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REVIEW

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Literature survey of subseasonal-to-seasonal predictions in the southern hemisphere

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Abstract

Subseasonal-to-seasonal (S2S) prediction has gained momentum in the recent past as a need for predictions between the weather forecasting timescale and seasonal timescale exists. The availability of S2S databases makes prediction and predictability studies possible over all the regions of the globe. Most S2S studies are, however, relevant to the northern hemisphere. In this review, the S2S literature relevant to the southern hemisphere (SH) are presented. Predictive skill, sources of predictability, and the application of S2S predictions are discussed. Indications from the subseasonal predictability studies for the SH regions suggest that predictive skill is limited to 2 weeks in general, particularly for temperature and rainfall, which are the variables most frequently investigated. However, temperature has enhanced skill compared to rainfall. More S2S prediction studies that include the quantification of the sources of predictability and the identification of windows of opportunity need to be conducted for the SH, particularly for the southern African region. The African continent is vulnerable to weather- and climate-related disasters, and S2S forecasts can assist in alleviating the risk of such disasters.

KEYWORDS

S2S predictions, sources of predictability, southern hemisphere, southern Africa

1 | INTRODUCTION

Weather forecasting and climate predictions have been in existence for the past few decades (Cohen et al., 2018; Hudson et al., 2011). National Meteorological and Hydrological Services (NMHS) have been providing weather forecasts and seasonal climate forecasts for surface temperature and precipitation (Phakula et al., 2018; Saha et al., 2014), leading to decision-making that is therefore generally based on weather or seasonal forecasts (Crochemore et al., 2021). There is a need for predictions of meteorological conditions outside weather forecasting timescales (Mariotti et al., 2020). Forecasts between weather and seasonal timescales are referred to as the subseasonal-to-seasonal (S2S) forecasts (Vitart et al., 2017). The S2S timescale is generally defined as ranging from 2 weeks to 2 months (de Andrade et al., 2021; Klingaman et al., 2021; Mariotti et al., 2018; Moron et al., 2018; Mundhenk et al., 2017; Wang & Robertson, 2018; White et al., 2017) and is inherently difficult to predict (Li & Robertson, 2015; Luo & Wood, 2006; Vitart, 2014). The difficulty in S2S prediction is due to the lead time being sufficiently long that much of the memory of the atmospheric initial conditions is lost and it is too short for the variability of the ocean to have a strong influence on the atmosphere (Black et al., 2017; DelSole et al., 2017).

Predictability for forecasting the day-to-day weather comes primarily from accurate initial conditions (Landman et al., 2012; Vitart et al., 2017) that are well represented in the Numerical Weather Prediction (NWP) models. The dependency of the forecasts on accurate initial conditions originates from the chaotic and non-periodic characteristics of the atmosphere. Reliability of the weather forecasts is limited to about 7 days due to uncertainties in the observations and the imperfections in the prediction models (Krishnamurthy, 2019). Beyond the synoptic weather timescale of about 10 days, day-to-day weather forecasting becomes challenging (Hudson et al., 2013; Lin et al., 2017; Weyn et al., 2021).

Seasonal forecasts depend on the slowly evolving components of the earth system such as sea-surface temperatures (SSTs), soil moisture, and sea ice components (Conil et al., 2007; Huang & Shin, 2019; Shin et al., 2020; Tian et al., 2017; White et al., 2017). Moreover, skillful seasonal forecasts are possible due to the predictability of the slowly evolving SST anomalies of the equatorial Pacific El Niño–Southern Oscillation (ENSO) (Flugel & Chang, 1998). In fact, ENSO is regarded as the primary climate driver for seasonal forecasting (Choi & Son, 2022; Huang & Shin, 2019). Over southern Africa, seasonal forecast skill is highest in summer during the El Niño and La Niña phases, with the El Niño phases usually resulting in anomalously dry conditions and the La Niña phases in anomalously wet conditions.

Recent studies suggest that the Indian Ocean Dipole (IOD) plays an important role in predicting the ENSO in the tropical Pacific through teleconnections (Li et al., 2022; Liu et al., 2023). The positive IOD events are associated with reduced rainfall over western and southern Australia (Zhao et al., 2019), enhanced rainfall in eastern and southern Africa (Black et al., 2003), and reduced rainfall over central and southeastern Brazil and enhanced rainfall over the Amazon (Sena & Magnusdottir, 2021). Furthermore, ENSO can modulate the Madden Julian Oscillation (MJO) through teleconnection (e.g., Lee et al., 2019; Wei & Ren, 2019; Fernandes & Grimm, 2023). MJO is regarded as the main source of subseasonal forecasting (Alvarez et al., 2020; Waliser et al., 2006; Woolnough, 2019). MJO modulates rainfall variability during the main wet season in southern Africa (Pohl et al., 2007), in Australia (Cowan et al., 2019), and in South America (Grimm et al., 2021; Klingaman et al., 2021). Stratosphere–troposphere interaction is another potential source of S2S predictability (e.g., Mariotti et al., 2020). Stratospheric processes have a longer memory than tropospheric processes, and as a result, this coupling provides a potential source of extended-range predictability of surface weather and climate (Lim, Hendon, & Thompson, 2018). The atmospheric climate models coupling to the ocean, and land surface and sea ice models led to improved seasonal climate forecasts, including in South Africa.

