Rosen et al.*, 2012), as input for our time-series InSAR analysis. We leverage the publicly available ARIA tools suite of software (https://github.com/aria-tools) for pre-processing and manipulation of the GUNW products (*Bekaert et al.*, 2019b). Although we no longer need to process the InSAR data ourselves, the challenges for time-series InSAR related to decorrelation (*Zebker and Villasenor*, 1992), atmospheric noise (*Hanssen*, 2001; *Bekaert et al.*, 2015a; *Murray et al.*, 2019), and unwrapping errors remain to be addressed (*Hooper et al.*, 2012).

Decorrelation (loss of signal) is introduced due to changes in surface scattering, while atmospheric noise is related to propagation delays in the troposphere and ionosphere. We attempted tropospheric noise correction using the Generic Atmospheric Correction Online Service (Yu et al., 2018) but found the 12 km weather model not capable of capturing the complex tropospheric noise patterns observed over flat terrain; rather, it introduced additional high-frequency noise. Therefore, we use visual inspection to drop interferograms with clear high-frequency fringe patterns that show unrealistic deformation (> cm/yr).

We further reduced the impact of decorrelation and atmospheric noise by applying time-series InSAR processing using the MintPy software (*Zhang et al.*, 2019). During time-series processing we invert our redundant small baseline interferograms to a time-series referenced to March 10<sup>th</sup>, 2015, after which we estimate with simple least-squares the linear displacement rate (LoS velocity) and bias (residual reference atmosphere and noise) from the data. We bootstrap our time-series 2500 times (*Efron and Tibshirani*, 1986) and compute the standard deviation to estimate the corresponding uncertainty of

both the LoS velocity and residual reference atmosphere and noise. We drop noisy pixels (coherence less than 0.215) and invert our redundant small baseline interferograms to a time-series referenced to March 10<sup>th</sup>, 2015. We only consider motion in the vertical, which is the dominant contributor to the LoS in our tectonically stable study area.

During unwrapping, a continuous surface is constructed by adding  $2\pi$  moduli to the wrapped phase. Unwrapping between islands is not trivial as water bodies are decorrelated in interferograms. This represents a challenge in Hampton Roads due to the confluence of the Atlantic Ocean and James River, which bisect our study area. We address this by masking out water and by performing the above time-series analysis separately for the regions of land to the north and south of the James River. We generate a water mask by combining a mask derived from the Global Self-consistent, Hierarchical, High-resolution Shoreline Database Wessel and Smith (1996) with a mask generated by thresholding mean amplitude, masking values less than 500, which are proxies for water. We then reference the InSAR vertically projected displacement rates for each north/south subregion to local GPS stations to generate a VLM map. We compute the residual between the region north of the James River and the VLM at GPS station VAHP and apply the offset to shift InSAR pixels accordingly. Although the VAHP time-series ended shortly after the Sentinel-1 satellite began acquiring images in 2015, the MIDAS displacement rate (-1.2  $\pm$ 1.0 mm/yr; Blewitt et al., 2016) is dominated by GIA (-1.3  $\pm$  0.2 mm/yr; Engelhart et al., 2009). This is a strong indication that the VLM rate estimated at VAHP is maintained through the end of our analysis in June 2019. As an additional check, we referenced the region north of the James River to station LNG4 and found agreement within uncertainty (not shown).

In the southern region, several of the GPS stations - especially LOY2 and SPVA - suffer from noise, data gaps, and/or short records. To address these challenges, we combine the VLM rate at station LOY2 with an average residual, weighted by GPS uncertainties, between each of the GPS stations and its surrounding InSAR pixels. We only use GPS stations that have temporal overlap and coherent InSAR pixels within a 300 m radius: LOY2, LS03, LOYZ and SPVA (blue squares in Fig. 35). We also apply a correction to the individual time-series of InSAR VLM histories to show the deformation of the pixel in the IGS14 framework. As the InSAR time-series processing is done relative to local GPS stations, the corrected VLM history can be obtained by adding in local GPS VLM history, which we reconstruct over time by multiplying the GPS VLM rate with the duration of the InSAR time-series. Although this does not provide an absolute reference to IGS14, it allows us to make a comparison between the IGS14 VLM rate maps and the corrected InSAR VLM history.

#### 4.4.4 RESULTS

Our regional VLM rate map with corresponding uncertainties as derived from Sentinel-1 data, spanning March 2015 to June 2019, and GPS referenced to the IGS14 reference frame is shown in Figure 38. Square colored markers show the VLM rate of the GPS stations used as a tie-in for InSAR. We find good agreement between InSAR and GPS with an RMSE of 0.9 mm, for all stations within our study area (see Table 3 for individual station residuals) On average we find Hampton Roads to be subsiding with a VLM rate of  $-3.6 \pm 2.3 \text{ mm/yr}$ , Norfolk with a VLM rate of  $-4.4 \pm 2.5 \text{ mm/yr}$ , and Virginia Beach with a VLM rate of  $-3.8 \pm 2.5 \text{ mm/yr}$ .



Figure 38: vertical land motion (VLM) rate map (a) and corresponding 1-sigma uncertainties (b) as estimated from Sentinel-1 derived interferograms spanning March 2015 to June 2019. To minimize long-wavelength noise, we tie VLM rates on the upper peninsula to GPS station VAHP. Southern VLM rates are tied to station LOY2 combined with an average residual, weighted by GPS uncertainties, between each of the GPS stations and its surrounding InSAR pixels. The square and circular markers correspond to GPS stations used and not used, respectively, for the IGS14 tie-in of the InSAR line-of-sight (LoS) displacement rates.

Within our study area, we find 85.7% of our estimated VLM rates to be significant at 1-sigma confidence. This includes nearly all of Norfolk, Virginia Beach, and Hampton (Fig. 39). We additionally find 12.5% of our VLM rates to be significant at 2-sigma confidence, correlating with subsiding residential areas in Norfolk and Portsmouth. Uncertainty increases with distance from the reference GPS stations, resulting in increased error along the coast in south of the James River and in western rural areas.





37.2

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Figure 39: Significant vertical rates at the 1- $\sigma$  (a) and 2- $\sigma$  (b) uncertainty thresholds, where significant is defined as the absolute rate minus the uncertainty larger than zero.

To highlight particularly important sections of Hampton Roads, we draw 3 transects through the regions (Fig. 40, a-c). Transect a-a' starts in the northwestern-most part of our study area, extends southward through station VAHP and ends at GPS station LOY2. Both the subsidence and unwrapping errors (discontinuities) at Craney Island are apparent. Hampton and Newport News show relative stability. Transect b-b' begins at First Landing State Park, runs southwest through central Virginia Beach and Norfolk, and ends at GPS station LOY2. The entire transect is subsiding, especially at First Landing State Park and in many densely populated suburban regions. Transect c-c' begins at Smithfield near GPS station LOYZ. It extends across the James River into Hampton, crossing GPS stations DRV5/6, VAHP, and LNG4. There is good agreement with all the GPS stations despite the high spatial variability along the transect, and a loss of coherence in the rural areas of the southwest and northeast.

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Figure 40: (a-c) Transects across the regional vertical land motion (VLM) map highlight spatial variation in VLM across Hampton Roads for the period March 2015 - June 2019. The 1 and 2-sigma InSAR uncertainty is shown with dark and light gray shading, respectively, along each transect. Each measurement along the transect is obtained by including the InSAR VLM rates within a 500 m radius about the point along the profile. 2-sigma vertical GPS VLM rates are colored blue if used in the referencing and gold otherwise. (d-g) VLM history of locations (shown in inset map) in the IGS14 geodetic reference frame. InSAR observations (black markers) are averaged within a 300 m radius around each location and weighted by the uncertainty. The linear least-squares VLM rate is shown by the red dashed line, with both the magnitude and 1-sigma uncertainty reported within each panel.

