Assessing CESM2 Clouds and Their Response to Climate Change Using Cloud Regimes

ISAAC DAVIS\textsuperscript{a,b} AND BRIAN MEDEIROS\textsuperscript{b}

\textsuperscript{a} Department of Atmospheric and Oceanic Sciences, University of Colorado Boulder, Boulder, Colorado
\textsuperscript{b} Climate and Global Dynamics Laboratory, National Center for Atmospheric Research, Boulder, Colorado

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ABSTRACT: The Community Earth System Model, version 2 (CESM2), has a very high climate sensitivity driven by strong positive cloud feedbacks. To evaluate the simulated clouds in the present climate and characterize their response with climate warming, a clustering approach is applied to three independent satellite cloud products and a set of coupled climate simulations. Using $k$-means clustering with a Wasserstein distance cost function, a set of typical cloud configurations is derived for the satellite cloud products. Using satellite simulator output, the model clouds are classified into the observed cloud regimes in both current and future climates. The model qualitatively reproduces the observed cloud configurations in the historical simulation using the same time period as the satellite observations, but it struggles to capture the observed heterogeneity of clouds which leads to an overestimation of the frequency of a few preferred cloud regimes. This problem is especially apparent for boundary layer clouds. Those low-level cloud regimes also account for much of the climate response in the late twenty-first century in four shared socioeconomic pathway simulations. The model reduces the frequency of occurrence of these low-cloud regimes, especially in tropical regions under large-scale subsidence, in favor of regimes that have weaker cloud radiative effects.

KEYWORDS: Cloud forcing; Cloud retrieval; Clustering Clouds; Cloud radiative effects; Climate models

1. Introduction

Climate models have significantly varying responses to greenhouse gas forcing (e.g., Meehl et al. 2020a). Uncertainty in cloud feedback—the change in top of atmosphere radiative flux as a result of clouds responding to warming—is the largest contributing factor to these varying responses (Zelinka et al. 2022). It is imperative to gain a better understanding of the cloud feedback to reduce uncertainties in climate sensitivity. The Community Earth System Model, version 2 (CESM2), has a very high climate sensitivity (greater than 5-K warming for a doubling of CO$_2$), and this is largely attributed to strong, positive cloud feedbacks (e.g., Bacmeister et al. 2020; Gettelman et al. 2019; Bjordal et al. 2020; and others). Regions of low-level cloud cover are especially implicated in the overall cloud response, including the Southern Ocean and the subtropical oceans (Zelinka et al. 2020; Schneider et al. 2022). In this work, we are motivated to investigate global cloud characteristics in CESM2 compared to satellite observations and explore how these cloud characteristics respond to warming.

Several satellite products, starting with the International Satellite Cloud Climatology Project (ISCCP; Rossow and Schiffer 1991, 1999), produce histograms of cloud-top pressure and optical depth (CTP–τ histograms). These CTP–τ histograms put two key cloud properties into a two-dimensional space that captures the dominant factors in the cloud radiative effect: the cloud-top pressure is closely related to the cloud-top temperature which is the primary controlling factor in the longwave cloud radiative effect, and the optical depth is directly proportional to the liquid water path and the albedo (Stephens 1978). Following ISCCP, similar cloud histograms have been produced using observations from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the Multiangle Imaging SpectroRadiometer (MISR). Comparisons across the products are provided by Marchand et al. (2010) and Pincus et al. (2012). Satellite simulators run within climate models produce analogous histograms, and allow for detailed comparisons between observations and models (Kay et al. 2012; Medeiros et al. 2023).

Jakob and Tselioudis (2003) introduced the concept of cloud regimes (CRs, sometimes also called weather states) which makes use of CTP–τ histograms to describe typical arrangements of clouds. Cloud regimes are constructed by applying $k$-means clustering (Anderberg 1973) to CTP–τ histograms. Using an iterative approach, each CTP–τ histogram is assigned to one of a prescribed number $k$ of clusters in such a way as to minimize the distance of the histogram from the cluster center. The result is that each cluster contains the subset of histograms that are most similar to each other (by some objective measure). Averaging all the histograms in each cluster provides the “centroid” of the cluster: a composite view of the characteristics represented by the cluster. Jakob and Tselioudis (2003) showed that the resulting composite histograms were interpretable in terms of physical understanding of the meteorology and cloud types observed in the western Pacific region. Rossow et al. (2005) built upon the...
analysis in Jakob and Tselioudis (2003) to extend to the whole tropics using observations from 1983 to 2004. They argued that long-term climate variations can be understood as changes in the frequency of occurrence of distinct meteorological states described by CRs. Tselioudis et al. (2013) derived global ISCCP CRs and examined their distributions spatially and assessed the vertical structure by comparison with active remote sensing products. They also contextualized the CRs by compositing vertical velocity to confirm that some CRs are dominated by convective activity, and a similar compositing of cloud radiative effects showed how the CRs vary in their radiative impact. Oreopoulos et al. (2016) applied the same CR approach to MODIS observations to investigate cloud radiative effects by cloud regime.

Cloud regimes have also been used for investigating clouds in climate models by using the CTP–τ histograms provided by satellite simulators. Williams et al. (2005) provide an early example wherein ISCCP observations and ISCCP simulator output were separately clustered into CRs in four geographic regions to evaluate model representations of the clouds. In recent years, several studies have leveraged the systematic use of satellite simulators in Coupled Model Intercomparison Project (CMIP) experiments to provide similar evaluations. Jin et al. (2017) use ISCCP CRs as an observational reference and then assigned the climate model (and MODIS) CTP–τ histograms to those CRs to assess the performance of the models when forced by observed sea surface temperature and sea ice cover (so-called AMIP simulations). That study suggested the models generally do not perform well at reproducing the observed cloud distribution. Tselioudis et al. (2021) provide a similar assessment but using CRs derived from the updated ISCCP-H data. They apply the updated CRs to CMIP6–AMIP simulations that provide daily ISCCP simulator output similarly to the methodology of Jin et al. (2017) for the earlier generation of models. Although some improvements over CMIP5 models were noted, Tselioudis et al. (2021) point out several substantial deficiencies among the models, including substantial spread among models within several of the CRs that suggest large discrepancies in the representation of clouds among the models.

