**The SCM concept and creation of forcing datasets**

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**Abstract**

This chapter discusses the concept of Single-Column Models (SCM) and the required forcing data of these models. The ARM variational analysis method to derive the forcing data is described, along with the input data and ongoing research to improve the data accuracy. Available ARM forcing data at various sites are presented. The chapter also discusses selected applications of SCMs by using the ARM forcing data to understand model physical processes and improve physical parameterizations. .

**1.1 The concept of SCM**

A single-column model (SCM) is a one-dimensional (vertical) computational model of a specific columnar region of the atmosphere. It may be thought of as being extracted from the array of such columns which make up the atmospheric portion of a global climate model or general circulation model (GCM). In the GCM, this atmospheric model column would interact at each vertical level and at every time step with neighboring columns, providing horizontal fluxes of heat, water and momentum to and from these neighbors. By contrast, a SCM requires these fluxes to be specified, either from model data or observations or some combination of the two. If the fluxes are set to zero, the SCM becomes one type of a radiative-convective model (RCM). One way to think of a RCM (Ramanathan and Coakley, 1978) is as a horizontally averaged GCM, with the horizontal averaging over a global domain resulting in zero horizontal flux convergence.

Many climate modeling research groups have developed and used single-column models (SCMs) as tools for parameterization development. These SCM efforts have sometimes not been published in the open scientific literature, remaining instead as technical reports in the “grey literature.” ARM has historically been a significant source of support to the small community of SCM modelers, by providing research grants, observational data, and computational resources. In particular, observational data from the ARM Southern Great Plains (SGP) site has been a major stimulus to the development and use of SCMs. The ARM success with research involving SCMs has encouraged several modeling groups to make their own internally developed SCMs publicly available, sometimes with professionally programmed and well-documented codes. The NCAR climate modeling group, for example, has made single column versions of its global climate models available for many years.

A great deal of experience has been gained in using single-column models with ARM data, and over time, the role of SCMs in climate research has been expanded and clarified. SCMs clearly have a valuable place in the hierarchy of modeling approaches which is needed to improve the realism and trustworthiness of climate models. Of course, a wide variety of techniques has long been employed to test and validate physical process parameterizations in both weather and climate models. One straightforward method is to compare the results of full three-dimensional GCM simulations, using different parameterizations, against global observations. Another is to carry out numerical weather prediction (NWP) experiments initialized with realistic data and to compare the effects of different parameterizations on short- and medium-range forecast skill. Both of these approaches have provided valuable information. However, carrying out a carefully coordinated model parameterization intercomparison program with 3-dimensional models, even when the same basic model is used as the vehicle, is time-consuming and computationally expensive.

**1.2 Early studies using SCMs**

The semi-prognostic model of Lord (1982) and the convective adjustment tests of Betts and Miller (1986) are early examples of the idea of using a model of a single atmospheric column. The basic concept of an SCM is to force and constrain an isolated time-dependent atmospheric GCM column with estimates of observed advective flux convergences, then to compare the output with observations to judge the realism of the parameterizations. Because the SCM has only one space dimension (vertical), it is very fast, and it is practical to explore large segments of parameter space by making hundreds or even thousands of integrations, which is impossible with a full GCM. In ARM, SCMs have been widely used to investigate parameterizations of cloud-radiation processes.

This approach typically involves evaluating parameterizations directly against measurements from ARM field programs, and using this validation to tune existing parameterizations and to guide the development of new ones. The single-column model is thus used to make the link between observations and parameterizations. Surface and satellite measurements are both used to provide an initial evaluation of the performance of the different parameterizations. The results of this evaluation are then used to develop improved cloud-precipitation schemes, and finally these schemes are tested in GCM experiments (e. g., Lee et al., 1997). An early example of using a single-column model in this way is described by Iacobellis and Somerville (1991a,b).

