The dynamical core of the Aeolus 1.0 Statistical-Dynamical Atmosphere Model: Validation and Parameter Optimization

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Abstract. We present and validate a set of equations for representing the atmosphere's large-scale general circulation in an Earth System Model of Intermediate Complexity (EMIC). These dynamical equations have been implemented in Aeolus 1.0, which is a Statistical-Dynamical Atmosphere Model (SDAM) and includes radiative transfer and cloud modules (Coumou et al., 2011; Eliseev et al., 2013). The statistical dynamical approach is computationally efficient, and thus enables us to perform climate simulations at multi-millennia timescales, which is a prime aim of our model development. Further, this computational efficiency enables us to scan large and high-dimensional parameter space to tune the model parameters for e.g. sensitivity studies.

Here, we present novel equations for the large-scale zonal mean wind as well as those for planetary waves. Together with synoptic parameterization (as presented by Coumou et al., 2011), these form the mathematical description of the dynamical core of Aeolus 1.0.

We optimize the dynamical core parameter values by tuning all relevant dynamical fields to ERA-Interim reanalysis data (1983-2009) forcing the dynamical core with prescribed surface temperature, surface humidity and cumulus cloud fraction. We test the model's performance in reproducing the seasonal cycle and the influence of ENSO. We use a Simulated Annealing optimization algorithm, which approximates the global minimum of a high-dimensional function.

With non-tuned parameter values, the model performs reasonably in terms of its representation of zonal-mean circulation, planetary waves and storm tracks. The Simulated Annealing optimization improves in particular the model's representation of the northern hemisphere jet stream and storm tracks as well as the Hadley circulation.

The regions of high azonal wind velocities (planetary waves) are accurately captured for all validation experiments. The zonal-mean zonal wind and the integrated lower troposphere mass flux show good results in particular in the Northern Hemisphere. In the Southern Hemisphere, the model tends to produce too weak zonal-

mean zonal winds and a too narrow Hadley circulation. We discuss possible reasons for these model biases as well as planned future model improvements and applications.

5   **Keywords:**

Earth System Model of Intermediate Complexity, Statistical-Dynamical Atmosphere Model, Optimization, model parameter tuning

1   Introduction

Numerical models of the Earth system play a key role in our understanding of physical processes in Earth and
10   Atmosphere and can be used to simulate past and future climate changes.

General Circulation Models (GCMs) are physically the most realistic tools for studying and modelling climate variability and climate change in the Earth system. However, due to their relatively high resolution, they are costly in terms of CPU runtime, limiting their applicability to study climate variability over long (~millennia) timescales.

15   On the other hand, highly idealized and computational efficient models for the climate system are able to simulate long time periods, but those are often box or 1- or 2-dimensional models describing only a limited number of processes or feedbacks of the real world. Hence their application is limited, but they have been applied to study paleo climate (Berger et al., 1992; Harvey, 1989) and future global change (Xiao et al., 1997).

A third class of models are so-called Earth System Models of Intermediate Complexity (EMICs) which form a
20   compromise between the computationally expensive (but more realistic) GCMs and the highly simplified models (Claussen et al., 2002). The number of processes and feedbacks are comparable to GCMs, however due to a reduction in resolution and/or complexity of some model components, it is possible to study climate simulations up to multi-millennia timescales (Eliseev et al., 2014a, 2014b; Ganopolski et al., 2001; Montoya et al., 2005). Other applications include determining quick assessments of climate change impacts or run thousands of
25   parameter sensitivity experiments (Knutti et al., 2002; Schmittner and Stocker, 1999).

EMICs are thus particularly useful for understanding the roles of different Earth components on very long timescales (multi-millennia and longer) and consequently form useful tools complementary to GCMs. Internal climate processes on such very long timescales are primarily driven by ocean and ice dynamics (Holland et al., 2001; Latif, 1998; Polyakov et al., 2003), with the atmosphere's role being likely limited to globally distributing
30   any perturbations to the system. In GCMs, it is however often the atmosphere which takes most of the computational load due to the need to resolve synoptic weather systems, which requires a high-resolution discretization in space and time. For these reasons, a key step in the development of EMICs intended for studying ocean and ice dynamics on multi-millennial timescales is the derivation and validation of statistical-dynamical equations which accurately represent atmosphere dynamics (Coumou et al., 2011).

35   EMICs have been used in many climate studies and several different types of simplified atmospheric components that form part of an EMIC exist including 2-dimensional, zonally averaged atmosphere models, 2.5-

dimensional atmosphere models (the vertical dimension is reconstructed using 2-dimensional fields) with a simple energy balance, or Statistical-Dynamical Atmosphere Models (SDAMs) (Claussen et al., 2002; McGuffie and Henderson-Sellers, 2005). Most EMIC studies focus on climate variability on very long timescales (e.g. glacial cycles), and therefore fast processes are normally parameterized. In particular, SDAMs parameterize smaller scale (and more short-lived) processes like synoptic eddy activity in terms of the large-scale, long-term fields. The assumption of those models is thus that atmospheric variables can be expressed in separate terms of a large-scale, long-term component, with characteristic spatial and temporal scales of L>1000 km and T>10 days, and a small-scale component like ensembles of synoptic-scale eddies and waves. The latter are then parameterized by their averaged statistical characteristics (e.g. their total kinetic energy and heat, their moist and momentum fluxes, …). This means that transport effects of the fast moving weather systems on the large-scale, long-term atmospheric motion are averaged (Ehlers et al., 2001).

The essential difference to GCMs is the point of truncation in the frequency spectrum of atmospheric motion (Saltzman, 1978). GCMs solve all phenomena of frequencies lower than and including synoptic cyclones (and sometimes even mesoscale systems), whereas Statistical-Dynamical (SD) models parameterize all scales smaller and equal to synoptic. Much of the difficulty in SD models is to define physically reasonable parameterizations occurring in the equations (Saltzman, 1978). For Aeolus the synoptic parameterization has been described in detail in Coumou et al. (2011).

As written above, SD models are also spatially averaged since for long-term climate simulations, we are typically interested in the large spatial aspects of the climate. It is further practical to split the large-scale, long-term field into two components: the zonally averaged mean field, and the asymmetric departure of the field from the zonally averaged fields characterizing the East-West variations. The azonal variables can be, for example, resolved by 1-dimensional Fourier components around latitude circles or into spherical harmonics (Saltzman, 1978).

Here, we present the Aeolus 1.0 dynamical core, developed at the Potsdam Institute for Climate Impact Research (PIK), a new SD model for the atmosphere. It uses some aspects of the atmosphere module of the EMIC CLIMBER-2 developed by Petoukhov et al. (2000). The dynamical core is completely new with novel equations for the large-scale meridional wind speed as well as quasi-stationary planetary waves. Together with the synoptic parameterizations presented in Coumou et al. (2011), these equations form the new dynamical core of Aeolus 1.0. The model is coupled with the cloud module consisting of a 3-layer stratiform plus convective cloud scheme as presented and validated in Eliseev et al. (2013).

Further, we present the equations of the model and validate the dynamical core using a parameter optimization experiment. Aeolus 1.0 is forced with prescribed surface temperature, surface humidity and cumulus cloud fraction to test the model's performance. In particular we examine the reproduction of the seasonal cycle and the influence of ENSO and compare relevant dynamical fields of the model output against seasonal means of ERA-Interim reanalysis data (climatology 1983-2009). The effects of parameter tuning are evaluated to improve the performance of the model.

In section 2 we present the novel equations of the Aeolus 1.0 dynamical core with the derivation of these equations presented in the Supplementary Information (S1 – S2). The dynamical core is coupled with a

convective plus 3-layer stratiform cloud scheme (which includes low-level, mid-level and upper-level stratiform clouds) developed by Eliseev et al. (2013). In section 3 we describe the experiment setup and the used reanalysis data sets. In section 4 we explain the model discretization and in section 5 we introduce our specific calibration method. For parameter optimization of the wind velocities we use Simulated Annealing which approximates the global minimum of a high-dimensional function (Flechsig et al., 2013). In section 6 we present Aeolus' dynamical fields with pre-optimized and optimized parameters and compare them with observations and output from models of the Coupled Model Intercomparison Project Phase 5 (CMIP5). We conclude by discussing performance and limitations of the model in section 7.

2   Governing Equations

2.1   General structure of the atmosphere

Aeolus 1.0 is a 2.5-dimensional SD model, with the vertical dimension being largely parameterized and only coarsely resolved and it therefore belongs to the class of intermediate complexity atmosphere models. Water and energy conservations is achieved via a set of 2-dimensional, vertically averaged prognostic equations for temperature and specific humidity (Petoukhov et al., 2000).

The 3-dimensional structure is described by these 2-dimensional surface fields with the vertical dimensions reconstructed using an equation for the lapse rate and assuming an exponential profile for specific humidity (Petoukhov et al., 2000).

For given temperature and specific humidity fields, the 3-dimensional wind field is calculated using a set of diagnostic equations. These statistical-dynamic equations for the wind fields are coupled and thus need several time steps or iterations to equilibrate.

