

Lawrence Berkeley National Laboratory

LBL Publications

Title

Extreme Water Vapor Transport During the March 2021 Sydney Floods in the Context of Climate Projections

Permalink

<https://escholarship.org/uc/item/67n1d9xi>

Journal

Geophysical Research Letters, 48(22)

ISSN

0094-8276

Authors

Reid, Kimberley J
O'Brien, Travis A
King, Andrew D
[et al.](#)

Publication Date

2021-11-28

DOI

10.1029/2021gl095335

Copyright Information

This work is made available under the terms of a Creative Commons Attribution-NonCommercial License, available at <https://creativecommons.org/licenses/by-nc/4.0/>

Peer reviewed

1 **Extreme Water Vapor Transport during the March 2021 Sydney**
2 **Floods in the Context of Climate Projections**

3
4 **Kimberley J. Reid¹, Travis A. O'Brien^{2,3}, Andrew D. King¹ and Todd P. Lane¹**

5
6 *¹Australian Research Council Centre of Excellence for Climate Extremes and School of*
7 *Geography, Earth and Atmospheric Sciences, The University of Melbourne, Parkville,*
8 *Australia*

9 *²Earth and Atmospheric Sciences Department, Indiana University, Bloomington, IN, USA*

10 *³Climate and Ecosystem Sciences Division, Lawrence Berkeley National Lab, Berkeley, CA,*
11 *USA*

12
13 **Abstract**

14 During March 2021, large regions of Eastern Australia experienced prolonged heavy rainfall
15 and extensive flooding. The maximum daily mean column integrated water vapor transport
16 (IVT) over Sydney during this event was within the top 0.3% of all days since 1980, and the
17 10-day mean IVT was in the top 0.2%. In this study, we have examined the change in
18 frequency of extreme IVT events over Sydney in sixteen climate models from the Coupled
19 Model Intercomparison Project 6 under two Shared Socioeconomic Pathways (SSP245 and
20 SSP585). Generalized Extreme Value modelling was used to further analyze the change in
21 frequency of extreme IVT events. We found the probability of long duration high IVT events
22 is projected to increase by 80% at the end of the century, but the future change in IVT is
23 correlated to the rate of global and regional warming in each model.

24
25 **Plain Language Summary**

26 During March 2021, large regions of Eastern Australia experienced prolonged heavy rainfall
27 and extensive flooding. This was associated with strong horizontal water vapor transport over
28 this region that persisted for approximately 10 days. The amount of water vapor transported
29 over Sydney during this event was extreme and within the top 0.3% of all days since 1980. In
30 this study, we used climate models to project how much more often events such as these may
31 occur by the end of the 21st Century under two greenhouse gas emission scenarios. We found
32 that the probability of long duration high water vapor transport over Sydney, as in March
33 2021, may increase by 80%.

34 **Key Points**

35

36 Sydney's March 2021 floods were associated with persistent high water vapor transport.

37

38 The probability of long-duration high IVT events should increase by the end of the 21st
39 Century.

40

41 Differences in climate sensitivity within the CMIP6 ensemble may increase the spread of
42 moisture flux projections.

43

44 **Introduction**

45 Between the 17th and 24th of March 2021, much of eastern Australia experienced heavy

46 rainfall and wide-spread flooding. During that period, the entire coastline of New South

47 Wales (NSW) received more than 200mm of rain and in some locations more than 400mm of

48 rain fell (The Bureau of Meteorology, 2021). Sydney (Observatory Hill Automatic Weather

49 Station) recorded 212.4mm of rain between the 19th-21st of March 2021 with 110.4mm falling

50 on the 21st.

51

52 The March 2021 event was associated with a blocking anticyclone in the Tasman Sea; the
53 easterly flow advected moist air over the east coast (Fig 1a) followed by the convergence of
54 moisture from two regions (Fig1b-c). Most of the rainfall records occurred on the 23rd of
55 March when the intense Atmospheric River moved over the east coast. This event received
56 much media attention and public commentary about the potential role of climate change in
57 this event. However, weather events like this are not necessarily uncommon. For example, in
58 January 2012, a blocking high in the Tasman followed by strong southward moisture flux led
59 to wide-spread flooding over eastern NSW (The Bureau of Meteorology, 2012). For both
60 events the strength and duration of the moisture flux is likely of critical importance. The
61 purpose of this paper is to place this recent event in the context of the prior observational
62 record and future climate projections by examining the water vapor transport.

63

64 Atmospheric rivers (ARs) are associated with localized regions of high integrated vapor
65 transport (IVT), which is defined as the column-averaged horizontal transport of water vapor
66 mass. A northwesterly AR impacted Sydney between the 21st-23rd of March. However, there
67 was high IVT over Sydney in the days prior which does not continuously satisfy the criteria
68 for an AR. For this reason, we focus on IVT throughout this study.

69

70 It has been established that IVT is a strong predictor for precipitation (Lavers & Villarini,
71 2015) and Rutz et al., (2014) showed that the spatial extent of IVT correlated more strongly
72 with precipitation than total column water vapour over land. Lavers et al., (2014) found that
73 large scale horizontal moisture transport is more predictable than precipitation and could be
74 used to extend the forecast lead time of extreme precipitation by up to 3 days in some
75 locations over Europe. There is a large body of literature documenting the association of IVT,

76 extreme rainfall, flooding and ARs worldwide (e.g. Corringham et al., 2019; Gimeno et al.,
77 2016; Reid et al., 2021; Viale et al., 2018).

