Representing Mesoscale Variability in Superparameterized Climate models

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Key Points:

- Superparameterization in weather models is used to improve the representation of clouds
- We show that superparameterization suppresses the transport of clouds
- A scheme for controlling the humidity variation improves cloud advection in super-parameterized models

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Abstract

In atmospheric modeling, superparameterization has gained popularity as a technique to improve cloud and convection representations in large scale models, by coupling them locally to cloud-resolving models. We show how the different representations of cloud water in the local and the global models in superparameterization lead to a suppression of cloud advection and ultimately to a systematic underrepresentation of the cloud amount in the large scale model. We demonstrate this phenomenon in a regional superparameterization experiment with the global model OpenIFS coupled to the local model DALES (the Dutch Atmospheric Large Eddy Simulation), as well as in an idealized setup, where the large-scale model is replaced by a simple advection scheme. To mitigate the problem of suppressed cloud advection, we propose a scheme where the spatial variability of the local model's total water content is enhanced in order to achieve the correct cloud condensate amount.

Plain Language Summary

In this article we investigate a technique called superparameterization for improving how global weather and climate models represent clouds and convection. In current operational global weather and climate models, the resolution is limited to 10–100 km by computational resources. This is not sufficient to resolve cloud and convective processes. The effect of these processes must then be approximated by so-called parameterizations. Superparameterization uses another, local atmospheric model with a higher resolution, nested inside the columns of the global model, to evaluate the effects of clouds and convection. By analysing results from a superparameterized simulation, we show that superparameterization as it is generally implemented suppresses advection of existing clouds from one grid column to another in the global model, leading to a severe underestimation of the amount of shallow clouds. The suppression occurs because the global and local models represent clouds in different ways, and the commonly used superparameterization scheme does not communicate the full cloud information from the global model to the local one. Adding such a coupling of the cloud information to the superparameterization scheme improves the advection of clouds.

1 Introduction

Many of the systematic biases and uncertainties in conventional general circulation models (GCMs) can be attributed to the highly parameterized representation of clouds, turbulence and convection. It is even questionable whether these biases will be eliminated unless resolutions of GCMs become fine enough for these processes to be numerically resolved. As pointed out by *Arakawa et al.* [2011, 2016] there are essentially two possible routes toward such global large eddy models (GLEMs).

Route 1 follows the traditional approach of continuously refining the resolution until clouds, convection and turbulence are sufficiently resolved. This requires scale aware parameterizations for these processes that are gradually switched off with increasing resolution in a physically consistent manner. Alternatively one can make large jumps in the used resolution so certain parameterizations can be switched off abruptly. At present, a horizontal resolution of around 1 km is the highest possible resolution for subseasonal global simulations of the atmosphere [*Stevens et al.*, 2019a; *Satoh et al.*, 2019]. For such storm resolving resolutions, the general belief is that deep moist convective overturning is sufficiently well resolved to the extent that any additional deep convection parameterization will deteriorate the skill of the simulation. Obviously, at these storm resolving resolutions there is still a turbulence parameterization required as well as some parameterized representation of boundary layer cloudiness and shallow cumulus convection.

Route 2 makes use of a "multi-scale modeling framework" (MMF). In its original form, deep moist convection parameterization was replaced (or "superparameterized") by a 2D storm resolving model (2D SRM) in each cell of a GCM [*Grabowski and Smolarkiewicz*, 1999; *Grabowski*, 2001]. More recently, the use of a 3D large eddy model as a superparameterization (SP) for clouds, convection and turbulence has been proposed [*Grabowski*, 2016; *Parishani et al.*, 2017; *Jansson et al.*, 2019]. This approach has the advantage that most of the small scale dynamics and cloud microphysics is well represented while the GCM can still be formulated in an efficient hydrostatic manner. Further computational advantages of this approach over a GLEM are discussed in *Grabowski* [2016]. Because the use of a 3D large eddy model as a superparameterization on a global scale is computationally not yet feasible, *Jansson et al.* [2019] implemented the possibility of using a 3D Large Eddy Model (LEM) on a regional scale in the global Integrated Forecasting System (IFS) of the ECMWF [*Malardel et al.*, 2016]. This implies that a number of grid cells in the IFS can be selected to be superparameterized while the remaining part of the IFS will use the conventional parameterizations for clouds, convection and turbulence. In the study by *Jansson et al.* [2019] the implementation of the Dutch Atmospheric Large Eddy Simulation (DALES, *Heus et al.* [2010]) model as a superparameterization into the IFS was documented, along with a case study of local shallow cumulus convection over land to demonstrate the potential of this approach.

Despite the many advantages, the MMF does not come without problems. One drawback of this approach is that the communication between neighboring GCM cells can only occur by the advection of the variables of the GCM. Therefore it is not possible in the superparameterized framework to advect a spatial structure, as resolved by a local LEM, to a neighboring GCM grid cell — only the mean state of a GCM grid cell can be advected to a neighboring cell. In other words, the MMF introduces a scale break as it does not allow structures, or even variability, to grow upscale to scales beyond the size of the GCM grid size. Another related but more severe drawback of the MMF follows from the fact that while most GCMs carry separate prognostic variables for the water vapor and the water in the condensed phase, this is not the case for the local LEM. Most local models use the total water specific humidity q_t, i.e the sum of water vapor and the condensed water, as a prognostic variable. This implies that while the GCM separately advects the amount of condensed water and water vapor from one grid cell to a neighboring one, the local LEM of the neighboring cell is incapable of digesting this information and can only take the sum of the advected vapor and condensed water as input.

As will be demonstrated in detail, this implies that a cloud which is advected to a neighboring grid cell by the GCM will be directly diluted and dissipated in the local LEM of the neighbouring cell. This dissipation of advected clouds is likely a general problem in all published studies of superparameterizations that make use of SRMs with total water specific humidity as a prognostic variable.

In short, the main purpose of this paper is i) to show that most superparameterizations as they are used today dissipate most of the advected cloud condensate, leading to strong underestimation of cloud condensate and ii) to offer a simple solution by advecting the appropriate variance of humidity between GCM grid cells that are commensurate with the advected cloud condensate.

The paper is organised as follows. In section 2, we analyse the SP procedure and its consequences for cloud advection. As an example, we show a regional SP simulation with the LEMs located over the subtropical Northern Atlantic Ocean, in the vicinity of Barbados. The example shows almost complete suppression of cloud advection into the superparameterized region. In section 3 we propose an extension of the SP scheme with a procedure to adjust the small-scale variability in the local models, in order to better preserve the cloud condensate. In section 4 we present an idealized SP experiment where the large-scale model consists of only advection, to demonstrate the lack of cloud advection in SP and to see the impact of the variability coupling scheme in a simple setup. The effects of the variability coupling procedure on the full Barbados simulation is evaluated in section 5. In the concluding section 6 we discuss the impact of the cloud advection issue on SP experiments.

