South Pacific Ocean Climate Dynamics and Predictability

by

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ABSTRACT

The mechanisms and predictability of Pacific decadal climate variability (PDV) is an active area of research in climate science and is one of high societal importance. To date, most research into PDV has been focused on mechanisms and responses in the North Pacific. This thesis presents a comprehensive investigation, based on the development and application of a family of hierarchical stochastically forced models, of the mechanisms underpinning PDV climate predictability and that focuses on the role of the South Pacific Ocean and coupling to the tropics.

First, a simple one-dimensional first-order autoregressive (AR1) model was used to understand the space and time variations of the South Pacific decadal oscillation (SPDO) – which represents the leading sea surface temperature (SST) mode in the South Pacific. The analysis revealed that the first Pacific-South American (PSA1) pattern is the key atmospheric driver of the SPDO. Further, the leading mode of integrated subsurface upper ocean temperature variability was shown to match expectations from the propagation of oceanic Rossby waves across the extratropical South Pacific, with the atmospheric PSA variability providing the high-frequency 'noise' source of the observed low-frequency ('reddened') SST SPDO response.

Second, the stochastically forced AR1 model was generalised to higher-dimensional fields with the inclusion of spatial features using a linear inverse model (LIM) approach. The deterministic dynamics underpinning the combined tropical and South Pacific system was investigated, with the seasonal predictive skill of the SPDO and El Niño–Southern Oscillation (ENSO) quantified under the LIM framework. It was found that, although the oscillatory periods of ENSO and the SPDO are distinct – the former oscillating on interannual timescales and the latter oscillating on (inter-)decadal timescales – their damping time scales were very similar, and their predictive skill comparable. With the inclusion of subsurface processes in the extratropical South Pacific, the linear predictive skill of both ENSO and the SPDO was found to be enhanced. Overall, the study showed that Pacific SST variability forecast skill from the computationally cheap LIMs was competitive with state-of-the-art operational seasonal forecast systems that employ sophisticated initialisation schemes and general circulation models, thus providing a useful benchmark for these operational systems.

Third, the LIM framework was applied to gain a deeper understanding of the role of stochastic forcing from the atmospheric PSA variability and to determine the optimal structures for initialised forecasts of the tropical and South Pacific climate system and its variability. This analysis revealed the spatial imprint of atmospheric PSA variability combined with temporal stochastic forcing that acts to drive the low frequency oceanic SST variability across the tropical and South Pacific, and excites optimal initial perturbations for the prediction of ENSO and the SPDO.

Finally, informed by the aforementioned hierarchy of stochastically forced linear reduced space models, the thesis culminates with an overarching framework that links the atmosphere to the surface and subsurface oceans across a range of time scales from (intra-)seasonal to (inter-)decadal. Hence, the thesis provides, for the first time, a mechanistic framework and integrated understanding of the drivers of large-scale South Pacific climate variability and predictability.

CHAPTER 1

Introduction

Large-scale modes of climate variability of the atmosphere and ocean over the Pacific basin significantly affect the weather and climate systems around the globe (Mo and Ghil 1987; Mantua et al. 1997; Power et al. 1999; McPhaden et al. 2006; Di Lorenzo et al. 2008; Chen and Wallace 2015; Newman et al. 2016; Amaya 2019). These intrinsic modes of variability oscillate on a wide range of time scales from days to seasons, and years to decades. Due to the great volume and large heat capacity of the Southern Hemisphere oceans, the South Pacific Ocean provides one of the major sources of seasonal to interannual climate predictability, and therefore is one of high societal importance.

El Niño–Southern Oscillation (ENSO; Fig. 1.1) is the dominant mode of interannual climate variability across the globe (McPhaden et al. 2006; 2020) arising from coupled air-sea interactions in the tropical Pacific Ocean. On (inter-)decadal timescales, a number of intrinsic modes of variability have been proposed to represent the main variations in the Pacific basin. For example, the Pacific decadal oscillation (PDO: Mantua et al. 1997; Mantua and Hare 2002) was proposed to track the leading sea surface temperature (SST) mode in the North Pacific Ocean (Fig. 1.1). Some studies (Power et al. 1999; Folland et al. 2002) then extended the PDO to the entire Pacific Ocean by introducing the interdecadal Pacific oscillation (IPO) with the emphasis on the low-frequency (~decadal) SST variations. The IPO has been shown to impact global mean surface temperature trends (e.g., England et al. 2014; Trenberth 2015), precipitation (Hsu and Chen 2011; Dai 2013; Bo and Dai 2015) and ecosystems (Miller and Schneider 2000; Di Lorenzo et al. 2013). Although the Pacific-wide IPO shares a various range of spatiotemporal similarities with the PDO in the North Pacific, they are not identical. Recently, the South Pacific decadal oscillation (SPDO: Chen and Wallace 2015) has been proposed as the analogue of the PDO, representing the leading SST mode of variability in the South Pacific Ocean (Fig. 1.1). In a re-examination, Newman et al. (2016) refer to the PDO and SPDO respectively as the North Pacific and South Pacific centres of action of the Pacific-wide IPO. For consistency, in this thesis, we make use of Pacific decadal variability (PDV) to refer broadly to internal climate variability fluctuating on (inter-)decadal (> 10 years) time scales over the Pacific basin, such as the IPO, PDO, and the SPDO.

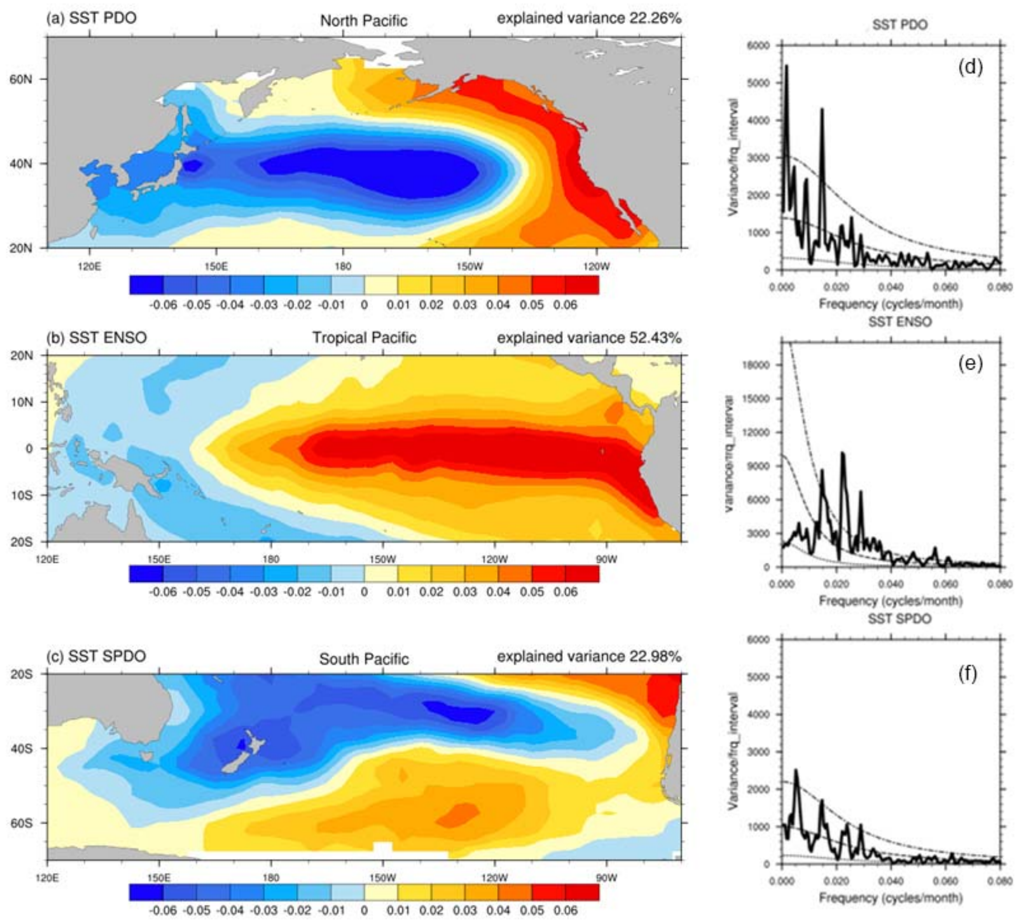

Figure 1.1: The spatial patterns (a-c) of the PDO, ENSO, and SPDO, defined as the leading mode of the monthly SST anomalies [taken from Hadley SST (HadISST) dataset and for the period of 1870-2016] in the North Pacific, tropical Pacific, and South Pacific, respectively, and the corresponding spectral analysis (d-f) of the time series of the PDO, ENSO, and SPDO.

Even a cursory reading of the literature indicates that the impacts, mechanisms and predictability of PDV in the North Pacific (e.g., Alexander et al. 2002; Newman et al. 2016, and references therein) have been well-documented, and are currently active areas of research in climate science. In contrast, our understanding of PDV in the South Pacific is lacking. This in part might be mainly due to the sparse coverage of observed data in the South Pacific Ocean (Rhein et al. 2013) and partly due to the fact that the observed variability in the South Pacific is not as high as in the North Pacific (see, for example, Figs. 1.1d and f). This study aims to reveal the mechanisms underpinning PDV with a specific focus on the South Pacific Ocean and to investigate the predictability of PDV in the South Pacific on a multiple range of time scales.

1.1 Mechanisms of Pacific decadal variability

In order to understand the dynamics of PDV, previous studies (e.g., Chen and Wallace 2015; Liu and Di Lorenzo 2018) tend to decompose the whole Pacific region into three latitudinal domains, including two extratropical regions poleward of 20ºN and 20ºS (referred to as the North Pacific and South Pacific, respectively), and a broad tropical region between 20ºS-20ºN (referred to as the tropical Pacific), primarily according to geophysical characteristics of each domain. In the extratropical Pacific, many previous studies (e.g., Latif and Barnett 1994; Deser et al. 1996; Pierce et al. 2001; Fu and Qiu 2002; Di Lorenzo et al. 2010; 2011, and references therein) investigate the dynamics of PDV confined to the Northern Hemisphere. It has recently been recognised that the PDO is not a single physical mode of variability, but instead largely represents multiple processes operating on a range of timescales from seasonal to (multi-)decadal (see, for example, Schneider and Cornuelle 2005; Newman et al. 2016). These processes primarily include stochastic forcing, ENSO teleconnections, and oceanic dynamics (summarized in Fig. 1.2). While a number of dynamical mechanisms have been proposed, debate still remains as to the relative importance of each mechanism and what is the dominant cause of the observed PDV.

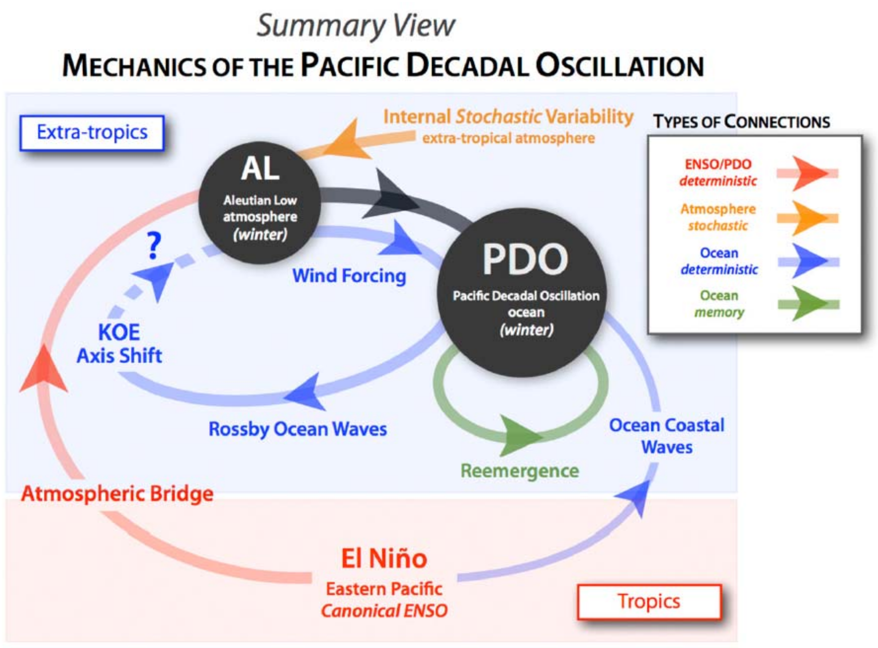

Figure 1.2: Schematic of the main processes involved in the PDO (source: Newman et al. 2016). The schematic shows that the PDO is not a single phenomenon, but is instead the result of a combination of different physical processes, including stochastic forcing (i.e, Aleutian Low (AL)), ENSO teleconnections via the atmospheric bridge or ocean coastal waves, and oceanic process (for example, oceanic Rossby waves, the Kuroshio and the Oyashio Extensions (KOE), and reemergence).

In the extratropical South Pacific, some studies emphasize the relative roles of the atmosphere and ocean in contributing to the observed PDV. Shakun and Shaman (2009) highlight that the tropical Pacific is the dynamical origin of the South Pacific decadal variability. Okumura (2013) suggests that the atmospheric Pacific-South American (PSA: Karoly 1989; Ghil and Mo 1991; O'Kane et al. 2017) pattern is the dominant driver of the PDV in the South Pacific. Power and Colman (2006) stress the importance of oceanic Rossby waves in maintaining observed decadal variability in the South Pacific. Since the relative importance of these proposed mechanisms in affecting the observed PDV in the South Pacific remains unclear, we adapted the dynamical framework originally proposed for the PDO in the North Pacific (i.e., Fig. 1.2) and hypothesized that the SPDO in the Southern Hemisphere also integrates multiple dynamics including stochastic forcing, ENSO teleconnections, and oceanic processes in this study.