The equations of the dynamical core of Aeolus 1.0 are separated into equations for the (1) synoptic-scale transient waves (or storm tracks), (2) quasi-stationary planetary waves and (3) the zonal-mean wind. Thus, following classical statistical-dynamical approaches (Dobrovolski, 2000; Imkeller and von Storch, 2012), the key assumption is that the wind velocity field V can be split into a synoptic scale component V' (2-6 days period) and a large-scale long-term component $\langle V \rangle$ (Fraedrich and Böttger, 1978) such that

$$V = \langle V \rangle + V' = \{\langle u \rangle, \langle v \rangle, \langle w \rangle\} + \{u', v', w'\} \qquad (1)$$

The variables u, v and w describe the wind velocity in zonal, meridional and vertical direction. The brackets ($\langle ... \rangle$) symbolize time averaged quantities and the prime ($...'$) indicates deviations from this time averaged field. The large-scale long-term component $\langle V \rangle$ is subdivided into a zonal-mean $\overline{\langle V \rangle}$ and an azonal component $\langle V^* \rangle$:

$$\langle V \rangle = \overline{\langle V \rangle} + \langle V^* \rangle \qquad (2)$$

The large-scale, zonal-mean zonal wind velocity $\overline{\langle u(z, \phi) \rangle}$ with height above surface z and latitude ϕ is assumed to be geostrophic (resulting in the thermal wind balance):

$$\overline{\langle u(z,\phi)\rangle} = -\frac{1}{a\,f}\left(\frac{1}{\rho_0}\langle\overline{\frac{\partial p_0}{\partial \phi}}\rangle + \int_0^z \frac{g}{T_0}\langle\overline{\frac{\partial T}{\partial \phi}}\rangle\,\mathrm{d}z\right), \tag{3}$$

where the sea level pressure gradient is calculated by $\langle\overline{\frac{\partial p_0}{\partial \phi}}\rangle = \frac{a v^* \rho |f|}{-C_\alpha \sin\alpha}$ with ageostrophic velocity parameter $C_\alpha = 5$ and the Earth radius a (derived and explained by Pethoukov et al. (2000), eq.(13)) and α is the cross-isobar angle defined as in Coumou et al. (2011), eq. (A31). The variable v^* is the azonal meridional wind velocity, ρ is the air density with the reference air density ρ_0, f the Coriolis parameter, ϕ is the latitude, T_0 is the reference temperature and g the gravitational acceleration (see Petoukhov et al., 2000).

As derived in the Suppl. Inf. in S2, the large-scale, zonal-mean meridional wind velocity $\overline{\langle v(z,\phi)\rangle}$ is given by

$$\overline{\langle v(z,\phi)\rangle} \tag{4}$$
$$= \frac{d1*\left(-2\tan(\phi)\left(\overline{\langle u^*v^*\rangle} + \overline{\langle u'v'\rangle}\right)\right) + d2*\left(\frac{\partial}{\partial\phi}\left(\overline{\langle u^*v^*\rangle} + \overline{\langle u'v'\rangle}\right)\right) + d3*\left(\left(-\frac{dK_z}{dz} + \frac{K_z}{H_0}\right)\frac{\partial\overline{\langle u\rangle}}{\partial z}a\right) + d4*(A)}{n1*\left(\tan(\phi)\overline{\langle u\rangle}\right) + n2*\left(-\frac{\partial\overline{\langle u\rangle}}{\partial\phi}\right) + n3*\left(2\Omega a\sin(\phi)\right)},$$

Where d_1, d_2, d_3, d_4, n_1, n_2 and n_3 are tunable parameters and A represents the convection-related term

$$A = \frac{\mathcal{L}\overline{\langle P_{co}\rangle}}{H_0}\frac{\overline{\langle u_{sf}\rangle}}{\Gamma_a - \Gamma_0 - \Gamma_1(T_a - T_0)\left(1 - a_q q_s^2\right) + \Gamma_2 n_c}.$$

The atmospheric scale height H_0, the exchange for the momentums K_z, the the Earth's angular velocity Ω as well as the dry adiabatic lapse rate Γ_a, latent heat of evaporation $\mathcal{L}$ and model parameters $\Gamma_0, \Gamma_1, \Gamma_2, a_q, T_0$ are explained in **Table 1**. T_a is a temperature which would occur near the surface if the lapse rate did not change within the planetary boundary layer (PBL), q_s is the surface air specific humidity and n_c is the cumulus cloud amount. The latter variable is either computed by the cloud module or, as in this experiment, observational data is used. The variable P_{co} is the convective precipitation rate and is calculated by the cloud model (Eliseev et al., 2013). The variable u_{sf} is the zonal surface wind, see eq. (S10) in the Suppl. Information.

The azonal component of the large-scale wind field describes quasi-stationary planetary waves and depends on latitude, longitude and height. At the equivalent barotropic level (EBL), azonal geostrophic components of horizontal velocities are computed employing the definition of the stream function ψ depending on latitude ϕ and longitude λ,

$$\langle u_{EBL}^*(\lambda,\phi)\rangle = -\frac{1}{a}\nabla_\phi\langle\psi_{EBL}^*\rangle \tag{5}$$

$$\langle v_{EBL}^*(\lambda, \phi)\rangle = \frac{1}{a}\nabla_\lambda\langle\psi_{EBL}^*\rangle \qquad (6)$$

whereby the stream function can be subdivided into contributions from thermally and orographically induced waves depicted by subscript *th* and *or* respectively. They are considered to be additive due to linearity of the barotropic vorticity equations such that

$$\langle\psi_{EBL}^*\rangle = \Psi_0 \cdot \langle\psi_{th,EBL}^*\rangle + \langle\psi_{or,EBL}^*\rangle \qquad (7)$$

The parameter Ψ_0 is a tuning parameter which is necessary since smoothing is applied to dampen local moisture feedbacks in the model. This smoothing however reduces spatial gradients in ψ_{EBL}^* and therefore u_{EBL}^* and v_{EBL}^* itself. The equation for the orographically induced waves is introduced in the Suppl. Inf. S1.2.

The zeroth order solution of the thermally induced waves of the barotropic vorticity equation is given by (see Suppl. Inf. S1.3.):

$$\langle\psi_{th,0,EBL}^*\rangle = -\langle T_{EBL}^*\rangle\frac{g}{\Omega\rho_0 T_0^2\cos\phi}\nabla_\phi\int_0^{z_{EBL}}\rho\langle[T(z)]\rangle\,dz \qquad (8)$$

It is solved at two beta-planes, for the Northern and Southern Hemisphere, respectively:

$$\langle\psi_{th,0,EBL}^*\rangle_{NH} = -\langle T_{EBL}^*\rangle\frac{g}{\Omega\rho_0 T_0^2\cos\beta_{NH}}\nabla_\phi\int_0^{z_{EBL}}\rho\langle[T(z)]\rangle\,dz \qquad (9)$$

$$\langle\psi_{th,0,EBL}^*\rangle_{SH} = -\langle T_{EBL}^*\rangle\frac{g}{\Omega\rho_0 T_0^2\cos\beta_{SH}}\nabla_\phi\int_0^{z_{EBL}}\rho\langle[T(z)]\rangle\,dz \qquad (10)$$

The beta-plane is an approximation, in which the Coriolis parameter is linearized to a reference latitude, β_{NH} and β_{SH} for the Northern Hemisphere and Southern Hemisphere, respectively. In the tropical belt the variable $\langle\psi_{th,0,EBL}^*\rangle$ is interpolated linearly between the two beta-planes

The standardized integrated heat content in equation (8) ($I_v = \int_0^{z_{EBL}}\rho\langle[T(z)]\rangle\,dz$) is calculated analytically by assuming a lapse rate $\Gamma = \Gamma_0 + \Gamma_1(T_a - T_0)(1 - a_q q_s^2) - \Gamma_2 n_c$ such that $T(z) = T(z_{EBL}) - \Gamma(z - z_{EBL})$. One obtains

$$I_v = \rho_0([T(z_{EBL})] - [\Gamma]z_{EBL})H_0\left(1 - e^{-\frac{z_{EBL}}{H_0}}\right) - \Gamma\rho_0 H_0\left\{(H_0 - z_{EBL})\left(e^{-\frac{z_{EBL}}{H_0}} - 1\right)\right\}$$

In addition, I_v is smoothed by five points in latitude to avoid numerical artefacts which may arise due to spatial differentiating.

To remove possible singularities near the poles, at high latitudes the stream function is dampened by a fourth order interpolation function. Planetary waves at other tropospheric levels are directly calculated from those at the EBL (see in the Suppl. Inf. S1.1).

