flight time in summer and of the order of 35–40 % of the flight time in winter in the troposphere between 350 and 190 hPa in the Northern Hemisphere, over a region ranging from North America to Europe. These seasonal frequencies are very low in the lower stratosphere because of the low water content (Sanogo et al., 2024). Above 200 hPa, ISSRs is more frequent in tropical deep convective regions and over the North Atlantic Ocean (Spichtinger et al., 2003). In terms of size, more than 80% of ice-supersaturated path lengths measured along aircraft flight routes in the North Atlantic are shorter than 10 km (Reutter et al., 2020; Wolf et al., 2024). The occurrence of ISSRs is favored by particular meteorological conditions such as deep convection, mesoscale gravity waves (Spichtinger, Gierens, & Dörnbrack, 2005), a divergent flow (Gierens & Brinkop, 2012; Krämer et al., 2009; Wilhelm et al., 2022), or the moist air streams in synoptic disturbances (e.g., warm conveyor belt, cold and warm fronts) (Gierens & Brinkop, 2012; Wolf, Bellouin, & Boucher, 2023).

Si tout ce paragraph concerne la basse stratosphère par opposition à ce qui est dit au dessus, je suggère un changement de paragraphe ou/et de changer "are very lower" en "are much lower".

The occurrence of an ISSR is a prerequisite for the in situ formation of natural cirrus clouds, persistent contrails and contrail-induced cirrus (Minnis et al., 2004; Krämer et al., 2016; Kärcher, 2018). Natural cirrus play an important role in the energy budget and may form in situ via homogeneous nucleation at temperatures below −38°C and RHi exceeding 140 % (Heymsfield et al., 2017; Kanji et al., 2017) or via heterogeneous freezing at temperatures lower than 0°C and RHi above 100 % in the presence of ice nucleating particles (Heymsfield et al., 2017). For a pressure range between 325 and 175 hPa, aircraft flying using the kerosene as fuel can produce contrails for 1 to 15 % of the flight time in the tropics and 6 to 20 % of the flight time in the mid and high latitudes regions (Sanogo et al., 2024). Contrails can persist and grow for several hours in the ISSRs (Kärcher, 2018). Over time, such persistent contrail cirrus can evolve into cirrus clouds and meteorological conditions such as wind shear and turbulence can extend their spatial coverage and reduce their ice crystal concentrations (Kärcher, 2018). Contrails can thus enhance the coverage of cirrus clouds (Stubenrauch & Schumann, 2005) ~~and together~~. Contrails and contrail cirrus, together ~~are~~ referred to as aviation-induced cloudiness (AIC), ~~which is~~ are associated with a potentially significant radiative impact (Boucher et al., 2013; Bock & Burkhardt, 2016; Lee et al., 2021), at least in comparison to the CO_2 radiative forcing due to aviation.

Je ne peux pas signer un papier qui écrit ça

Reducing the climate impact of AIC, along with other environmental and climate impacts, is one of the main challenges facing the aerospace industry. In this perspective, both academia and the private sector are looking into how aircraft trajectories can be optimized to minimise fuel consumption (and the associated CO_2 emissions) while avoiding regions favorable to the formation of contrails. This strategy requires accurate forecasts of ISSRs but also a better understanding of the physical mechanisms involved in the formation and dissipation of contrails and induced cirrus (Kärcher, 2018).

c'est quoi les chiffres

Climate models are essential for studying contrails and their radiative effects. However, the formation of ISSRs and contrails occurs at scales smaller than the grid size of these models, requiring the parameterization of the small scale processes. In the LMDZ model, the ISSR formation processes are parameterized using a statistical treatment of sublimation and condensation based on the total water distribution, as detailed in Section 2.1. It is known that parameterizations are a significant source of uncertainty in climate models (Hourdin et al., 2017). For instance, a study by Perini et al. (2023) have shown that the radiative effects of AIC are sensitive to the values of free parameters in the climate model (e.g., those that control the contrail lifetime), underscoring the fact that many of these parameters do not have a unique value. To reduce these uncertainties, machine learning methods are more and more used to tune and rigorously select the best value of the free parameters for a given physical process under observational constraints (Jebeile et al., 2023). For example, D. Williamson et al. (2015) used a tuning method based on History Matching and iterative refocusing (see Section 3.1) to explore the parametric uncertainties associated with the global mean temperature and salinity

Pour moi : insister sur l'intérêt d'ajuster / si nous améliorer le modèle

Rm

Si je me trompe pas l'approche est de Vernon, Goldstein, & Bower, 2010 et de Williamson et al., 2013 (qui a notemment ajouté les emulateurs à la méthode proposé par Vernon 2010). Fred que tu cites après est plus utilisateur de la méthode pour les modèles de climat. Alors que Daniel Williamson fait vraiment toute la recherche qu'il y a dans l'aspect mathématiques de la méthodes. Je pense que c'est bien que cette différence ce sente dans ton introduction ; qu'ils ne soient pas mis au même niveau.