The SCM thus is a versatile and economical one-dimensional model, containing the full set of parameterizations of subgrid physical processes that are normally found in a modern GCM. The SCM is applied at a specific site having a horizontal extent typical of a GCM grid cell. Its input is typically an initial state, plus the time-dependent advection terms in the conservation equations, provided at all model layers. Its output is a complete heat and water budget for the study site, including temperature and moisture profiles, clouds and their radiative properties, diabatic heating terms, surface energy balance components, and hydrologic cycle elements, all specified as functions of time.

Single-column models may be looked on as a means of isolating the behavior of a model atmosphere over a single horizontal grid cell. Viewed in this way, they enable one to study the comparative merits and drawbacks of alternative parameterizations of physical processes, for example, or the sensitivity to errors in advective forcing. When detailed observational data are available, they provide a way to evaluate local model behavior comprehensively. In brief, they are a means of zooming in microscopically onto the model grid scale itself, to diagnose both the GCM physics and the actual atmosphere.

By perturbing the advective forcing, for example, one can explore the dependence of the diabatic heating rates and other subgrid parameterization outputs on the accuracy of the horizontal flux convergences. Similarly, for a given advective forcing, one can test how these model products depend on the choice of parameterizations. For a discussion of limitations of single-column modeling, including issues of sensitivity to errors in forcing data and consequences of constraining the SCM temperature and humidity profiles from departing too far from observations, see, e. g., Randall et al. (1996), Lee et al. (1997), Iacobellis and Somerville (1991a,b) and references therein.

A major result in ARM is that SCMs have proven themselves capable of directly validating parameterization results against ARM measurements. Because climatically critical observable quantities such as column liquid water and downwelling surface shortwave and longwave radiation can be both derived from SCM results and inferred from observations at the SGP site. It is safe to say that with extensive examples of this type of research in ARM, a major step has been achieved in fulfilling the original promise of the SCM approach.

The SCM is a convenient testbed for examining many aspects of the ways in which GCMs treat subgrid physical processes. For example, Lane et al. (2000) found strong sensitivity to vertical resolution in several test integrations in which they increased the number of layers substantially. Several possibilities are raised by this result. One is that the parameterizations are constructed around implicit assumptions as to how many layers are involved, so that they do not generalize to arbitrary vertical resolution and converge at sufficiently small vertical grid sizes. Another is that typical GCM and NWP vertical resolutions are simply inadequate for some aspects of parameterized subgrid physics, although they may generally be satisfactory from the viewpoint of large-scale dynamics.

**1.3 Requirement on large scale forcing data**

In the simplest setting, the SCMs calculate the time evolution of the vertical distributions of temperature and water vaper, schematically written as:

 (1)

, (2)

where  and *q* are potential temperature and water vapor mixing ratio; subscript “*m*” denotes model values; “*LS*” stands for prescribed large-scale fields; “*phy*” represents physical parameterizations; other symbols are as commonly used. In the vertical advection terms of the Equations (1) and (2), the last term on the right hand side, the simulated profiles of  and *q* are used, and so the vertical advection terms retain some feedback of the simulated fields to the forcing fields. The horizontal advective tendencies  and the vertical velocity  are the large-scale forcing (*Randall and Cripe*, 1999). It is sometimes referred as “2-D” forcing. In another formulation, the observed profiles of  and *q* are used in the vertical advection term. Therefore  is prescribed as the large-scale forcing, which is often referred as “3-D” forcing. In calculating the and  physical tendencies, the first term on the right hand side of Equations (1) and (2), SCMs compute the clouds, convection, precipitation, radiation and turbulent mixing that can be compared with observations.

The same forcing fields can be also applied to Cloud Resolving Models (CRM) and Large Eddy Simulation (LES) models. The CRMs and LESs simulate  and *q*, or more often their corresponding conservative variables of liquid water potential temperature and total liquid water. The forcing terms in Equations (1) and (2) are applied to all model grids, but with and in the vertical advection terms replaced by domain averaged values from the CRMs and SCMs.

