Supplement of

Seasonal crop yield prediction with SEAS5 long-range meteorological forecasts in a land surface modelling approach

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1 Supplement to chapter 2.2: State-wide agricultural statistics

Table S1: Cropping area and production of major cash crops in Victoria, Australia, from 2014/15 to 2020/21, and six year average (Source: ABARES, 2020).

Year	Area (''000 ha)	Production (kt)	Yield (t/ha)
Wheat			
2014-15 to 2020-21 average	1455.43	3348.24	2.30
2014-15	1492.66	2631.30	1.76
2015–16	1,342	1,815	1.35
2016–17	1,454	4,665	3.21
2017–18	1,447	3,682	2.54
2018–19	1,403	2,277	1.62
2019–20 *	1,450	3,600	2.48
2020–21 *	1,600	4,768	
Barley			
2014-15 to 2020-21 average	876.17	2042.15	2.33
2014-15	916.08	1373.83	1.50
2015–16	844	1,107	1.31
2016–17	946	3,083	3.26
2017–18	844	2,110	2.50
2018–19	893	1,337	1.50
2019–20 *	820	2,500	3.05
2020–21 *	870	2,784	3.20
Canola			
2014-15 to 2020-21 average	411.12	646.71	1.57
2014-15	483.27	558.68	1.16
2015–16	277	287	1.04
2016–17	327	633	1.94
2017–18	542	938	1.73
2018–19	414	511	1.23
2019–20 *	385	650	1.69
2020–21 *	450	950	
Oats			
2014-15 to 2020-21 average	128.84	250.15	1.94
2014-15	133.21	179.47	1.35
2015–16	140	185	1.32
2016–17	162	493	3.05
2017–18	97	188	1.94
2018–19	134	165	1.23
2019–20 *	100	175	1.75
2020–21 *	135	365	2.70

*ABARES estimate

Table S2: Cropping area and production of main cash crops (grain crops, wheat, corn, canola, potatoes and sugar beet) in North Rhine-Westphalia, Germany, from 2016 to 2020, and five year average (Source: BMEL, 2022).

Year	Area (''000 ha)	Production (kt)	Yield (t/ha)
Grain crops (without corn)			
2013 to 2018 average	610.9	4036.4	7.87
2016	514.2	3852.6	7.49

2017	502.4	3694.6	7.35
2018	485.5	3534.1	7.28
2019	498.6	3826	7.67
2020	490.00	3700.30	7.55
Wheat (winter and summer wheat)			
2013 to 2018 average	270	2292.5	8.49
2016	268.6	2161.3	8.05
2017	265	2098.3	7.92
2018	247.2	1955.5	7.91
2019	253.5	2063.7	8.14
2020	230.60	1996.56	8.66
Corn			
2013 to 2018 average	98.3	984.2	10.01
2016	88.6	873.7	9.86
2017	99.8	1071.1	10.74
2018	88.5	690.2	7.8
2019	85.8	724.5	8.44
2020	79.73	836.60	10.49
Canola			
2013 to 2018 average	60.8	240.8	3.96
2016	58.7	226.0	3.85
2017	56.7	221.2	3.9
2018	57.2	198.8	3.48
2019	40.3	148.6	3.69
2020	42,3	158,5	3.74
Potatoes			
2013 to 2018 average	31.1	1502.7	48.28
2016	31	1457.2	46.95
2017	31.1	1627.0	52.26
2018	33.2	1322.8	39.83
2019	40.5	1885.7	46.53
2020	36.7	1694.9	46.16
Sugar beet			
2013 to 2018 average	-	-	-
2016	-	-	-
2017	61	5411.5	88.7
2018	61.7	3958.1	64.2
2019	59.3	4450	75.1
2020	52.7	4183.9	79.3

2 Supplement to chapter 2.4: Processing and analysis of seasonal forecasts

2.1 Precipitation bias

In the next step, we compared the ECWMF SEAS5 seasonal precipitation forecasts initialized on the first of April with 7 month lead time for the years 2017 and 2018 to corresponding data from the bias-adjusted global reanalysis dataset WFDE5 (Cucchi et al., 2020).

