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Climate sensitivity to tropical land surface changes with coupled versus prescribed SSTs

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Abstract Tropical land cover change experiments with fixed sea-surface temperatures (SSTs) and with an interactive ocean are compared to assess the relevance of including the ocean system in sensitivity studies to land surface conditions. The results show that the local response to deforestation is similar with fixed and simulated SSTs. Over Amazonia, all experiments simulate a comparable decrease in precipitation and no change in moisture convergence, implying that there is only a change in local water recycling. Over Africa, the impact on precipitation is not identical for all experiments; however, the signal is smaller than over Amazonia and simulations of more than 50 years would be necessary to statistically discriminate the precipitation change. We observe small but significant changes in SSTs in the coupled simulation in the tropical oceans surrounding the deforested regions. Impacts on mid and high latitudes SSTs are also possible. As remote impacts to deforestation are weak, it has not been possible to establish possible oceanic feedbacks to the atmosphere. Overall, this study indicates that the oceanic feedback to land surface sensitivity studies is of second importance, and that the inclusion of the oceanic system will require ensembles of long climate simulations to properly take into account the low frequency variability of the ocean.

1 Introduction

The influence of land surface properties on climate has been extensively studied in the past few decades. Many sensitivity studies have simulated massive tropical deforestation by replacing all tropical forests by grassland. While the first experiments only modified a single surface parameter like albedo (Charney 1975), more complex experiments have modified all vegetation properties including roughness length, rooting depth, and leaf area index (Sud et al. 1996). More realistic land cover change experiments have investigated the impact of observed land cover changes (Maynard and Royer 2004; Zhao et al. 2001). Other recent experiments have also focussed on the large-scale impacts of tropical deforestation on climate (Zhang et al. 1996; Sud et al. 1996; Werth and Avissar 2002). All these experiments used various experimental designs. In particular, the simulation lengths have varied from 1 year (Polcher and Laval 1994) to more than a decade (Lean and Rowntree 1997). The models employed were also different. However, few of these studies have put the emphasis on the influence of the experimental design employed.

Recently, an analysis has been carried out with a coupled atmosphere-ocean general circulation model (AOGCM) of intermediate complexity over the Indonesian region (Delire et al. 2001). This study has shown that deforestation had an impact on the ocean surrounding the Indonesian Archipelago. This study emphasizes that the "ocean climate" (average surface fluxes and temperature) can be modified by land cover changes. It is thus possible that the inclusion of oceanic feedbacks may modulate the response of the climate system to deforestation. Indeed, potential feedbacks to mid-latitudes might be modified in a fully coupled atmosphere-ocean system.

A few studies have used a slab-ocean model coupled to an AGCM to simulate the African and/or Amazonian deforestation (Costa and Foley 2000; Zhang et al. 1996). In these studies, it was argued that the use of a slab-ocean model increases the realism of the simulated climate and its variability. However, the impact of including the ocean component has not been specifically addressed. Zeng et al. (1996) used a sim-

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plified atmospheric model asynchronously coupled to a slab-ocean to simulate tropical deforestation and showed that SST gradients were modified in the Tropics. However, they did not investigate this issue in further detail. On the other hand, a slab-ocean model has been used by Bonan et al. (1992) to simulate high-latitude deforestation. It was found that the ocean component amplified the cooling effect of deforestation in boreal winter and that it introduced a thermal lag that inhibited the warming in the summer. Even though this feedback was partly related to sea-ice albedo and the mechanisms involved would be different in the Tropics, this pioneering study emphasized the possible role of the ocean component on land sensitivity experiments. A more recent study by Zhao et al. (2001) supports this idea. They used a mixed-layer ocean model and simulated realistic land use changes in mid-latitudes. The results suggest that the ocean component could have modulated the impact of land cover change on the large-scale dynamics. Unfortunately, due to the experimental design, this could not be confirmed.

As suggested by these studies, the inclusion of the ocean component in land cover sensitivity studies could have an effect on the climate response. Here, we aim to quantify the potential role of the inclusion of an ocean GCM in a comprehensive tropical deforestation study. A theoretical land cover change experiment is conducted rather than a more realistic land use change to enhance the signal to noise ratio. As suggested by Delire et al. (2001), deforestation could have an impact on the surrounding oceans. The African and Amazonian areas of deforestation are larger than over Indonesia and, as their impact on climate is potentially stronger, they may also be expected to have an impact on the ‘‘ocean climate’’.

The model and experiment design are presented in Sect. 2. As the mean climate simulated by the coupled AOGCM and the AGCM are quite different, a comparison of their respective climatology biases is given in Sect. 3. In Sect. 4, the local impacts of deforestation with and without the ocean model are compared, while remote impacts are investigated in Sect. 5. Conclusions are drawn in Sect. 6.

2 Model and experiment design

2.1 Model

The main objective of this study is to repeat the deforestation experiments presented by Voldoire and Royer (2004) with a coupled AOGCM instead of an atmospheric model alone. As in this previous study, we use the ARPEGE-Climat atmospheric GCM (version 3) from CNRM (Déqué 1999) and the ISBA land surface scheme (Noilhan and Planton 1989). ARPEGE-Climat is a spectral model with a progressive hybrid sigma-pressure coordinate, and a two-time-level semi-Lagrangian semi-implicit integration scheme (Côté and Staniforth 1988). For this study, we used a configuration with 31 levels in the vertical and a horizontal resolution of 2.8°. Physical parameterizations include the turbulence scheme of Louis et al. (1982), the statistical cloud scheme of Ricard and Royer (1993), and the radiative scheme of Morcrette (1990), which includes the effect of several greenhouse gases (CO_2, CH_4, N_2O and CFCs), water vapour and ozone. For convection, the Bougeault (1985) mass-flux convective scheme with Kuo-type closure is used. The land surface scheme ISBA computes moisture and energy fluxes over continental boundaries. Heat and water transfers in the ground are based on the force restore method (Deardorff 1978) and a single surface temperature, which is representative of the soil-snow-canopy system, is calculated. The surface hydrology is based on four reservoirs: a canopy interception reservoir, a snow reservoir, a surface volumetric water content and a total volumetric water content.

The ocean GCM used in this study is the OPA8.0 model developed at LODYC (Madec et al. 1997), which is a finite difference model. It is based on primitive equations in which the thin shell, hydrostatic and Boussinesq approximations are assumed. The rigid lid assumption is made, so that surface gravity waves are filtered. The ocean model is spatially discretized on a three-dimensional generalization of the Arakawa C-grid. The time-step for coupling atmosphere and ocean is one day.

2.2 Land Cover maps

The land surface characteristics of forested and deforested experiments are exactly the same as presented by Voldoire and Royer (2004). The initial land cover distribution is given by the IMAGE2.2 land cover map for 1980 (IMAGE-team 2001). This is a simulated distribution, which compares well with observed data sets (Alcamo et al. 1998). This map is used to ensure consistency with another ensemble of experiments (not presented here) comparing the impact of realistic land cover change and increasing concentrations of greenhouse gases. This map has a 0.5°×0.5° horizontal resolution and is based on 18 different land cover classes, including crop and pasture.

In the deforested experiments, tropical forest and tropical woodland vegetation types of the initial map are replaced by grazing land. Three regions are affected by deforestation: equatorial Africa, Amazonia, and Indonesia (Fig. 1). For each land cover class, we have specified the eight vegetation parameters needed by the ISBA land surface scheme (albedo, roughness length, stomatal minimum resistance, leaf area index, vegetation cover, rooting depth, emissivity and fraction of forest) according to the recent ECOCLIMAP database (Masson et al. 2003). The parameters are