This thesis aims to illustrate the different roles of these mechanisms in generating overall SPDO variability. It is worth noting that it is not our intention to clarify the relative importance of each mechanism in generating South Pacific decadal variability since the dominant driver varies from case to case. Rather, the focus is on how the overall SPDO variability incorporates those different processes operating on different time scales and exhibits the observed spatiotemporal features.

1.1.1 Stochastic forcing and stochastically forced models

The idea that fast-moving atmospheric variability may act as stochastic forcing of observed low-frequency PDV has been extensively discussed in the literature, beginning with the classic studies by Hasselmann (1976) and Frankignoul and Hasselmann (1977). In climate science, a time series x_t can be decomposed into a dynamically determined component s_t and a stochastic component ξ_t, such that

$$x_t = s_t + \xi_t. \qquad (1.1)$$

If the time evolution of s_t is independent of the stochastic component ξ_t, it follows that the evolution of s_t is deterministic (e.g., tides that are externally forced). In this thesis, the dynamically determined component s_t largely depends on the stochastic changes ξ_t. Such processes become deterministic when the stochastic forcing is absent. In this simplified scenario, Fig. 1.3 illustrates how the sea surface variability in the extratropical Pacific may be considered as the superposition of fast-moving atmospheric noise forcing and slowly varying subsurface oceanic variability. The addition of the atmospheric noise introduces some uncertainty and reduces the predictability of the surface ocean, but it does not significantly modify the period or phase of the surface ocean oscillations. In contrast, the subsurface variability acts as a potentially predictable background state, which modulates the low-frequency flavours of the surface variability and tends to add predictability to the surface system.

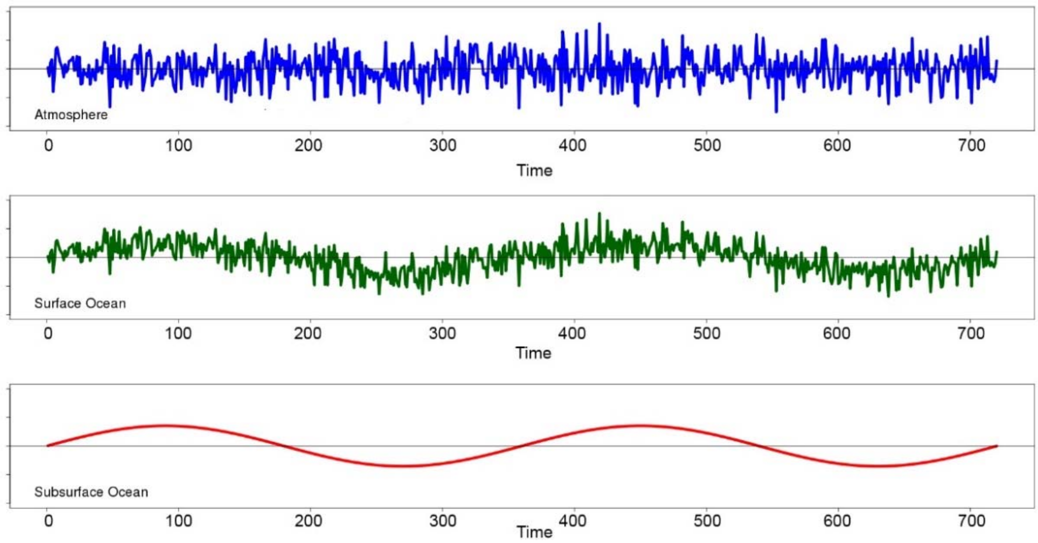

Figure 1.3: An idealised scenario showing how the SST variability is considered as the superposition of atmospheric variability and subsurface processes in the extratropical Pacific. Noise time series (upper) is generated from random values satisfying a normal distribution to mimic fast-moving atmospheric variability. Subsurface time series (bottom) is a pure sine function to mimic the slowly varying

subsurface oceanic variability. The surface time series (middle) is the superposition of the time series from the atmosphere and subsurface ocean.

Hasselmann (1976) and Frankignoul and Hasselmann (1977) first introduced the first-order autoregressive (AR1) model to climate science, where the dynamically determined component s_t linearly depends on the previous value of $x_{t+\tau}$ (i.e., $s_t = \alpha_\tau x_t$, where α_τ describes the decorrelation time scale of the variability). Now, Eq. 1.1 can be written as

$$x_{t+\tau} = \alpha_\tau x_t + \xi_t, \qquad (1.2)$$

where the predictability of the evolution of x depends on the decorrelation time scale α_τ. Without stochastic forcing ξ, the evolution of x decays monotonically under the AR1 framework.

Many previous studies applied this AR1 hypothesis to assess changes of physical ocean variables in response to atmospheric forcing. For example, Di Lorenzo and Ohman (2013) suggest that the PDO can be regarded as the integrated version of the atmospheric Aleutian Low (AL) in the North Pacific. By integrating this AR1 process twice, Di Lorenzo and Ohman (2013) further argue that cumulative responses to atmospheric forcing (i.e., AL) explain a large fraction of long-term state transitions in marine ecosystems.

Although useful conceptually, stochastically forced one-dimensional AR1 models are limited by their simplicity (Newman 2007). For example, AR1 models cannot reveal spatial features due to there being only one spatial degree of freedom in their construction. In addition, the growth of the deterministic system and the corresponding optimal initial conditions cannot be examined due to the time series that decays monotonically without stochastic forcing. This motivated the development of higher-dimensional multivariate AR1 processes in a methodology known as principal oscillation pattern (POP) analysis (von Storch et al. 1995) or, alternatively, linear inverse modelling (LIM: Penland and Sardeshmukh 1995). As follows:

$$\mathbf{X}_{t+\tau} = \boldsymbol{A}_{\tau}\mathbf{X}_{t} + \boldsymbol{\xi}_{t}. \tag{1.3}$$

POP/LIM approaches provide an observationally based, stochastically forced model where the evolution of the state vector $\mathbf{X}$ can be approximated as slowly varying dynamical processes via a linear deterministic dynamical operator $\boldsymbol{A}_{\tau}$, and the effect of fast processes $\boldsymbol{\xi}_{\mathrm{t}}$ as Gaussian white noise.

Since the late 1980s, POP/LIM techniques have been widely used to empirically infer the characteristics of spatiotemporal variations and to quantify the predictive skill of a complex system in a high-dimensional space. POP/LIM techniques have been successfully applied to investigate, for example, the atmospheric Madden-Julian oscillation (von Storch and Xu 1990; Cavanaugh et al. 2014), ENSO (Penland and Magorian 1993; Penland and Matrosova 1993, 2006; Tang 1995; Gehne et al. 2014) and the related ENSO diversity (Newman et al. 2011; Vimont et al. 2014; Capotondi and Sardeshmukh 2015; Capotondi et al. 2015; Thomas et al. 2018), Atlantic Multidecadal Variability (Zanna 2012; Huddart et al. 2016), North Pacific decadal variability (Alexander et al. 2008), tropical Indo-Pacific SST (Newman et al. 2017), tropical and North Pacific SST (Newman 2007), Atlantic sea surface height (SSH) (Fraser et al. 2019), and global surface air temperature (Newman 2013). Under the POP/LIM framework, Newman (2007) suggested that the dynamics of the PDO could be decomposed into several phenomena, each of which represents a different red noise spectrum with its own spatial pattern and decorrelation time scale.

In this thesis, we apply the stochastically forced POP/LIM framework for the first time to investigate the tropical and South Pacific combined system with inclusion of subsurface processes in the extratropical South Pacific. We use this approach to systematically investigate the dynamics of the reduced-order system and to examine the seasonal to multiyear predictability of the leading modes in the tropical and South Pacific oceans.

1.1.2 ENSO teleconnections

To first order, not only does extratropical PDV act to redden the local atmospheric noise, but also the tropical ENSO signal. Some studies (e.g., Newman et al. 2003; Power and Colman 2006; Shakun and Shaman 2009) argue that the PDO and SPDO can be viewed as the reddening version of tropical ENSO variability under the simple AR1 framework. Specifically, ENSO-driven changes in the tropical Pacific affect the extratropical Pacific Ocean via two main pathways – an atmospheric bridge (e.g., Alexander 1992; Lau and Nath 1994, 1996; Alexander et al. 2002) and oceanic pathways (Power and Colman 2006). The atmospheric bridge links the tropical Pacific and extratropical Pacific through changes in, for example, the Hadley and Walker cells (Gill 1980; Feng and Li 2013; Adam et al. 2014; Bayr et al. 2020), atmospheric Rossby waves (Hoskins and Karoly 1981; Hamilton 1985; Hoskins and Ambrizzi 1993; Ambrizzi et al. 1995), and interactions between the mean flow and the subtropical and polar jet streams (Held et al. 1989; Trenberth et al. 1998; Freitas and Ambrizzi 2012;

Freitas et al. 2016). Previous studies (e.g., Alexander et al. 2002; Alexander and Scott 2008) argue that when tropical ENSO variability peaks in boreal wintertime, the enhanced cyclonic circulation around a deepened AL over the North Pacific changes the surface heat fluxes, wind stress curl, and oceanic Ekman transport, after which a positive PDO pattern (i.e., positive PDO defined as shown in Fig. 1.1 a) tends to be manifest.

In the South Pacific, some studies (e.g., Mo 2000; Mo and Paegle 2001; Cai et al. 2011) argue that the atmospheric PSA variability is associated with tropical ENSO and acts as a teleconnection mode that links the tropics to the South Pacific. For example, Mo and Paegle (2001) suggest that the low frequency variability of the PSA patterns is attributed to stationary atmospheric Rossby waves generated by large-amplitude tropical SST anomalies associated with ENSO. Cai et al. (2011) suggest that the PSA patterns occurring and radiating poleward and eastward from the central Pacific convective anomalies are predominantly related to ENSO variability. In contrast, O'Kane et al. (2017) examined the multiscale spectral features of the PSA and found that the majority of the PSA patterns on synoptic to intra-seasonal timescales might be considered as a manifestation of internal midlatitude waveguide dynamics and local disturbances. Renwick and Revell (1999) argue that linear atmospheric Rossby wave propagation provides the link between anomalous convection in the tropics and the occurrence of blocking over the southeast Pacific Ocean on synoptic scales. It has been recognised that the PSA variability on interannual timescales is closely associated with ENSO (e.g., Mo and Paegle 2001, and references therein). However, how PSA variability on synoptic to intra-seasonal timescales connects to the tropical ENSO variability remains unclear.

The oceanic pathways link the tropical Pacific to the extratropical Pacific through changes in, for example, thermocline conditions, Ekman transport (Alexander and Scott 2008), and interactions between oceanic Kelvin waves and Rossby waves (e.g., Power and Colman 2006). In theory, tropical wind stress variability associated with ENSO forces the oceanic equatorially trapped Kelvin waves that propagate eastward to the eastern boundary, where Kelvin waves excite coastally trapped waves along the eastern boundary and reflect equatorially trapped Rossby Waves. Although the former impacts the ocean only within about 50 km of shore (e.g., Gill 1982, Power and Colman 2006), they can excite oceanic Rossby waves at higher latitudes, which propagate westward back into the interior of the ocean and affect changes of PDV basin wide.

1.1.3 Oceanic processes

Due to the thermal inertia of the ocean, the dynamical time scale of the upper ocean is on the order of months and longer (e.g., Deser et al. 1996). Among all the proposed mechanisms, oceanic Rossby wave propagation (e.g., Gill 1982, pg. 159-175) has long been identified as the key driver to modulate the phase and period of the observed extratropical ocean PDV. Oceanic baroclinic Rossby waves primarily generated by the wind stress curl anomalies have been shown to have the capability of shaping the patterns of SST and SSH on months to multi-year time scales (e.g., White 1977; Chelton and Schlax 1996; Holbrook and Bindoff 1999; Capotondi and Alexander 2001; Fu and Qiu 2002; Capotondi et al. 2003; McGregor et al. 2004, 2007; 2008; 2009;

Maharaj et al. 2005; Qiu and Chen 2006; Holbrook 2010; Holbrook et al. 2011; Lyu et al. 2017; Chapman et al. 2020; Li et al. 2020).

Deser et al. (1999) show that the dynamical adjustment of the extratropical ocean gyre circulation via westward-propagating first-order baroclinic Rossby waves to stochastic wind stress forcing may lead to SST variability on decadal timescales in the North Pacific Ocean. Qiu and Chen (2006) argue that wind driven Rossby waves play an important role in generating observed decadal SSH variability in the interior of South Pacific Ocean. Maharaj et al. (2005) found that the presence of bottom topography (e.g., meridional ridges) can lead to long Rossby wave refraction and dispersion, and therefore creates higher order Rossby wave modes which tend to enhance low-frequency variability of the mid-latitude ocean system. Holbrook and Bindoff (1999) and Kessler and Gourdeau (2007) demonstrate that annual thermocline depth variability in the southwest interior South Pacific is related to linear wind forcing via baroclinic Rossby wave dynamics. Holbrook et al. (2011) show that planetary linear baroclinic Rossby waves provide an important mechanism for modulating western boundary current transports and corresponding observed sea level variations in Sydney Harbour on ENSO to decadal time scales.