2 Suppressed cloud advection in superparameterization

In this section, we show that a SP scheme can lead to suppressed advection of cloud condensate in the large-scale model.

2.1 Superparameterized Barbados experiment

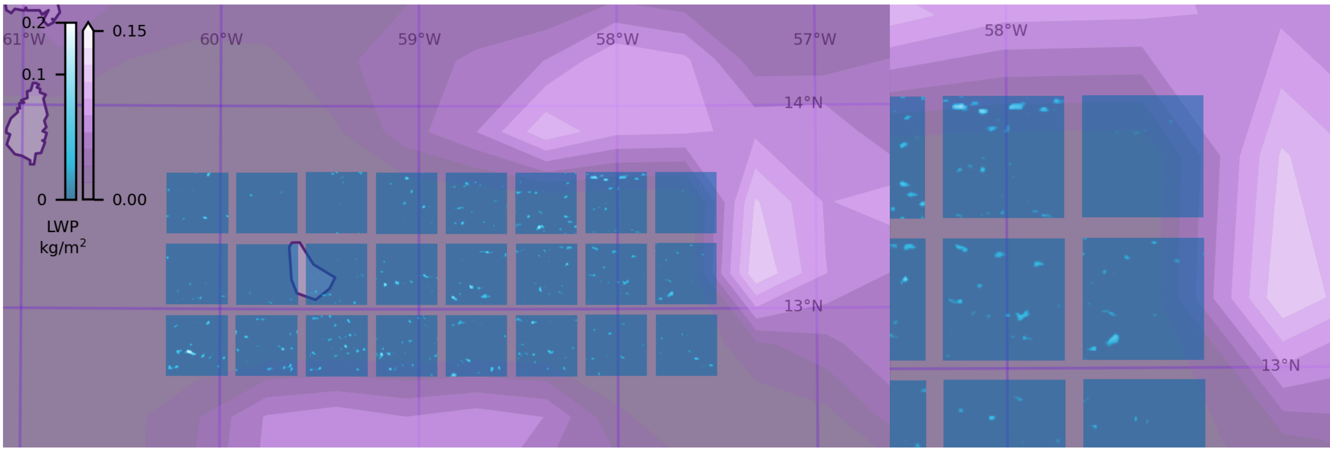


Figure 1. A superparameterized simulation over Barbados on 2013-12-15 at 9:30 UTC, showing that incoming clouds in the large-scale (purple) model do not easily advect into the superparameterized region (blue boxes). The right hand-image shows a magnification of the eastern (upwind) part of the SP region.

We demonstrate this lack of cloud advection in an experiment with the regional SP of OpenIFS with DALES [*Jansson et al.*, 2019], with the SP region located over Barbados, as shown in figure 1. This case has a wind from the east which brings clouds into the superparameterized region. A satellite image of the same area is shown in figure 2.

The region features persistent shallow cumulus clouds transported by the trade winds, with cloud patterns and cloud organizations occurring on widely different length scales. It is an interesting test case for SP, in particular to investigate how well SP represents cloud organization. The time and the location were chosen to coincide with the NARVAL [*Stevens et al.*, 2019b] observation campaign. The location is also part of the recent EUREC4A campaign [*Bony et al.*, 2017; *Stevens et al.*, 2021].

Figure 3 shows the liquid water path and total water path in the GCM from the SP simulation mentioned above, compared to a corresponding simulation without SP, i.e. using the standard OpenIFS. The SP columns show virtually no clouds as opposed to the neighboring columns. The figure shows that the total water path in the two simulations are similar, while the liquid water path is markedly lower in the SP columns.

We will argue that the reason for the lack of clouds in the SP columns is because advection of clouds into the SP columns is suppressed by the SP coupling.

This cloud suppression issue is especially visible in a regional SP model where the global model contains both superparameterized and regular columns next to each other as

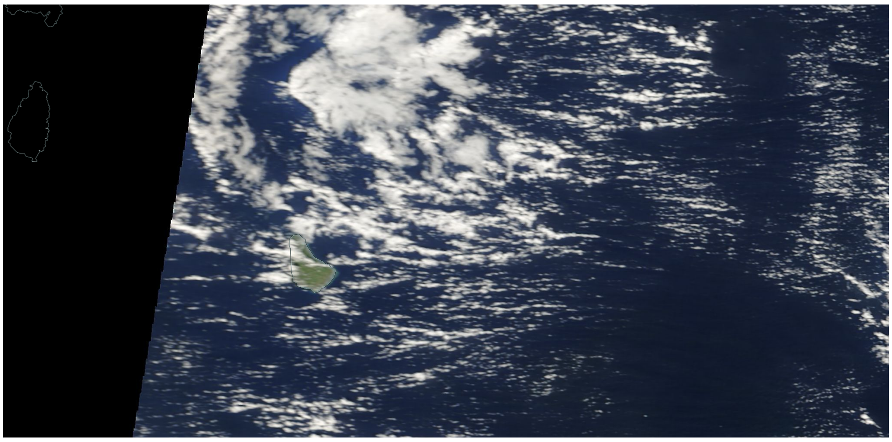


Figure 2. Satellite image from Terra/MODIS over the same region as figure 1, on 2013-12-15 13:55 UTC.

illustrated in Fig. 3. The problem is not, however, restricted to regional superparameterizations but can be expected also in uniformly superparameterized models.

2.2 Model coupling in superparameterization

For the physical model coupling between a LEM or another local model and some or all columns of a GCM, we have followed the same approach as described by *Grabowski* [2004]. Since this coupling plays a crucial role in the cloud suppression, we briefly review the procedure here.

The general idea is that for each coupled variable, a forcing is introduced, which keeps the states of the two models consistent with each other,

$$\Phi(X, Y, Z, t) = \langle \phi(x, y, z, t) \rangle. \tag{1}$$

The brackets $\langle \cdot \rangle$ here denote a spatial average over the LEM domain in the horizontal directions. Capital letters denote variables in the GCM, small letters denote variables used in the LEM. Φ and ϕ here may represent any of the prognostic variables. The details of the regional SP setup used here are given in *Jansson et al.* [2019]; we here give the coupling equations for reference.

The GCM first performs a single time step from time T to $T + \Delta T$, after which the LEM is evolved over the same time interval, in multiple smaller time steps of length Δt. Before the time evolution of each model, forcings are calculated based on the difference between the most recently obtained states of the two models, chosen such as to keep equation (1) satisfied. The coupling and the time stepping of the system are described in the following 4 steps.

(i) Given the state of both models at time T, represented by $\Phi(T)$ for any of the GCM variables and $\phi(T)$ for the corresponding LEM variable, the forcing F_Φ on the variable Φ in the GCM is calculated as

$$F_\Phi(T) = \frac{\langle \phi(T) \rangle - \Phi(T)}{\Delta T}. \tag{2}$$

(ii) Time-step the GCM

$$\Phi(T + \Delta T) = \Phi(T) + \Delta T \left[A_\Phi(T) + S_\Phi(T) + F_\Phi(T) \right], \tag{3}$$

where $A_\Phi(T)$ represents advection terms and $S_\Phi(T)$ represents source terms for the variable Φ during the step from T to $T + \Delta T$.