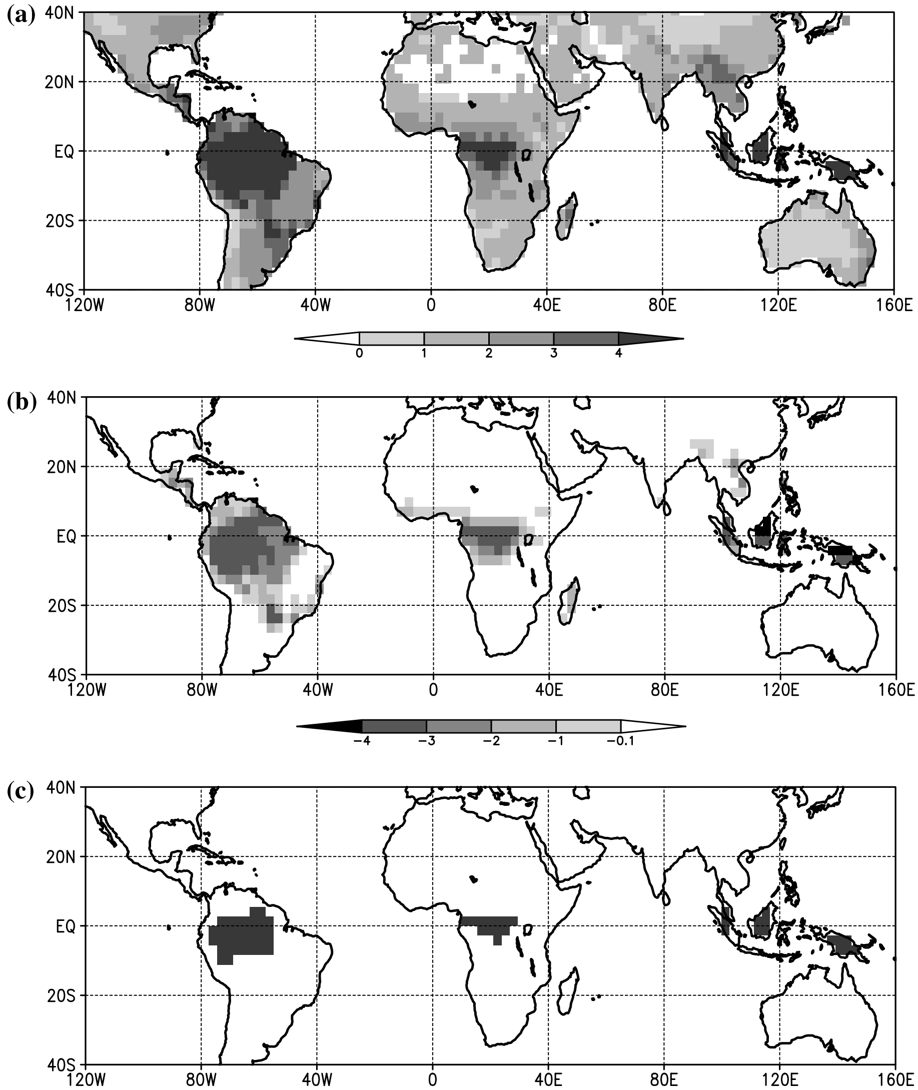


Fig. 1 **a** Annual mean leaf area index used in control simulations and **b** its anomaly after deforestation. **c** indicates the domains used for averages presented in Tables 4, 5, 6 and 7

thus specified at the 0.5°×0.5° resolution and spatial averages are then computed to obtain effective parameters over the GCM mesh. In the ISBA scheme, the averaging operators are chosen in order to be consistent as far as possible with an arithmetic averaging of the fluxes themselves (Masson et al. 2003). As deforested areas are defined at the 0.5°×0.5° resolution and parameters aggregated afterwards, the differences in parameter maps at the model resolution are not uniform (Fig. 1).

Table 1 ISBA vegetation parameters in the control maps and their anomalies in the deforested maps, averaged over the three domains of interest

Parameter	Amazonia		Africa		Indonesia	
	Ctrl	Def	Ctrl	Def	Ctrl	Def
Albedo (%)	13.5	3.5	14	3	14	2
Roughness length (m)	2.8	−1.8	2.5	−1.6	3.1	−0.8
Vegetation cover (%)	94	−14	92	−27	79	−25
Leaf area index	5.5	−3.5	4.8	−3.6	4.9	−3.9
Rooting depth (m)	7.1	−5.2	6.6	−5.3	6.0	−4.7
Emissivity (%)	97	−0.4	97	−0.8	97	−0.9
Stomatal resistance	43	20	48	34	45	37
Percentage of forests	98	−98	98	−98	96	−96

Table 2 Experiments performed

Control	Deforested	Ocean characteristics	Other	Simulation length
FCL	FDF	Observed Reynolds SSTs	Incorrect Z0	30 years
CCTL	CDEF	Ocean GCM	Incorrect Z0	20 years
FCTL	FDEF	SSTs from CCTL	Incorrect Z0	20 years
CCTZ	CDEZ	Ocean GCM	Corrected Z0	20 years

Table 3 Average vegetation roughness length in meters over the deforested regions in the experiments CCTL and CCTZ and their anomalies in the corresponding deforested simulations. Experiments FCTL and FCL have the same roughness length as CCTL

	CCTL	CCTZ	CDEF-CCTL	CDEZ-CCTZ
Amazonia	2.69	3.25	−1.81	−2.96
Africa	2.35	2.91	−1.60	−2.87
Indonesia	1.98	1.46	−0.83	−1.42

Values of the different surface parameters averaged over the three regions are shown in Table 1. The anomalies subsequent to deforestation are quite similar to those of previous deforestation experiments (Zhang et al. 2001; Sud et al. 1996). However, the main difference is the weaker change in albedo. In ECOCLIMAP, tropical forest albedo is in the higher range of what is prescribed in other studies, and the albedo of grazing land is 0.19, which is in the lower range of estimates. As a consequence, the change imposed in our experiment is weaker than in other deforestation experiments.

2.3 Experiment description

Eight simulations have been performed, summarized in Table 2:

- FCL: a control experiment with the atmospheric model alone and forced with observed SSTs from the Reynolds climatology (Reynolds 1988) for the period 1970–1999 (30 years simulation).
- FDF: a deforestation experiment with the same model and SSTs as in FCL. This pair of simulations has already been analysed in detail by Voldoire and Royer (2004).

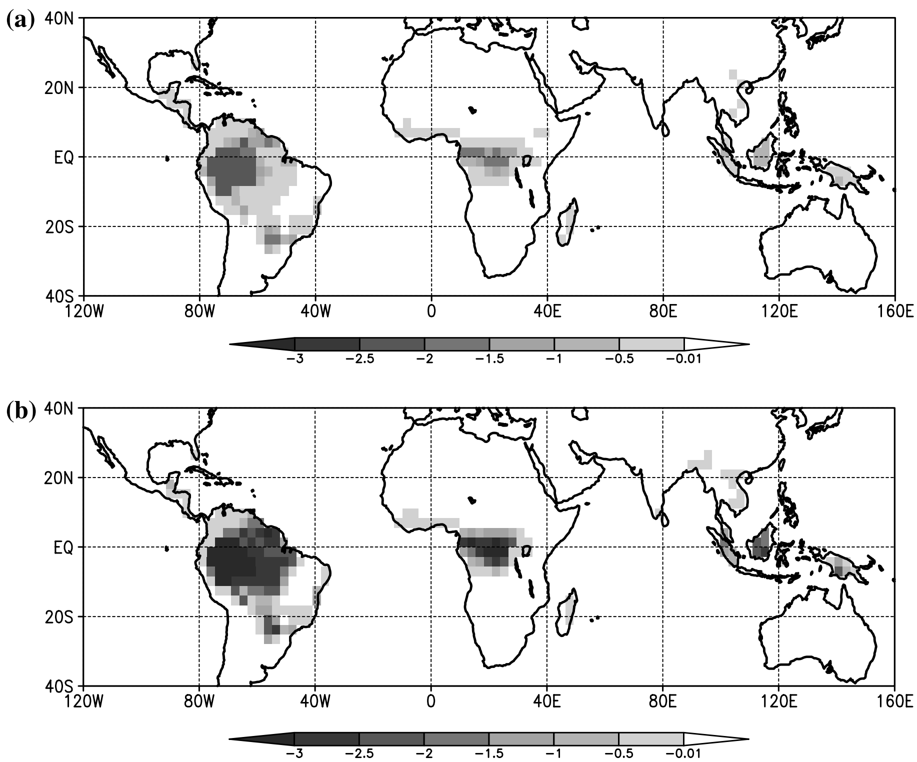


Fig. 2 Change in roughness length in meters imposed in **a** the first three deforested experiments (FDF, CDEF and FDEF) and **b** in the last experiment CDEZ as compared to their respective control simulations