Finally, the time averaged kinetic energy of transient eddies $\langle E'_k \rangle = \frac{1}{2}(\langle u'^2 \rangle + \langle v'^2 \rangle)$ is determined using the statistical-dynamical equations as described in Coumou et al., (2011). Since detailed derivations are provided in Coumou et al. (2011), we only briefly discuss the diagnostic equations for transient eddy activity here. The equations are derived starting from the equation of the kinetic energy of transient eddies:

$$\frac{\partial \langle E'_k \rangle}{\partial t} = -\langle \boldsymbol{V} \rangle \cdot \nabla \langle E'_k \rangle + \langle u' \boldsymbol{V}' \rangle \cdot \nabla \langle u \rangle - \langle v' \boldsymbol{V}' \rangle \cdot \nabla \langle v \rangle +$$

$$K_{fh} \Delta_H \langle E'_k \rangle + K_{fz} \Delta_z \langle E'_k \rangle - K_{fs} \langle E'_k \rangle + f(\langle u' v'_{ag} \rangle - \langle v' u'_{ag} \rangle) \tag{11}$$

By assuming that the vertical (baroclinic) flux term is equipartitioned between the zonal and the meridional kinetic energy component, we can split Eq. (11) into three separate equations for $\langle u'^2 \rangle$, $\langle v'^2 \rangle$ and $\langle u'v' \rangle$:

$$\frac{\partial \langle u'^2 \rangle}{\partial t} = -\langle \boldsymbol{V} \rangle \cdot \nabla \langle u'^2 \rangle - 2\langle u'^2 \rangle \frac{\partial \langle u \rangle}{\partial x} - 2\langle u'v' \rangle \frac{\partial \langle u \rangle}{\partial y} + K_{syn}\left[\left(\frac{\partial \langle u \rangle}{\partial z}\right)^2 + \left(\frac{\partial \langle v \rangle}{\partial z}\right)^2\right] + K_{fh} \Delta_H \langle u'^2 \rangle$$

$$+ K_{fz} \Delta_z \langle u'^2 \rangle - K_{fs} \langle u'^2 \rangle + f(\langle u' v'_{ag} \rangle - \langle v' u'_{ag} \rangle) \tag{12}$$

$$\frac{\partial \langle v'^2 \rangle}{\partial t} = -\langle \boldsymbol{V} \rangle \cdot \nabla \langle v'^2 \rangle - 2\langle v'^2 \rangle \frac{\partial \langle v \rangle}{\partial y} - 2\langle u'v' \rangle \frac{\partial \langle v \rangle}{\partial x} + K_{syn}\left[\left(\frac{\partial \langle u \rangle}{\partial z}\right)^2 + \left(\frac{\partial \langle v \rangle}{\partial z}\right)^2\right] + K_{fh} \Delta_H \langle v'^2 \rangle \tag{13}$$

$$+ K_{fz} \Delta_z \langle v'^2 \rangle - K_{fs} \langle u'^2 \rangle + f(\langle u' v'_{ag} \rangle - \langle v' u'_{ag} \rangle)$$

$$\frac{\partial \langle u'v' \rangle}{\partial t} = -\langle \boldsymbol{V} \rangle \cdot \nabla \langle u'v' \rangle - \langle u' \boldsymbol{V} \rangle \cdot \nabla \langle v \rangle - \langle v' \boldsymbol{V} \rangle \cdot \nabla \langle u \rangle + K_{fh} \Delta_H \langle u'v' \rangle + K_{fz} \Delta_z \langle u'v' \rangle - K_{fs} \langle u'v' \rangle$$

$$+ f(\langle v' v'_{ag} \rangle - \langle u' u'_{ag} \rangle) \tag{14}$$

10 Here, K_{fh} and K_{fz} are internal atmospheric small-/meso-scale friction coefficients in the horizontal and vertical direction respectively, K_{fs} is the surface friction coefficient, f the Coriolis parameter and the subscript "ag" denotes ageostrophic terms.

The terms for K_{syn}, the vertical macro-turbulent diffusion coefficient, and $f(\langle v' v'_{ag} \rangle - \langle u' u'_{ag} \rangle)$ need to be parameterized which is derived in Coumou et al. (2011). This way, a set of diagnostic equations for synoptic

15 transient eddies is derived which, as also seen in equations (12) − (14), are all coupled to the large-scale wind field.

This provides us with a coupled set of equations for $\overline{\langle u \rangle}, \overline{\langle v \rangle}, \langle u^* \rangle, \langle v^* \rangle, \langle u'^2 \rangle, \langle v'^2 \rangle$ and $\langle u'v' \rangle$, which can be solved. Cross terms like $\overline{\langle u^* v^* \rangle}$ can be determined by multiplying $\langle u^* \rangle$ with $\langle v^* \rangle$ and taking the zonal-mean of that quantity. All derivatives are determined numerically. The values of the parameters are listed in **Table 1**.

3   Forcing data and Reanalysis data sets

The simulations were forced by multi-year averages of monthly mean climatological, El Niño and La Niña months data (surface temperature, surface specific humidity, temperature at 500mb, geopotential height at 500mb and 1000mb) using ERA-Interim Reanalysis Data (Dee et al., 2011) for 1983-2009 as our aim is that Aeolus captures year-to-year variability associated with the ENSO cycle. We identified 87 El Niño (74 La Niña) months using 3 month running means of ERSST v4 anomalies (Huang et al., 2016) using the definition that at least 5 consecutive overlapping seasons of SST anomalies are greater than 0.5K (less than -0.5K) for El Niño (La Niña) events.

Multi-year averages of monthly mean, El Niño and La Niña months cumulative cloud fraction are taken from ISSCP (Rossow and Schiffer, 1999). The spatial resolution is 2.5×2.5 degrees lat $\times$ lon and the time range is 1983-2009.

We chose this time period, because the cumulative cloud fraction data, which is needed to calculate the lapse rate is only available for this time period.

To avoid strong temperature gradients in the specified boundary conditions for the numerical experiments, we use the lapse rate equation to calculate temperatures at 1000mb from those at 500mb. We first calculate the lapse rate using the temperature field and specific humidity using the equation as given in Petoukhov et al. (2000) at 1000mb. Then, we recalculate the temperature field at 1000mb by using the temperature field at 500 mb and the linear lapse rate equation. This way we ensure that the temperature at 500mb is close to observations, and at the same time we have a vertical temperature realistic profile for a model like Aeolus. Since the ERA-Interim 500mb temperatures contain an orographic component, we exclude $\langle \psi^*_{or,EBL} \rangle$ in equation (7) in order not to incorporate orographic forcing of planetary waves twice.

We optimized the parameters for the numerical solutions of the wind velocities u^*, v^* and $\overline{\langle u \rangle}$ as well as eddy kinetic energy $\langle E'_k \rangle$ at 500mb. To compare the strength and position of the Hadley and Ferrell cells between observation and model, we calculate a zonal-mean mass flux $\overline{\langle m \rangle}$ in the lower troposphere using the zonal-mean meridional wind velocity $\overline{\langle v \rangle}$ at levels between 1000mb–500mb, assuming exponential decay of air density with height (Petoukhov et al., 2000).

For use with Aeolus, all data sets are interpolated to 3.75×3.75 degrees lat $\times$ lon spatial resolution.

4   Model discretization

Aeolus operates on a reduced grid to overcome the restriction of small time steps near the poles due to the CFL criteria (Jablonowski et al., 2009). In the grid generation, longitudinally adjacent cells are merged, if their zonal width in meters would be less than half of the cell width at the equator.

This way the reduced grid has the same resolution as a regular grid at the equator, but, at nominal resolution 3.75×3.75 degrees, around the poles only 6 cells are defined. On the regular grid, the maximum permissible time step due to the CFL criteria would be approx. 5 min, while the limit for the reduced grid is approx. 2 hours.

5   Calibration

The equations (1) – (14) are implemented in Aeolus and numerically solved on a 3.75×3.75 degrees reduced grid with 4 tropospheric height levels (1000m, 3000m, 5000m, 9000m).

The calibration of the winds is divided into two parts. First, we optimize the dynamical variables primarily driven by the thermal state of the atmosphere: The azonal velocities in zonal and meridional direction $\langle u^* \rangle$ and $\langle v^* \rangle$ as well as the zonal-mean zonal wind velocity $\overline{\langle u \rangle}$. In the second step, we tune the zonal-mean synoptic kinetic energy $\overline{\langle E_k' \rangle}$ and the lower troposphere integrated mass flux $\overline{\langle m \rangle}$, which solely depend on the zonal-mean meridional wind $\overline{\langle v \rangle}$.

A common approach for parameter tuning is Simulated Annealing (Ingber, 1996; Kirkpatrick, 1984). It is one experiment type in the multi-run simulation environment SimEnv for sensitivity and uncertainty analysis of model output (Flechsig et al., 2013) which we use for all calibration experiments. A schematic plot of the optimization process is shown in Suppl. Inf. S3.

For each model run, the thermal state of the atmosphere is kept constant (and initialized as described above) and the dynamical core is equilibrated to this thermal state. This typically requires only a few time steps. Since we tune only the parameters of the dynamical core, Aeolus first calculates the clouds using its cloud scheme (Eliseev et al., 2013) to determine the lapse rate and initialize the 3-dimensional thermal state. After that only the state of the dynamical core is updated each time step.

5.1   Dynamical core Tuning - Step 1

For a good starting point the parameters are first tuned manually, providing "pre-optimized" values. Next, we define physically realistic parameter ranges for automatic tuning as listed in **Table 2**.

For the azonal wind velocities we use a weighting function which excludes the tropics (from 10°S to 10°N) and polar regions (poleward of 60°S for the Southern Hemisphere to exclude influences of Antarctica and poleward of 70°N for the Northern Hemisphere) such that the mid-latitudes, where planetary waves are important, are optimized.

The non-excluded grid as well as the zonal-mean zonal wind is weighted by $w(\phi) = |\cos(\phi)|$.

The total skill score for the scheme in step 1 is calculated by multiplying the individual skills for the azonal velocities in zonal and meridional direction (S_{u^*}, S_{v^*}) and the skill for the zonal-mean zonal wind velocity $(S_{\overline{\langle u \rangle}})$:

$$S = S_{u^*} S_{v^*} S_{\overline{\langle u \rangle}}$$

The goal of the optimization procedure is to maximize the skill S.

