

# The Influence of Arctic Clouds on Fall SST in the Community Earth System Model

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## 1. Introduction

- As Arctic sea ice retreats during the melt season, the upper ocean warms in response to atmospheric heat fluxes.
- Overall, clouds reduce these fluxes in summer, but how the radiative impacts of clouds on ocean warming could change as sea ice declines has not been documented.

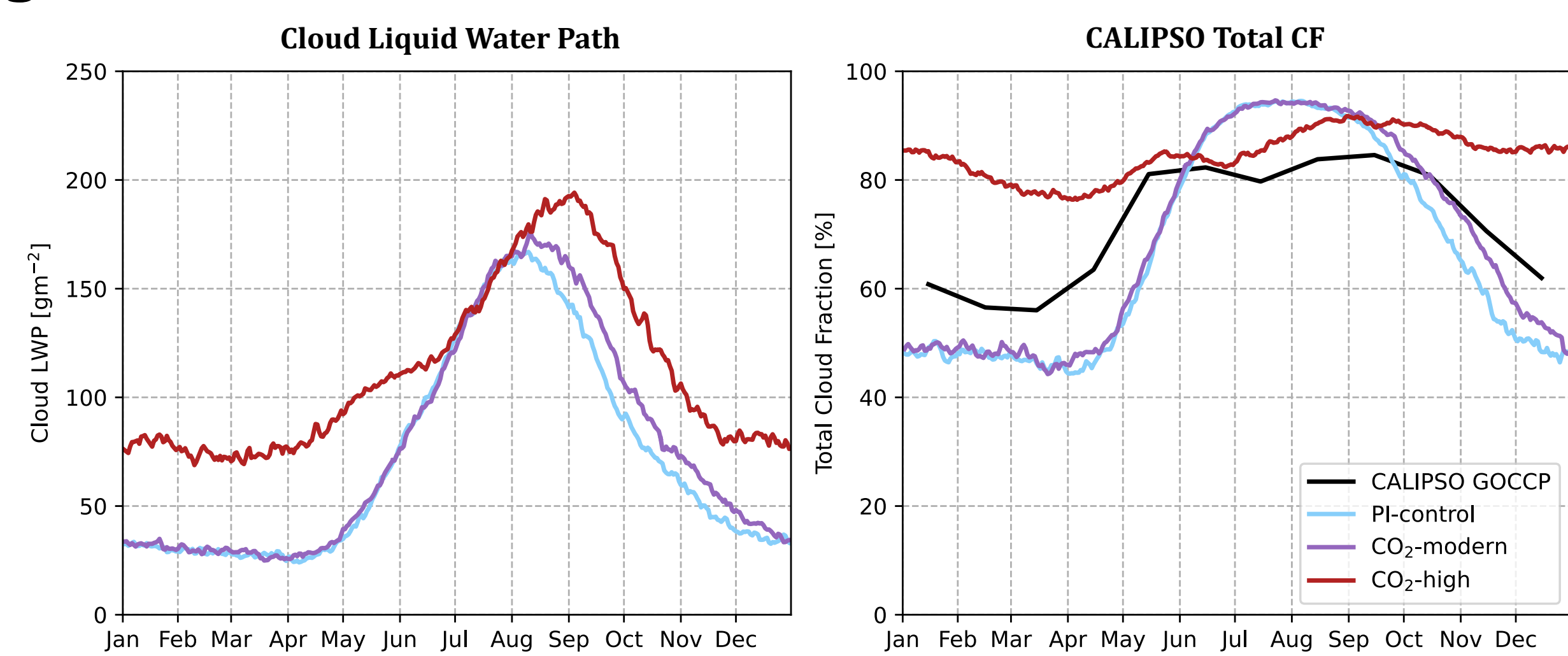
Science questions:

- Can clouds affect ocean surface warming in the Arctic, and if so is it through warming or cooling effects?
- Do the impacts of clouds on SST change with a warming climate?