in the NEMO (Nucleus for European Modelling of the Ocean) ocean model. Similarly, Hourdin et al. (2021) applied the same approach to LMDZ, identifying model configurations that were more consistent with observations than the manually fine-tuned base configuration. The use of this method can also avoid the underestimation of uncertainty in climate change projections (Hourdin et al., 2023). In this study, we apply this approach of D. Williamson et al. (2015); Hourdin et al. (2021, 2023) to investigate errors in the atmospheric component (LMDZ) of the IPSL climate model, focusing on the spatial and temporal distributions of ice-supersaturated regions (ISSRs). Furthermore, we aim to identify LMDZ configurations that not only match observed ISSR properties but also align with observations of high-level cloud fractions and radiative fluxes, to ensure that the model's performance on other critical properties, such as the radiation budget, is preserved.

more ? ou plutôt equal nan ? à vérifie

This method can also b used to explore (quantify ?) the paramet uncertainty of climate change projection.

:loud cover plutôt non ?

Trop flou ; préciser le type d'erreur ; et je comprend pas très bien la phrase. Pour moi c'est des truc différents :
- exploration de l'erreur paramétriqu
- exploration de l'erreu paramétrique en ayant contraint BLABLA (= tes métriques)

This manuscript is structured as follows. Section 2 describes LMDZ and its parameterizations of ISS and cloud. Section 3 details the experimental setup and our tuning approach while Section 4 presents our results. Finally, Section 5 summarizes our main findings.

2 LMDZ and its parameterizations of cloud

LMDZ is the atmospheric component of the Institute Pierre-Simon Laplace climate model known as IPSL-CM which is used for understanding the climate system and its response to various perturbations. The version used in this study is LMDZ6A, noted LMDZ in the following for the sake of simplicity, and described in details in Hourdin et al. (2020), Boucher et al. (2020) and Lurton et al. (2020). Its dynamical core is based on a mixed finite difference/finite volume discretization of the primitive equations of meteorology and transport equations and is coupled to a set of physical parameterizations (Hourdin et al., 2013).

Eventuellement inversé

(positive)

independent on the location or the planet

The parameterization of clouds in LMDZ is based on the representation of sub-grid total water (q) using a probability density function (PDF, noted $P(q)$), whose variance and skewness ~~towards large humidity values~~ increase when convective plumes bring humid air from the surface to the drier free and upper tropospheres (Hourdin et al., 2020; Madeleine et al., 2020). For convective and high-level clouds (i.e., at altitude typically above ~6.5 km), $P(q)$ ~~of the specific humidity~~ is a generalized log-normal distribution (Bony & Emanuel, 2001; Madeleine et al., 2020). It is determined by its first and second moments, defined here as the mean (q_t) and the standard deviation σ ~~$= \xi(p)\,q_t$~~ ~~of~~ the gridbox total water ~~distribution, respectively~~. The function $\xi(p)$ is used to impose a variation of σ as a function of pressure p. The function $\xi(p)$ increases as pressure decreases to reach an asymptotic value of ξ_{300} at 300 hPa and in the upper troposphere. This parameter has been used as a tuning coefficient (Madeleine et al., 2020). The gridbox-averaged total humidity ~~value q_t is related to $P(q)$ through the following equation:~~ reads

1) q_t =
α =

2) Thermiques

3) Dans le cas qui nous intéresse, modèle plus simple

Due to a lack of physical modeling, the standard deviation is simply specified as $\sigma = \xi(p)\, q_t$ where q_t is ...

of the specific

$$q_t = \int_0^{+\infty} q\, P(q)\, dq \tag{1}$$

Given $P(q)$

~~Knowing $P(q)$ which is prescribed, one can determine~~ the cloud fraction α_{cld} ~~as~~ and

$$\alpha_{cld} = \int_{q_{sat}}^{+\infty} P(q)\, dq \tag{2}$$

to account for the fact that σ/q_t increases generally

where q_{sat} is the specific humidity at saturation. ~~In~~ the case of shallow convection, the subgrid water distribution is described by a bi-Gaussian distribution where the thermal plumes and their environment correspond to the small and the main modes of the distribution, respectively (Hourdin et al., 2013, 2020; Madeleine et al., 2020). The parameters required for the computation of this bi-Gaussian distribution are given by a thermal plume scheme. For a full description of the parameterization of clouds in LMDZ, the reader is referred to Madeleine et al. (2020).

RM

Note that for

which will not be considered here

C'st vrai ?

ce serait pareil à 20 km non ?