Aside from the classic first-order planetary baroclinic Rossby wave theory, some studies highlight the nonlinear and multiscale characteristics of oceanic Rossby waves. For example, O'Kane et al. (2014a) show that nonlinear instabilities associated with baroclinically unstable Rossby waves in ocean storm tracks in the extratropical South Pacific are key to the multiscale properties of extratropical Rossby waves and further enhance decadal variability over the South Pacific. In a recent study, Travis and Qiu (2017) investigate the decadal variations of baroclinic instability in the South Pacific Subtropical Counter-current (STCC) region, where the baroclinic Rossby wave dynamics break down (Qiu and Chen 2006). Travis and Qiu (2017) found that the decadal changes are mainly attributed to a combination of variations of vertical velocity shearing and stratification.

1.1.4 Extratropical Pacific impacts on the tropics

With specific focuses on how tropical ENSO variability affects the extratropical Pacific in Section 1.1.2, here we focus on the mechanisms by which the extratropical Pacific modulates ENSO events and the decadal flavours of the ENSO-related variability in the tropics. The extratropical influence may occur through, for example, the seasonal footprinting mechanism (Vimont et al. 2001, 2003; Alexander et al. 2010), Pacific meridional modes (PMM) and associated wind-evaporation-SST (WES) feedback (Chiang and Vimont 2004; Chang et al. 2007; Zhang et al. 2014; You and Furtado 2017; Larson et al. 2018; Liguori and Di Lorenzo 2019; Amaya 2019; Chung et al. 2019), oceanic Rossby waves (Capotondi and Alexander 2001; Capotondi et al. 2003; McGregor et al. 2007, 2009), and oceanic temperature and salinity (spiciness: the temperature and salinity of seawater of a given density) variability (Schneider 2004; O'Kane et al. 2014b).

The seasonal footprinting mechanism proposed by Vimont et al., (2001, 2003) established a seasonal connection between midlatitude atmospheric variability and tropical zonal wind stress anomalies associated with ENSO variability. They argue that atmospheric fluctuations in the midlatitude Pacific create an anomalous SST "footprint" in boreal spring via changes in surface heat flux, which then persists through boreal summer, and sustains sea level pressure (SLP) and wind stress anomalies that are effective initiators of ENSO events. Vimont et al. (2003) suggest that the seasonal footprinting mechanism might be less effective in linking the atmospheric variability in the South Pacific to tropical variability in comparison to that between the North Pacific and tropics. However, Ding et al. (2015) argue that the PSA-forced SST footprint variability in the South Pacific still plays an important role in forcing the observed tropical ENSO variability.

Recent growing evidence suggests that PMMs (see the recent review paper by Amaya 2019) in the North Pacific [referred to as the North PMM (NPMM: Chiang and Vimont 2004; Di Lorenzo et al. 2015)] and South Pacific [referred to as the South PMM (SPMM: Zhang et al. 2014)] play a role in triggering/modulating ENSO evolutions and ENSO diversity. As illustrated in Fig. 1.4, atmospheric North Pacific oscillation-induced modulations of the trade winds can lead to SST anomalies in the extratropical North Pacific that propagate south-westward via a WES mechanism (Xie and Philander 1994; Xie 1999) which can initiate an ENSO event as they reach the equator (Chiang and Vimont, 2004; Chang et al., 2007). A similar mechanism has been identified in the South Pacific via an SPMM-WES feedback (see, for example, Zhang et al. 2014; You and Furtado 2017). Liguori and Di Lorenzo (2019) and Chung et al. (2019) compared the relative role of the NPMM and SPMM in affecting tropical ENSO variability. They found that the absence of the SPMM significantly reduces tropical PDV by 30%, while the NPMM significantly affects tropical ENSO variability on interannual timescales.

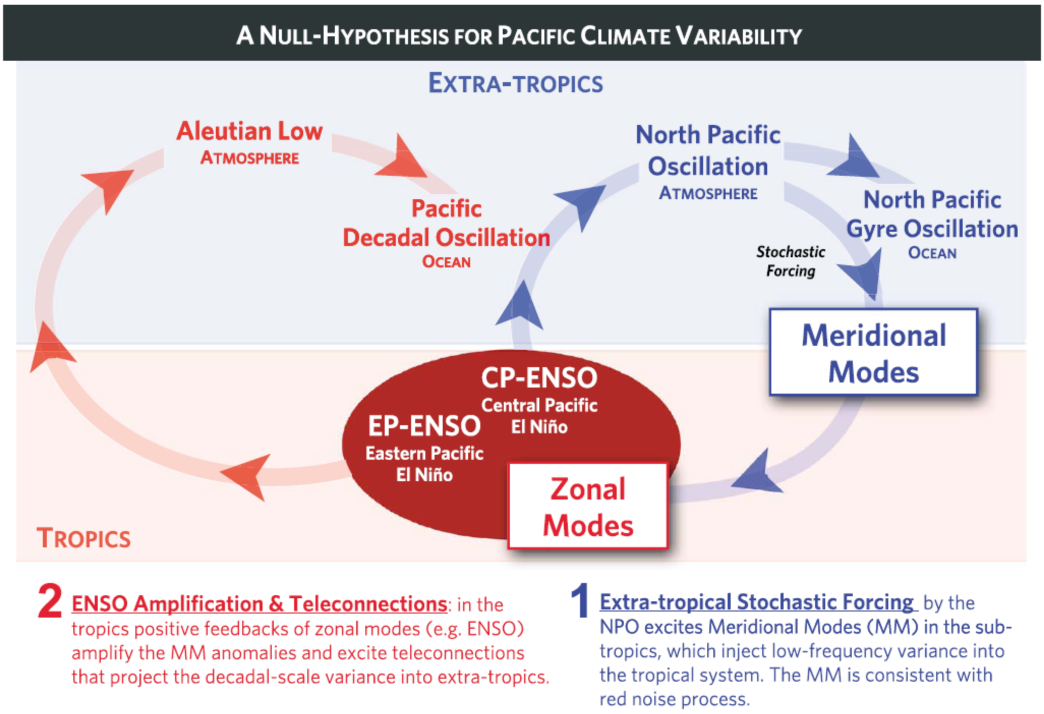

Figure 1.4: A schematic of the interactions between tropical and extratropical Pacific. (Source: Di Lorenzo et al. 2015)

Aside from atmosphere – ocean interactions, many previous studies highlight the importance of interior ocean dynamics in affecting the tropical ENSO variability. Gu and Philander (1997) argue that exchanges between extratropical and tropical water masses through thermocline ventilation can modulate the decadal flavours in the depth of the thermocline in the equatorial Pacific, which in turn can cause changes in tropical SST and a modulation of ENSO variability. Giese et al. (2002) suggest that warm spiciness anomalies in the tropical South Pacific Ocean propagating towards the equator are amplified by air–sea interactions and account for the observed tropical climate regime shift to warmer conditions in 1976/77. O'Kane et al. (2014b) further show that South Pacific ocean spiciness anomalies have a considerable impact on the decadal climate shift to a regime favouring strong El Niño events in the late 1970s.

Although we did not attempt to address the origins of the tropical ENSO variability in this thesis, and it is nevertheless correct that individual ENSO events and decadal flavours of ENSO differ substantially in triggers, drivers, amplitudes, spatial patterns, and temporal evolutions, the influence from the extratropical Pacific should be included when considering the contribution that affects the tropical ENSO variability (e.g., Boschat et al. 2013; Ding et al. 2014; Min et al. 2017).

1.2 Predictability of the Pacific decadal variability and ENSO

Owing to societal needs and economic benefits, seasonal to decadal climate predictions are emerging as one of the hot research areas in climate science (Goddard et al. 2001; Meehl et al. 2009, Kushnir et al 2019). Climate predictions can be made using numerical tools and statistical methods. The former typically proceed by integrating the governing equations forward in time from observational-based initial conditions (e.g., Meehl et al. 2016). The latter relate current to future conditions using statistical relationships estimated from past system behaviour (e.g., Alexander et al. 2008; Newman et al. 2011). Generally, numerical methods are used to solve the governing equations on a discrete grid at particular resolutions, and the physical processes that occur on the sub-grid scales or within time intervals need to be represented by parameterizations. Such approximations suggest that even if a perfect initial condition could be provided to initialize the equations, errors associated with, for example, model discretization, and parameterization, in climate predictions are inevitable (Bengtsson et al. 2019). On the other hand, statistical predictions are relatively easy and computationally cheap to perform, and their skill can be sufficiently comparable relative to the nonlinear general circulation models (GCMs) (e.g., Newman 2013). In practice, statistical methods are therefore useful in providing empirical knowledge that may lead to more skilful forecasts in the absence of explicit physical understanding and serving as benchmarks for the more sophisticated state-of-the-art GCMs.

Formally, predictability is an intrinsic attribute of a physical system itself and indicates the extent to which two initially close states of the system diverge with time (i.e., the rate of separation in, for example, Boer 2000, 2004; Kirtman et al. 2013). If one of the states is referred to as the true state of this system and the other is considered as the true state with some errors, then the rate of separation can be interpreted as the rate of error growth. However, since in any practical case, different sources of errors can be involved, predictability in this sense does not represent a practical ability to predict the future evolutions of the system (e.g., Boer 2004). Predictability is then used in a less restrictive and loose way to measure our current "ability to make skilful predictions/forecasts", which is then equivalent to the definition of predictive/forecast skill and largely depends on, for example, the accuracy of predictive models and initial conditions and the correctness of external boundary conditions (see, for example, the review paper of Goddard et al. 2001).

There are two broad perspectives to investigate predictability – a) potential predictability (Boer 2004, 2010; Power and Colman 2006; Frederiksen et al. 2015; Lou et al. 2016) and b) practical predictability (Boer 2000; Meehl et al. 2009, 2010; Nadiga and O'Kane 2017). The former is not a direct measure of predictability in the classical sense of the rate of separation of initially close states or the rate of error growth. Rather, it is a diagnostic analysis of variance which attempts to quantify the fraction between the variance of the long timescale variability of interest and the total. As such it implies long timescale variability is an appreciable fraction of the total variance, and hence predictions on these long timescales might be possible. Without considering uncertainties from the initial conditions, parameterization schemes of the models, and other sources of errors, potential predictability assumes a perfect or idealized situation and represents an upper bound to the skill that might be attained for prediction of this long timescale component (Boer 2010). Practical predictability takes account of the multiple sources of errors arising from models and observations (e.g., initial conditions, model characteristics, parameterizations, coupling formulations, and observational errors, etc.) and reflects our actual ability to make predictions. Boer (2000) documents that the practical predictability is limited and may be out of reach on long timescales due to the lack of sufficient oceanographic observations to specify initial conditions. In what follows, we discuss the predictability of the PDV and ENSO from the perspectives of numerical and statistical modelling.

1.2.1 Numerical modelling

Historically, climate predictions have been made using numerical models of varying complexity, ranging from; intermediate coupled models, where the interactions between atmosphere and ocean are simulated under a simplified physical framework within the tropical Pacific domain (e.g., Cane et al. 1986; Zebiak and Cane 1987); hybrid coupled models that incorporate a physical ocean model with coupling to a statistical atmosphere model (e.g., Barnett et al. 1993; Balmeseda et al. 1994; McGregor et al. 2008); and coupled GCMs (e.g., Kirtman et al. 1997; Stockdale et al. 1998; Saha et al. 2006).

The complexity of state-of-the-art coupled GCMs over the past decade has increased dramatically. For example, improved model resolutions – in particular increased vertical resolution in the stratosphere has allowed complex middle atmosphere chemistry to be incorporated, added optimized parameterization schemes (e.g., representations of clouds), and inclusion of important Earth system modules (e.g., biogeochemistry, ice sheets, etc.). These additional processes are fundamentally important to represent key climate feedbacks and to better estimate climate sensitivity, however they may also increase the spread of climate simulations and predictions among the multi-model ensembles (Eyring et al. 2019). In addition, a lack of historical ocean observations for testing and evaluating numerical models will continue to make it challenging to comprehensively address the mechanisms and processes that produce decadal climate variability (Balmaseda et al. 2013; Stouffer et al. 2017), which, in turn, limits our understanding of the origins of predictability on the dynamical timescales of the oceans. While significant challenges remain (Stouffer et al. 2017), there are now nearly a dozen operational centres for near-term climate predictions https://hadleyserver.metoffice.gov.uk/wmolc/, including the first in the Southern Hemisphere (O'Kane et al 2020).

Model-based ENSO predictions have existed for a few decades (Latif 1994, 1998; Barnston et al 2012; O'Kane et al 2019, 2020). Early in the 21st century, ENSO predictions on seasonal timescales have transitioned from experimental to operational stage primarily due to improved observing and assimilation systems, improved parameterizations, higher model resolutions, and better understanding of tropical atmospheric and oceanic processes underlying the ENSO events (Guilyardi et al. 2009; Barnston et al. 2012, O'Kane et al 2020).

Improved ENSO predictions have now been shown to have utility across a wide variety of stakeholders (Jin et al. 2008; Johnson et al. 2019). However, the success of any particular ENSO prediction strongly depends on the season, ENSO phase, and ENSO intensity. For example, the skill of ENSO forecasts initiated during the boreal spring (March, April, and May) drops faster than those initiated during the boreal wintertime. This behaviour is often referred to as the ENSO boreal spring predictability barrier (e.g., Barnston et al. 2012; Duan and Wei 2012; Lai et al. 2018; Liu et al. 2019; Chen et al. 2020). Because of this, state-of-the-art forecasting schemes traditionally do not predict beyond the ENSO boreal spring barrier. Skilful long-range (beyond seasonal timescales) forecasts of ENSO are in high demand but are statistically unreliable.