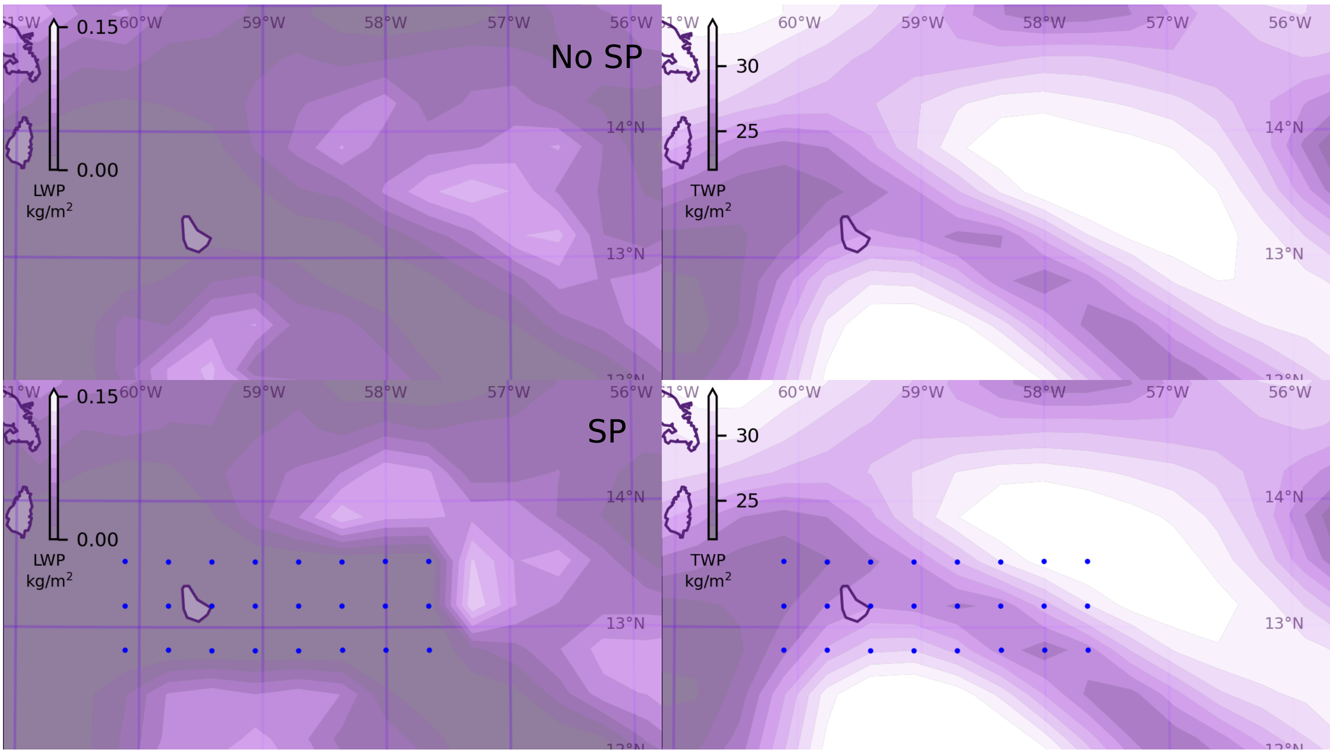


Figure 3. Comparing dynamics of the liquid water path and total water path in standard OpenIFS (top) and an SP setup (bottom), in a simulation over Barbados. Superparameterized grid columns are marked with blue dots. The wind is from the east, advecting clouds in to the superparameterized regions. In the normal superparameterization, there is a hole in the cloud cover (seen in the liquid water path (LWP, left) over the superparameterized region, compared to standard OpenIFS. The total water path (TWP, right) is similar between the two simulations, and does not show different behaviour in the superparameterized columns. The simulation was initialized on 2013-12-15 at 00 UTC, the image shows the state at 09:30.

(iii) Now the forcing on ϕ in the LEM is calculated as

$$f_\phi(T) = \frac{\Phi(T+\Delta T) - \langle \phi(T) \rangle}{\Delta T}. \tag{4}$$

(iv) and finally the time-step the LEM is executed as

$$\phi(T+\Delta T) = \phi(T) + \sum_{t=T}^{T+\Delta T} \Delta t \left[a_\phi(t) + s_\phi(t) + f_\phi(T) \right]. \tag{5}$$

The sums over t here represent evolving the LEM over several time steps, with $a_\phi(t)$ denoting advection terms and $s_\phi(t)$ denoting source terms for ϕ.

2.3 Coupling of DALES and OpenIFS

The SP of OpenIFS with DALES s formulated with couplings of variables for the horizontal wind velocities, temperature, and humidity. A summary the coupling is provided in table 1. While OpenIFS uses the regular temperature T as a variable, DALES is formulated using the liquid water potential temperature θ_l,

$$\theta_l \approx \frac{T}{\Pi(p)} - \frac{L}{c_{pd}\Pi(p)} q_c. \tag{6}$$

Coupled variables

OpenIFS	direction	DALES	description
U, V	$\leftrightarrow$	u, v	horizontal velocity
T	$\leftrightarrow$	θ_l	temperature / liquid water potential temperature
$Q_V + Q_L + Q_I$	$\rightarrow$	q_t	specific total humidity
Q_V	$\leftarrow$	$q_t - q_c$	specific water vapor humidity
Q_L, Q_I	$\leftarrow$	q_c	specific condensed water humidity

Table 1. Summary of the coupling of OpenIFS and DALES. U and V are horizontal velocities, T is the temperature in OpenIFS, and θ_l is the liquid water potential temperature in DALES. Q_V, Q_L and Q_I are the specific water vapor, cloud liquid, and cloud ice amounts in OpenIFS, while q_t and q_c are the specific total water and cloud condensate amounts in DALES.

where q_c is the specific cloud condensed water content and $c_{pd} \approx 1004$ J/kg K is the specific heat of dry air at constant pressure. The Exner function $\Pi(p)$ is defined as

$$\Pi(p) = \left(\frac{p}{p_0}\right)^{R_d/c_{pd}}, \tag{7}$$

where $L \approx 2.5 \cdot 10^6$ J/kg is the latent heat of water vaporization, and $R_d \approx 287.04$ J/kg K is the gas constant for dry air.

In the experiments shown here, IFS was operating at an effective horizontal resolution of 40 km (T511L91 grid), while the DALES domains cover 12.8 × 12.8 km with a resolution of 200 m. Further details are given in [*Jansson et al.*, 2019].