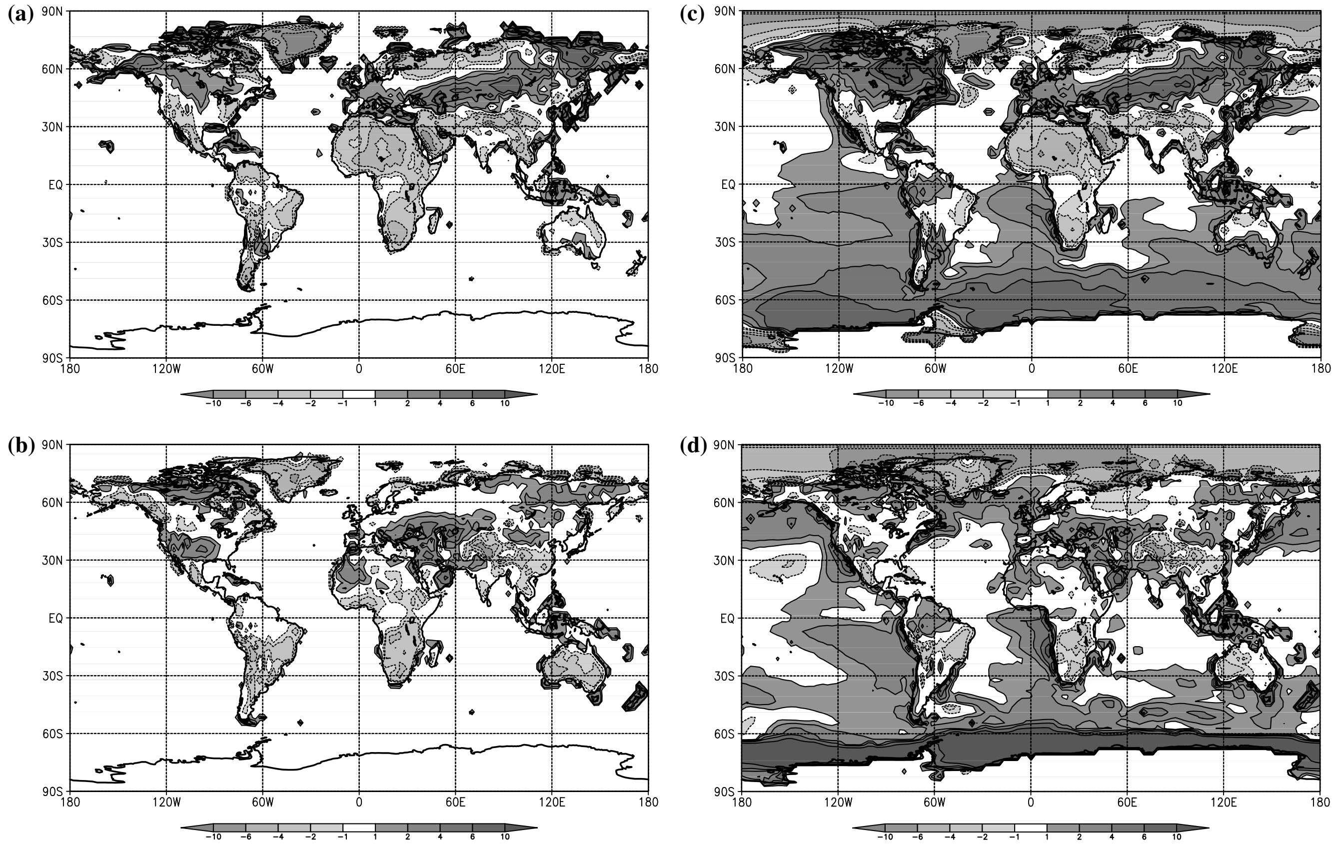


Fig. 3 Surface temperature anomalies (°C) of experiments FCL (**a, b**) and CCTL (**c, d**) compared to the CRU climatology over continents and to the Reynolds climatology over oceans in DJF (*top*) and JJA (*bottom*)

– CCTL: a control experiment with the coupled atmosphere-ocean model.
– CDEF: a deforestation experiment with the coupled atmosphere-ocean model, to assess the impact of deforestation in coupled mode.

The climate simulated by the coupled model can be quite different from the one simulated using observed SSTs. Thus, for the purpose of studying the impact of using a coupled model in deforestation studies, comparing FDF and CDEF experiments would lead to an open question: are the impacts different because the model includes ocean interactions or because the mean climate is different? This is the main reason to run forced experiments with SSTs from the coupled model.

– FCTL: a control experiment with the atmospheric model driven by monthly mean SSTs derived from the CCTL simulation.
– FDEF: a deforestation experiment with the atmospheric model driven by the same SSTs as in FCTL. This pair of simulation is analogous to FCL/FDF but with the climate of the coupled model.

During processing of the results, an error in the specification of roughness lengths for several vegetation classes was discovered in these simulations. However, it has been decided to present these results for several reasons. Firstly, the aim of this study is to investigate the role of including the ocean component in land surface sensitivity studies, and these experiments allow for the analysis of the main aspects of this question. Secondly, the main conclusion of this study will be that quantifying the effect of the ocean response on the atmosphere requires using another experimental design. Hence, we decided not to re-run all the experiments previously listed with the corrected roughness length. However, because the control climate could be different with the correct roughness length and because roughness length is a key parameter in such land cover change experiments, it has been necessary to redo the experiments CCTL and CDEF. This allows us to assess whether the higher sensitivity to land cover change could lead to notably higher ocean impacts and to quantify the difference in the control climate. The last pair of simulations in which roughness length has been corrected are named:

– CCTZ: a control simulation with the coupled model with corrected roughness length.
– CDEZ: the corresponding deforestation experiment.

In the first set of experiments, a value between 1 m and 3 m was specified for pasture roughness length

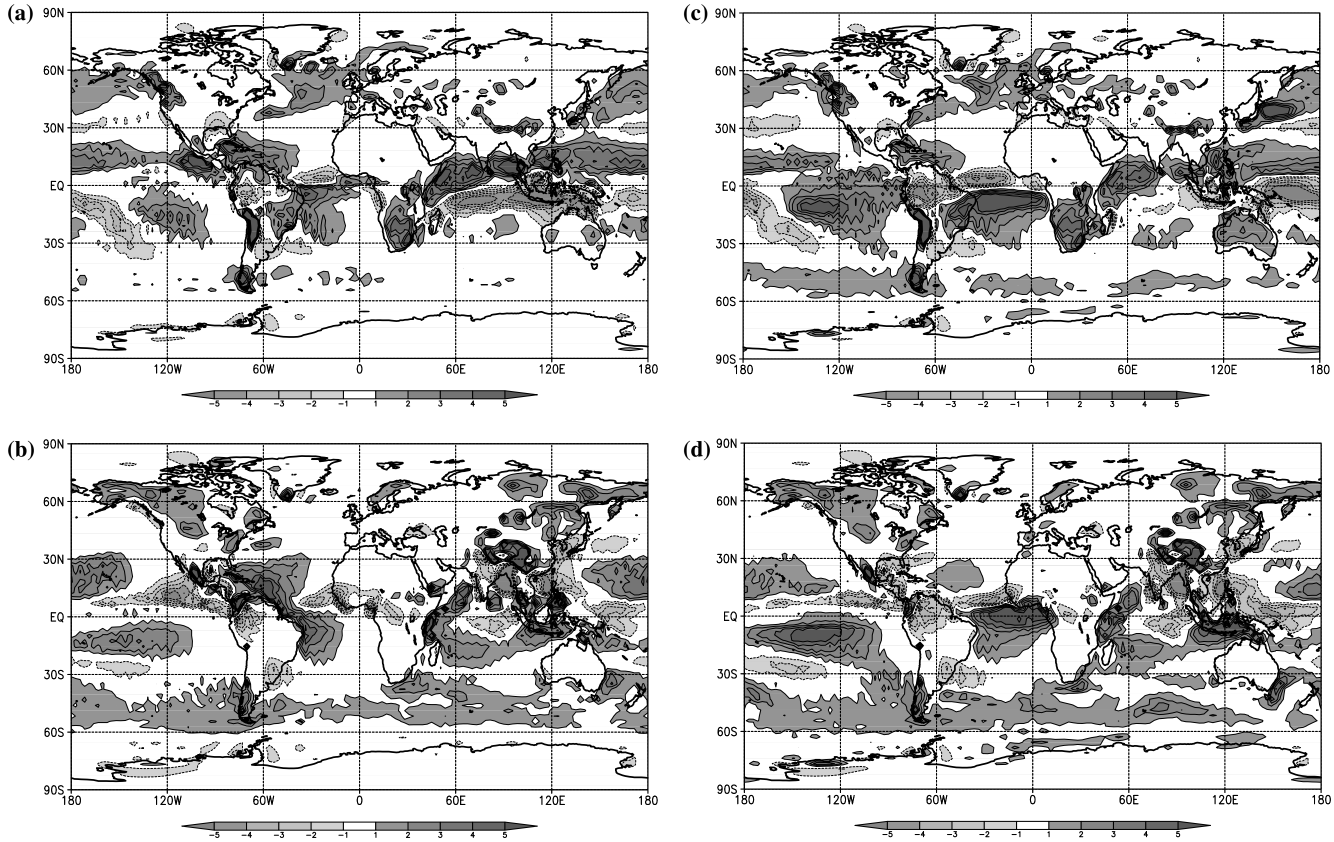


Fig. 4 As Fig. 2 for precipitation (mm day^{-1}) compared to the Xie and Arkin (1996) climatology

depending on the regions. In the new simulations, the pasture roughness length is reduced to 0.3 m over Amazonia and 0.03 m over Africa. Thus the decrease in roughness length with deforestation is much more important than in the first set of experiments (Table 3). Consequently, the last pair of experiments differs from the pair CCTL/CDEF in the initial conditions and assumes a stronger reduction in roughness length (Fig. 2).

The simulations FCL/FDF are integrated for 31.5 years and the last 30 years are analysed to avoid spin-up problems. Each coupled experiment is a 25-year integration with the first 5 years discarded to allow for model equilibration with the new land cover map. The experiments FCTL and FDEF have used monthly mean SSTs from the last 20 years of the CCTL coupled experiment.