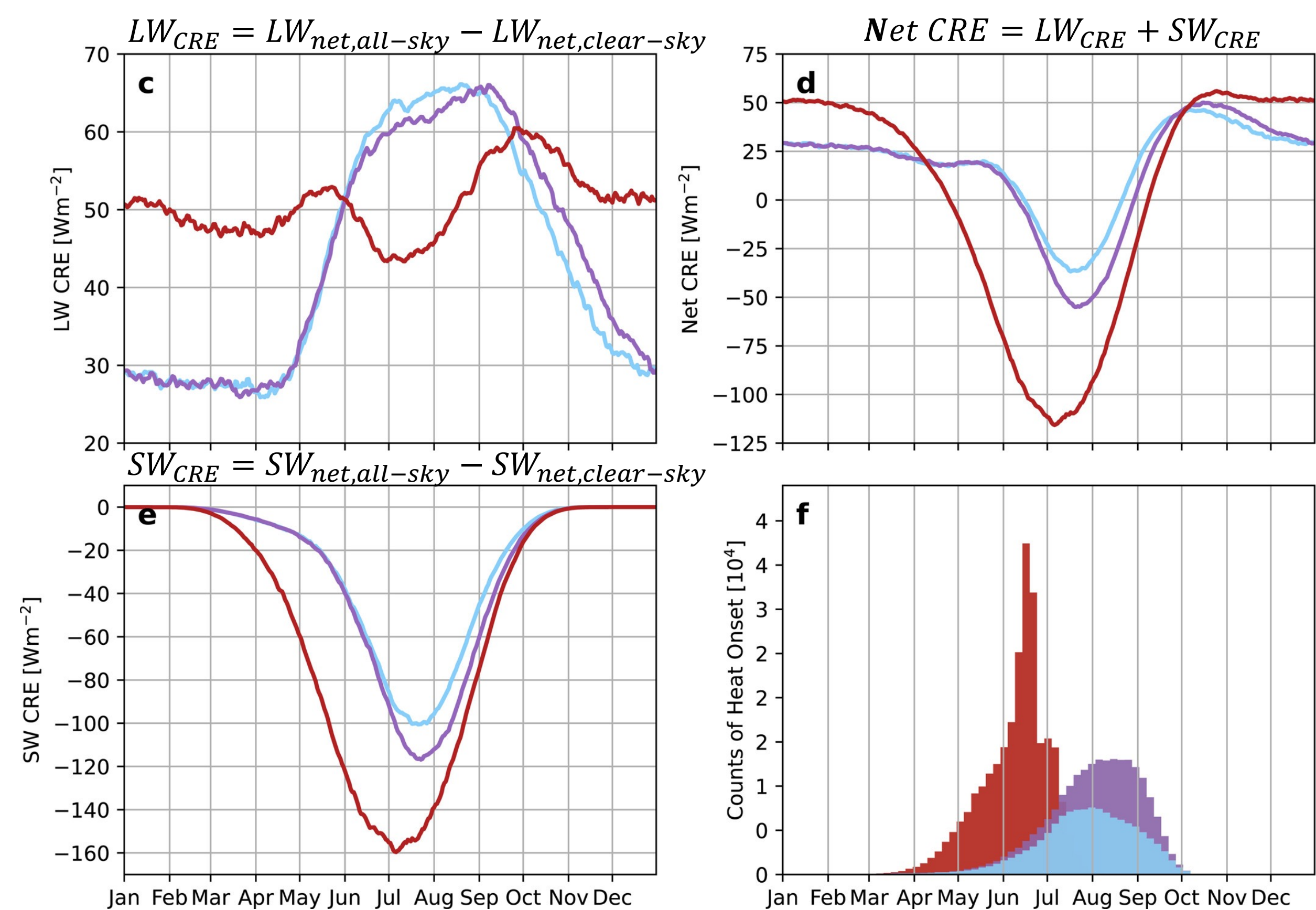
## 2. Model runs using CESM2 w/ CAM6:

- Pre-industrial (PI)-control: 287 ppm CO<sub>2</sub>
- CO<sub>2</sub>-modern: 424 ppm CO<sub>2</sub>
- CO<sub>2</sub>-high: 1139 ppm CO<sub>2</sub>
- Each run is 100 years long. Equilibrium is not reached for CO<sub>2</sub>-high, but the Arctic climate is fundamentally different, e.g., seasonally ice-free.