Specific locations subjected to further time series analysis (Fig. 40d-g) are marked as follows: (d) Central Hampton, (e) Norfolk Naval Shipyard, (f) Craney Island, (g) First Landing State Park. To reduce noise in the time-series we average the VLM history of all pixels within a 400 m radius around each of the individual locations. We then difference this time series with the VLM of the InSAR values near the closest GPS station to reduce long-wavelength atmospheric noise. For further validation, b, c, and d were also differenced to the second-closest GPS station, with similar results. With the exception of the Central Hampton, where no VLM is found, the VLM rates show subsidence trends that are significant at the 1-sigma level.

To assess the impact of the SWIFT pilot injection project on local VLM, we compare the VLM at the injection with that of the surrounding area (Fig. 41). We reference the relative InSAR LoS displacement rates to the location of the injection site and difference the spatially averaged VLM history within the cyan torus with that near the injection site (magenta circle). The injected waters will spread through the Potomac Aquifer (*McFarland and Bruce*, 2006), thus any impact on subsidence will manifest as an uplifting trend near the injection site relative to the surrounding area.



Figure 41: Assessing the impact of the SWIFT pilot injection project on local vertical land motion (VLM) by comparing how the VLM history at the injection site (within magenta circle) changes with respect to that of the surrounding area (cyan torus). The overview figure shows which data have been used in the relative comparison. The green dotted line and gray shaded region mark the start of injection and a groundwater withdrawal period, respectively.

The overview panel (Fig. 41a) shows the data which have been used in the comparison. The magenta circle and cyan torus each have a radius of 1 km and are separated by 7 km. Craney Island, Newport News and Isle of Wight are omitted from the regional analysis as compaction of the Craney Island reclamation site and potential unwrapping errors linking Portsmouth, and Newport News/Isle of Wight could bias the comparison. In addition to the configuration shown in the overview plot of Figure 41a, we test a variety of radii lengths for the inner circle and outer torus, and distances between them (Figure 42). We do not yet observe surface uplift induced by the injection in our experiments.



Figure 42: Similar to Fig. 41, except here each row tests a different distance combination, with the marked radii corresponding to the inner, middle and outer radii, respectively.

### 4.4.5 DISCUSSION

This study provides information on VLM in Hampton Roads between 2015 and 2019. Earlier InSAR studies have focused on the period between 1992-1998 (*Fiaschi and Wdowinski*, 2020), 2007 and 2011 (Section 4.3) and 2011-2017 (*Morgan et al.*, 2017). In agreement with these studies, we find the subsidence to spatially vary across Hampton Roads, with exceptionally high VLM rates occurring at Craney Island and First Landing State Park. Our VLM rates fall within the uncertainties of *Morgan et al.* (2017), increasing our confidence in the results. We also make an assessment of the rate and uncertainty from Sentinel-1 (Fig. 38) with respect to our previous findings from ALOS (Fig. 32). Although not directly comparable due to the difference in time intervals, our findings along the transects agree well with those found in Section 4.3 (Fig. 33), with VLM rate uncertainties improving by a factor between 2-3 (Fig. 43).



Figure 43: Comparison of 1 sigma uncertainties between ALOS-1 data sensed between 2007-2011 (dashed line; Section 4.3, Fig. 33) and data from this Section (gray shading). GPS station locations used in the referencing are colored in blue while those not used are in gold.

Unlike Section 4.3, this study does not apply a full-resolution persistent-scatterer approach; instead we apply Small Baseline processing leveraging multi-looked 90 m products as provided through the JPL ARIA project, increasing our signal to noise ratio and enabling sustained monitoring as new Sentinel-1 images are acquired.

Our transects (Fig. 40a-c) highlight the subsidence occurring along the banks of the Elizabeth and Lafayette rivers, which are notorious for flooding, both due to regular tides and events including storm surges and prolonged rainfall. We also find neighborhoods near the Norfolk/Virginia Beach border that experienced recent prolonged flooding caused by Hurricane Matthew to be experiencing downward displacement. The time-series analysis (Fig. 40b-f) highlights the VLM occurring at several points of interest. As in Section 4.3, we observe a hotspot of subsidence on Craney Island, which is a land reclamation site. In contrast, we observe the stabilization of the Norfolk Naval Shipyard, which previously had been subsiding at a rate of ~10 mm/yr. Loading operations at the shipyard ceased at the end of 2010, explaining the stability for the current sensing period (March 2015 - June 2019). Coastal Virginia Beach is a regionally important economic driver that is subsiding at rates between 2-6 mm/yr, with the fastest subsidence rates in First Landing State Park and the wetlands along the northern boundary of Back Bay National Wildlife Refuge.

The considerable scatter about the trends at locations e, f, and g (Fig. 40), is driven by both the scattering and tropospheric noise in the data. Sentinel-1 operates at C-band and thus is more sensitive to vegetation induced decorrelation noise than the ALOS L-band data used in Section 4.3. Although the GUNW products used in our analysis are multi-looked to a 90 m resolution to increase the signal-to-noise ratio, pixels along water bodies are affected by averaging both water and land which leads to increased noise that can be observed in our time-series analysis of Craney Island and First Landing State Park. Additional scatter can be observed as a result of tropospheric noise, which increases away from the reference GPS tie-in station.

As a first order investigation into the relative contributions of GIA and anthropogenic drivers of VLM, we remove the GIA model value of  $-1.3 \pm 0.2$  mm/yr from our VLM map and propagate the uncertainty (Fig. 44; *Engelhart et al.*, 2009). We find an overall anthropogenic subsidence rate in Hampton Roads of  $-2.3 \pm 2.4$  mm/yr, with  $-3.1 \pm 2.5$ mm/yr in Norfolk, and  $-2.5 \pm 2.5$  mm/yr in Virginia Beach. While the anthropogenic VLM rates are largely driven by groundwater extraction, the complex hydrogeologic framework underlying Hampton Roads combined with the paucity of groundwater level data prevents a simple attribution of VLM to groundwater extraction rates (*McFarland and Bruce*, 2006; *Eggleston and Pope*, 2013). However, recent studies have shown correlations between groundwater extraction and land surface subsidence in Hampton Roads and highlighted the role of diverse spatiotemporal processes in driving coastal flooding (*Karegar et al.*, 2016, 2017).

While we were unable to observe land surface uplift as a response to the SWIFT injection at the current time (Figs. 41, 42), we have developed here a methodology capable of doing so in the future. Given that injection has only been ongoing for 16 months (at time of analysis), the time series is not long enough to separate a signal from the surrounding noise (e.g., *Blewitt and Lavallée*, 2002). Further, the injection rate of 1 MGD



Figure 44: Vertical land motion rate map (a) and corresponding 1-sigma uncertainties (b) as estimated from Sentinel-1 derived interferograms spanning March 2015 to June 2019 after removing the GIA contribution and propagating its uncertainty (-1.3  $\pm$  0.2 mm/yr; *Engelhart et al.*, 2009).

is a fraction of the regional groundwater withdrawal rates of  $\sim 150$  MGD (*Heywood and Pope*, 2009; *Holloway et al.*, 2017). More injections sites are under construction as the SWIFT project advances past the pilot stage, and we expect the combination of a longer time-series and greater injections rates to counteract the regional withdrawal and manifest as land surface uplift observable by InSAR.

Although valuable for many purposes, the GPS network is too spatially sparse for capturing the regional variability of subsidence in coastal settings. InSAR is able to bridge this knowledge gap, and with the continued acquisitions made by Sentinel-1, our confidence in the VLM rates will improve. Here we have established a cost-effective workflow for generating the time-series InSAR product necessary for such monitoring. By leveraging the operational archive of standard InSAR displacement products from the ARIA project, we are able to rapidly conduct and seamlessly update our time-series InSAR analysis as new acquisitions become available.

This study demonstrates a specific value for sustained monitoring of VLM in relation to mitigation and adaptation of RSLR by evaluating the ongoing SWIFT project in Hampton Roads, Virginia. More generally, the ARIA archive covers much of the North American coastline, such that our strategy is widely applicable in the many other communities experiencing high rates of RSLR. Detailed subsidence knowledge is essential for developing targeted policy and engineering solutions that increase resilience in the most vulnerable neighborhoods. In addition to providing this information, our approach enables continual evaluation and - if necessary - adjustment of the implemented solutions to best respond to the ongoing threats of RSLR.