Land–atmosphere feedback can play an important role in exacerbating weather extremes and could also contribute to their predictability on subseasonal timescales (Dirmeyer et al., 2021). In a warming climate, land surface feedback associated with soil moisture availability can play an important role in amplifying hot extremes (Wehrli et al., 2019). A positive relationship between soil dryness and heat exists such that high air temperatures are conductive to drying soil by increasing evaporative demand (Dirmeyer et al., 2021). Furthermore, land–atmosphere feedback alters daytime atmospheric boundary layer, in turn affecting cloud formation, precipitation, and the state of the free atmosphere beyond the boundary layer (Dirmeyer et al., 2021).

Despite the challenges associated with S2S prediction, there has been an increasing demand for such forecasts (Alvarez et al., 2020; Pendergrass et al., 2020; Robertson et al., 2019; Ruiz-Vasquez et al., 2022; Viguad et al., 2017; Zamora et al., 2021). The demand for S2S forecasts is due to their relevance for decision-making and early warnings across a range of sectors, such as agriculture, water, energy, and disaster risk management (e.g., Black et al., 2017; Endris et al., 2021; Mariotti et al., 2018). The establishment of the S2S Prediction Project (Vitart et al., 2017) and its associated public available database facilitated a notable increase in S2S-related studies over the different regions of the globe. A Scopus search (performed on December 1, 2022) with the search criteria "TITLE (subseasonal, OR subseasonal, OR s2s, AND prediction, OR predictability, OR forecasts) AND (LIMIT-TO (DOCTYPE, "ar"))" resulted in 319 studies that were identified. After these studies were examined, two of the articles were found not to fit into the climate discipline. Figure 1 shows the yearly frequency of the 317 S2S studies that were identified in this specific Scopus search. Of the 317 studies, only 34 studies (about 11%) were performed specifically for regions or countries within the southern hemisphere (SH).

Due to the potential applications of S2S predictions and the increasing demand for such forecasts, the World Weather Research Programme (WWRP) and World Climate Research Programme (WCRP) jointly established the S2S Project database that contains near-real-time forecasts and reforecasts from 11 operational centers (Lim, Son, & Kim, 2018; Vitart et al., 2017). The freely available S2S project database provides a great opportunity for

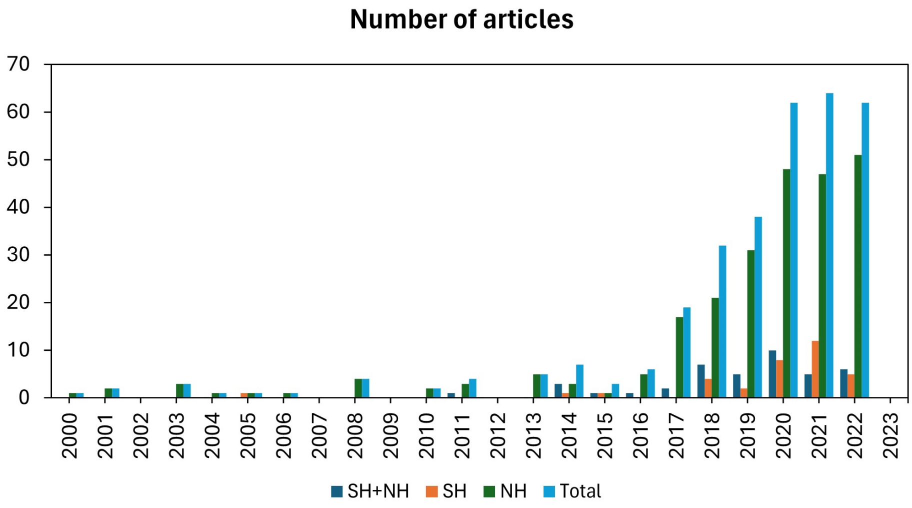

FIGURE 1 Number of articles per calendar year from the Scopus search based on the following criteria: TITLE (sub-seasonal, OR subseasonal, OR s2s, AND prediction, OR predictability, OR forecasts) AND (LIMIT-TO (DOCTYPE, "ar")) totaling to 317 from 2000 to 2022. SH + NH is for both the southern and northern hemispheres, SH is for southern hemisphere, and NH is for the northern hemisphere.

researchers to evaluate and compare the forecast skill of the state-of-the-art global prediction systems (Endris et al., 2021; Lim, Hendon, & Thompson, 2018; Yang et al., 2018). In addition, the US National Oceanic and Atmospheric Administration (NOAA) established the Subseasonal Experiment (SubX) Project mainly for research and operations related to S2S predictions and model development (Pegion et al., 2019). The SubX provides a publicly available database of 17 years of reforecasts and more than 18 months of real-time forecasts from seven US and Canadian modeling groups. The atmospheric chaotic nature might limit the S2S predictability (e.g., Mariotti et al., 2018; Peng et al., 2023; Zuo et al., 2016). However, with the availability of S2S databases, improvement of numerical prediction models, improved ensemble prediction systems, and initialization in the recent past, skillful S2S predictions are possible (Hudson et al., 2013; Vitart et al., 2008).

The main purpose of this review article is to provide a comprehensive background on the state of S2S prediction relevant to the SH. This includes a summary of S2S prediction skill and predictability, a comprehensive summary of the studies that have highlighted the need for S2S predictions and to identify the gap(s) that still need to be addressed. This research is focused on the SH region because there are many studies conducted for the northern hemisphere (NH), with fewer for the SH. Moreover, SH is equally affected by weather and climate extremes that fall in the S2S timescales. The remainder of this paper is organized as follows. Section 2 gives a summary of the sources of S2S predictability, with an emphasis on SH, Section 3 briefly provides the progress of the S2S predictions in SH, Section 4 provides a summary of the need for S2S predictions, and summary and conclusion is presented in Section 5.