A natural extension from evaluating climate model clouds is to apply cloud regimes to investigate cloud feedbacks, and a few studies have laid groundwork for this application. Williams and Tselioudis (2007) derived global CRs for six climate models with slab ocean components and investigated the changes in CRs for a climate change experiment. Williams and Webb (2009) expanded to 10 models and developed a method for assigning model histograms to observed CRs using a reduced three-element feature vector instead of the full histogram. Both studies showed errors across models in terms of both radiative effects of CRs and the frequency of occurrence of regimes and showed large intermodel spread in the climate response of low-cloud regimes. Tsushima et al. (2016) applied the methods of Williams and Webb (2009) to CMIP5 simulations, investigating the cloud response to an imposed pattern of SST warming on top of the observed monthly SST. That study highlighted the relevance of within-regime albedo errors versus the frequency of occurrence errors for the feedback and especially noted the importance of subtropical cloud regimes. Recently, Zelinka et al. (2023) followed a similar methodology combined with a cloud radiative kernel analysis to investigate the cloud feedbacks across regimes in five CMIP5 and five CMIP6 models with an imposed, uniform 4-K warming on top of the observed monthly SST. That study was able to identify that within-regime and across-regime cloud feedback components contributed to the overall cloud feedback and emphasized that intermodel spread in feedbacks differed with within-regime changes being more spatially uniform and consistent in sign across models while across-regime changes showed more intermodel spread.

We build upon these previous studies in a few key ways to explore how the cloud regime concept can be applied to better understand the clouds produced by CESM2 and how they respond under climate change. First, we introduce a modified k-means algorithm that uses the Wasserstein distance (aka Earth mover’s distance) instead of Euclidean distance. The Wasserstein distance is a better distance metric between CTP–τ histograms because it accounts for the two-dimensional parameter space (section f and discussion in Medeiros et al. 2023). Second, while previous studies have mainly used ISCCP as the basis of CRs, and a few have expanded to using MODIS, we conduct all analyses with ISCCP, MODIS, and also MISR. Using the ISCCP, MODIS, and MISR simulators in CESM2, the model’s CTP–τ histograms are classified with the derived CRs for each satellite product. The same cluster centroids are then used to classify the simulated clouds in the late twenty-first century in four climate projections. Another difference from previous studies is that the climate simulations analyzed here are coupled atmosphere–ocean climate simulations. We investigate how the changes in the total cloud radiative effect (CRE) can be attributed to the changes in the frequency of occurrence of the CRs versus the changes in CRE within the CRs. Links between the large-scale circulation and CRs are illustrated by conditionally sampling the CRs based on large-scale vertical motion. As the circulation changes with climate, we show that the distribution of CRs adjusts to favor regimes with weak CRE, consistent with the positive cloud feedback that has been diagnosed in CESM2.

2. Data and methods

This section provides brief descriptions of the satellite data sources, the climate model, and the statistical methods used. Details of instruments, retrievals, and products are omitted but can be found in the provided references. Similarly, the satellite simulators and the CESM2 are described in broad terms, and details are provided in the references.

a. ISCCP

The ISCCP data merge satellite observations from geostationary and polar-orbiting satellites with visible and infrared channels (Rossow and Schiffer 1999; Rossow et al. 2022). The polar-orbiting satellites utilize advanced very high-resolution radiometers, while a variety of imagers are onboard the geostationary satellites. Measurements are made only over daylight areas and aggregated into a coarse-resolution product with geophysical quantities. The H-series, used here, is the
successor to the earlier D-series, as described by Rosswow et al. (2022). A major strength of ISCCP products comes from the length of the data record, reaching back to 1983 and extending to 2017, and updates to include recent years are expected. Crucial for the present work is that cloud amount is recorded in CTP–τ histograms; there are seven bins for cloud-top pressure and six bins for cloud optical depth. As described above, these CTP–τ histograms have been used in previous studies to define cloud regimes that are thought to provide a compact summary of the mesoscale cloud structures within the large grid cells of the product (e.g., Jakob and Tselioudis 2003; Rosswow et al. 2005). Our analysis is based on the ISCCP Basic high-resolution global hourly (HGH) 3-hourly data provided on a regular (equal angle) 1° × 1° latitude–longitude grid and we use the combined cloud properties from the Aqua and Terra satellites. For all analysis here, the most recent v6.2 collection MCD06COSP data files are used (https://doi.org/10.5067/MODIS/MCD06COSP_M3...MODIS.062). Those data were processed to combine cloudy and partly cloudy retrievals into a single normalized CTP–τ histogram. This processing essentially follows the procedure provided by Pincus et al. (2023). The MODIS histograms are similar to the ISCCP ones, but MODIS has one additional τ bin (seven total) that adds information for clouds with τ < 0.3; these are tenuous clouds and retrievals at such low τ come with large uncertainties (Platnick et al. 2017). MODIS data span 18 years (from 2002 to 2020) of which we use 2002–15 to correspond with the historical CESM2 simulation.

c. MISR

MISR is an array of nine push broom cameras aboard the Terra satellite that produces cloud-top height–optical depth (CTH–τ) histograms with 16 bins of cloud-top height and six bins of cloud optical depth (Diner et al. 2005; Marchand et al. 2007). Different from ISCCP and MODIS, MISR uses a stereographic method to surmise cloud-top height. A significant advantage of this method is that it is geometric and thus does not rely upon instrument calibration. The optical depth retrieval is similar to that of ISCCP and MODIS. We use the level 3 monthly product (version 7) described by Marchand et al. (2010). It has a data record from 2003 to 2021, of which we use 2002–15 as the historical period. The MISR data are on a 1° × 1° latitude–longitude grid with valid measurements restricted to ice-free ocean locations.