### CHAPTER 5

# DISCUSSION

### 5.1 SUMMARY

Coastal oceans are dynamic environments, hosting interactions between land, ocean, and atmosphere vital to life and economy. Sea level at the coast is an important indicator of the physical interactions, and directly impacts the resulting ecosystems. This dissertation was focused on investigating coastal sea level on global, regional, and local scales. To that end, three research questions were posed:

- 1. To what extent can ICESat-2 observations improve our understanding of sea surface height trends and variability?
- 2. What are the relative contributions of GIA and mass redistribution between land and ocean to 20<sup>th</sup> century sea-level change along the U.S. East Coast?
- 3. What are the spatiotemporal patterns and trends of vertical land motion in Hampton Roads?

Question 1 arose from the ongoing challenge to measure coastal sea level, which stems from both sparse *in-situ* sampling of coastlines tide gauges (TGs) and the degradation of conventional radar altimeter measurements near land. Chapter 2 addresses Question 1 by assessing linear trends in SSH from ICESat-2 over the global oceans. Excellent agreement was found with equivalent measurements from the conventional radar altimeter aboard the Jason-3 satellite (Fig. 6). Good agreement was also found with *in-situ* TG measurements, indicating that the ICESat-2 data performs well at the the coast (Fig. 5). While the ICESat-2 has a decreased SNR ratio relative to TGs and conventional radar altimeters, this will improve over time as the time series lengthens (Fig. 9). Thus in coming years, data from ICESat-2 could be included with the measurements from the existing suite of altimeters used to create gridded sea-level products (e.g., *CNES*, 2018; *Zlotnicki et al.*, 2019).

In Chapter 3, the spatial focus was narrowed from global coastlines to the U.S. East Coast. Much of this relatively well sampled coastline is experiencing exceptionally fast sea-level rise that negatively impacts coastal communities. While important steps have been taken in previous research to characterize the causes of spatial variability in East Coast sea level (e.g., *Ezer and Dangendorf*, 2020), the geophysical processes driving the variability are not fully understood. Research Question 2 aimed to address this by quantifying the relative importance of large-scale processes to observed relative sea-level (RSL) over the 20th century. A statistical methodology was pursued that rigorously combined state-of-the-art knowledge of each component contribution to coastal sea-level changes. Robust estimates of the total VLM and SSH contributions to RSL (Figs 14, A62a-c), and the barystatic contributions to VLM and SSH (Figs 14, A62h-i) were found. However, model estimates of VLM and SSH due to GIA were sensitive to the prior estimate of GIA (Figs 14, A62e-f). Nevertheless, findings support previous studies that show the large-scale pattern of total RSL is due to tectonic processes that are likely to continue at similar magnitudes into the future.

Superimposed on the robust regional total VLM field (Fig. 14, A62b) is smaller scale spatial variability which can serve to exacerbate or alleviate impacts of RSL in coastal communities. Chapter 4, through Research Question 3, was tasked with understanding this local scale VLM variability in the coastal metropolitan region of Hampton Roads, VA. To do so, the maturing remote-sensing method of Interferometric Synthetic Aperture Radar (InSAR) was applied using two distinct processing methods, each with a different data source (Sections 4.3, 4.4). Results of the analysis show considerable spatial variability in the InSAR VLM rates over 2007-2011 (Fig. 32) and 2014-2019 (Fig. 38). High rates of negative VLM (subsidence) contribute to enhanced flood risk and coincide with locations known to experience 'sunny day' flooding from regular tides, as well as prolonged inundation typically associated with cyclonic events (Fig. 40a-c). However, the extent to which VLM rates are sensitive to the temporal interval is not well quantified, with more research needed to understand the specific geophysical drivers of the local-scale trends and variability. While localized models are imperative for creating such understanding, the methods developed in Chapter 4 demonstrate the potential for ongoing monitoring of VLM, an important aspect of RSL adaptation strategies underway in coastal communities.

### 5.2 SIGNIFICANCE

In addition to their focus on sea-level change, the Chapters are united in their datadriven approach. Taken together, these Chapters demonstrate a comprehensive overview of sea level that enables a better scientific understanding of the holistic processes operating on different spatial scales. This understanding begins to shed light on the the impacts of RSL on coastal communities which are increasingly a cause of concern to societal stakeholders.

Chapter 2 is the first time SSH observations from ICESat-2 have been studied on a global scale. While the spatial structure of the observations is not surprising given current understanding from conventional radar altimetry, the improved spatial coverage offers new insight into historically under-sampled areas, including the coast and polar oceans. Indeed, the basin-scale climate variability seen in Figure 6 highlights SSH trend variability on interannual time-scales. Especially with respect to the transition from the open ocean to the coast and at high latitudes, ICESat-2 SSH measurements can begin to constrain the geophysical dynamics governing the generation and propagation of SSH changes throughout the ocean.

Chapter 4 leverages new spaceborne observations to reveal VLM at much higher spatial resolution than previously understood. As with measurements of sea level, SAR measurements combined through the InSAR methodology provide kinematic constraints on terrestrial processes. The VLM maps shown in Figures 32 and 38 reflect the surface expression of complex subsurface geophysics that are notoriously difficult to understand, especially on spatial scales on the order of a few km or more (*Fetter*, 2014). Thus, the knowledge produced with InSAR is a valuable tool for calibrating and validating numerical models concerned with understanding subsurface geology and change.

Keeping with the data-driven approach, Chapter 3 demonstrates a methodology to combine process-based understanding into an united whole. Relying on existing understanding and state-of-the-art datasets, the Bayesian assimilation provides a transparent quantification of the processes contributing to East Coast RSL. It enables a robust quantification of total VLM and SSH contributions to RSL along the East Coast and their uncertainty, while bringing to the forefront knowledge gaps that need to be remedied with future research.

While the research undertaken in this dissertation is primarily scientific, there is a unifying thread concerned with relevance to coastal communities. For example, Research Question 1 and the resultant analysis in Chapter 2 was conceived of to address the lack of sea-level observations specifically along coastlines. Additionally, the regional differences in rates of RSL change seen in Chapter 2 (Fig. 14) are important for developing locally specific adaptation strategies. Most directly, in Section 4.4 an assessment of the Sustainable Water Initiative for Tomorrow (SWIFT) project was conducted, which is an ongoing adaptation strategy to address RSL change. Although the impacts of SWIFT on VLM are currently below detection levels, the methodology explicitly demonstrates a strategy for using state-of-the-art science to support societal needs. Together, the Chapters in this dissertation provide foundational scientific knowledge important for communities striving to enhance their resiliency to climate change and sea-level rise.

# 5.3 LIMITATIONS AND FUTURE WORK

While the research undertaken in this dissertation advances the current state of knowledge, it nevertheless suffers from limitations that require further work. While the data-driven approach just described enables a clearer understanding overall constraints, it sheds little light on the dynamical underpinnings that generate and maintain the broad-scale trends and variability. This is a particularly stark shortcoming given the emphasis on supporting coastal stakeholders to develop and monitor RSL adaptation strategies. Moreover, the implicit assertion that scientific research translates directly to sound policy exemplifies an overly simplistic view of how science is used to make decisions (*Jasanoff and Wynne*, 1998).

The research presented in Chapter 2 finds that ICESat-2 provides new measurements of SSH in regions that have been historically hard to observe. Despite the wealth of possible new science questions enabled by these observations, none are pursued. For example, in the coastal zone, the dynamics that govern the propagation of sea level from the open-ocean to the shore are typically highly idealized but are important for understanding the sea-level changes experienced at the coast (*Woodworth et al.*, 2019, and references therein). As the SNR ratio improves through time (Fig. 9), ICESat-2 SSH measurements could shed new light on coastal dynamics. The trend map from ICESat-2 (Fig. 6) shows large rates of sea-level fall around Greenland which is not observed by the majority of radar altimeters (which like Jason-3, follow the Topex/Poseidon orbit). Understanding the drivers of these trends and others in the cryosphere is important for improving representation of ocean/ice interactions in ice-sheet models, a key uncertainty that propagates to future sea-level projections (*Edwards et al.*, 2021). Furthermore, as ICESat-2 can sense individual wind-waves, it can provide new insights into wave propagation and air/sea interactions that should be further explored as in, e.g., *Horvat et al.* (2020).