78

79 Understanding extreme rainfall and flooding events around Sydney is important due to its
80 large population and economic value (Nicholls, 2006), but precipitation, and especially
81 extreme precipitation, is poorly simulated in global climate models (Stephens et al., 2010).
82 Given the strong relationship between IVT and precipitation, the prominent role of IVT
83 during the March 2021 (and previous) East Australian flooding, and the higher predictability
84 of IVT compared to extreme precipitation (Lavers et al., 2014), understanding changes to
85 IVT in a warmer world is necessary for preparing for future hydrological extremes in this
86 region. Hence, the aim of this paper is to understand IVT over Sydney in the context of
87 climate projections.

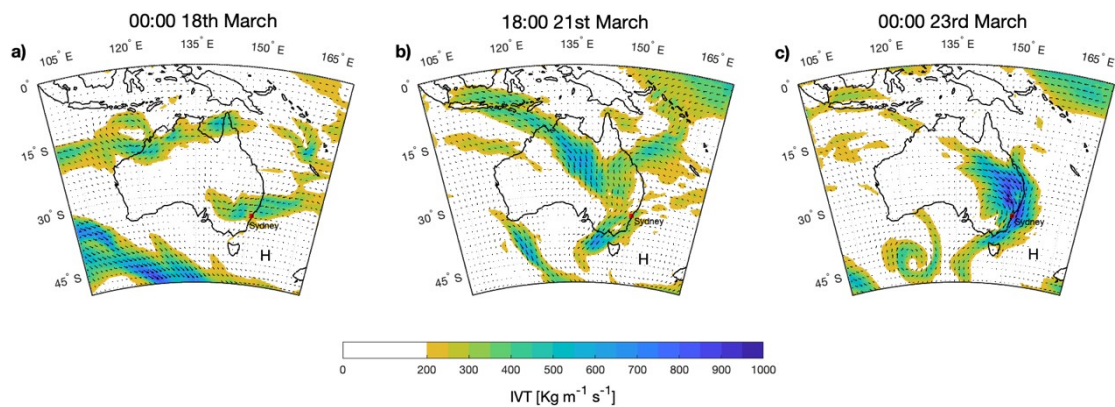
88

89 Warner et al., (2015) analysed IVT projections along the West Coast of the USA in the
90 Coupled Model Intercomparison Project (CMIP) 5 models under Representative
91 Concentration Pathway (RCP) 8.5 and found significant increases in water vapor transport as
92 anthropogenic greenhouse gas concentrations rise. Studies of Southern Hemisphere ARs have
93 suggested a poleward shift in ARs in recent decades, and hence regions of enhanced IVT, due
94 to changes in the location of the westerly jet (Ma et al., 2020; Swart et al., 2015). However,
95 projections of IVT over Australia have not been adequately assessed.

96

97 In this paper, we evaluated the CMIP6 multi-model ensemble of IVT over Sydney
98 (Australia's most populated city) and used the best performing models to project the end-of-
99 century IVT response to 'middle-of-the-road' and 'business-as-usual' climate change

100 scenarios using simulations from the ScenarioMIP (Eyring et al., 2016). We also use
101 Generalized Extreme Value (GEV) modelling to estimate the change in likelihood of extreme
102 IVT events that are a similar duration and intensity to the March 2021 event under global
103 warming. Finally, we assessed the role that the rate of global and regional warming in models
104 may contribute to uncertainty in IVT projections.
105



107 *Figure 1: Integrated Water Vapour Transport from ERA5 at a) 0000z 18th March, b) 1800z*
108 *21st March and c) 0000z 23rd March 2021. Colors show the magnitude and vectors show the*
109 *direction of IVT. The H symbol indicates the quasi-stationary high pressure.*

110

111 **Methods**

112 We used daily IVT (determined from hourly data) between 1980-2014 (end of the historical
113 model runs) from ERA5 Copernicus Climate Change Service (Hersbach et al., 2019) along a
114 transect of the East Australian Coast (28°S to 38°S) to evaluate the climatology of IVT in this

115 region and determine how unusual the March 2021 event was. We also used daily
116 atmospheric surface temperature, specific humidity, and horizontal winds from sixteen
117 CMIP6 models (Supplementary Table 1) and evaluated IVT by calculating the mass-
118 weighted integral of the product of specific humidity and horizontal winds between 300hPa
119 and 1000hPa (or the surface where topography exceeded the 1000hPa level). Only the first
120 ensemble member was used, as in Warner et al., (2015), to avoid biasing towards models
121 with more ensemble members. We used the historical (1980-2014) run for model evaluation
122 and our climate baseline, and the Shared Socioeconomic Pathways (SSP) SSP245 and
123 SSP585 future scenarios (2080-2100; O'Neill et al., 2016). We chose to focus on the period
124 between 2080 and 2100 to maximise the warming signal and better understand the climate
125 change influence on IVT.

126

127 All models and the ERA5 reanalysis were regridded to a $2^\circ \times 2^\circ$ horizontal resolution using
128 bilinear interpolation. We used an initial domain of 150°E - 154°E longitude, and 28°S to 38°S
129 latitude. The IVT was averaged across the longitude dimension to produce a transect of IVT
130 approximately parallel to the East Coast of Australia. We then focussed on the grid centered
131 on 34°S , which includes Sydney. Sixteen CMIP6 models were chosen based on data
132 availability. We used quantile-quantile analysis and calculated the root mean squared error
133 (RMSE) of the historical model runs versus ERA5 quantiles (Supplementary Table 1) and the
134 reference line (ERA5 versus ERA5) similar to Perkins et al., (2007). We calculated the
135 RMSE for all quantiles and for just the upper quartile. We then selected the best eight models
136 based on which models produced the lowest RMSE over the whole distribution and the upper
137 quartile, which happened to be the same models. Model evaluation is discussed further in the
138 results section.