d. CESM2

CESM2 is the current generation of the National Center for Atmospheric Research’s CESM, which is an open source and fully coupled climate model (Danabasoglu et al. 2020). We use simulations prepared for the CESM2 contribution to CMIP6: a historical simulation and four shared socioeconomic pathway (SSP) simulations. The historical simulation is forced by CMIP6 historical forcings except several chemical and stratospheric forcings, nitrogen deposition, and ozone which are derived from a stratosphere-resolving simulation performed with CESM2 (see Danabasoglu et al. 2020). The SSP simulations are driven based on datasets for land use, greenhouse gases, aerosols, precursor gases, and that are derived based on results from integrated assessment models. The SSPs are meant to represent the possible climate outcomes based on different scenarios of society’s future response to the changing climate. The four SSPs we use represent the low end (SSP1-2.6), intermediate (SSP2-4.5 and SSP3-7.0), and high end (SSP5-8.5) of future forcing pathways (O’Neill et al. 2016). For simplicity, we hereafter refer to these as SSP1, SSP2, SSP3, and SSP5. The historical simulation runs from 1850 to 2015, while the SSPs run from 2015 to 2100. The warming in the early part of the twenty-first century is similar among the SSPs but diverges after about 2050 (Meehl et al. 2020b). To highlight the differences across SSPs, the analysis of cloud changes in them is taken over 2071–2100. By analyzing 30 years, interannual variability is relatively well sampled; we have tested this by repeating some aspects of the analysis with multiple realizations (where possible) to confirm that results are robust to sampling. The historical period used in CESM is taken to match the historical period of each respective data product, being from the year of the product’s first observation until 2015. Similar to the SSPs, we have investigated whether the internal variability of the coupled system during the historical period impacts the comparison between observations and CESM. Examining the historical period across members of the CESM2 large ensemble (Rodgers et al. 2021), we find that, at least globally, the model difference with observations is relatively robust.

The forcing data used for CMIP simulations have been called into question in several regards which may impact cloud properties through aerosol–cloud interactions. For example, Wang et al. (2021) show that the historical emissions data miss a change in the trend over parts of Asia in recent years. Another example shows a change in warming in CESM2 because of a change in biomass burning emission interannual variability (Fasullo et al. 2022). In that case, clouds thin and warm the climate. Models show diverse aerosol–cloud interactions that lead to a range of effective radiative forcing (Smith et al. 2020); CESM2 has a strong aerosol effective radiative forcing that may arise from the susceptibility of low-level clouds to aerosol perturbations (Medeiros 2020). While the effective radiative forcing and regional climate in CESM2 may be impacted by these issues, Smith et al. (2020) find no correlation between aerosol forcing and climate sensitivity.

The CESM2 performance has been evaluated in a number of studies and is generally among the best performing CMIP-class models. Danabasoglu et al. (2020), for example, show that the CESM2 historical simulation captures the observed warming and variability of the twentieth century global average surface air temperature along with other improvements compared to earlier versions of the model. Capturing the
twentieth century, however, may be achieved with different balances of sensitivity and aerosol forcing (e.g., Watson-Parris and Smith 2022). Fasullo (2020) compares multiple models (through several phases of CMIP) during the observational record using a multivariate assessment, and CESM2 is the highest ranked model. In an investigation of the large-scale circulation, Simpson et al. (2020) show that CESM2 is among the best CMIP-class models in many aspects of the circulation. Although CESM2 compares well with the historical record, it has a very high climate sensitivity, with more than 5 K of warming for a doubling of CO₂ (e.g., Bacmeister et al. 2020; Gettelman et al. 2019). The transient warming, however, is similar to the previous generation CESM1 (Meehl et al. 2020b).

e. Satellite processing and COSP

All of the analyses presented here are based on monthly average data, all of which are based on aggregated high-frequency data. The ISCCP-H data products provide 3-hourly average CTP–τ histograms from which we calculate monthly averages. For ISCCP, we use measurements made only from 65°N to 65°S to avoid observations made over ice, which may be less accurate than those made over land and water. Both MISR and MODIS products are supplied as monthly averages. As noted above, the MODIS data are preprocessed to combine partly cloudy and cloudy histograms. A daily MODIS product is also available. Previous studies have used higher frequency CTP–τ histograms. The choice to use monthly mean histograms was motivated by the availability of the Cloud Feedback Model Intercomparison Project (CFMIP) Observation Simulator Package (COSP) output from the CESM2 simulations: only monthly means are available across the ISCCP, MISR, and MODIS simulators for the historical and SSP simulations. Experimentation with the ISCCP data (starting from 3-hourly) indicated modest sensitivity to the temporal averaging for the resulting cluster centroids. Similar sensitivity testing showed that MODIS centroids vary more significantly using daily versus monthly histograms. We have no high frequency CR precedent for MISR and therefore cannot comment on how the frequency of the data affects the outcome.

The satellite simulators in CESM2 are part of the COSP (Bodas-Salcedo et al. 2011; Swales et al. 2018). COSP simulates satellite measurements of numerous cloud data products using the model atmospheric state and produces CTP–τ histograms directly comparable to those produced by ISCCP, MODIS, and MISR. Satellite simulators make some simplifying assumptions to approximate the retrieval methodologies and therefore may introduce some of their own biases and limitations (n.b., Pincus et al. 2012). In addition to those simplifications, the sampling differs between the real satellites and the simulators. At each model grid point, a set of subcolumns is generated to approximate subgrid-scale variability, and the number of subcolumns is a model parameter. Sampling also differs between model and observation because COSP output is given at every sunlit point every time the radiation scheme is run. In our analysis, we have made no attempt to reduce the model sampling to be more comparable to the satellite products.

f. k-means

Following Tselioudis et al. (2021) and others (see above), we apply k-means clustering with each of the monthly satellite datasets to create sets of CRs. The algorithm requires the number of clusters k as a parameter. To determine how many CRs are most appropriate for each dataset, we follow the methods established in previous studies as described below. The algorithm also needs a quantitative measure of “distance” between the CTP–τ histograms to assign each CTP–τ histogram to a cluster. Conventionally, a simple Euclidean distance is used for this distance. While this is easy to implement and well-established, it does not account for the two-dimensional nature of CTP–τ histograms and we propose the Wasserstein distance (aka Earth mover’s distance) as an alternative.

To provide a rationale for the choice to use the Wasserstein distance instead of the Euclidean distance, we briefly review why the Euclidean distance is insufficient for the task at hand and then provide an overview of the Wasserstein approach. Recall that each histogram is an m × n array with m and n representing the number of CTP and τ bins, so the Euclidean distance between two such arrays, a and b, is constructed as

\[ d = \sqrt{\sum (a_i - b_i)^2}, \]

where \( i \) is a one-dimensional index of the “flattened” histograms. The Euclidean distance, therefore, can only distinguish differences on a per-element basis. Consider three hypothetical histograms that each contains 50% cloud cover in a single bin: in the first, the cloud is in the thickest, highest cloud-top bin, the second is shifted one τ bin lower, and the third has the cloud in the thinnest, lowest cloud-top bin. The Euclidean distances between the three histograms are the same, but we would hope that a one-bin shift would be “nearer” than a multibin shift. This ambiguity causes problems during the clustering step. This issue was noted by Williams and Webb (2009), and they highlighted that this became particularly problematic when fitting climate model histograms into observation-based CRs because the models tended to misplace cloud in the CTP–τ space, so many histograms have a minimum Euclidean distance to whichever CR is closest to the origin (i.e., low cloud amount spread through all bins, usually a shallow cumulus CR). Williams and Webb (2009) addressed this problem by creating three-element vectors of the mean albedo, cloud-top height, and total cloud cover of each CR. These three-element vectors were derived from the model CTP–τ histograms and were then classified into CRs using Euclidean distance to the observed albedo, cloud-top height, and total cloud cover of the observational CRs. Their method is efficient but neglects potentially useful information embedded in the two-dimensional histogram.