While InSAR is a rapidly technology (*Biggs and Wright*, 2020), there are still a variety of challenges that can be addressed in order to better meet the SNR necessary for supporting coastal studies. As described in Section 4.2, correcting for noise sources in InSAR displacement retrievals is an active area of research (e.g., *Shamshiri et al.*, 2020; *Zhang et al.*, 2019). There is much ongoing work to best utilize the GNSS networks in conjunction with InSAR (e.g., *Parizzi et al.*, 2020; *Shen and Liu*, 2020). As these improve, it increasingly become possible to understand the contributors of deformation to InSAR measured velocities (e.g., *Yu et al.*, 2020; *Xu and Sandwell*, 2020). Understanding these process contributions, both from data analysis linked to independent data sources (e.g., *Chaussard et al.*, 2014; *Karegar et al.*, 2020), and modeling studies (see *Shirzaei et al.*, 2021, and references therein), is a necessary prerequisite for projecting InSAR VLM rates and their impact on RSL into the future.

As detailed in Section 3.6, an outstanding next step is to determine the cause of the spatial bias in the residual VLM field (Figs. 14, A62). After resolving that, there is much potential to investigate the SD component of RSL and the relative contributions of thermosteric and regional dynamics. Depending on the magnitude of uncertainties on the regional dynamics, it may be possible to use simple dynamical balances to constrain changes in Atlantic ocean circulation during the  $20^{\text{th}}$  century. Specifically, a future research goal is to use geostrophy (Eq. 12) to further investigate the AMOC trend over the last 100 years. Similarly, by leveraging the relationship between coastal and interior sea levels (*Wise et al.*, 2018, their Eq. 1), it may be possible to gain insight into  $20^{\text{th}}$  century subtropical and/or subpolar gyre trends. Applying a similar modeling strategy to other coastlines, and indeed globally, are additional research directions that would benefit the scientific community and may be useful for societal stakeholders. However,

as clearly stated by *Sobel* (2021), science aimed at supporting climate adaptation should be cognizant of the complex challenges in the policy sphere and consider its input at all stages of the research process.

# 5.4 CONCLUDING REMARKS

This dissertation undertakes an investigation of sea level and its contributing processes across spatial scales. From a global perspective, measurements from the new ICESat-2 satellite are shown to have high potential for bridging observational gaps at the coast and poles. As the SNR ratio improves with time, a variety of important science questions can be addressed. Along the East Coast, regional scale VLM, primarily due to GIA dominates the spatial variability. The Bayesian framework developed for the investigation provides a powerful constraint on the current scientific understanding, elucidating both its strengths and shortcomings. On local scales, VLM in Hampton Roads, VA is precisely measured using InSAR technology. The observations show that VLM varies spatially over small scales and should be considered when developing strategies to adapt to RSL change. Together with future modeling studies, these precise measurements can improve our understanding of the geophysical processes driving VLM at the surface. In short, this work extends our knowledge of the Earth System in several distinct but intricately linked and important ways.

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#### APPENDIX A

## ABBREVIATIONS

ALOS Advanced Land Observing Satellite. 5, 64, 79, 82, 85–87, 92, 105

AMOC Atlantic Meridional Overturning Circulation. 29, 33–35, 37, 111

**APS** atmospheric phase screen. 67, 74

- AR autoregressive. 38, 43–45
- ARIA Advanced Rapid Imaging and Analysis. 76, 79, 96–98, 107

ATLAS Advanced Topographic Laser Altimeter System. 17, 18

CalTech California Institute of Technology. 76

CMIP-5 Coupled Model Intercomparison Project 5. 34

**CSEOF** cyclostationary empirical orthogonal function. 15

CTW coastal trapped wave. 31–33

**DEM** digital elevation model. 66, 67, 75, 85

**DOT** dynamic ocean topography. 6, 13, 20, 21, 23, 27

ECCO Estimating the Circulation and Climate of the Ocean. 16

**EMD** Empirical Mode Decomposition. 35

**ENSO** the El Niño-Southern Oscillation. 2, 10, 13, 43

EOF empirical orthogonal function. 14, 15, 37

- **ESA** European Space Agency. 65, 66, 76
- GCM general circulation model. 15
- GHG greenhouse gas. 29
- **GIA** glacial isostatic adjustment. ix, 1, 3, 4, 9, 12, 15, 29, 38–40, 42–45, 47, 49, 50, 52, 54–61, 76, 77, 79, 93, 99, 106, 108, 109, 112, 175–180

GIAnT Generic InSAR Analysis Toolbox. 70, 72, 73

- GMSL global-mean sea-level. 1, 2, 6–10, 12–15, 29, 92, 93
- GNSS global navigation satellite system. 3, 37, 38, 77, 78, 111
- **GPS** Global Positioning System. 41, 42, 46, 50, 55–59, 79, 80, 83–89, 92, 95, 97–103, 105–107
- **GRACE** Gravity Recovery and Climate Experiment. 9, 10
- GRACE-FO GRACE Follow-On. 9, 10
- GRD gravitation, rotation and deformation. 46, 49, 50, 61
- **GS** Gulf Stream. 33, 34
- GUNW UNWrapped Geocoded interferogram. 96–98, 106
- **GW** ground-water. 12
- ICESat-2 Ice, Cloud, and land Elevation Satellite 2. 2, 4, 6, 17–19, 27, 28, 108, 109, 111, 112
- **IID** independent and identically distributed. 44, 45, 61
- **InSAR** Interferometric Synthetic Aperture Radar. i, 3, 4, 63, 64, 66, 67, 70, 73, 75, 76, 78, 79, 81, 83–89, 92, 95–100, 102, 103, 105, 107, 109–112
- **JASL** Joint Archive for Sea Level. 20–22
- **JPL** Jet Propulsion Laboratory. 72, 76
- LoS line-of-sight. 64, 85, 95, 98–100, 103
- MCMC Markov chain Monte Carlo. 49, 152
- MGD Million Gallons per Day. 93, 94, 106, 107
- MIDAS Median Interannual Difference Adjusted for Skewness. 97–99
- MintPy Miami InSAR Time-series software in Python. 70, 73, 74, 79, 98
- **MInTS** Multiscale Interferometric TimeSeries. 73
- MSL mean sea-level. 6
- MT-InSAR Multi-temporal InSAR. 68, 70, 72, 73, 76–78, 81
- NADW North Atlantic Deep Water. 33, 34, 37

- NAM North Annual Mode. 33
- NAO North Atlantic Oscillation. 2, 29, 33, 36, 37
- **NASA** National Aeronautics and Space Administration. 76
- NISAR NASA-ISRO SAR. 76, 95
- **NOAA** the National Ocean and Atmospheric Administration. 11, 19
- **NSBAS** New Small Baseline Subset. 73
- PCA principal component analysis. 14
- PS Persistent Scatterer. 5, 70, 72–76
- **PSMSL** Permanent Service for Mean Sea Level. 11, 41
- **RSL** relative sea-level. 1–4, 11, 15, 16, 35, 37–46, 49, 50, 52–54, 59–61, 63, 108–112, 176, 178, 180
- **RSLR** relative sea-level rise. 15, 16, 63, 64, 79, 81, 92–95, 107
- SAR Synthetic Aperture Radar. ix, 3–5, 17, 65, 66, 68, 70–73, 75–78, 81, 82, 84, 85, 87, 92, 95, 98, 110
- **SBAS** Small Baseline Subset. 5, 70–76
- **SD** sterodynamic. 1, 38–40, 53–55, 60, 61, 111
- **SDFP** slowly-decorrelated filtered phase. 76
- SED solid-Earth deformation. 38, 39
- **SL** sea-level. 35, 77, 78
- **SLA** sea-level anomaly. 13
- SLC single look complex. 66–68, 73
- **SLP** sea-level pressure. 15, 36
- SLR sea-level rise. 2–4, 9, 13, 15, 34, 77
- SNAHPU Statistical-cost, Network-flow Algorithm for Phase Unwrapping. 70
- **SNR** signal-to-noise ratio. 70, 74, 75, 108, 111, 112
- SODA Simple Ocean Data Assimilation. 15