2.1 Ice-supersaturation parameterization

2.1.1 The basic framework

Ne pas mélanger dans la même phrase les motivations et la description du modèle

The parameterizations of clouds in LMDZ briefly introduced in the previous section are based on the assumption that water is always at thermodynamic equilibrium between the vapor and liquid phases or between the vapour and solid (ice) phases. However, this assumption is not always met in the atmosphere, as some regions can be supersaturated with respect to ice without being condensed (see Sect. 1). Our objective is that the model is able to create and maintain such ice supersaturated conditions in a realistic way so that ~~contrail cirrus~~ can be simulated and their effects and uncertainties be evaluated. Given the ~~coarse~~ resolution of ~~the~~ atmospheric model, we consider that a given gridbox can be ~~partitioned~~ between an ice-subsaturated ~~region (a~~ thermodynamic equilibrium state with $q < q_{sat}$), an ISS region (a metastable thermodynamic state with $q > q_{sat}$), and a cloud fraction (in thermodynamic equilibrium state with total water $q > q_{sat}$). These three fractions are labelled *sub*, *ss* and *cld*, respectively. For this purpose, the parameterization needs to have a memory of the cloud fraction from one timestep to the next to track the fraction of the gridbox where condensation has occurred. The rationale for such a memory is that an ISS fraction can be converted into a cloudy fraction but the opposite is not true as the cloud can only sublimate in subsaturated conditions. The cloud cover α_{cld} is therefore used as semi-prognostic variable, by considering it as an additional tracer ~~and~~ advected by the dynamical core, along with the humidity variables, but it does not formally follow a prognostic equation. We further assume, that cirrus clouds form only by homogeneous nucleation. It Note that The treatment of cirrus cloud formation by heterogeneous nucleation would imply a representation of ice nuclei in the model, which is outside the scope of this study ~~that~~ simply aims to show the feasibility of introducing ice supersaturation in the model and tune the parameterization against large-scale observables. Ice clouds can form through homogeneous freezing when ice supersaturation exceeds a threshold $\gamma_{ss}\, q_{sat}$ that is a function of temperature as specified by Koop et al. (2000) and Ren and Mackenzie (2005). The threshold of ice supersaturation ratio, γ_{ss}, is expressed as:

Ça veut dire quoi ?

Here, we

$$\gamma_{ss} = \gamma_0 - T/T_\gamma \tag{3}$$

where T is the temperature (in K) in the gridbox. The values of γ_0 and T_γ are 2.349 and 259 K, respectively (Ren & Mackenzie, 2005). ~~However~~, here, γ_0 and T_γ, denoted TGO and TG in Table 4, ~~respectively~~, are considered as tuning parameters, because the data used to determine Equation 3 are subject to uncertainty. We characterize the three fractions of the gridbox through their respective cover, α_k (dimensionless) and their average total water, q_k (kg kg^{-1}), expressed as a gridbox average. Thus the following conservation equations apply:

were fixed to

$$\alpha_{sub} + \alpha_{ss} + \alpha_{cld} = 1 \tag{4}$$

bof

and

$$q_{sub} + q_{ss} + q_{cld} = q_t \tag{5}$$

when developing the model

where q_t is the total water in the gridbox.

2.1.2 Subgrid water vapour distribution

This parameterization fits well the pre-existing one in that is also based on a statistical treatment of water vapour at the subgrid scale (see Sect. 2). $P(q)$ is separated into three sub-PDFs P_{sub}, P_{ss} and P_{cld} that describe the total water in the *sub*, *ss*, *cld* regions, respectively. The three PDF are linked by the following relationship:

$$P(q) = \alpha_{sub}\, P_{sub}(q) + \alpha_{ss}\, P_{ss}(q) + \alpha_{cld}\, P_{cld}(q) \tag{6}$$

S that

The inclusion of P_{cld} is a new feature of this parametrization compared ~~to the~~ one introduced in Sect. 2. For q values above q_{sat}, P_{cld} is assumed to be proportional to P,

$P_{cld} \neq P \; \alpha_{cld}$

Je ne comprends pas

otherwise it is equal to 0 (see below). The lower bound of q for P_{cld}, denoted q^{vc}, corresponds to the in-cloud water vapour. It is set equal to the specific humidity at saturation in the gridbox at the previous physical timestep and depends only on the temperature. It should be noted that the evaluation of q^{vc} is an approximation since it relies on the temperature of the gridbox at the previous timestep, while all the other quantities have been advected. This shortcoming is being addressed in the next version of the parameterization that is currently under development.

The coefficient of proportionality between P_{cld} and P for $q > q^{vc}$ is denoted N, and derived from the following equation:

$$N = \alpha_{cld,adv} / \int_{q^{vc}}^{+\infty} P(q)\, dq \tag{7}$$

As q values can exceed saturation in both the ISS and the cloudy fractions, N is in the range 0 to 1 by construction. Specifically, $N \in]0,1[$ corresponds to situations where the three fractions coexist in the gridbox, $N = 0$ corresponds to situations where only subsaturated region and ISS fractions coexist, while $N = 1$ corresponds to situations where only subsaturated region and cloudy fractions coexist. Knowing N and q^{vc}, the normalised PDFs of P_{sub}, P_{ss} and P_{cld} are determined as follows:

$$P_{sub}(q) = \begin{cases} P(q)/\alpha_{sub} & \text{if } q < q^{vc} \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$P_{cld}(q) = \begin{cases} 0 & \text{if } q < q^{vc} \\ N\, P(q)/\alpha_{cld,adv} & \text{otherwise} \end{cases} \tag{9}$$

$$P_{ss}(q) = \begin{cases} 0 & \text{if } q < q^{vc} \\ (1-N)\, P(q)/\alpha_{ss} & \text{otherwise} \end{cases} \tag{10}$$

where $\alpha_{clr} = \int_0^{q^{vc}} P(q)\, dq$ and $\alpha_{ss} = 1 - \alpha_{clr} - \alpha_{cld,adv}$ at this stage.