Although some studies (e.g., Jin 2001) argue that PDV might simply be the product of the background amplitude modulation of tropical ENSO events, many other studies (Pierce et al. 2001; Power and Colman 2006; Meehl and Hu 2006; Meehl et al. 2009; Holbrook et al. 2014) consider that PDV might have deterministic dynamics that are distinct from the interannual ENSO and therefore might be predictable beyond ENSO timescales. Power and Colman (2006) investigate the integrated upper ocean temperature in the Pacific Ocean and suggest that the source of the predictability of PDV resides in the subsurface upper ocean in the extratropical Pacific, whereas the main deterministic dynamics are associated with the mid-latitude oceanic Rossby wave propagations. Hermanson and Sutton (2010) report that subsurface oceanic variables (e.g., ocean heat content) are more predictable than atmospheric and surface variables. Mochizuki et al. (2010) further show that such deterministic mechanisms may arise from the subsurface ocean based on modelling studies where the inclusion of the observed historical upper ocean in the initial forecast conditions were shown to be effective for generating successful hindcasts of the PDO. This work has great implications for future developments in numerical climate prediction. However, the degree to which these specific deterministic mechanisms enhance predictability of PDV remains to be determined.

1.2.2 Statistical modelling

Predictability can also be understood by using statistical tools (referred to as diagnostic predictability in Kirtman et al. (2013)) including linear methods such as multiple linear regression (Landsea and Knaff 2000; Lean and Rind 2009; Branstator et al. 2012), autoregressive integrated moving average (ARIMA) models (Ho et al. 2012), canonical correlation analysis (Barnett et al. 1988; Barnston and Ropelewski 1992; Barnston 1994), POPs/LIMs (Penland 1989; von Storch et al. 1995; Penland and Sardeshmukh 1995, and references therein), decadal variance decomposition methods (Frederiksen et al. 2015; Lou et al. 2016; Ying et al. 2018); constructed analogue methods (Barnston et al. 1994; Ho et al. 2012), nonlinear techniques such as nonlinear neural networks (Tangang et al. 1998), nonlinear principal component analysis (Monahan 2001), machine learning (Dijkstra et al. 2019), and quadratic inverse models (Kondrashov et al. 2005).

The predictive skill from these diverse statistical tools can be sufficiently high that they are useful both in their own right and for providing empirical knowledge that may lead to more skilful forecasts in the absence of explicit physical understanding and as benchmarks for more complex numerical models (e.g., Krueger and von Storch 2011). Some other simple statistical benchmarks such as persistence, damped persistence (i.e., AR1 process), and climatology have been extensively used as thresholds in the evaluation of seasonal and near-term climate predictions (e.g. Barnston et al 1994; Colman and Davey 2003; Alexander et al. 2008; Newman 2013).

With specific interest in POPs/LIMs, some applications of POP/LIM predictions are discussed next. As shown in Eq. (1.3), the POP/LIM technique involves a linear transformation of a predictor field $\mathbf{X}_t$ to produce a forecast of a predictand field $\mathbf{X}_{t+\tau}$, which is the predictor field at some later time. Then, the POP/LIM is built upon the eigen-decomposition as a result of minimizing the errors between the predictand and the transformed predictor (e.g., Penland and Magorian 1993).

The linear deterministic dynamics are encapsulated in the dynamical operator $\boldsymbol{A}_\tau$ in Eq. (1.3) and can be estimated from the Green's function (Penland and Sardeshmukh 1995), that is,

$$\boldsymbol{A}_\tau = \langle \mathbf{x}_{\mathbf{t}+\tau}\mathbf{x}_{\mathbf{t}}^{\mathrm{T}} \rangle \langle \mathbf{x}_{\mathbf{t}}\mathbf{x}_{\mathbf{t}}^{\mathrm{T}} \rangle^{-1}, \qquad (1.4)$$

where the dynamical operator $\boldsymbol{A}_\tau$ can be estimated from the time-lag covariance matrix $\langle \mathbf{x}_{\mathbf{t}+\tau}\mathbf{x}_{\mathbf{t}}^{\mathrm{T}} \rangle$ and the inverse matrix of concurrent covariance $\langle \mathbf{x}_{\mathbf{t}}\mathbf{x}_{\mathbf{t}}^{\mathrm{T}} \rangle^{-1}$. $\boldsymbol{A}_\tau \mathbf{x}_{\mathbf{t}}$ represents the "best" prediction (in a least square sense) of $\mathbf{x}_{\mathbf{t}+\tau}$ (Alexander et al. 2008).

POPs/LIMs have been widely used in diagnosing dynamics (see in Section 1.1.1) and investigating predictability since the late 1980s (Hasselmann 1988; Penland 1989). After a few decades of development and applications, POPs/LIMs have been shown to be effective at providing skilful predictions over a wide range of time scales from weeks to years (Penland and Magorian 1993; Newman et al. 2003; Newman 2013, and references therein). LIMs (Penland and Matrosova 1994; Penland and Sardeshmukh 1995) are now successfully applied to make real-time tropical SST forecasts that are incorporated in the National Oceanic and Atmospheric Administration (NOAA) regular Climate Diagnostic Bulletin.

Newman (2007) and Alexander et al. (2008) constructed stochastically forced LIMs from observationally based SSTs finding that predictability of PDV and ENSO are generally limited to the order of a year, although at times exceeding this. Newman and Sardeshmukh (2017) compared the forecast skill of tropical Indo-Pacific SSTs made by the operational National Multi-Model Ensemble (NMME) and LIMs and found that the NMME and LIM skills closely track and are only slightly lower than the idealized potential predictability, indicating that we might be approaching the predictability limit of tropical Indo-Pacific SSTs. Dias et al. (2018) applied the LIM technique to investigate the seasonal to decadal predictive skill of the Pacific SSTs finding that, on seasonal timescales, the predictive skill of the LIMs is comparable with those from three operational forecast systems in the NMME and exhibited increased skill in some specific areas, for example, northeast Pacific. Dias et al. (2018) showed that the seasonal forecast skill of ENSO is enhanced with the inclusion of the extratropical Pacific, suggesting that interactions between different time scales and regions may be crucial to understanding the predictability limit of PDV and ENSO. However, as documented in Newman (2007), most GCMs underestimate interactions between the North Pacific SSTs and the tropical SSTs. Crucially, there are few if any comparable studies of interactions between the South Pacific SSTs and the tropical SSTs using the POP/LIM framework.

Without fully understanding of our changing climate system, statistical tools, such as LIMs that capture linear predictability and uncertainty of a dynamical system, offer an effective perspective for harnessing the predictable multivariate GCM information as a low-cost climate forecast alternative and benchmark (Perkins and Hakim 2020).

1.3 Thesis aim and objectives

The overall aim of this thesis is to better understand South Pacific decadal climate variability and predictability. The main objectives are 1) to explore the spatiotemporal features of the dominant modes of variability in the South Pacific Ocean, 2) to identify the key atmospheric drivers in generating and maintaining South Pacific Ocean decadal variability, 3) to understand the source of predictability and identify key locations where the predictable signal is amplified to enable climate monitoring, and 4) to evaluate the extent to which the low-frequency variability is predictable.

In this thesis, we seek to understand how South Pacific decadal variability incorporates different atmospheric and oceanic processes that operate on different time scales from seasonal to decadal and exhibits the observed spatiotemporal features. By better understanding the mechanisms underlying the dominant modes of variability in the tropical and South Pacific oceans, we first seek to identify where the source of low-frequency (~decadal) climate variability is located. With the inclusion of such low-frequency variability, we aim to understand to what extent the dominant modes of variability in the tropical and South Pacific oceans are predictable on seasonal to (inter-)annual timescales. In order to achieve those objectives, we make use of a series of diagnostic analyses and a family of hierarchical stochastically forced models with different complexity to investigate the mechanisms through which PDV occurs and its predictability with a specific focus on the South Pacific Ocean and coupling to the tropics.

The rest of the thesis is organised as follows. Chapter 2 is presented in the form of a published paper in the *Journal of Climate* that explores the leading decadal climate variability in the South Pacific from the surface ocean to the subsurface ocean. The chapter identifies the role of oceanic processes and atmospheric forcing in generating the observed PDV in the South Pacific by applying a series of diagnostic analyses and a double integrated AR1 model. Chapter 3 comprises a paper published in the *Journal of Climate* that extends the univariate stochastically forced AR1 model to a high-dimensional multivariate field fitted into a LIM to diagnose the dynamics underpinning the reduced-order tropical and South Pacific combined system and to understand the predictive skill of the SPDO and ENSO. Chapter 4 comprises a paper that is published in the *Journal of Climate*. It is based on the POP/LIM framework illustrated in Chapter 3, in which we explore the optimal initial conditions for maximum growth of the SPDO and ENSO by separating the contribution from deterministic evolution and the unpredictable noise-forced evolution associated with the atmospheric PSA variability. Chapter 5 will be converted into a paper for submission to an international journal, which seeks to propose an overarching big picture for understanding the large-scale South Pacific climate dynamics and predictability that links the atmosphere to the surface ocean and to the subsurface ocean across a range of time scales from (intra-)seasonal to (inter-)decadal.

CHAPTER 2

South Pacific Decadal Climate Variability and Potential Predictability

2.1 Chapter overview

This chapter explores and analyses the spatiotemporal features of the dominant South Pacific decadal climate variability from the surface ocean to the subsurface upper ocean by applying a series of diagnostic statistics and a doubly integrated AR1 model. Specifically, we seek to characterise the mechanisms that give rise to South Pacific Ocean decadal variability in terms of local oceanic processes and atmospheric forcing. The potential predictability of the SPDO is then examined using a variance fraction and the AR1 model.

The main text of this section is a paper published in the *Journal of Climate* (Lou, J., N. J. Holbrook, and T. J. O'Kane, 2019: South Pacific decadal climate variability and potential predictability. *J. Climate*, **32**, 6051-6069. https://doi.org/10.1175/JCLI-D-18-0249.1). The American Meteorological Society (AMS) publishers of the corresponding paper incorporating in this Chapter hold the copyright for this content, and access to the material

Candidate's contribution to this paper

The analysis methods were jointly discussed between Dr. Holbrook, Dr. O'Kane and myself. Dr. O'Kane supplied the ACCESS-O model output data used in this study, and Dr. Holbrook provided the MATLAB code to perform the significance test. I performed all the data analysis, however input from Dr. Holbrook and Dr. O'Kane was attained regularly throughout the process. All sections of the co-authored *Journal of Climate* publication and the peer-review processes were led by myself under the supervision of both co-authors.

It is the following published article: Lou, J., Holbrook, N. J., O'Kane, T. J., 2019. South Pacific decadal climate variability and potential predictability, Journal of climate, 32(18), 6051-6069. https://doi.org/10.1175/JCLI-D-18-0249.1

2.3 Chapter summary

This chapter reveals the spatiotemporal characteristics of the SPDO and the role of extratropical oceanic processes and atmospheric forcing in contributing to the SPDO by using a series of diagnostic statistics and a double integration of univariate AR1 models based on the observations and model simulation. The spatiotemporal details of the leading surface and subsurface temperature variability have been first examined based on the empirical orthogonal function (EOF)/principal component (PC) analysis. The dynamical interactions between the atmosphere, surface and subsurface ocean in the South Pacific have then been illustrated using univariate AR1 models, in which the slowly varying oceanic temperature variability is explained as the integral response to continuous 'random' atmospheric variability.

We found that the first Pacific-South American (PSA1) pattern is the dominant atmospheric driver of the SPDO. The large fraction of the subsurface counterpart of the SPDO can be viewed as cumulative integrations of the atmospheric PSA1 variability exciting internal ocean processes. Our results suggest that the source of the predictability of Pacific decadal variability resides in the subsurface upper ocean in the extratropical Pacific, whereas the main deterministic dynamics are associated with the mid-latitude oceanic Rossby wave propagation. In particular, Rossby waves interacting with bottom topography (i.e., large meridional sea ridges) in the extratropical South Pacific tend to enhance the low-frequency variability, and, therefore, increase the variance fraction explained by the decadal variability, and lead to increased potential predictability of the observed SPDO.

CHAPTER 3

A Linear Inverse Model of Tropical and South Pacific Seasonal Predictability

3.1 Chapter overview

The previous Chapter concluded that with the inclusion of subsurface processes in the South Pacific, the predictability of the SPDO is increased. The nonlinear baroclinic Rossby waves in the extratropical southwest Pacific Ocean act as the lowpass filter of oceanic variability and add potential predictability to the SPDO. By applying the univariate AR1 model, the previous Chapter also showed that the subsurface SPDO can be considered as the reddened response to the corresponding surface variability or cumulative integrated version of white-noise atmospheric variability (i.e., PSA1). However, limited by the simplicity of AR1 models, they are not capable of revealing spatial variability of a system since AR1 models only have one degree of freedom.

In this Chapter, we extended the univariate stochastically forced AR1 model discussed in the previous Chapter to a multivariate field by applying a Principal oscillation pattern (POP) /Linear inverse model (LIM) approach to understand the spatiotemporal dynamics of tropical and South Pacific combined system and to investigate the seasonal predictability of ENSO and the SPDO.