- **SSH** sea surface height. 6, 13–16, 18–20, 38–40, 44, 45, 47, 49, 50, 52–55, 59–61, 108–111, 176, 178, 180
- SSHA sea surface height anomaly. 13, 19, 20, 23
- **SST** sea surface temperature. 15, 36
- StaMPS Stanford Method for Persistent Scatterers. 70, 74–76, 84
- SVD singular value decomposition. 71
- SWIFT Sustainable Water Initiative for Tomorrow. 94, 110
- T/P TOPEX/Poseidon. 13, 15
- **TG** tide gauge. 2, 11–16, 18–22, 27, 29, 31–33, 35, 37, 38, 41, 45, 46, 50, 55, 61, 76–78, 108
- TimeFun Temporally Parameterized Inversion. 73
- TWS terrestrial water storage. 7, 10, 43, 48, 61
- UNR University of Nevada, Reno. 55–58
- VLM vertical land motion. 1, 3–5, 12, 14, 30, 37–39, 41–50, 52–55, 57–64, 77–81, 87–95, 99, 100, 102, 103, 105–107, 109–112, 176, 178, 180
- WBC Western Boundary Current. 36

#### APPENDIX B

### FULL CONDITIONAL DISTRIBUTIONS

For a process or parameter X, the full conditional  $p(X|\cdot)$  is derived only from terms in the full posterior (Eq. 37) with X as a variable. Annotations denoting vector or matrix dimensions are omitted for simplicity. Eq. 37 cannot be evaluated analytically, as the normalizing constant in Bayes Rule' is unknown (*Gelman et al.*, 2013). Therefore, the MCMC algorithm described in Section 3.4 is used to evaluate the conditional distributions on all processes and parameters. Here are included the derivations of the conditional distributions for all terms that differ from *Piecuch et al.* (2018). Note that superscript tildes demarcate hyperparameters that are fixed apriori, **bold** non-italic indicate matrices, and **bold italic** script indicate vectors.

The full conditional distribution on the ice mass loss term M is multivariate normal:

$$p(\boldsymbol{M}|\cdot) \propto p(\boldsymbol{M}) \ p(\boldsymbol{u}|\boldsymbol{u}_g, \boldsymbol{M}, \alpha, \omega^2, \rho) \ p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_g, \boldsymbol{M}, \mu, \pi^2, \lambda)$$
 (56)

$$\boldsymbol{M} \sim \mathcal{N}(\tilde{\boldsymbol{\eta}}_M, \tilde{\mathbf{Z}}_M)$$
 (57)

$$\boldsymbol{u} \sim \mathcal{N}(\alpha \boldsymbol{1} + \boldsymbol{u}_g + \boldsymbol{M} \hat{\boldsymbol{u}}_m + \boldsymbol{u}_{TWS}, \boldsymbol{\Omega})$$
(58)

$$\boldsymbol{b} \sim \mathcal{N}(\mu \boldsymbol{1} + \boldsymbol{w}_g + \boldsymbol{M} \hat{\boldsymbol{w}}_m + \boldsymbol{w}_{TWS} - \boldsymbol{u}, \boldsymbol{\Pi})$$
(59)

(60)

Thus:

$$p(\boldsymbol{M}|\cdot) \sim \mathcal{N}(\boldsymbol{\Psi}_M \boldsymbol{V}_M, \boldsymbol{\Psi}_M)$$
 (61)

$$\hat{\Psi}_M = \left[ \mathbf{Z}_m^{-1} + \hat{\boldsymbol{w}}_m^T \Pi^{-1} \hat{\boldsymbol{w}}_m + \hat{\boldsymbol{u}}_m^T \Omega^{-1} \hat{\boldsymbol{u}}_m \right]^{-1}$$
(62)

$$\boldsymbol{V}_{M} = \boldsymbol{Z}_{M}^{-1} \boldsymbol{\eta}_{M} + \boldsymbol{\hat{w}}_{m}^{T} \Pi^{-1} (\boldsymbol{b} + \boldsymbol{u} - \boldsymbol{w}_{g} - \boldsymbol{w}_{TWS} - \mu \boldsymbol{1}) + \boldsymbol{\hat{u}}_{m}^{T} \Omega^{-1} (\boldsymbol{u} - \boldsymbol{u}_{g} - \boldsymbol{u}_{TWS} - \alpha \boldsymbol{1})$$
(63)

The full conditional distribution on the contemporary RSL process trend  $p(\boldsymbol{b}|\cdot)$  is multivariate normal:

$$p(\boldsymbol{b}|\cdot) \propto p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_g, \boldsymbol{M}, \mu, \pi^2, \lambda) \prod_{k=1}^{K} p(\boldsymbol{y}_k | \boldsymbol{y}_{k-1}, \boldsymbol{b}, r, \sigma^2, \phi)$$
 (64)

$$\boldsymbol{b} \sim \mathcal{N}(\mu \boldsymbol{1} + \boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} - \boldsymbol{u}, \boldsymbol{\Pi})$$
(65)

$$\boldsymbol{y_k} \sim \mathcal{N}(r(\boldsymbol{y_{k-1}} - \boldsymbol{b}t_{k-1}) + \boldsymbol{b}t_k, \boldsymbol{\Sigma})$$
(66)

Thus:

$$p(\boldsymbol{b}|\cdot) \sim \mathcal{N}(\boldsymbol{\Psi}_b \boldsymbol{V}_b, \boldsymbol{\Psi}_b)$$
 (67)

$$\Psi_b = \left[ \Pi^{-1} + \Sigma^{-1} \sum_{1}^{k} (t_k - rt_{k-1})^2 \right]^{-1}$$
(68)

$$V_b = \boldsymbol{\Sigma}^{-1} \sum_{1}^{K} (t_k - rt_{k-1}) (\boldsymbol{y}_k - r\boldsymbol{y}_{k-1}) + \boldsymbol{\Pi}^{-1} (\mu \boldsymbol{1} + \boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} - \boldsymbol{u})$$
(69)

The full conditional distribution on the regional VLM  $p(\boldsymbol{u}|\cdot)$  : is multivariate normal:

$$p(\boldsymbol{u}|\cdot) \propto p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_g, \boldsymbol{M}, \boldsymbol{\mu}, \pi^2, \boldsymbol{\lambda}) p(\boldsymbol{u}|\boldsymbol{u}_g, \boldsymbol{M}, \boldsymbol{\alpha}, \omega^2, \rho) p(\boldsymbol{\nu}|\boldsymbol{u}, \varepsilon^2)$$
(70)

$$\boldsymbol{b} \sim \mathcal{N}(\boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} + \mu \boldsymbol{1} - \boldsymbol{u}, \boldsymbol{\Pi})$$
(71)

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha \boldsymbol{1}, \Omega)$$
(72)

$$\boldsymbol{\nu} \sim \mathcal{N}(\boldsymbol{u}, \varepsilon^2 \mathbf{I}) \tag{73}$$

Thus:

$$p(\boldsymbol{u}|\cdot) \sim \mathcal{N}(\boldsymbol{\Psi}_{u}\boldsymbol{V}_{u},\boldsymbol{\Psi}_{u})$$
 (74)

$$\Psi_{u} = \left[ \Pi^{-1} + \Omega^{-1} + \frac{1}{\epsilon^{2}} \mathbf{I} \right]^{-1}$$
(75)

$$\boldsymbol{V}_{u} = \boldsymbol{\Pi}^{-1}(\boldsymbol{\mu}\boldsymbol{1} + \boldsymbol{w}_{g} + \hat{\boldsymbol{w}}_{m}\boldsymbol{M} + \boldsymbol{w}_{TWS} - \boldsymbol{b})$$
(76)

$$+ \boldsymbol{\Omega}^{-1}(\alpha \mathbf{1} + \boldsymbol{u}_g + \boldsymbol{\hat{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS}) + \frac{\boldsymbol{\nu}}{\varepsilon^2}$$
(77)