## 3. Under higher CO<sub>2</sub> clouds have a larger cooling effect for longer at the surface



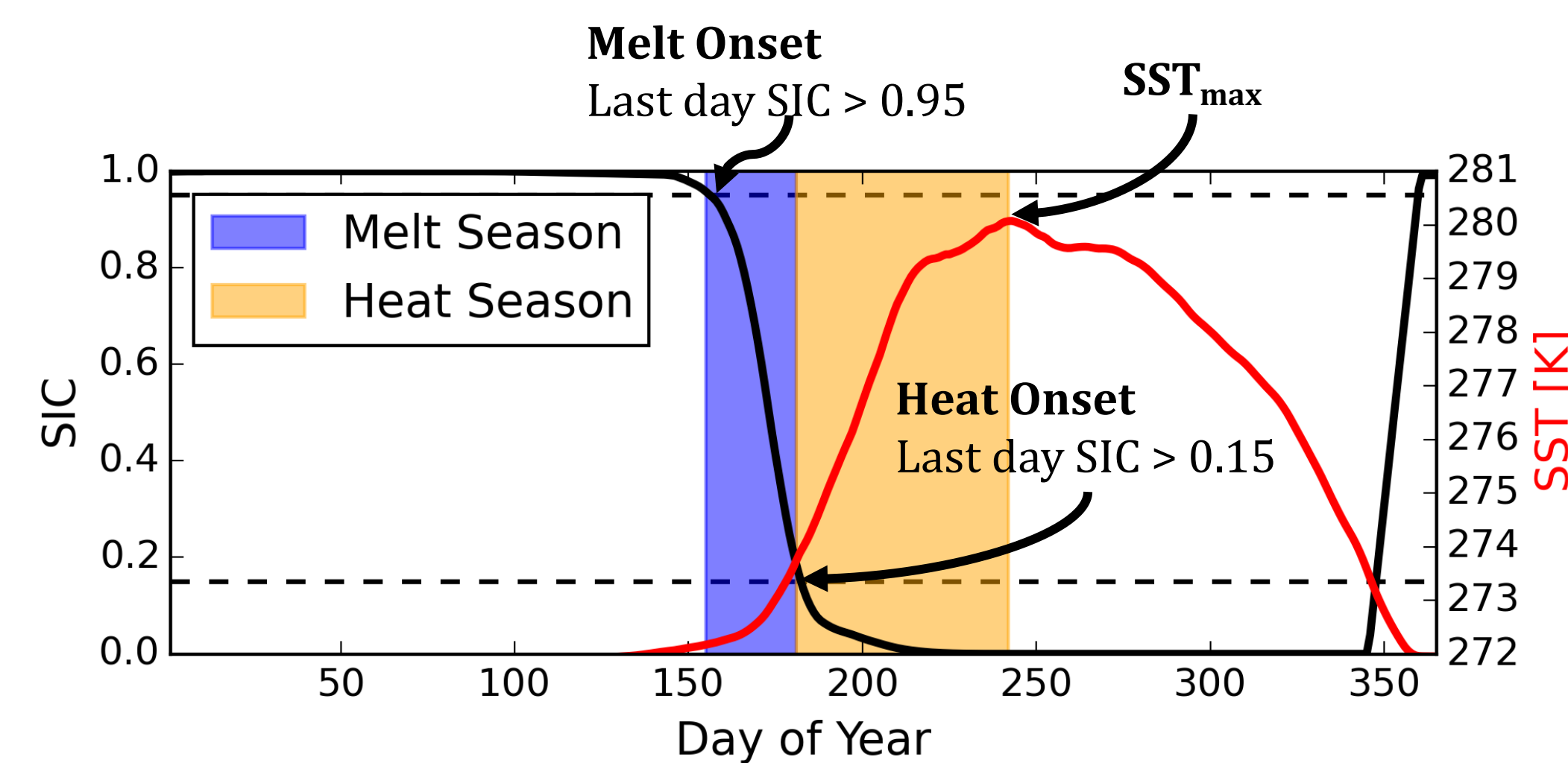
Annual cycles of (left) cloud liquid water path (LWP) and (right) total cloud fraction (CF<sub>tot</sub>). For all CESM2 data in (a-e), only ocean grid cells poleward of 70°N are included. Observed CF<sub>tot</sub> are from CALIPSO GOCCP (2006-2018). CESM CF<sub>tot</sub> is from the COSP lidar simulator.