Skill score functions for individual variables are computed as in Taylor (2001)

$$S(\phi, \lambda, t) = \frac{(1 + r_X)^4}{\left(A_X + \frac{1}{A_X}\right)^2}$$ (15)

In Eq. (15) r_X is the coefficient of the spatial correlation between the area-weighted modelled and observed fields of X; and A_X is the so-called relative spatial variation calculated according to

$$A_X = \frac{A_{X,M}}{A_{X,O}}.$$ (16)

Here, the variable $A_{X,M}$ is the spatial average of $|X_M - X_{M,g}|$ and $X_{M,g}$ is a globally averaged value of the modelled field X_M. The observed field is similarly defined by $A_{X,O}$.

5.2 Dynamical core Tuning - Step 2

For tuning the zonal-mean meridional wind velocity $\overline{\langle v \rangle}$ and in particular the strength and width of the Hadley cell we use the vertical integral of the lower tropospheric integrated mass flux $\overline{\langle m \rangle}$. In addition, we tune the zonal-mean area-weighted synoptic kinetic energy $\langle E_k' \rangle$. Both variables strongly depend on the dynamic fields tuned in step 1, which is the reason for tuning them in a separate second step.

Total skill score for the scheme in step 2 is calculated by multiplying the individual skills for the vertical integral of lower troposphere mass flux ($S_{\overline{\langle m \rangle}}$) as well as the eddy kinetic energy ($S_{\langle E_k' \rangle}$)

$$S = S_{\overline{\langle m \rangle}} S_{\langle E_k' \rangle}$$

The goal of the optimization procedure is again to maximize skill S.

The skill score function for the eddy kinetic energy is given by the Taylor skill score function Eq. (15).

The skill score is then calculated by

$$S_{\overline{\langle m \rangle}} = \left(\text{mean}_{\text{Hadley\_Obs}} - \text{mean}_{\text{Hadley\_Model}}\right)^2 r_X^2$$ (17)

Here r_X is the coefficient of the spatial correlation between area-weighted modeled and observed fields (as in Eq. (15)), $\text{mean}_{\text{Hadley\_Model}}$ and $\text{mean}_{\text{Hadley\_Obs}}$ are the mean values of the area-weighted modeled and observed mean mass flux. We use this more elaborate skill function to promote a proper Hadley circulation in the model.

The weights of the lower troposphere mass flux $\overline{\langle m \rangle}$ are calculated according to:

$$w(\phi) = \begin{cases} |\cos(\phi)|, & \phi > 60°S \\ 0 & \phi \leq 60°S \end{cases}.$$

For calculating the mean intensity of the Hadley cell we determine the roots of the mass flux in observation data close to 0° and 30° which determine the Hadley cell latitudinal boundaries. This way, we have 36 values for the boundaries of the northern Hadley cell. Between these latitudinal borders we calculate the mean strength of the Hadley cell.

In **Table 3** the manually tuned (or pre-optimized) parameters and their ranges are listed.

6   Results

6.1   Results of Calibration – Step 1

We compared the numerical solutions using the optimized parameters for the wind fields $\langle u^* \rangle$, $\langle v^* \rangle$ and $\overline{\langle u \rangle}$ of climatological monthly averages, El Niño and La Niña months from ERA-Interim Reanalysis (Dee et al., 2011) for 1983-2009.

The figures for azonal wind velocities are divided into six subplots: The left column shows observational data and the right column model data. The top row shows climatological monthly averages, the middle multi-year averages of El Niño months and the bottom row multi-year averages of La Niña months.

In **Figure 1** and **Figure 2** the azonal component of the zonal wind velocities ($\langle u^* \rangle$) for February and August at 500mb are displayed, respectively. The figures show that with optimized parameters the model reasonably reproduces the main observed features both in terms of spatial position and magnitude. In particular the extra-tropical planetary waves are well captured with some minor discrepancies in the tropics. Both the seasonal cycle and the response to the ENSO cycle are well captured by the model.

Figure 3 and **Figure 4** show the same type of plots for the azonal meridional wind velocity ($\langle v^* \rangle$). Also for the meridional wind velocity the most important features of the reanalysis data are well represented in the model. The model results coincide well in wind strength and spatial pattern with the reanalysis data. The wind strength in winter, for both climatological and El Niño months are stronger than for La Niña months. In summer the opposite is seen for both model and reanalysis data.

In **Figure 5** the zonal-mean zonal wind velocity ($\overline{\langle u \rangle}$) at 500mb is shown with the orange line representing reanalysis data, red representing model data with optimized parameters, and gray representing model data with pre-optimized parameters. The figure is subdivided into six subplots: The top row depicts $\overline{\langle u \rangle}$ in February and the bottom row shows $\overline{\langle u \rangle}$ in August, while the columns show climatological data, El Niño data and La Niña data, respectively. It is noticeable that the results obtained with pre-optimized parameters are already reasonable. Apparently the initial choice of tuning parameter values were already near the optimum and hence the optimized parameters lead only too small improvements of the model results. The Northern Hemisphere $\overline{\langle u \rangle}$ profile is well resolved in both seasons for both El Niño and La Niña months. Parameter optimization slightly improves the results in the tropics. The modeled amplitude of $\overline{\langle u \rangle}$ in the Southern Hemisphere is too small in February for all plots, and too high in August.

The optimized parameters are listed in **Table 2**. The β_{NH} in the Northern Hemisphere has a higher value, whereas the β_{SH} in the Southern Hemisphere has a lower value than the pre-optimized parameter values.

The last parameter is Ψ_0 and is changed to a higher value in order to strengthen speeds in $\langle v^* \rangle$ and $\langle u^* \rangle$.

6.2 Results of Calibration – Step 2

We compared the numerical solutions using the optimized parameters for the zonal-mean lower troposphere integrated mass flux $\overline{\langle m \rangle}$ and eddy kinetic energy $\overline{\langle E_K' \rangle}$.

The plots in **Figure 6** show that in general the monthly mean zonal-mean mass flux calculated with optimized parameters matches better with observational data. Here, the gain of the parameter optimization is clearly better than we saw with calibration step 1. The ENSO cycle is clearly visible. However, the width of the Hadley cell (especially in August) is still too small compared to the width of the Hadley cell obtained by reanalysis data. The figure shows only plots with a latitudinal range from 60°S to 90°N as reanalysis data is spikey over Antarctica.

Figure 7 shows the zonal-mean eddy kinetic energy $\overline{\langle E_K' \rangle}$. We show the same color code as in **Figure 6.** Northern Hemisphere modeled $\overline{\langle E_K' \rangle}$ profile is again well resolved in both seasons and for El Niño and La Niña months with the parameter optimization. Smaller spikes vanish such that the modeled $\overline{\langle E_K' \rangle}$ better matches the observed data. The parameter optimization gained more improvement in NH than in SH.

In **Figure 8** and **Figure 9** the eddy kinetic energies $\langle E_K' \rangle$ for February and August are displayed. The left column shows observational data and the right column model data. The top row presents climatological monthly averages, the middle El Niño months and the bottom row La Niña months.

The spatial position and the magnitude are well captured, seasons and the ENSO-cycles are also well resolved, with some discrepancies in the tropics (i.e. the region over the Atlantic and Pacific Ocean) and the Southern Hemisphere. In February and August $\langle E_K' \rangle$ is stronger in the Northern Hemisphere than in the Southern Hemisphere for both the climatology and in El Niño months. Only in La Niña months, $\langle E_K' \rangle$ is weaker in the Northern Hemisphere.

The optimized parameters are listed in **Table 3**. The parameters U_0 and m for optimizing the eddy kinetic energy are greater than the manually tuned values.

The parameters d_3 and n_3 are close to 1, whereas the parameters d_2, d_4 and n_1 are close to 2 and have a strong impact on the amplitude of the Hadley cell and the Ferrell cell. The parameter with the smallest influence is d_1.

6.3 Comparison to CMIP5 Models

Figure 10 shows the comparison of February and August $\overline{\langle E_K' \rangle}$, $\overline{\langle u \rangle}$ and $\overline{\langle m \rangle}$ between CMIP5 models (grey lines), Aeolus (red) and ERA-Interim data (orange). In General CMIP5 models represent the $\overline{\langle E_K' \rangle}$ and $\overline{\langle u \rangle}$ very well in both Hemispheres. However, in the Southern Hemisphere, the storm tracks, i.e. $\overline{\langle E_K' \rangle}$, of all models are too weak compared to observations with Aeolus on the lower end of the CMIP5 range. Further, some individual CMIP5 models can have too low or too high $\overline{\langle E_K' \rangle}$ and $\overline{\langle u \rangle}$ compared to ERA-Interim, similar to Aeolus.

The CMIP5 multi-model mean of $\overline{\langle m \rangle}$ appears to be close to the reanalysis and most models reproduce this well. Still, some CMIP5 models can differ strongly from $\overline{\langle m \rangle}$ in ERA-Interim with some spikey behavior. Nevertheless, the width and strength of the Hadley cell is in most models well presented, but the Ferrell cell is

often too strong. Aeolus' results give reasonable strength and width of the Ferrell cell, but the width of the Southern Hemisphere Hadley cell in August is too small compared to both reanalysis and CMIP5 models.