2 | SOURCES OF S2S PREDICTABILITY WITHIN THE CONTEXT OF THE SOUTHERN HEMISPHERE

Improving the skill of S2S forecasts is paramount to increasing their value to society. Enhancing forecast skill begins with understanding the sources and limits of S2S predictability within the Earth system. Previous studies revealed that there are potential sources of predictability for the S2S timescales, including the MJO, the state of ENSO, soil moisture, snow cover and sea ice, stratosphere–troposphere interaction, and tropical–extratropical teleconnections (e.g., Ferreira et al., 2022; Ichikawa & Inatsu, 2017; Kim et al., 2014; Mariotti et al., 2020; Wang et al., 2016). The sources of S2S predictability are each briefly discussed as follows:

2.1 | Madden Julian oscillation

The MJO is regarded as the dominant mode of subseasonal (intraseasonal) variability in the tropics that couples with organized convective activity (Jones et al., 2004; Krouma et al., 2023; Liess et al., 2005; Neena et al., 2014; Pobon & Dorado, 2008; Pohl et al., 2007; Pohl & Camberlin, 2014; Sultan et al., 2009; Tam & Lau, 2005; Wang et al., 2011) and represents a primary source of predictability in the intraseasonal timescales and modulates and influences different scales of atmospheric and oceanic variability from the tropics to the extratropics (Wang et al., 2018). According to Vitart et al. (2017), the S2S project models can skillfully predict the MJO up to 3–4 weeks ahead. Grimm et al. (2021) established that the subseasonal prediction skill of the ECMWF and NCEP models in predicting the active and break phases of the South American monsoon modulated by the MJO was up to week 3. According to Marshall and Hendon (2015), the predictive skill of POAMA-2 in predicting Australian monsoon rainfall is limited to about 2 weeks, and the predictability beyond week 1 is primarily provided by the MJO. de Andrade et al. (2021) demonstrated that the MJO improves subseasonal rainfall skill, by showing that removing the MJO signal from the models reduces the skill. The MJO can influence the South Atlantic convergence zone (SACZ) in the intraseasonal timescales (Carvalho et al., 2004; Cunningham & Cavalcanti, 2006; Rosso et al., 2018). The SACZ is the main summer atmospheric phenomenon occurring in South America, and it is of great importance because it regulates the rainy season in the most populated regions of Brazil (Rosso et al., 2018). Cavalcanti et al. (2017) established that the BAM system was able to reproduce the precipitation dipole between southeast and south of Brazil in the summer season related to the SACZ variability.

2.2 | El Niño–Southern Oscillation

ENSO plays an important role in the S2S timescale in that it provides a large source of equatorial Pacific SST boundary forcing that can act as an important source of subseasonal prediction (e.g., Cavalcanti et al., 2021). ENSO is a coupled atmosphere–ocean mode of variability that involves slow variations in the equatorial Pacific that impact SSTs in the central and eastern Pacific, and associated changes in surface pressure and winds in the atmosphere that extend over most of the tropical regions (e.g., Horel & Wallace, 1981; Izumo et al., 2010; Rautenbach & Smith, 2001; Ropelewski & Halpert, 1987). In South America, Klingaman et al. (2021) established that the ECMWF, UKMO, NCEP, and BAM S2S models captured very well the spatial pattern and magnitude of ENSO-driven rainfall in week 1, and by week 5, these anomalies weakened substantially, suggesting inability of the models to maintain the ENSO-driven anomalous meridional overturning circulation. Moreover, de Andrade et al. (2019) found improved subseasonal rainfall forecast skill when the ENSO signal was present and reduced skill after removing ENSO-related precipitation pattern. The ENSO phase may impact the nature of the MJO and subseasonal anomalies in the SH (Shimizu & Ambrizzi, 2015). The interplay between ENSO and MJO teleconnections raises the prospect of an enhanced “window of opportunity” for skillful S2S predictions when and where these teleconnections are active and interacting (Johnson et al., 2014). According to Pohl et al. (2007), intraseasonal variability is higher during El Niño events than during La Niña events, even though the convection itself is less active during El Niño events. Furthermore, Hoell et al. (2021) found that there is an ENSO effect in monthly precipitation in southern Africa.

2.3 | Soil moisture

Soil moisture is one of the most important land surface features for S2S predictability and significantly modulates evaporation and ultimately precipitation through local and regional water and energy circles (Cavalcanti et al., 2021; Chevuturi et al., 2021). The memory of soil moisture can last several weeks, which can influence the atmosphere through changes in evaporation and surface energy budget and can affect the forecast of air temperature and precipitation on subseasonal timescales (Arsego et al., 2023; Koster et al., 2000). Moreover, Hirsch et al. (2014) showed that realistic soil moisture initialization in models improved skill of predicting maximum temperatures in southeast Australia up to 16–30 days in advance. Wang, Chen, et al. (2020) established that soil moisture has large variance in South Africa and Australia, with variations of 10–30 days dominant in South Africa and 30–50 days for Australia. Soil moisture memory is controlled by the seasonality of the atmospheric state, the dependence of evaporation on soil moisture, the variation of runoff with soil moisture, and the coupling between soil moisture and the atmosphere (Conil et al., 2007).