To make use of as much of the histogram information as possible, we use the Wasserstein distance. Wasserstein distance measures the distance between distributions by solving the optimal transport problem that finds the best transport plan that transforms one distribution to another (Engquist and Froese 2014; Villani 2003). It is also known as the Earth mover’s distance because it can be understood as the minimum
work needed to transport material from one location to another within a site. In our case, it is the minimum work to transform one CTP–τ histogram into another. It understands the distance between bins of the histograms and thus is a better choice of distance metric than Euclidean. As a test of its fitness for this task, we estimated the average distance between pairs of points within a cluster and divided it by an estimate of the average distance between any two points in the dataset. This provides a measure of cluster compactness that is independent of distance metric. This ratio was 0.7 for the Euclidean clusters and 0.54 for the Wasserstein clusters. This indicates that the Wasserstein distance creates more compact clusters. It is, however, computationally slower than Euclidean distance, and consequently, we were unable to run as many initiations with the Wasserstein-based k-means algorithm as in previous studies using conventional k-means. It also requires the histograms to be normalized which means differences in total cloud amount are not included in the distance, only the relative arrangement of cloud; this limitation seems to pose little issue in practice.

As part of the implementation of our k-means algorithm, we included an option to provide weights for histograms. This allows for area weighting during the clustering step rather than after the fact. This results in more accurate clusters by avoiding giving disproportionate influence to high-latitude locations. In practice, the differences in final clusters were minimal between weighted and unweighted clustering.

Choosing the number of clusters largely follows from previous descriptions of CRs. First, clustering is performed for a
range of \( k \) (the number of clusters), \( k \in [4, 13] \); the clustering results in \( k \) CTP-\( \tau \) histograms representing the cluster centroids. For each value of \( k \), the correlation coefficients between the cluster centroids are calculated to produce a correlation matrix. A second correlation matrix is calculated for the pattern correlations of the global frequency of occurrence between each CR. These correlation coefficients are then used to determine if each increment of \( k \) produced a genuinely new CR or if an already present CR has split to create two clusters that are nearly indistinguishable. If the new CR has a high pattern correlation with an already existing one and a high correlation between CTP-\( \tau \) histograms, then it is unlikely that a distinct CR has appeared. Thus, an increase in \( k \) has provided no added utility for evaluating clouds. We performed this analysis with the conventional Euclidean distance metric for computational efficiency; the resulting best value of \( k \) for each data product was then used with the Wasserstein distance version of \( k \)-means. Another condition imposed on the choice of \( k \) is that the final CRs must not be sensitive to the choice of the initial seed. The \( k \)-means algorithm uses a seed to randomly select \( k \) vectors as initial cluster centers. A different seed will result in different initial clusters, so it is necessary to check that the algorithm converges to very similar final cluster centroids. We check this by repeating the clustering three times for the final \( k \) value and ensuring that the resultant cluster centers have correlation coefficients > 0.8 through each trial. For our conventional \( k \)-means setup, which determines the final value of \( k \), we used a graphics processing unit (GPU)-accelerated implementation utilizing the RAPIDS Artificial Intelligence (AI) Compute Unified Device Architecture Machine Language package (cuML) (Raschka et al. 2020). It ran with a maximum of 100 iterations and 350 random initiations. We used scalable \( k \)-means++ (or \( k \)-means||) to initialize the algorithm. Scalable \( k \)-means++ is an implementation of \( k \)-means++ that scales well onto a GPU or multiple processors. The \( k \)-means++ itself is a method of selecting initial cluster centers that are vectors with a large spread between them. This ensures that the initial centroids are spread out and serves to accelerate the convergence of the \( k \)-means algorithm. Our custom Wasserstein distance \( k \)-means was also initiated with a version of \( k \)-means++ that uses Wasserstein distance. It is worth noting that in previous studies, clear-sky histograms were removed before clustering and added back afterward as a clear-sky CR. Using monthly data reduces the frequency of occurrence of fully clear-sky histograms to the point where removing them is unnecessary, and therefore, clear-sky histograms are included in the clustering.

We found the optimal value of \( k \) to be 8 for ISCCP. Notably, at \( k = 6 \), one CR splits into two very similar CRs with

![Fig. 2. The RFO of each CR in ISCCP observations from 1983 to 2015.](image-url)
very similar geographic distributions, but at $k = 7$ and $k = 8$, distinct CRs appear. As a result, the split CR was recombined as the weighted average of the two qualitatively indistinguishable CRs, so the final result has seven CRs, as shown in Fig. 1.

For both MODIS (Fig. 3) and MISR (Fig. 5), $k = 6$ was found to be optimal. For MODIS, the $k = 6$ value is much less than the 11 plus clear-sky cluster used by Cho et al. (2021). However, Cho et al. (2021) use daily data and a...
slightly different method to decide on $k$. Their clustering produced about five high-cloud CRs with low frequencies of occurrence, and our monthly clustering does not differentiate these rare CRs.

The cloud regimes derived from each satellite dataset are used to categorize the CESM2 clouds produced by COSP. Monthly average CTP–r histograms are assigned to the most similar cluster centroid using the Wasserstein distance. Using
the observed CRs to classify simulated histograms is similar to the approach taken by Tselioudis et al. (2021) and several other previous studies. Alternative approaches have been explored by previous studies. One is to perform clustering with the model output, as in Williams and Tselioudis (2007). Another is to use reduced feature vectors like Williams and Webb (2009). An advantage of directly clustering the model data is that it allows the clusters to be more compact and better represent the model’s cloud regimes, but the disadvantage, as discussed also in Williams and Webb (2009), is that it makes comparison with the observations more difficult because the analysis may produce a different number of clusters and introduces more subjectivity to the process. Mason et al. (2015) propose a hybrid method that clusters observations and model output simultaneously, and they also discuss the relative advantages and disadvantages of the various approaches.