2.4 Representation of clouds and small-scale variability

In this section we will show how the different representations of clouds in the GCM and the LEM lead to an insufficient coupling of cloud quantities in SP and reduced advection of existing clouds into SP columns.

While the SP coupling described above conserves the amount of water in the system, it does not conserve the amount of condensed water. In global atmospheric models, the horizontal extent of a grid column is typically tens of kilometers, large enough to host numerous clouds. GCMs keep track of the amount of water vapor Q_V, liquid water Q_L, and ice water Q_I in each grid cell, along with the cloud-fraction A indicating that only a fraction of the grid cell is cloudy while the rest remains unsaturated.

LEM's on the other hand, generally assume that the grid cells are either uniformly cloudy or unsaturated. Therefore cloud condensation only occurs if the grid cell is supersaturated by an all-or-nothing procedure. This allows the use of total specific humidity q_t, i.e the sum of condensed water and water vapor, as a prognostic variable from which the condensed water is only determined diagnostically. Virtually all atmospheric LEMs (e.g. SAM *Khairoutdinov et al.* [2005], DALES *Heus et al.* [2010], PALM [*Maronga et al.*, 2015], microHH [*van Heerwaarden et al.*, 2017], NICAM and SCALE [*Tomita*, 2008], and UCLALES [*Stevens et al.*, 2005]) use q_t as a prognostic variable.

In SP schemes, the q_t variable of the LEM is forced towards the total specific humidity of the global model. If q_t increases above its saturation value, clouds will form in the LEM. However, GCM grid cells containing both clouds and unsaturated air are usually unsaturated on average, and as a result the LEM will be forced towards a cloud-free state, even though the GCM column contains clouds.

It is difficult to couple the amount of cloud condensed water in the same way as the other coupled quantities in a SP setup, as it is not a prognostic variable in the LEM but diagnosed from the local total specific humidity for each cell and time step. The amount of clouds in the LEM thus depends on fluctuations in state variables in the horizontal direction, which is a degree of freedom that so far is left uncoupled in SP schemes. In other words, the information contained in the GCM variables Q_L, Q_I and A is not transferred to the LEM in a standard SP scheme, since the LEM does not have corresponding prognostic variables to couple with these quantities.

Since clouds consist of local regions with higher humidity and/or lower temperature than their surroundings, we suggest that a way to control the cloudiness of the LEM is to nudge not just the horizontal average of the variables (as usually done in SP) but also the magnitude of their fluctuations from the average, in order to match the cloud-related variables of the large-scale model. This can be done in a way that leaves the fundamental relation (1) unchanged. A method to do so is described in section 3.

Note that even without adjusting the horizontal fluctuations, the LEM can generate clouds through convection if the conditions are favorable. The difficulties described above appear only when existing clouds in the global model should be advected into a model column with an embedded LEM, which happens to be cloud-free.

3 Variability coupling procedure

In order to couple the cloud water content of the LEM with the global model, we propose an extension to the SP coupling scheme to influence not just the horizontal averages but also the horizontal variability. In particular, by changing the amplitude of the fluctuations of the total specific humidity in each horizontal grid plane, the condensed water amounts there will be influenced. If the fluctuations are adjusted without altering the horizontal average, this scheme is still compatible with the superparameterization procedure. In other words, our proposed humidity variability coupling scheme amounts to redistributing the total water content of each horizontal layer in the LEM, in such a way that the condensed water content matches the value from the GCM for each layer.

This adjustment scheme is in the spirit of the traditional SP formulation, where the two models are forced towards each other during each time step. Our scheme extends this idea to the condensed water content, which the traditional scheme doesn't couple from the GCM to the LEM. Coupling cloud condensate information in the other direction, from the LEM to the GCM, is easily handled: the forcing on the GCM can be derived from the diagnosed specific condensed water humidity q_c of the LEM.

3.1 Humidity variability

There are many ways to adjust the total humidity field - any perturbation which leaves the horizontal average unchanged, and does not introduce negative humidity values could be considered. We choose to scale the amplitude of existing variations in each horizontal layer. In this way, we do not have to specify the length scales of the variability we add, but merely amplify the existing variability, as illustrated in figure 4. Let q_t be the total humidity, and q_{sat} the saturation humidity for each cell in the LEM. The condensed water humidity is then

$$q_c = \max[0, q_t - q_{\text{sat}}(p, T)]. \tag{8}$$

The modified q_t field can be written as

$$q_t^* = \beta(q_t - \langle q_t \rangle) + \langle q_t \rangle \tag{9}$$

where β is a scaling factor, chosen separately for each horizontal layer. If $\beta = 0$ all variations of q_t around its mean are removed, if $\beta = 1$ q_t is left unchanged, and for $\beta > 1$ the variability is amplified. This scaling leaves the average of q_t unchanged. A consequence

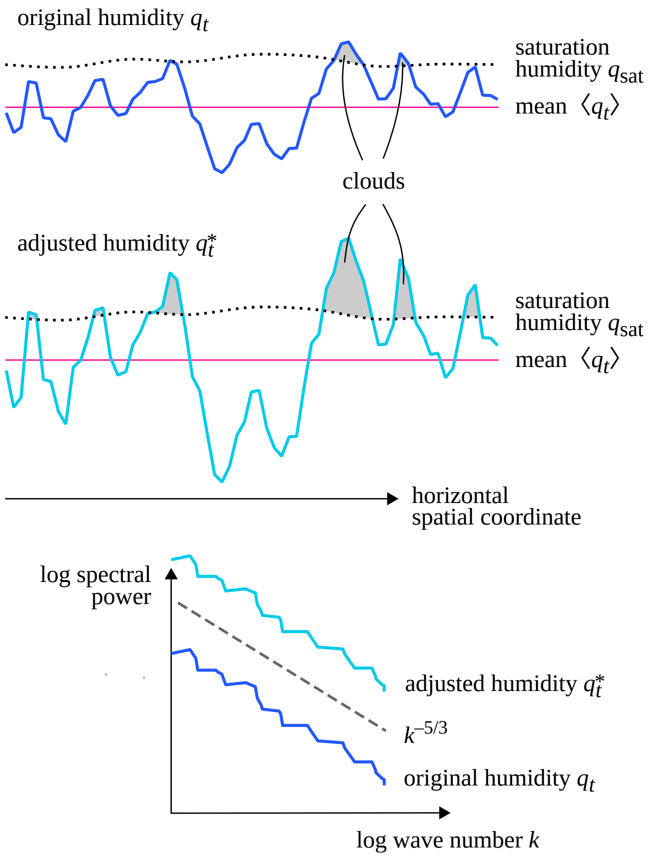


Figure 4. Illustration of the variability coupling procedure. Cells where q_t is above q_{sat} are saturated, and contribute to the condensed water content. The condensed water amount in each horizontal slab is controlled by adjusting the amplitude of the q_t fluctuations around the mean $\langle q_t \rangle$. This procedure preserves the shape (typically a $-5/3$ slope) of the humidity power spectrum.

of this manner of adjusting the variability is that the spatial Fourier spectrum of the q_t-field retains its shape, only the amplitude is changed. Another choice we make here is to keep the temperature T in each grid cell unchanged while adjusting q_t, which requires adjusting the liquid water potential temperature θ_l. This choice, which is further discussed below, has an important consequence for the coupling procedure, namely that the saturation humidity q_{sat} in each grid cell, which depends on temperature and pressure, remains unchanged during the adjustment.