2.4 | Snow cover and sea ice

The cryosphere plays an important role in the Earth's climate system. Snow cover is a key component of the cryosphere, with high reflectivity of sunlight, high infrared emissivity, and low thermal conductivity compared to other natural land components (Cohen & Rind, 1991). Snow cover imposes a significant impact on the surface radiation budget, turbulent energy fluxes, and local hydrological fluxes in the atmosphere (Xu & Dirmeyer, 2011). In addition, the positive snow–albedo feedback can further amplify this impact as a strong forcing to the lower boundary of the atmosphere. Furthermore, snowmelt in the spring season may impact local soil moisture variability and further influence the local precipitation–soil moisture feedback in the following summer (Cohen & Rind, 1991). Snow cover also plays an important role in the radiative and thermal properties of widespread snow cover anomalies and has the potential to modulate local and remote climate over monthly to seasonal timescales (Sobolowski et al., 2010). Because of the significant effects of the continental snowpack, accurate snow simulation in a Land

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Surface Model (LSM) is critical to climate predictions (Wang, Xie, et al., 2020). Inaccurate representation of snow within an LSM could lead to substantial errors in the atmospheric state in coupled simulations (Benjamin & Rodell, 2008).

Sea ice plays a major role in the climate system and has an impact on Earth's energy and water budget, which, in turn, have an impact on atmospheric and oceanic circulations (Vihma et al., 2016). The atmosphere plays a major role in driving sea ice variability, and if predictable, the atmospheric circulations can therefore contribute to the prediction of the sea ice conditions (Guemas et al., 2016). The long memory of the ocean makes it a major source of climate predictability. The origin of the predictability of sea ice is mainly from the persistence or advection of sea ice anomalies, interactions with the ocean and atmosphere, and changes in radiative forcing (Guemas et al., 2016). Sea ice prediction at S2S timescales was found to be challenging due to a lack of in situ observations to develop adequate sea ice models and initialization techniques (Subramanian et al., 2019). In fact, Zampieri et al. (2019) evaluated the ability of six operational forecasting system from the S2S project in predicting the evolution of the sea ice edge around the Antarctic continent and found that only the ECMWF system has skill up to 1 month in advance. In general, the skill for the other forecasting systems was marginal. Furthermore, the skill in the prediction of sea ice in the Antarctic was found to be significantly lower compared to the Arctic continent.

2.5 | Stratosphere–troposphere interaction

The stratosphere is coupled to the troposphere through teleconnections between atmospheric waves and large-scale circulation drive weather patterns (Lim, Son, & Kim, 2018). Byrne et al. (2019) demonstrated that the stratosphere can be a source of S2S predictability of SH circulation during austral spring and early summer seasons through its influence on the zonal-mean eddy-driven jet. However, the potential predictive skill gained from stratospheric variability can be limited by biases in representation of stratospheric processes and coupling of the stratosphere with surface climate in forecast systems (Lawrence et al., 2022). These biases can affect both the mean state and the variability in the stratosphere and have negative impact on troposphere coupling (Lawrence et al., 2022). The sudden stratospheric warmings (SSWs) are driven by the stratosphere–troposphere dynamical coupling and are predictable at subseasonal timescale (e.g., Karpechko et al., 2018; Rao et al., 2020). In austral spring, when the SH stratosphere–troposphere coupling is at its strongest, the S2S prediction skill of SSWs is enhanced due to a well-resolved stratosphere (Rao et al., 2020). Using the S2S project models, Rao et al. (2020) showed that the models were able to predict the September 2019 SSW in the SH up to 18 days in advance. It is worth noting that the SSW events are rare in the SH (e.g., Kozubek et al., 2020). Nevertheless, the status of the polar vortex can be a source of predictability (Byrne et al., 2019). Son et al. (2020) assessed the skill of 10 S2S project models in predicting both the extratropical stratosphere and troposphere and found that most models reliably predicted the stratospheric circulation up to about 4 weeks ahead and about 2 weeks for the troposphere during austral summer and winter seasons. The stratosphere prediction skill is higher than the troposphere skill in austral spring (Son et al., 2020).

Signals of changes in the polar vortex and Southern Annular Mode (SAM) are believed to come from the stratosphere with the anomalous tropospheric flow lasting up to about 2 months (Ashok et al., 2007). The SAM signal corresponds to 22%–34% of the SH atmospheric circulation variance (Prado et al., 2021). SAM is the leading mode in middle- to high-latitude atmospheric circulation (Prado et al., 2021; Thompson et al., 2005). The weakening and intensification of the SH polar vortex can lead to the negative and positive phases of the tropospheric SAM in spring, respectively (Lim, Hendon, & Thompson, 2018). SAM presents positive and negative phases, with the positive phase corresponding to negative mean sea-level pressure anomalies north of 60° S and positive mean sea-level pressure anomalies south of 60° S, and is associated with stronger circumpolar westerlies, increased cyclone activity, and stronger zonal winds (Prado et al., 2021). Furthermore, the positive phase of SAM is associated with anomalously wet conditions over most of Australia and Southern Africa (Gillett et al., 2006). The positive phase of SAM is associated with anomalously high surface pressures near New Zealand and southwest Australia (Cowan et al., 2019). According to Yang et al. (2017), the MJO also plays an important role in modulating the stratosphere by triggering anomalous planetary waves and gravity waves. Furthermore, Alexander et al. (2018) suggested that the tropical gravity waves drive subseasonal stratospheric zonal wind anomalies that descend with increasing MJO phases 3 through 7.

