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RESEARCH ARTICLE

Atmospheric water vapour transport in ACCESS-S2 and the potential for enhancing skill of subseasonal forecasts of precipitation

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Abstract

Extended warning of above-average and extreme precipitation is valuable to a wide range of stakeholders. However, the sporadic nature of precipitation makes it difficult to forecast skilfully beyond one week. Subseasonal forecasting is a growing area of science that aims to predict average weather conditions multiple weeks in advance using dynamical models. Building on recent work in this area, we test the hypothesis that using large-scale horizontal moisture transport as a predictor for precipitation may increase the forecast skill of the above-median and high-precipitation weeks on subseasonal time-scales. We analysed retrospective forecast (hindcast) sets from the Australian Bureau of Meteorology's latest operational subseasonal-to-seasonal forecasting model, ACCESS-S2, to compare the forecast skill of precipitation using integrated water vapour transport (IVT) as a proxy, compared to using precipitation forecasts directly. We show that ACCESS-S2 precipitation generally produces more skilful forecasts, except over some regions where IVT could be a useful additional diagnostic for warning of heavy precipitation events.

KEYWORDS

application/context, atmosphere, forecasting (methods), physical phenomenon, rainfall, subseasonal prediction, subseasonal, synoptic, tools and methods

1 | INTRODUCTION

The science and application of subseasonal prediction are rapidly growing fields (e.g., Robertson and Vitart, 2019). Over the last decade, subseasonal prediction has been a key focus of the World Weather Research (WWRP) and World Climate Research Programmes (WCRP) through the Subseasonal-to-Seasonal (S2S) Prediction Project (Brunet *et al.*, 2010; Robertson *et al.*, 2015). The potential benefits of accurate enhanced warnings, particularly of rainfall, are enormous to a variety of stakeholders, and the uptake of subseasonal forecasts for decision-making is rapidly increasing (White *et al.*, 2022). The Australian Bureau of Meteorology has been providing subseasonal forecasts to the public as part of its regular operations since August 2019 using ACCESS-S (Australian Community Climate and Earth System Simulator–Seasonal; Hudson *et al.*, 2017; Wedd *et al.*, 2022). In this study, we use

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ACCESS-S to examine the subseasonal prediction of rainfall.

There has also been an increasing interest in the ability to predict extremes on subseasonal time-scales (e.g., Domeisen *et al.*, 2022; Vitart and Robertson, 2018; Vitart *et al.*, 2019), including for Australia using the ACCESS-S system (Lim *et al.*, 2021; King *et al.*, 2020a; Marshall *et al.*, 2021; Cowan *et al.*, 2022). Rainfall extremes over Australia are strongly modulated by natural modes of variability (e.g., Min *et al.*, 2013; King *et al.*, 2014; 2020b; Marshall and Hendon, 2019). King *et al.* (2020a) evaluated the potential of using the ACCESS-S version 1 (Hudson *et al.*, 2017) to predict various extreme rainfall indices on S2S time-scales over Australia. They found there was the potential to produce useful operational forecasts of extreme rainfall indices on these time-scales. In addition, the Bureau of Meteorology is now providing forecasts to the public of the chance of having unusually dry/wet conditions in the weeks to seasons ahead. 'Unusually' is defined as being in the top or bottom 20% of climatology for the selected outlook period (http://www.bom.gov.au/climate/outlooks). There are, however, challenges associated with predicting rainfall, especially extremes. Rainfall is highly variable in space and time, and its irregular nature makes it difficult to forecast well beyond one week. For example, for the extreme rainfall event over north-eastern Australia in the summer of 2019 the ACCESS-S1 model only indicated above-average rainfall in the region up to one week ahead (Cowan *et al.*, 2019), and all 11 models from the S2S prediction project database failed to simulate this event more than a few days in advance (Vitart *et al.*, 2017; Domeisen *et al.*, 2022). Additionally, ACCESS-S1 failed to predict a drier than usual Austral spring in 2020 over Australia due to the La Niña signal dominating the forecast and the influence of the Indian Ocean Dipole (IOD) and the Madden Julian Oscillation (MJO) being under-represented (Lim *et al.*, 2021). However, other extreme events across the world, such as the heavy rain that led to flooding in Ecuador in January 2016, were apparent in the European Centre for Medium-Range Weather Forecasts (ECMWF) re-forecasts up to three weeks ahead (Pineda *et al.*, 2023). The predictability of the Ecuador floods was likely enhanced by a strong El Niño and active MJO. These studies suggest there is variable skill in extreme rainfall prediction on subseasonal time-scales that is particularly dependent on the phase of relevant climate modes, and perhaps the location of the event.

There might be more scope for useful S2S prediction of synoptic-scale weather systems due to their longer lifetime and larger spatial scales compared with mesoscale rain-bearing systems (Robertson *et al.*, 2020). Integrated water vapour transport (IVT) is a measure of horizontal water vapour flux throughout the column of the atmosphere, which is a key ingredient in rainfall generation (Zhu and Newell, 1998). There is a wealth of literature demonstrating the strong connection between enhanced IVT and rainfall globally often in the context of atmospheric rivers (ARs), which are narrow regions of enhanced IVT in the lower troposphere (Ralph *et al.*, 2006; Lavers *et al.*, 2011; Waliser and Guan, 2017; Viale *et al.*, 2018; Reid *et al.*, 2021a; 2021b). Studies of AR predictability in operational numerical weather prediction models over western North America found skill in AR forecasts out to 10-day lead times (Wick *et al.*, 2013). It has only been recently that analyses of ARs in the S2S context have been conducted. Mundhenk *et al.* (2018) found that AR activity along the west coast of North America could be skilfully predicted up to five weeks ahead depending on the phases of the MJO and Quasi-Biennial Oscillation (QBO) and Huang *et al.* (2021) also found the S2S forecasting skill of ARs was strongly related to El Niño and the MJO. A global evaluation of AR subseasonal prediction skill in the ECMWF S2S forecast system found that the forecast outperformed climatology out to a three-week lead time over broad regions of the subtropics and midlatitudes (DeFlorio *et al.*, 2019b). Experimental operational S2S forecast products of ARs have been developed over the western USA (DeFlorio *et al.*, 2019a).

On medium-range time-scales (one- to two-week lead times), Lavers *et al.* (2014) showed that IVT had higher predictability than rainfall over Europe during the 2013/2014 winter. Moreover, using water vapour transport had the potential to extend the forecast lead time of extreme hydrological events by up to three days relative to rainfall forecasts. This suggests that rainfall predictability is more susceptible to uncertainties associated with mesoscale dynamics and horizontal mass convergence, whereas IVT is largely driven by synoptic-scale processes. Synoptic-scale features should be represented more physically in the model than smaller-scale precipitation features which suffer due to resolution and imperfect parameterisation schemes (Lin *et al.*, 2022). Similarly, Ramos *et al.* (2020) showed that during extreme rainfall over Portugal, IVT forecasts had greater predictive skill than rainfall beyond approximately five days lead time.

