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The impact of bias correction on reference evapotranspiration and its climate change signal

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Abstract: This paper estimates future reference evapotranspiration at a daily time step using bias-corrected regional climate modelling data under high emission scenario (RCP8.5) for Queensland, Australia. We use the CCAM (Conformal Cubic Atmospheric Model) at a 10km resolution, driven by 11 CMIP5 global climate models, to provide input datasets for evapotranspiration computations. We adopted the Penman–Monteith method for reference evapotranspiration for both short crop and tall crop.

We assessed the impact of three bias correction methods (linear scaling, two versions of quantile mapping, and a statistical distribution-based transfer function) on present day mean climatology and climate change signal for reference evapotranspiration. Results show that all bias-correction methods are effective in removing the systematic model biases for historical simulations. We also compared the station-based interpolation dataset, the ERA5-Land reanalysis-based dataset and the best bias-corrected model reference evapotranspiration datasets. The results suggest that the three models of evapotranspiration are comparable though there are some differences in climatological spatial patterns. For reference evapotranspiration, raw and bias corrected regional climate simulations project an annual increase of about 8%-11% on average by the end of this century under high emission scenario (RCP8.5) in Queensland.

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Keywords: *Conformal Cubic Atmospheric Model, evapotranspiration, bias correction, quantile mapping, linear scaling, transfer functions*

1. INTRODUCTION

The combined processes of evaporation and transpiration, known as evapotranspiration (ET), play a key role in the water cycle. Evapotranspiration is needed to calculate regional water and energy balance and soil water status and provides key information for water resource management. The accurate calculation of evapotranspiration is crucial in applications such as crop water management, irrigation planning, basin water balance, climate characterization and climate change studies (Ghiat et al., 2021). With regards to climate change, it is critical to understand how the ET process, a key component of the hydrological cycle, responds to variability in climate factors (i.e., temperature and precipitation).

The rate of evapotranspiration is determined by a complex combination of plant physiology and environmental conditions. For example, the degree of stomatal opening in the leaves regulates transpiration and consequently affects the evapotranspiration flux. To eliminate the impact of plant specific characteristics on the evapotranspiration estimate, reference evapotranspiration (ET_0) is typically used. Reference evapotranspiration is the evapotranspiration from a crop with specific characteristics and which is not short of water (Allan et al., 1998). Two kinds of reference evapotranspiration are estimated in this work: a) The evapotranspiration from a hypothetical reference crop with an assumed crop height of 0.12 m, a fixed surface resistance of 70 sec/m and an albedo of 0.23, closely resembling the evapotranspiration from an extensive surface of green grass of uniform height, actively growing, well-watered, and completely shading the ground (Allan et al., 1998). Grass is defined as the reference crop and it is assumed to be free of water stress and disease. We term this Food and Agriculture Organization of the United Nations (FAO), as it is based on the FAO calculation; b) American Society of Civil Engineers (ASCE)'s "tall crop" version of FAO, which assumes the crop height is 0.5m.

Given the difficulty in measuring evapotranspiration directly, many models have been developed since 1950s to estimate reference evapotranspiration with meteorological data (Allan et al., 1998). In general, these models can be classified into two types – fully physical based models and empirical/semi-empirical models. Empirical models can be further classified into temperature-based, radiation-based, and mass transfer-based models according to the climatic factors incorporated. Penman and Penman-Monteith FAO (Allan et al., 1998) models are fully physiological based and take the related meteorological factors into consideration. The advantage of these two models is that they are able to offer reasonably accurate result against measured ET independent on climate conditions.

We focus on the Penman-Monteith method in this work for estimating reference evapotranspiration (ET_0), as it is the most widely applied method and recommended as the sole standard method by FAO, with strong likelihood of correctly predicting ET_0 in a wide range of locations and climates. It requires the least empirical parameterization or local calibrations compared with empirical/semi-empirical models, yet it includes the effect of most climate variables which affect evapotranspiration (solar radiation, wind, and vapour pressure deficit). As a consequence, the FAO method provides values that are consistent with actual crop water use data worldwide (Allan et al., 1998).