The derivations of the large-scale forcing data from field measurements are subject to uncertainties that can directly impact the simulated cloud and radiation fields by the SCMs. These errors originate from two sources. One is the instrument and measurement errors. The second is errors from scale aliasing, or sampling biases. Both depend on scales because horizontal derivatives are involved. Generally speaking, the smaller the scale is, the larger the errors.

If the accuracy requirement of the physical parameterization terms in Equations (1)-(2) are 1 (K/day) and 1 (g/kg/day), the comparable accuracy requirements on the errors of the horizontal differences of temperature () and humidity () over a distance can be estimated as the followings:





Given | and over a distance of 200 *km*, the above inequalities require that

 (3)

. (4)

It should be emphasized that these are the relative errors across the distance of . The requirement on the pressure vertical velocity error is:

 or

.

The requirement on the difference of horizontal winds across the domain is:

.

Assuming a vertical layer of 100 hPa, we get:

  (5)

The error bounds of the spatial differences in Equations (3)-(5), corresponding to accuracy requirement of 1 (K/day) and 1 (g/kg/day) in the forcing data, need to be scaled proportionally if the horizontal scale is different from 200 km. These magnitudes are comparable to instrument errors (Zhang and Lin 1996), but since they are relative errors across the space, the systematic instrument errors are removed if the same equipment is used over the domain, and the random errors can be suppressed by averaging over vertical levels. The more problematic errors are those caused by scale aliasing or sampling bias. These errors are often handled by using statistical approaches. In ARM, they are additionally dealt with by using known physical constraints.

**1.4 Forcing data from field experiments prior to ARM**

In the objective analysis of field experimental data of a sounding array, both the horizontal advective tendencies and the large-scale vertical velocity can be obtained by using finite difference approximation of the horizontal derivatives when the input data are regularly spaced. Since balloon sounding stations are never regularly distributed, interpolations and extrapolations are needed to preprocess the atmospheric temperature, water vapor and winds into a regular set of grids. This method is referred to as “regular grid method” in Zhang et al. (2001). In this method, the forcing data is calculated at each grid and area averages are performed to obtain forcing for the study domain. An alternate method is to write the advective tendencies in flux form. The horizontal flux divergence terms, when averaged over a domain, is calculated by line integrals at the lateral boundaries of the study domain. This approach is referred to as the “line-integral method”.

A key element in the regular grid method is the fitting of atmospheric state variables to the desired grids. The fitting results depend on the choice of the assumed functional form, which can be quite subjective. Commonly used methods are linear fitting, the quadratic and spline fittings (Davis-Jones 1993; Thompson et al. 1979). The more convenient algorithms are the Barnes (1964) and the Cressman (1959) schemes (Lin and Johnson 1996). In these schemes, a background field (or initial guess) is used at the observational locations, the difference between the observation and the initial guess field is then interpolated to the regular set of grids to adjust the background fields at these grids. The calculation can be performed iteratively to reach the desired corrections. Both the interpolation method and the number of integrations can affect the final analysis. More sophisticated method uses statistical interpolation scheme such as Ooyama (1987).

The line integral method depends on the number of atmospheric measurements at the boundary of the study domain. It therefore contains fewer subjective assumptions than the regular grid method. An important requirement is that there needs to be sufficient amount of measurement stations at the domain boundary. The line integral method typically does not use measurements inside the study domain in calculating the lateral boundary fluxes.

The regular grid method is more suited to analyze data with many scattered measurement stations, while the line integral method is more suited for a well-positioned sounding array with few measurement stations. Zhang et al. (2001) presented a hybrid approach in which the regular grid method is used to improve the lateral boundary fluxes in the line integral method.

Both methods have been used in the past to derive SCM large-scale forcing data in field experiments. One of the most widely used legacy data was from the Global Atmosphere Research Experiment (GARP) Atlantic Tropical Experiment (GATE) in 1974. Ooyama (1987) derive the GATE objective analysis by designing a statistical regular grid method to which a penalty function is imposed to ensure smoothness of the fields. While the GATE data by Ooyama (1987) has been widely used, a standard analysis algorithm is not available because many subjective procedures and judgments were made through trial and error tests for each data point.