In summary, subseasonal forecasting of rainfall, especially extreme rainfall, is a developing research area and skilful, useful predictions could have considerable value to society. However, there are major uncertainties associated with rainfall prediction on subseasonal time-scales. IVT has strong correlations with extreme rainfall and is modulated by climate modes that lend predictability on S2S time-scales. Some studies have shown that IVT can extend the lead time of rainfall forecasts on medium-range time-scales by a few days. This research foundation has led to the question we aim to answer in this study: can the most recent version of ACCESS-S simulate and predict global IVT, and can we use IVT to increase the forecast skill of predicting above-average and extreme rainfall events on subseasonal time-scales?

2 | DATA AND METHODS

We use data from a dynamical S2S prediction system to examine the performance in predicting atmospheric water vapour transport and rainfall. Observational data and reanalyses are used for verification.

2.1 | Access-S2

This study evaluates the performance in predicting IVT and rainfall using the most recent version of the ACCESS-S seasonal prediction system (ACCESS-S2), which became operational in 2021 (Wedd *et al.*, 2022). ACCESS-S2 uses the same coupled model as the UK Met Office GloSea5-GC2 model (Maclachlan *et al.*, 2015), and remains unchanged from ACCESS-S1 (Hudson *et al.*, 2017), aside from minor corrections and enhancements (Wedd *et al.*, 2022). The primary difference between ACCESS-S1 and ACCESS-S2 lies in the data assimilation, which generates the initial conditions for the forecasts (Wedd *et al.*, 2022). The GC2 coupled model (Williams *et al.*, 2015) comprises the Unified Model (UM) atmosphere model (Walters *et al.*, 2017), the NEMO3.4 ocean model (Madec and the NEMO team, 2008; Megann *et al.*, 2014), the Joint UK Land Environment Simulator (JULES) land surface model (Best *et al.*, 2011) and the Los Alamos Sea Ice Model (CICE) (Hunke *et al.*, 2015). These components are coupled hourly using the Ocean Atmosphere Sea Ice Soil coupler (OASIS3; Valcke, 2013). Additional details of these models can be found in Figure 1.

The ACCESS-S2 hindcast period extends from 1981 to 2018, with nine ensemble members per hindcast. Unlike ACCESS-S1, the hindcast configuration employs a time-lagged ensemble approach in which the number of ensemble members depends on the start date of the hindcast (Wedd *et al.*, 2022). In our study, we used a 27-member ensemble that is valid on the 1st of every month. This comprised nine ensemble members from three successive days: the 1st of the month plus the two days prior. The first one or two days were excluded, as

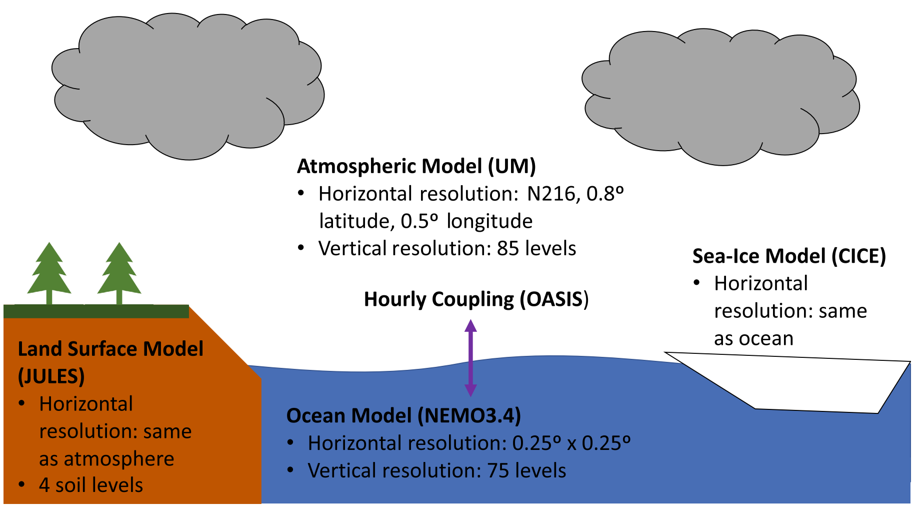

FIGURE 1 Schematic and details of the ACCESS-S2 component models. [Colour figure can be viewed at wileyonlinelibrary.com]

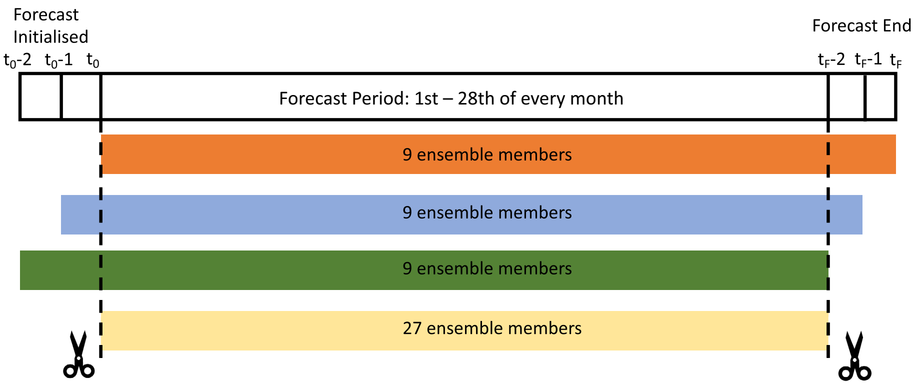

FIGURE 2 Schematic of time-lagged ensemble method. [Colour figure can be viewed at wileyonlinelibrary.com]

necessary, to ensure that the data analysed for all ensemble members start on the 1st of the month (see Figure 2). The months were analysed and grouped into meteorological seasons. For brevity, we present the summer and winter results.

We used weekly total rainfall which was coarsened to $2° \times 2°$ horizontal resolution using conservative regridding. Horizontal winds and specific humidity on vertical levels between 950 hPa and 300 hPa were used to calculate the IVT as in Reid *et al.* (2020). The IVT was also coarsened to $2° \times 2°$ using a bilinear interpolation. A benefit of using coarse resolution data is that near misses will not be punished as much during verification (Ebert, 2008). This is especially important for highly inhomogeneous variables such as rainfall where small spatial errors can lead to unfairly poor skill scores.