P_{cld} and P_{ss} are diagnosed at each timestep, and are proportional. When a cloud form above $\gamma_{ss} q_{sat}$, the distributions are not proportional anymore. When they are rediagnosed in the following timestep and are proportional one to another, there is therefore a non-physical humidity flux from high humidities to low humidites in the cloud, and the other way around in the ISSR. This leads to an overestimation of the cloud formation. To address this limitation, it is assumed that a larger part of the region with $q < \gamma_{ss}\, q_{sat}$ is covered by clouds. For that purpose, the value of the proportionality coefficient N is increased to $N_2 = \Phi_N\, N$ for $q > \gamma_{ss}\, q^{vc}$ and to $N_1 = \Phi_N\, N$ for $q^{vc} < q < \gamma_{ss}\, q^{vc}$, where Φ_N is a tuning parameter that can take values in the range 1 to 2. It is worth noting that P_{sub} in the subsaturated region is determined by the knowledge of q^{vc} and $P(q)$. The characteristics of P_{sub} are imposed by the pre-existing parameterization whereas that of the cloudy fraction is imposed by the new parameterization. This sometimes creates situations where $\alpha_{cld,adv} + \alpha_{clr} > 1$, leading to a loss of memory as we impose $\alpha_{cld,adv} + \alpha_{clr} \leq 1$. To avoid losing the memory, $P(q)$ has been slightly modified so that when $\alpha_{cld,0}$ is high, the PDF is not constraining the subsaturated region to be large. In the former parameterization, the PDF was very unlikely to diagnose a large cloud fraction, whereas this is often the case in the new one. The function $\xi(p)$ for the new parameterization is then computed as follows:

$$\xi(p, \alpha_{cld,adv}) = \frac{\xi_o ldp}{1 + \beta \cdot \alpha_{cld,adv}} \tag{11}$$

where β is a tuning parameter whose value is between 0 and 5.

Table 1. List of ice saturation parameterisation parameters. For each parameter, the range of values, the default or First Guess (FG) value and the physical process controlled are indicated. The names of the parameters as used in the tuning process are given in brackets.

Name	Unit	Range	FG value	Controlled processes
T_γ (TG)	K	[249, 269]	259	Saturation rate for homogeneous nucleation
γ_0 (TG0)	–	[2.3, 2.4]	2.349	Saturation rate for homogeneous nucleation
N (TN)	–	[1, 2]	1.1	Ratio between the ISSR and in-cloud water distributions PDFs
ratqs (RQST)	–	[1, 5]	3.0	Width of the sub-grid relative humidity PDF
ξ (KHI)	–	[1, 10]	1.1	Boundary size between ISSR, clear sky and cloudy region
lturb (LTURB)	m	[25, 200]	50.0	Turbulent mixing length around the cloud

2.1.3 Sublimation and condensation

In this work, the treatment of sublimation and condensation are not diagnosed from pronostic equations, but from the distribution $P(q)$. Ice clouds sublimate when q_{cld} becomes smaller than q_{sat}. The condensed excess moisture is the fraction that exceeds the nucleation threshold $\gamma_{ss}\, q_{sat}$, according to the PDF of P_{ss}. These two processes are computed using the semi-prognostic value of $\alpha_{cld,adv}$. The variations of α_{cld} due to sublimation, $(\Delta\alpha_{cld})_{sub}$, and condensation, $(\Delta\alpha_{cld})_{cond}$, are computed first. These tendencies are added to $\alpha_{cld,adv}$ to obtain α_{cld} for the current timestep.