Evapotranspiration estimations reply on several types of climate data as input. For historical evaluations, we can use either global / regional climate model (GCMs and RCMs) datasets as input or ground-based observational data / remote sensing data as input. However, for future projections, GCMs and RCMs are the most common approach and have the greatest promise for this type of work into the near future. In this work, we first evaluate the performance of global and regional climate models in estimating evapotranspiration against those derived from observation based meteorological data or from reanalysis data. Then we will project the changes for evapotranspiration under climate change conditions based on regional climate models for Queensland, Australia.

Projections of ET under future climate scenarios are necessary to assess the possible influence of climate change on water resources, agricultural production and hydrological regimes (Wang et al., 2015). A commonly used method to evaluate the impact of climate change on ET is to use climate model outputs from different emission scenarios as inputs into an ET model (Kirono et al., 2009). This method has been adopted in the assessment of climate change influence on evapotranspiration that vary in scale from major river basins to medium sized catchment, the national, and global scales (Wang et al., 2015; Kirono & Kent, 2011).

The outputs of global and regional climate models (GCMs and RCMs) have to be bias-corrected before assessing the impact of climate change on evapotranspiration. Several bias correction methods ranging from simple linear scaling to sophisticated quantile mapping have been developed (Maraun, 2016; Piani et al., 2010). Bias correction is the process of scaling climate model outputs to account for their systematic errors in order to improve their fit to observations. Bias correction methods may alter the climate change signal due to intensity-dependent biases. For this reason, when evaluating bias correction methods, it is important to evaluate the impact on the climate change signal. Most bias correction studies only examine the impact of bias-correction on temperature and precipitation variables, however other variables are required in evapotranspiration estimations (i.e., radiation, mean sea level pressure, vapour pressure and 2m wind speed). In this work we assess the performance of the three bias-correction methods for removing biases in mean climate for reference evapotranspiration and then assess the impact of the bias-correction methods on the climate change signal.

2. DATA AND STUDY AREA

2.1. Study area

We estimate evapotranspiration and evaluate bias-correction methods over Queensland, Australia. Queensland provides a useful study area for estimating evapotranspiration and evaluating bias correction methods due to its diverse environment, including equatorial, tropical, sub-tropical, temperate and arid regions, and the presence of mountainous and coastal areas.

2.2. Climate models

We dynamically downscaled 11 CMIP5 GCMs to a 10km resolution over Queensland using the Conformal Cubic Atmospheric Model (CCAM) developed by CSIRO. The dynamical downscaling is described in previous work (Trancoso et al., 2020; Chapman et al. 2020; Eccles et al., 2021). We bias corrected daily datasets for precipitation, minimum and maximum temperature, mean sea level pressure, radiation, 2m wind speed, and vapour pressure, and then used raw and bias-corrected datasets to estimate evapotranspiration and examine the impact of bias correction on the climate change signal for RCP8.5 by comparing 2079-2098 to the reference period (1986-2005).

2.3. Observation based datasets

We used the Australian Climate Project observational dataset (also known as SILO) to correct raw CCAM model results. The SILO dataset interpolates Australian Bureau of Meteorology (BoM) weather stations and additional observational sources to provide daily gridded surfaces for Australia. The gridded SILO datasets cover the period from 1880s to the present, and are updated daily (Jeffrey *et al.*, 2001). Since SILO datasets have a 5 km resolution, SILO was regridded to 10 km prior to performing bias correction and evapotranspiration computations. We also compare CCAM model results with a high-resolution evapotranspiration dataset called “hourly potential evapotranspiration (hPET)” developed recently by Singer et al. (2021), which is based upon ERA5-Land reanalysis datasets.

2.4. Bias correction approaches

We apply the following three bias correction methods to individual climate model outputs for seven daily variables using observational data from the Australian Climate Project (SILO) as the reference dataset. Linear scaling (LS) is the simplest method which only used monthly mean to correct model output. Statistical distribution-based transfer functions (Dis_T_F) technique is the most sophisticated bias-correction technique, which used all the individual quantiles (daily values) to construct the transfer functions (Piani et al., 2010). In between these two techniques, there are various parametric and non-parametric quantile matching variations, and we used both parametric quantile mapping (QM) and empirical quantile mapping (EQM) to bias correct the seven climate variables. For the parametric implementation (QM_Monthly), the cumulative distribution functions (CDF) for each month were calculated using daily data for each month, drawn from all years in the calibration period. A linear regression is then used to fit the model and observed CDF, which provides the parameters. The second quantile matching version is non-parametric, namely, empirical quantile matching (EQM) using monthly data (EQM_Monthly). It differs from parametric QM in that, rather than using linear regression, it used a minimization scheme to find the unavailable quantile values.

