Representing Mesoscale Variability in Superparameterized Climate 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.
Supporting Information for "Representing Mesoscale Variability in Superparameterized Climate models"
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Movie S1. A comparison of three simulations, showing a simplified superparameterization setup where the large-scale model consists of only advection. A single wide domain (top), superparameterization with four coupled models (middle), and superparameterization with variability coupling (bottom). The initial state contains a bubble of air with added humidity, which forms a single cloud. With regular superparameterization, the cloud is not advected between the domains. With the addition of variability coupling, clouds are advected between the domains, however their shapes are not preserved. This movie shows the same simulations as in figures 5–7 in the main text.

Movie S2. A comparison of three simulations over Barbados. Regular non-superparameterized OpenIFS (top), superparameterized OpenIFS (middle), and superparameterized OpenIFS with the addition of variability coupling (bottom). In the usual form of superparameterization (middle) clouds are not easily advected into the superparameterized domain. Variability coupling (bottom) increases the amount of cloud condensate in the small-scale models. This movie shows the same simulations as in figures 1, 3, and 8 in the main text.

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Key Points:

\begin{itemize}
  \item Superparameterization in weather and climate models is used to improve the representation of clouds
  \item We show that superparameterization suppresses the transport of clouds
  \item A scheme for controlling the humidity variation partially improves cloud representation in superparameterized models
\end{itemize}

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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. As a starting point for mitigating 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 match the global model’s cloud condensate amount. The proposed scheme enhances the cloud condensate amount in the test cases, however a large discrepancy remains, caused by rapid dissipation of the clouds added by the proposed scheme.

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 partially improves the advection of clouds. The remaining discrepancies indicate that there are still missing processes in the superparameterized representation of boundary layer 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 (GLEM). 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; Randall et al., 2003; Khairoutdinov et al., 2005; Tao et al., 2009].
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 ef-
ficient 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 super-
parameterization 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; Spar-
row et al., 2021]. 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 parameter-
izations for clouds, convection and turbulence. In the study by Jansson et al. [2019] the im-
plementation 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 draw-
back of this approach is that the communication between LEMs embedded in neighboring
GCM columns can only occur through the GCM, primarily through advection of the vari-
ables in the GCM. Therefore it is not possible in the superparameterized framework to ad-
vect a spatial structure, as resolved by a local LEM, to a neighboring GCM grid column —
only the mean state of a GCM grid column can be advected to a neighboring column. In
other words, compared to a global LEM, 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. The same scale cutoff is naturally present in a GCM, where processes on scales
smaller than the grid size are parameterized. Superparameterization should be viewed as
an attempt for a better and model-informed parameterization, rather than a substitute for a
global LEM. Chern et al. [2020] evaluates biases in the size of rain events simulated in the
Goddard MMF, caused by the size constraint imposed by the cloud-resolving model. On the
other hand, other phenomena such as mesoscale convective systems and tropical cyclones
have been shown to be able to grow across the scales of the two models when simulated with
SP [Pritchard et al., 2011; Tulich, 2015; Lin et al., 2022].

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 con-
densed 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 va-
por and condensed water as input.

As will be demonstrated in detail, this implies that a cloud which is advected to a neigh-
boring grid column by the GCM will be directly diluted and dissipated in the local LEM
of the neighbouring column. This dissipation of advected subgrid clouds, such as cumu-
lus types, 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. Marine shal-
low cumulus is an abundant cloud type, with important but not precisely known climate feed-
back properties [Bony and Dufresne, 2005; Bony et al., 2020].
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 of sub-grid-scale clouds, leading to strong underestimation of cloud condensate and ii) to explore a simple solution by coupling the appropriate variance of humidity between GCM grid cells that are commensurate with the advected cloud condensate.

The paper is organized 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](image-url)  
**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. The IFS model, initialized from ERA5 as in Jansson et al. [2019], shows only shallow clouds entering the SP region, cloud base varies between 500m and 800m, while the cloud top varies between 1.4 and 3 km during the simulation (this can be seen below in figure 11 showing vertical profiles of cloud condensate in selected grid points). In the experiments shown here, IFS was operating at an effective horizontal resolution of 40 km (T511L91 grid). The DALES domains cover 12.8 × 12.8 km with a horizontal resolution of...
200 m. The DALES domains are 5 km high, with a vertical resolution of 20 m. Further details are given in [Jansson et al., 2019]. 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].