3. Results

a. Observed cloud regimes

In this section, we present the results of clustering the monthly observed cloud histograms. To begin, Fig. 1 shows the composite histograms for the monthly ISCCP cloud regimes constructed by averaging all histograms assigned to the cluster (i.e., the cluster centroid). We subjectively arrange the CR labels to place high-cloud regimes first and low-cloud regimes later in the sequence. The CRs shown in Fig. 1 can be
compared with those of Tselioudis et al. (2021) who performed a similar clustering but used conventional $k$-means with Euclidean distance, 3-hourly data rather than monthly, included polar regions (rather than 65°N–65°S), and separately created a clear-sky regime. Despite the methodological differences, the CRs in Fig. 1 are subjectively similar to those of Tselioudis et al. (2021). Our CR numbers 1–5, in fact, appear to map directly to regimes in Tselioudis et al. (2021) (their labels 3, 1, 4, 2, and 5, respectively). Our CR2 and CR5 occur more frequently than their counterparts in Tselioudis et al. (2021). The discrepancies are probably partly because they have eight cloud regimes and a clear-sky regime compared to our seven and also because the monthly averaging obfuscates higher frequency cloud variability toward the forms of CR2 and CR5.

The relative frequency of occurrence (RFO) of the ISCCP CRs is shown in Fig. 2 which demonstrates the spatial distribution of the CRs. Again the qualitative comparison with Tselioudis et al. (2021) is quite good. We interpret the high-cloud regimes (CRs 1 and 2) to represent cirrus and deep convective anvil clouds found across the tropics. Thin cirrus appears to occur frequently in regions of elevated terrain (e.g., western North America and the Himalayas), but these heterogeneous regions pose some challenges for the ISCCP retrieval and are less certain than marine locations (e.g., Knapp et al. 2021). CR3 also has substantial high-level cloud, but with a mix of lower and optically thicker clouds, and appears predominantly at high latitudes; this regime is similar to the polar cloud regime in Tselioudis et al. (2021). CR4 occurs mainly over the oceans with midlevel cloud tops; this regime is described as midlatitude storm clouds by Tselioudis et al. (2021). Optically thick, mid- and low-level clouds make up CR5 and also occur mainly in the midlatitude storm tracks and generally poleward from the clouds of CR4, but some coastal stratiform cloud also appears in the subtropics. The most noticeable discrepancy from Tselioudis et al. (2021) comes in the low-cloud regimes. Their “fair weather” regime occurs with a frequency making up nearly 40% of their data, and they have a separate stratocumulus regime. We interpret CR6 as being composed of shallow convection (and possibly also deeper cumulus congestus) with a low cloud amount. Our most frequent regime is CR7 (20% RFO), and it accounts for most of cloud-topped boundary layers of the subtropics including stratocumulus, trade wind cumulus, and the transition between them. One possible explanation for the disagreement in the fair weather regime is that using the conventional Euclidean distance tends to favor having a regime with a small cloud amount across many of the histogram bins; indeed, that regime in Tselioudis et al. (2021) occurs across many geographic regions and has a comparatively uniform histogram.
Turning to the MODIS results, Fig. 3 shows the histogram centroids and Fig. 4 shows the spatial distribution of CRs. Along with having one fewer cloud regime than ISCCP (following the procedure of section 2f), there are a few differences from the ISCCP results. The MODIS CRs tend to concentrate cloud in the highest pressure bin, emphasizing low-level clouds. The CRs transition from high-level clouds with only optically thin low clouds to being dominated by low-level clouds with nearly no higher clouds. The distinctions across the MODIS CRs appear even more stark in the spatial distributions of Fig. 4. CR1 contains the most high cloud and captures tropical deep convection. CR2 has less high cloud, more low-level cloud, and appears frequently over land (similar to ISCCP CRs 1 and 3). MODIS CR3 has a small cloud amount with a mix of low, thin and higher, thicker cloud; it occurs mainly over warm ocean regions, so appears associated with shallow to moderate cumulus convection. The clouds of CR4 and CR5 have more low cloud and occur in the midlatitudes; they appear similar to ISCCP CRs 4 and 5, but the MODIS CRs emphasize low-level clouds. CR6 is also low thick cloud, has little upper-level cloud, and occurs mainly over subtropical oceans, corresponding to stratocumulus and shallow cumulus like ISCCP CR7. The analysis of MODIS by Cho et al. (2021) reported a “low cloud” regime with RFO of 37%, similar to the fair weather ISCCP regime of Tselioudis et al. (2021). As in the ISCCP case, we suspect that the use of Euclidean distance in previous studies favors a single regime with a small cloud fraction but an indistinct structure.

The MISR results are shown in Figs. 5 and 6 and are broadly consistent with the ISCCP and MODIS results. As in the other observations, the high cloud regimes (CRs 1 and 2) are especially prevalent in regions of tropical convection. Also similar to the MODIS results, through the transition from high-cloud to low-cloud regimes, the high clouds become less frequent, while low clouds become more frequent and optically thicker. Some high-level cloud remains in CR3, but Fig. 6 shows that the regime occurs broadly across the warm tropical ocean. Along with its increased low, thin cloud, we postulate this to be a shallow convection regime (like MODIS CR3 and ISCCP CR6). MISR CR4 consists of thicker low- to midlevel cloud and occurs in midlatitude storm tracks. With optically thicker and predominantly low-level clouds, CR5 likely captures stratocumulus across the subtropics and mid-latitudes. Finally, with optically thinner clouds than CR5 and being constrained mainly to the tropics, we interpret CR6 as being dominated by shallow cumulus. The higher vertical resolution of the MISR product likely allows a more subtle distinction between stratocumulus and shallow cumulus than ISCCP and MODIS.