Another widely used SCM forcing data were from the Tropical Ocean and Global Atmosphere Coupled Ocean–Atmospheric Response Experiment (TOGA COARE) from November 1992 to February 1993. Lin and Johnson (1996) used the Barns analysis and the regular grid method to derive the forcing data. Frank et al. (1996) also analyzed the TOGA COARE data but used the line-integral method. The difference of the moisture budgets from these two analyses over the Intensive Flux Array (IFA) was large. The time averaged diagnosed precipitation over the experiment period is 5.7–6.1 mm/day in Lin and Johnson (1996) and 10.5–11.8 mm/day in Frank et al. (1996). Therefore, although the analyzed data can be used to study the qualitative temporal variation of the large-scale atmospheric phenomena such as the Maddan-Julian Oscillation (MJO), their use to simulate the observed cloud fields for direct comparison with transient measurements of clouds can have large biases.

SCM forcing data have been calculated for other shorter field experiments. Many of these are in regions of Asian and Australian monsoons. They were summarized in Zhang et al. (2001). Uncertainties of the analyzed data are likely similar to those in TOGA-COARE. These uncertainties represent fundamental limits of data from the balloon sounding arrays caused by scale aliasing, as stated succinctly by Ooyama: “To make gold, one must start with gold.”

Atmospheric reanalysis or operational analysis can also be used to obtain the large-scale forcing. However, because the operational models suffer from biases of cloud and precipitation parameterizations that ARM aims to improve, these products are not always suited for SCM results to be compared with observations. For example, operational models typically cannot simulate the timing and magnitude of observed precipitation, which implies bias in the large-scale velocity in these products. Evaluations of the large-scale forcing in the ECMWF operational analysis and the North American Regional Reanalysis (NARR) have been done in Xie et al. (2003; 2006) and Kennedy et al. (2011) and it has been shown that cloud fields in these products contain large errors and the biases in the vertical may be large during precipitation events.

**1.5 The ARM variational analysis of forcing data**

Recognizing the accuracy limit in large-scale forcing data and the need of transient forcing data in ARM, Zhang and Lin (1996) developed a constrained variational algorithm to incorporate more measurements to improve the SCM forcing data. Physical constraints are enforced. These constraints include column-integrated conservations of atmospheric masses of moist air and water vapor as well as heat and momentum. They are written as:

 (6)

 (7)

 (8)

 (9)

In the above equations, u, v, *s, q* are the atmospheric state variables of winds, dry static energy, and water vapor; *ps* is the surface pressure; *ql* is the cloud liquid water content; *φ* denotes the geopotential height. The bracket represents vertical integration. *Es* is the surface evaporation. *Prec* is the surface precipitation. *R* is the net downward radiative flux; the subscript TOA and SRF represent the top-of-the-atmosphere and the surface. *L* is the latent heat. *SH* is the surface sensible heat flux. denotes the wind stress at surface. Other variables are as commonly used.

The final analysis is obtained by minimizing the cost function of:

 (10)

where variables with the subscript “*o*” represent first guess from preprocessed balloon sounding and wind profiler measurements or operational analysis; *B* is the error covariance matrix of the state variable.

Terms on the right hand sides of Equations (6)-(9) are obtained from ARM and satellite measurements at the surface and TOA. Area averaged precipitation is from radar measurements. Other surface variables are from the suite of stations deployed within a sounding array. These are described in **Section 1.6**. In some cases, fluxes are derived from statistical interpolation between the limited number of stations and the background fields from the reanalysis products. Since each field experiment has different instrumentation and measurement configurations, the preprocessing of surface and atmospheric measurements may be specific to different experiments, and visual inspections of all input data are necessary.