139

140 We calculated the March-April-May (MAM) maximum of the 10-day average IVT
141 (IVTx10day) for each model as that was the approximate duration for the March 2021 event.
142 We fit a non-stationary GEV to the IVTx10day combined data from the historical and
143 SSP245 simulations and historical and SSP585 simulations, modelling the location parameter
144 (μ) as varying linearly in time (t) as in Risser and Wehner, (2017): $\mu(t) = c_\mu t + \mu_0$. The
145 posterior distribution was sampled using a Bayesian approach and the Emcee package
146 (Foreman-Mackey et al., 2019). The quasi-uniform prior restricts the posterior distribution to
147 Type I (Gumbel) and Type II (Fréchet) distributions, based on the prior assumptions that the
148 distribution of IVTx10day should be positively skewed. Ten Markov Chain Monte Carlo
149 (MCMC) chains for 11,000 steps were run retaining only the final 100 samples. This
150 calculation was repeated on each of the CMIP6 models. This results in 1,000 estimates i of
151 the GEV model parameters $c_\mu^{i,m}$, $\mu_0^{i,m}$ (*location* \vee *mean*), $\sigma^{i,m}$ (*scale* \vee *variance*),
152 $\xi^{i,m}$ (*shape* \vee *skewness*) for each CMIP6 model m .

153

154 We do a similar GEV fit to ERA5 data and calculate the percentile of the March 2021 event;
155 we use the mode of the percentiles as the 2021 reference value from which to calculate
156 probability ratios. We then determine the percentile value of IVT, X_t , in the year 2021 from
157 the model-based MCMC samples. We refer to these IVT values as $IVT_0^{i,m}$. We calculate the
158 Probability Ratio (PR) of such an IVTx10day value occurring in the years 2080-2100 as:

159

$$160 \quad PR^{i,m} = \frac{P\left(IVT > IVT_0^{i,m} \mid t=2021, c_\mu^{i,m}, \mu_0^{i,m}, \sigma^{i,m}, \xi^{i,m}\right)}{P\left(IVT > IVT_0^{i,m} \mid t=2100, c_\mu^{i,m}, \mu_0^{i,m}, \sigma^{i,m}, \xi^{i,m}\right)}$$

161

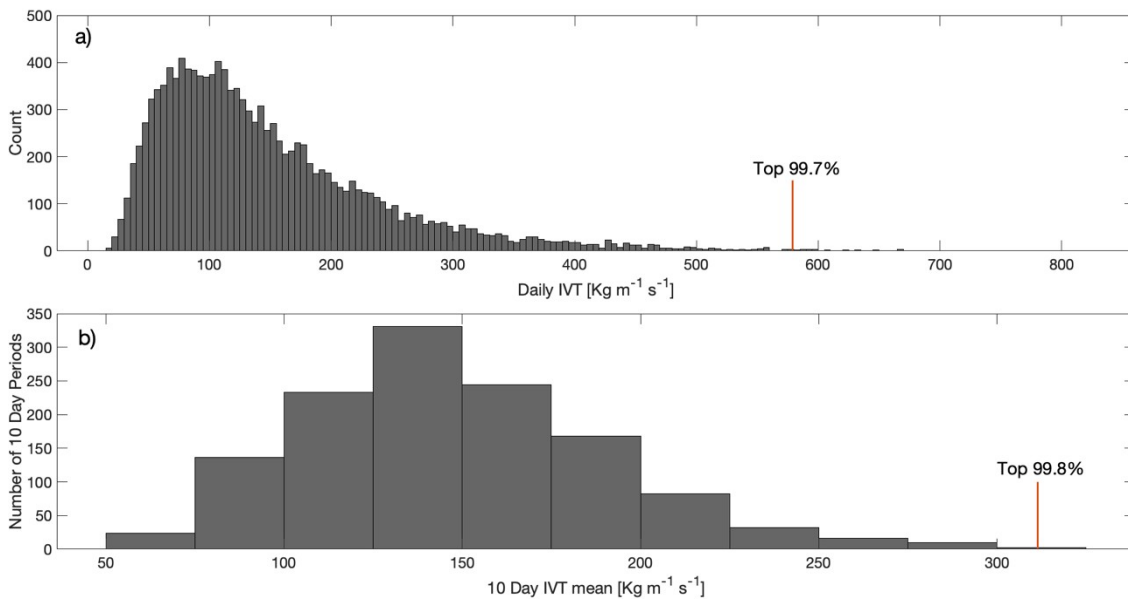
(1)

162 $\hat{c} \frac{1 - X_i/100}{P(IVT > IVT_0^{i,m} | t \in (2080, 2100), c_\mu^{i,m}, \mu_0^{i,m}, \sigma^{i,m}, \xi^{i,m})}$

163

164 **Climatology and Context**

165



167

168 *Figure 2: Histograms of a) daily mean IVT over Sydney and b) 10-day mean IVT between*
 169 *1980-2014 from ERA5. The red lines indicate the peak daily (a) and 10-day mean (b) IVT*
 170 *during the March 2021 flooding event and the values above the red lines are the percentiles*
 171 *of that IVT value relative to the climatology.*