Several observed CRs exhibit a marked seasonality in their occurrence, which is mirrored in the model’s CRs discussed next. The seasonality is likely linked to fundamental connections between clouds and the large-scale circulation and may
offer valuable insights for interpreting model biases. However, unraveling the intricacies of this seasonal variability is left for future work, and we focus instead on longer time scales.

b. Evaluation of clouds in the historical simulation

Figure 7 shows the composite histograms that result from averaging monthly CESM2 ISCCP simulator output that gets assigned to each ISCCP CR. Differences between Figs. 1 and 7 indicate intra-CR differences between the model and observations. As expected, the composite histograms are similar; the largest differences are in CR4 and CR6. In CR4, ascribed to midlatitude storms above, CESM2 has a lower cloud amount and appears to lack much of the observed cloud with $\tau < 9.4$.

In CR6, CESM2 lacks the low, thin cloud structure seen in the ISCCP CR6.

The composite histograms that result from fitting CESM2 to the observed MODIS and MISR CR centroids follow similar patterns. These are shown in Figs. S1 and S2 in the online supplemental material. Briefly, CESM2 captures the MISR CRs fairly well, with similar accuracy to ISCCP. There are greater discrepancies with the amount of low-level cloud in the MODIS CRs; CESM2 has less low-level cloud but more mid- to high-level cloud across CRs. These figures are also available as difference plots with the observational cluster centers in Figs. S3–S5.

The match between the observed and modeled composite histograms for each CR occurs essentially by construction since each monthly mean histogram at each model grid point is placed in the nearest observed cluster. A more informative evaluation of the model comes from comparing the relative frequency of occurrence for each CR and the spatial distributions of CRs. These are shown in Figs. 8–10, for comparison with Figs. 2, 4, and 6, respectively. These are also available as difference plots in Figs. S6–S8.

For all three satellite products, CESM2 is able to roughly capture the spatial distribution of most of the cloud regimes. The RFO, however, shows some systematic differences that hint at model deficiencies in representing several cloud types. In all three sets of observational CRs, the first two CRs correspond to high-level cloud; CESM2 tends to overestimate the RFO of these regimes, dramatically in the case of MODIS. Within the high-cloud regimes, CESM2 also shows a tendency to favor higher optical thickness clouds. In every case, CESM2 massively overrepresents the RFO of one or two low-cloud CRs at the expense of others. CR5 is an example in all three comparisons. In the observations, these regimes are low-level, mostly high-latitude, stratiform clouds (MISR also includes subtropical stratocumulus in its CR5). In CESM2, however, most low-level cloud cover ends up in CR5. This blends subtropical cloud-topped boundary layers and extratropical stratiform clouds into a single regime. In the MISR case, CESM2 also overrepresents the frequency of CR4.
which is broadly midlatitude storm clouds in the observations. By overemphasizing one or two low-level regimes, CESM2 appears to miss the distinctions between stratiform and shallow cumulus clouds that are apparent in the observed regimes.

c. Cloud response to warming

The climate warms under all the SSPs, and in all cases, the global cloudiness decreases. By the end of the twenty-first century (averaging 2071–2100), the change in the global mean near-surface air temperature ranges from about 2.2 K in SSP1 to nearly 5 K in SSP5 with respect to the late nineteenth century (1871–1900) (see also Meehl et al. 2020b, who used a much later base period). Global cloud cover decreases similarly, with greater decreases accompanying stronger forcing, as seen in the first panel of Fig. 11 for the ISCCP simulator total cloud cover. The other panels of Fig. 11 show the time series for the frequency of occurrence for each of the ISCCP cloud regimes. The decrease in global cloud cover is composed of shifts between regimes, with some becoming more frequent and others less frequent. An interesting aspect of the CR time series is that while the total cloud cover climate response appears to be stratified by the magnitude of the forcing (i.e., SSP1 shows the smallest decrease and SSP5 the largest), changes in individual CRs are not always commensurate with the warming. Similar time series for MODIS and MISR are provided in Figs. S9 and S10.

Clouds cool the earth by reflecting the sun’s shortwave (SW) radiation back to space. Conversely, they can warm the earth by emitting longwave (LW) radiation downward. The net effect of these two competing effects, relative to the clear-sky radiative fluxes, is called the net CRE (Ramanathan et al. 1989). Figure 12 shows the violin plots of the CRE in each CR in the historical simulation for ISCCP (top), MODIS (middle), and MISR (bottom). The dots and lines show the medians and interquartile range of the CRE for the historical and SSP
In ISCCP, the CRE in each CR remains relatively constant across simulations. For most cloud regimes, the shortwave component slightly weakens, i.e., becomes less negative, with warming, while the longwave component sees a similar magnitude decrease. The net effect is a relatively constant net CRE (left panels), but it should be noted that even small changes in net CRE over large areas can provide a strong climate feedback. The apparent stability of CRE across simulations suggests that the ISCCP CRs provide a way of selecting cloud configurations that preserve their radiative effects independent of the warming. If that is the case, the cloud radiative feedback (as indicated by changes in CRE) is not due to the changes of cloud properties within the cloud regimes but to the changes in their spatiotemporal patterns of occurrence. This follows from a decomposition of the mean change in CRE:

**FIG. 12.** Violin plots of the CRE of each CR in (top) ISCCP, (center) MODIS, and (bottom) MISR broken down into total, SW, and LW components. The blue shaded violins represent the distribution of CREs in the historical simulation, while the colored lines represent the 25th–75th percentile of data in the historical run or the respective SSP according to the legend. Dots on each line indicate the median. SSP data are used from 2071 to 2100.
\[ \Delta \text{CRE} = \sum_i \Delta \text{CRE}_i P_i + \sum_i \text{CRE}_i \Delta P_i + \sum_i \Delta \text{CRE}_i \Delta P_i, \]

where \( i \) represents the CRs and \( P \) is the RFO of each CR that provides the statistical weight. The first term on the right-hand side is associated with changes in CRE within CRs, while the second term is associated with changes in the statistical weight of CRs (i.e., their relative spatial distributions), and the third term captures the covariability of the cloud properties and spatial distribution. Figure 13 shows a breakdown of the components of Eq. (1) from each satellite simulator, CR, and SSP. The top panel shows that the majority of \( \Delta \text{CRE} \) in ISCCP across SSPs is due to the \( \text{CRE} \Delta P \) term. This confirms that in ISCCP, the changes in total CRE are mainly attributable to changes of spatiotemporal patterns of occurrence of the regimes, and cloud property changes within CRs are only a secondary contribution.

The ISCCP CRs again show similar results to ISCCP and MODIS in Fig. 12, with relatively constant net CRE with canceling changes in the shortwave and longwave components. CRs 3 and 6 show larger CRE changes across the SSPs, but Fig. 13 shows that the majority of \( \Delta \text{CRE} \) is once again due to the \( \text{CRE} \Delta P \) term and especially from CR4.