The minimization of the cost function in Equation (10) requires the specification of the error covariance matrices. These errors are taken as the sum of instruments and measurement biases and sampling biases. The instrument and measurement biases are assumed to be 0.5 m/s for winds, 0.2 K for temperature, and 3% of the specific humidity for water vapor. These were estimated by instrument mentors. The sampling biases are estimated to be twenty percent of the temporal variances of the fields. In the past analyses, the errors are assumed to be independent among different locations and variables. This assumption is being revised to allow error covariance. Zhang and Lin (1997) described the minimization algorithm of Equation (10).

The final analysis therefore is the closest to preprocessed balloon sounding and wind profiler data or operational analysis that satisfies the required constraints of Equations (6)-(9). The divergence terms in these equation terms are calculated by using the line-integral method. The atmospheric state variables at the boundary stations are preprocessed by using the regular grid method so that data from all profiling stations are used.

The constraining requirements ensure that what enters into the atmospheric column is equal to what exits from the column and at the TOA as well as at the surface after adjusting for column integrated temporal change. The forcing data can be considered as a better fitting of the atmospheric analysis to more observational measurements.

The terms on the right hand side of Equations (6)-(9) are currently treated as known fields. Sensitivities of the analyzed fields to their uncertainties are used to characterize the errors in the forcing data (Zhang et al. 2001). In theory, these constraining variables can be also subject to variational adjustments based on their uncertainties. The imposed constraints can be expanded to include other known physical relationships and measurements, such as clear-sky water vapor and thermodynamic equations and radiance measurements at various wavelengths. The atmospheric state variables should ideally also include cloud hydrometeors, in which case radar reflectivity and cloudy-sky radiance measurements can be used as constraints. Additionally, the error covariance matrices in the cost function should be better calculated. Research is ongoing to make improvements in all these aspects.

**1.6 Input data for the ARM variational analysis**

The input data for the ARM variational analysis include measurements of both adjustment variables and constraint fields. The adjusted variables are the large-scale state variables, namely, winds, temperature, and humidity. The constraints include surface pressure, surface latent and sensible heat fluxes, wind stress, precipitation, net radiation at the surface and at the top of the atmosphere (TOA), as well as column total cloud liquid water.

The large-scale state variables are obtained primarily from balloon-borne sounding measurements. During ARM Intensive Operational Periods (IOPs), radiosondes are usually launched every three hours to measure the vertical profiles of winds, temperature, and water vapor mixing ratio over a well-defined sounding array. Hourly profiler measurements of winds are also available at the National Oceanic and Atmospheric Administration (NOAA) wind profiler stations, which can be merged with the soundings in the analysis. At the ARM SGP site, there are ARM five sounding stations: the central facility (C1) and four boundary facilities (B1, B4, B5, and B6), as well as a number of NOAA wind profiler sites to provide the needed upper-air measurements (**Figure 1a**).

The variational analysis analyzes the original upper-air measurements from radiosondes and wind profilers over the analysis grid points (Figure 1a) using the Cressman interpolation scheme (Cressman 1959), which requires a background field from numerical weather prediction (NWP) centers’ operational analyses. Current variational analysis uses the operational analyses from the NOAA mesoscale model Rapid Update Cycle (RUC) for SGP (**Figure 1b**) and the European Center for Medium-Range Weather Forecasts (ECMWF) for other ARM sites. Note that the NWP operational analysis itself can be used as the input of the large-scale state variables for the variational analysis to create the so-called “continuous forcing” datasets over a long term period (multiple years) where there are no soundings available. In this case, NWP analyses are adjusted through the variational analysis method to balance the observed column budgets of mass, heat, moisture, and momentum rather than the NWP model-produced budgets. The use of the observed constraints in the analysis has significantly improved the accuracy of the forcing data derived from NWP analyses (Xie et al. 2004).

The required constraint variables are derived from measurements of surface observational networks and satellites. Around the ARM SGP site, there is a dense surface network (**Figure 1c**). The observation platforms include the follows.