2.1.4 Turbulence

Small-scale turbulence may mix the cloudy region in the gridbox with the subsaturated and ISS regions. The turbulence is parameterized using a characteristic velocity, v_{turb}, and a characteristic length, l_{turb}. The v_{turb} variable is determined as an approximation of the diagnosed Turbulent Kinetic Energy (TKE) and l_{turb} is a tuning parameter with a typical value of the order of ten to a hundred metres but we used a default value of 50 m. It is also assumed that cirrus clouds have the shape of a prolate spheroid shape (Fig. 1). This approximation has the advantage of being relevant to model both natural cirrus and contrails. It is also assumed that all the mass that is transferred from the cloud to the environment, or vice versa, occurs within an area around the cloud delimited by a length $L = \min(v_{turb}\Delta t, l_{turb})$. In the environment, this area is that between the boundary (distance R from the centre) and that at distance $R+L$ from the centre (Fig. 1). In the cloud, it is the area between the boundary and that at distance $R-L$ from the centre. It also assumed that these two areas are well mixed by turbulence. The volume of the cloud environment, V_{env}, is the sum of the volumes of the subsaturated region, V_{sub}, and ISS, V_{ss}, which can be expressed through the introduction of a parameter σ, such that $V_{ss} = \sigma\, V_{env}$ and $V_{sub} = (1-\sigma)\, V_{env}$. However σ may deviate from $\alpha_{ss}/(\alpha_{ss}+\alpha_{sub})$ because the three fractions are distributed homogeneously in the gridbox. Thus another tunable parameter χ is introduced so that $\sigma = \alpha_{ss}/(\chi\alpha_{sub} + \chi\alpha_{ss})$. This formulation of σ accounts for the fact that there is a higher probability that the cloud and ISS fractions are in contact (which implies $\chi > 1$). In the ISSR, the diffusion of crystals leads to further condensation of ice so that part of the ISSR becomes cloud, with corresponding changes in their fraction and total water content. The equations of the parameterization of turbulence and the full description of the parameterization are provided in detail in Borella et al. (2021). It should be noted that this parameterisation in LMDZ is only applied for temperatures below −30°C, which corresponds to the temperature at altitudes in the upper troposphere where contrails can form.

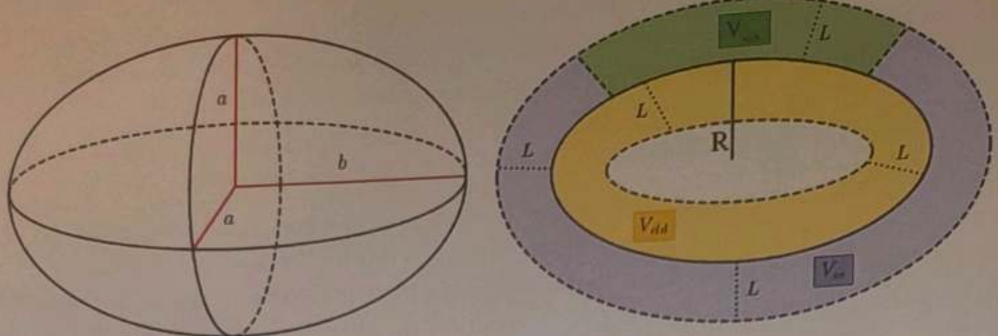

Figure 1. Left panel: Prolate spheroid illustrating our assumption on the shape of clouds. The spheroid has semi-axes a and b. This assumption allows us to take into account the wispy nature of cirrus clouds and the very high surface-to-volume ratio of contrails, but not the fact that the stratified atmosphere at this altitude limits the vertical extension of these clouds. Right panel: Schematic distribution of the quantities V_{cld}, V_{ss} and V_{sub} in the cloud boundary layer. L is the width of the turbulent mixing zone while R is the distance from the centre of the cloud to the border of the environment around the cloud.

On met l'erreur d'incertitude dans la "tolérance à l'erreur"

3 Experimental Setup

3.1 History matching and iterative refocusing

targets

Comme dit Maëlle (A)

a priori OU range {min, max}

The history matching with iterative refocusing is based on the idea of i) running a perturbed physics ensemble (PPE) of simulations with the climate model in a pre-defined parameter space, ii) using the output to train statistical emulators that predict the metrics of interest, and then iii) using the emulator to rule out regions of parameter space for which its predictions are "too far" from observations (D. B. Williamson et al., 2017). The process is iterative: at the end of each iteration, a new PPE is run in order to improve the quality of the emulator and refine the search for potentially good model configuration, but only in a relevant subspace, i.e. outside the region of space already ruled out. This introduces the notion of the Not-Ruled-Out-Yet (NROY) space, which evolves during the iterative process. The method rigorously takes into account the various sources of uncertainties (from both the emulator and the observations) and a tolerance level in order to avoid over-tuning the climate model. It is implemented in different steps, as described in the following subsections.

(A)

NROY parameter space pour être plus précis ?

1. Je suis pas 100% d'ac avec cette phrase -> il n'y pas que les err d'emulateurs et d'observations qu'il faut prendre en compt mais bien TOUTES les sources d'incertitudes entre ton setup experimental et tes références, ce qui peut inclure beaucoup de choses comme la variabilité interne du modèle, la sensibilité à tes forçages etc. Je trouve ça dommage de laisser entendre qu'il n'y aurait en toute généralité que ces deu sources d'erreurs à quantifier

…n toute riguer …r éviter …er-tuning / …rfitting …udrait par …nce connaître …reur structurelle …modèle ; ce qui …st en pratique …ais le cas avec nos …dèles de climat. Mais …t-être un peu pointu …r une intro de partie

3.1.1 Selection of the targeted metrics

a series of

The first step consists of defining ~~the target~~ metrics (f), ~~which are~~ scalars ~~that are used to quantify the behaviour of a simulation~~. For each metric, we set a reference value (r_f) and an associated uncertainty ($\sigma_{r,f}$). The different metrics used are described in Section 3.3 and their reference values are provided in Tables 2 and 3.