2.2 | Verification datasets

We used IVT from ERA5 (Hersbach *et al.*, 2019) also regridded bilinearly to a $2° \times 2°$ grid. The Global Precipitation Climatology Project version 1.3 (GPCP; Adler *et al.*, 1994) daily global rainfall dataset was used as our reference rainfall. The rainfall data was also coarsened to $2° \times 2°$ horizontal resolution using conservative regridding. We use relative magnitudes (i.e., exceedance of a percentile) throughout this study because we do not expect such a coarse rainfall grid to capture realistic magnitudes of rainfall extremes, and we assess the model against its own percentile climatology (which is dependent on start date and location) in order to take into account model biases and as suggested by Nayak *et al.* (2014). All percentiles were calculated using rainfall weeks, that is, weeks where rainfall exceeded 1 mm at each grid point. The observational rainfall dataset limits our period of analysis to 1997–2018. However, given the 27-member ensemble, this gives us a sample size of $n = 1782$ for each season and lead time.

2.3 | Verification skill scores

To verify the model predictors, contingency tables were constructed.

In the contingency table shown in Table 1, a is a *hit*, b is a *miss*, c is a *false alarm* and d is a *correct negative*.

TABLE 1 Contingency table schematic

	Event (model predictor)	**Non-event (model predictor)**
Event (observations)	a	b
Non-event (observations)	c	d

The Critical Success Index (CSI; Wilks, 2019) is defined as:

$$\text{CSI} = \frac{a}{a+b+c}. \quad (1)$$

The CSI is a measure of the proportion of correct forecasts that excludes correct negatives, which is useful for forecasts where the 'yes' event occurs less often than the 'no' event as is typically the case when evaluating rainfall and extremes. CSI has been used by the US National Weather Service and is a valuable measure of skill when event frequency is consistent (Schaefer, 1990). As we use a percentile-based definition for events, the frequency will be consistent by definition (except for comparing skill of predicting above-median rainfall with >80th percentile rainfall) and therefore CSI is a simple and useful verification measure for this analysis. A CSI of 0 is the worst possible score and a CSI of 1 is the best possible score.

Binary masks were developed for each of the predictors and observation datasets to indicate events (e.g., when weekly total rainfall is above the 80th percentile). All percentile values are relative to the dataset that they are then applied to, to account for climatological biases. This means the magnitude of the 80th percentile of precipitation in ACCESS-S2 will be different from the 80th percentile of precipitation in GPCP. This also allowed for the comparison of different variables, that is, using high IVT occurrence as a predictor for rainfall. Grid points where the IVT exceeded the 80th percentile were categorised as events in the same way as described above for weekly rainfall. Figure 3 is an illustrative example of this method. For every week and ensemble member, we constructed binary latitude–longitude masks of the ACCESS-S2 precipitation data that indicated which grid points exceeded the 50th or 80th percentile threshold (1 indicates percentile threshold exceeded). The same was done for the ACCESS-S2 IVT and the observations. Then for each grid point we made contingency tables as in Table 1 and calculated the skill score shown in Equation (1). In the example given in Figure 3, green boxes show hits, red boxes show misses, blue boxes show false alarms, and white boxes show correct negatives. Figure 3 illustrates one forecast start date, lead time and ensemble member. The skill scores shown in Figure 4 onwards are calculated from the total number of hits, misses and false alarms at each lead time for every start date and ensemble member.

3 | RESULTS

The logical structure of the results is presented as follows: we first present the CSI scores for ACCESS-S2 precipitation in forecasting observed precipitation (Figure 4) and ACCESS-S2 IVT in forecasting observed

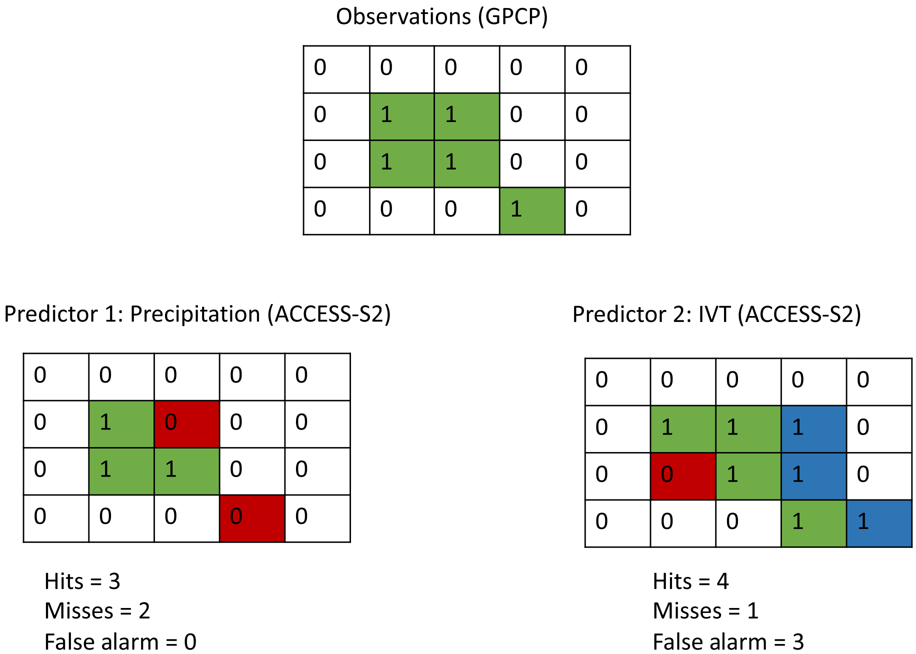

FIGURE 3 Example schematic of how the contingency tables were developed. Boxes represent a latitude–longitude grid with binary mask to indicate the occurrence of an event. Green boxes show where the predictor correctly predicted an event (i.e., a hit), red boxes show misses, blue boxes show false alarms and white boxes show correct negatives. [Colour figure can be viewed at wileyonlinelibrary.com]