DALES on its own, like several other atmospheric LEMs, has been evaluated under similar conditions - subtropical marine shallow cumulus convection. See for example the LES model intercomparison studies for the non-precipitating BOMEX and ATEX cases [Siebesma et al., 2003; Stevens et al., 2001] and the precipitating RICO case [vanZanten et al., 2011].

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

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 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.
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 into 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 behavior in the superparameterized columns. The simulation was initialized on 2013-12-15 at 00 UTC, the image shows the state at 09:30.

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,

$$\Phi(X, Y, Z, t) = \langle \phi(x, y, z, t) \rangle.$$  (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. $\Phi$ and $\phi$ 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 $\Delta t$. 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 $F_{\Phi}$ on the vari-
Coupled variables

<table>
<thead>
<tr>
<th>OpenIFS</th>
<th>direction</th>
<th>DALES</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$U, V$</td>
<td>$\leftrightarrow$</td>
<td>$u, v$</td>
<td>horizontal velocity</td>
</tr>
<tr>
<td>$T$</td>
<td>$\leftrightarrow$</td>
<td>$\theta_l$</td>
<td>temperature / liquid water potential temperature</td>
</tr>
<tr>
<td>$Q_V + Q_L + Q_I$</td>
<td>$\rightarrow$</td>
<td>$q_t$</td>
<td>specific total humidity</td>
</tr>
<tr>
<td>$Q_V$</td>
<td>$\leftrightarrow$</td>
<td>$q_t - q_c$</td>
<td>specific water vapor humidity</td>
</tr>
<tr>
<td>$Q_L, Q_I$</td>
<td>$\leftrightarrow$</td>
<td>$q_c$</td>
<td>specific condensed water humidity</td>
</tr>
<tr>
<td>$A$</td>
<td>$\leftarrow$</td>
<td>$a$</td>
<td>cloud fraction</td>
</tr>
</tbody>
</table>

Table 1. Summary of the coupling of OpenIFS and DALES. $U$ and $V$ are horizontal velocities, $T$ is the temperature in OpenIFS, and $\theta_l$ 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. The cloud fraction $A$ is coupled only from DALES to OpenIFS.

The SP of OpenIFS with DALES is 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 $\theta_l$.

Further, the specific cloud condensed water content $q_c$ is approximated using the liquid water potential temperature $\theta_l$,

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

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

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

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.
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.

LEMs 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, see table 1. 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 $Q_L$ and $Q_I$ 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. We here consider clouds where the condensate consists of water only. If the fluctuations are adjusted without altering the horizontal average, this scheme is still com-
compatible with the superparameterization procedure. In other words, our proposed humidity variability coupling scheme amounts to re-distributing 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

![Diagram](image-url)

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

(8)

The modified \( q_t \) field can be written as

\[ q_t^* = \beta(q_t - \langle q_t \rangle) + \langle q_t \rangle \]  

(9)

where \( \beta \) is a scaling factor, chosen separately for each horizontal layer. If \( \beta = 0 \) all variations of \( q_t \) around its mean are removed, if \( \beta < 1 \) the variability of \( q_t \) is decreased, 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 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 \( \theta_t \). This choice, which is further discussed below, has an important consequence for the coupling procedure, namely that the saturation humidity \( q_{\text{sat}} \) in each grid cell, which depends on temperature and pressure, remains unchanged during the adjustment.

Next we determine \( \beta \) so that the average condensed water humidity \( q_c \) in the horizontal layer matches the condensed water humidity \( Q_C = Q_L + Q_T \) of the GCM,

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

(10)

Combining equations (9) and (10) gives

\[ Q_C = \langle \max[0, \beta q_t + (1 - \beta) \langle q_t \rangle - q_{\text{sat}}] \rangle. \]  

(11)

The max operator makes this equation difficult to handle analytically, so we solve it numerically for each horizontal layer. If \( Q_C > \langle q_t \rangle \), we obtain a \( \beta > 1 \) and the LES \( q_t \) variability and the cloud amount is increased, if \( Q_C < \langle q_t \rangle \), \( \beta < 1 \) and the LES cloud amount is decreased.

### 3.2 Maintaining a constant temperature while coupling humidity

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

\[ \Delta \theta_t = -\frac{L}{c_p \Pi(p)} \Delta q_c. \]  

(12)

where \( \Delta q_c \) 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.