The full conditional distribution on the contemporary VLM due to GIA  $p(u_g|\cdot)$  is multivariate normal:

$$p(\boldsymbol{u}_g|\cdot) \propto p(\boldsymbol{u}_g)p(\boldsymbol{u}|\boldsymbol{u}_g, \boldsymbol{M}, \alpha, \omega^2, \rho)p(\boldsymbol{Y}|\boldsymbol{w}_g, \boldsymbol{u}_g, \boldsymbol{T}, \boldsymbol{\iota}, \epsilon^2)$$
(78)

$$\boldsymbol{u}_g \sim \mathcal{N}(\tilde{\boldsymbol{\eta}}_{\boldsymbol{u}_g}, \mathbf{Z}_{\boldsymbol{u}_g})$$
 (79)

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha, \Omega)$$
(80)

$$Y \sim \mathcal{N}(\sum_{i}^{Nd} \boldsymbol{e}_{i} \boldsymbol{e}_{i}^{T} \mathbf{G}(\boldsymbol{w}_{g} - \boldsymbol{u}_{g}) \boldsymbol{e}_{i}^{T}] \boldsymbol{T} + \mathbf{D}_{i}, \epsilon^{2} \mathbf{I}_{Nd})$$
(81)

Thus:

$$p(\boldsymbol{u}_g|\cdot) \sim \mathcal{N}(\boldsymbol{\Psi}_{\boldsymbol{u}_g} \boldsymbol{V}_{\boldsymbol{u}_g}, \boldsymbol{\Psi}_{\boldsymbol{u}_g})$$
 (82)

$$+ \frac{1}{\epsilon^2} \mathbf{G}^T \operatorname{diag}(\mathbf{T})^T [\operatorname{diag}(\mathbf{T}) \mathbf{G} \mathbf{w}_g + \mathbf{D}\iota - \mathbf{Y})]$$

$$\boldsymbol{V}_{\boldsymbol{u}_g} = \left[ \tilde{\mathbf{Z}}_{\boldsymbol{u}_g}^{-1} + \boldsymbol{\Omega}^{-1} + \frac{1}{\epsilon^2} \mathbf{G}^T \operatorname{diag}(\boldsymbol{T})^T \operatorname{diag}(\boldsymbol{T}) \mathbf{G} \right]^{-1}$$
(84)

The full conditional distribution on the contemporary SSH due to GIA  $p(w_g|\cdot)$  is multivariate normal:

$$p(\boldsymbol{w}_g|\cdot) \propto p(\boldsymbol{w}_g)p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_g, \boldsymbol{M}, \boldsymbol{\mu}, \pi^2, \lambda)p(\boldsymbol{Y}|\boldsymbol{w}_g, \boldsymbol{u}_g, \boldsymbol{T}, \boldsymbol{\iota}, \epsilon^2)$$
(85)

$$\boldsymbol{w}_g \sim \mathcal{N}(\tilde{\eta}_{\boldsymbol{w}_g}, \tilde{\mathbf{Z}}_{\boldsymbol{w}_g})$$
 (86)

$$\boldsymbol{b} \sim \mathcal{N}(\boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} + \mu \boldsymbol{1} - \boldsymbol{u}, \boldsymbol{\Pi})$$
<sub>Nd</sub>
(87)

$$\boldsymbol{Y} \sim \mathcal{N}([\sum_{i}^{Na} \boldsymbol{e}_{i} \boldsymbol{e}_{i}^{T} \mathbf{G}(\boldsymbol{w}_{g} - \boldsymbol{u}_{g}) \boldsymbol{e}_{i}^{T}] \boldsymbol{T} + \mathbf{D}_{i}, \epsilon^{2} \mathbf{I}_{Nd})$$
(88)

Thus:

$$p(\boldsymbol{w}_g|\cdot) \sim \mathcal{N}(\boldsymbol{\Psi}_{\boldsymbol{w}_g} \boldsymbol{V}_{\boldsymbol{w}_g}, \boldsymbol{\Psi}_{\boldsymbol{w}_g})$$
(89)

$$\Psi_{\boldsymbol{w}_g} = \tilde{\mathbf{Z}}_{\boldsymbol{w}_g}^{-1} \tilde{\boldsymbol{\eta}}_{\boldsymbol{w}_g} + \boldsymbol{\Pi}^{-1} (\boldsymbol{b} + \boldsymbol{u} - \mu \mathbf{1} - \hat{\boldsymbol{w}}_m \boldsymbol{M} - \boldsymbol{w}_{TWS})$$

$$\frac{1}{1} \mathbf{e}_{TT} \mathbf{x}_{TT} (\boldsymbol{\sigma}_{TT})^{T} \mathbf{e}_{TT} \mathbf{x}_{TT} \mathbf{x}_{TT} \mathbf{x}_{TT} \mathbf{x}_{TT} (\boldsymbol{\sigma}_{TT})^{T} \mathbf{e}_{TT} \mathbf{x}_{TT} \mathbf{x}_{TT}$$

$$+\frac{1}{\epsilon^2}\mathbf{G}^T\mathrm{diag}(\boldsymbol{T})^T[\boldsymbol{Y}+\mathrm{diag}(\boldsymbol{T})\mathbf{G}\boldsymbol{u}_g-\mathbf{D}\boldsymbol{\iota})]$$

$$\boldsymbol{V}_{\boldsymbol{w}_g} = \left[ \tilde{\mathbf{Z}}_{\boldsymbol{w}_g}^{-1} + \boldsymbol{\Pi}^{-1} + \frac{1}{\epsilon^2} \mathbf{G}^T \operatorname{diag}(\boldsymbol{T})^T \operatorname{diag}(\boldsymbol{T}) \mathbf{G} \right]^{-1}$$
(91)

The full conditional distribution on the mean non-GIA VLM rate  $p(\alpha|\cdot)$  is normal:

$$p(\alpha|\cdot) \propto p(\alpha)p(\boldsymbol{u}|\boldsymbol{u}_g, \boldsymbol{M}, \alpha, \omega^2, \rho)$$
 (92)

$$\alpha \sim \mathcal{N}(\tilde{\eta}_{\alpha}, \tilde{\zeta}_{\alpha}^2) \tag{93}$$

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha, \boldsymbol{\Omega})$$
 (94)

Thus:

$$\alpha | \cdot \sim \mathcal{N}(\psi_{\alpha} V_{\alpha}, \psi_{\alpha}) \tag{95}$$

$$\psi_{\alpha} = \left[\frac{1}{\tilde{\zeta}_{\alpha}^2} + \mathbf{1}^T \mathbf{\Omega}^{-1} \mathbf{1}\right]^{-1}$$
(96)

$$V_{\alpha} = \frac{\tilde{\eta}_{\alpha}}{\tilde{\zeta}_{\alpha}^{2}} + \mathbf{1}^{T} \mathbf{\Omega}^{-1} (\boldsymbol{u} - \boldsymbol{u}_{g} - \hat{\boldsymbol{u}}_{m} \boldsymbol{M} - \boldsymbol{u}_{TWS})$$
(97)

The full conditional distribution on the mean of non-GIA contemporary RSL trend  $p(\mu|\cdot)$  is normal:

$$p(\mu|\cdot) \propto p(\mu)p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_g, \boldsymbol{M}, \mu, \pi^2, \lambda)$$
(98)

$$\mu \sim \mathcal{N}(\tilde{\eta}_{\mu}, \tilde{\zeta}_{\mu}^2) \tag{99}$$

$$\boldsymbol{b} \sim \mathcal{N}(\boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} + \mu \boldsymbol{1} - \boldsymbol{u}, \boldsymbol{\Pi})$$
(100)

(101)