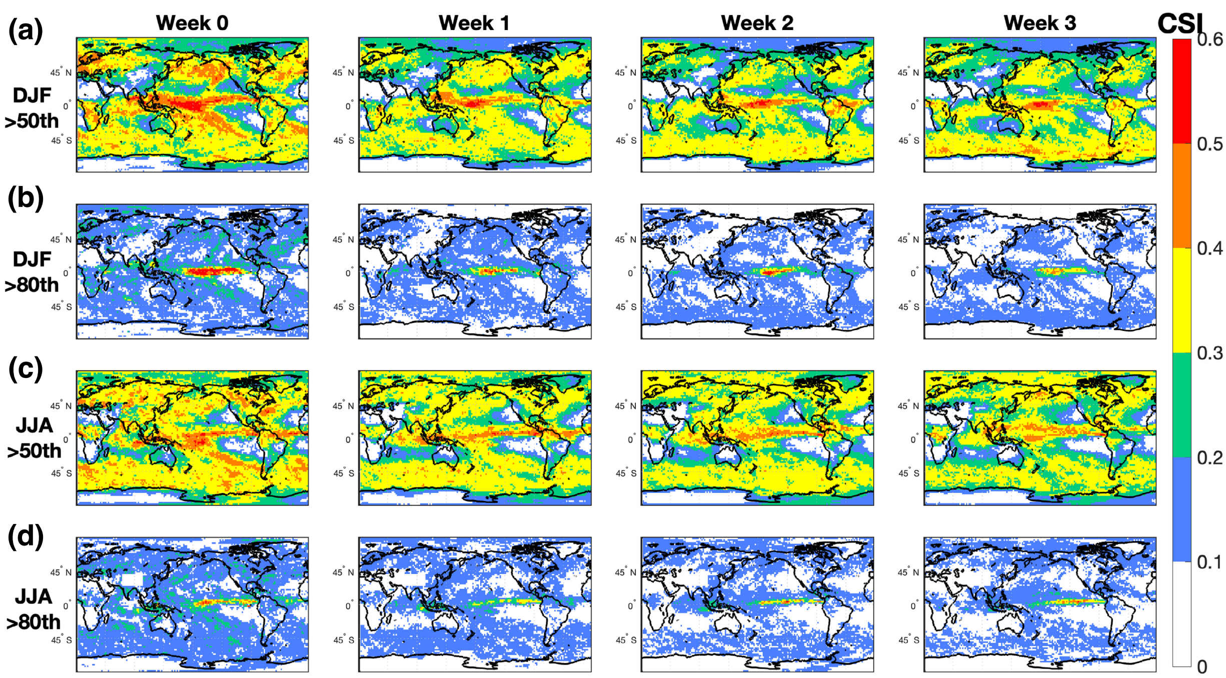

FIGURE 4 Critical Success Index for forecasting weeks with above-50th-percentile precipitation in (a) December–January–February (DJF) and (c) June–July–August (JJA), and above the 80th percentiles of precipitation in (b) DJF and (d) JJA using ACCESS-S2 verified against Global Precipitation Climatology Project (GPCP) precipitation. Week *n* indicates forecast lead time where week 0 is the first week of the forecast. [Colour figure can be viewed at wileyonlinelibrary.com]

IVT (Figure 5). Next, we present the difference between these two scores to highlight the skill in forecasting IVT compared to the skill in forecasting precipitation in ACCESS-S2 (Figure 6). The second hypothesis we test is that IVT could be used as a proxy for precipitation forecasts by presenting the CSI score where we use weekly mean observed IVT as a predictor for weekly total observed precipitation (Figure 7; using the method described in Figure 3). Finally, we show the key result for this study which is the CSI score for using ACCESS-S2 IVT to forecast observed precipitation (Figure 8) and the difference between the CSI scores obtained when using ACCESS-S2 precipitation and IVT as predictors for observed precipitation (Figure 9).

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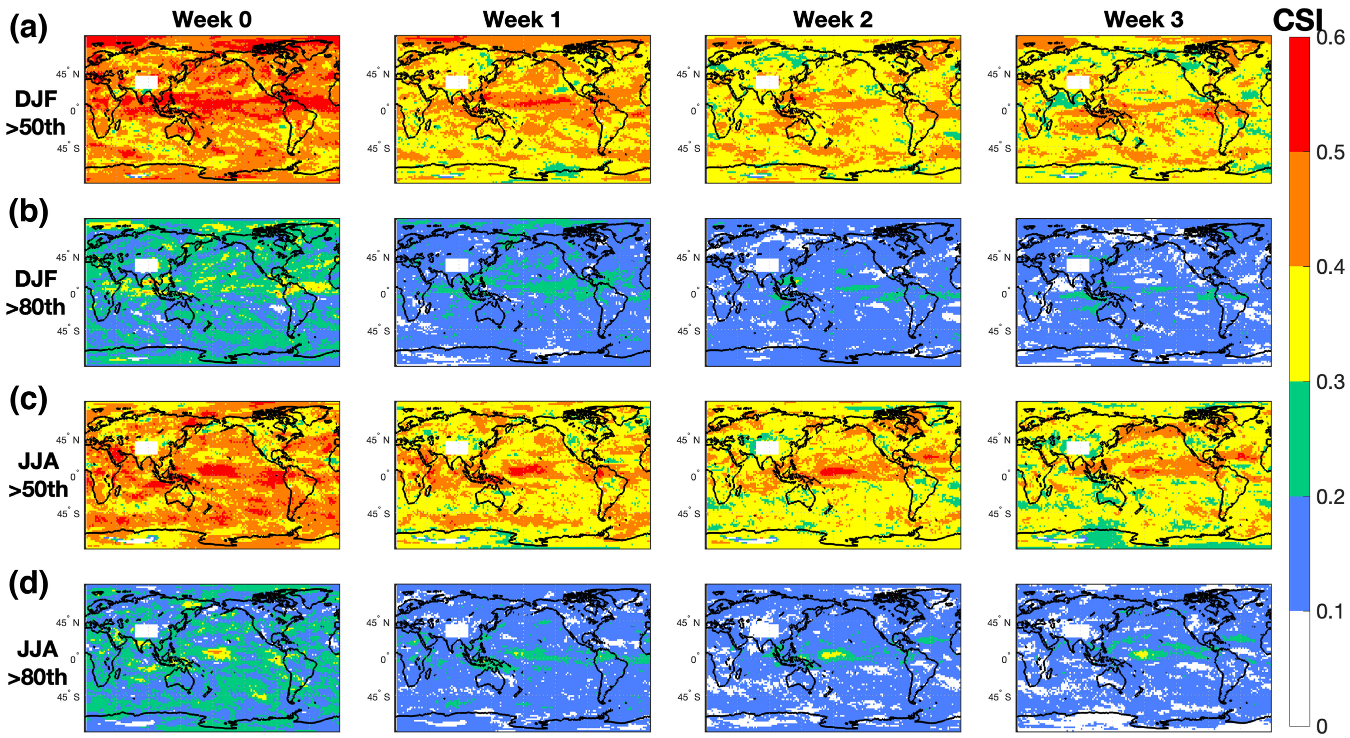

FIGURE 5 Critical Success Index for forecasting weeks with above-50th-percentile integrated water vapour transport (IVT) in (a) December–January–February (DJF) and (c) June–July–August (JJA), and above the 80th percentiles of IVT in (b) DJF and (d) JJA using ACCESS-S2 verified against ERA5 IVT. Week *n* indicates forecast lead time where week 0 is the week the forecast was initiated. The Tibetan Plateau and Himalayan Mountains have been masked due to high uncertainties with modelled IVT at those altitudes. [Colour figure can be viewed at wileyonlinelibrary.com]