Next we determine β so that the average condensed water humidity q_c in the horizontal layer matches the condensed water humidity $Q_C = Q_L + Q_I$ of the GCM,

$$Q_C = \langle q_c(\beta) \rangle = \Big\langle \max[0, q_t^*(\beta) - q_{sat}] \Big\rangle. \tag{10}$$

Combining equations (9) and (10) gives

$$Q_C = \Big\langle \max\left[0, \beta q_t + (1-\beta)\langle q_t \rangle - q_{sat}\right] \Big\rangle. \tag{11}$$

The max operator makes this equation difficult to handle analytically, so we solve it numerically for each horizontal layer.

3.2 Maintaining a constant temperature while coupling humidity

In determining the variability scaling β above, it was assumed that q_{sat} remains unchanged as β is varied. Since q_{sat} is a function of temperature and pressure, this assumption holds if the temperature remains constant as β is varied, as pressure is assumed to be a function only of height. In order to keep the temperature T constant while adjusting q_c, θ_l has to be adjusted as well.

$$\Delta\theta_l = -\frac{L}{c_{pd}\Pi(p)}\Delta q_c, \tag{12}$$

where Δq_c is the change in cloud condensate caused by the change in q_t.

Also for physical reasons it is preferable to adjust the humidity while keeping the temperature constant. In cloud parameterization schemes, it is generally assumed that variability in humidity is decisive for cloud formation, while variability in temperature plays a minor role [*Price and Wood*, 2002]. When adjusting the variability of the humidity, we change the condensed water content of the local model. There is no latent heat or temperature change associated with this re-distribution, in the same way as advection of clouds from one grid cell to another leaves the temperature unaffected.

3.3 Implementation details

While the coupling tendencies on the local models in an SP setup are generally applied gradually over time, we have implemented the variability changes instantly at every time step of the large-scale model. One reason for this is that the small-scale fields move due to advection over the course of one large-scale time step, which means that the tendencies need to move as well in order to achieve the desired final structure. Also with an instant adjustment, it is easier to verify that the procedure actually achieves the correct cloud condensate amounts.

Some practical issues in the adjustment procedure need to be handled:

1) Equation (11) for β may give an unreasonably large β as the solution. As this can make the local model unstable, we restrict β to the range $0\ldots5$. The permissible range of β is typically exceeded when large-scale advection would add clouds above the boundary layer, where the local model has a small variability in the horizontal direction. In this case, we add white noise to q_t, again with the amplitude selected to give the desired amount of cloud condensate.

2) q_t is not allowed to become negative in the adjustment. We have found that when limiting β as above, the procedure does not cause negative q_t values. As a precaution, one can set negative q_t values to 0, and adjust the other cells in the same horizontal layer to conserve the total mass of water.

3) If $Q_C = 0$, β is not uniquely determined. If q_c is also 0, we set $\beta = 1$, implying no variability adjustment. If $q_c > 0$ we nudge the layer towards just below saturation i.e. $\beta < 1$ but as large as possible.

4) With OpenIFS as the global model, sometimes Q_C is positive but tiny, on the order of 10^{-12} kg/kg. We choose to ignore condensed water humidities $< 10^{-9}$ kg/kg, when they would result in a nudge towards more variability.

4 Advection and variability coupling in a simplified SP setup

To illustrate the problems with cloud advection in SP as well as the solutions and limitations provided by the proposed humidity variability coupling scheme, we show a simplified SP setup where the large-scale model consists of only (upwind) advection of the prognostic variables, with a fixed large-scale wind. We construct this model as a realization of the following thought experiment: consider an SP simulation where a single

LEM contains a cloud but has an average humidity below saturation, and ask if or how this cloud can be advected into an LEM at a neighboring grid point. This model provides a simple setting to illustrate the cloud advection problem in SP and to see how the variability coupling approach mitigates the problem.

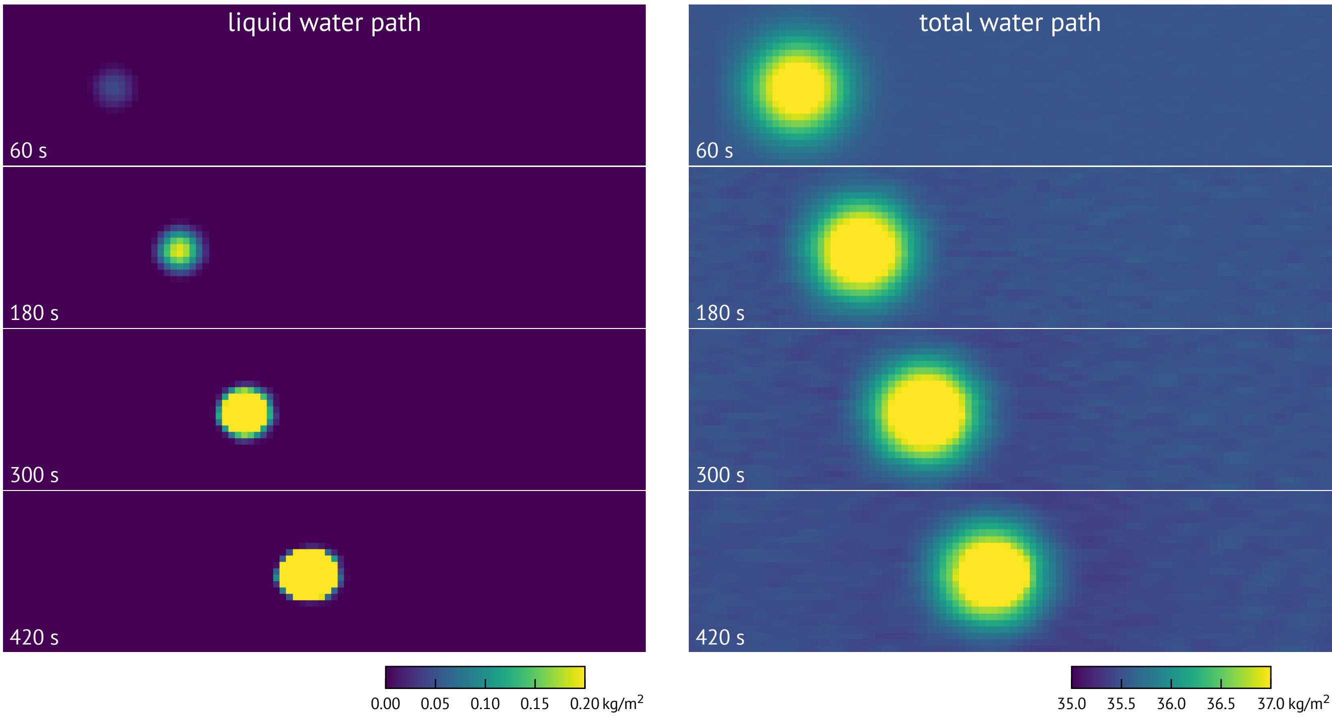


Figure 5. A moist-bubble experiment with a single large-eddy simulation domain. The plots show the liquid water path and total water path.