7 Summary and Discussion

In this paper we presented the atmosphere model Aeolus, which is a Statistical-Dynamical Atmosphere Model and belongs to the class of intermediate complexity models. The equations of Aeolus are time-averaged and the model has a spatial resolution of $3.75° \times 3.75°$ degrees lat × lon. The 3-dimensional structure of Aeolus is reconstructed using a set of 2-dimensional, vertically averaged prognostic equations for temperature and water vapor (Petoukhov et al., 2000). The advantage of such type of models is the fast computation time and for that reason the possibility to study and simulate long time periods as well as conduct sensitivity experiments.

We performed parameter optimization of the dynamical core consisting of a large multi-dimensional parameter space and can be searched due to its fast computation time. For this approach we used the optimization algorithm Simulated Annealing, which approximates the global minimum of a high-dimensional function. We divided the calibration into two parts. First, the azonal velocities in zonal and meridional direction as well as the zonal-mean zonal wind velocity were optimized, because they are primarily driven by the thermal state of the atmosphere. In the second step we optimized the zonal-mean synoptic kinetic energy and the lower troposphere integrated mass flux, and hence the zonal-mean meridional velocity, since those variables depend strongly on variables of step 1.

The results of the winds and eddy kinetic energy are in reasonable agreement with the reanalysis data and showed that our model is able to reproduce the dynamic response from the seasonal cycle as well as the ENSO cycle which is a prime goal of our model development efforts. Parameter optimization in particular improves representation of the Hadley cell in terms of strength and width.

In the Southern Hemisphere the dynamical fields tend to be too weak. This model bias might be related to the missing Antarctic ice sheet, upper-tropospheric ozone, the constant lapse rate assumption, or fundamental limitations of the equations. These possibilities will be analysed in future work using the Potsdam Earth Model (POEM) to which Aeolus has been coupled.

Compared to CMIP5 models, Aeolus reasonable well captures the dynamical state of the atmosphere in the Northern Hemisphere, particularly for monthly mean eddy kinetic energy $\overline{\langle E_K' \rangle}$, zonal-mean wind velocity $\overline{\langle u \rangle}$ and mass flux $\overline{\langle m \rangle}$. Especially the mass flux of the Ferrell cell is better captured than in other models, whereas the Southern Hemisphere Hadley cell width of Aeolus in August is too small compared to CMIP5 models.

8 Code and data availability

Code and data are stored in PIK's long term archive, and are made available to interested parties on request

9 Team list

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10   Competing interests

The authors declare that they have no conflict of interest.