2.6 | Ocean conditions

SST anomalies lead to changes in air–sea heat flux and convection, which affect atmospheric circulation (Cronin et al., 2019). The timescale of subseasonal prediction is such that the influence of atmospheric initial conditions on the predictability is decreasing, while the contribution from slowly evolving oceanic conditions is increasing (Hudson et al., 2013). For this timescale, a realistic representation of ocean–atmosphere coupling can be important. It is possible that as the contribution of atmospheric initial conditions on the prediction skill decreases, the relative contribution of including a realistic ocean–atmosphere coupling on prediction skill increases. Ma et al. (2021) using the NCEP, ECMWF, and UKMO S2S project ocean–atmosphere coupled models and the GEPS, ISAC-CNR, and Global Ensemble Forecast System (GEFS) atmospheric models showed that the predictability of the atmosphere in coupled models is higher than in uncoupled models. Moreover, MJO prediction skill at S2S timescales was found to be higher in coupled models compared to uncoupled atmosphere-only models (Subramanian et al., 2019). Zhao et al. (2021) showed that in the NCEP system, the predictability limit of the lower troposphere is significantly higher than in the GEFS due to the contribution of low-frequency boundary signs from air–sea interactions.

2.7 | Tropical–extratropical teleconnections

Skillful subseasonal forecasts generally depend on the skillful prediction of the large-scale atmospheric circulation, which is closely linked to large-scale teleconnection patterns (Black et al., 2017). These teleconnection patterns reflect large-scale changes in the atmospheric wave and jet stream patterns and thus have strong impacts on temperature, precipitation, and storm tracks over vast geographical areas (Black et al., 2017). In the SH, only two climatic teleconnection patterns, namely, the Pacific–South American (PSA) and SAM patterns, have been identified (Cavalcanti et al., 2021; Stan et al., 2017). Cavalcanti et al. (2021) investigated the skill of the ECMWF and NCEP S2S project models in predicting the PSA and SAM patterns and found skill up to 4 weeks and 3 weeks ahead, respectively. Precipitation anomaly signals associated with these teleconnection patterns were well predicted 2 weeks ahead. The importance of the two-way interactions between the tropics and the midlatitude and high latitude on intraseasonal timescales of 10–100 days has been acknowledged (Stan et al., 2017).

3 | S2S PREDICTIONS IN THE SOUTHERN HEMISPHERE

Since the establishment of the S2S databases, research studies to evaluate the skill of the S2S models in different regions have been conducted. It is worth mentioning that in the SH, only Australia and Brazil developed and run S2S models, to our knowledge. Most of these studies are conducted in the NH compared to the SH, with very few studies for southern Africa. Hence, the focus of this review is on the SH.

3.1 | South America

Klingaman et al. (2021) investigated the subseasonal forecast skill of the European Centre for Medium-Range Weather Forecasts (ECMWF; Vitart, 2014), National Centres for Environmental Prediction (NCEP; Saha et al., 2014), and United Kingdom Meteorological Office (UKMO; MacLachlan et al., 2015) models from the S2S Prediction project and the Brazilian Global Atmospheric Model version 1.2 (BAM-1.2; Guimaraes et al., 2020) in predicting austral summer South American rainfall for week 1 (1–7), week 2 (8–14), week 3 (15–21), and week 4 (22–28) averages. Their result suggests that most of the models have forecast skill in week 1 and week 2 over the South American region, except that the skill was poor over southern Amazonia and near the Andes. By week 3, forecast skill was only found in northern, northeastern, and southeastern South America and no forecast skill beyond week 3.

The skill of the individual SubX models, as well as their Multi-Model Ensemble (MME), was evaluated in predicting anomalous temperature and precipitation for week 3 in South America (Pegion et al., 2019). Most models and the MME have skill for temperature forecasts over the whole of South America for all months. The skill of the individual models and the MME was higher than the skill of a persistence forecast, indicating that the skill come from sources other than the trend and/or ENSO. The MME has improved skill when compared to individual models. In predicting the precipitation, the only region of statistical significance over all months in South America was over the northeastern parts of Brazil. This region of precipitation skill was consistent across the individual models and has higher skill than a persistence forecast. Again, the MME has higher skill than individual models.

Alvarez et al. (2020) assessed the ECMWF S2S model at predicting anomalously cold and warm week over central and southeastern South America during July 2017 and found skill in predicting cold temperatures 1 week in advance, and 2 weeks ahead for warm anomalies. Fernandes et al. (2022), using SubX MME of week 2 precipitation, found that fire probability can be skillfully predicted over a large part of the Amazon. Osman and Alvarez (2018) assessed the Predictive Ocean Atmosphere

Model for Australia (POAMA) and Beijing Climate Center Climate Prediction System version 1 (BCC-CPS) from the S2S project at predicting an intense heat wave that occurred during December 2013 in southern South America and found that both models have high skill for weeks 1 and 2. In South America, Coelho et al. (2018) evaluated the skill of the ECMWF S2S model at predicting precipitation and found high skill in weeks 1 and 2 compared to weeks 3 and 4.