The ideal behavior in this experiment is shown in figure 5 with a single wide LEM. A superparameterized version is shown in figure 6, with four LEMs placed side by side. The LEMs are initialized with vertical profiles from the BOMEX case included with the DALES model. The left-most LEM is perturbed with a bubble of moist air, chosen to develop into a single cloud. There is a uniform wind to the right, advecting the cloud. The figure shows snapshots of the liquid water path and total water path in both simulations. In this experiment, the wind is 10 m/s to the east, the DALES domains are 2.5 × 2.5 km in the horizontal direction with a 100 m resolution, and 5 km high with a 40 m resolution in the vertical. The initial bubble perturbation of q_t in the left-most LEM has a shape Gaussian with standard deviation of 500 m and a central amplitude of 1.5 g/kg, with the center at 800 m above the ground.

The experiment shows that with superparameterization, the cloud stays in the left-most LEM where it was created, cycling around the periodic boundary conditions of the domain. The large-scale advection of total humidity and temperature is not sufficient to transfer the cloud to the neighboring LEM. This experiment shows that even though the total humidity q_t is advected correctly according to the idea of SP, this is not sufficient for clouds (as measured with cloud cover or cloud condensed water content) to be advected.

Figure 7 shows the simplified SP setup with the same moist bubble perturbation as in figure 6. With the variability coupling scheme, we can see that clouds are advected between the LEMs. The increased variability in the total water content from the variability coupling procedure can be seen in the total water path on the right.

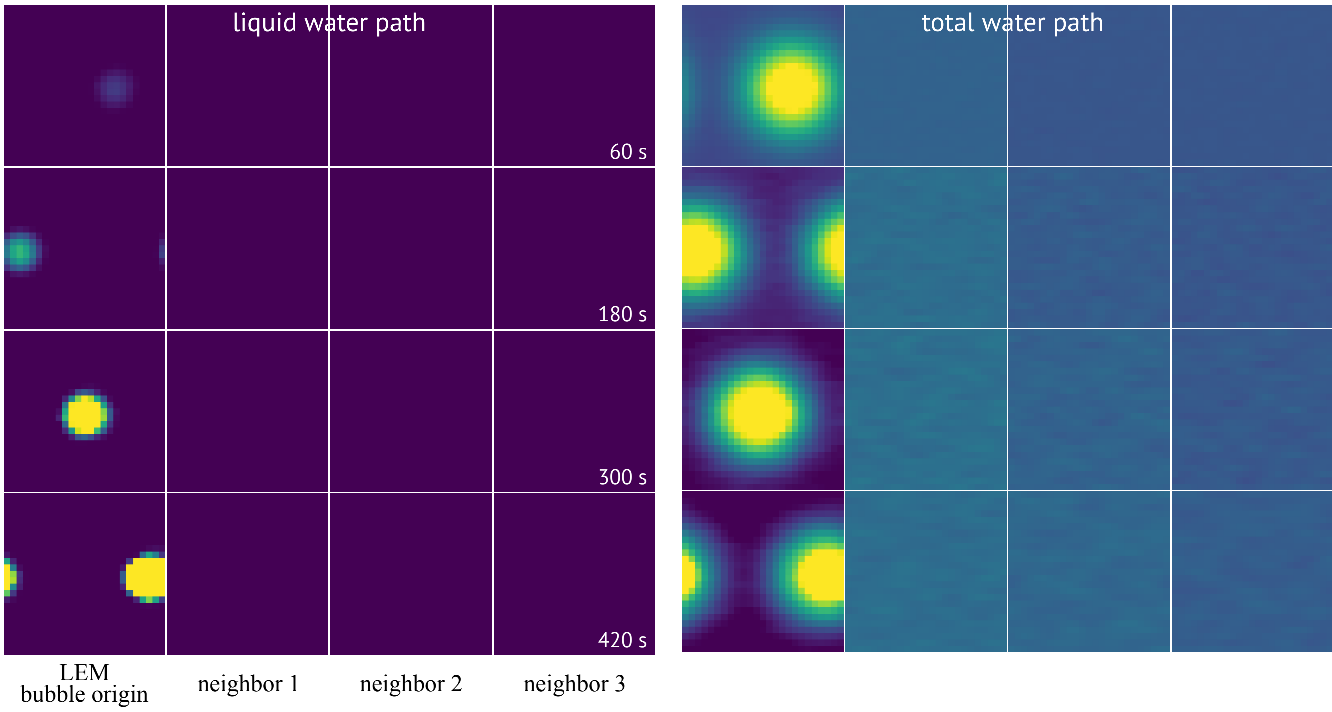


Figure 6. A superparameterized moist-bubble experiment with four small-scale domains and where the large-scale model consists of advection only.

In the total water path plots, one can see how the variability coupling scheme causes an increase of spatial variability in the total water content. An animation of the three simulations with this simplified SP setup is available as supporting information S1.

Even with the variability coupling, the bubble experiment is a particularly difficult case for superparameterization: the cloud in the leftmost LEM forms a single coherent structure, which is absent in the other LEMs. Figure 7 shows that the shape of the clouds is not preserved when they move between the LEMs - this would require an even more detailed coupling of the LEMs.

Experiments with the simplified SP model shows that the clouds added with variability adjustment tend to dissipate over time — even though the adjustment initially generates the desired amount of $\langle q_c \rangle$, the local models may not retain the imposed amounts of clouds when evolved in time, showing that the cloud condensate amount is a difficult property to control. This can be seen as fluctuations in the cloud condensate amount in the animation of these experiments, in supporting information S1.

5 Results of superparameterized Barbados simulation with variability coupling

To see the full effects of the variability coupling procedure introduced above, we repeat the Barbados simulation from section 2 with the variability coupling scheme (9) enabled.

Figure 8 show the Barbados simulation repeated with the variability coupling scheme. The LEMs clearly contain more clouds compared to the standard SP coupling scheme (figure 1), and clouds can be advected into the SP region to a significantly higher degree than with the standard scheme. An animation comparing the three simulations shown in figures 1, 3, and 8 is available as supporting information S2.