If one makes a different choice here, to for example keep \( \theta_t \) constant during the adjustment, the following issues should be noted. The temperature-dependence of \( q_{\text{sat}} \) must be considered while solving equation (11). Otherwise the adjustment scheme will add less clouds than intended, because \( q_t \) increases with the addition of cloud condensate. Allowing \( T \) to change in the adjustment affects the buoyancy of the newly added clouds, which may in turn affect their lifetime. Adjusting variability at constant \( T \) adds less buoyancy to the new clouds than adjusting at constant \( \theta_t \).
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 \( \beta \) may give an unreasonably large \( \beta \) as the solution. As this can make the local model unstable, we restrict \( \beta \) to the range \( 0 \ldots 5 \). The permissible range of \( \beta \) 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 \( \beta \) 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 \( Q_C = 0 \), \( \beta \) 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.

The choices in 3) and 4) seem less critical than the rest in our experience, our motivation is to make the smallest possible intervention in the case where the size of the required variability adjustment is not uniquely defined.

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.

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 \( 2.5 \times 2.5 \) 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 Gaussian shape with standard
Figure 10. 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.

6 Discussion and conclusions

We have used DALES as a superparameterization in the IFS for a region over the subtropical Atlantic Ocean that is dominated by shallow cumulus convection. When DALES is coupled in the traditional way, as described in Sections 2.2 and 2.3, the cloud amount in the superparameterized region is strongly underestimated both in cloud cover as well as in liquid water content. One possible cause for this underestimation of cloud amount that has been hypothesised in this study is the use of moist conserved prognostic variables by DALES, such as the total specific humidity $q_t$, rather than the liquid water and the water vapor separately. As a result any changes of the cloud liquid water in the IFS, for instance by advection, has to be passed on to DALES via $q_t$. In practice this means that the liquid water from the IFS is distributed uniformly as an increment of $q_t$ for all gridpoints in the LEM. Since the LEM is usually only partially cloudy this effectively implies that most of the liquid water from the IFS is added as water vapor to the LEM unsaturated gridpoints. To illustrate this problem we have analysed in Section 4 an evolving single cloudy updraft that is advected from West to East in an unsaturated environment. When superparameterizing this case, it is easy to observe and understand that the liquid water advected out of the cloud-containing LEM
Figure 11. Vertical profiles of cloud liquid water in the superparameterized simulations. A) The non-superparameterized column just upwind (to the east) of the middle row of the SP domain. B) The middle row, easternmost LES of the SP domain, with variability coupling. C) The same LES, without variability coupling. In panel B, the time steps of the GCM, 15 minutes apart, show up as sharp features due to the variability adjustment of the total humidity. Note that panel A has a different color scale with higher cloud condensate amounts.

In Section 3 we propose an alternative approach that allows the communication of the advected liquid water between the IFS to the LEM. In doing so it is important to realise that liquid water in a partially cloudy atmosphere is the result of spatial variability of the total water specific humidity, where the condensed water is merely the result of the positive fluctuations in the total water that exceed saturation. Therefore it is proposed to include the advected liquid water from the IFS into the LEM by increasing the variability of $q_t$ accordingly. In doing so we have imposed two extra constraints: i) the added moisture variability should not change the domain averaged total water specific humidity and ii) the added variability should not have a preferred length scale, i.e. variability has to be added equally at all spatial length scales. A simple procedure that fulfills all these conditions is given by Eq. (9) where the scaling factor $\beta$ has to be chosen such that the increased moisture variability precisely provides the desired liquid water change as dictated by the IFS.

Unfortunately the improvement due to this humidity variability coupling is only marginal, both for the Barbados experiment as well as for the the idealised bubble experiment. In both cases the LEM diffuses the added variability away within the time step of the large scale model. As a result, the more downstream LEMS receive ever smaller amounts of liquid water by advection which explains why the improvement of proposed modification deteriorates strongly in the more downstream LEMS.