Thus:

$$\mu | \cdot \sim \mathcal{N}(\psi_{\mu} V_{\mu}, \psi_{\mu}) \tag{102}$$

$$\psi_{\mu} = \left[ \frac{1}{\tilde{\zeta}_{\mu}^2} + \mathbf{1}^T \mathbf{\Pi}^{-1} \mathbf{1} \right]^{-1}$$
(103)

$$V_{\mu} = \frac{\tilde{\eta}_{\mu}}{\tilde{\zeta}_{\mu}^{2}} + \mathbf{1}^{T} \mathbf{\Pi}^{-1} (\boldsymbol{b} + \boldsymbol{u} - \boldsymbol{w}_{g} - \hat{\boldsymbol{w}}_{m} \boldsymbol{M} - \boldsymbol{w}_{TWS})$$
(104)

The full conditional distribution on the mean of partial sill of the contemporary RSL process  $p(\pi^2|\cdot)$  is inverse gamma:

$$p(\pi^2|\cdot) \propto p(\pi^2) p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_g, \boldsymbol{M}, \mu, \pi^2, \lambda)$$
(105)

$$\pi^2 \sim \mathcal{G}^{-1}(\tilde{\xi}_{\pi^2}, \tilde{\chi}^2_{\pi^2})$$
 (106)

$$\boldsymbol{b} \sim \mathcal{N}(\mu \boldsymbol{1} + \boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} - \boldsymbol{u}, \boldsymbol{\Pi})$$
(107)

(108)

Thus:

$$p(\pi^2) \sim \mathcal{G}^{-1}\left[\tilde{\xi}_{\pi^2} + \frac{N}{2}, \tilde{\chi}_{\pi^2} + \frac{1}{2}(\boldsymbol{b} - \hat{\boldsymbol{b}})^T \mathbf{L}^{-1}(\boldsymbol{b} - \hat{\boldsymbol{b}})\right]$$
(109)

With:

$$\hat{\boldsymbol{b}} = \mu \boldsymbol{1} + \boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} - \boldsymbol{u}$$
(110)

$$\mathbf{L}_{ij} = \exp(-\lambda |\boldsymbol{s}_i - \boldsymbol{s}_j|) \tag{111}$$

The full conditional distribution on the partial sill of the regional VLM Rate  $p(\omega^2|\cdot)$  is

inverse gamma:

$$p(\omega^2|\cdot) \propto p(\omega^2)p(\boldsymbol{u}|\boldsymbol{u}_g, \boldsymbol{M}, \alpha, \omega^2, \rho)$$
 (112)

$$\omega^2 \sim \mathcal{G}^{-1}(\tilde{\xi}_{\omega^2}, \tilde{\chi}^2_{\omega^2}) \tag{113}$$

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha, \Omega)$$
 (114)

Thus

$$p(\omega^2) \sim \mathcal{G}^{-1}\left[\tilde{\xi}_{\omega^2} + \frac{N}{2}, \tilde{\chi}_{\omega^2} + \frac{1}{2}\left((\boldsymbol{u} - \hat{\boldsymbol{u}})^T \mathbf{T}^{-1}(\boldsymbol{u} - \hat{\boldsymbol{u}})\right)\right]$$
(115)

With:

$$\hat{\boldsymbol{u}} = \boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha \boldsymbol{1}$$
(116)

$$\mathbf{T}_{ij} = \exp(-\rho|\boldsymbol{s}_i - \boldsymbol{s}_j|) \tag{117}$$

The full conditional distribution on the inverse range of the non-GIA RSL rate  $p(\lambda|\cdot)$  is nonstandard. The log transform is used such that  $\Lambda = \ln \lambda$  and the Metropolis step has a symmetric proposal distribution.

$$p(\lambda|\cdot) \propto p(\lambda)p(\boldsymbol{b}|\boldsymbol{u}, \boldsymbol{w}_q, \boldsymbol{M}, \mu, \pi^2, \lambda)$$
 (118)

$$\lambda \sim \mathcal{N}_{log}(\tilde{\eta}_{\lambda}, \tilde{\zeta}_{\lambda}^2) \tag{119}$$

$$\boldsymbol{b} \sim \mathcal{N}(\mu \boldsymbol{1} + \boldsymbol{w}_g + \boldsymbol{\hat{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} - \boldsymbol{u}, \boldsymbol{\Pi})$$
(120)

(121)

Thus

$$p(\Lambda) \propto |\mathbf{L}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2\tilde{\zeta}_{\lambda}^{2}}[\Lambda - \tilde{\eta}_{\lambda}]^{2} - \frac{1}{2\pi^{2}}[\boldsymbol{b} - \hat{\boldsymbol{b}}]^{T}\mathbf{L}^{-1}[\boldsymbol{b} - \hat{\boldsymbol{b}}]\right\}$$
(122)

With:

$$\Lambda = \ln \lambda \tag{123}$$

$$\hat{\boldsymbol{b}} = \boldsymbol{w}_g + \hat{\boldsymbol{w}}_m \boldsymbol{M} + \boldsymbol{w}_{TWS} + \mu \boldsymbol{1} - \boldsymbol{u}$$
(124)

$$\mathbf{L}_{ij} = \exp(-e^{\Lambda}|\boldsymbol{s}_i - \boldsymbol{s}_j|) \tag{125}$$

$$p(\Lambda) \propto \exp\left(-\frac{\Lambda - \tilde{\eta}_{\lambda}}{2\tilde{\zeta}_{\lambda}^{2}}\right)^{2} \propto \frac{1}{\lambda \tilde{\zeta}_{\lambda}^{2} \sqrt{\pi}} \exp\left(-\frac{\ln \lambda - \tilde{\eta}_{\lambda}}{2\tilde{\zeta}_{\lambda}^{2}}\right)^{2} \propto p(\lambda)$$
 (126)

The full conditional distribution on the inverse range of the non-GIA VLM rate  $p(\rho|\cdot)$  is nonstandard. The log transform is used such that  $\rho = \ln \rho$  and the Metropolis step has

$$p(\rho|\cdot) \propto p(\rho)p(\boldsymbol{u}|\boldsymbol{u}_g, \boldsymbol{M}, \alpha, \omega^2, \rho))$$
 (127)

$$\rho \sim \mathcal{N}_{log}(\tilde{\eta}_{\rho}, \tilde{\zeta}_{\rho}^2) \tag{128}$$

$$\boldsymbol{u} \sim \mathcal{N}(\boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha, \Omega)$$
(129)

Thus:

$$p(\rho) \propto |\mathbf{T}|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2\tilde{\zeta}_{\rho}^{2}} [\rho - \tilde{\eta}_{\rho}]^{2} - \frac{1}{2\omega^{2}} [\boldsymbol{u} - \hat{\boldsymbol{u}}]^{T} \mathbf{T}^{-1} (\boldsymbol{u} - \hat{\boldsymbol{u}})\right\}$$
(130)

With:

$$\varrho = \ln \rho \tag{131}$$

$$p(\varrho) \propto \exp\left(-\frac{\varrho - \tilde{\eta}_{\rho}}{2\tilde{\zeta}_{\rho}^{2}}\right)^{2} \propto \frac{1}{\rho\tilde{\zeta}_{\rho}^{2}\sqrt{\omega}} \exp\left(-\frac{\ln\rho - \tilde{\eta}_{\rho}}{2\tilde{\zeta}_{\rho}^{2}}\right)^{2} \propto p(\rho)$$
(132)

$$\hat{\boldsymbol{u}} = \boldsymbol{u}_g + \hat{\boldsymbol{u}}_m \boldsymbol{M} + \boldsymbol{u}_{TWS} + \alpha \boldsymbol{1}$$
(133)

$$\mathbf{T}_{ij} = \exp(-e^{\varrho}|\boldsymbol{s}_i - \boldsymbol{s}_j|) \tag{134}$$

### APPENDIX C

# PRIOR AND POSTERIOR COMPARISON

These demonstrate the extent to which the Bayesian assimilation has incorporated information from the data into its posterior prediction. Narrow posteriors relative to their priors indicate a information has been 'learned' beyond the priors by the model from the data.



Figure A45: Mean regional vertical land motion process trend unrelated to GIA. The prior on  $\alpha$  is normally distributed with mean  $\tilde{\eta}_{\alpha}$  and variance  $\tilde{\zeta}_{\alpha}^2$ .