2.5. Evapotranspiration estimates

We provide the estimates of reference evapotranspiration for both short crop (FAO) and tall crop (ASCE). It is documented in Food and Agriculture Organization Paper No. 56 (Allan *et al.*, 1998). The FAO estimate is mainly used for irrigation purposes: multiplying the reference value by a crop coefficient will yield an estimate of the actual crop evapotranspiration for an extensive irrigated field of the given crop. The Penman-Monteith formula is used to estimate FAO and ASCE. The Penman-Monteith method uses two coefficients to incorporate the effects of aerodynamic and bulk surface resistance. The FAO and ASCE estimates differ only in the values of these two coefficients.

Penman-Monteith equation requires input data on maximum and minimum air temperatures, vapour pressure, solar radiation and wind speed at 2 m height. We recently constructed a gridded roughness map for Australia based on observational station data (Zhang *et al.*, 2022), which are used in this work to convert 10m wind speed datasets to 2m. We compare bias corrected ET and climate change signal with raw CCAM results to assess the bias correction impacts.

3. RESULTS

3.1. Historical mean climatology

Annual and seasonal ensemble mean biases for evapotranspiration variables (ASCE and FAO) are shown in the first, second and third columns in Figure 1. After bias-correction, the model biases are reduced significantly for all the variables and seasons. The three bias correction methods based on monthly data (QM_Monthly, LS and EQM_Monthly) have larger improvements in DJF (austral summer) than the bias correction methods that use all available data (Dis_T_F). However, Dis_T_F is performing better than other three approaches for reducing biases in JJA (austral winter). On average, bias correction approaches can reduce annual bias from around 5% down to 2-3%, which highlights the usefulness of these approaches.