So why does the humidity variability coupling give such a marginal improvement? And is it not possible to avoid the need for introducing the variability coupling in first place?
One might be tempted to answer the last question positively by using a LEM that employs liquid water and ice as prognostic variables and couple these to the IFS in the same manner as the other prognostic quantities. However, in that case the advected liquid water into the local LEM will be uniformly distributed over the horizontal grid of the LEM. As a result all the advected liquid water in the unsaturated grid points will evaporate almost instantaneously. So also in the case of using a LEM with prognostic cloud condensate, dedicated choices need to be made how to spatially distribute the advected liquid water into the local LEM. The Goddard multiscale modeling framework [Tao et al., 2009; Chern et al., 2016, 2020] for instance, is using a LEM with prognostic cloud condensate. In their framework the large scale advected cloud condensate is only added to saturated grid points of the LEM and proportionally to the already existing cloud amount in each grid point, very similar to the humidity variance coupling proposed in this study. So the use of prognostic cloud condensate in the local LEM requires similar redistribution choices as in the present case where we use a LEM with moist conserved variables.

This leaves us with the question why the SP so strongly underestimates the cloud condensate, even when the humidity variability coupling is in place. We can think of at least two reasons. First, it is well possible the parameterized convection outside the SP region results in mean thermodynamic profiles that are too stable for a local LEM to generate moist convection and clouds. Although the local LEMs are only active inside the SP region where convection parameterization is switched off, we verified that the SP grid cells directly neighbouring the upstream parameterized grid cells have very similar vertical thermodynamic structures as their parameterized grid point neighbours. So it is well possible that these thermodynamic structures support parameterized clouds but not necessarily resolved clouds. In that case the added liquid water in the SP grid cells will be largely evaporated by the local thermodynamics of the LEM within the IFS timestep. A second reason is related to the (in)capability of the LEMs to represent the observed cloud structures (see figure 2) that have spatial scales well beyond the domain size of the local LEMs. These large mesoscale cloud structures are the rule rather than the exception [Stevens et al., 2020]. The employment of a local LEM with periodic boundary conditions and a rather small domain size of only 12.8 km will only show up as spatially unorganised sample of saturated updrafts with possibly a resulting cloud fraction much lower than the actual observed mesoscale cloud structure. Organised cloud structures in this region associated with cold pools, aka ‘gravel’, have been shown be the most abundant type of organisation [Bony et al., 2020] but are only faithfully simulated by LEMs with domains larger than 25 km [Seifert and Heus, 2013]. Furthermore shallow cumulus convection such as observed during ATEX where the clouds are topped by spreading anvils below a sharp inversion are difficult to simulate consistently by LEMs and depend strongly on the used vertical resolution [Stevens et al., 2001]. These outflow structures for which now the name ‘flowers’ has been coined [Stevens et al., 2020] are frequently observed structures over the subtropical Atlantic ocean.

Likely, both proposed mechanisms are responsible for the observed cloud dissipation. One way to find out which is the most dominant process is to conduct a very large eddy simulation over a domain at least as large as the SP region indicated in figure 1 as a benchmark using periodic boundary conditions. Repeating the simulation by dividing it up as a collection of smaller LEMs coupled in the same spirit as the bubble experiment and comparing the results of the large domain simulation and the SP-version over the same domain should allow to reveal the error in the cloud amount of the small LEMs due to their incapability of representing the mesoscale organisation. Such a Big Brother experiment might also be instructive for testing the realism of exascale high resolution SP enterprises on GPUs [Hannah et al., 2020].

Finally, one may also wonder whether the negative cloud bias in the SP region would also show up in “stand-alone” Large Eddy Simulations that are forced with dynamical advection tendencies from a large scale model rather than with the nudging procedure explained in section 2.2. The answer to this question is yes when it concerns errors and biases related
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to domain size and resolution. It is more difficult to answer whether driving the LEM with
large scale tendencies would be more accurate than forcing it with the nudging process. Us-
ing large scale tendencies rather than nudging to thermodynamics profiles with too short
timescales has the advantage that one avoids the risk of imposing profiles that are never in
quasi-equilibrium with the smaller scale turbulence state. The risk of imposing only advective
large scale tendencies on the other hand is that LEM might give a more realistic response
but related to a large scale state that has drifted away from the desired large scale state.

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Code availability

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

DALES: [Arabas et al., 2021], https://github.com/dalesteam/dales, DOI: 10.5281/zeno-
do.3759192

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

SP coupler: [Jansson et al., 2018], https://github.com/CloudResolvingClimateModeling/sp-
coupler, DOI: 10.5281/zenodo.1968304. Version 1.1 which was used in this work contains
the variability coupling. Version 1.0 was used in our previous study [Jansson et al., 2019].

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 pro-
cedure. 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 and PS wrote the article text, with contributions and editing by all other
authors.
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