For the AUS-VIC domain, both the seasonal and sub-seasonal forecasts were not able to capture the wet period in August 2017. A slightly better correspondence was reached for the late growing season of 2018 (August, September and October) both in the seasonal and sub-seasonal forecasts (Figure S1). No systematic or consistent improvement in terms of total predicted precipitation amounts respective to the WFDE5 data can be observed in the sub-seasonal forecasts starting on the 1st of July of the respective years compared to the seasonal forecasts that are initialized on the 1st of April (Figure S1).

For the DE-NRW domain the predicted rainfall amounts in the seasonal forecasts are too large compared to WFDE5, especially in the beginning of the growing season (April, May, June) of 2017, and towards the end of the growing season of 2018 (especially September and October), where the forecasts were not able to capture the dry spell that corresponds to the 2018 European drought. The sub-seasonal forecasts performed better for September 2018, while still overestimating the overall rainfall amounts of the second half of the growing season (July, August and October). Both the seasonal and sub-seasonal forecast predicted a generally dry year in 2018 (with the exception being September 2018 in the seasonal forecasts), but did not reflect the extreme drought conditions that were recorded in 2018 (Figure S1).

In general, the correspondence of predicted total monthly rainfall amounts in seasonal and sub-seasonal forecasts with the WFDE5 reanalysis is better for the AUS-VIC domain than for the DE-NRW domain. The bias is much smaller over the Australian continent, with a maximum of +/- 0.90 mm/day, than for Germany (and Europe), where a maximum bias of up to 2.70 mm/day (local maximum, 2018) can be observed.

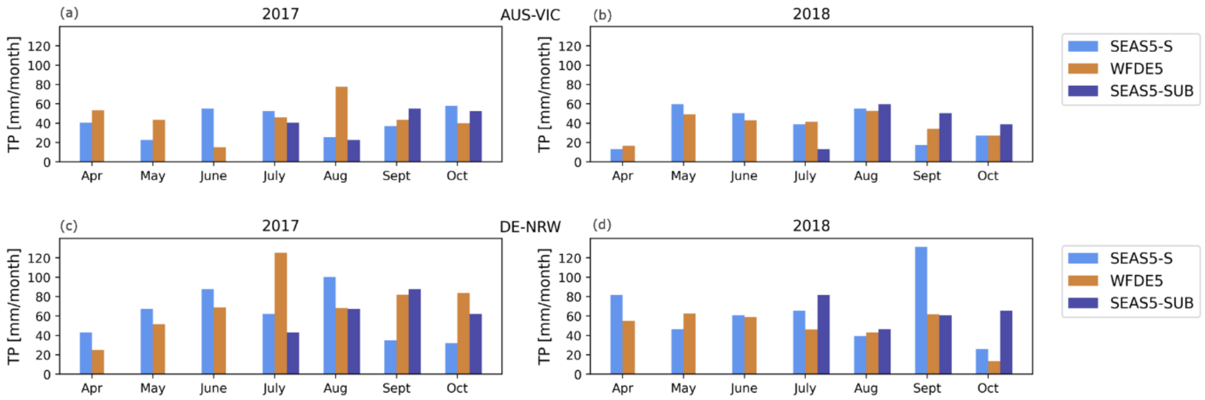

Figure S1: SEAS5 total monthly precipitation amounts from seasonal forecasts starting on the 1st of April (SEAS5-S) and sub-seasonal forecasts starting on the 1st of July (SEAS5-SUB) for the years 2017 and 2018, for (a,b) the AUS-VIC domain and (c,d) the DE-NRW domain, compared to WFDE5 data for the respecitve domains.