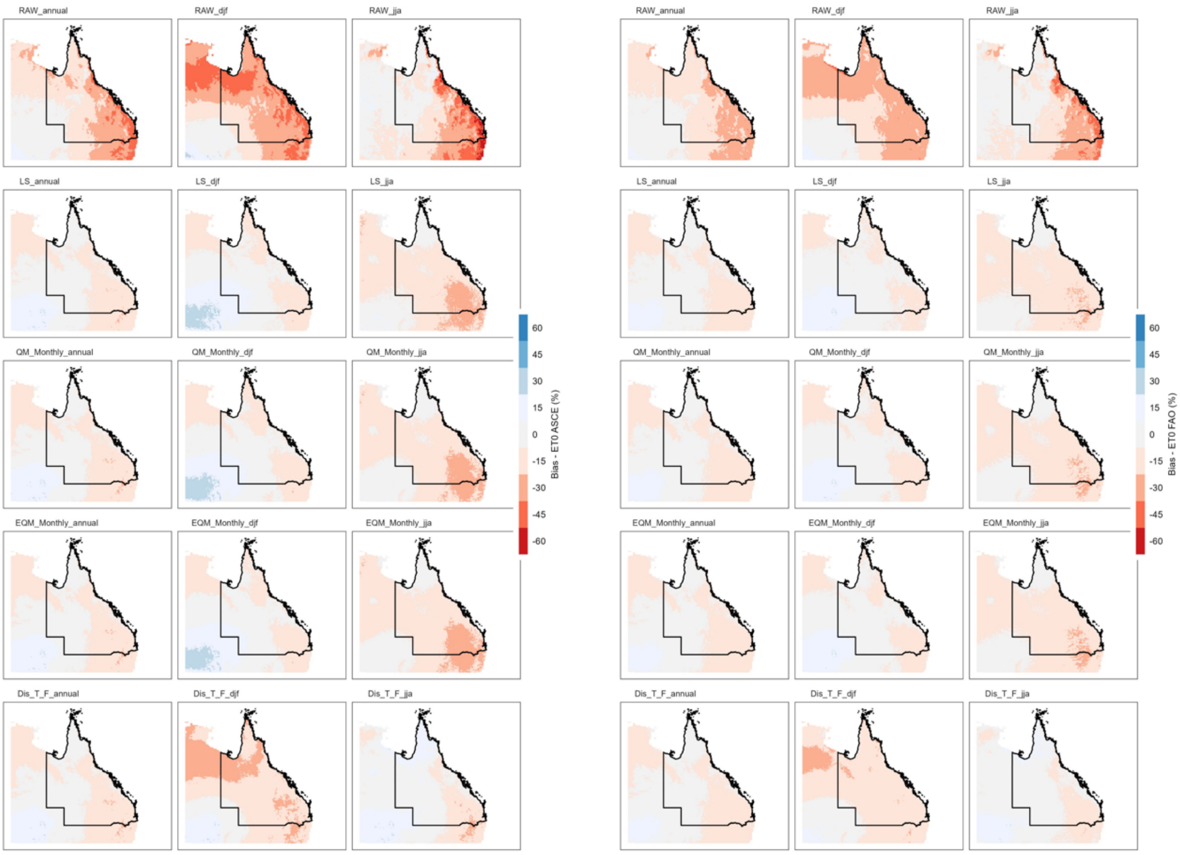

Figure 1. Annual / seasonal mean percentage bias maps (before and after bias corrections) for reference evapotranspiration ET_0 (ASCE and FAO) for historical period 1981–2010. Raw and bias-corrected CCAM results are shown for ensemble mean of the eleven CMIP5 models. Observation-based datasets (SILO) are used to correct CCAM models.

We also evaluated bias-correction performance using the Kling-Gupta efficiency (KGE) for seasonal mean climatology. The KGE combines the three components of Nash-Sutcliffe efficiency, correlation, bias and variability, into one metric. The closer to 1.0 the KGE is, the better the bias correction performs. Raw CCAM model's mean KGE scores are relatively low (*0.43*). After bias corrections, mean KGE score can be improved substantially. Overall, Dis_T_F approach has the highest mean KGE score (0.78), followed by EQM_Monthly and LS (0.*75***)**, and QM_Monthly (0.*73*) for mean climatology. The mean KGE score is the average over the two variables (FAO / ASCE) and the three seasons.

3.2. Climate change signal

In Figure 2, we investigated the impact of the bias correction methods on the climate change signal. All methods maintain the direction of change in the climate change signal. For both FAO and ASCE, most models and bias correction methods projected an increase of the magnitude for the climate change signal. Seasonally there are more increases of the magnitude for the climate change signal in JJA for most models and there are less increases of the magnitude for the climate change signal in DJF (several models project even decreases in DJF). Annually most models project an increase of the magnitude for the climate change signal.

Bias correction impacts the magnitude for the climate change signal for reference evapotranspiration (ASCE and FAO). Prior to bias correction, the ensemble mean increase for FAO was 11% annually, after bias correction, the increase was between 9%–10% annually. For ASCE, prior to bias correction, the ensemble mean increase was 11% annually, after bias correction, the increase was between 8%–10% annually. Seasonally all the bias correction methods reduce the magnitude of the climate change signal with LS preserving the climate change signal (CCS) the best.