The main text of this Chapter is a paper published in the *Journal of Climate* (Lou J, T. J. O'Kane, and N. J. Holbrook, 2020: A linear inverse model of Tropical and South Pacific

Candidate's contribution to this paper

The experiments and analyses are a natural multivariate generalization of the previous chapter. All the experiments and analyses were conducted on my own. At its initial stage, Dr. Holbrook and I came up with the idea of using LIM techniques to understand the predictability of the SPDO after constructive discussion with Dr. Craig Bishop at the IMAS, and at the same time Dr. O'Kane was interested in adapting the POP methods to the South Pacific Ocean. Those two methods are equivalent. Thus, both of my co-authors and I contributed to the primitive ideas of this chapter. The LIM experiment design was jointly discussed with Dr. O'Kane and Dr. Holbrook throughout the process. The simulated data from the ACCESS-O model is the same as used in the previous chapter, which was provided by Dr. O'Kane. All the LIM experiments, data analysis and the co-authored *Journal of Climate* paper was led by myself with input from the other two co-authors.

It is the following published article: Lou, J., O'Kane, T. J., Holbrook, N. J., 2019. A linear inverse model of tropical and South Pacific seasonal predictability. Journal of climate, 33(11), 4537-4554, https://doi.org/10.1175/JCLI-D-18-0249.1

3.3 Chapter summary

The one-dimensional univariate AR1 models introduced in Chapter 2 were generalized to a high-dimensional multivariate field in this chapter with inclusion of the spatial features in the tropical and South Pacific oceans. We developed the POP/LIM technique linking the tropical Pacific with the South Pacific to investigate the deterministic dynamics and predictability of the dominant modes of SST variability. The predictive skills of three LIM configurations were further evaluated based on the combination of modes, variables, and regions.

As the South Pacific has received considerably less attention in comparison to numerous studies of North Pacific Ocean variability, this chapter makes an important contribution to our understanding of the mechanisms underlying the SPDO and its predictability. The results suggest that the SPDO can be viewed as a collection of multiple processes operating on distinct time scales. Although ENSO and the SPDO have distinct oscillatory periods – primarily, the former oscillates on interannual timescales and the latter on decadal timescales – they have very close damping time scales, indicating the predictive skills of ENSO and the SPDO are comparable. Reduced-order LIM predictions of ENSO and the SPDO are comparable with state-of-the-art general circulation models. The ENSO boreal spring predictability barrier (MAM) is similarly apparent in LIM predictions.

CHAPTER 4

Optimal Structure and Stochastic Forcing of Tropical and South Pacific Climate Variability

4.1 Chapter overview

The previous chapter demonstrated the deterministic dynamics and seasonal predictability of the dominant modes of variability from the tropical and South Pacific oceans by applying the POP/LIM technique. This chapter is a companion work to the information presented in Chapter 3. Here, we explore the optimal initial conditions for maximizing the linear growth of the SPDO and ENSO using a POP/LIM framework to separate the contribution from the deterministic dynamics and the unpredictable noise-forced SST evolutions associated with the atmospheric PSA variability.

The main text of this Chapter is a paper published in the Journal of Climate (Lou, J., T. J. O'Kane, and N. J. Holbrook, 2021: A Linear Inverse Model of Tropical and South Pacific Climate Variability: Optimal Structure and Stochastic Forcing. *J. Climate*, **34**, 143-155. Doi: https://doi.org/10.1175/JCLI-D-19-0964.1. The AMS publishers of the corresponding paper incorporating in this Chapter hold the copyright for this content, and

Candidate's contribution to this paper

The experiments and analyses are a natural follow-on work from the Chapter 3. Namely, the LIM experiment design and data analyses were conducted on my own. Finer details of the LIM methods were refined through the discussion between Dr. O'Kane, Dr. Holbrook, and myself. The simulated ACCESS-O model data are the same as used in the previous chapters, which were provided by Dr. O'Kane. All the experiments, data analysis and the co-authored *Journal of Climate* paper was led by myself with input from the other two co-authors.

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It is the following published article: Lou, J., O'Kane, T. J., Holbrook, N. J., 2021: A Linear Inverse Model of Tropical and South Pacific Climate Variability: Optimal Structure and Stochastic Forcing. Journal of climate, 34(1), 143-155, https://doi.org/10.1175/JCLI-D-19-0964.1

4.3 Chapter summary

This chapter continues the work presented in Chapter 3 by utilizing the same POP/LIM framework, but with a specific focus on the identification of optimal perturbations for maximizing the linear growth of the SPDO and ENSO and the role of atmospheric stochastic forcing associated with the variability in the PSA sector. In this Chapter, the contribution from the deterministic dynamics and the unpredictable noise-forced SST evolutions has been separated.

The results suggest that a specific set of initial conditions can optimally determine how the system will evolve along its deterministic (linear) trajectory. The South Pacific meridional mode is found to be an optimal SST precursor for the development of the SPDO and ENSO. The subsurface SST variability associated with oceanic Rossby wave propagation sets a background state to modify and guide the SST evolutions. The atmospheric propagating PSA patterns (i.e., PSA1 and PSA2) are associated with higher-order noise-forced SST variability and contribute not only to excite the optimal initial perturbations that maximize ENSO and SPDO development, but in general to activate the stochastic SST forcing.

CHAPTER 5

A New Paradigm of Large-scale South Pacific Climate Variability and Predictability

5.1 Chapter overview

Informed by the systematic development and utilisation of a family of stochastically forced reduced order models illustrated in Chapter 2 to Chapter 4, this chapter proposes an overarching paradigm linking atmospheric variability to the surface ocean and subsequently the subsurface ocean across a range of time scales from (intra-)seasonal to (inter-)decadal. This provides, for the first time, an integrated framework to understand the ocean-atmosphere coupling and potentially predictable time and space scales of South Pacific climate variability.

5.2 The importance of the atmospheric Pacific-South American mode

The Pacific-South American (PSA) mode comprises of two important patterns, referred to here as PSA1 and PSA2 (Mo and White 1985; Mo and Ghil 1987; Karoly 1989; Mo and Higgins 1998; O'Kane et al. 2017) (Figs. 5.1 a-d), that strongly influence the weather and climate across the extratropical South Pacific. The PSA mode is represented by an eastward-propagating wave train extending from eastern Australia to Argentina characterised in mid-tropospheric geopotential height by either by a single complex empirical orthogonal function (EOF) or in terms of two invariant patterns identified as the second (PSA1) and third (PSA2) real EOFs whose phases are nearly in quadrature with each other and whose associated eigenvalues are of nearly equal amplitude (Lau et al. 1994) (see Chapter 2 to Chapter 4).

Previous studies (e.g. Karoly 1989; Mo and Paelge 2001; and references therein) argue that the PSA mode is in part an atmospheric response to the tropical El Niño–Southern Oscillation (ENSO). Regression analysis shows that there is indeed a very close relationship between PSA1 and ENSO (Fig. 5.1 a). However, the connection between atmospheric PSA2 and tropical sea surface temperature (SST) variability is less clear. Mo and Paegle (2001) argue that PSA2 is responsible for the quasi-biennial component of ENSO, which is evidenced in Fig. 5.1b.

Despite clear evidence showing that the PSA mode is connected to ENSO, there are diverse views on the mechanisms that link the atmospheric PSA mode with tropical ENSO. Some studies (Karoly 1989; Renwick and Revell 1999; Mo and Paegle 2001; Cai et al. 2011) argue that the ENSO-PSA connection is directly linked via atmospheric Rossby wave propagation, and many other studies (McIntosh and Hendon 2018; Rodrigues et al. 2019) also highlighted the importance of Indian Ocean in generating Rossby wave trains. However, other studies (Ambrizzi et al. 1995; Ambrizzi and Hoskins 1997; Li et al. 2015) point out that Rossby waves are primarily generated and trapped within the Southern Hemisphere subtropical and polar jet streams according to ray tracing theory. Unlike the MJO-NAO teleconnection (Lin and Brunet 2018), there is little direct dynamic evidence in terms of Rossby wave source or wave activity flux (see for example Karoly et al. 1989; O'Kane et al 2015; Li et al 2015) to suggest that poleward propagating large scale tropical Pacific Rossby waves initiated by ENSO variability tele-connect the PSA to ENSO. Even if sufficient Rossby wave sources were to be generated in the equatorial Pacific, ray tracing theory and wave activity flux calculations make it readily apparent that they are blocked by a reflecting barrier, associated with the presence of the subtropical jet, and low latitude wave breaking, from propagation to the midlatitudes. Instead, O'Kane et al. (2017) argue that the PSA mode is linked to ENSO via a direct modulation of the midlatitude jets by the thermal winds generated by tropical convection and highly correlated with ENSO, and indirectly influencing the interannual variability of coherent synoptic features forming within these midlatitude waveguides where local Rossby waves sources are prevalent.

5.3 Reddening processes driven by the PSA mode

Analysis of South Pacific SST shows that the first two SST modes of variability, referred to as the South Pacific decadal oscillation (SPDO) (Chen and Wallace 2015; Lou et al. 2019) and South Pacific quadrupole SST pattern (Ding et al. 2014), are primarily driven by the atmospheric PSA1 and PSA2 patterns (Figs. 5.1e and f), respectively. In Chapter 2 of this thesis, it was shown, using a univariate first-order autoregressive model (AR1) (Frankignoul and Hasselmann 1977; Hasselmann 1976), that the integrated atmospheric PSA1 and PSA2 variability could explain a significant fraction of the variance of the first two SST modes in the South Pacific Ocean (Figs. 5.1 e and f; R=0.76 and 0.71, respectively; significant at >99% level).

Taken one step further, we applied a second integration of the AR1 model (following a similar approach to Di Lorenzo and Ohman (2013)) – with the first integration being from the atmosphere to the surface ocean, and the second integration from the surface ocean to the subsurface ocean (refer to Chapter 2 in this thesis or Lou et al. (2019)). This double integration reveals that the leading SST mode is further reddened by the extratropical upper ocean (Fig. 5.1 e). The integrated SPDO signal (blue curve in Fig. 5.1 e) resembles the time evolution of the leading vertically averaged temperature (VAT) mode of the upper 300 m of the ocean, with a temporal correlation of R=0.88 (statistically significant at the 99% level). To first order, we concluded that the South Pacific Ocean integrates the fast-varying atmospheric “noise” forcing to produce a ‘‘reddened’’ oceanic signal, with a pronounced increase in amplitude of the spectrum at low frequencies and decreased amplitude at high frequencies, where the main potentially predictable signal is generated on the timescales of the ocean dynamics.

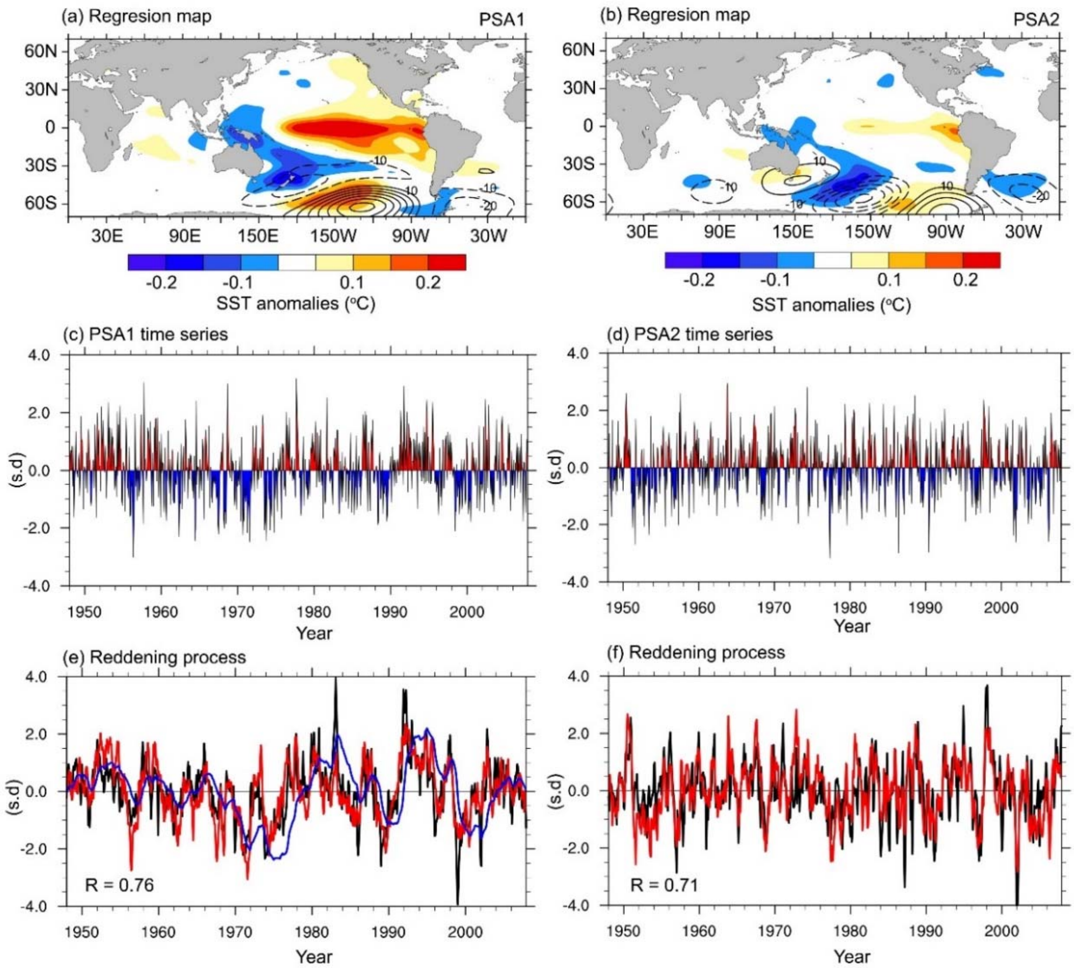

Figure 5.1 | **The atmospheric forcing of the leading two SST modes in the South Pacific Ocean. a**, **b**, The PSA1 (**a**) and PSA2 (**b**) patterns are obtained by regressing the monthly near-global Z500 anomalies (NCEP-NCAR; contour) and monthly SST anomalies (ACCESS-O; shade) onto the PSA1 and PSA2 time series, respectively. The PSA1 and PSA2 are derived from the second and third EOF modes of the monthly Z500 anomalies (NCEP-NCAR) in the Southern Hemisphere. (**c**) and (**d**), The corresponding normalized PSA1 and PSA2 time series. (**e**) and (**f**), The time series of the leading two SST modes of variability in the South Pacific Ocean (ACCESS-O; black) are reconstructed (red) using an AR1 model forced by the PSA1 and PSA2 time series. The blue curve in (**e**) indicates the second integration forced by the SST SPDO time series. The units are in standard deviations (s.d.). The significance of the temporal correlations

(R=0.76 and 0.71; >99%) is estimated taking account of the effective number of degrees of freedom due to serial correlation (Davis 1976).