Table 4 Mean annual parameters over the Amazonian deforested region for the control simulations and their anomalies in the corresponding deforested experiments

Parameter	FCL	FCTL	CCTL	CCTZ	FDF-FCL	FDEF-FCTL	CDEF-CCTL	CDEZ-CCTZ
Surface Temperature (°C)	26.2	28.2	29.1	28.7	−0.1 (68)	−0.2 (24)	−0.2 (24)	+**0.6** (59)
Daily minimum temperature (°C)	22.8	24.8	25.0	24.8	**−1.3** (100)	**−1.6** (100)	**−1.5** (100)	**−1.2** (100)
Daily maximum temperature (°C)	30.5	34.0	34.3	33.9	+**1.3** (100)	+**1.3** (100)	+**1.3** (100)	+**1.8** (100)
Sensible Heat F. (W m^{-2})↑	26	47	49	46	+**7** (85)	+**8** (85)	+**8** (88)	+**13** (94)
Latent Heat F. (W m^{-2})↑	107	90	89	93	**−12** (97)	**−11** (97)	**−12** (97)	**−19** (100)
Surface Net Solar F. ↓ (W m^{-2})	173	187	189	188	**−3.5** (76)	−1.9 (35)	+2.2 (56)	+1.4 (59)
Surface Net IR F. (W m^{-2})↑	40	50	51	49	+**1** (68)	+2(29)	+1 (26)	+**7** (100)
Surface wind mag. (m s^{-1})	0.68	0.82	0.83	0.72	+**0.23** (97)	+**0.28** (94)	+**0.28** (100)	+**0.72** (100)
Precipitation (mm day^{-1})	4.57	3.37	3.32	3.52	**−0.42** (74)	**−0.45** (94)	**−0.44** (91)	**−0.74** (100)
Cloudiness (%)	71	67	66	66	**−1.4** (62)	**−2.5** (68)	**−1.4** (47)	**−3.6** (74)
Run off (mm day^{-1})	0.76	0.14	0.13	0.18	−0.01 (62)	−0.04 (38)	−0.03 (26)	**−0.06** (29)
P-E (mm day^{-1})	0.84	0.21	0.20	0.27	−0.02 (50)	−0.06 (18)	−0.04 (9)	−0.09 (15)

Values in *italics* indicate anomalies significant at the 90% level. The number between *brackets* indicate the percentage of grid cells for which grid anomalies are significant at the 90% level in the domain (this gives an indication of the homogeneity of the response)

Table 5 Mean annual parameters over the African deforested region for the control simulations and their anomalies in the corresponding deforested experiments

Parameter	FCL	FCTL	CCTL	CCTZ	FDF-FCL	FDEF-FCTL	CDEF-CCTL	CDEZ-CCTZ
Surface temperature (°C)	24.3	25.2	25.3	25.2	−0.03 (42)	−**0.3** (67)	−**0.3** (75)	+**0.4** (83)
Daily minimum temperature (°C)	21.5	22.3	22.4	22.3	−**0.7** (100)	−**0.9** (100)	−**0.9** (100)	−**0.5** (83)
Daily maximum temperature (°C)	29.0	30.1	30.2	30.1	+**0.8** (100)	+**0.6** (92)	+**0.5** (92)	+**0.8** (92)
Sensible Heat F. (W m^{-2})↑	15	15	15	15	+**6** (83)	+**4** (92)	+**3** (83)	+**5** (92)
Latent Heat F. (W m^{-2})↑	105	106	107	109	−**10** (100)	−**9** (100)	−**6** (92)	−**15** (100)
Surface Net Solar F. ↓ (W m^{-2})	155	157	160	160	−**3** (67)	−**4** (100)	−**4** (92)	−**6** (92)
Surface Net IR F. (W m^{-2})↑	36	37	37	37	+1 (50)	+0 (0)	−0 (0)	+**4** (92)
Surface wind mag. (m s^{-1})	0.52	0.47	0.47	0.43	+**0.20** (100)	+**0.17** (100)	+**0.16** (100)	+**0.49** (100)
Precipitation (mm day^{-1})	4.64	4.80	4.80	4.86	−**0.34** (92)	−**0.27** (58)	−0.05 (0)	−**0.29** (67)
Cloudiness (%)	78	76	76	75	−0.3 (33)	+0.8 (42)	+0.9 (25)	+**1.2** (67)
Run off (mm day^{-1})	0.92	1.04	0.97	0.99	−0 (17)	+0.04 (8)	+**0.19** (50)	+**0.24** (58)
P-E (mm day^{-1})	1.00	1.11	1.06	1.08	−0.0 (17)	+0.04 (8)	+**0.18** (42)	+**0.23** (58)

Values in *italics* indicate anomalies significant at the 90% level. The number between *brackets* indicate the percentage of grid cells for which grid anomalies are significant at the 90% level in the domain (this gives an indication of the homogeneity of the response)

Table 6 Mean annual parameters over the Indonesian deforested region for the control simulations and their anomalies in the corresponding deforested experiments

Parameter	FCL	FCTL	CCTL	CCTZ	FDF-FCL	FDEF-FCTL	CDEF-CCTL	CDEZ-CCTZ
Surface temperature (°C)	24.4	24.9	25.0	24.9	−**0.1** (71)	0.0 (43)	0.0 (79)	+**0.2** (57)
Daily minimum temperature (°C)	21.9	22.4	22.4	22.4	−**0.5** (100)	−**0.3** (71)	−**0.5** (71)	−**0.3** (79)
Daily maximum temperature (°C)	27.4	28.0	28.0	28.0	+**0.2** (57)	+**0.3** (50)	+**0.4** (71)	+**0.4** (64)
Sensible Heat F. (W m^{-2})↑	8	10	10	10	+**2** (57)	+**2** (43)	+**4** (57)	+**3** (57)
Latent Heat F. (W m^{-2}) ↑	114	115	115	117	−**2** (50)	−**6** (79)	−**6** (71)	−**7** (79)
Surface Net Solar F. ↓ (W m^{-2})	151	156	156	157	−0.2 (0)	−**3.6** (36)	−0.1 (0)	−1.9 (14)
Surface Net IR F. (W m^{-2}) ↑	29	30	30	30	+0.5 (7)	−0.4 (21)	+1.1 (14)	+**2.1** (57)
Surface wind mag. ($m.s^{-1}$)	0.79	0.81	0.80	0.72	+**0.09** (71)	+**0.09** (64)	+**0.09** (57)	+**0.32** (86)
Precipitation (mm day^{-1})	6.45	6.4	6.29	6.31	−**0.29** (43)	+0.06 (7)	−0.22 (7)	−0.12 (29)
Cloudiness (%)	83	81	81	81	−0.6 (7)	−0.1 (0)	−**1.5** (29)	−**1.4** (36)
Run off (mm day^{-1})	2.41	2.30	2.20	2.15	−0.20 (50)	+0.26 (36)	−0.03 (14)	+0.13 (50)
P-E (mm day^{-1})	2.50	2.39	2.29	2.24	−0.20 (36)	+0.25 (36)	−0.03 (14)	+0.13 (36)

Values in *italics* indicate anomalies significant at the 90% level. The number between *brackets* indicate the percentage of grid cells for which grid anomalies are significant at the 90% level in the domain (this gives an indication of the homogeneity of the response)

3 Control climate

3.1 Global scale

The control climate of the coupled simulation (CCTL) is compared to the control simulation using observed SSTs (FCL). Surface temperature biases of both simulations are compared to the historical climate database from the Climate Research Unit of the University of East Anglia (Norwich, UK; Mitchell et al. 1995) hereafter referred as the CRU climatology over the continents, and to the Reynolds (1988) climatology over the oceans (Fig. 3). In the coupled experiment, there are mostly warm biases over the oceans. We observe warm biases west of the coast of South America and Africa in both seasons. This depicts an accumulation of warm waters on the eastern side of the tropical basins. There is also a strong warming around the Antarctic in DJF, which is due to a too small sea-ice extent simulated by the ice model. There is also a warm bias between 40°N and 60°N in JJA.

Over the continents, biases are similar most of the time for the two experiments. There is a large warm bias over the Eurasian continent in DJF in both simulations. The warm bias over America in DJF is strongly enhanced in coupled mode. The cold bias over Africa in DJF is somewhat reduced in coupled mode. In JJA, a warm bias appears over the tropical forests regions of Africa and Amazonia in the coupled simulation.