172

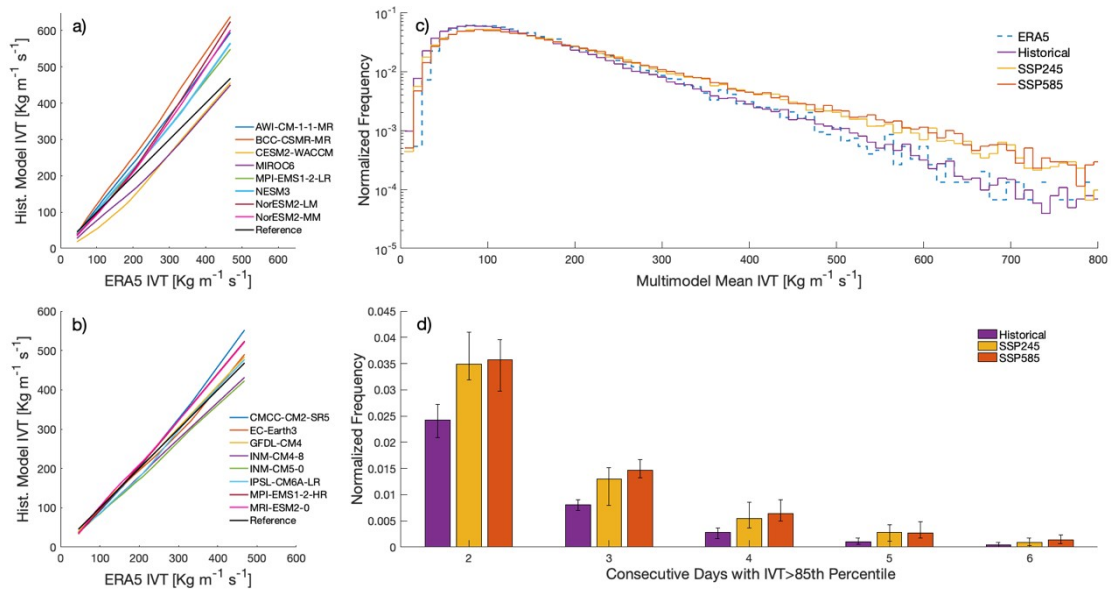
173 Figure 2 shows the distribution of IVT values over Sydney between 1980-2014 for all
 174 seasons. Extreme IVT events are not limited to MAM so we include all seasons for the
 175 analysis in Figures 2 and 3. The climatology of IVT indicates that water vapor flux during

176 this flooding event was unusual in both peak intensity and persistence (indicated by the 10-
 177 day mean IVT). Over the Sydney region, the maximum daily mean IVT was in the top 0.3%
 178 and the 10-day mean IVT was the 3rd highest since 1980 (Figure 2b). The two 10-day mean
 179 IVT events that exceeded the March 2021 event were also associated with widespread heavy
 180 rainfall and flooding. Similar, to the 2021 event, both events were associated with a large-
 181 scale cloudband extending from the northwest (satellite imagery; not shown). The rank of the
 182 March 2021 IVT in the climatology indicates that this was indeed an extreme IVT event as
 183 well as an extreme rainfall and flooding event. The next section of this paper looks at how
 184 IVT over these locations may change with anthropogenic climate change. We note that we do
 185 not observe a trend in IVT over the historical period in ERA5 (1980-2014) for this domain
 186 and there is strong interannual variability in annual mean and maximum IVT over Sydney.

187

188 Future Projections of IVT

189



191

192

193 *Figure 3: Quantile-quantile plot of ERA5 IVT and historical model IVT [$\text{Kg m}^{-1} \text{s}^{-1}$] for the*
194 *worst 8 (a) and best 8 (b) models at 34S. The black line represents the ERA5 IVT quantiles*
195 *plotted against itself which serves as the reference line. c) Semi-log probability distribution*
196 *of multimodel mean IVT at 34S in the historical 1980-2014 (purple), SSP245 2080-2100*
197 *(yellow) and SSP585 2080-2100 (orange) model runs, and ERA5 IVT distribution 1980-2014*
198 *(blue dashed line). d) Consecutive days exceeding the 85th percentile IVT in the historical run*
199 *of each model for the historical (purple), SSP245 (yellow) and SSP585 (orange) scenarios.*
200 *Bar values are the multimodel mean while error bars represent the model spread. All*
201 *multimodel means only include the top 8 models.*

202

203 We evaluated the model simulations of IVT over Sydney by comparing the probability
204 distributions of each model to the probability distribution of IVT in ERA5. Figures 3a-b show
205 the quantile-quantile plot of ERA5 IVT versus each model. The black line is the ERA5
206 distribution plotted against itself which serves as a reference line. The closer the models are
207 to this reference line the better they simulate the observed distribution of IVT over Sydney.
208 The eight best-performing models are displayed in Figure 3b. The model spread and
209 displacement from the black reference line is considerably smaller in Figure 3b compared to
210 Figure 3a. The multimodel mean values calculated in subsequent figures only incorporate the
211 best eight models.

212

213 The models typically have a negative IVT bias at lower values. However, the models perform
214 well above the commonly used IVT threshold for defining ARs ($250 \text{Kg m}^{-1} \text{s}^{-1}$ [Shields et al.