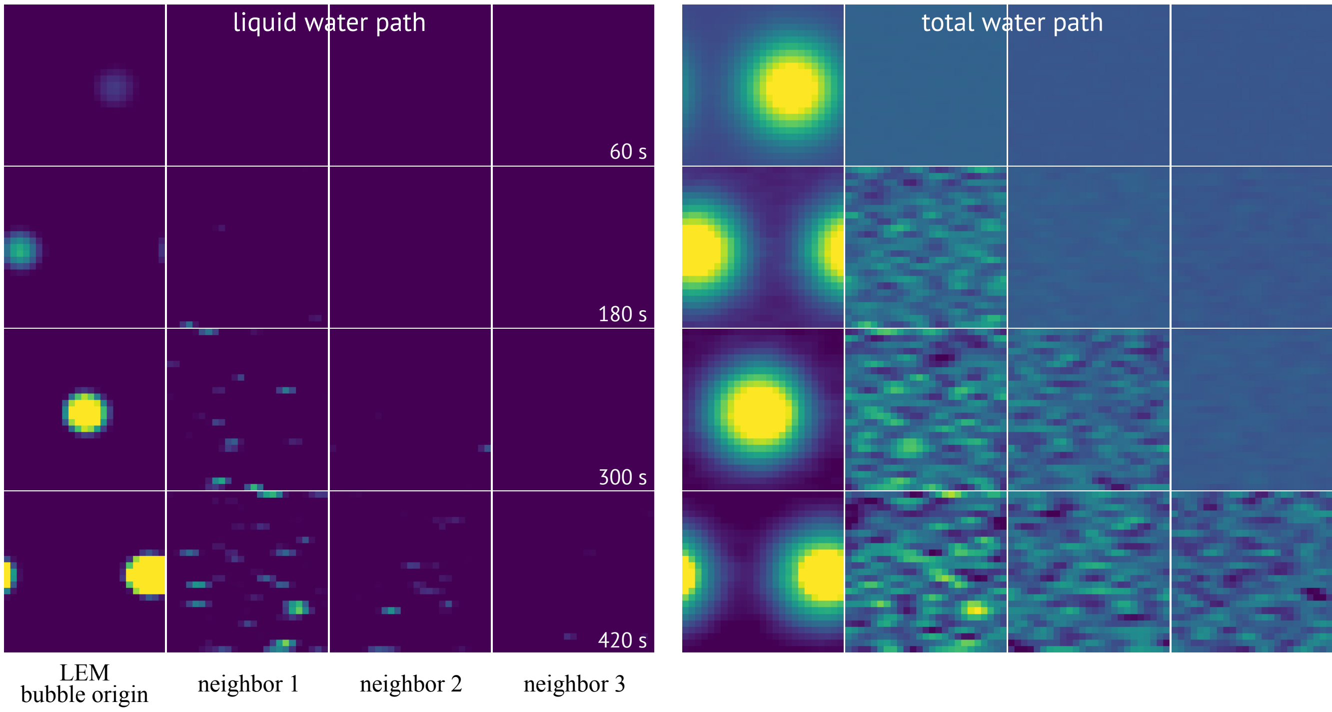


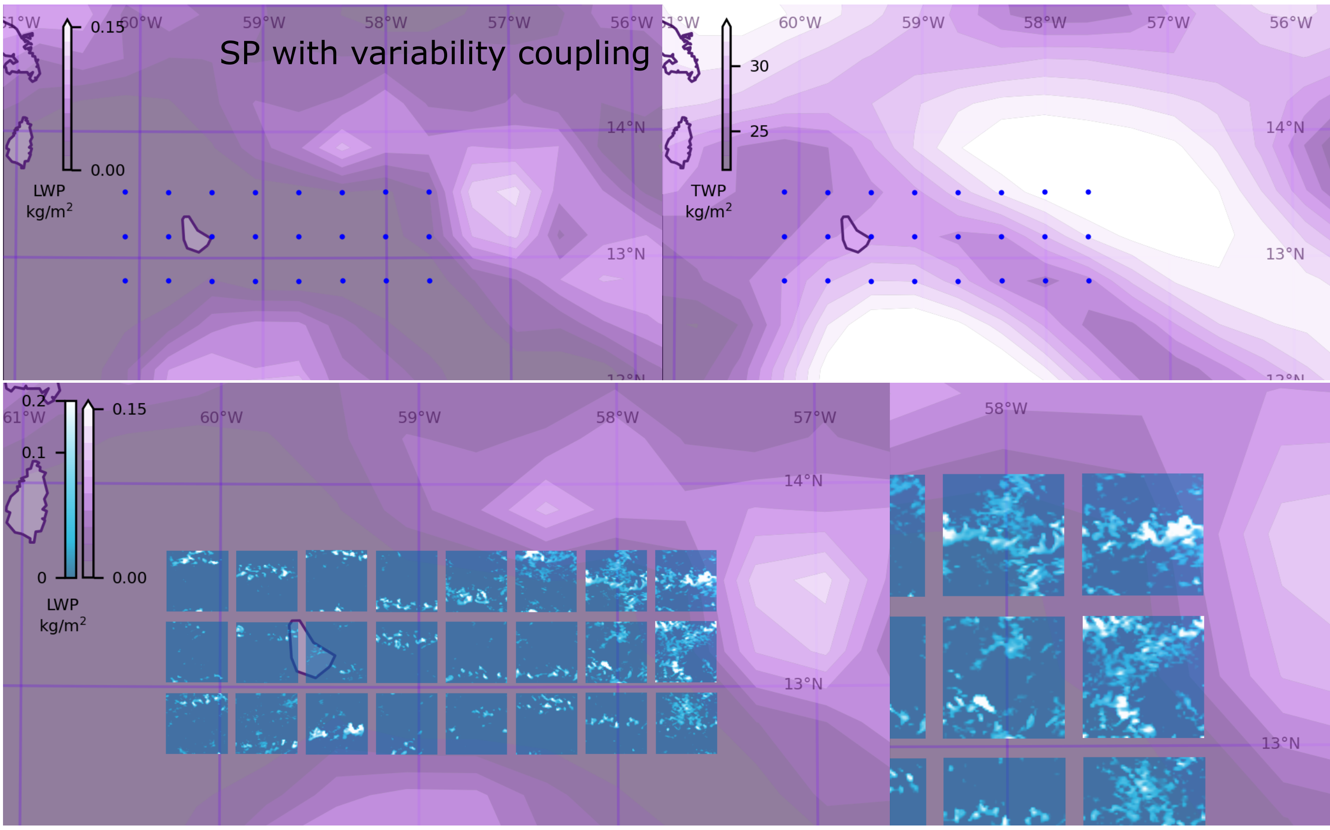
Figure 7. The moist-bubble experiment with four coupled local models shown in figure 6 repeated with variability coupling.