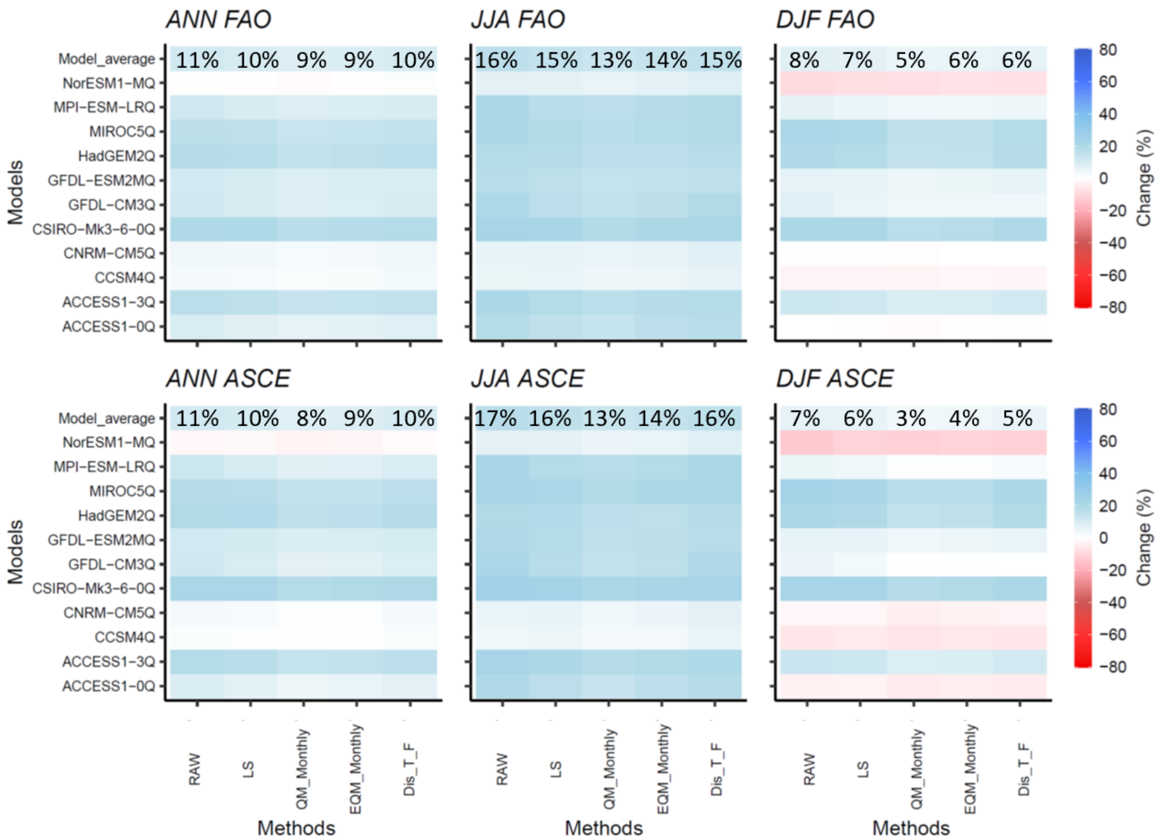

Figure 2. Heatmaps for climate change signal (from 1986–2005 to 2079–2098) for reference evapotranspiration across annual (ANN), summer (DJF) and winter (JJA) seasons in Queensland. Raw and bias-corrected CCAM results were shown in each column and individual models and ensemble mean were shown in each row.

4. DISCUSSION

The FAO Penman–Monteith method is widely used and accepted as one of the most representative ET estimations, because it works with accurate lysimeter observations. From our analysis of mean climatology, we found that CCAM models perform generally well for reference evapotranspiration (FAO) after bias correction. We also compared our FAO reference evapotranspiration results with another high-resolution re-analysis evapotranspiration called "hourly potential evapotranspiration (hPET)" developed recently (Singer *et al.*, 2021). hPET is based on the output from recently developed ERA5-Land reanalysis dataset (1981 to present) and corresponds to our estimation of reference evapotranspiration (FAO) with some variations for albedo. Figure 3 shows the station-based interpolation dataset (SILO), the reanalysis-based dataset (hPET) and one of the bias corrected CCAM model results (EQM_Monthly) for reference evapotranspiration (FAO). The three kinds of datasets have similar patterns though there are some differences in finer structures as they used different methods to derive the FAO datasets. Through comparisons we can see that the DJF spatial patterns for FAO agree well among the three products. In JJA, there are some differences in northwest parts of the studied area. Annually the broad patterns are similar, but the fine structures in the inland areas are different.

In terms of climate change signal, we found that the projected changes in reference evapotranspiration (FAO / ASCE) are consistent among most CCAM climate models. The annual average increases at the end of this century are roughly 11% annually for raw CCAM models. Bias corrections won't change the direction of such increases instead they only change the magnitude for such increases.

In Australia, Kirono et al. (2009) analyzed the temporal evolution of pan-evaporation and point potential evaporation from 1970 to 2004, claiming that both pan evaporation and point potential evaporation showed a general increasing trend. Similarly, CSIRO and BOM (2015) in Australia also demonstrated that Morton's potential evaporations has increased in the last hundred years and will keep increasing in the future based on the output from global climate models (GCMs). A related study by Kirono and Kent (2011) reported that most regions in Australia are going to experience increasing evapotranspiration. In addition to increasing trend in evaporation, negative trend (or no trend) has also been found across Australia since 1970 (Jovanovic *et al.*, 2007). The unexpected decreasing evapotranspiration with increasing temperature has been known as evaporation paradox (Brutsaert & Parlange, 1998; Roderick & Farquhar, 2002). The discrepancy highlights the importance to do further research on evapotranspiration to reconcile the differences between estimations from models and / or instrumental records.