C'est pas une associated uncertainty, c'est une tolérance à l'erreur > l'incertitude quantifiée (ici j'imagine que c'est l'incertitude de tes obs et éventuellement liée à ta configuration). En toute logique ce serait mieux qu'elle s'appelle pas sigma

3.1.2 Identification of the free parameters

(A)

…e free paramters to be …ned must be selected …h their range of …ceptable values, that …find the initial …rameter space.

The free parameters to be tuned must be selected and a range of acceptable values defined for each of them, as well as their initial input space (I), need to be defined. The chosen parameters must be compatible with the target metrics. In this work, a set of 23 parameters, presented in Table 4, are selected as candidates for the tuning. Any combination of these parameters is called a vector and denoted λ in the following.

← Ce n'est pas ça une "combinaison" je crois

J'ai pas compris ce que tu voulais dire ici

pourquoi candidates ?

…roposition : The method required that the various sources of uncertainties occuring in the comparison between model output …nd observations be quantified in order to avoid over-tune the model. (eventuellement :) An estimation of the uncertainty of the …rediction of the emulators is also accounted for in the method.

C'est ça. C'est pour ça qu'on a décidé de tout mettre dans "tolérance à l'erreur"

3.1.3 Experimental design

The experimental design consists of drawing a sample of values (λ) of parameters from the initial parameter space. For each of these λ (here 300), a simulation is run with the climate model, the output of which are used to calculate the metrics that serve as a training set for the statistical emulators. To ensure optimal sampling of the input parameter space, a Latin hypercube method is used (D. Williamson et al., 2015).

as un problème
notation,
st la fois
ı input space
l'implausibilité.
pourrais choisir
autre non pour
put space,
OY_0 par exemple,
mme après tu
lis NROY_11)?

3.1.4 Building of the surrogate models

An emulator based on Gaussian Processes (GP) is then built for each metric. The emulator gives a statistical estimate of the corresponding metric value at any point of the parameter space (I for the first wave and the successive Not-Ruled-Out-Yet (NROY) space for subsequent waves), providing both the expectation ($E[f(\lambda)]$) and the variance ($Var[f(\lambda)]$) of the uncertainty associated with the statistical emulator prediction of each metric.

?

3.1.5 History matching

The history matching aims to identify the subspace of free parameter values compatible with the reference data, under the constrains (metrics) chosen in step 1 (Section 3.1.1). For a vector λ of parameters, a measure noted $I_f(\lambda)$ is introduced to quantify its implausibility:

that matchs a set
of metrics, given
their tolerance to
error

ım, depuis quelques temps on a tendance à regrouper
s deux termes en disans que c'est la tolérance à
rreur, et à expliquer qu'elle est choisi
périeur aux
certitudes quantifiées
piquement
ıcertitude de l'obs)
stement parce que
rreur structurelle
ı modèle n'est pas
ıantifiable "en sois"
est peut-être possible
n avoir une idée)
n'est même pas
ictement définie.
ne sais pas à quel
ıint c'est important
ıe tu fasses
choix aussi.

$$I_f(\lambda) = \frac{|r_f - E[f(\lambda)]|}{\sqrt{\sigma^2_{r,f} + \sigma^2_{t,f} + Var[f(\lambda)]}} \tag{12}$$

where r_f and $\sigma_{r,f}$ are the target reference value for the metric f and the associated uncertainty (whose distribution is assumed to be Gaussian), respectively. $Var[f(\lambda)]$ is the variance of the uncertainty associated with the statistical emulator prediction and $\sigma_{t,f}$ is the structural error (also assumed to follow a Gaussian distribution) of the climate model for the metric f (D. Williamson et al., 2015). This structural error can be difficult to estimate and D. Williamson et al. (2015) suggest that it should be interpreted as a tolerance to error. We have considered a tolerance to error of 0.1 (i.e., 10 % for the RHi and the high-level cloud metrics. A tolerance to error of 10 % is considered for the IWP metrics (i.e., 10 % of the value of each metric) given the large uncertainties associated with them.

Parce que du coup la on sait pas si ces valeurs inclues l'incertitude liées aux obs ou pas

Oui, mais par contre la
tolérance à l'erreur
regroupe
cette "structural
model error" et
les autres incertitudes
que tu as pu quantifier
= celle de l'obs ici
(mais pas celle de
la prédiction de
l'émulatuer)

The NROY space is defined from the implausibility in a multi-metric framework as follows:

$$NROY = \bigcap_f \left\{ \lambda \mid I_f(\lambda) < T \right\} \tag{13}$$

where T a threshold to be defined. Here it is set to 3 according to the rule of Pukelsheim (1994) which indicates that 95% of any unimodal Gaussian distribution lies within ± 3 standard deviations around its mean value. This choice implies that there is a 5% risk of discarding a plausible value from the $NROY_f$ space.