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Figures
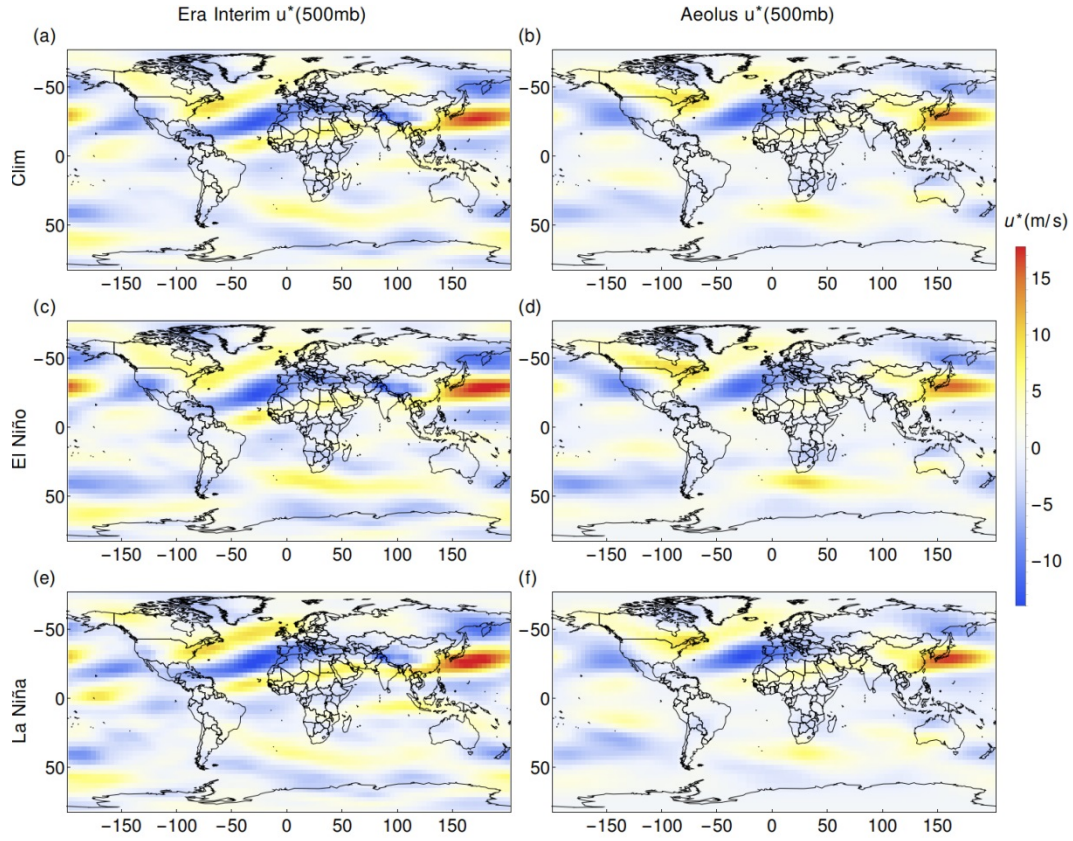
Figure 1 Azonal large-scale zonal wind u* at 500mb for all February months/ El Niño February months/ La Niña February months. The left column shows the results from reanalysis data and the right column shows the results from Aeolus received by optimized parameters. The model is forced by surface temperature, humidity and cumulus cloud fraction.
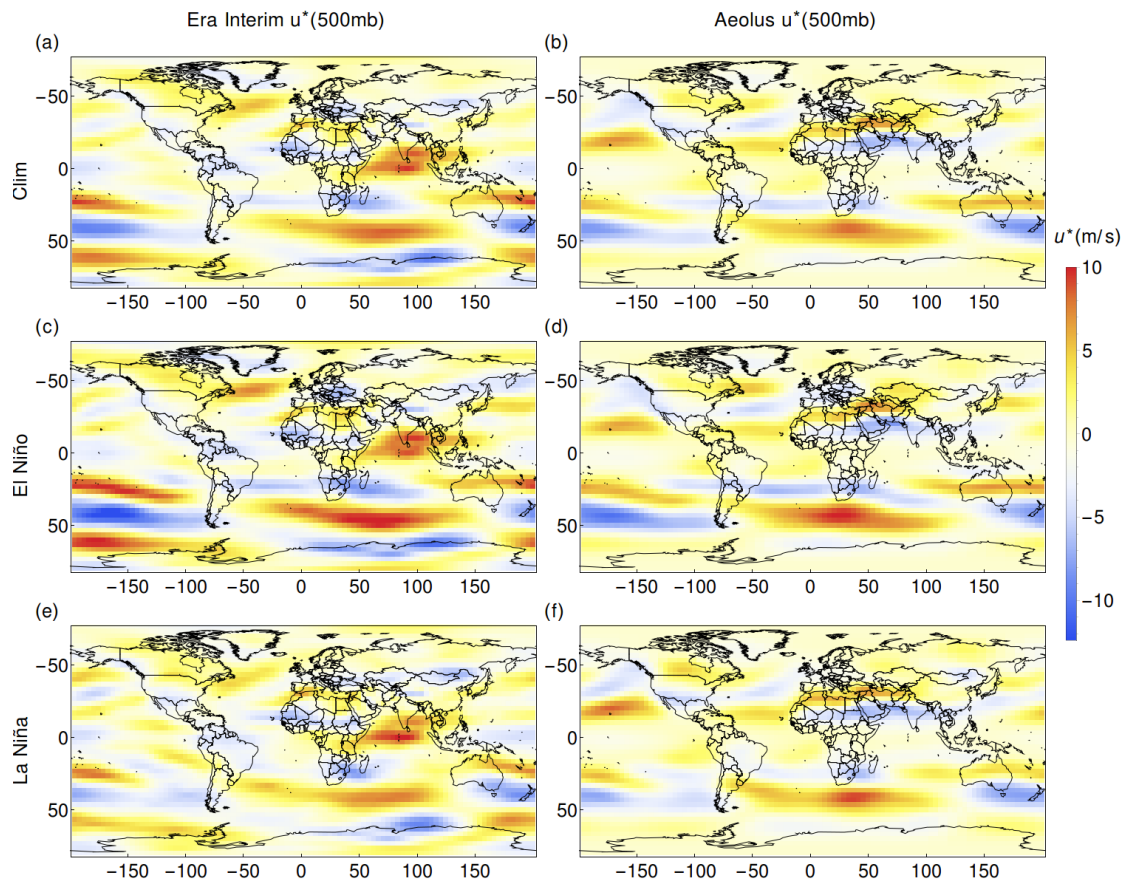
Figure 2 Azonal large-scale zonal wind velocity u* at 500mb for August (compare Fig. 1).
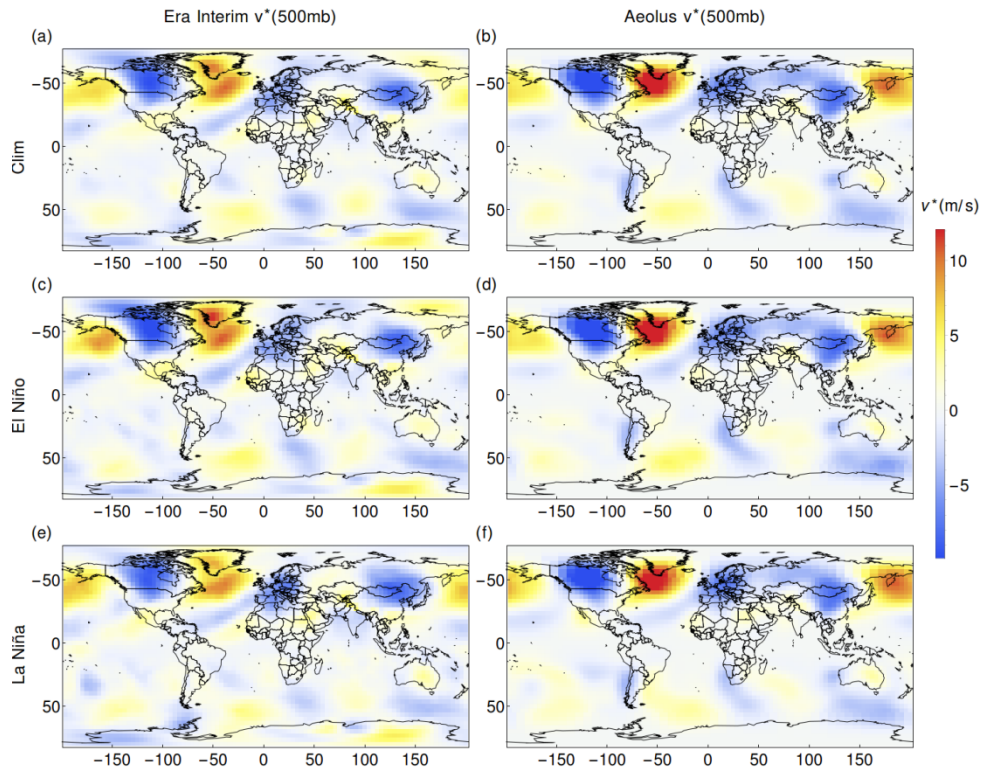
Figure 3 Azonal large-scale meridional wind velocity v* at 500mb for February (compare Fig. 1).
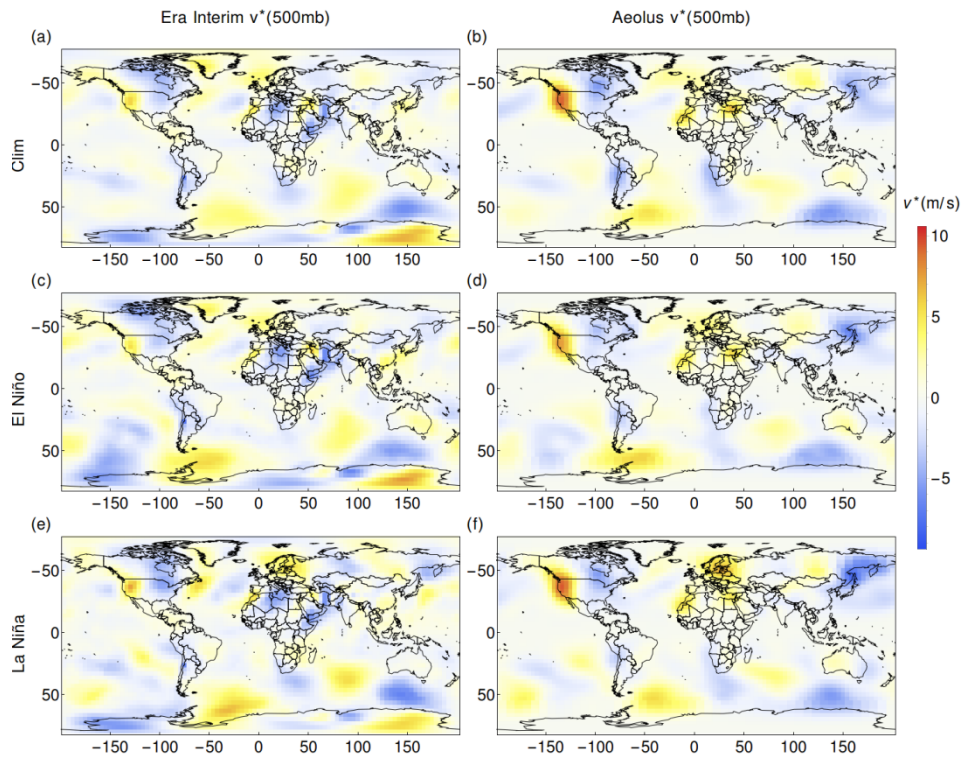
Figure 4 Azonal large-scale meridional wind velocity v* at 500mb for August (compare Fig. 1).
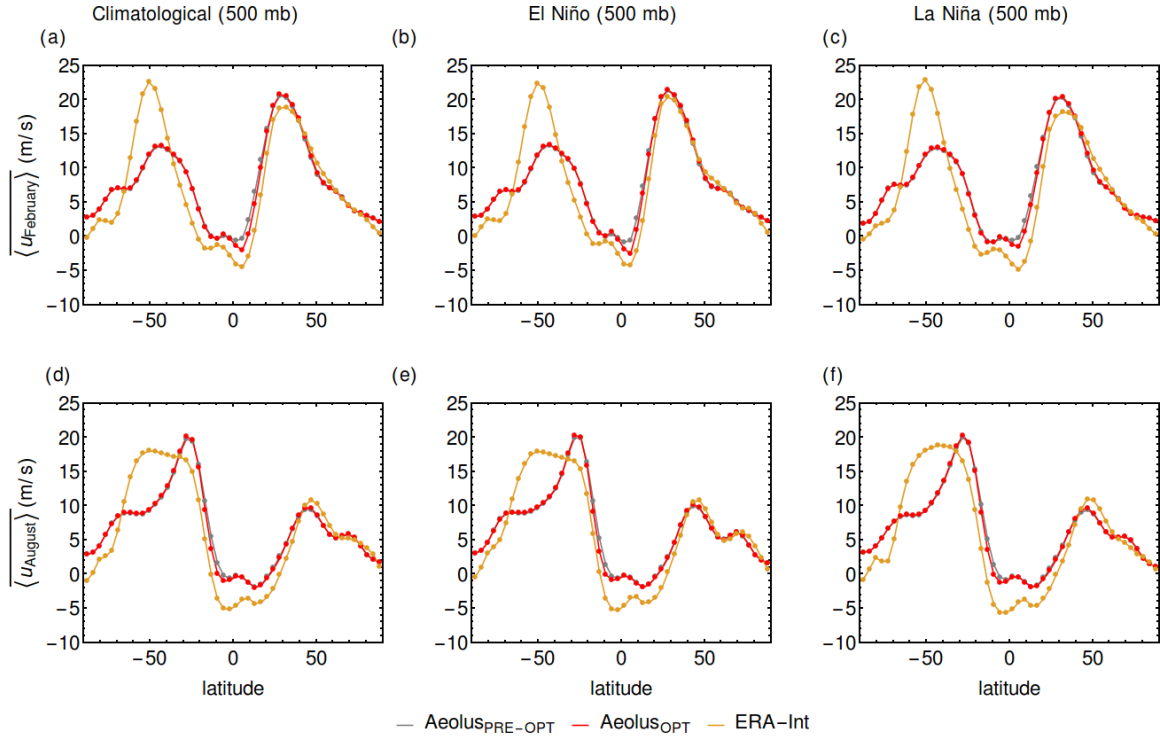
Figure 5 Zonal-mean large-scale zonal wind velocity $\overline{\langle u(z, \phi)\rangle}$ at 500mb. (a) shows the climatological monthly mean zonal-mean zonal velocity in February, (b) depicts the monthly mean zonal-mean velocity of El Niño Februaries and (c) the monthly mean zonal-mean velocity of La Niña Februaries. (d) displays the monthly mean climatological zonal-mean zonal velocity in August, (e) shows the monthly mean zonal-mean velocity in El Niño Augusts and (f) depicts the monthly mean zonal-mean velocity in La Niña Augusts. The yellow line represents zonal-mean large-scale zonal wind obtained by reanalysis data, the gray line is zonal-mean large-scale zonal wind velocity from Aeolus using pre-optimized parameters, and the red line represents zonal-mean large-scale zonal wind velocity from Aeolus using optimized parameters.