Simulated precipitation is compared to the Xie and Arkin (1996) climatology based on in situ and satellite observations collected between 1979 and 1996 (Fig. 4). In DJF, there is a large underestimate of precipitation over Amazonia in the coupled simulation as compared to the climatology and to the forced simulation. There is also a large overestimate of rainfall over the tropical South Atlantic Ocean. Unlike temperature biases, precipitation biases are not systematically enhanced in the coupled simulation. For instance, in DJF, the excess of precipitation south of the Asian continent is reduced together with the dry bias over Indonesia. In JJA, the wet bias to the northeast of South America is strongly

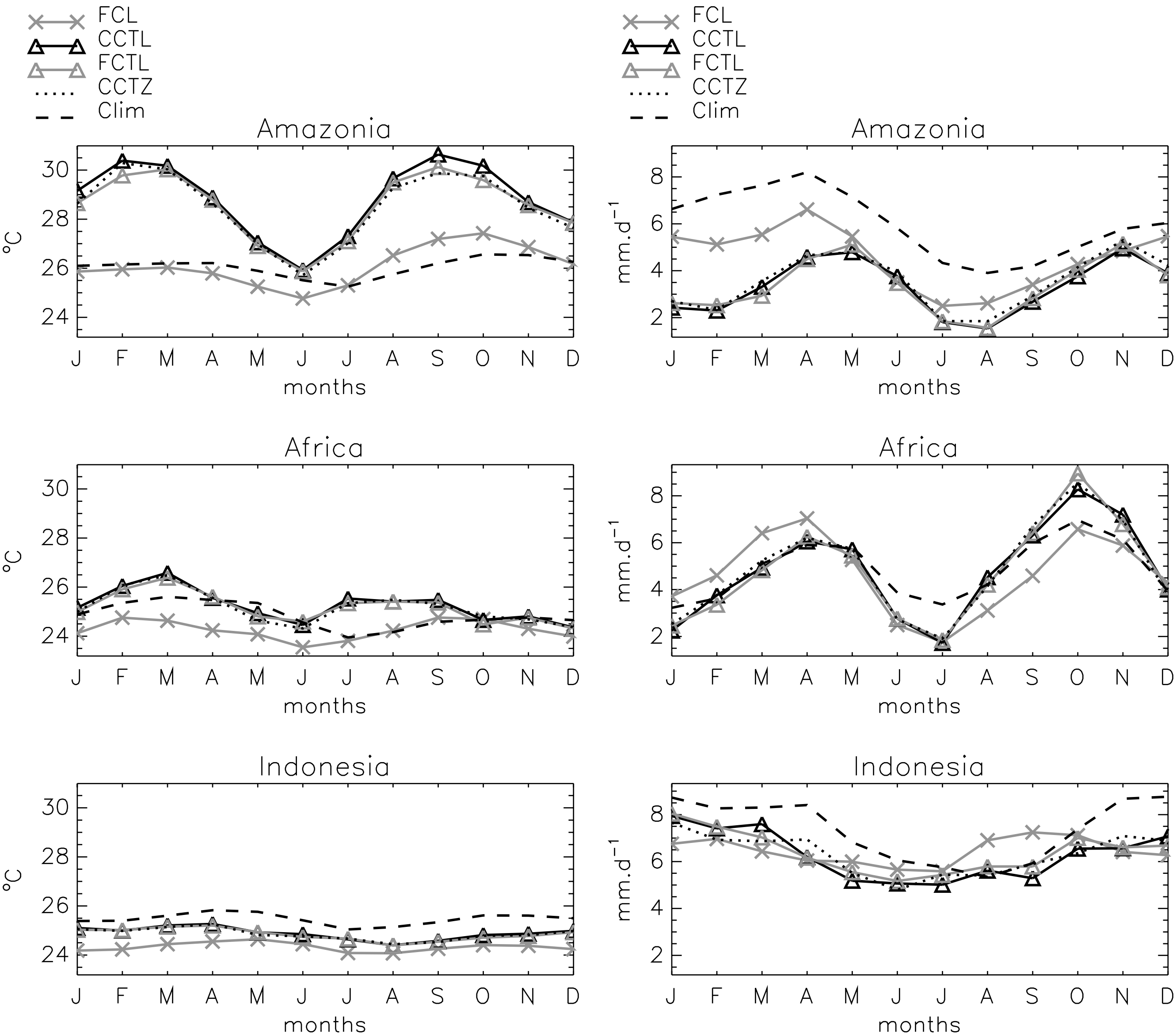


Fig. 5 Seasonal cycle of near surface temperature (*on left*) in °C and precipitation (*on right*) in mm day^{-1} for Amazonia, Africa and Indonesia for all the control simulations and the CRU climatology

reduced in the coupled experiment. However, a large wet bias appears over the equatorial part of the Atlantic and of the Pacific, especially in JJA. This corresponds to a southward shift of the maximum precipitation zone. For the Atlantic, this can be connected to the warm ocean anomaly in the Gulf of Guinea, which modifies the monsoon characteristics. This stresses the need for the simulation FDEF that uses the same SSTs as CDEF to discriminate between the impact of the control climate and the impact of including the ocean component.

The climatology of the coupled model is deteriorated to a certain extent as compared to the forced simulation. However, the biases are acceptable for state-of-the-art atmosphere-ocean models. As the mean climate has changed, the impact of deforestation in FDF and CDEF could be different.

3.2 Deforested regions

The annual mean climate of the control simulations and the impact of deforestation are presented in Tables 4, 5 and 6 for Amazonia, Africa and Indonesia, respectively. The diagnostics are averaged over the domains presented in Fig. 1c. We note that the mean climate over Amazonia is much drier and warmer in the coupled experiments and in the experiment with SSTs from the coupled run (CCTL, CCTZ and FCTL), compared with the experiment with observed SSTs (FCL). As shown in the previous section, this corresponds to a bias of the model as compared to observations. When using observed SSTs, the mean temperature of Amazonia is reduced by 3°C and the average daily maximum temperature is reduced by

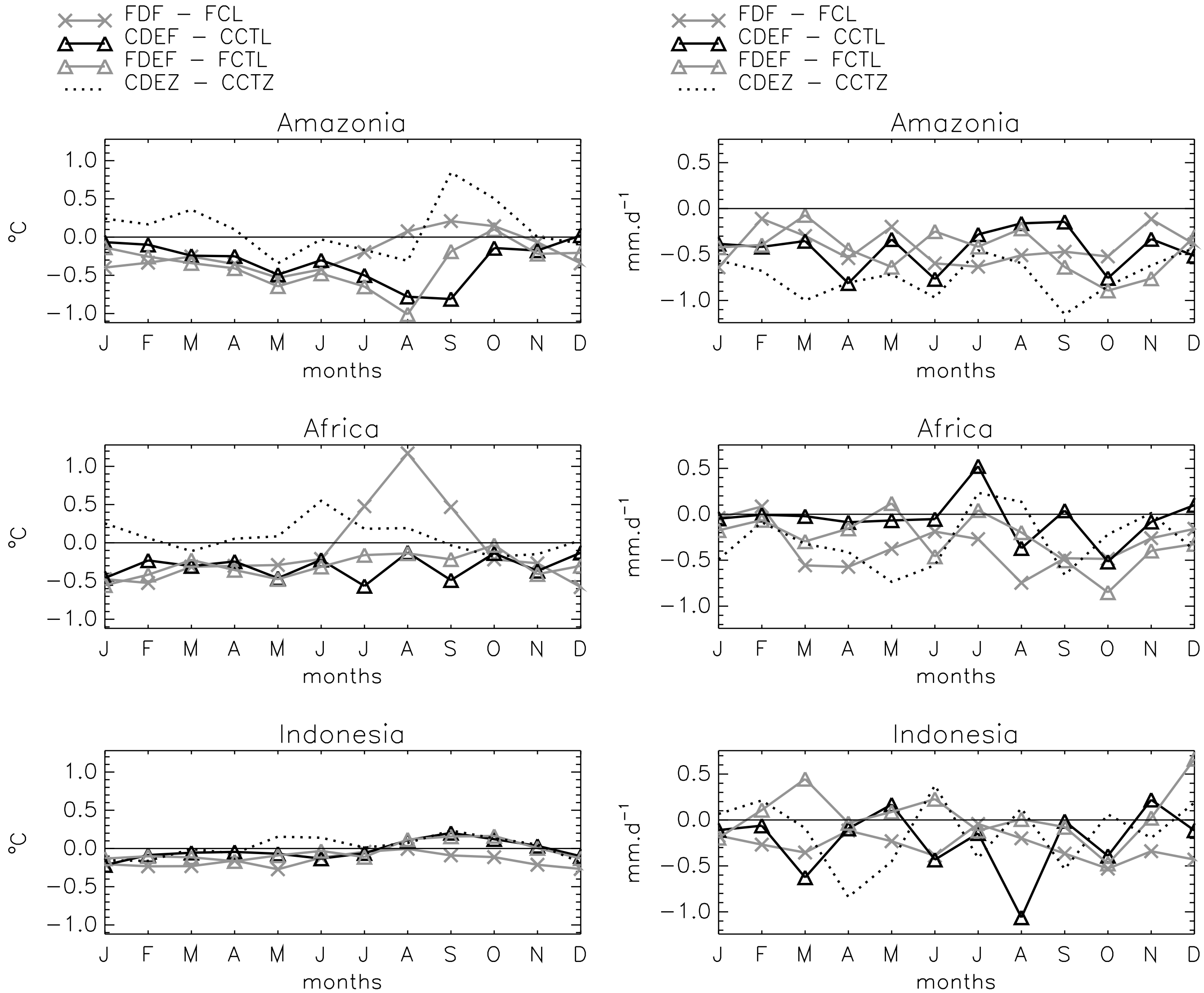


Fig. 6 Seasonal cycle of monthly mean anomaly of near surface temperature in °C (on *left*) and precipitation in mm day^{-1} (on *right*) for Amazonia, Africa (*right*), for the deforested experiments compared to their respective control experiment

almost 4 °C. Consistently, the sensible heat flux is much weaker and the latent heat flux increases by more than 15 W m^{-2}. There are also more clouds and precipitation.