* Surface Meteorological Observation Stations (SMOS) measuring surface precipitation, surface pressure, surface winds, temperature, and relative humidity.
* Energy Budget Bowen Ratio (EBBR) stations measuring surface latent and sensible heat fluxes and surface broadband net radiative flux.
* Eddy Correlation Flux Measurement System (ECOR) providing in situ averages of the surface vertical fluxes of momentum, sensible heat flux, and latent heat flux.
* Oklahoma and Kansas mesonet stations (OKM and KAM) measuring surface precipitation, pressure, winds, and temperature.
* Microwave Radiometer (MWR) stations measuring the column precipitable water and total cloud liquid water.
* Solar and Infrared Radiation Station (SIRS) providing continuous measurements of broadband shortwave (solar) and longwave (atmospheric or infrared) irradiances for downwelling and upwelling components.
* WSR-88D Nexrad radar and rain gauge providing hourly surface precipitation data to the Arkansas-Red Basin River Forecast Center (ABRFC).

The Geostationary Operational Environmental Satellite (GOES) provides satellite measurements, clouds, and broadband radiative fluxes at TOA over the 0.50 x 0.50 grids (**Figure 1d**) (Minnis et al. 1995). All the constraint variables are area-averaged quantities over the analysis domain. To avoid biases of using overcrowding measurement stations in some areas, the algorithm first lays the 0.50 x 0.50 GOES grids over the analysis domain, and then derives the required quantities in each small grid box. If there are actual measurements within the subgrid box, simple arithmetic averaging is used to obtain the subgrid box means. Some variables are available from several instruments as indicated above. They are merged in the arithmetic averaging process. If there is no actual measurement in the small box, the Barnes scheme (Barnes 1964) is used to fill the missing data. Domain averages of these constraint quantities are obtained by using values from the 0.50 x 0.50 grid boxes within the analysis domain.

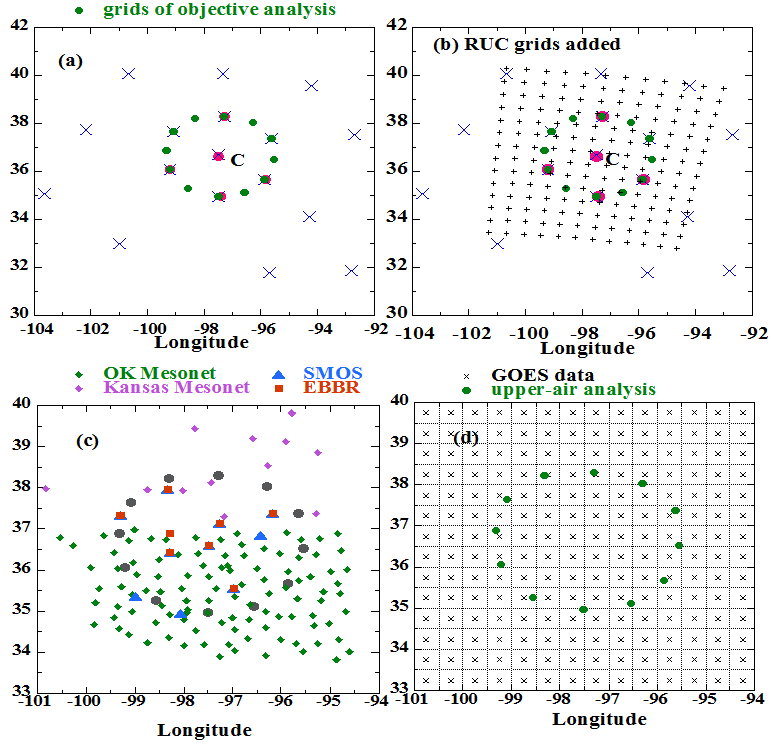


Figure X1. Locations of the ARM upper-air data streams and the analysis grid points. (a) sounding stations (red cicle), wind profilers (blue crosses), and final analysis grids (green circiles). (b) RUC grids overlaid on other grids. (c) ARM surface data streams (see text for complete instrument names). (d) GOES grids over the analysis domain. (Adapted from Zhang et al. 2001)