A quantitative comparison of the clouds in the three different Barbados simulations is given in figure 9, which shows east–west profiles of the liquid water path and low cloud cover. The data has been averaged over time, 04h–12h UTC, and over the north–south extent of the SP domain i.e. three rows of GCM grid points. Comparing the experiments shows that SP causes a marked drop in clouds in the SP domain, both in liquid water path and in cloud cover, compared to the non-SP simulation. The variability coupling method increases the cloud content compared to standard SP, but is not sufficient to reach the levels of the non-SP simulation. One reason the variability coupling shows a lack of cloud condensate is that the clouds added by variability adjustment dissipate too quickly - most likely due to a lack of organization (the dissipation can be seen in the animations S1 and S2).

6 Discussion and conclusions

As shown in section 2.4, the difficulties of coupling cloud condensate in an SP setup are related to the global and local models being formulated using different prognostic variables. The standard SP approach couples temperature, total humidity and horizontal wind velocities, which are well-defined prognostic variables in both the local and the global model. Thus one may ask if introducing prognostic cloud condensate variables in the local model would improve the situation - we argue that this is not automatically the case, and that variability related to clouds in the local model still plays a role.

Consider a cloud-resolving model with prognostic cloud condensate. The condensate would be advected like the other atmospheric quantities, and the model would contain expressions for the conversion rates between water vapor and condensate, and between condensate and precipitation. With such a model in an SP setup, it would be straight-forward to couple the cloud condensate between the two models in the same manner as the other



380 **Figure 8.** Superparameterization with variability coupling, in a simulation over Barbados on 2013-12-15.

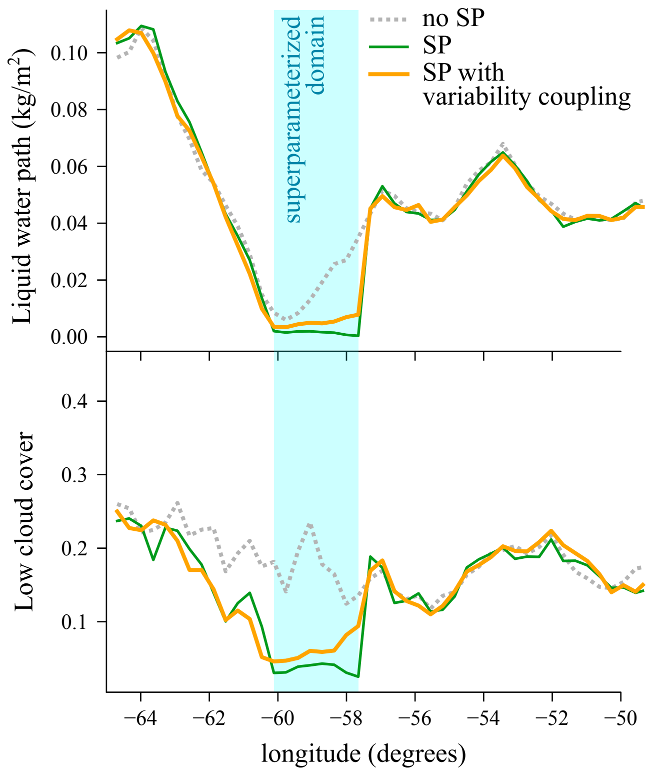


Figure 9. East–west profiles of low cloud cover and liquid water path for the three Barbados simulations: no SP, SP, and SP with variability coupling. The data is averaged over 8h (04–12 UTC) and over the north–south extent of the SP domain. The SP domain is indicated with a blue background. The low cloud cover measure is from OpenIFS and is defined as the cloud cover between the surface and the height of 80% of the surface pressure (roughly 2 km). SP = superparameterization.

prognostic quantities. However, when a cloud is advected into a local model, the cloud condensate will be uniformly spread out in the horizontal direction. Now, if the air in this layer is not saturated, the cloud condensate will evaporate. Thus it is not only the conversion between different sets of prognostic variables, but the difference in representing the small-scale variations that leads to the problems in advecting clouds in an SP setup.

We emphasize that the issue of advecting existing clouds in an SP model is general, and not specific to our regional SP implementation. However, the regional approach clearly shows that clouds are lost when transported over the boundary between SP and non-SP regions.

Adjusting the small-scale variability in the local models as described in section 3 improves the cloud advection in SP, but does not make the agreement in cloud condensate amounts perfect. One reason for the remaining deficiency of advected cloud condensate is that the clouds created by the variability adjustment procedure tend to shrink by evaporation.

Also regular cloud parameterizations in global models suffer from uncertainty in the small-scale structure of the clouds. With Q_V, Q_L, A known in a grid cell, the cloud processes still depend on the details of how the clouds are distributed in the grid cell on the subgrid scales. Thus, cloud advection in global models is well defined but the cloud processes are uncertain.

We advice caution in interpreting SP results since the advection of clouds is problematic. At a minimum, SP results should be compared with the results from GLEM and other high-resolution global models that are now becoming available. [*Stevens et al.*, 2019a]. Even if advection of clouds in SP is problematic, we see potential for SP as a benchmark for parameterizations, offering the possibility to compare parameterizations and cloud-resolving models under similar conditions.

Acknowledgments

We thank Glenn Carver at the ECMWF for help with OpenIFS and for providing us with initial states for the simulation.

We acknowledge the use of imagery from the NASA Worldview application (https://worldview.earthdata.nasa.gov/) operated by the NASA/Goddard Space Flight Center Earth Science Data and Information System (ESDIS) project.

This work was supported by the Netherlands eScience Center (NLeSC) under grant no. 027.015.G03. Furthermore, we acknowledge the use of ECMWF's computing and archive facilities in the research reported here. Also SURFsara provided computing resources.

Code availability

DALES, OMUSE, the SP coupler for DALES and OpenIFS, and the Simple SP experiment are available on GitHub under open-source licenses.

DALES: [*Arabas et al.*, 2021], https://github.com/dalesteam/dales, DOI: 10.5281/zenodo.3759192

OMUSE: [*Pelupessy et al.*, 2021], https://github.com/omuse-geoscience/omuse, DOI: 10.5281/zenodo.3755558.

SP coupler: [*Jansson et al.*, 2018], https://github.com/CloudResolvingClimateModeling/sp-coupler, DOI: 10.5281/zenodo.1968304.

The simple SP experiment: [*Jansson et al.*, 2021], https://github.com/CloudResolvingClimateModeling/Simple-SP DOI: 10.5281/zenodo.5511753

For OpenIFS, a license can be requested from ECMWF. For details of the SP setup with OpenIFS with DALES, see also *Jansson et al.* [2019]. The Python interface to DALES using OMUSE is described in *van den Oord et al.* [2020].

Author contributions

DC and PS conceived of the project. FJ, GvdO, DC, PS defined the SP coupling procedure. FJ, GvdO, IP, MC wrote the superparameterization coupler and Python interfaces to OpenIFS and DALES. FJ ran the simulations. JHG and FJ developed the visualizations. JHG drew the figures. FJ wrote the article text, with contributions and editing by all other authors.

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