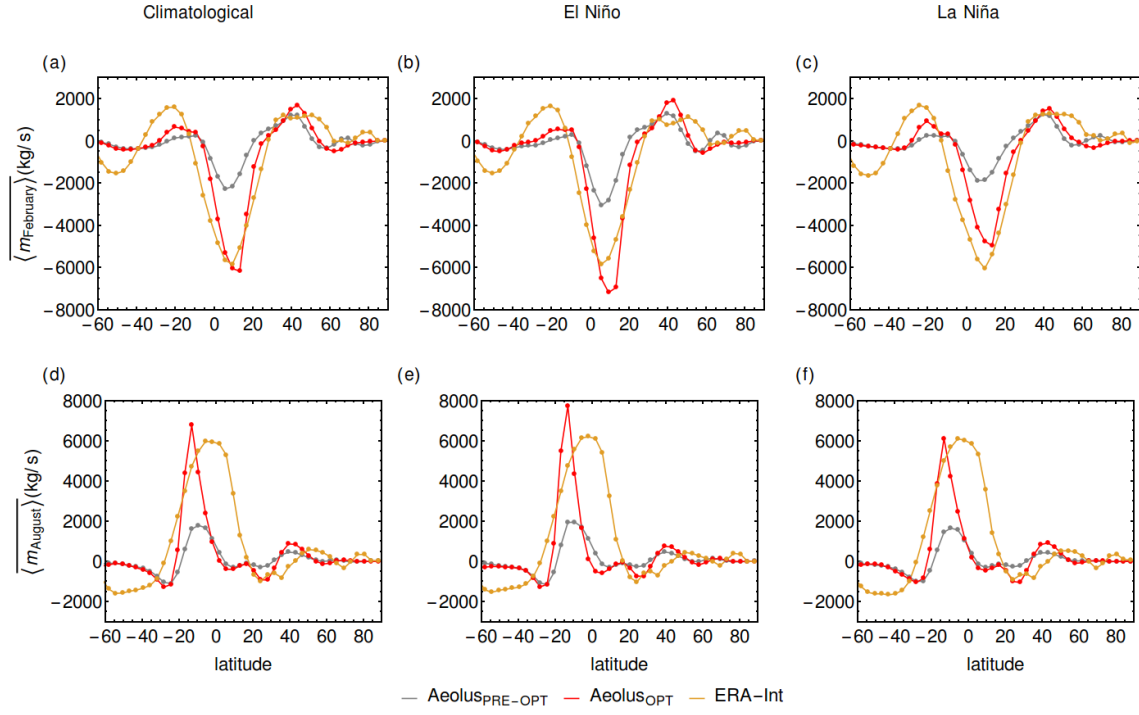
Figure 6 Zonal-mean large-scale mass flux $\overline{\langle m \rangle}$. (a) shows the climatological monthly mean zonal-mean mass flux in February, (b) depicts the monthly mean zonal-mean mass flux of El Niño Februaries and (c) the monthly mean zonal-mean mass flux of La Niña Februaries. (d) displays the monthly mean climatological zonal-mean mass flux in August, (e) shows the monthly mean zonal-mean mass flux in El Niño Augusts and (f) depicts the monthly mean zonal-mean mass flux in La Niña Augusts. The yellow line represents zonal-mean large scale mass flux obtained by reanalysis data, the gray line is the zonal-mean large scale mass flux from Aeolus using pre-optimized parameters, and the red line represents the zonal-mean large scale mass flux from Aeolus using optimized parameters.
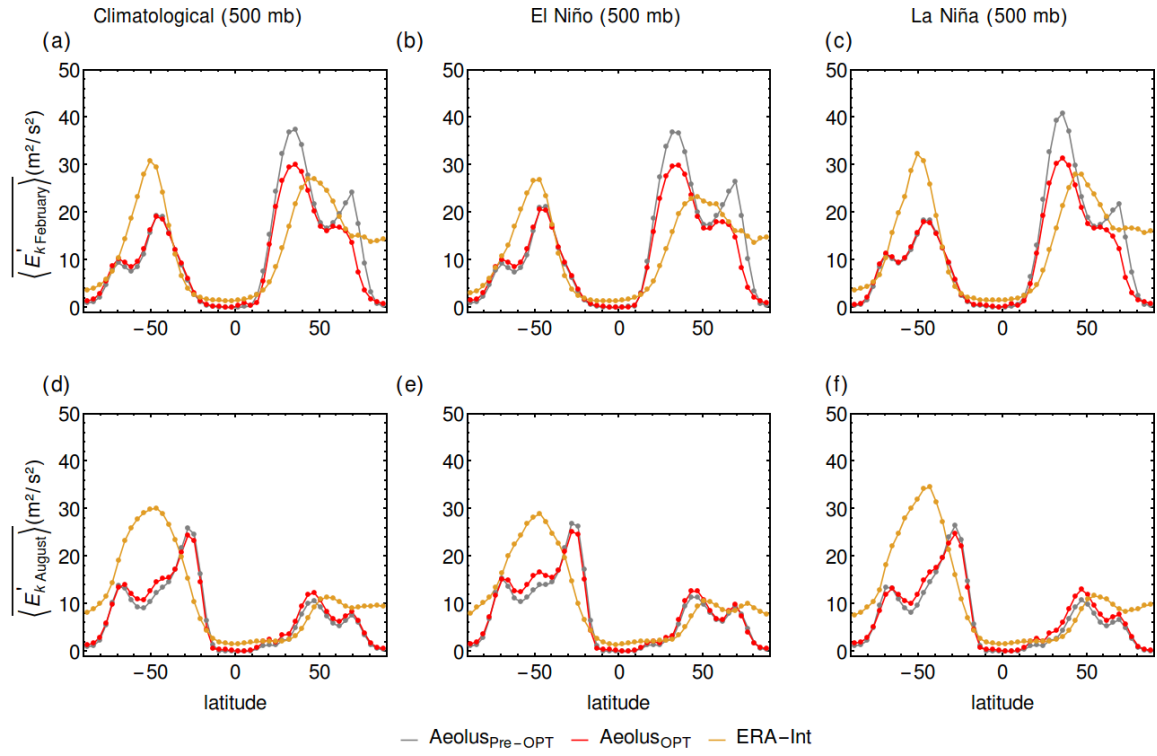
Figure 7 Zonal-mean time averaged eddy kinetic energy $\overline{\langle E'_k \rangle}$ (compare Fig. 6).
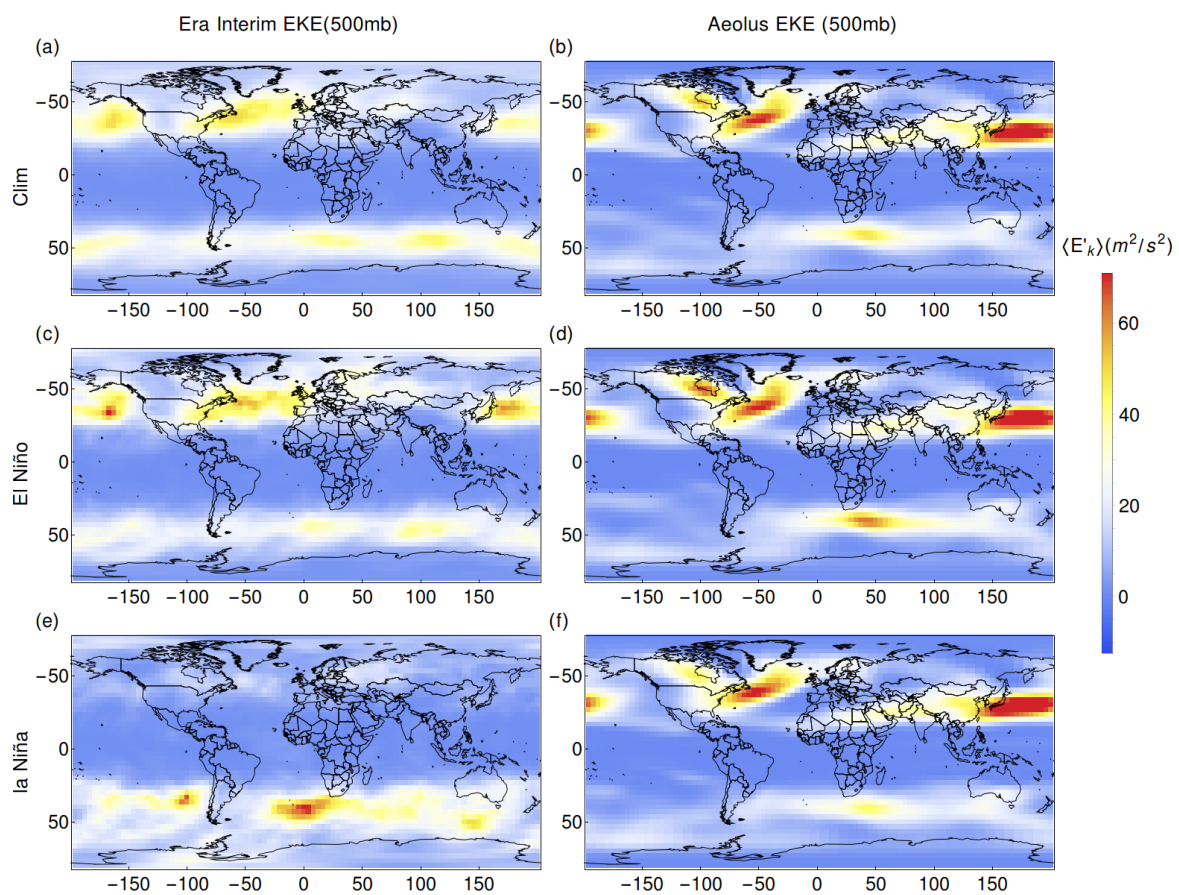
Figure 8 Eddy kinetic energy $\langle E'_k \rangle$ in February at 500mb (compare Fig. 1).
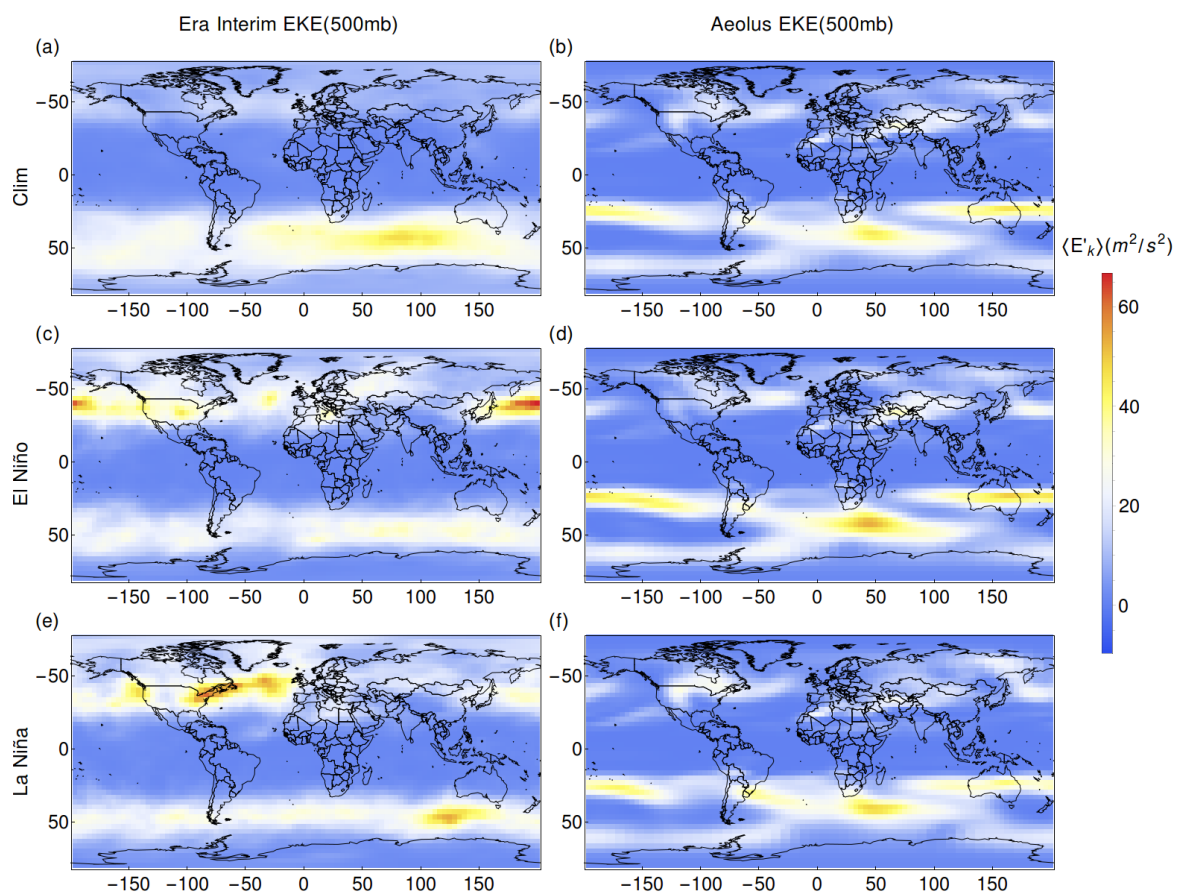
Figure 9 Eddy kinetic energy $\langle E'_k \rangle$ in August at 500mb (compare Fig. 1).
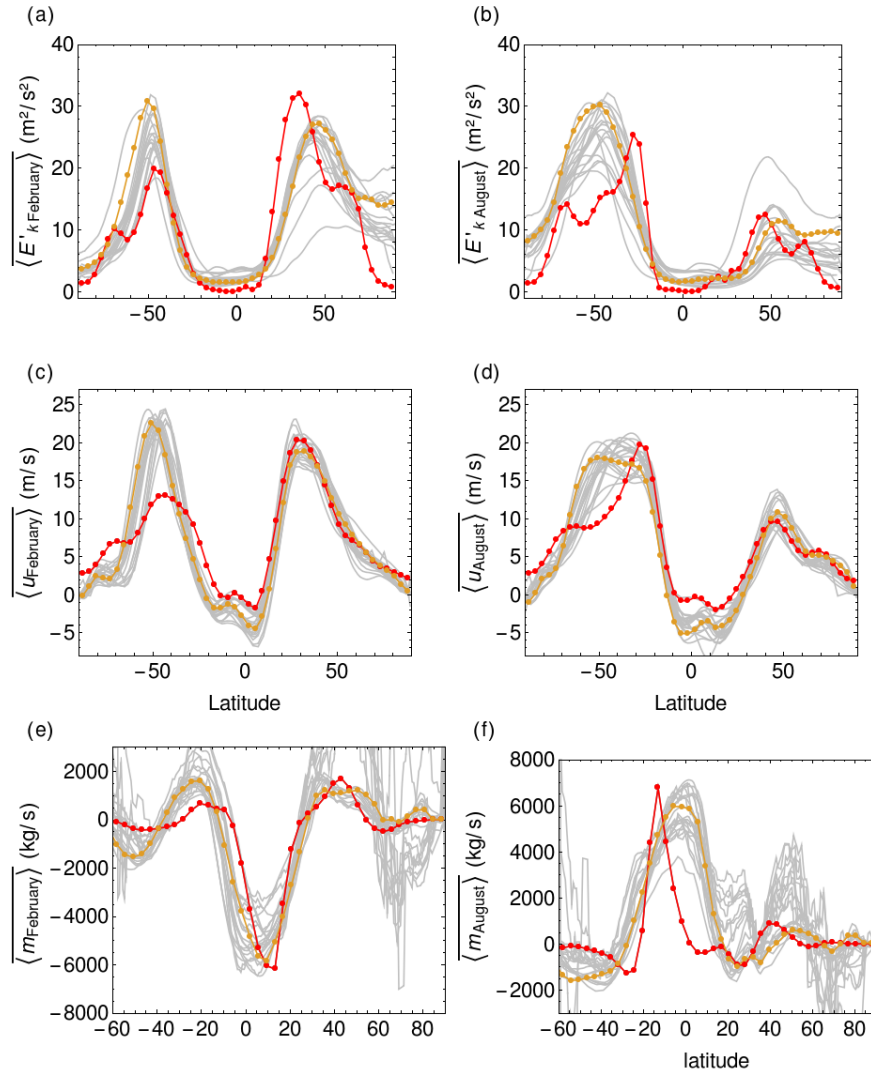
Figure 10 Comparison to CMIP5-Models. The orange line represents Era Interim data, the red line results from Aeolus, and grey lines CMIP5 Models (annual mean zonal-mean data).