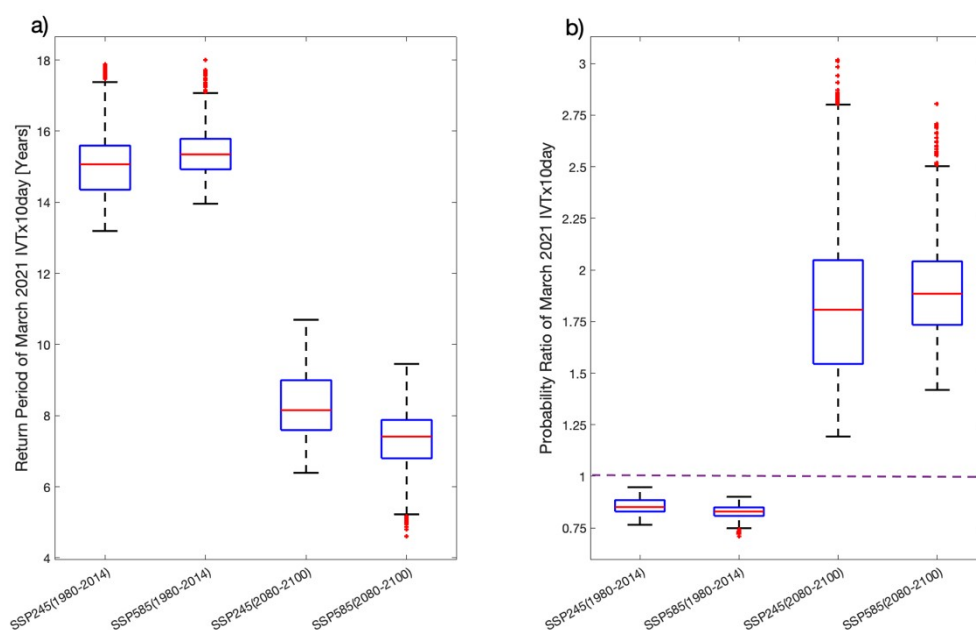
215 2018]), which is when we expect to observe more impactful rain events. The worst
216 performing model deviates from the ERA5 99th percentile IVT by $130\text{Kg m}^{-1} \text{s}^{-1}$ (BCC-
217 CSM2-MR), while the best performing model deviates by only $15.5\text{Kg m}^{-1} \text{s}^{-1}$ (EC-Earth3).
218 We note that we did also examine the projections in all models, including the models that
219 performed poorly in our historical evaluation, and found the sign of future IVT change was
220 consistent across all models though the magnitude varied considerably. The range of IVT
221 magnitude projections narrowed when we excluded the weaker models. We include versions
222 of Figures 3C and 4 that incorporate all models in the Supplementary Material.

223

224 After evaluating the models, we could then analyze their IVT projections with some
225 confidence. Figure 3c shows the multimodel mean normalized probability distribution of IVT
226 for the historical period (1980-2014) and future (2080-2100) under SSP245 and SSP585. The
227 probability distribution is shown as a semi-log plot so that the relative difference in frequency
228 at the extreme end of the distribution is clearer. The distribution in ERA5 is also shown in
229 blue. We see a positive shift in both future distributions with respect to the historical period.
230 Above about $300 \text{Kg m}^{-1} \text{s}^{-1}$, the difference in frequency between the historical and future IVT
231 values exceeds the difference between the frequency in the historical and ERA5 distributions.
232 This indicates that there is a robust projected increase in extreme IVT by the end of the
233 century under both SSPs, however the magnitude of change in the median IVT is much more
234 uncertain. The question of when a climate change signal in IVT emerges over this region is a
235 potential avenue for future research as we found a minimal shift in the IVT probability
236 distribution between 2030-2050, but a stronger signal between 2080-2100 (Supplementary
237 Figure 3).

238

239 The duration of high IVT over a region is an important factor that determines the severity of
 240 extreme hydrological events and was particularly notable during the March 2021 floods.
 241 Therefore, we examined the projected future changes to the duration of high IVT events in
 242 Figure 3d. High IVT events were defined using a relative threshold to account for differences
 243 in the water vapor content of the models as recommended by Rutz et al., (2019). We used the
 244 85th percentile of IVT in the historical run of each model because this value is often used to
 245 define the boundary of ARs (Shields et al., 2018) and is approximately $250 \text{ Kg m}^{-1} \text{ s}^{-1}$ in
 246 ERA5. We then calculated the consecutive number of days exceeding this threshold in the
 247 historical and future projections. Our results indicate that the frequency of multiday high IVT
 248 events is likely to increase under SSP245 and SSP585. We see a robust increase in the
 249 frequency of 2-day high IVT events of about 40%, as indicated by the model range (error
 250 bars) of the historical period not overlapping with the range in the future scenarios, and a less
 251 robust increase in 3-day and 4-day events. Although, we cannot confidently draw conclusions
 252 about the highest impact 5-day and longer events likely due to a very limited sample size.
 253



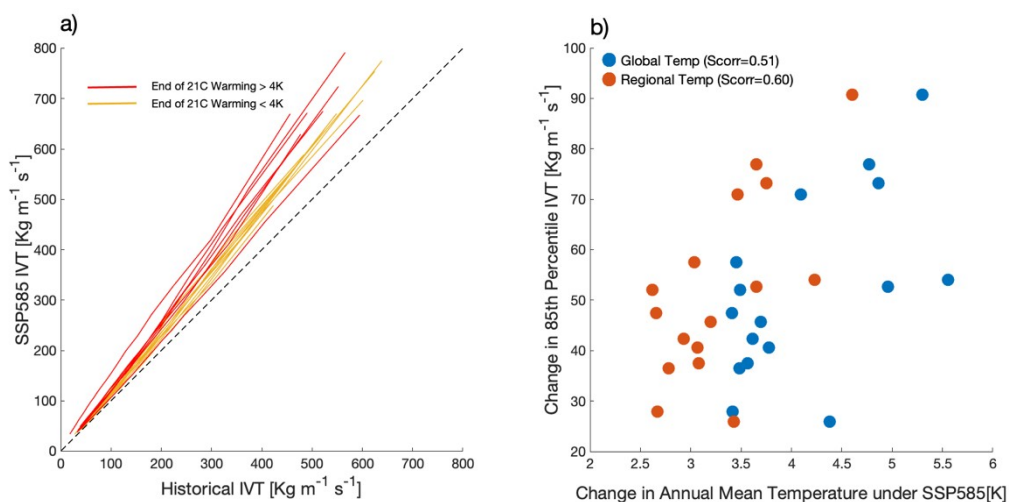
255 *Figure 4: a) Range of return period and b) probability ratio of an IVTx10day event of*
 256 *equivalent magnitude to the March 2021 event under historical (1980-2014) and future*
 257 *(2080-2100) SSP245 and SSP585 conditions.*