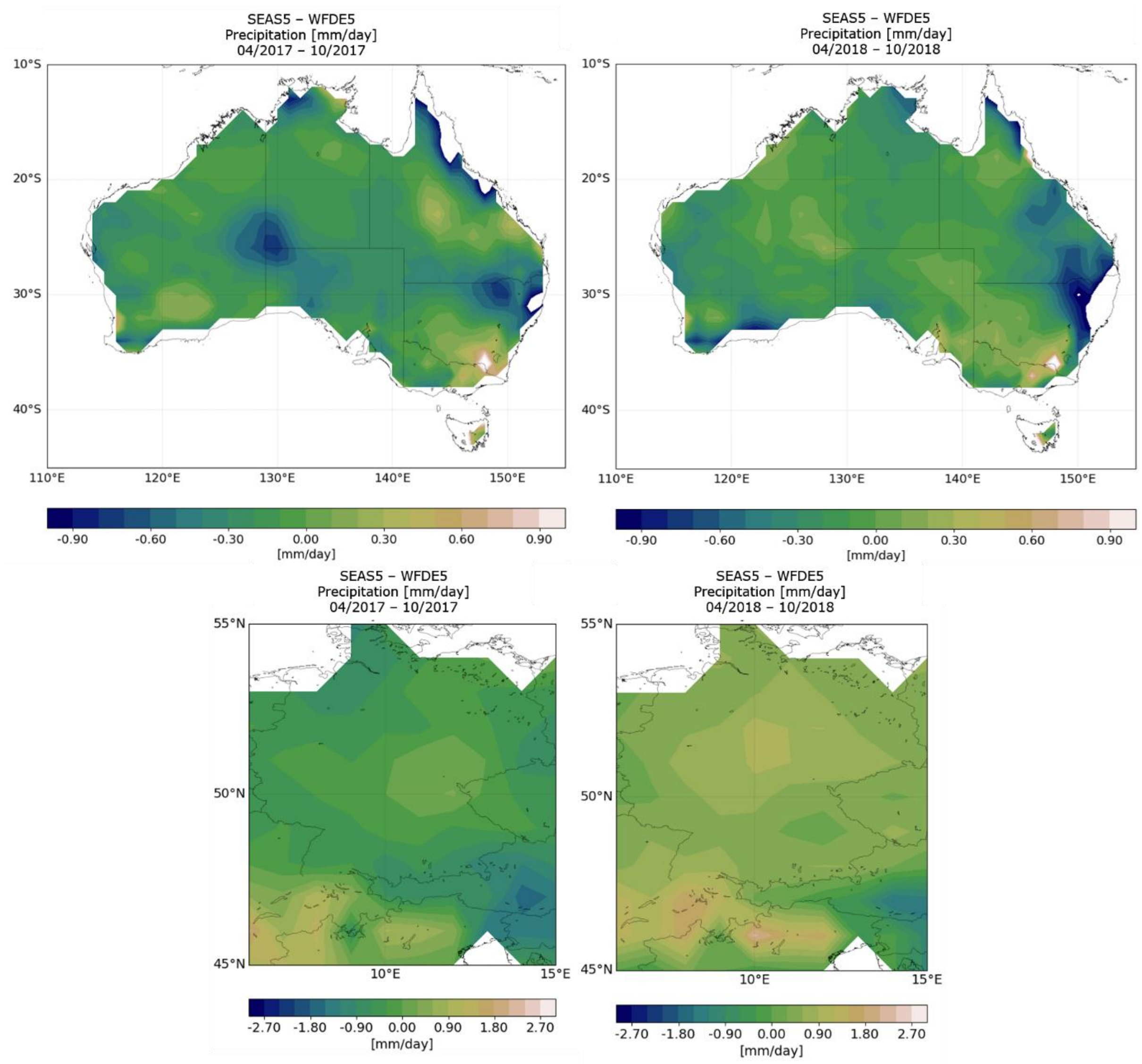

Figure S2: Bias (forecast – reference data) for ECMWF SEAS5 mean daily rainfall amount [mm/day] with 51 ensemble members for (top) Australia and (bottom) Germany. Forecast period initialized on the 1st of April until the 31st of October of (left) 2017 and (right) 2018 respectively. The bias was computed with respect to the WFDE5 data set.