C'est quoi le f de NROYf space ?

3.1.6 Iterative Refocusing

(so that λ is plausible and not ruled out yet)

The implausibility $I_f(\lambda)$ for a vector (λ) of parameters can be small either because the simulated metric is close to its reference, or because the emulator uncertainty at λ is high. Iterative Refocusing aims to reduce the uncertainty due to the emulator. Consequently, several iterations (or waves) of steps 3–5 (Sections 3.1.3, 3.1.4 and 3.1.5) are performed, using for the wave n the NROY issued from the wave $n-1$ ($NROY^{n-1}$). The process is stopped when the NROY space is stable because the emulator uncertainty is sufficiently reduced so that the other uncertainty types dominate the Implausibility. In

Je trouve qu'il manque
l'information que
l'incertitude de la
prédiction de l'émulateur
réduit au cours des
itérations parce que les
emulateurs sont constru
dans des espaces où
ils sont + échantillonées
(tu as le même nombre d
"training data set" = 300
pour un espace de plus
en plus petit
au fur et à mesure des
itérations)

Ce n'est malheureusement pas toujours le cas. Tu peux ne plus diminuer ton NROY au cours des itérations et avoir certaines métriques qui gardent une incertitudes des prédictions de l'émulateur du même ordre de grandeur que ta tolérance à l'erreur (voir des fois beaucoup plus grande). Je ne sais pas ce que ça donne dans ton expérience.

In peu plus généralement sur 3.1.5 et 3.1.6 : tu dis au début de 3.1.5 que l'objectif de l'history mathing c'est de trouver les sous-espace des paramètres ccéptables ; mais enfait cet objectif c'est celui de toute la méthode. Je pense que cette phrase devrait apparaître dans ton premier paragraphe du coup

J n'as pas introduit 1D avant, c'est peut etre pas très compréhensible comme ça. D'ailleurs je sais pas si 1D/3D c'est bien compréhens…
n utilise plus SCM vs global.
roposition : In this study, we follow the approach of Hourdin et al 2021 and start by carrying out 9 successive waves with (the same) metrics
ngle column (SCM) test cases. We then carry out 3 waves with additional metrics evaluated on global simulations

this study, we followed Hourdin et al. (2021) by carrying out 9 tuning successive waves of the 1D version of the model, followed by 3 waves combining the 1D and 3D versions of the model. It is the result of the last wave, i.e. the twelfth, that is essentially discussed in what follows.

3.2 Simulations and forcing

th the first year nsidered as in-up (?)

Simulations with the 3D and 1D (single column) versions of LMDZ are carried out in this study. The 3D simulations are forced by the seasonal cycle of SST and Sea Ice Cover (SIC) following the Atmospheric Model Intercomparison Project (AMIP) protocol. The duration of 3D simulations is 2 years. LMDZ turns out to have a temperature bias in the upper troposphere and lower stratosphere (Fig. 2), which can impact the frequency of occurrence of ISSRs since homogeneous nucleation is controlled by temperature (Sections 2 and 2.1). This cold bias is observed both with the pre-existing and the new parameterization, which means it is a likely a model structural deficiency that is independent of the representation of ISSRs. As our objective is to show the feasibility of tuning the ISS parameterization, reducing this longstanding temperature bias by new model developments would involve complex research beyond the scope of this study, instead we reduce using temperature nudging. To this effect, we first performed a nudged simulation, whereby the LMDZ meridional (u) and zonal (v) wind and the temperature (T) fields are relaxed toward those of the fifth generation of the European Centre for Medium-Range Weather Forecasts atmospheric reanalysis (ERA5) as formalized in the following equation:

En fait

Mériterait une section à part. C'est pas anodin d'aller mettre de la correction de biais dans un exercice de tuning. Bien le justifier.

$$\frac{\partial X}{\partial t} = F(X) + \frac{X^a - X}{\tau} \tag{14}$$

where F is the operator describing the dynamical and physical processes that determine the unconstrained evolution of X, X^a is the 6-hourly u, v and T fields from ERA5, interpolated to the model grid and model timestep, and τ is a relaxation time constant (Coindreau et al., 2007; Krinner et al., 2020), set to 1 day in this study. The nudging is not applied in the atmospheric boundary layer. The nudged simulation is carried out for 10 years and the error terms $(X^a - X)/\tau$ are archived. The 10-year (i.e., climatological) monthly-averages of $(X^a - X)/\tau$ are then computed and used to correct the model online in all the remaining simulations of this study. More details on this bias correction method, their benefits and their limitations can be found in Krinner et al. (2020). We tested the bias correction method using the averaged relaxation terms of u, v and T and u and v only. The former approach is retained for this study because it allows a better correction of the LMDZ bias in temperature in the UTLS. Fig. 2 illustrates the remaining error for the North atlantic and Europe At 250 and 200 hPa. The error that persists is greater at 200 hPa in Europe.

Pk ?