5.4 Coherence resonances driven by the PSA mode

The ocean not only responds via the reddening processes to the fast-varying atmosphere but also via the coherence resonance (Pierini 2011). Specifically, the atmospheric forcing imprints its variations onto the surface ocean and further enhances internal SST variability at its preferred frequency, subject to forcing due to coherent disturbances in the synoptic atmosphere. To take this further, we generalized the univariate AR1 model to a higher-dimensional multivariate field through inclusion of SST anomalies in the tropical and South Pacific oceans using a linear inverse modelling approach (e.g. Penland and Sardeshmukh 1995) (LIM; see Chapters 3 and 4 for details). Previous studies (Penland and Magorian 1993; Penland and Sardeshmukh 1995; Newman 2007; Capotondi and Sardeshmukh 2015; Lou et al. 2020) show that the tropical and South Pacific oceans can be approximated as a stochastically forced linear system, where different dynamical processes are represented by distinct damping time scales via the decomposition of the LIM.

Fig. 5.2 shows the fastest damped SST mode pair with a damping time scale of two months. This pair of real and imaginary patterns (Figs. 5.2 a and b) constitutes a single propagating wave with a complete cycle of 26 months. Along with the propagating features, the spatial patterns of the fastest damped modes also bear a strong resemblance to the atmospheric PSA1 and PSA2 patterns. We then projected the corresponding time series of the real and imaginary components of the fastest damped mode onto the monthly

Z500 anomalies. The regression maps (Figs. 5.2 c and d) closely resemble the atmospheric PSA1 and PSA2 with spatial correlations of 0.74 and 0.69 (statistically significant at the 95% level), respectively, in the South Pacific region. This suggests that the high-frequency atmospheric PSA fluctuations can excite SST modes whose frequencies are subject to the atmospheric drivers. However, in contrast to the reddening processes that acts to excite the potentially predictable low frequency ocean signal, the leading complex SST damped modes are correlated with the atmospheric PSA forcing and act as noise forcing of the system.

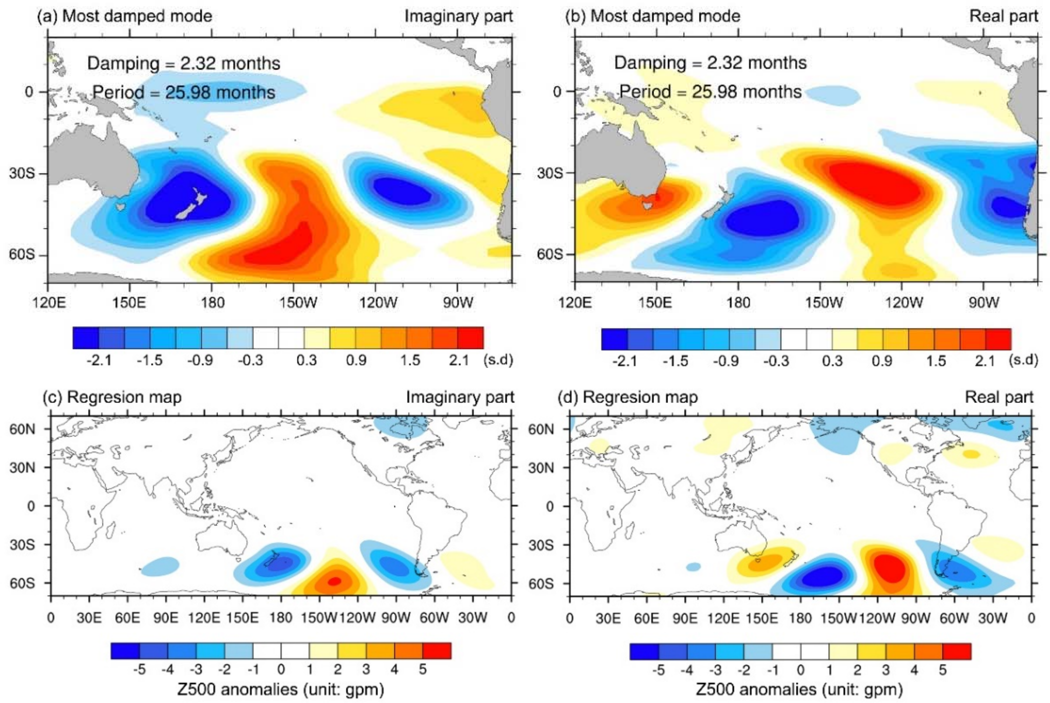

Figure 5.2 | **The fastest damped SST modes**. **a**, **b**, The imaginary (**a**) and real (**b**) parts of the fastest damped SST modes are obtained by using a reduced-order linear inverse model (see Chapter 3 and 4 for details). The pair of the SST modes shown has the fastest damping time scales of 2.3 months. **c**, **d**, the regression maps are obtained by regressing

the monthly Z500 anomalies (NCEP-NCAR) onto the time series of the imaginary (**c**) and real (**d**) parts of the quickest damped modes.

5.5 The optimal growth and extratropical precursor

Previous studies have extensively discussed the tropical and extratropical precursors of ENSO including those that maximize ENSO development (Penland and Sardeshmukh 1995; Penland and Matrosova 2006; Ding et al. 2014; Zhang et al. 2014; Liguori and Di Lorenzo 2019). Despite there being little direct evidence, in terms of atmospheric dynamics, to show that the atmospheric PSA patterns can directly modulate ENSO evolution in the tropics (O'Kane et al. 2017), the indirect influence (i.e. correlation between low pass filtered PCs 2 and 3 of geopotential height and ENSO interannual variability) has nevertheless been widely identified in both observations (You and Furtado 2017) and model simulations (Zhang et al. 2014: Liguori and Di Lorenzo 2019) via the "atmosphere → extratropical ocean → tropical ocean" pathway. One mechanism by which this indirect influence may occur is through a "seasonal footprinting" mechanism (Vimont et al. 2003), where the atmospheric forcing drives an extratropical anomalous SST "footprint" in the boreal spring, which persists through boreal summer, and sustains wind stress anomalies in the tropics that are conducive to trigger ENSO events.

The LIM approach enables an objective determination of the optimal initial perturbations that maximize ENSO and SPDO growth, providing an ideal framework through which to investigate the dynamical precursors to, and predictability of, mature (peak phase) ENSO and SPDO. Unlike lead-lag correlations that have been widely applied to identify ENSO precursors (Ding et al. 2014; You and Furtado 2017; Zhao and Di Lorenzo 2020), the LIM is a dynamical approximation and, as the LIM is a multivariate linear stochastic model, implies conditionally causal (Grainger 1988) relationships between the optimal precursors and their peak phases. The connection between the reduced-order LIM and physical reality is described by Hasselmann (1976), who identifies "slow" processes that constitute the deterministic system and "fast" processes that constitute the noise forcing.

ENSO and SPDO growth is non-normal, i.e. it is primarily due to the non-orthogonality of the damping SST modes that are able to interact with each other, giving rise to a transient amplification of the variance of the system at a preferred growth temporal scale. Such transient amplification is useful in sampling and interpreting errors in initial conditions (Moore and Kleeman 1996) and explains the actual variance growth in the system (Penland and Sardeshmukh 1995). Transient amplification of monthly tropical and South Pacific SST anomalies allows a specific set of initial perturbations to develop into the peak phases that are found to exist at 6- to 10-month lead times (Penland and Sardeshmukh 1995; Newman et al. 2011; Capotondi and Sardeshmukh 2015; Zhao and Di Lorenzo 2020; Lou et al. 2020). Our LIM experiment results show that, with consideration of SST anomalies from the tropical and South Pacific oceans, the optimal growth time (see Chapter 4 for details) is 9 months. These results imply that potentially predictable linear growth events that maximize ENSO and SPDO development can exist if the initial perturbations are well specified.

The spatial patterns of the initial SST perturbations in the tropical Pacific and South Pacific are shown in Figs. 5.3 a and c, respectively. These initial patterns co-evolve over nine months into the optimal final peak phases in Figs. 5.3 b and d, which are closely associated with ENSO and the SPDO with pattern correlations of 0.99 and 0.97 (statistically significant at the 99% level), respectively. The tropical ENSO precursor (Fig.

5.3 a) has been discussed in previous studies (Capotondi and Sardeshmukh 2015; Penland and Sardeshmukh 1995; Penland and Matrosova 2006) and is associated with the recharge-discharge mechanism as first described by Jin (1997). The extratropical precursor (Fig. 5.3 c) resembles a quadrupole structure similar to the second South Pacific SST mode with the pattern correlation of 0.85 (significant at the 95% level). The initial and final spatial patterns (Figs. 5.3 c and d) were projected onto the monthly SST anomalies to reconstruct the time series. The reconstructed time series of the optimal initial perturbations and final peak phases in the South Pacific (Figs. 5.3e and f) are highly correlated with the second and first South Pacific SST modes with temporal correlations of 0.86 and 0.98 (statistically significant at the 99% level) respectively, suggesting that the South Pacific quadrupole SST pattern is the optimal local (linear) precursor that maximizes the SPDO growth. Given the almost synchronous features between ENSO and the SPDO (Chen and Wallace 2015; Lou et al. 2019), these results imply that the extratropical SST precursor of ENSO is also related to the quadrupole SST pattern in the South Pacific Ocean. Our results agree with the "seasonal footprinting" mechanism whereby the atmospheric PSA2 excites the South Pacific quadrupole SST anomalies, which then persist through the boreal summer to initiate ENSO growth.

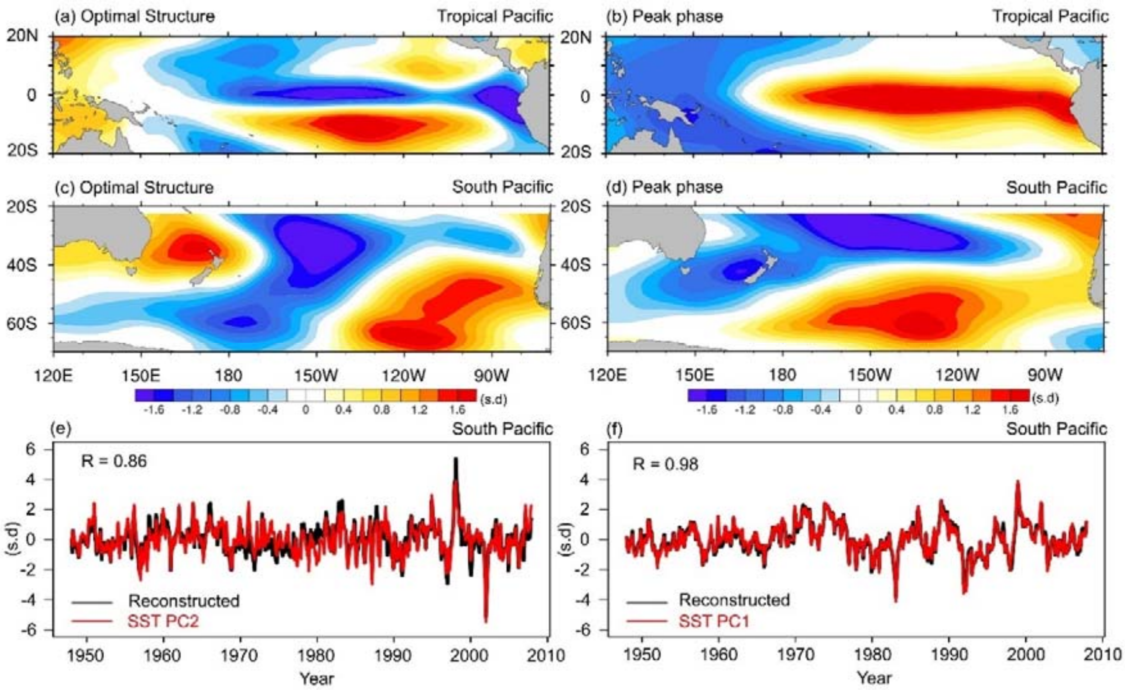

Figure 5.3 | **The optimal evolution of the tropical and South Pacific SST.** The optimal initial structures in the (**a**) tropical Pacific and (**c**) South Pacific are obtained by using a linear inverse model (see Chapter 3 and Chapter 4 for details), which linearly co-evolve 9 months later into their peak phases in the (**b**) tropical Pacific and (**d**) South Pacific. The spatial patterns shown in **a-d** are normalized according to the variance in each domain. **e** and **f**, the reconstructed time series of the (**e**) optimal initial structure and (**f**) peak phase in the South Pacific (black) are compared with the time series of the leading two South Pacific SST modes (red).