The South American summer monsoon is the main driver of rainfall variability across tropical and subtropical South America (e.g., Campos et al., 2019; Sena & Magnusdottir, 2020). Active (break) phases of the South American monsoon are associated with cyclonic westerly (anticyclonic easterly) winds (Ferreira & Gan, 2011). According to Grimm et al. (2021), skillful prediction of active and break periods of the South American summer monsoon at subseasonal timescales has great economic and social importance. Grimm et al. (2021) assessed the subseasonal prediction skill of the ECMWF and NCEP models in predicting the active and break phases of the South American monsoon and found that the models have skill up to week 3 for both active and break phases.

3.2 | Australia

Hudson et al. (2011) assessed the forecast skill of the POAMA1.5 system in predicting precipitation and minimum and maximum temperatures over Australia. Their focus was on the first fortnight (averaged days 1–14 of the forecast) and the second fortnight (averaged days 15–28) for winter through to spring (June–November) over a 27-year hindcast dataset. Their results showed that the model has the highest skill in predicting the first fortnight compared to the second fortnight for both the precipitation and temperatures. It is worth noting that the Bureau of Meteorology upgraded the ACCESS-S1 system to ACCESS-S2; however, there is no significant skill improvement in predicting rainfall and maximum and minimum temperature for multi-week forecasts in the latter (Wedd et al., 2022).

Hudson et al. (2015), as part of the Managing Climate Variability (MCV) project, investigated the skill of the POAMA-2 at predicting heat extremes on weekly to seasonal timescales over Australia. Their result showed that the week 3 and week 3 + 4 forecasts are the least skillful. For week 2 + 3, forecast skill was found in the autumn and winter months, with high skill over the southeastern parts in the spring months. In general, the highest skill is found over northern Australia from late summer through to winter and over the eastern to southeastern parts in the winter and spring months.

Hudson and Marshall (2016) also assessed the forecast skill of the POAMA-2 system at predicting the heatwaves during December–January–February (DJF) for week 2, week 3, week 1 + 2, week 3 + 4, and month timescales. They used the Relative Operating Characteristic (ROC) to discriminate between events and non-events of the forecast and reliability diagrams to determine the usefulness (reliability) of the forecasts. Their result indicated that all of Australia exhibits ROC significantly >0.5 for all forecast lead times, implying good forecast discrimination in general. The ROC showed better forecast discrimination for the week 1 + 2 forecasts. There is particularly good forecast discrimination over northern tropical Australia at all lead times. In terms of reliability, the model seems to be either over-confident or over-forecasting, particularly for the week 3 + 4 forecasts. Reliability is worst for the week 3 forecasts and best for the month forecasts. Forecasts over southeastern Australia tend to be over-confident, while forecasts over northern Australia tend to be over-forecasting. It is worth noting that the finding of Hudson et al. (2015) are mostly in agreement with the finding of Hudson and Marshall (2016).

Marshall and Hendon (2015) investigated subseasonal prediction skill of POAMA-2 for predicting Australian summer monsoon anomalies. Their results showed that forecast model can predict the local large-scale zonal wind anomalies beyond 4 weeks and monsoon rainfall anomalies up to 2 weeks ahead, with the active episodes more predictable than the break episodes. Like the South American monsoon, active and break Australian monsoon rainfall phases during summer are associated with large-scale cyclonic westerly and anticyclonic easterly winds, respectively (Marshall & Hendon, 2015). King et al. (2020) evaluated Australian Bureau of Meteorology Seasonal Prediction System (ACCESS-S1) for predicting rainfall extreme indices over Australia and found skill up to 1 month ahead. However, they indicated that the skill drops at lead time of a week or more.

Tsai et al. (2021) examined four S2S models at predicting the subseasonal forecasts of the northern Queensland floods of February 2019, and their findings suggest that the models were able to predict the event up to 8–10 days in advance. Cowan et al. (2019) showed that ACCESS-S1 predicted a 40%–60% probability of extreme rainfall, cold temperatures, and high winds up to 2 weeks in advance. They also showed that ACCESS-S1 skillfully predicted the anomalous surface pressure ridge to the south of Australia. In Australia, Schepen et al. (2018) evaluated the skill of the ACCESS-S1 system at predicting rainfall for 12 catchments and found good skill for 2–10 day forecasts, with skill gradually weakening for days 11–19 and 20–28.

Benthuysen et al. (2021) assessed the skill of the ACCESS-S1 at predicting the 2020 marine heatwave

(MHW) in the Great Barrier Reef and the Coral Sea. Their results showed that the model was able to capture the observed MHW's severity and spatial extent for the week 1 forecasts. Hirsch et al. (2014) showed that subseasonal forecast skill is sensitive to the land surface initialization methods over southeastern Australia. Using the Weather Research and Forecasting (WRF) model coupled to the Community Atmosphere-Biosphere Land Exchange (CABLE) model, they showed that initialization from prior offline simulations improved subseasonal predictability for temperature, particularly maximum temperature. Oh et al. (2022) investigated the impact of stratospheric ozone on the subseasonal prediction in the SH spring. Their results showed that the Global Seasonal Forecasting System version 5 (GloSea5) has skill at predicting the stratospheric ozone several weeks ahead and has improved skill in week 6–7 maximum surface air temperature over Australia.