258

259 Given the high uncertainty in the most extreme IVT events due to the small sample size, we
 260 undertook a GEV modelling analysis to further understand how the likelihood of extreme
 261 IVT events may change in a warmer climate. The return period of IVTx10day equivalent to
 262 the March 2021 event almost halves between the historical and future periods under both
 263 SSPs. We observe a strong reduction in the return periods (Figure 4a) indicating that events
 264 akin to that of March 2021 would become more regular under the projected scenarios. While
 265 the end-of-century return periods are significantly lower than the historical return periods, the
 266 differences between return periods projected by the two scenarios are statistically
 267 indistinguishable. The probability ratio of IVTx10day has a large uncertainty range under
 268 both scenarios but is consistently greater than one indicating that all CMIP6 models indicate
 269 an increase in probability of events as rare as the observed March 2021 event.

270

271



273 *Figure 5: a) Quantile-quantile plot of historical (1980-2014) versus SSP585 (2080-2100) IVT*
274 *for each of the 16 models. Yellow lines indicate models where the difference in global mean*
275 *temperature between the pre-industrial period (1850-1880) and end of 21st Century (2080-*
276 *2100) was below 4K, while red lines are models where the change in global mean*
277 *temperature exceeded 4K. The black dashed line is the one-to-one reference. b) Scatter plot*
278 *of the change in global (blue) and regional (orange; 80-180E, 50-0S) mean temperature*
279 *under SSP585 in each model versus the change in the 85th percentile of IVT between the*
280 *historical and future periods. Scorr is the Spearman Rank Correlation Coefficient and both of*
281 *these were statistically significant ($p < 0.05$).*

282

283 Given the range in climate sensitivity within the CMIP6 ensemble (Meehl et al., 2020;
284 Zelinka et al., 2019) we hypothesized that differences in climate sensitivity may affect out
285 results. To test this, we calculated the change in global mean temperature between the pre-
286 industrial period (1850-1880) and end of 21st Century (2080-2100). We found that the models
287 with a faster rate of warming all projected higher IVT increases (Figure 5a) except for one
288 model which we discuss in the following paragraphs. This is an important result as it
289 indicates that uncertainty of climate sensitivity may increase the spread of projections of
290 moisture flux and therefore affect projected changes in precipitation extremes.

291

292 Moreover, we found a strong relationship between the global and regional mean temperature
293 change and the value of the 85th percentile of IVT which is commonly used to define
294 Atmospheric Rivers (Figure 5b). Regional here refers to between 80°E-180°E longitude and
295 50°S-0°S latitude. IVT appears to be slightly more correlated to regional temperatures than

296 global temperatures, suggesting that studies of moisture flux and climate change should
297 consider the rate of global and regional warming in the models.
298
299 Model representation of the jet stream and associated storm tracks likely affects IVT
300 projections. Simpson et al., (2020) evaluated CMIP6 representation of midlatitude
301 phenomena and found that the majority of CMIP6 models positioned the Southern
302 Hemisphere (SH) jet too far equatorward. We note that the ensemble member that
303 overestimated IVT the most in the historical model run (BCC-CSM2-MR) also considerably
304 overestimates the speed of the SH jet (Simpson et al., 2020). Furthermore, despite a relatively
305 fast rate of warming in AWI-CM-1-1-MR, that model projects the smallest IVT increase over
306 Sydney by the end of the 21st Century, whereas across the other models there is a strong
307 relationship between rate of warming and IVT increase. However, according to Simpson et
308 al. (2020), AWI-CM-1-1-MR is one of the best models at simulating both the position and
309 speed of the SH jet. Global circulation changes such as the position and speed of the jet and
310 frequency of blocking are likely sources of uncertainty in future precipitation changes
311 (Nishant & Sherwood, 2021)

312

313 **Conclusion**

314 IVT is a useful tool for understanding how hydrological extremes may change in the future.
315 IVT is often better represented in models than precipitation and is highly correlated to
316 precipitation. Extreme multi-day rainfall and flooding in Sydney occurred in March 2021
317 during a period of persistent and intense water vapor transport over the region. We have
318 examined the IVT for this event, placed it in the context of the observational record, and
319 evaluated how the distribution of IVT changes in a warmer climate using CMIP6 models.

320 The maximum daily IVT during the event was the top 0.3% of daily IVT since 1980 and the
321 3rd highest 10-day IVT mean. We found that both the intensity of IVT and the frequency of
322 persistent IVT events will likely increase under SSP245 and SSP585, with SSP585 leading to
323 stronger increases. The probability of events of a similar magnitude to the March 2021 event
324 will increase by approximately 80% with the interquartile range of estimates varying from
325 50-100% (Figure 4) by the end of the 21st Century over Sydney under both moderate and high
326 emissions scenarios. Lastly, we found that the change in IVT is proportional to the rate of
327 warming. Models with faster warming tend to project larger increases in IVT. We have not
328 considered, and there has been limited research to date on, the weather systems that produce
329 these extreme IVT events and their representation in climate models over this region. The
330 analysis herein has demonstrated that the IVT associated with this event was extreme, but not
331 unprecedented. However, the balance of evidence from the considered climate projections
332 suggests that intense and persistent IVT events like this will occur more often in the future.