Single Column Model (SCM or 1D) simulations are performed for four observational case studies for which Large Eddy Simulations (LES) have been developed. The first case is an almost cloud-free convective boundary layer case observed on June 14, 2002 over the Southern Great Plain during the International H_2O Project (IHOP) campaign (Couvreux et al., 2005). The second case deals with the diurnal cycle of shallow convection over land observed on June 21, 1997, with fairly well-developed cumulus at the Atmospheric Radiation Measurement site in Oklahoma (Brown et al., 2002). The third case is about a rain cumulus over the ocean (VanZanten et al., 2011). The fourth case is a composite transition case of stratocumulus to cumulus clouds, as described by Sandu and Stevens (2011). These case studies are named IHOP/REF, ARMCU/REF, RICO and SANDU, respectively. The different SCM simulations carried out are not nudged and are described in details with those of the associated LES in Couvreux et al. (2021) and Hourdin et al. (2021).

3.3 Tuning metrics and references

3.3.1 SCM Metrics

Eventuellement expliquer en deux mots l'intérêt de faire ça = enlever les vecteurs de paramètr qui font de la "mauvaise" convection peu profonde ?

The SCM metrics used are the mixed layer potential temperature and humidity, the average cloud height and the height of the maximum cloud fraction. LES are used as reference. These metrics and the LES simulations are described in details in Couvreux et al. (2021) and Hourdin et al. (2021).

3.3.2 Metrics of radiative fluxes and precipitation

Dire que ces métriqu sont le moyen choisi actuellement pour régler LMDZ afin qu'il simule un bon climat ? Ou qu'on considère que ces métriques définissent ce qu'est bon climat pour l'atmosphère ?

Oui : je pense que ça manque de qqchose qui dirait clairement ce qu'on essaie de faire :

The radiative metrics considered in this work are those used in Hourdin et al. (2021). They include metrics of global net radiation (i.e. the imbalance between shortwave (SW) and longwave (LW) and global top-of-atmosphere (TOA) SW upward radiation). As the SW downward radiation is imposed on the model, the global outgoing LW radiation will be constrained automatically by the constraints on the SW and total radiation (Hourdin et al., 2021). Metrics also consider regional averages of the TOA outgoing LW and SW radiation, distinguishing convective, subsidence and intermediate regimes in the tropics and a contrast in latitude between the roaring forties and tropical oceans targeting a circum-Antarctic warm bias in coupled ocean-atmosphere simulations. A specific metric is dedicated to the SW contrast between Eastern Tropical Oceans and the rest of the tropics following (Hourdin et al., 2015). The CERES-EBAF L3b observational dataset (Loeb et al., 2009) is used as reference. The locations where these metrics are computed are indicated in Hourdin et al. (2021) and their values and associated uncertainties are presented in Table 2.

The rainfall metrics used are the global mean rainfall of daily rainfall larger than 50 mm (PR>50), the mean annual rainfall over a box over Western Africa used for the African Monsoon Multi-disciplinary Analysis (AMMA) campaign, and finally an estimate of the intra-seasonal variability over the ocean in the region of the Madden-Julian Oscillation (MJO), computed from the daily rainfall as the standard deviation of the 20-day running average minus the 120-day running average using the Global Precipitation Climatology Project (GPCP, Huffman et al., 2001) daily precipitation data as reference. The values of these metrics and the associated uncertainties are provided in Table 2.

= Retuner le modèle avec la nouvelle para exactement comme on fait en ce moment pour LMDZ en ajoutant des métriques spécifiques.

3.3.3 RHi metrics

In addition to the metrics used in Hourdin et al. (2021), we selected a range of metrics that relate more specifically to our ISS parameterization. These metrics include the 80^{th} (P1) and 95^{th} (P2) percentiles of the RHi distributions at 250 and 200 hPa above the North Atlantic (NA hereafter) and Europe (EU hereafter) (see Table 3). Data used as reference are from the Measurement of OZone and water vapour on AIrbus airCraft In-service (MOZAIC) programme (Marenco et al., 1998) over the period 1995-2014 and from the In-service Aircraft for a Global Observing System (IAGOS) programme (Petzold et al., 2015) over the period 2011-2023. For the sake of simplicity, we refer to these two databases as IAGOS in the following. These data are measured every four seconds with uncertainties ranging from 2% to 8% (5% on average) at the cruising altitude (Smit et al., 2014; Petzold et al., 2020). Due to the inhomogeneous sampling in time (e.g., more measurements in summer) and space (e.g., more measurement at 250 hPa than 200 hPa in the North Atlantic) by the IAGOS and MOZAIC aircraft, some atmospheric conditions are potentially oversampled and this may lead to biases in the long-term RHi distribution at the regional scale (Sanogo et al., 2024). This temporal and spatial sampling uncertainty is difficult to characterize (Sanogo et al., 2024). To partly take this into account, we consider a total uncertainty of 8%. A moving average of 17 minutes (corresponding to ~255 km at cruising speed) is also applied to these RHi observations to make them comparable to the gridbox average of RHi in LMDZ. It should be noted that IA-