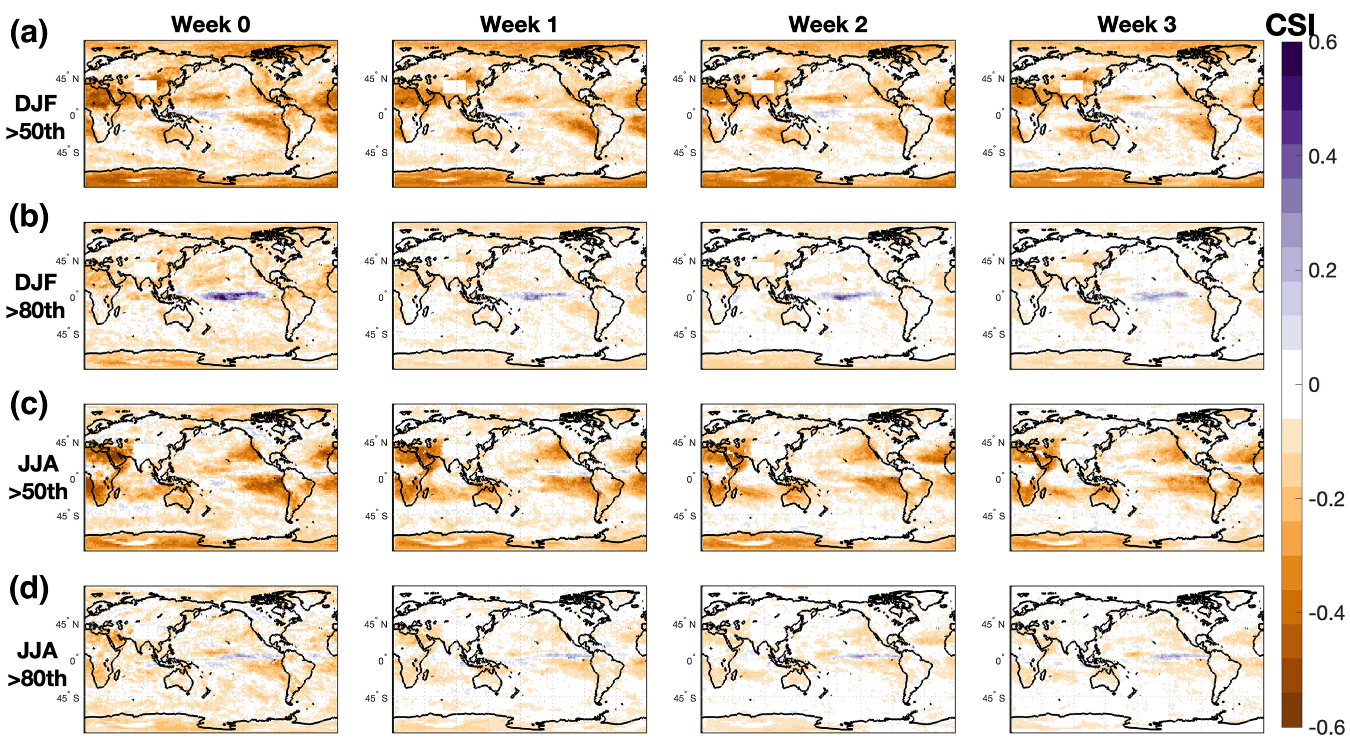

FIGURE 6 Difference in Critical Success Index (CSI) for forecasting precipitation versus forecasting integrated water vapour transport (IVT) above the 50th percentiles in (a) December–January–February (DJF) and (c) June–July–August (JJA), and above the 80th percentiles in (b) DJF and (d) JJA (i.e., difference between Figures 4 and 5). Positive values (purple) indicate that precipitation is forecasted with higher skill while negative values (orange) indicate that IVT is forecasted with higher skill. [Colour figure can be viewed at wileyonlinelibrary.com]

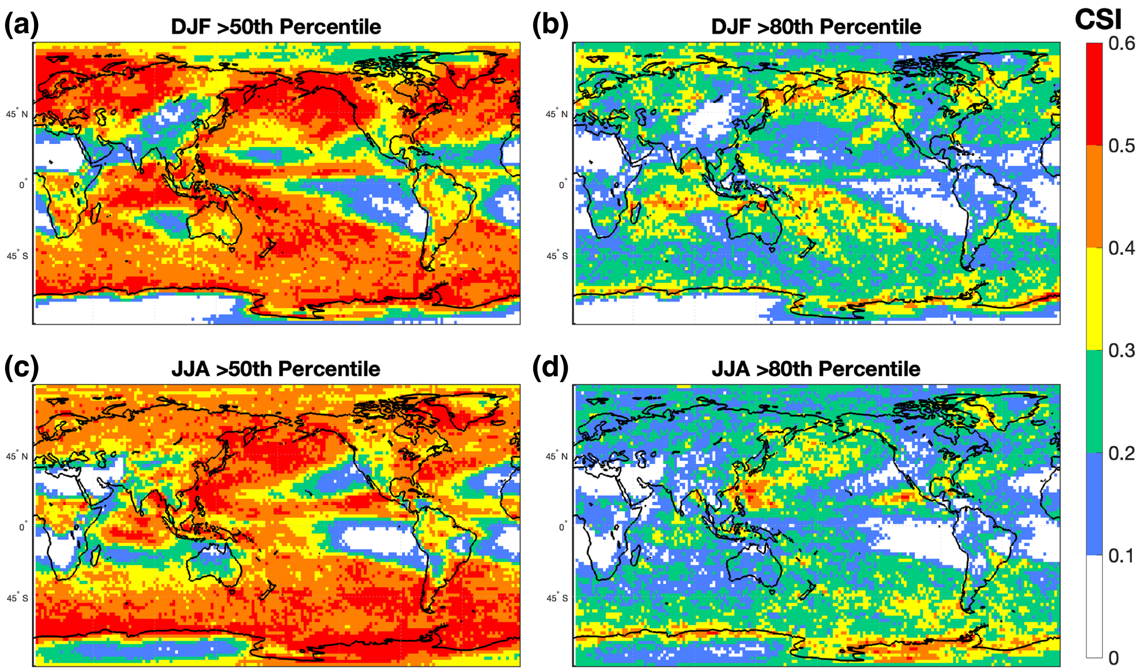

FIGURE 7 Critical Success Index skill score for predicting the occurrence of (a) above-50th-percentile precipitation in December–January–February (DJF), (c) June–July–August (JJA) and (b) above-80th-percentile precipitation in DJF, and (d) in JJA in Global Precipitation Climatology Project (GPCP) using ERA5 integrated water vapour transport (IVT). [Colour figure can be viewed at wileyonlinelibrary.com]