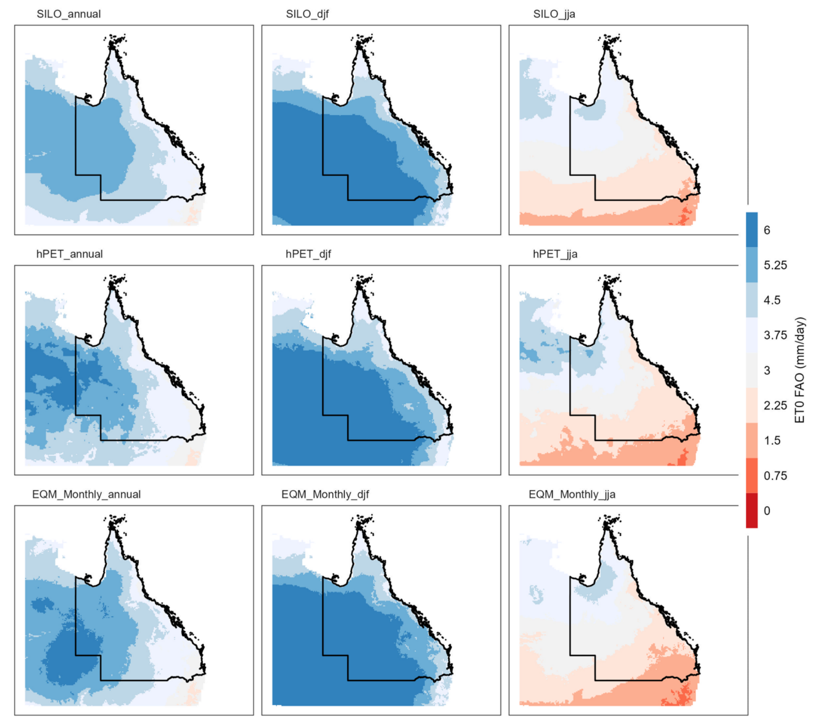

Figure 3. Seasonal climatology of reference evapotranspiration (FAO) for three comparative datasets (1981 to 2010). The observation-based datasets (SILO) and reanalysis-based datasets (hPET) were shown in the first and second row. Both were derived via the Penman–Monteith (PM) equation. One of the bias corrected CCAM model results (EQM_Monthly) were shown in the last row.

In the study by CSIRO and BOM in Australia (2015), the authors pointed out that there is high confidence in increasing potential evapotranspiration closely related to local warming, although there is only medium confidence in the magnitude of change. Generally, it is expected that potential evapotranspiration will increase with increasing temperatures and an intensifying hydrologic cycle (Huntington, 2006). Our study confirms an increasing annual evapotranspiration under RCP8.5 for both raw and bias corrected regional climate simulations (2079–2098 relative to reference period 1986–2005) in Queensland. The climate change signal is generally consistent for reference evapotranspiration for most CCAM runs. Our projections of change for reference evapotranspiration are also in general agreement with previous research using Random Forest-based models and empirical models (Shi *et al.*, 2020), though they used only eight stations located in south-eastern Australia.

6. CONCLUSION

In this work we carried out reference evapotranspiration computations using raw and bias corrected regional climate simulations. We found all bias-correction methods improved results when compared to raw CCAM. Most bias correction methods will impact the climate change signal with linear scaling preserving the climate change signal better than other methods. The bias corrected CCAM model results are in general agreements with the station-based interpolation dataset and the ERA5-Land based reanalysis dataset for reference evapotranspiration. The results indicate that the three types of evapotranspiration are comparable despite some differences in spatial patterns.

Climate modelling is the primary way to estimate future changes in evapotranspiration. The projected changes in reference evapotranspiration (FAO / ASCE) are generally consistent across CCAM ensemble runs. The annual average increases at the end of this century are roughly 8%-11% annually in Queensland considering both raw and bias corrected CCAM models.

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