13 Tables

Table 1 Atmosphere model parameters

Symbol	Description	Value
a	Earth's radius	$6.4 \cdot 10^6$ m
ρ_0	Reference air density	1.3 kg m^{-3}
g	gravitational acceleration	9.8 ms^{-2}
T_0	Reference Temperature	273.16 K

f	Coriolis parameter	$2\Omega \sin(\phi)$
Ω	Earth's angular velocity	$7.3 \cdot 10^{-5}\,\mathrm{rad\ s^{-1}}$
C_α	Ageostrophic velocity parameter	5
α	cross-isobar angle	$\leq 10°$
H_0	Atmosphere scale height	$8 \cdot 10^3\,\mathrm{m}$
L	Latent heat of evaporation	$2.257 \cdot 10^6\,\frac{\mathrm{J}}{\mathrm{Kg}}$
Γ_a	Dry adiabatic Lapse Rate	$9.8 \cdot 10^{-3}\,\frac{\mathrm{K}}{\mathrm{m}}$
Γ_0	Temperature lapse rate parameter	$5.2 \cdot 10^{-3}\,\frac{\mathrm{K}}{\mathrm{m}}$
Γ_1	Temperature lapse rate parameter	$5.5 \cdot 10^{-5}\,\frac{1}{\mathrm{m}}$
Γ_2	Temperature lapse rate parameter	$10^{-3}\,\frac{\mathrm{K}}{\mathrm{m}}$
a_q	Temperature lapse rate parameter	$10^3\,\left(\frac{\mathrm{kg}}{\mathrm{kg}}\right)^2$
K_z	coefficient of the small-scale and meso-scale turbulent exchange for the momentums	$0.005\,z\,\frac{m^2}{s}$

Table 2 Pre-optimized and optimized Parameter set and parameter ranges for optimization step 1

Parameters	Optimized value	Range	Pre-optimized value
ϕ_{flat0}	56.5	56.0:84.0	70.0
β_{NH}	57.2	30.0:60.0	37.5
β_{SH}	-31.3	-60.0:-30.0	-52.5
Ψ_0	10.14	7.4 : 12	8.0

Table 3 Pre-optimized and optimized Parameter set and parameter ranges for optimization step 2

Parameters	optimized value	Range	Pre-optimized value
U0	5.86	3.5:6.5	5
m	0.7849	0.4662:0.86658	0.6666
d1	0.41	0.:2.	1.0
d2	2.36	0.:2.5	1.0
d3	0.83	0.:2.5	1.0
d4	1.84	0.:2.5	1.0
n1	2.16	0.:2.5	1.0
n2	1.63	0.:2.	1.0
n3	1.06	0.:2.	0.5