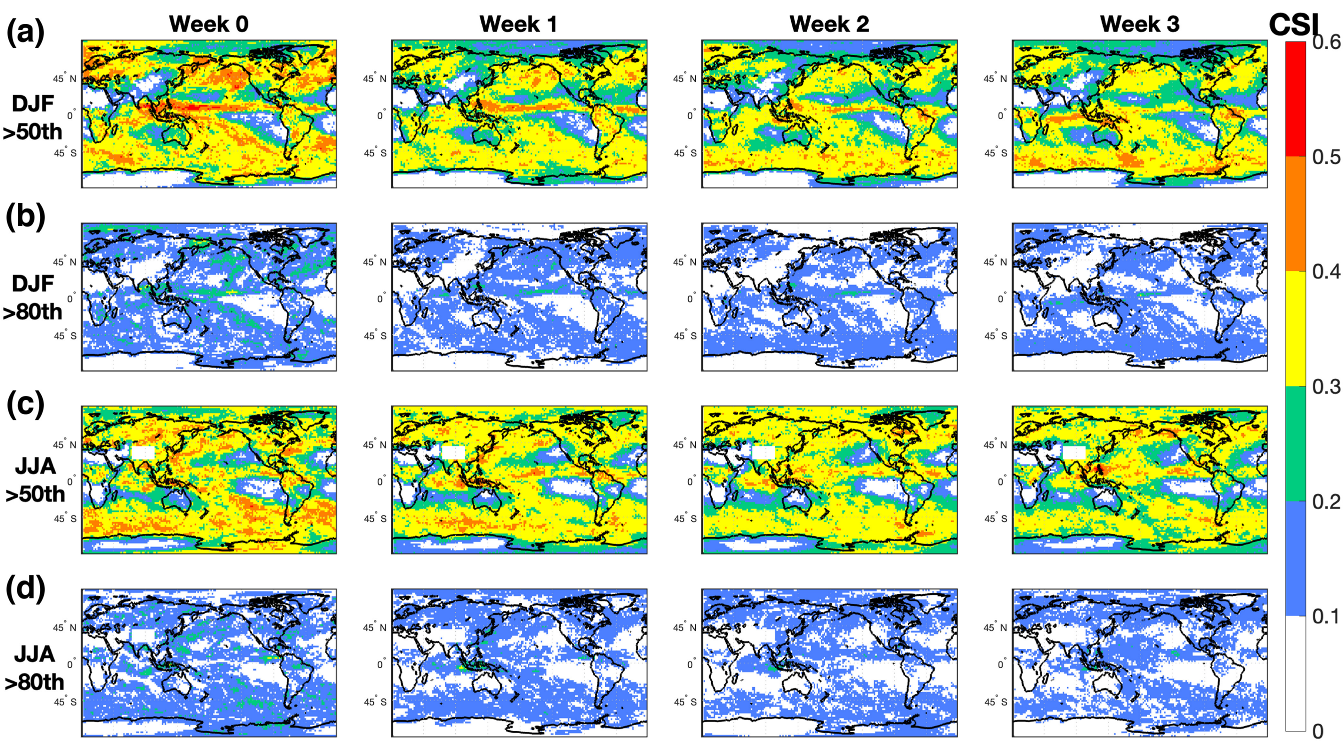

FIGURE 8 Critical Success Index for forecasting weeks with above-50th-percentile precipitation in (a) December–January–February (DJF), and (c) June–July–August (JJA), and above-80th-percentile precipitation in (b) DJF and (d) JJA using ACCESS-S2 integrated water vapour transport (IVT) as a predictor for precipitation. Predictions are verified against Global Precipitation Climatology Project (GPCP) precipitation. Week n indicates the forecast lead time as before. [Colour figure can be viewed at wileyonlinelibrary.com]

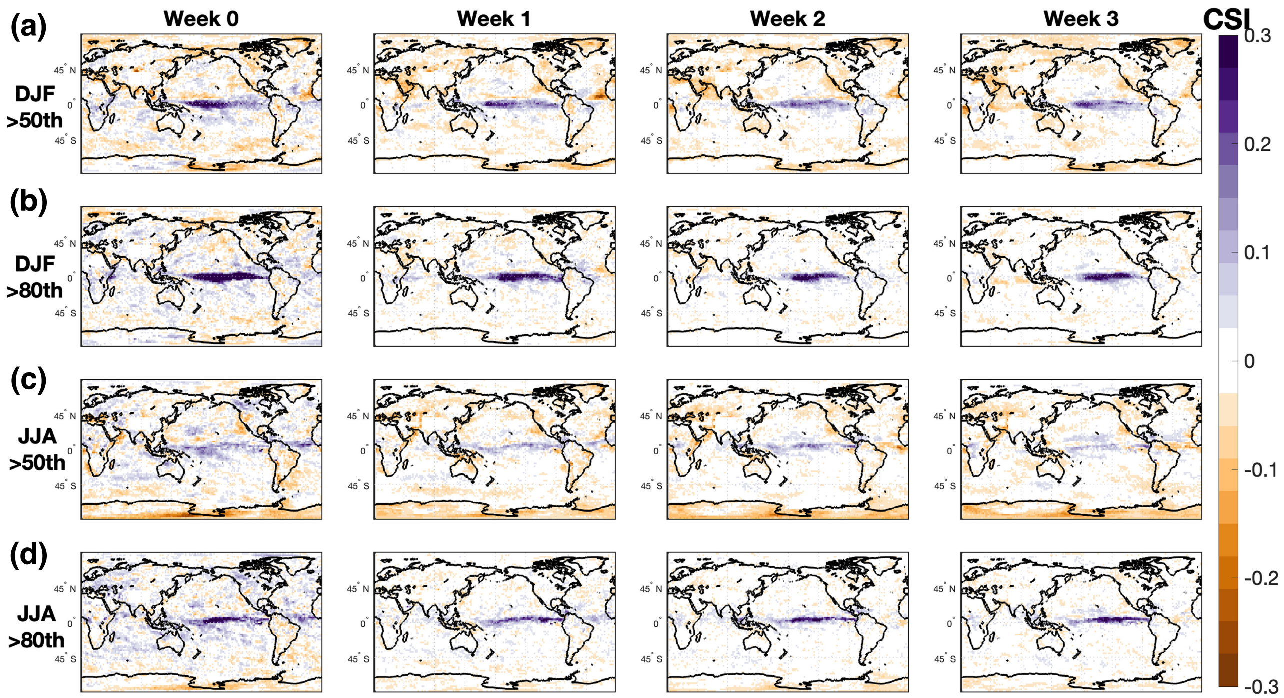

FIGURE 9 Difference between ACCESS-S2 rainfall and ACCESS-S2 integrated water vapour transport (IVT) Critical Success Index for predicting above 50th percentiles of precipitation in (a) December–January–February (DJF), and (c) June–July–August (JJA), and above 80th percentiles in (b) DJF and (d) JJA (i.e., difference between Figures 4 and 8). Purple colours indicate that ACCESS-S2 rainfall has higher skill and orange colours indicate that ACCESS-S2 IVT has higher skill. Week *n* indicates the forecast lead time. Positive values (purple) indicate that precipitation is a better predictor while negative values (orange) indicate that IVT is a better predictor. [Colour figure can be viewed at wileyonlinelibrary.com]

3.1 | How well does ACCESS-S2 forecast precipitation and IVT?