2.2 Supplement to Appendix A: Effect of temporal forcing data resolution – a synthetic experiment (extended)

In a first step, we analysed the performance of MetSim as a disaggregation tool for solar radiation by using MetSim to disaggregate the daily averaged variables to an hourly time step and comparing the output to the hourly observations (Figure S3a, Table S3). Comparing the time series of disaggregated shortwave radiation at hourly time step with the initial hourly measurement data, we see that the disaggregated data set has slightly higher monthly sums of solar radiation and a higher mean value over the entire time series of 7 years (Figure S3a, Table S3), while underestimating the peak daily value compared to the initial observations (Figure S3b, Table S3). The disaggregated data set represents a realistic diurnal cycle with reasonable magnitudes of solar incoming radiation.

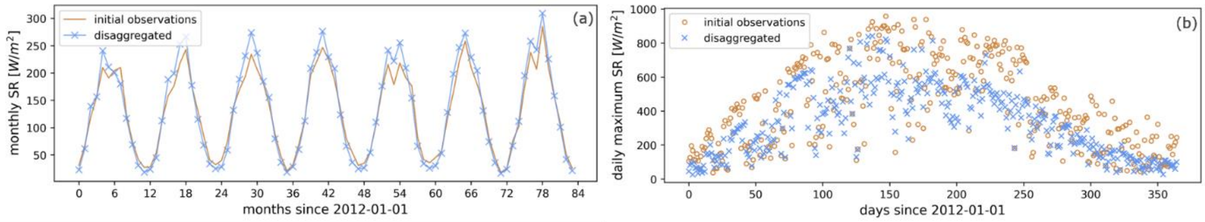

Figure S3: Comparison of MetSim disaggregated data with initial observations of incoming shortwave radiation (SR): (a) averaged for each months over 7 years, and (b) the respective daily maximum values for one selected year.

Table S3: Comparison of MetSim disaggregated incoming shortwave radiation [W m^{-2}] at hourly time step with the original hourly observation data over the time period of 7 years.

Data	Min	Max	Mean	Total (7 year sum)	Bias	RMSE
Initial observation	0.00	988.24	127.81	7843522.00	0.04	41.23
Disaggregated	0.00	867.26	132.42	8126221.50		

For statistical evaluation of the results, the root mean square error (RMSE) and the bias were chosen as performance metrics:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(X_i - X_{obs,i})^2}, \quad (1)$$

$$\text{bias} = \sum_{i=1}^{n}(X_i - X_{obs,i}) / \sum_{i=1}^{n}(X_{obs,i}), \quad (2)$$

where i is time step and n the total number of time steps, X_i and $X_{\mathrm{obs},i}$ are the simulated and the observed values at every time step with μ_{sim} and μ_{obs} being the respective mean values.

The statistical evaluation was conducted against the reference simulation results resulting from the original hourly observation forcing for multiple simulated variables: leaf are index (LAI), latent heat flux (LH), sensible heat flux (SH), evapotranspiration (ET), ground evaporation (Qsoil), transpiration (QVegT), soil water content at different depths (SWC) and surface runoff (Qover).

In general, the 6 hourly disaggregated data, both for single forcing variables as well as for combined forcing data sets performed better for all individual output variables than the daily data in terms of RMSE and bias (Figure S4, Table S5). The daily forcing data set with all variables at daily time step performed the most poorly compared to the reference forcing, thus resulting in high RMSE and high biases for all output variables that were analysed. The effect is especially prominent for the soil water content and the surface runoff.

For the individual forcing variables, the temporal resolution of incoming shortwave radiation had slightly higher effects on simulation results than the resolution of precipitation for most of the analyzed output, such as leaf area index, soil water content at different depths of the soil profile, ground evaporation, evapotranspiration and energy fluxes, except for surface runoff, where daily precipitation data resulted in a higher bias than daily shortwave radiation (Figure S4, Table S5).

The simulated grain yield was the model output variable least affected by the temporal resolution of forcing data (Table S4). Here, most of the forcing data set combinations resulted in similar or slightly higher grain yields compared to the reference data set, except for the all daily and all 6 hourly forcings and the 6 hourly precipitation data set (Table S4).