Figure A46: Spatial mean of site-specific intercepts  $\boldsymbol{\iota}$  on the pre-industrial relative sea level process  $\boldsymbol{Y}$ . The prior on  $\beta$  is normally distributed with mean  $\tilde{\eta}_{\beta}$  and variance  $\tilde{\zeta}_{\beta}^2$ .



Figure A47: Instrumental tide gauge error variance. The prior on  $\delta^2$  has an inverse gamma prior with shape  $\tilde{\epsilon}_{\delta^2}$  and inverse scale  $\tilde{\chi}_{\delta^2}$ 



Figure A48: Spatial variance of spatiotemporally random residuals  $\boldsymbol{f}$  on the pre-industrial sea-level process  $\boldsymbol{Y}$ .  $\epsilon^2$  has an inverse gamma prior distribution with shape  $\tilde{\zeta}_{\epsilon^2}$  and inverse scale  $\tilde{\chi}_{\epsilon^2}$ .



Figure A49: Nugget effect of vertical land motion trend.  $\varepsilon^2$  has an inverse gamma prior distribution with shape  $\tilde{\zeta}_{\varepsilon^2}$  and inverse scale  $\tilde{\chi}_{\varepsilon^2}$ .



Figure A50: Variance of the tide gauge error trend.  $\gamma^2$  has an inverse gamma prior with shape  $\tilde{\zeta}_{\gamma^2}$  and inverse scale  $\tilde{\chi}_{\gamma^2}$ .



Figure A51: Spatial variance of site-specific intercepts  $\iota$  on the pre-industrial relative sea-level process  $\mathbf{Y}$ .  $\kappa^2$  has an inverse gamma prior with shape  $\tilde{\zeta}_{\kappa^2}$  and inverse scale  $\tilde{\chi}_{\kappa^2}$ .



Figure A52: Inverse range of regional absolute sea level trends.  $\lambda$  has a log-normal distribution with 'mean'  $\tilde{\eta}_{\lambda}$  and 'variance'  $\tilde{\zeta}_{\lambda}^2$ .



Figure A53: Mean regional absolute sea level process trend unrelated to GIA.  $\mu$  has a log-normal distribution with mean  $\tilde{\eta}_{\mu}$  and variance  $\tilde{\zeta}_{\mu}^2$ .



Figure A54: Spatial mean of tide gauge data biases.  $\nu$  has a log-normal distribution with mean  $\tilde{\eta}_{\nu}$  and variance  $\tilde{\zeta}_{\nu}^2$ .



Figure A55: Partial sill of regional vertical land motion trend.  $\omega^2$  has an inverse gamma prior with shape  $\tilde{\zeta}_{\omega^2}$  and inverse scale  $\tilde{\chi}_{\omega^2}$ .



Figure A56: Inverse range of relative sea-level process innovations.  $\phi$  has a log-normal distribution with 'mean'  $\tilde{\eta}_{\phi}$  and 'variance'  $\tilde{\zeta}_{\phi}^2$ .


Figure A57: Partial sill of regional absolute sea level trend.  $\pi^2$  has an inverse gamma prior with shape  $\tilde{\zeta}_{\pi^2}$  and inverse scale  $\tilde{\chi}_{\pi^2}$ .



Figure A58: Unitless AR(1) coefficient of the relative sea-level process innovations. r has a uniform prior distribution with lower bound  $\tilde{\mu}_r$  and upper bound  $\tilde{\nu}_r$ .



Figure A59: Inverse range of regional vertical land motion trends.  $\rho$  has a log-normal distribution with 'mean'  $\tilde{\eta}_{\rho}$  and 'variance'  $\tilde{\zeta}_{\rho}^2$ .



Figure A60: Partial sill of relative sea-level innovations.  $\sigma^2$  has an inverse gamma prior with shape  $\tilde{\zeta}_{\sigma^2}$  and inverse scale  $\tilde{\chi}_{\sigma^2}$ .



Figure A61: Spatial variance in tide gauge data biases.  $\tau^2$  has an inverse gamma prior with shape  $\tilde{\zeta}_{\tau^2}$  and inverse scale  $\tilde{\chi}_{\tau^2}$ .

### APPENDIX D

# BAYES SENSITIVITY EXPERIMENTS

### D.1 ICE6G-MITROVICA



Figure A62: Posterior median (thick line) and 95% credible interval of regional trends for Bayesian solution with mean GIA priors from ICE-6G and covariance priors from Mitrovica (Cf. Figures 14, A64, A66).



Figure A63: Percent of alongshore variance in total RSL (Fig. A62a) explained by VLM or SSH related processes for Bayesian solution with mean GIA priors from ICE-6G and covariance priors from Mitrovica (Cf. Figures 16, A65, A67).



Figure A64: Posterior median (thick line) and 95% credible interval of regional trends for Bayesian solution with mean GIA priors from ICE-6G and covariance priors from (*Caron et al.*, 2018, Cf. Figures 14, A62, A66). )



Figure A65: Percent of alongshore variance in total RSL (Fig. A64a) explained by VLM or SSH related processes for Bayesian solution with mean GIA priors from ICE-6G and covariance priors from (*Caron et al.*, 2018, Cf. Figures 16, A63, A67.)



Figure A66: Posterior median (thick line) and 95% credible interval of regional trends for Bayesian solution with mean and covariance GIA priors from *Caron et al.* (2018, Cf. Figures 14, A62, A64.)



Figure A67: Percent of alongshore variance in total RSL (Fig. A66a) explained by VLM or SSH related processes for Bayesian solution with mean GIA priors from ICE-6G and covariance priors from (*Caron et al.*, 2018, Cf. Figures 16, A63, A65.)

#### AFTERWORD

Around the same time, Monk and Kuhn - in very different ways - showed that mistakes are innovation. Not random but intentional mistakes, with some insight into the problems with the prevailing ideas of 'correct'. Some immediately see the circumference of their field and start making the right mistakes. Others, like myself, have been making the wrong mistakes for years; but I don't think this is too unusual.

Indeed, in a (somewhat idealized) sense, higher education is about learning how to make better mistakes. Looking under many metaphorical stones, slowly narrowing the search until settling on a few to consider more closely. Of course, constantly correcting course is exhausting and requires some vulnerability, some sacrifice of ego, that becomes more uncomfortable as you approach the right mistakes. But exposure to the discomfort of uncertainty is, I think, a prerequisite to creative progress in any aspect of life.

I've spent a lot of time looking under a lot of stones. Most of that time was spent figuring out what mistakes to start making. It was finally through formally studying literature and political theory that I started to realize Nature and Society were tied together far more intricately than I'd formerly understood. I looked to Science to start investigating Nature. Settling on Earth Science, which is fundamentally interdisciplinary, I kept looking under multiple stones. Now using global satellite observations to understand local coastal impacts, the entanglement of Nature and Society is brought further into focus.

Over the last few centuries, Science has generally been advanced through increasingly specialized knowledge. I've instead been allowed to walk along the intersection of disciplines, acquiring some specific expertise while maintaining a general perspective. This has only been possible with support from an incredible cast of family, friends, colleagues and advisers, who have patiently waited, supported and encouraged me throughout my life. This dissertation marks the latest milestone along an atypical path that began well before I started college. Within it are not only concrete contributions to Science, but also a first expression of my cross-disciplinary perspective.

Moving forward, I'm hopeful I can continue to develop this perspective, further specializing in order to find connections between ideas. I think this is increasingly important, as the disconnect between human society and natural ecology underlies the problems of our time. Reharmonizing their relationship requires innovative and integrative perspectives that transverse traditional boundaries. Through the specific science I've investigated through my graduate degrees, I've finally begun to understand the Earth from such a systems perspective, and see where the limits of understanding lie. In other words, I've finally learned how to to make the right mistakes.

# VITA

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## PUBLICATIONS

Buzzanga, B., Heijkoop, E., Hamlington, B., Nerem, R. S., & Gardner, A. (2021). An assessment of regional ICESat-2 sea-level trends. Geophysical Research Letters, 48, https://doi.org/10.1029/2020GL092327.

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