Figure 4 presents the CSI for forecasting weeks above the 50th and 80th percentiles of weekly precipitation using ACCESS-S2 precipitation verified against GPCP precipitation. The model generally performs better in regions with higher precipitation such as over the equatorial Pacific Ocean. Forecasts of above-median rainfall are considerably better than forecasts of above 80th percentile rainfall. As illustrated in Figure 6, ACCESS-S2 generally forecasts future IVT better than future precipitation. In particular, IVT is forecast with higher skill over the northeastern Pacific winter storm tracks where ARs (i.e., regions of high IVT) are responsible for a considerable proportion of western US winter rainfall at all lead times (Ralph *et al.*, 2006).

These results support the hypothesis that model IVT has higher forecast skill than model precipitation over large regions of the globe. Similar results were also shown by Lavers *et al.* (2014) over Europe and Lavers *et al.* (2016) over North America using the ECMWF forecasting system on NWP time-scales. They suggest this is likely due to IVT being associated with synoptic-scale processes, which models can simulate better than the mesoscale processes that influence precipitation generation.

3.2 | Can observed IVT be used as a proxy for precipitation?

To test whether modelled IVT could be used as a predictor for precipitation we first test whether there is skill in using observed IVT as a predictor for observed precipitation (Figure 7). As in the previous figures, forecast skill is lower for above 80th percentile rainfall when using above 80th percentile IVT as a proxy. These results could be interpreted as the upper limit of skill that could be obtained from using IVT to predict precipitation; however, this interpretation should only apply to regions where observations are more robust such as at lower latitudes and over land (Manton *et al.*, 2020).

3.3 | Can modelled IVT be used as a proxy for precipitation?

After establishing the skill of ACCESS-S2 in predicting IVT and precipitation, and that using IVT as proxy for precipitation has skill in the observations, we now test whether modelled IVT can be used as a predictor for precipitation up to three weeks ahead. Importantly, we assess whether using IVT as a predictor for precipitation provides any additional skill for precipitation forecasts given that IVT has a higher forecast skill than precipitation over large regions of the globe. The rationale for this is that IVT could be a useful additional diagnostic for warning of extreme precipitation events. Figure 8 shows the CSI score for using ACCESS-S2 IVT as a predictor for precipitation verified against GPCP precipitation. To compare the two predictors (ACCESS-S2 IVT and ACCESS-S2 precipitation), we plotted the difference between Figures 4 and 8 to show which predictor has a higher CSI value for forecasting observed precipitation (Figure 9). The purple regions in Figure 9 indicate locations where using the model precipitation leads to a higher skilled forecast of observed precipitation and the orange indicates locations where using the model IVT as a proxy for precipitation actually leads to a higher skilled forecast. Figure 10 illustrates the same information as Figure 9, but we show the percentage increase (instead of absolute difference) in the forecast skill from using IVT as proxy for precipitation relative to the using the model precipitation.

Precipitation is generally a better predictor in DJF except over some key regions including the Middle East and northeast Pacific midlatitude storm tracks at longer leads. These are regions where synoptic-scale systems involving high IVT are a key source of rainfall in DJF (Ralph *et al.*, 2006; Esfandiari & Lashkari, 2020). This is not particularly surprising; however, it does provide some physical reasoning for the results we are observing and why using IVT as a predictor may be useful in some regions but not others.

During JJA, IVT performs well as a predictor off the southwest coast of North America and the Middle East again as well as over parts of South America where ARs are most active in austral winter (Viale *et al.*, 2018). The results also indicate skill in using IVT to forecast winter precipitation over Antarctica, especially West Antarctica. Strong moisture flux from lower latitudes over Antarctica can drive considerable wintertime melting (Wille *et al.*, 2019); however, satellite observations of precipitation are prone to considerable uncertainties at high latitudes (Manton *et al.*, 2020).

4 | DISCUSSION

The results shown here suggest that ACCESS-S2 has greater skill in forecasting IVT than precipitation and in some regions IVT can be used as a proxy for precipitation at lead times of 2–4 weeks to produce more skilful forecasts. However, model precipitation is more skilled during the week of model initialisation and over regions of high convection. It is worth noting that over large