3.3 | Southern Africa

The skill of the ECMWF, UKMO, and Centre National de Recherches Meteorologiques (CNRM; Voldoire et al., 2013) S2S project models and their MME was investigated in predicting minimum and maximum temperatures for days 1–14 (week 1 + 2), days 11–30, and days 1–30 (full month calendar) over South Africa (Phakula et al., 2020). Higher skill was found for week 1 + 2 in predicting both minimum and maximum temperatures, with the MME outperforming the individual models. All individual models and the MME have a higher skill for days 1–30 compared to days 11–30 in predicting minimum and maximum temperatures, again the MME outperforms the individual models. In fact, the skill has significantly reduced for days 11–30 compared to days 1–14 and days 1–30 timescales. Using the NCEP CFSv2 and ECMWF hindcasts of 850-hPa geopotential heights of the S2S prediction project, Engelbrecht et al. (2021) assessed the subseasonal deterministic prediction skill of low-level circulation for week 3 and week 4 that are relevant to weather and climate of southern Africa. They found skill relative to persistence into week 3 for some warm and cold months. Their findings further revealed that the hindcasts initialized in the warmer months seem to have higher skill than the cold month hindcasts.

In Africa, de Andrade et al. (2021) evaluated subseasonal precipitation forecasts using hindcasts from the ECMWF, UKMO, and NCEP S2S project models. They divided Africa into sub-regions, namely, West Africa Monsoon (WAM), Equatorial West Africa (EWA), Equatorial East Africa (EEA), and Southern Africa (SA). Here, the focus is on SA and DJF seasons. The DJF season is the main rainy season in SA. Using Pearson's correlation coefficient (deterministic verification) between the hindcast ensemble mean and observed precipitation anomalies, their result showed that all the models have high skill in week 1, and skill drops significantly in weeks 2–4. ROC and attribute diagrams (probabilistic verification) showed high skill in week 1 and week 2, with reduced skill in week 3 and week 4. Musonda et al. (2021) evaluated the ECMWF S2S 20 years reforecast for monthly rainfall over Zambia, and their findings indicated that the model realistically simulates the mean annual cycle skillfully by identifying the wet season from November–March and the dry season from June–September.

There is a huge gap between the S2S prediction studies in the NH compared to the SH. For the NH, the various aspects relevant to subseasonal prediction such as prediction skill, sources of predictability, and windows of opportunity are actively being investigated. This is also the case for South America and Australia, although to a lesser extent in terms of the number of studies, while for southern Africa, only a few studies on subseasonal prediction skill have been performed so far. To that effect, there is a need for more S2S studies in the SH, particularly for the southern African region. Most of African countries are dependent on rain-fed agricultural activities and are vulnerable to climate extreme events that have detrimental socioeconomic impacts. Moreover, there is a need to develop temperature and rainfall prediction systems at S2S timescales in the African region, particularly to facility readiness for high-impact events such as flood events along the Mozambique coast (e.g., Tropical Cyclone Idai) and the eastern coast of South Africa as have happened in April 2019 (Bopape et al., 2021). Furthermore, it is imperative that governments in the region invest more resources in S2S prediction studies, particularly with the changing climate challenges that the world is facing.

3.4 | Southern mid- and high-latitude regions

Wang, Liu, et al. (2020) assessed the S2S predictive skill of the Amundsen Sea Low (ASL) in two state-of-the-art forecasting systems and found that the ASL predictability during austral spring is higher than in the other seasons for lead time up to 4 weeks. The highest skill is found in weeks 1–2 compared to weeks 3–4. Their findings further suggested that the stratosphere–troposphere coupling provides an important source of predictability for the Antarctic surface weather and climate on the S2S timescale. Rao et al. (2020) tested the skill of the 11 S2S models in predicting the SH minor SSW of September

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2019. Their results indicated that the predictability of the event was about 18 days in the high-top forecasting models. Zampieri et al. (2019) evaluated the ability of 6 S2S operational forecasting systems in predicting the evolution of the sea ice edge around the Antarctic and found that only one system produced a potentially useful forecast for up to 1 month. Gregory et al. (2020) assessed the subseasonal tropical cyclone forecasts from the ECMWF and ACCESS-S1 systems for the 2017/18 and 2018/19 SH cyclone seasons. Both systems showed good skill in forecasting cyclone activity out to 3 weeks in advance. Pérez-Fernández and Barreiro (2023) evaluated the forecast skill of the NCEP CFSv2 and IAP-CAS (Bao et al., 2018) S2S models in predicting the evolution of observed Rossby wave pockets (RWPs) that last more than 8 days during SH summer. Their results revealed that both models forecasted the RWPs that rapidly lose energy after the 6–7 lead days, which potentially limit RWPs prediction to the synoptic time range.

4 | NEED FOR S2S PREDICTIONS

The S2S timescale is relevant to planning and preparedness in sectors such as public health, water management, energy, and agriculture (e.g., Cavalcanti et al., 2021; White et al., 2017). The potential application sectors are briefly discussed below:

4.1 | Public health sector

S2S prediction can have a very valuable applications for high-impact weather events that have a societal impact on public health (Li & Robertson, 2015; Robertson et al., 2019). Extreme weather events, such as heat waves, are common in SH, for example, the heatwaves of 2015/16 austral summer in southern Africa, extreme heat waves in the summer of 2008 and 2009 that lasted for 15 and 13 days in Adelaide, South Australia (Nitschke et al., 2011), and the heat wave of October 2020 in central South America (Marengo et al., 2021). Extreme high-temperature events over a prolonged period can lead to hyperthermia (van der Walt & Fitchett, 2021). S2S forecasts of heat waves can aid decision-makers in the health sector in planning and preparedness ahead of the events.