Annual cycles of (c) LW cloud radiative effect (CRE), (d) net CRE, (e) SW CRE, and (f) histograms of heat onset. All CRE are calculated at the surface. For all CESM2 data in (a-e), only ocean grid cells poleward of 70°N are included. Observations in (b) are from CALIPSO GOCCP.

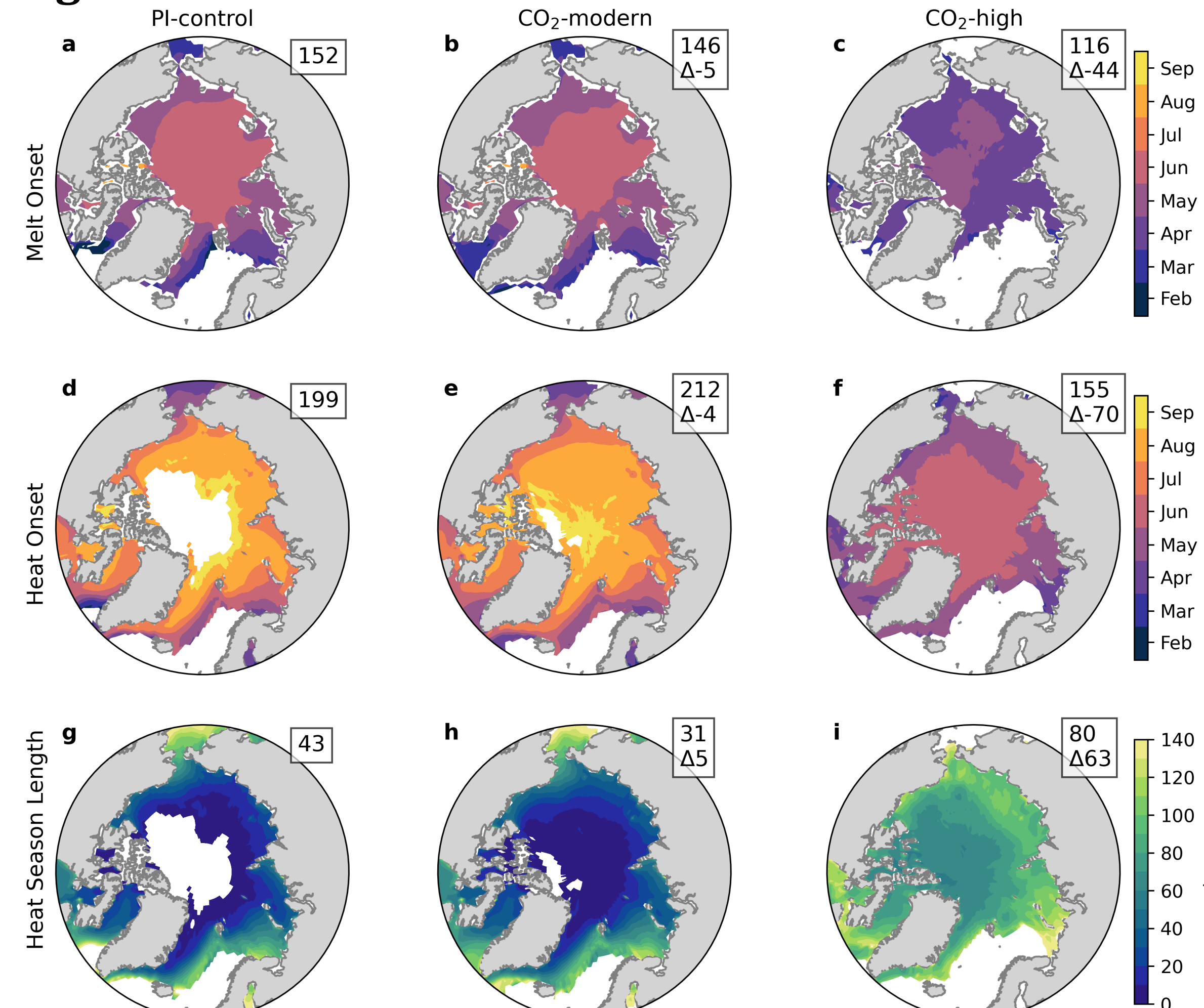
## 4. Seasonal definitions from Steele and Dickinson (2016)