Table S4: Simulation results for grain yield [t/ha] calculated with different forcing data sets at different temporal resolutions; all forcing variables (Incoming shortwave and longwave radiation, precipitation, temperature, relative humidity, wind speed and pressure) at either daily or 6 hourly disaggregated resolution, and only shortwave or precipiation as well as a combination of both shortwave and precipitation at daily and 6 hourly resolution with all other forcing varibales at hourly time step.

Temporal resolution	**Grain yield [t/ha]**
Hourly forcing	4.90
All - 6h	4.71
All - daily	4.13
SW+Precip - 6h	5.41
SW+Precip - daily	5.75
SW - 6h	5.40
SW - daily	5.66
Precip - 6h	4.74
Precip - daily	5.13

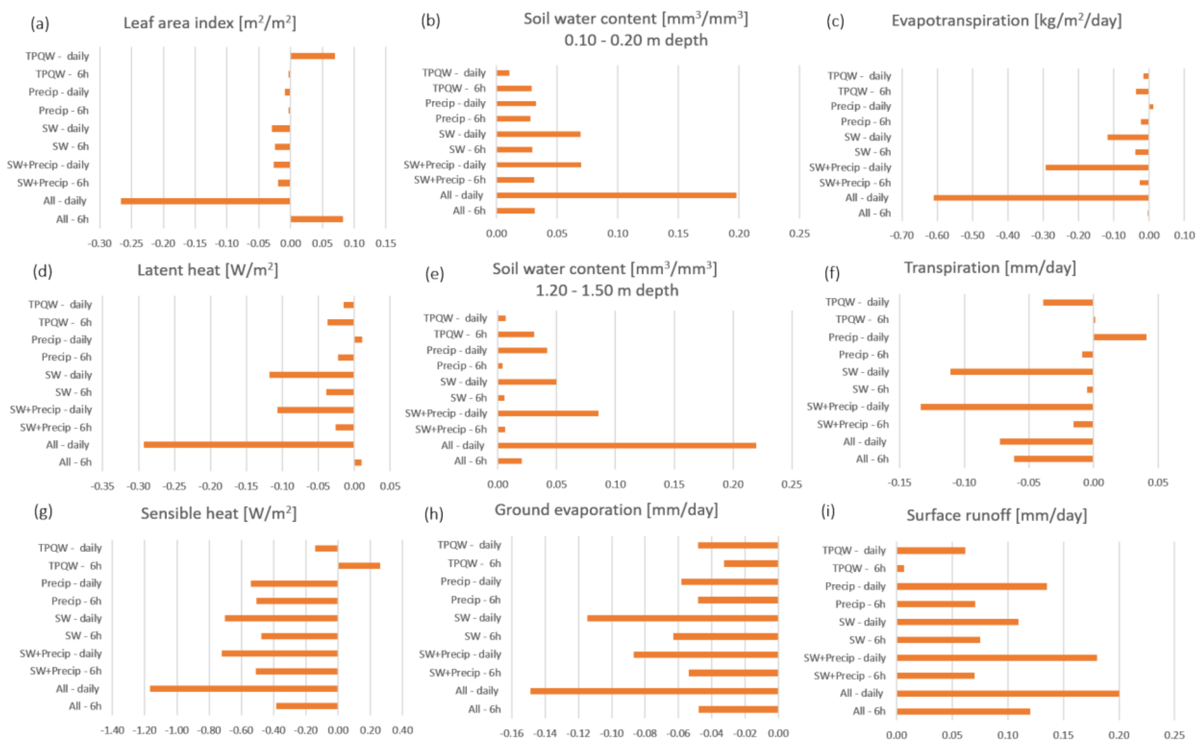

Figure S4: (a-i) Illustration of biases introduced by different temporal forcing data resolutions and combinations on various output variables. Corresponding data is listed in Table S5.

Table S5: Bias and RMSE calculation for model output produced with different sets of forcing data at different temporal resolutions; all forcing variables (Incoming shortwave and longwave radiation, precipitation, temperature, relative humidity, wind speed and pressure) at either daily or 6 hourly disaggregated resolution, a combination of both shortwave and precipitation, as well as only shortwave or precipitation and TPQW at daily and 6 hourly resolution with all other forcing variables at hourly time step respectivvely. The bias and RMSE were calulated with the model output produced with hourly forcings as validation data set.