**1.7 Available ARM variational analysis forcing datasets**

The constrained variational analysis method has been applied to routinely derive the large-scale forcing data from ARM measurements for SCM and CRM studies. There are two types of variational analysis forcing data products available for the ARM permanent research sites and ARM Mobile Facilities (AMF). The first is the “IOP forcing”, which is derived using sounding data collected during ARM major IOPs. The second is the “continuous forcing”, which is derived using NWP operational analyses for multi-year continuous periods where sounding measurements are not available. For both types of the forcing datasets, the large-scale state variables are constrained with surface and satellite observations.

**Table 1** lists the available ARM variational analysis forcing datasets. These forcing datasets can be obtained from the ARM Archive (http://iop.archive.arm.gov/arm-iop/0eval-data/xie/scm-forcing). Over the past two decades, ARM has conducted numerous field campaigns in diverse climate regimes around the world to collect detailed observations of clouds and radiation, as well as related atmospheric variables for climate model evaluation and improvement. The majority of these field campaigns were conducted at the ARM SGP site, probably the largest and most extensive climate research site in the world. Major field campaigns at SGP include the June-July 1997 SCM IOP for midlatitude land convection, the March 2000 cloud IOP for frontal system, the June 2007 Cloud LAnd Surface Interaction Campaign (CLASIC), as well as the April-May 2012 Midlatitude Continental Convective Clouds Experiment (MC3E). At the ARM North Slope of Alaska (NSA) site, ARM conducted the Mixed-phase Arctic Cloud Experiment (M-PACE) in October 2004 to study mixed-phase clouds and the Indirect and Semi-Direct Aerosol Campaign (ISDAC) in April 2008 to study the aerosol-cloud interaction in the Arctic region. In the tropics, the Tropical Warm Pool International Cloud Experiment (TWPICE) took place in January and February 2006 around the ARM Tropical Western Pacific (TWP)-Darwin site to improve the understanding the interaction of tropical convection with its environment. In addition, ARM also regularly deploys its AMF in various climate regimes not previously explored. More details about these field campaigns can be found via http://www.arm.gov/campaigns.

The variational analysis forcing data products have been developed for all the major field campaigns conducted at the ARM permanent research sites and some of the AMF deployments. For the SGP and TWP-Darwin sites, ARM has also created the continuous forcing data over multiple years. These large scale forcing datasets provide the needed initial and boundary conditions for SCMs and CRMs in studying various observed cloud systems and testing physical parameterizations in climate models.

Table 1. Available ARM variational analysis forcing datasets. The numbers indicate the “month/year” when the forcing data are available.

|  |  |  |
| --- | --- | --- |
|  | IOP Forcing | Continuous Forcing |
| SGP | 07/95, 04/97, 06/97, 09/97, 04/98, 01/99, 03/99, 07/99, 03/00, 09/00, 11/00, 11/02, 05/03, 06/07, 04/12 | 01/99 – 06/11 |
| TWP-Darwin | 01/06 | Three wet seasons between 2004 and 2007 |
| NSA | 10/04 | 04/08 |
| AMF-China |  | 11/08 |
| AMF-AMIE-Gan |  | 11/11 |

* 1. **Applications of SCMs and ARM forcing data to understand and improve models**

It is now well-recognized in the GCM and NWP communities that single-column models (SCMs) are tools which have a valuable role to play in testing and improving parameterizations by evaluating them empirically against field observations. Early surveys of SCM research have been published by Randall et al. (1996) and Somerville (2000). Since then, many papers have been published by using SCMs and ARM forcing data.