- 15-day moving average is applied to daily average SIC and SST time series in each grid cell
- “melt season” = melt onset to heat onset
- “heat season” = heat onset to day of SST max



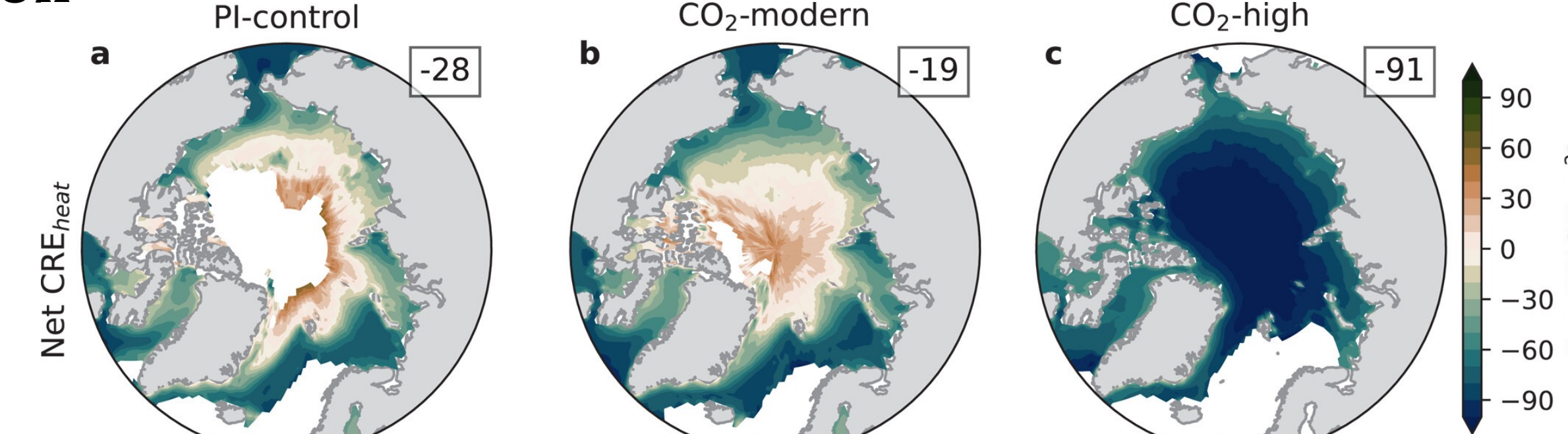
Example identification of dates for melt onset, heat onset, and SST maximum from one grid cell in one year.