Like ISCCP, the MODIS simulator results in Fig. 12 show that the CRE of each CR stays steady across the SSPs. Again, we observe compensating changes in the shortwave and longwave components. CR2 does see a small overall decrease in CRE magnitude and that regime appears in Fig. 13 as a contributor to an overall positive \( \Delta \text{CRE} \). On the whole, Fig. 13 suggests that the MODIS CRs are more prone to having intra-CR CRE changes (i.e., \( \Delta \text{CRE}/\Delta P \neq 0 \)) than the ISCCP CRs, but the largest single contribution is the positive \( \Delta \text{CRE} \) in CR5 that arises from the \( \text{CRE} \Delta P \) term of Eq. (1).

The MISR CRs again show similar results to ISCCP and MODIS in Fig. 13, with relatively constant net CRE and canceling changes in the shortwave and longwave components. CRs 3 and 6 show larger CRE changes across the SSPs, but Fig. 13 shows that the majority of \( \Delta \text{CRE} \) is once again due to the \( \text{CRE} \Delta P \) term and especially from CR4.

Figures 14–16 show the spatial pattern that makes up \( \Delta P \) of Eq. (1) for SSP3 (2071–2100) relative to the historical simulation sampled during the observation period of each data product. We only show SSP3 as an example. Plots of the other SSPs are available in Figs. S11–S19. In ISCCP (Fig. 14), the largest radiative change is seen in CR5. CR5 has the strongest CRE (Fig. 13) and decreases in relative frequency of occurrence by 2.3% in SSP3 (Fig. 11). In CESM2, CR5 represents low-level clouds in the storm tracks and across the tropical oceans (Fig. 8). The change in the RFO of CR5 shown in Fig. 14 indicate a strong decrease in this regime across the subtropical oceans; in contrast, the regime appears to become even more common across the Southern Ocean. The decrease in CR5 in the subtropics is compensated mainly by an increase in CR7 which is populated by optically thinner low-level clouds (Figs. 7 and 8). This essentially shows the radiatively important stratocumulus cloud decks shrinking and thinning, which is a positive contribution to the net cloud feedback in CESM2.

MODIS shows a similar low-cloud signal to ISCCP in Fig. 15. The subtropical stratocumulus clouds in CR5 reduce in frequency and regimes with weaker CRE (CR6, CR4, and CR3) compensate reduction.
The MISR CR5, largely made up of stratocumulus, decreases by 1.8% by the late twenty-first century. As clouds become less frequent, CRs 6, 3, and 2, all of which are radiatively weaker than CR5, become more frequent. The three perspectives of cloud changes shown here all indicate that CESM2 loses optically thick stratocumulus-like clouds over subtropical oceans in favor of optically thinner cloud types as the climate warms.

Recall from Fig. 10 that the MISR CRs divide the low-level clouds into CR4 (predominantly extratropical) and CR5 (subtropical cloud-topped boundary layers and the Arctic). These regimes have strong, negative CRE (Fig. 12), carry most of the CRE response (Fig. 13), and most of that response is from changes in RFO. Figure 16 shows this change. The patterns of change for CR4 and CR5 are anticorrelated in many regions, showing shifts in the cloud structure as climate changes. In SSP3, the total ΔCRE comes from reduced occurrence of CR5, especially in the southern subtropical oceans, along with reduced occurrence of CR4 that happens widely.

One of the notable regions of anticorrelation in the SSP3 MISR result between CR4 and CR5 is in the North Atlantic. That region shows a reduced frequency in CR4 and increased frequency in CR5. That would indicate an enhanced cloud albedo and stronger shortwave CRE (Fig. 12). The ISCCP and MODIS simulator results also indicate an increase in the frequency of low-level clouds in that region (Figs. 14 and 15). This feature appears robust in CESM2, as it also appears in the other SSPs, but with differing magnitudes commensurate with the warming (e.g., Figs. S13, S16, and S19). This regional feature that acts counter to the global trend may be worth additional future study and may be associated with the damped warming in the North Atlantic (e.g., Keil et al. 2020).

Another robust feature of the cloud response that is seen across the three sets of CRs is a strong increase in frequency of a high-cloud regime in the tropical Pacific and Atlantic. This might be associated with a southern shift of the ITCZ in response to warming (Nicknish et al. 2023). The global radiative response of this regime is negative in SSP3 and SSP5, seen in Fig. 13 for CR2 in ISCCP, and CR1 in MODIS and MISR.

Because the formation of clouds is so dependent on large-scale circulation, first-order differences between clouds in a climate model and satellite measurement may just reveal differences in large-scale circulation. To control for this, we can investigate the frequency of occurrence of cloud regimes by dynamical regime. For tropical ocean regions (30°S–30°N), we sample CRs by the large-scale vertical velocity at 500 hPa (\(v_{500}\)). This analysis allows us to assess how much of the cloud...
response can be attributed to changes in large-scale circulation versus thermodynamic changes. If the relative partitioning of CRs did not change within $\omega_{500}$ bins, that would indicate that the cloud response was due primarily to the change in the large-scale circulation. A repartitioning of the CRs within $\omega_{500}$ bins would be indicative of thermodynamic changes since CRE is relatively stable within CRs, as shown in Fig. 12.

Figure 17 shows the distribution of CRs for each observational data source (using ERA5 values for $\omega_{500}$) in the left column, the CESM2 historical simulation in the middle column, and the change from CESM2 historical to SSP3 in the right column. The tropical $\omega_{500}$ distributions produced by ERA5 and CESM2 are similar to each other with the peak of the distribution in weak subsidence regimes and negative skewness showing a long tail into strong convective regimes. The breakdown of the CRs in each $\omega_{500}$ bin corroborates the inferences made earlier based on the CTP–t histograms and the RFO maps. The high-cloud regimes occur mainly in ascending dynamical regimes where convection is frequent. The spatial biases exhibited in CESM2 are evident in Fig. 17 as differences in the partitioning of CRs in the $\omega_{500}$ bins. The shallow cumulus regimes in MODIS and MISR CR3 provide a clear example of the inability of the model to represent these clouds that are somewhat deeper than the low-cloud regimes of the subtropics. The model’s tendency to put all low clouds into a single cloud regime is also evident in the large contribution of CR5 for all three versions of the model’s CR distribution in subsidence regimes in contrast to the observed distributions where CR5 is predominantly a high-latitude regime for ISCCP and MODIS (and only occurs in the stratocumulus decks for MISR).