333

334 **Acknowledgements:**

335 The work of K J Reid was funded by an Australian Government Research Training Program
336 (RTP) Scholarship and the Australian Research Council (ARC; DE180100638), the work of
337 A D King was funded by the ARC (DE180100638), and the work of T P Lane was funded by
338 the ARC Centre of Excellence for Climate Extremes (CE170100023).

339 We acknowledge the World Climate Research Programme, which, through its Working
340 Group on Coupled Modelling, coordinated and promoted CMIP6. We thank the climate
341 modelling groups for producing and making available their model output, the Earth System
342 Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding
343 agencies who support CMIP6 and ESGF.

344 The work of T.A. O'Brien was supported in part by the U.S. Department of Energy, Office of
345 Science, Office of Biological and Environmental Research, Climate and Environmental
346 Sciences Division, Regional & Global Model Analysis Program, under Award Number DE-
347 AC02-05CH11231; in part by the Environmental Resilience Institute, funded by Indiana
348 University's Prepared for Environmental Change Grand Challenge initiative and in part by
349 Lilly Endowment, Inc., through its support for the Indiana University Pervasive Technology
350 Institute.

351 This research was undertaken with the assistance of resources from the National
352 Computational Infrastructure (NCI Australia) supported by the Australian Government.
353 Additionally, we thank Scott Wales for helping write the script used to obtain the CMIP6
354 data.

355 K.J. Reid ORCID: 0000-0001-5972-6015

356 T.A. O'Brien ORCID: 0000-0002-6643-1175

357 A.D. King ORCID: 0000-0001-9006-5745

358 T.P. Lane ORCID: 0000-0003-0171-6927

359

360 **Data Availability:**

361 The ERA5 ([10.24381/cds.adbb2d47](https://cds.adbb2d47)) and CMIP6
362 (<https://esgf-node.llnl.gov/projects/cmip6/>) datasets used in this study are publicly available.

363

364

365 **References:**

366 The Bureau of Meteorology. (2021). *Special Climate Statement 74-extreme rainfall and*
367 *flooding in eastern and central Australia in March 2021.*

368 The Bureau of Meteorology. (2012). *Monthly Weather Review New South Wales.* Retrieved
369 from <http://www.ag.gov.au/cca>.

370 Corringham, T. W., Martin Ralph, F., Gershunov, A., Cayan, D. R., & Talbot, C. A. (2019).
371 Atmospheric rivers drive flood damages in the western United States. *Science Advances*,
372 5(12), eaax4631. <https://doi.org/10.1126/sciadv.aax4631>

373 Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., & Taylor, K. E.
374 (2016). Overview of the Coupled Model Intercomparison Project Phase 6 (CMIP6)
375 experimental design and organization. *Geoscientific Model Development*, 9(5), 1937–
376 1958. <https://doi.org/10.5194/GMD-9-1937-2016>

377 Foreman-Mackey, D., Farr, W. M., Sinha, M., Archibald, A. M., Hogg, D. W., Sanders, J. S.,
378 et al. (2019). emcee v3: A Python ensemble sampling toolkit for affine-invariant
379 MCMC. *Journal of Open Source Software*, 4(43), 1864.
380 <https://doi.org/10.21105/joss.01864>

381 Gimeno, L., Dominguez, F., Nieto, R., Trigo, R., Drumond, A., Reason, C. J. C., et al.
382 (2016). Major Mechanisms of Atmospheric Moisture Transport and Their Role in
383 Extreme Precipitation Events. *Annual Review of Environment and Resources*, 41(1),
384 117–141. <https://doi.org/10.1146/annurev-environ-110615-085558>

385 Hersbach, H., Bell, B., Berrisford, P., Horányi, A., Sabater, J. M., Nicolas, J., et al. (2019).
386 Global reanalysis: goodbye ERA-Interim, hello ERA5. *ECMWF Newsletter*, (159), 17–
387 24. <https://doi.org/10.21957/vf291hehd7>

388 Lavers, D. A., & Villarini, G. (2013). The nexus between atmospheric rivers and extreme
389 precipitation across Europe. *Geophysical Research Letters*, 40(12), 3259–3264.
390 <https://doi.org/10.1002/grl.50636>

391 Lavers, D. A., & Villarini, G. (2015). The relationship between daily European precipitation
392 and measures of atmospheric water vapour transport. *International Journal of*
393 *Climatology*, 35(8), 2187–2192. <https://doi.org/10.1002/joc.4119>

394 Lavers, D. A., Pappenberger, F., & Zsoter, E. (2014). Extending medium-range predictability
395 of extreme hydrological events in Europe. *Nature Communications*, 5(1), 1–7.
396 <https://doi.org/10.1038/ncomms6382>

397 Ma, W., Chen, G., & Guan, B. (2020). Poleward Shift of Atmospheric Rivers in the Southern
398 Hemisphere in Recent Decades. *Geophysical Research Letters*, 47(21),
399 e2020GL089934. <https://doi.org/10.1029/2020GL089934>

400 Meehl, G. A., Senior, C. A., Eyring, V., Flato, G., Lamarque, J. F., Stouffer, R. J., et al.
401 (2020, June 1). Context for interpreting equilibrium climate sensitivity and transient
402 climate response from the CMIP6 Earth system models. *Science Advances*. American
403 Association for the Advancement of Science. <https://doi.org/10.1126/sciadv.aba1981>

404 Nicholls, N. (2006). *Introduction: what is climate change detection and attribution?*
405 *Detecting and attributing Australian climate change: a review. Aust. Met. Mag* (Vol.
406 55).