4.2 | Energy sector

Energy resources are a primary driver of sustainable growth and development of a country's economy. A deficit in energy resources can affect key economic sectors such as agriculture, manufacturing, and households, among others. Knowledge of climatic conditions at S2S timescales can improve the decision-making of renewable energy generation and electricity demand (Soret et al., 2019). S2S rainfall variation on local and regional scale has an impact on hydropower generation (Klingaman et al., 2021). Most of the Brazilian energy system is associated with hydroelectric generation, responsible for 53.7% of the total energy generation (Arsego et al., 2023). Extreme weather-related events, particularly cold and heat waves, have a negative impact on energy production and consumption and introduce a level of unpredictability affecting operations and price volatility, impacting energy security (Anel et al., 2017). S2S forecasts of cold and heat waves can be beneficial for energy supply and demand decision-making.

4.3 | Water management

Prolonged drought can lead to a shortage of water supply to citizens, particularly with an increasing population. One such example was during the 2014–2017 drought in Cape Town, South Africa, where overall dam levels supplying the city dropped from 92.5% to 23%, resulting in the city water management announcing a "Day Zero" in January 2018 (Calverley & Walther, 2022). "Day Zero" meant that the city's dam levels will reach 13.5% and water supply would be impossible. In South Australia, freshwater managers and users rely on weather and climate information for water resource management, particularly during the Millennium Drought (Rayner, 2019). On the other hand, excess of rainfall can have detrimental socioeconomic effects. For example, according to Begg et al. (2021), on average, Figi's economy suffers flood losses of approximately US$9.7 million per annum and about 10 people lose their lives annually due to floods. S2S forecasts cannot be used to make specific flood predictions but could be used to identify the increased likelihood of flooding where stream flows have already been predicted to be high (White et al., 2017).

4.4 | Agricultural sector

Skillful subseasonal forecasts have potential applications to provide valuable guidance in the decision-making process in the agricultural sector. Rainfall extremes, both excess and lack, can be devastating to farmers. For example, during the austral summer of 2018/2019, devastating floods in northeast Australia killed approximately 625,000 head of cattle and 48,000 sheep (Tsai et al., 2021). The 2015/2016 devastating drought in southern Africa affected about 40 million people and resulted in a cereal deficit of 9.3 million tons and more than 643,000 livestock deaths (Matlou et al., 2021). According to Thomasz et al. (2023), Argentina produces 50 million tons of soybean annually and is the third largest in the world after the USA and Brazil, and water deficit during critical period and excess during harvest affect output. The 1997/98 El Niño drought had a major impact on New Zealand agriculture and resulted in a loss of $618 million to the GDP (Salinger & Porteous, 2014). Agricultural activities in the South Pacific region are heavily dependent on rainfall due to the absence of extensive irrigation (Beischer et al., 2021). South Pacific Convergence Zone (SPCZ) affects rainfall variability of the South Pacific region (e.g., Beischer et al., 2021; Higgins et al., 2020; Narsey et al., 2022). Variations in the SPCZ location, slope, and intensity affect water availability and as a result, productivity of subsistence crops is affected (Beischer et al., 2021). Forecasts on the S2S lead times could also be used to support dynamic updates of crop yield estimates, which could support early planning to alleviate food security issues.

5 | SUMMARY AND CONCLUSIONS

This study reviewed the S2S prediction and predictability with a focus on SH. This is because there are less studies on S2S timescales conducted for SH compared to NH. However, SH is equally affected by weather and climate extremes that fall in S2S timescales. To lay a good foundation for our study, we first reviewed the S2S prediction in general. S2S timescale (between 2 weeks and 2 months) bridges the gap between weather forecasting (0–7 days) and seasonal climate predictions (3–6 months). Due to its relevance for decision-making and early warnings across a range of sectors, there has been an increasing demand for accurate S2S predictions from the applications community. The availability of S2S databases, such as the S2S prediction and SubX projects, makes S2S prediction possible. Previous studies reveal that there are potential sources of predictability for the S2S time range, including the MJO, the state of ENSO, soil moisture, snow cover and sea ice, stratosphere–troposphere interaction, and tropical–extratropical teleconnections. In this study, we review the S2S predictions focusing on South America, Australia, and southern Africa. From the studies we have looked at, it seems that the S2S prediction skill in SH is limited to 2 weeks ahead, irrespective of the variables of interest. However, temperature forecasts have enhanced skill compared to rainfall forecasts. It is worth noting that these studies used different methods and skill metrics to assess the prediction skill of the model forecasts, and that is a challenge. The use of standard verification skill metrics for S2S predictions for operational forecasts is required. Looking at the number of S2S studies on the SH, there is a need to conduct more studies for the SH, particularly for the African continent. In fact, there are very few applications S2S prediction studies compared to seasonal prediction studies in both hemispheres (Osman et al., 2023). The African continent is vulnerable to weather- and climate-related disasters, and S2S forecasts can assist in alleviating the risk of such disasters.

AUTHOR CONTRIBUTIONS

Steven Phakula: contributed to investigation writing the original draft, and review and editing the manuscript. **Willem A. Landman, and Christien J. Engelbrecht**: helped in supervision. **Willem A. Landman and Christien J. Engelbrecht**: contributed to project administration. **Willem A. Landman**: contributed to funding acquisition. All authors have read and agreed to the published version of the manuscript.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data openly available in a public repository that issues datasets with DOIs.

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