The changes in the CR occurrence in the SSP3 simulation are shown in the right column of Fig. 17. For each data product, the change in the $\omega_{500}$ distribution in the third column of Fig. 17 is very similar. They differ only because the historical simulation is sampled to correspond to the observational time interval of each satellite product. For all practical purposes, the change in $\omega_{500}$ is the same, with a small shift toward upwelling regimes. For a purely dynamical response, the changes in RFO within each $\omega_{500}$ bin would simply be a proportional version of the middle column; that is, the mixture of CRs within a dynamical regime would remain constant. Instead, we find shifts in the model’s CR distribution with convective regimes showing mainly increased frequency of high clouds and the subsidence regimes showing mainly losses of the low-cloud types. Generally, we find that as the climate warms in CESM2, there is reduced frequency of low-cloud regimes with strong, negative CRE that occur mainly in subsiding regions. Figure 17 indicates that this cloud response is not...
simply a result of subsidence regimes becoming less frequent because the model preferentially reduces the low-cloud types with stronger CRE.

4. Summary and conclusions

In this work, we have applied a modified version of \( k \)-means clustering to three sources of long-term satellite cloud data: ISCCP, MODIS, and MISR. The three products are similar in that they produce joint histograms that have a vertical dimension (cloud-top height or pressure) that is associated with the temperature of cloud-top (and therefore longwave CRE) and a cloud optical thickness dimension that is associated with the cloud albedo (and therefore shortwave CRE). The products differ in the details of their retrievals and therefore produce slightly different perspectives of the observed cloud cover.

The clustering methodology is applied to each of the products to produce sets of “cloud regimes” that are indicative of the mixture of clouds that are detected. The \( k \)-means clustering method used here is adapted to use the Wasserstein distance as the distance metric. While the computation is more expensive, the Wasserstein distance provides a more accurate comparison of histograms than the conventional Euclidean distance. In particular, it is able to use the two-dimensional distance from each CTP–\( r \) bin to all other bins to accurately determine the similarity of histograms. The resulting CRs are similar to previous studies, but one distinction is that the fair weather CR is much reduced in frequency of occurrence, and we attribute that to the improved distance metric. The generally good comparison with previous studies using ISCCP and MODIS suggests that our use of monthly data is reasonably accurate. Without previous results for MISR, and considering its dramatically different approach for retrieval of cloud-top height, there was no a priori assurance that MISR CRs would be similar to ISCCP or MODIS. That they are relatively similar is evidence that CRs derived from different observations should be qualitatively similar, so future studies with new satellite products can compare with earlier results in the absence of direct comparison of overlapping observational periods.

The observed CRs are used to evaluate clouds in CESM2 using satellite simulator software (COSP) to provide appropriate comparisons to each of the three data sources. Using the coupled climate model with historical forcings, many of the qualitative features of the observed CRs are captured. There are notable exceptions, however, where the model produces results that are inconsistent with the observations. In particular, CESM2 tends to overrepresent deep convection and has trouble distinguishing low-level cloud types: stratus, stratocumulus, trade wind cumulus, and cumulus congestus, often placing all of them into one or two CRs.

The response to climate change is investigated by using four SSP experiments from CESM2 that differ in their...
radiative forcing. The cloud response, which is to decrease global cloudiness in all cases, is investigated by decomposing the response into CRs (again using all three satellite simulators). To understand the changes across CRs, the response in each CR is further decomposed to account for changes in the radiative effects of the CR versus changes in the frequency of occurrence of CRs. The CRs show relatively constant within-regime CRE across climates (Fig. 12), so the changes in CRE are mainly associated with the changes in the frequency of occurrence of CRs (Fig. 13). Low-cloud regimes contribute strongly to the overall cloud radiative response of CESM2, and especially, the subtropical regions appear susceptible to changes in cloud regimes.

To make direct connections between the changes of CRs and the large-scale circulation, a dynamical regimes analysis is used. In previous uses of this methodology, CRE has been shown to change in climate models as the CRE (i.e., cloud properties) change within regimes. By sorting cloud regimes by the large-scale environment, it can be seen that part of what has previously been termed the “thermodynamic component” of the cloud change can be described by changes in the partitioning of cloud regimes. A prominent example from the MODIS simulator output shows that the CR5 in subsidence regimes is lost in the warmer climate and is replaced by optically thinner cloud.

The analysis presented here, applied to one climate model, provides a detailed diagnosis of clouds and their climate response. Combining several well-established approaches, and building upon those methods, this analysis may be usefully applied to other models or multimodel comparisons. In particular, the use of the Wasserstein distance in $k$-means clustering appears to provide a good alternative to previous approaches as it makes better use of the information in the CTP–$t$ histograms. The CR method provides a way to understand a model’s preferred cloud structures and the spatial distribution of those structures. Combining the CRs with dynamical regimes shows how these model-preferred cloud structures are organized within the large-scale circulation and allows additional perspective on the thermodynamic response by showing how the CRE response results from shifts in the distribution of cloud regimes. In CESM2, for example, our results show that the model struggles to differentiate important characteristics of low-level clouds, and those low-level clouds under large-scale subsidence are most susceptible to climate warming, being preferentially replaced with cloud regimes that are optically thinner with less cloud cover.

FIG. 17. Frequency of occurrence of each CR binned by values of large-scale vertical velocity at 500 hPa ($\omega_{500}$) for the ocean between 30°N and 30°S. Plots shown for (top) ISCCP, (middle) MODIS, and (bottom) MISR and (left) observation, (middle) CESM2 historical, and (right) SSP5 – CESM2 historical.
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Data availability statement. The satellite data used for this research are publicly available. The ISCCP data can be found at https://ftp.ftp.cdc.noaa.gov/DATA/ISCCP/ISCCP_HQ/DATA2/CONUS/. The CESM2 data are available from https://doi.org/10.5067/MODIS/MCD06COSP_M3_MODIS062, and MISR at https://atmos.uw.edu/~roj/MISR_observations/MISR_CTH_OD_histograms/V7/. The CESM2 data are publicly available via the Earth System Grid Federation, e.g., https://esgf-node.llnl.gov/projects/cmip6/.

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