## 5. Under higher CO<sub>2</sub> sea ice melts earlier and the ocean warms for longer



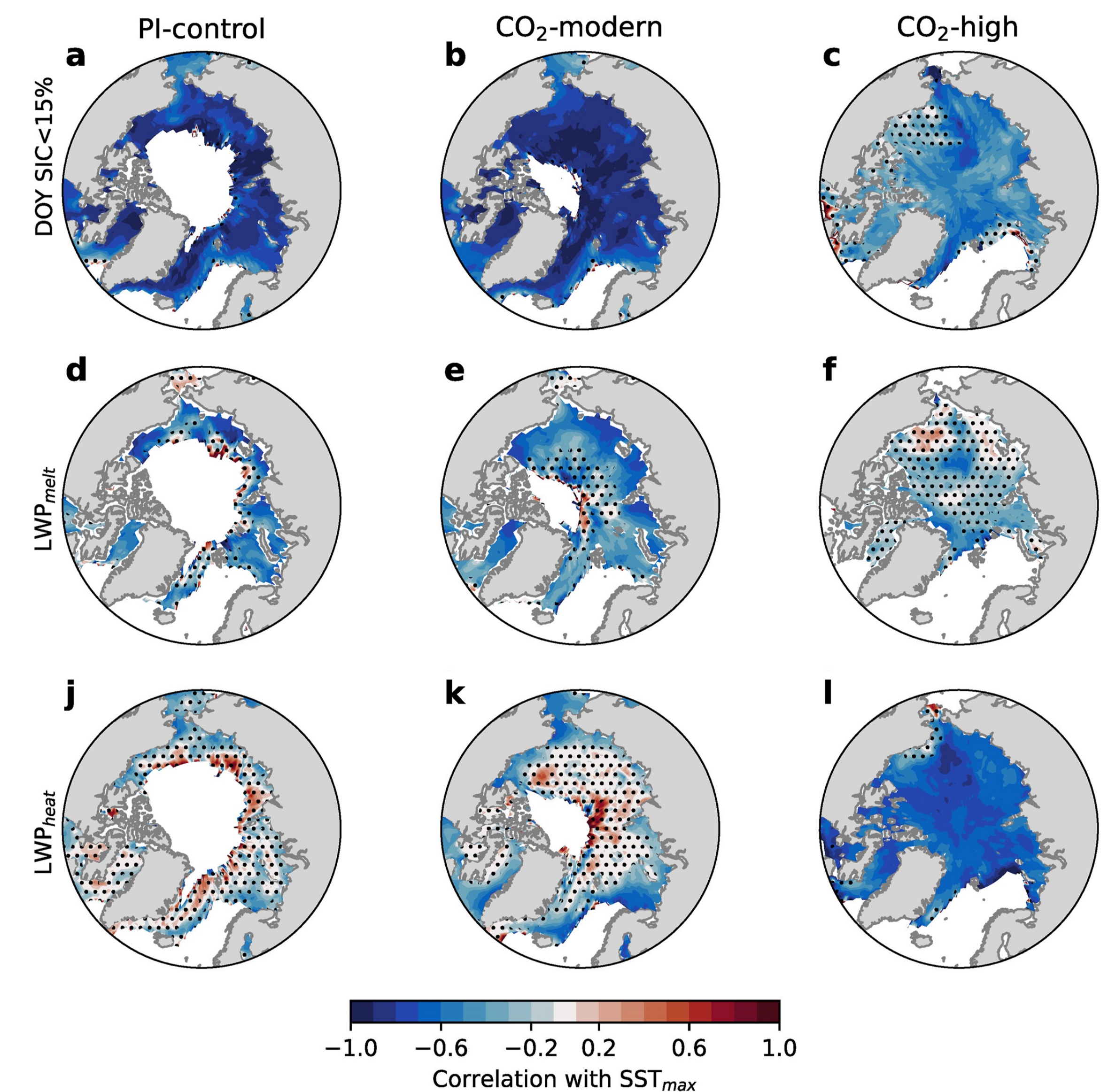
Average date of melt onset (a-c), heat onset (d-f) and length of heat season (g-i). Mean values are given in the upper right boxes of each subfigure, along with the average difference between CO<sub>2</sub>-modern and CO<sub>2</sub>-high experiments minus PI-control for only grid cells that experience heat and melt onset in both runs, indicated by Δ. Differences are given in days.