5.6 A new paradigm of South Pacific climate variability and predictability

Fig. 5.4 summarizes the atmospheric PSA mode and its South Pacific Ocean responses based on the combined results from the AR1 and LIM investigations. Our results suggest that the eastward-propagating PSA mode (identified by the PSA1 and PSA2 patterns) provides an important source of atmospheric forcing to excite the extratropical South Pacific Ocean responses that operate on multiple time scales via reddening processes and coherence resonances. To first order, the close relationships between the integrated PSA patterns and the leading South Pacific SST modes support the general concepts of the autoregressive processes that fast atmospheric variations are a critically important source for the excitation of low frequency oceanic variability, bearing in mind that the actual observed nonlinear dynamics are more complicated than the tangent linear dynamics that form the basis of the LIM propagator. The leading integrated subsurface temperature mode, that resembles the spatial pattern of its SST counterpart, can be regarded as a cumulative response to atmospheric PSA1 forcing. That is, the inclusion of extratropical subsurface processes further reddens the SST variations, whereby the most persistent and potentially predictable signal is enhanced. Furthermore, the atmospheric PSA1 and PSA2 patterns can excite SST variations via coherence resonance such that the resultant damping SST modes are slaves to the atmospheric forcing but synchronized to the spatiotemporal features of the real and imaginary components of the propagating PSA.

The extratropical SST precursor of ENSO and SPDO growth is strongly associated with the South Pacific quadrupole SST pattern. The set of initial conditions related to this quadrupole pattern can optimally determine how the SST anomalies will evolve along its deterministic (linear) trajectory and lead to the SPDO and ENSO peaks over the following nine months, and from which the linear predictability intrinsic to the SST system can be inferred. While the influence of the atmospheric PSA patterns on the tropical SST variability is less apparent than the influence of the tropical SST variability on the PSA patterns (Ding et al. 2014; Li et al. 2015; O'Kane et al. 2017), our results indicate that the South Pacific quadrupole SST pattern acts as an oceanic bridge that links the atmospheric PSA forcing to tropical ENSO, and represents the most probable pathway for midlatitude synoptic variability to influence tropical SST.

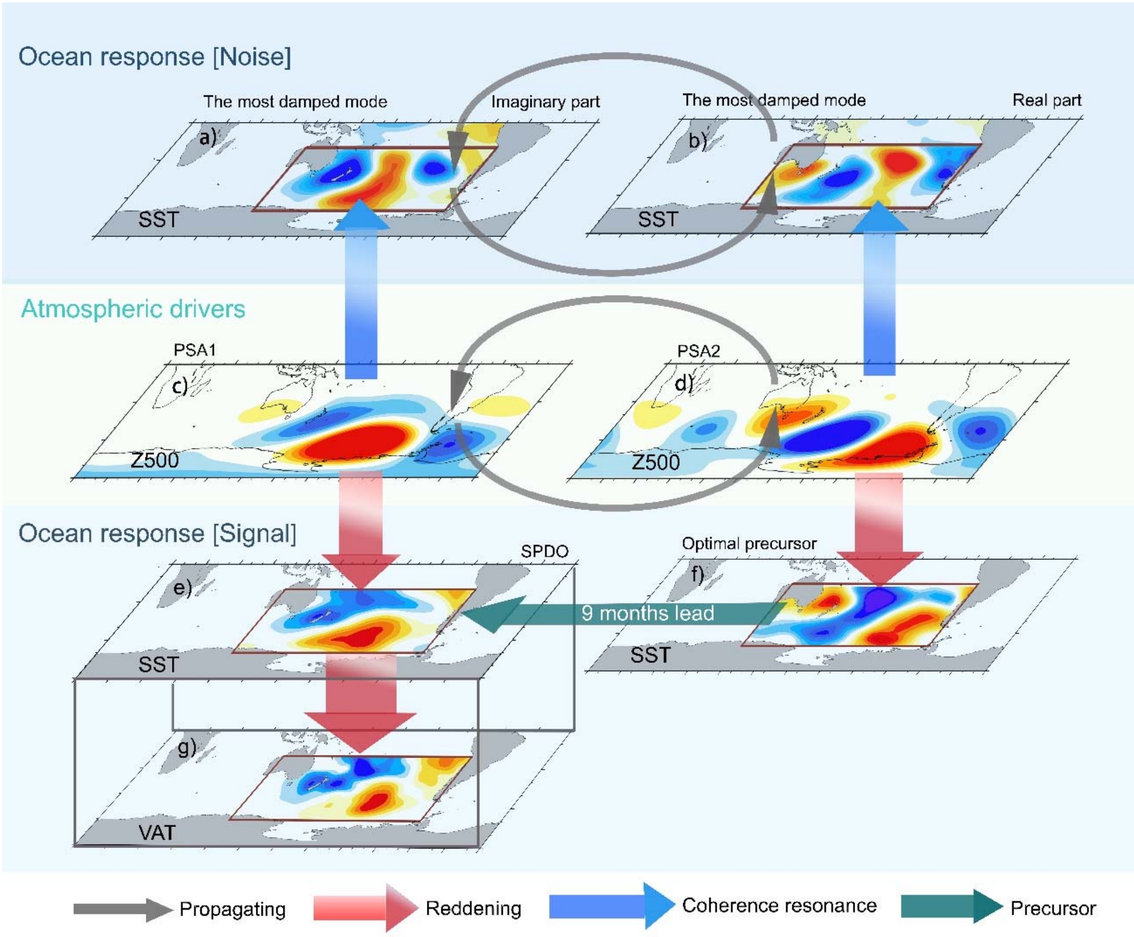

Figure 5.4 | Schematic of the atmospheric drivers and the corresponding South Pacific Ocean responses. a) and b) represent the fastest damped mode pair, which are the same as shown in Fig. 5.2. c) and d) are the second and third EOF modes of the monthly Z500 anomalies (NCEP-NCAR) in the Southern Hemisphere. e) and g) are the leading EOF modes of the monthly SST anomalies and VAT anomalies in the South Pacific Ocean, respectively. f) is the same as shown in Fig. 5.3 c indicating the optimal precursor of the SPDO (illustrated by the green arrow). Red arrows indicate reddening processes. Blue arrows indicate coherence resonances. Grey arrows indicate the propagating features of the corresponding modes.

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CHAPTER 6

Discussion and Conclusions

6.1 Aim and objectives

The overall aim of this thesis is to better understand South Pacific decadal climate variability and predictability. The main objectives of this thesis were 1) to explore the spatiotemporal features of the dominant modes of variability in the South Pacific Ocean, 2) to identify the key atmospheric drivers in generating and maintaining South Pacific Ocean decadal variability, 3) to understand the source of predictability and identify key locations where the predictable signal is amplified to enable climate monitoring, and 4) to evaluate the extent to which the low-frequency variability is predictable. Thus, this thesis examines and identifies the spatiotemporal characteristics of the dominant modes of climate variability and dynamical processes underpinning the leading mode of SST variability in the South Pacific Ocean. This is fundamentally important when attempting to understand the local and remote sources of predictability of the South Pacific decadal oscillation (SPDO), which can lead to more skilful predictions of both extratropical Pacific decadal variability (PDV) and El Niño–Southern Oscillation (ENSO) centred in the tropical Pacific.

The mechanisms previously proposed to explain PDV fall into three main categories. The first of these postulates that PDV is not self-sustained but rather forced by atmospheric variability (e.g., Trenberth and Hurrell 1994; Pierce 2001; Di Lorenzo and Ohman 2013). The second category argues that PDV is not an independent dynamical mode but instead a direct product of background amplitude modulation of interannual ENSO variability (Jin 2001) or a spectral reddening of ENSO (Newman 2003; Power and Colman 2006; Shakun and Shaman 2009), which highlights the role of tropical processes. The third category stresses that intrinsic oceanic processes (e.g., mid-latitude oceanic Rossby wave propagation) (e.g., Schneider and Miller 2001) contribute to the largest fraction of the low-frequency variability. To some extent it is highly likely that all three proposed mechanisms, which operate across a wide range of spatiotemporal scales, contribute to the overall observed PDV at some level. However, there is no clear consensus on their relative importance in explaining the observed PDV.

Recently, a growing number of studies (Newman et al. 2016; Liu and Di Lorenzo 2018) consider PDV as a combination of multiple dynamical processes, which include atmospheric forcing, ENSO teleconnections, and intrinsic ocean processes. We have, for the first time, endeavoured to systematically reveal how the overall SPDO variability arises, through a systematic examination of the individual and combined roles of the various atmospheric and oceanic processes operating on distinct time scales. This has been undertaken using a linear inverse model (LIM) framework applied to the generation of South Pacific Ocean variability and validated against observed spatiotemporal features.

The precise dynamics underpinning PDV is used to inform the level of predictability we might expect. By better understanding the underlying mechanisms of the SPDO, we have sought to identify deterministic PDV dynamics that might be used as a predictable signal beyond ENSO and interannual time scales. An earlier study by Power and Colman (2006) suggested that enhanced multiyear predictability of PDV and ENSO should mainly arise via the extratropical subsurface ocean whose dynamics have long damping time scales and strong persistence. With this in mind, the role of extratropical upper ocean variability is of particular interest in this thesis. Specifically, we have sought to identify the source of predictability of PDV, and to what extent the combined effects of tropical SST, South Pacific SST and subsurface ocean temperature variability may increase the predictive skill of linear stochastic models of PDV and ENSO.

6.2 Key findings and implications

To address the key aims and objectives of this thesis, we conducted a series of diagnostic analyses and made use of a family of different hierarchical stochastically forced reduced-order models to investigate the deterministic dynamics and the role of stochastic forcing with specific focus on the South Pacific Ocean and its coupling to the tropical Pacific. Motivated by previous studies (e.g., Liu 2002; Power and Colman 2006), which show for climate variability of timescales longer than interannual that the contribution mainly arises from the intrinsic oceanic dynamics that come from outside the Tropics, we included the extratropical upper ocean temperature variability in each chapter to better understand how the extratropical upper ocean interacts with the surface temperature variability and potentially contributes to the predictability.

In a re-examination of the Pacific decadal oscillation (PDO), Newman et al. (2016) systematically discussed the dynamics, impacts and predictability of the PDO in the North Pacific. Although Newman et al. (2016) broadly referred to the SPDO as the South Pacific centre of action of the Pacific-wide interdecadal Pacific oscillation (IPO) in comparing temporal relationships between the PDO and the IPO, further detailed examination of the dynamics of the SPDO remain unexplored. In a recent paper, Liu and Di Lorenzo (2018) reviewed progress in understanding the mechanisms and predictability of PDV in both the North Pacific and South Pacific. However, relative to well-documented PDO studies, the South Pacific contribution from the SPDO is simply treated as a mirror of its North Pacific counterpart, without further detailed dynamics discussed. This is insufficient to explain the asymmetric and asynchronous differences between the North Pacific and South Pacific interactions with the Tropics (Johnson and McPhaden 1999; Yang et al. 2005; McGregor et al. 2012; Liguori and Di Lorenzo 2019), responses to external forcing (Rathore et al. 2020) and intrinsic atmospheric variability (Ding et al. 2014; McGee et al. 2018). Therefore, it is of particular interest to systematically understand the mechanisms by which the SPDO variability arises in the South Pacific and is the subject of this thesis.

In order to understand the evolution and predictability of a geophysical system that exhibits complex variations over a wide range of spatial and temporal scales, a typical statistical perspective is to decompose the complex system into a simpler analog system that includes less degrees of freedom but nevertheless succeeds in representing the majority of the important dynamical processes of the entire system. In this thesis, various eigen-decomposition-based techniques have been applied to reduce the order of the system. For example, empirical orthogonal function/principal component (EOF/PC) analysis has been widely used in climate studies to reduce the degrees of freedom and to investigate the dominant modes of variability that maximize the explained variance of the system. However, classical EOF/PC analysis can only represent standing features/patterns over time, and is unable to detect propagating features (e.g., Penland 1989) and to reveal the internal dynamics of the system (e.g., Hasselmann 1988). Therefore, EOF/PC analysis by itself is not optimized for constructing reduced-order dynamical models. Instead, principal oscillation pattern (POP)/linear inverse model (LIM) approaches by construction are designed to satisfy the first-order Markov processes. The solution is based on eigen-decomposition of the deterministic feedback matrix, resulting from the multiplication of the time-lag covariance and concurrent covariance of the data, or, put in a perspective of prediction, resulting from minimizing the errors from the transformed predictor and predictand field. Unlike EOF analysis, the POP/LIM approach can either be used as a diagnostic tool to reveal the propagating features of the system and identify the characteristic time scales (i.e., damping time scales and/or oscillatory periods) of different processes or as a predictive tool to conduct time-evolving forecasts.