Over Amazonia, the near surface temperature seasonal cycle is close to observations when using observed SSTs (Fig. 5). In the coupled model, there is a warm bias of more than 4 °C when precipitation drops during JAS and JFM. For precipitation, the dry bias is generally constant for all months with observed SSTs and is enhanced in coupled mode from January to April. The biases observed for temperature and precipitation are probably linked, since less precipitation means less water for evaporation, thus an increase in energy at the surface and a subsequent temperature increase. We remark that the use of SSTs from the coupled simulation leads to the same control climate as when using the coupled model. The differences in the control climate are thus attributable to changes in SSTs rather than to the effect of coupling the ocean.

Over Africa, the mean climate is much more similar between the coupled experiments (CCTL and CCTZ) and the experiment with observed SSTs. All surface fluxes are of similar magnitude. There is only an increase in mean temperature by 1 °C and a weak increase in precipitation in the coupled experiments. The change in the seasonal cycle is also weaker. We also note that the characteristics of the climate are very similar for the experiments CCTL and FCTL, which use the same SSTs. The local characteristics of the CCTZ experiment are very close to those of the CCTL experiment. There is only a noticeable decrease in surface wind magnitude due to the increase in roughness length over tropical forests in this experiment.

Over Indonesia, the mean climate is the same whatever the ocean forcing is. The seasonal cycle is particu-

Table 7 Mean annual parameters over the African deforested region in JJA for the control simulations and their anomalies in the corresponding deforested experiments

Parameter	FCL	FCTL	CCTL	FDF-FCL	FDEF-FCTL	CDEF-CCTL
Daily maximum temperature (°C)	29.4	30.9	30.9	+**2.3** (100)	+**1.2** (92)	+**0.8** (67)
Sensible Heat F. (W m^{-2})↑	22.4	20.6	22.0	+**18.8** (92)	+**9.7** (92)	+**5.0** (67)
Evaporation (mm day^{-1})	3.7	3.7	3.7	−**0.9** (100)	−**0.5** (83)	−**0.4** (50)
Precipitation (mm day^{-1})	2.4	3.0	3.0	−**0.4** (100)	−0.2 (25)	0.0 (0)

Values in *italics* indicate anomalies significant at the 90% level. The number between *brackets* indicate the percentage of grid cells for which grid anomalies are significant at the 90% level in the domain (this gives an indication of the homogeneity of the response)

larly weak for temperature and precipitation. The annual variations of near surface temperature are well reproduced but with a constant bias of less than 2 °C. For precipitation, the cycle is better simulated in CCTL and FCTL, and the bias is generally negative. The robustness of the simulated mean climate when including the ocean model is quite surprising. As this is a maritime region, the influence of the ocean component was expected to be higher.

Overall, this analysis confirms that the coupled model simulates quite a different climate compared to that of the atmospheric model forced with observed SSTs. As expected, the atmospheric model forced with simulated SSTs correctly reproduces the climate of the coupled experiment. The comparison of FDEF to CDEF will thus only indicate the effect of the coupling. The results also confirm that the control climate is not modified in CCTZ as compared to CCTL.

4 Local impacts of deforestation

4.1 Annual mean impact

Tables 4, 5 and 6 show the annual mean anomalies averaged over each domain of deforestation. The significance of these anomalies is assessed with a Student t-test with a 90% confidence level (this is the significance of the averaged regional anomaly which is tested).

The annual mean impact on surface heat fluxes is very similar in all deforested experiments (Table 4). Over Amazonia, for the first three experiments (FDF, FDEF and CDEF), the sensible heat flux increases by 7 to 8 W m^{-2} and the latent heat flux decreases by 11 to 13 W m^{-2}. The magnitude of the anomalies is only slightly weaker over Africa and Indonesia. The experiment CDEZ is consistent with the other experiments, but with a stronger impact over Amazonia. Looking at the radiative fluxes over Amazonia, anomalies are not significant except for the decreases in net downward solar radiation and in net upward long-wave flux in the FDF experiment and the increase in upward long-wave radiation in experiment CDEZ. The weak impact obtained on the net surface solar flux is explained by the compensation between the increase in surface albedo, that tends to reduce the surface solar flux, and the decrease in cloudiness, that results in an increase in incident solar flux. Hahmann and Dickinson (1997) also found the same compensation effect. Over Africa, there is a more intense and significant reduction in net downward solar flux than over Amazonia. Indeed, over Africa, there is no significant reduction in cloud cover, thus the increase in albedo has a direct impact on the net surface solar flux. The impact on annual mean surface fluxes is very similar for the three experiments FDF, FDEF and CDEF, whereas the control climate is quite different in experiment CCTL and FCL. Over Indonesia, there are no significant impacts on radiative fluxes.

The impact on mean daily extreme temperatures is of the same magnitude for all experiments. However, the resulting change in mean temperature is quite different between the experiments due to the competing effects of the increase in maximum temperature and the decrease in minimum temperature. In the first three experiments (FCL, FCTL and CCTL), mean temperature tends to decrease (though generally below significant level) whereas in the CDEZ experiment, temperature tends to increase.

The surface wind magnitude is increased in all deforestation experiments. This impact is enhanced in the CDEZ experiment and is consistent with the greater reduction in roughness length imposed on this experiment.

Over Amazonia, there is a significant decrease in precipitation in the four experiments. As for surface fluxes, this reduction is of the same magnitude in the first three experiments and is enhanced in the CDEZ experiment. This decrease in precipitation is correlated to a decrease in cloud cover. The initial moisture convergence (approximated as precipitation minus evaporation) is only weakly reduced in all experiments and not significant. This suggests that the reduction in precipitation is directly induced by the reduction in local evaporation and there is no change in the large-scale moisture advection.

Over Africa, there is a reduction in precipitation for all experiments, except CDEF. The contrasted impact in the experiment FDEF as compared to CDEF suggests that there might be a significant SST feedback in the CDEF experiment, which cannot be captured in the FDEF experiment (as SSTs are fixed). However, we also observe a reduction in precipitation in the CDEZ experiment. As the impact is weak, it is hard to draw conclusions from the statistical significance of this effect. There may be an oceanic feedback in the CDEF experiment due to the use of a dynamic ocean. However, the