Most of these studies contribute to model improvements in one the following three ways. The first is the evaluation of the performances of physical parameterizations in operational and global climate models (e.g., Yang et al. 2006; Kennedy et al. 2010; Song et al. 2013). The second is the validation, improvement and development of parameterization, including the triggering and closure assumptions of convection parameterizations (e.g., Xie and Zhang 2000; Zhang 2003; Guichard, et al. 2004; Petch et al. 2007), cloud macrophysical schemes (e.g. Franklin et al. 2012), cloud microphysical parameterizations (e.g., Zhang et al. 2005), the mass flux parameterization of deep convection (Wu et al. 2009), the parameterization shallow convection and boundary-layer turbulence (Kay et al. 2012), among others. The third is to use SCMs under ARM forcing data to improve understanding of processes, including growth of ice particles (Comstock et al. 2008), cloud feedbacks (Del Genio et al. (2005), and land-atmosphere interactions (Sud et al. 2001). It should be noted that model development and improvement using SCMs are often done in conjunction with CRM or LES simulations under the same large scale forcing.

Several ARM SCM case studies have been organized with multi-authored publications. The first case used data from the ARM June 1995 SGP IOP (Ghan et al. 2000). SCMs and CRMs were used to simulate summertime continental convection. This case study settled the subsequent methods of how SCMs are run using observationally derived forcing data. Main results from the paper include the relative superior performance of the CRMs to SCMs, thus justifying the use of CRM results to improve SCMs.

Second ARM SCM case study by Xie et al. (2002) used the summer 1997 SGP IOP as a follow up of Ghan et al. (2000). It was shown that deficiencies in convective triggering mechanisms were ne of the major reasons of model biases. Using a triggering mechanism based solely on the vertical integral of parcel buoyant energy results in overactive convection, which in turn leads to large systematic warm/dry biases in the troposphere. It is also shown that a non-penetrative convection scheme can underestimate the depth of instability for midlatitude convection, which leads to large systematic cold/moist biases in the troposphere. All models significantly underestimate the surface stratiform precipitation.

Another ARM case study was published by Lenderink et al. (2004) using ARM June 1997 measurements to evaluate the SCM simulation of diurnal shallow convection. They found that the SCMs could be grouped in two different classes: one class with too strong mixing by the turbulence scheme, the other class with too strong activity by the convection scheme. They also showed that the coupling between (subcloud) turbulence and the convection scheme plays a crucial role.

The fourth ARM SCM case study was led by Xie et al. (2005) who used the ARM March 2000 SGP cloud IOP to investigate the parameterizations of frontal clouds. Most SCMs were found to underestimate cloud water and with huge biases of both signs in cloud ice. The SCMs overall underestimate middle clouds, which also appeared in CRMs. They attributed some of these biases to the lack of subgrid-scale dynamical

A case study for the ARM Mixed-Phase Arctic Cloud Experiment (MPACE) was reported by Klein et al. (2010) Morrison et al. (2010). They showed that for single-layer clouds, the simulated ice water path is generally consistent with observed values, the median SCM and CRM liquid water path is a factor-of-three smaller than observed. For multi-level clouds, however, the models generally overestimate liquid water path and strongly underestimate ice water path. Models with more sophisticated, two-moment treatment of cloud microphysics were found to produce a somewhat smaller liquid water path closer to observations.

The case study for the ARM  Tropical Warm Pool - International Cloud Experiment (TWP-ICE) experiment by using CRMs with ARM forcing data has been reported in Fridland et al. (2012). SCM intercomparions results have been reported in Davies et al. (2013) and Petch et al. (2013). All these studies showed how the ice microphysical parameterizations impact the simulated ice contents.

The most important contribution of the SCMs is perhaps that they have facilitated researchers to gain insights on the physical parameterizations by providing a convenient test models and to compare model results with observations and CRM/LES simulations. Results from the SCMs have motivated and led to many updates and modifications to the parameterizations in the current generation of global climate models. With the insights from SCMs, hypothesis and improvements can be first tested in SCMs, then evaluated against CRMs or LESs, and implemented in global models.

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