In Chapter 2, the role of extratropical oceanic processes and atmospheric forcing in contributing to the SPDO has been examined by using a series of diagnostic statistics and a doubly integrated autoregressive-1 (AR1) model. The potential predictability of PDV in the North and South Pacific has been investigated and compared in terms of both the variance ratio between the decadal component and the total variance, and in terms of the doubly integrated AR1 model. Although the former does not necessarily represent the actual upper bound of predictability, it nevertheless provides a simple and convenient metric to quantify the importance of the low-frequency variability that may be potentially predictable on timescales beyond interannual and ENSO (Boer 2000, 2004; Kirtman et al. 2013; Liu and Di Lorenzo 2018).

We examined the spatiotemporal details of the leading surface and subsurface temperature variability based on the EOF/PC analysis. The dynamical interactions between the atmosphere, surface and subsurface ocean in the South Pacific has been illustrated using univariate AR1 models, in which the slowly varying oceanic temperature variability is explained as the integral response to continuous ‘random’ atmospheric variability. The main purpose of such univariate AR1 models has been to explain the fundamental dynamics from a zero-order approximation (von Storch and Zwiers 1999). The connection between the stochastically forced reduced-order models and physical reality is described by the earlier work of Hasselmann (1976) who considered "slow" processes that constitute the deterministic system and "fast" processes that constitute the forcing noise. That is, the climate system is approximated as a continuous Markov (or AR1) process that has been discretely sampled. Our findings show the close relationship between the integrated Pacific-South American (PSA) variability and SPDO, supporting the general concepts of the autoregressive processes that fast atmospheric variations are critical to the excitation of the low frequency ocean variability – albeit that the actual dynamics are more complicated.

The simple univariate AR1 models introduced in Chapter 2 were generalized to a high-dimensional multivariate field in Chapter 3. There we developed the POP/LIM technique linking the tropical Pacific with the South Pacific to investigate the dynamics and predictability of the dominant modes of SST variability. The predictive skills of three LIM configurations were further evaluated based on the combination of modes, variables, and regions. As the South Pacific has received considerably less attention in comparison to numerous studies of North Pacific ocean variability, this chapter makes an important contribution to our understanding of the mechanisms underlying the SPDO and its predictability. It is worth noting that we have exclusively focused on the deterministic dynamics (i.e., the slow processes) in Chapter 3, which were decoupled from the stochastic forcing.

One of the advantages of the POP/LIM techniques is their built-in forecast capability. The skill of the POP/LIM forecast scheme has been extensively explored in the literature as cited earlier. However, it is worth noting that the POP/LIM, as a predictive tool, cannot seriously compete with operational ensemble general circulation model (GCM) approaches in the long term. Rather LIMs (or POPs) provide a computationally cheap and convenient benchmark for GCM predictions and assessments of skill in predicting, for example, SPDO evolution. To date, our study, along with many other studies of tropical SST, show the comparable predictive skill of the POP/LIM relative to those made by state-of-the-art GCMs.

Given the close relationship between ENSO and PDV, the predictive skill of the SPDO on seasonal to (inter-)annual timescales largely depends on ENSO forecast skill (e.g., Alexander et al. 2008; Wen et al. 2012; Saurral et al. 2020). For longer forecast leads, ENSO events turn out to be inaccurate and act mostly as high-amplitude noise for climate predictions (Newman 2013; Wittenberg et al. 2014). We found that, although the oscillatory periods of ENSO and the SPDO are distinct, they have close damping time scales. This may help explain why ENSO and SPDO forecast skill from LIM approaches are comparable. Nevertheless, we show that predictability beyond ENSO forecast skill originates in the dynamics of the subsurface South Pacific Ocean.

Chapter 4 continues the work presented in Chapter 3 by utilizing the same POP/LIM framework, but with a specific focus on the identification of optimal perturbations for maximizing the linear growth of the SPDO and ENSO and the role of atmospheric stochastic forcing associated with the variability in the PSA sector. In this Chapter, the contribution from the deterministic dynamics and the unpredictable noise-forced SST evolutions has been separated.

The assumption that the reduced-order system is driven by uncorrelated Gaussian white noise implies that the eigenmodes must all have exponentially decaying amplitudes and that any initial optimal perturbations to the system will eventually decay in the absence of noise forcing. If the linear growth of the reduced-order system only occurs as a result of stochastic forcing, it is within our expectation that the predictability of the system is limited since the white-noise forcing is not predictable. For example, as indicated in the univariate AR1 models shown in Chapter 2, the system monotonically decays in the absence of stochastic forcing, suggesting the predictability of the system cannot extend beyond the damped persistence time scales. If on the other hand, the system turns out to be linear with predictable growth, then there must be alternative mechanisms for such growth that does not solely arise from the stochastic forcing. Such mechanisms are found to be associated with the constructive non-modal interference of the non-orthogonal eigenmodes (Penland and Sardeshmukh 1995). That is, non-modal growth involving transient amplifications of anomalies are caused by interference of the non-orthogonal eigenmodes that dominate the evolution of the linear stable system. Linear optimal non-modal growth is found to be critically important in enhancing the variances and persistence of the deterministic system (e.g., Penland and Sardeshmukh 1995; Rashid and Simmonds 2005; Vimont et al. 2014; Capotondi and Sardeshmukh 2015), therefore providing an important perspective from which to understand linear sources of predictability.

It is common practice to restrict stochastic forcing in the POP/LIM to Gaussian white noise that is, by definition, state independent. This assumption is valid and useful only when the system is stable and can be adequately described by linear (or weakly non-linear) deterministic dynamics. Nevertheless, we have shown that the stochastic forcing is fundamentally important in, for example, maintaining the evolution of the internal dynamical behaviour of the deterministic system of interest (i.e., the ocean system in this thesis), generating teleconnections, and affecting the predictability.

Informed by the systematic development and utilisation of the aforementioned hierarchy of stochastically forced linear reduced-order models (i.e., univariate AR1 models and multivariate LIM), the thesis culminates with an overarching framework linking the atmosphere to the surface ocean and to the subsurface ocean across a range of time scales from (intra-)seasonal to (inter-)decadal. This provides a mechanistic framework enabling an integrated understanding of the drivers of large-scale South Pacific climate variability. We have shown that the leading two South Pacific SST modes can be viewed as the integrations of the atmospheric PSA patterns (i.e., PSA1 and PSA2), via which multiple time scales are connected. The oceanic response to PSA spatiotemporal variability can be either via a reddening process from which the main potentially predictable signal is generated or via (coherence) resonances between surface ocean anomalies and synoptic scale atmospheric variability whereby the preferred noise is produced. It is found that an extratropical quadrupole SST pattern can optimally determine how the system evolves 9 months later into the peak phases of the leading SST modes in the tropical and South Pacific oceans.

6.3 Conclusions

The key conclusions with respect to the aim and objectives (see Chapter 6.1) are summarized as follows:

1. The SPDO associated with the leading SST mode of variability in the South Pacific Ocean can be viewed as a collection of multiple processes operating on distinct time scales.
2. The PSA1 is the dominant atmospheric driver or stochastic forcing of the SPDO. The large fraction of the subsurface counterpart of the SPDO can be viewed as cumulative integrations of the atmospheric PSA1 variability exciting internal ocean processes. The PSA2 explains the large fraction of the second leading SST

mode in the South Pacific Ocean, which is referred to as the South Pacific SST quadrupole pattern.

3. The extratropical subsurface upper ocean is the main source of decadal variability. Topographically trapped oceanic Rossby waves east of New Zealand in the southwest Pacific may be the key oceanic mechanism that enhances observed decadal variability of the SPDO and may potentially be a critical area for future predictability studies.
4. Although ENSO and the SPDO have distinct oscillatory periods – primarily, the former oscillates on interannual timescales and the latter on decadal timescales – they have very close damping time scales, indicating the predictive skills of ENSO and the SPDO are comparable.

With respect to practical predictability within the LIM framework and the identification of optimal precursors for forecast initialisation we find the following additional five key conclusions:

5. Reduced-order LIM predictions of ENSO and the SPDO are comparable with state-of-the-art GCMs. The ENSO boreal spring predictability barrier (MAM) is similarly apparent in LIM predictions.
6. Predictability longer than ENSO skill resides in the extratropical upper ocean. With the inclusion of subsurface processes in the South Pacific Ocean, the predictability of ENSO and the SPDO was found to increase.
7. A specific set of initial conditions can optimally determine how the system will evolve along its deterministic (linear) trajectory. The South Pacific SST quadrupole pattern is found to be an optimal SST precursor for the development of the SPDO and ENSO. The subsurface SST variability associated with oceanic

Rossby wave propagation sets a background state to modify and guide the SST evolutions.

8. The atmospheric propagating PSA patterns (i.e., PSA1 and PSA2) are associated with higher-order noise-forced SST variability and contribute not only to excite the optimal initial perturbations that maximize ENSO and SPDO development, but in general to activate the stochastic SST forcing.
9. The PSA2 is the key forcing required to excite the SP SST quadrupole pattern which optimally determines the evolution of SST anomalies along its deterministic (linear) trajectory leading to the SPDO and ENSO peak phases nine months hence, and from which the linear predictability intrinsic to the SST system can be inferred.

6.4 Future research directions

An important outcome of this thesis is the identification of a physical framework for the large-scale South Pacific climate dynamics that links the air-sea coupled system, from the atmosphere to SST variability and in turn with the upper oceanic processes, across multiple time scales from (intra-)seasonal to (inter-)decadal. The relative importance of stochastic forcing, ENSO teleconnections and oceanic processes in contributing to the overall SPDO variability has not been quantified. Although Newman et al. (2016) suggest that each of those mechanisms play equivalent roles (approximately one-third) in the PDO variance for the North Pacific, it remains unclear if this is the case for the SPDO in the South Pacific. Future research is necessary to quantify the relative importance of those mechanisms by conducting some idealized experiments. In addition, those proposed physical drivers might vary in each SPDO phase. The extent to which the SPDO is predictable requires further case studies of how the relevant physical drivers and processes interact.

The reduced order stochastically forced AR1 model and POP/LIM have shown their capabilities in diagnosing the dynamics of the SPDO and in making predictions. However, due to the built-in limitations of such stochastically forced models, they are not able to conduct ensemble forecasts. Further research using other approaches and/or numerical tools are required to answer how different initial conditions might affect the SPDO evolution and predictability. In particular, beyond optimal perturbations identified using the relatively simple LIM framework, which cannot account for nonlinearity or red noise forcing, more advanced nonlinear ensemble prediction methods employing nonlinear generalizations of the leading Lyapunov or backwards Lyapunov vector are now being employed in climate prediction. We anticipate that, with better understanding of physical dynamics, predictions made by the state-of-the-art GCMs will eventually outperform reduced-order statistical models. Nevertheless, stochastically forced models are likely to remain very valuable tools for convenient and computationally cheap benchmarks for the validation of GCM outputs in the future.

APPENDIX A

A List of Acronyms

ACCESS-O	Australian Community Climate and Earth System Simulator Ocean Model
AL	Aleutian Low
AR1	Autoregressive of order 1
ARC	Australian Research Council
ARCCSS	The ARC Centre of Excellence for Climate System Science
ARIMA	Autoregressive Integrated Moving Average
AMS	American Meteorological Society
CLEX	The ARC Centre of Excellence for Climate extremes
CMIP5	The 5^{th} phase of Coupled Model Intercomparison Project
CMS	Computational Modelling Systems
CORE	Coordinated Ocean-Ice Reference Experiments
CSIRO	Commonwealth Scientific and Industrial Research Organisation
EAC	East Australian Current
ENSO	El Niño–Southern Oscillation
EOF	Empirical Orthogonal Function
ESCC	Earth Systems and Climate Change
GCM	General Circulation Model
GFDL	Geophysical Fluid Dynamics Laboratory
HadISST	The Hadley Centre Global Sea Ice and Sea Surface Temperature
IMAS	Institute for Marine and Antarctic Studies
IPO	Interdecadal Pacific Oscillation
KOE	Kuroshio and the Oyashio Extensions
LIM	Linear Inverse Model
MJO	Madden-Julian Oscillation
MOM4p1	Modular Ocean Model version 4.1
NAO	North Atlantic Oscillation
NCAR	National Center for Atmospheric Research

NCEP	National Centers for Environmental Prediction
NCI	National Computational Infrastructure
NMME	National Multi-Model Ensemble
NESP	National Environmental Science Project
NP	North Pacific
NPI	North Pacific Index
NPMM	North Pacific Meridional Mode
OGCM	Ocean General Circulation Model
OT	Ocean Temperature
PC	Principal Component
PDO	Pacific Decadal Oscillation
PDV	Pacific Decadal Variability
PMM	Pacific Meridional Mode
POP	Principal Oscillation Pattern
PSA	Pacific-South American Pattern
SLP	Sea Level Pressure
SP	South Pacific
SPDO	South Pacific Decadal Oscillation
SPMM	South Pacific Meridional Mode
SSH	Sea Surface Height
SST	Sea Surface Temperature
STCC	Subtropical Countercurrent
TP	Tropical Pacific
TPI	Tripole Index
UTAS	University of Tasmania
VAT	Vertically averaged temperature
WES	Wind-Evaporation-Sea surface temperature feedback
WKB	Ray tracing
Z500	500-hPa Geopotential Height

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