## 6. Earlier heat onset leads to more negative CRE during the heat season

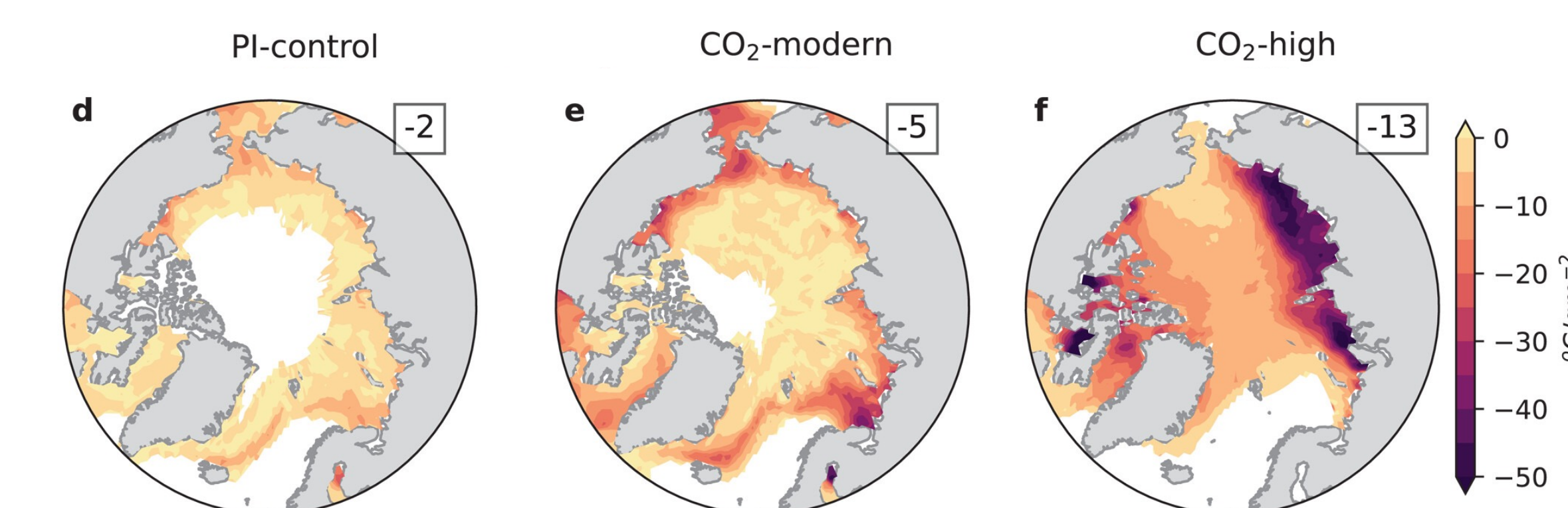


Average net CRE during heat season. Mean values are given in upper right boxes of each subfigure.

## 7. The earlier open ocean is exposed, the more negative the correlation between clouds and maximum SST and the more sensitive maximum SST is to clouds



Correlations between variables and maximum annual SST for runs with variable CO<sub>2</sub>. Stippling represents correlations that are not statistically significant with 95% confidence. Correlations between total CF in heat and melt seasons and SST<sub>max</sub> are similar to LWP.



Regressions between average heat season LWP and maximum annual SST for. Mean values are given in upper right boxes of each subfigure.

## 8. Conclusions

- During the pre-industrial era, sea ice retreat timing, not clouds, primarily explains maximum annual Arctic SST
- As sea ice retreats closer to the June solstice, clouds increasingly explain maximum annual SST
- When the Arctic is seasonally ice-free, maximum SST is 3X more sensitive to clouds than in the pre-industrial era

## References

- Steele and Dickinson (2016) doi:10.1002/2016jc012089
- Sledd et al. (2023) doi:10.1029/2023GL102850

## Acknowledgements

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