407 Nishant, N., & Sherwood, S. C. (2021). How Strongly Are Mean and Extreme Precipitation
408 Coupled? *Geophysical Research Letters*, 48(10), e2020GL092075.
409 <https://doi.org/10.1029/2020gl092075>

410 O'Neill, B. C., Tebaldi, C., Van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., et al.
411 (2016). The Scenario Model Intercomparison Project (ScenarioMIP) for CMIP6.
412 *Geoscientific Model Development*, 9(9), 3461–3482. [https://doi.org/10.5194/gmd-9-](https://doi.org/10.5194/gmd-9-3461-2016)
413 3461-2016

414 Perkins, S. E., Pitman, A. J., Holbrook, N. J., & McAneney, J. (2007). Evaluation of the AR4
415 climate models' simulated daily maximum temperature, minimum temperature, and
416 precipitation over Australia using probability density functions. *Journal of Climate*,
417 20(17), 4356–4376. <https://doi.org/10.1175/JCLI4253.1>

418 Reid, K. J., Rosier, S. M., Harrington, L. J., King, A. D., & Lane, T. P. (2021). Extreme
419 rainfall in New Zealand and its association with Atmospheric Rivers. *Environmental*
420 *Research Letters*, *16*(4), 044012. <https://doi.org/10.1088/1748-9326/abeae0>

421 Risser, M. D., & Wehner, M. F. (2017). Attributable Human-Induced Changes in the
422 Likelihood and Magnitude of the Observed Extreme Precipitation during Hurricane
423 Harvey. *Geophysical Research Letters*, *44*(24), 12,457-12,464.
424 <https://doi.org/10.1002/2017GL075888>

425 Rutz, J. J., Steenburgh, W. J., & Ralph, F. M. (2014). Climatological Characteristics of
426 Atmospheric Rivers and Their Inland Penetration over the Western United States.
427 *Monthly Weather Review*, *142*(2), 905–921. [https://doi.org/10.1175/MWR-D-13-](https://doi.org/10.1175/MWR-D-13-00168.1)
428 [00168.1](https://doi.org/10.1175/MWR-D-13-00168.1)

429 Rutz, J. J., Shields, C. A., Lora, J. M., Payne, A. E., Guan, B., Ullrich, P., et al. (2019). The
430 Atmospheric River Tracking Method Intercomparison Project (ARTMIP): Quantifying
431 Uncertainties in Atmospheric River Climatology. *Journal of Geophysical Research:*
432 *Atmospheres*, *124*(24), 13777–13802. <https://doi.org/10.1029/2019JD030936>

433 Shields, C. A., Rutz, J. J., Leung, L.-Y., Ralph, F. M., Wehner, M., Kawzenuk, B., et al.
434 (2018). Atmospheric River Tracking Method Intercomparison Project (ARTMIP):
435 project goals and experimental design. *Geosci. Model Dev*, *11*, 2455–2474.
436 <https://doi.org/10.5194/gmd-11-2455-2018>

437 Simpson, I. R., Bacmeister, J., Neale, R. B., Hannay, C., Gettelman, A., Garcia, R. R., et al.
438 (2020). An Evaluation of the Large-Scale Atmospheric Circulation and Its Variability in
439 CESM2 and Other CMIP Models. *Journal of Geophysical Research Atmospheres*, *125*.
440 <https://doi.org/10.1029/2020JD032835>

441 Stephens, G. L., L'Ecuyer, T., Forbes, R., Gettelmen, A., Golaz, J.-C., Bodas-Salcedo, A., et

442 al. (2010). Dreary state of precipitation in global models. *Journal of Geophysical*
443 *Research: Atmospheres*, 115(D24). <https://doi.org/10.1029/2010JD014532>

444 Swart, N. C., Fyfe, J. C., Gillett, N., & Marshall, G. J. (2015). Comparing trends in the
445 southern annular mode and surface westerly jet. *Journal of Climate*, 28(22), 8840–8859.
446 <https://doi.org/10.1175/JCLI-D-15-0334.1>

447 The Bureau of Meteorology. (2012). *Monthly Weather Review New South Wales*. Retrieved
448 from <http://www.ag.gov.au/cca>.

449 The Bureau of Meteorology. (2021). *Special Climate Statement 74-extreme rainfall and*
450 *flooding in eastern and central Australia in March 2021*.

451 Viale, M., Valenzuela, R., Garreaud, R. D., & Ralph, F. M. (2018). Impacts of Atmospheric
452 Rivers on Precipitation in Southern South America. *Journal of Hydrometeorology*,
453 19(10), 1671–1687. <https://doi.org/10.1175/JHM-D-18-0006.1>

454 Warner, M. D., Mass, C. F., & Salathé, E. P. (2015). Changes in Winter Atmospheric Rivers
455 along the North American West Coast in CMIP5 Climate Models. *Journal of*
456 *Hydrometeorology*, 16(1), 118–128. <https://doi.org/10.1175/JHM-D-14-0080.1>

457 Zelinka, M. D., Myers, T. A., Mccoy, D. T., Po-Chedley, S., Caldwell, P. M., Ceppi, P., et al.
458 (2019). Causes of Higher Climate Sensitivity in CMIP6 Models. *Geophysical Research*
459 *Letters*. <https://doi.org/10.1029/2019GL085782>

460