Output varibales	**LAI [m^2/m^2]**		**LH [W/m^2]**		**SH [W/m^2]**		**SWC [mm^3/mm^3]**		**SWC [mm^3/mm^3]**		**ET [$kg/m^2/day$]**		**Qsoil [mm/day]**		**Qover [mm/day]**		**QVegT [mm/day]**	
	RMSE	**bias**	**RMSE**	**bias**	**RMSE**	**bias**	**RMSE**	**bias**	**RMSE**	**bias**	**RMSE**	**bias**	**RMSE**	**bias**	**RMSE**	**bias**	**RMSE**	**bias**
									All forcing variables									
6 hourly	0.65	0.08	24.57	0.01	18.62	-0.38	0.03	0.02	0.03	0.03	0.85	0.00	0.42	-0.05	0.41	0.20	0.42	-0.06
daily	0.62	-0.27	23.96	-0.29	29.89	-1.17	0.08	0.22	0.29	0.20	0.83	-0.61	0.54	-0.15	1.70	0.12	0.89	-0.07
									Shortwave and Precipitation									
6 hourly	0.06	-0.02	17.32	-0.03	16.83	-0.51	0.03	0.01	0.02	0.03	0.60	-0.03	0.46	-0.05	0.49	0.07	0.31	-0.02
daily	0.38	-0.03	24.59	-0.11	25.87	-0.72	0.06	0.09	0.04	0.07	0.85	-0.29	0.57	-0.09	1.61	0.18	0.68	-0.13
									Shortwave									
6 hourly	0.10	-0.02	16.14	-0.04	16.02	-0.47	0.03	0.01	0.02	0.03	0.56	-0.04	0.43	-0.06	0.33	0.07	0.32	-0.01
daily	0.38	-0.03	24.99	-0.12	25.29	-0.70	0.05	0.05	0.03	0.07	0.86	-0.12	0.56	-0.11	0.82	0.11	0.64	-0.11
									Precipitation									
6 hourly	0.40	0.00	16.12	-0.02	14.27	-0.51	0.03	0.00	0.02	0.03	0.56	-0.02	0.44	-0.05	0.49	0.07	0.06	-0.01
daily	0.34	-0.01	19.96	0.01	16.18	-0.54	0.02	0.04	0.02	0.03	0.69	0.01	0.42	-0.06	1.63	0.14	0.32	0.04
									TPQW									
6 hourly	0.07	0.00	8.63	-0.04	7.60	0.26	0.02	0.03	0.01	0.03	0.30	-0.04	0.14	-0.03	0.29	0.01	0.40	0.00
daily	0.50	0.07	13.43	-0.01	15.43	-0.14	0.02	0.01	0.02	0.01	0.46	-0.02	0.26	-0.05	0.83	0.06	0.28	-0.04

3 Supplement to chapter 3.1.1: Comparison of simulation results with CRNS measurements – performance statistics

Table S6: RMSE, MBE and R^2 for CLM-S-, CLM-SUB- and CLM-WFDE5-simulated surface soil moisture from the 1st of April to the 31st of October of 2017, 2018, 2019 and 2020, compared to daily averaged CRNS measurements from the COSMOS-Europe sites Selhausen, Merzenhausen, Aachen and Heinsberg respectively. The simulation outputs were averaged using a physically based weighting approach after Schrön et al. (2017).