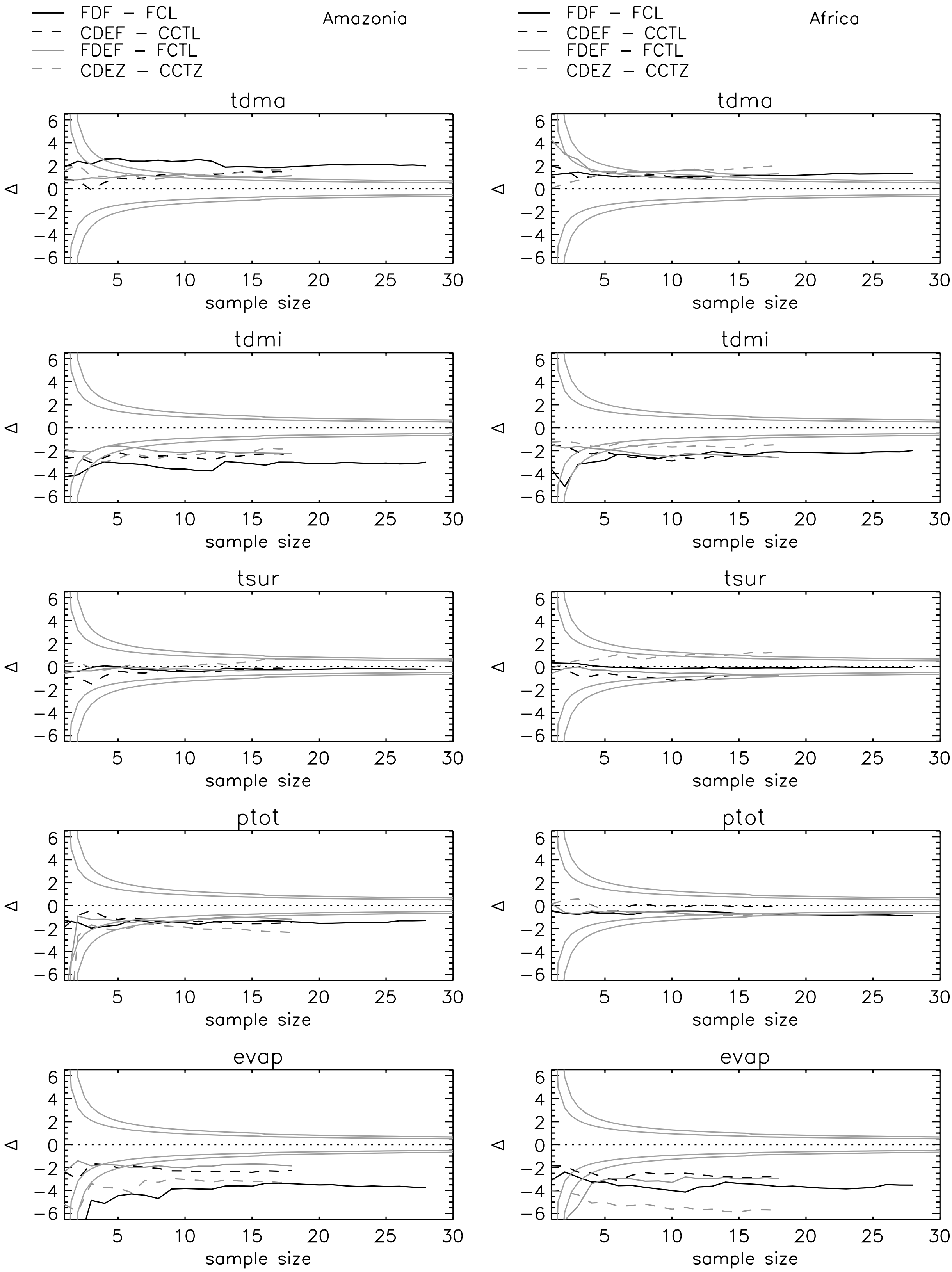
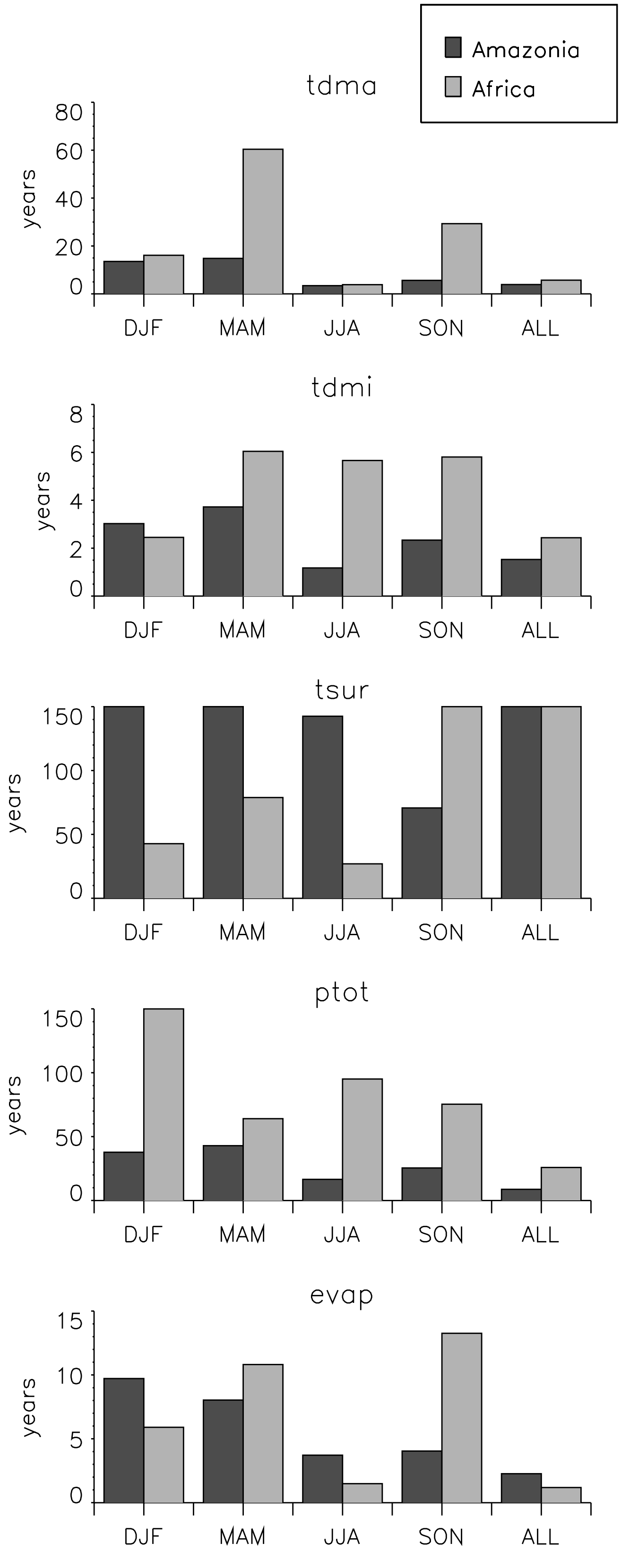


Fig. 7 Signal-to-noise function Δ as a function of sample size for annual mean anomalies of daily minimum temperature and maximum temperature, mean surface temperature, precipitation and evaporation for Amazonia (*left*) and Africa (*right*). *Grey curves* indicate the 95 and 99% significance levels according to a Student distribution



◀

Fig. 8 Theoretical sample size requested to statistically discriminate the seasonal and annual mean deforestation "signal" over Amazonia and Africa. The "signal" is defined as the mean anomaly between all deforested experiments and their respective control simulations. A 150-year control simulation that used the same AOGCM gives the variance (The *vertical axis* has been limited to 150 years but a few cases give higher values)

fact that we do not observe the same effect in CDEZ highlights the complexity of studying coupled atmosphere-ocean experiments and leads us to be cautious, since the sample is probably not large enough to analyse such weak differences. Unlike Amazonia where the pattern of precipitation change is located over the deforested area and is similar in all simulations, the patterns of precipitation anomalies are less robust over Africa (Fig. 13).

These results show that the indirect atmospheric impact of deforestation can be more easily detected over Amazonia than over Africa in such a GCM experiment. This can be partly due to the different large-scale circulation or variability of these regions, but the primary cause is mainly the extension of the deforested area. The region of uniform intense deforestation is three times larger in Amazonia. Over Africa, the extent of deforestation might not be large enough to consistently modify the moisture cycle.

Over Indonesia, impacts on diagnostics, which are directly determined by land surface properties, are consistent and significant. On the contrary, for radiative fluxes, precipitation and cloudiness, which are less directly dependent on the surface characteristics, the impacts are not significant in all experiments. As presented by Kanae et al. (2001), this region is subject to the Asian monsoon regime and land cover changes have a weak effect on the regional climate, except for the months when the external forcing of westerlies weakens. Our results seem to corroborate this analysis.

The impacts on annual means, which represent the broad response to deforestation, does not seem to depend much on the control climate. However, this might not be true on a monthly time-scale. A thorough analysis could reveal that mechanisms are somewhat different depending on the control climate and the model. The impact on precipitation over Africa is not similar in all experiments. This different response might reveal that the impact over this region depends more on the initial dynamics than over Amazonia, or that the signal is weak and the simulation lengths too short to detect it.

4.2 Monthly mean impact

For near surface temperature over Africa and Amazonia (Fig. 6), experiments CDEF and FDEF do not show an increase in JAS (end of the dry season) as for FDF. This is due to a weaker impact on maximum daily temperature in CDEF and FDEF in this season. The reason for the different impact on maximum temperature is still unclear. However, this is correlated to a weaker impact on surface evaporation and sensible heat flux in this season (Table 7). The weaker impact on surface fluxes might be a consequence of the weaker reduction in precipitation, which is more crucial during the dry season. Anomalies over Africa are somewhat more intense in FDEF than in CDEF but still weaker than in FDF. This suggests that the different control climate could be the cause, but that coupling with the ocean may also play a role. Only the changes in anomalies between CDEF and FDF for maximum temperature, evaporation and sensible heat flux are significantly different from zero at the 90% confidence level. Differences in anomalies between CDEF and FDEF are not statistically significant, and only the anomaly of evaporation is significantly different between FDF and FDEF. This points out the difficulty of discriminating the anomalies of different experiments.

For Indonesia, the impact on temperature is weak for all months. For precipitation, the impact has a great deal of variability and no consistent behaviour between the simulations is obtained. However, this region is somewhat difficult to analyse for several reasons. Firstly, the grid cells are not continuous, thus there is less homogeneity in the control climate between grid points in this region than in Amazonia or Africa. Secondly, as for Africa, the domain is small and the perturbation might be too weak to detect any impact on precipitation. Thirdly, this is a region where inter-annual variability is high and which is strongly governed by external factors, such as the monsoon and the ENSO. Hence, detecting the signal due to land cover change over this region is certainly more complex than over continental Amazonia and requires longer simulations so as to better sample