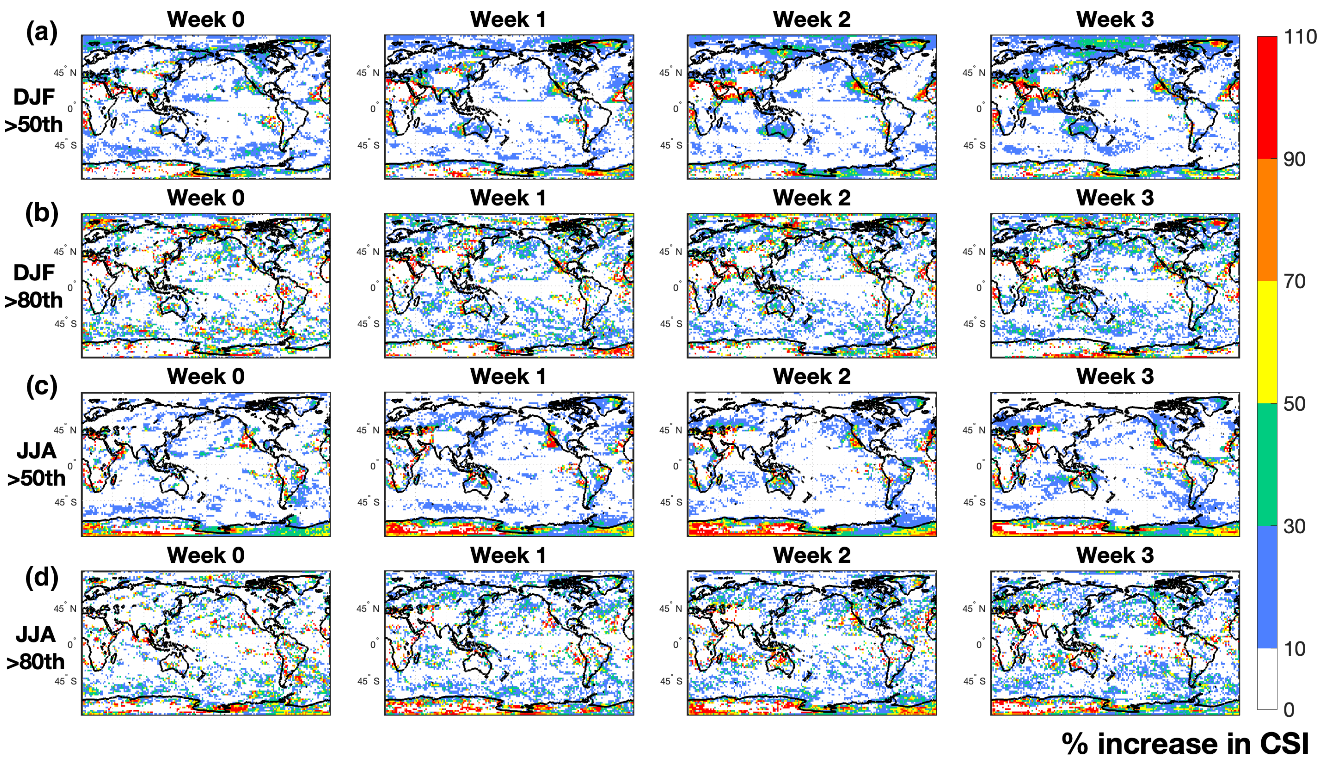

FIGURE 10 Same as Figure 9, but the results are presented as percentage increase in Critical Success Index (CSI) from using integrated water vapour transport (IVT) as a predictor relative to using model precipitation as a predictor for precipitation. [Colour figure can be viewed at wileyonlinelibrary.com]

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regions, especially over the ocean, there is not much difference in the skill between using precipitation to forecast precipitation and using IVT to forecast precipitation.

The skill scores for predicting extreme (>80th percentile) precipitation weeks are weaker than the scores for predicting the above-median precipitation weeks. This not unique to the use of IVT. Subseasonal prediction of extreme precipitation events is a major forecasting challenge (Vitart *et al.*, 2019; King *et al.*, 2020a). Moreover, the heaviest precipitation totals require ample moisture, adequate uplift and often slow-moving or stalled weather systems (Barnes *et al.*, 2023; King *et al.*, 2023). The use of IVT only captures the moisture component and therefore may have limitations in identifying the heaviest precipitation events.

Previous work examining the subseasonal forecasting skill for precipitation in all S2S models that were part of the World Climate Research Programme S2S Prediction project (Vitart *et al.*, 2017) also demonstrated skill in precipitation forecasts during weeks 1–2, but the skill diminished during weeks 3–4, except for over the tropical oceans (de Andrade *et al.*, 2019). They suggested the inherent variability of extratropical weather and model deficiencies in capturing tropical–extratropical processes may be to blame for the lack of skill outside the tropics. However, our findings indicate that ACCESS-S2 is capable of forecasting IVT over large subtropical and extratropical regions beyond two weeks (Figure 6). This indicates that the representation of extratropical weather systems may not be the main source of this uncertainty, but rather the conversion from atmospheric water vapour to precipitation in environments where forced rather than free convection is the key source of uplift for precipitation.

Furthermore, regions where IVT appears to show higher skill than model precipitation for forecasting precipitation also tend to be associated with a dry bias in precipitation in the Met Office Unified Model Global Atmosphere, which is the atmospheric model component used in ACCESS-S2 (Walters *et al.*, 2011; Walters *et al.*, 2017). Similarly, the northern Indian Ocean and off the northwest coast of Africa exhibit a positive bias in reflected shortwave radiation (in DJF) which is indicative of too much stratocumulus cloud and light rain (Walters *et al.*, 2011). This suggests that the higher skill that results from using IVT to predict precipitation in these regions may be related to uncertainties in the convection parameterisation, and that the dry biases in the Unified Model Global Atmosphere could be attributed to uncertainties in the parameterisation scheme rather than uncertainties in simulating the large-scale processes. This, of course, is worth further investigation in future work before robust conclusions can be drawn.

5 | CONCLUSION

In this study, we have examined the potential of IVT as a tool to enhance subseasonal prediction skill for forecasting precipitation using ACCESS-S2. We showed that ACCESS-S2 can simulate weeks with above-median IVT and precipitation reasonably well but has low skill in forecasting weeks with both IVT and precipitation above the 80th percentile. There is considerable spatial and seasonal variability in the IVT and precipitation skill.

However, the effectiveness of using IVT as a predictor for precipitation depends on the specific location. It works best in regions where high moisture flux plays a critical role in precipitation generation. In contrast, in areas where the atmosphere is already highly saturated, such as over the tropical Pacific Ocean, IVT is less useful. Therefore, our intention is not to propose that IVT be used instead of modelled precipitation as a predictor, but rather in conjunction with, to potentially enhance the skill of rainfall forecasts on multiweek time-scales. Combining the forecasts in such a way that they counteract each other's error could potentially lead to better operational forecasts of rainfall. The challenging aspect would be determining the weighting for the predictors, which would likely need to be dependent on location and season. Machine learning may be a useful tool for future analyses of this kind. We also note that this analysis is based on the raw hindcast data and operational bias-correcting techniques would potentially increase the skill scores reported here.

Using an approach that focuses on large-scale horizontal moisture flux may be a potential avenue for extracting additional skill from subseasonal models at longer lead times. Synoptic-scale weather systems can be directly modelled whereas precipitation is subject to parameterisation schemes, which may add additional uncertainty. Further research is required before this method could become operational, but our work suggests a potential pathway for improving rainfall forecasts on subseasonal time-scales, which could have significant societal benefits.

AUTHOR CONTRIBUTIONS

Kimberley Reid: Conceptualization; formal analysis; investigation; methodology; visualization; writing – original draft; writing – review and editing. **Debbie Hudson:** Conceptualization; data curation; methodology; supervision; writing – review and editing. **Andrew King:** Conceptualization; methodology; supervision; writing – review and editing. **Todd P Lane:** Methodology; supervision; writing – review and editing. **Andrew G Marshall:** Data curation; writing – review and editing.

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DATA AVAILABILITY STATEMENT

Link to ERA5 data: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=form. ACCESS-S2 data: https://geonetwork.nci.org.au/geonetwork/srv/eng/catalog.search#/metadata/f3311_4920_0252_8073. GPCP Data: https://climatedataguide.ucar.edu/climate-data/gpcp-daily-global-precipitation-climatology-project.

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