DE-NRW	2017			2018			2019			2020		
	RMSE	MBE	R^2	RMSE	MBE	R^2	RMSE	MBE	R^2	RMSE	MBE	R^2
Selhausen												
CLM-S	0.08	0.03	0.10	0.08	0.06	0.80	0.08	0.03	0.16	0.12	0.00	0.08
CLM-SUB	0.09	0.01	-0.01	0.08	0.06	0.79	0.08	0.03	0.22	0.11	0.01	0.17
CLM-WFDE5	0.08	0.07	0.69	0.10	0.09	0.82	0.09	0.05	-0.03	-	-	-
Merzenhausen												
CLM-S	0.09	0.06	0.27	0.10	0.09	0.78	0.11	0.08	0.34	0.10	0.08	0.45
CLM-SUB	0.09	0.05	0.11	0.10	0.09	0.75	0.10	0.08	0.42	0.10	0.08	0.45
CLM-WFDE5	0.11	0.11	0.81	0.12	0.11	0.85	0.12	0.10	0.25	-	-	-
Aachen												
CLM-S	0.10	-0.01	-0.31	0.06	0.01	0.70	0.08	0.00	0.42	0.11	-0.01	-0.18
CLM-SUB	0.11	-0.03	-0.36	0.06	0.01	0.72	0.08	0.00	0.50	0.10	-0.01	-0.13
CLM-WFDE5	0.07	0.03	0.22	0.07	0.05	0.75	0.08	0.01	0.34	-	-	-
Heinsberg												
CLM-S	0.08	0.04	0.34	0.08	0.06	0.78	0.08	0.04	0.53	0.08	0.05	0.50
CLM-SUB	0.08	0.03	0.30	0.07	0.06	0.81	0.07	0.04	0.60	0.08	0.05	0.49
CLM-WFDE5	0.08	0.08	0.87	0.08	0.08	0.84	0.08	0.04	0.45	-	-	-

Table S7: RMSE, MBE and R^2 for CLM-S-, CLM-SUB- and CLM-WFDE5-simulated surface soil moisture moisture from the 1st of April to the 31st of October of 2017 and 2018 compared to daily averaged CRNS measurements (Level 4) from the CosmOZ sites Hamilton, Bishes and Bennets respectively. The simulation outputs were averaged using a physically based weighting approach after Schrön et al. (2017).

AUS-VIC	2017			2018		
	RMSE	MBE	R^2	RMSE	MBE	R^2
Station 15 - Hamilton						
CLM-S	0.12	-0.07	0.48	0.10	-0.05	0.81
CLM-SUB	0.12	-0.07	0.43	0.09	-0.04	0.83
CLM-WFDE5	0.11	-0.07	0.63	0.10	-0.06	0.82
Station 18 - Bishes						
CLM-S	0.09	0.08	0.14	-	-	-
CLM-SUB	0.10	0.09	0.30	-	-	-
CLM-WFDE5	0.09	0.08	0.58	-	-	-
Station 19 - Bennets						
CLM-S	0.08	0.03	0.29	-	-	-
CLM-SUB	0.08	0.04	0.25	-	-	-
CLM-WFDE5	0.08	0.03	0.34	-	-	-

4 Supplement to chapter 3.1.3: Regional crop yield predictions for root crops

Despite earlier enhancements to the model code and parameterization scheme, the crop module of CLM5 does not include a proper representation of root crops. The harvesting scheme of root crops in CLM5 crop module is adapted to the one for grain crops. This resulted in large discrepancies between simulated and recorded crop yields for potatoes and sugar beet with recorded yields being up to 10 times larger (Table S8). [t/ha]

Table S8: Simulated crop yields [t/ha] for potatoes and sugar beet with seasonal (CLM-S), sub-seasonal (CLM-SUB) and reanalysis (CLM-WFDE5) forcing data for the years 2017 to 2020, compared to official crop statistics from (BMEL, 2022) for the DE-NRW domain. The colour coding indicates the ranking from lowest (red) to highest yield (green) amongst the respective years.

	DE-NRW			
	2017	2018	2019	2020
Potatoes				
BMEL	52.26	39.83	46.53	46.16
CLM-S	7.50	6.95	6.97	7.29
CLM-SUB	7.11	6.63	7.03	6.94
CLM-WFDE5	7.37	6.79	7.03	-
Sugarbeet				
BMEL	88.7	64.2	75.1	79.3
CLM-S	7.35	6.82	6.83	7.34
CLM-SUB	6.87	6.50	6.84	6.97
CLM-WFDE5	7.22	6.65	6.89	-
Ranking				

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