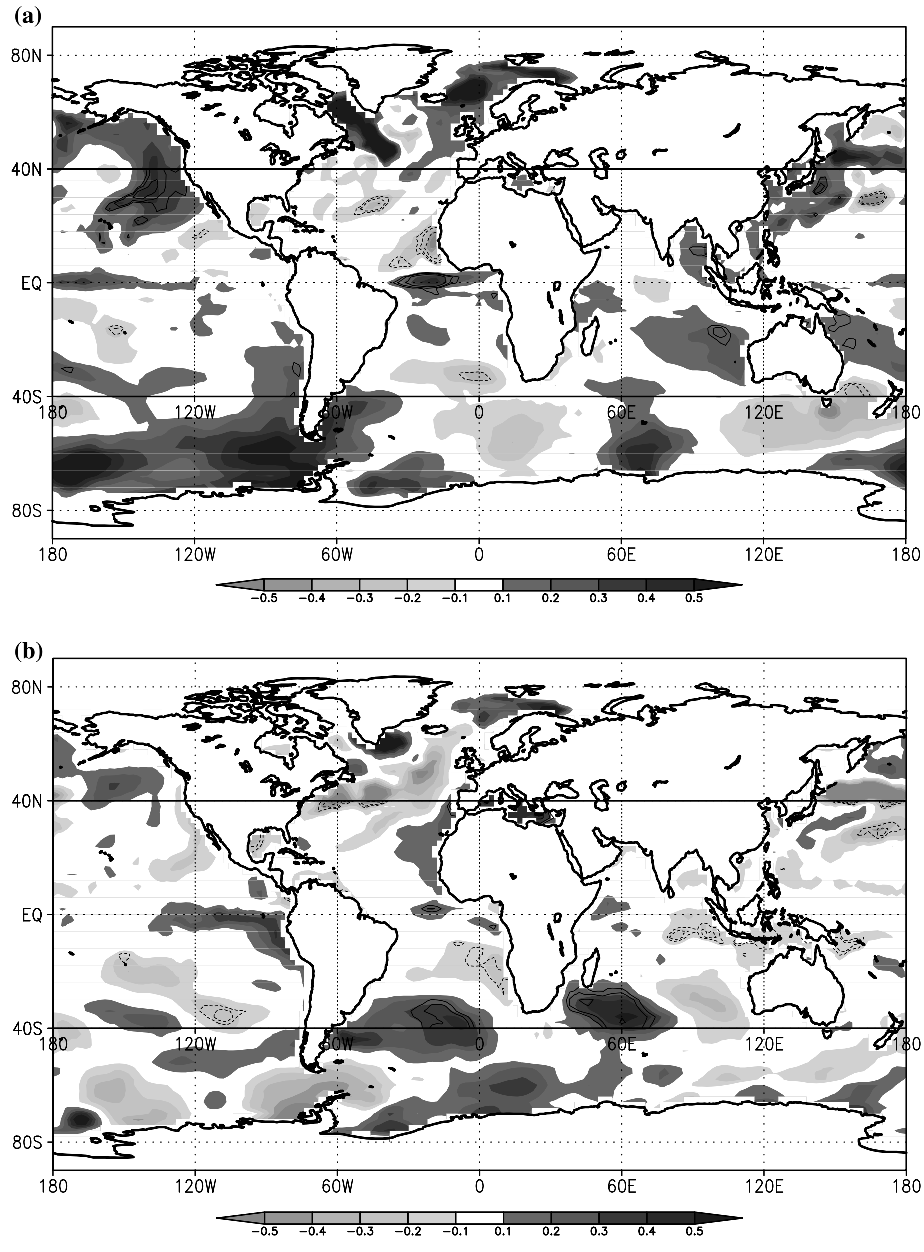
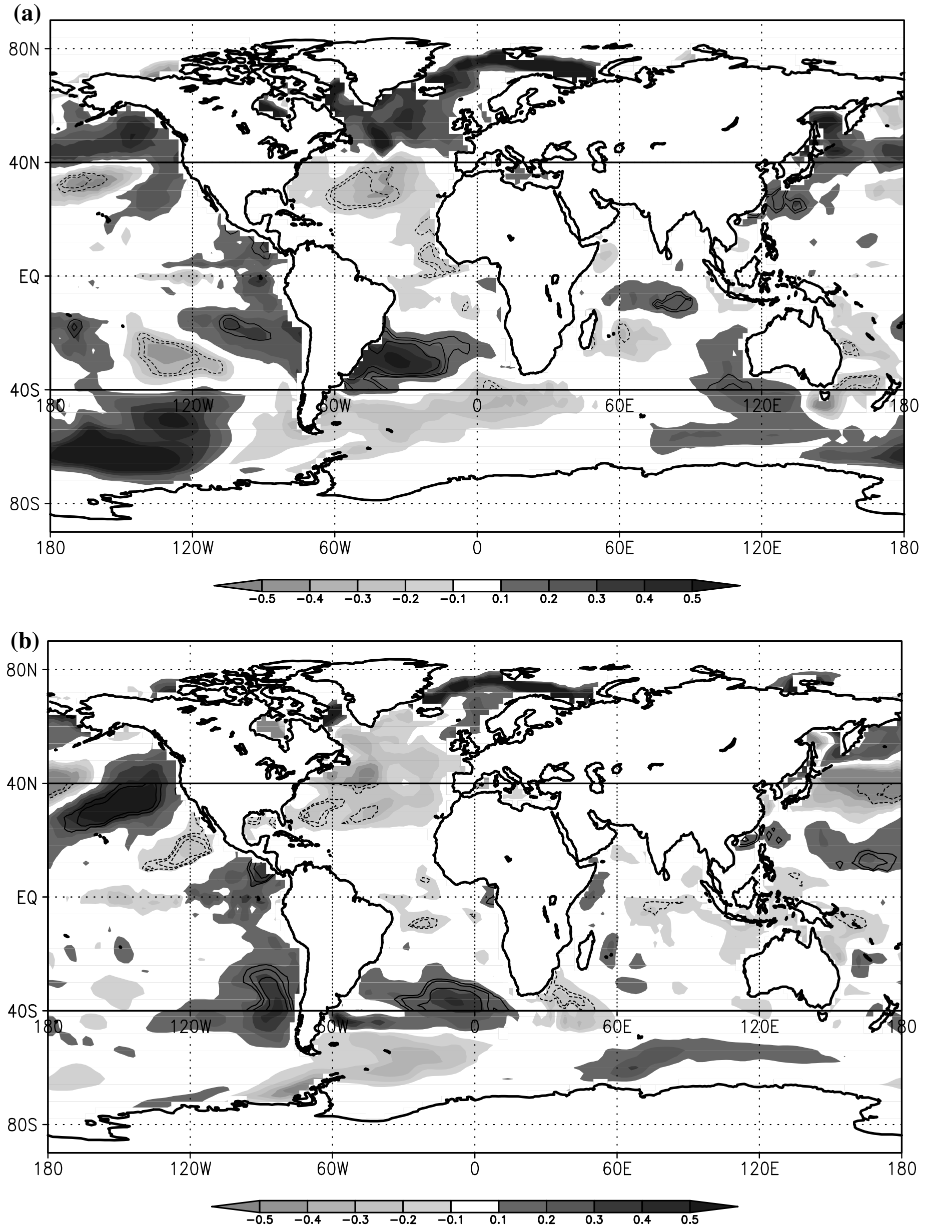


Fig. 9 SSTs anomalies (°C) in DJF between **a** CDEF and CCTL and **b** CDEZ and CCTZ. *Contours* indicate anomalies significant at the 90, 95 and 99% levels

Fig. 10 Same as Fig. 8 for JJA



ocean variability. As demonstrated by Delire et al. (2001), our results suggest that studying deforestation over Indonesia requires a special experimental design. The use of a regional climate model including the ocean component, allowing longer integrations, might be a good choice.

The impact on surface temperature in CDEZ is somewhat different than in the other experiments. This different impact is due to a different relative impact on maximum and minimum temperatures: the increase in maximum temperature is more intense due to the greater reduction in roughness length.

On a seasonal scale, there are more differences between the experiments than for annual means. However, the differences in anomalies are too weak to be statistically distinguished. A finer study of the response than the analysis of annual means reveals that the impact of deforestation is dependent on the control climate, and that the inclusion of the interaction with the ocean can have an impact on the response.

However, for precipitation, the annual cycle of anomalies does not present any particular behaviour. Even for Amazonia, there is a decrease for all months but the monthly anomaly differences seem to be due more to variability rather than to different mechanisms.

4.3 Signal-to-noise ratio

The simulations performed are at least 20-year-long runs, which is a rather long period compared to most previous deforestation experiments. It enables the study of the signal to noise ratio and we can try to investigate the length of simulation needed to detect the deforestation impact at a given level of confidence. The analysis is based on the Student t-test:

$$t = \frac{|\bar{x}_2 - \bar{x}_1|}{\sigma\sqrt{(2/n)}}, \tag{1}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the mean value of two n-year time series and σ the standard deviation of the time series. Here we suppose that deforestation has not modified the variance and that time series x_1 and x_2 have the same variance. This has been tested with a Fisher F-test and the hypothesis was, most of the time, justified. The anomaly $\bar{x}_2 - \bar{x}_1$ is said to be significantly different from zero at a 95% level of confidence if $t > t_{95}(n)$. In our experiments, we calculated the value:

$$\Delta(n) = \frac{\bar{x}_2(n) - \bar{x}_1(n)}{s'(n)} \quad \text{where } s'^2 = \frac{1}{2}(s_1'^2 + s_2'^2) \tag{2}$$

as a function of the number of years used to estimate the mean and variance of each experiments ($\bar{x}_1(n)$ and $s_1'^2(n)$). In Fig. 6, grey curves indicate the level of significance as calculated as a function of the sample size:

$$f_{95}(n) = t_{95}(n)\sqrt{\frac{n}{2}} \tag{3}$$

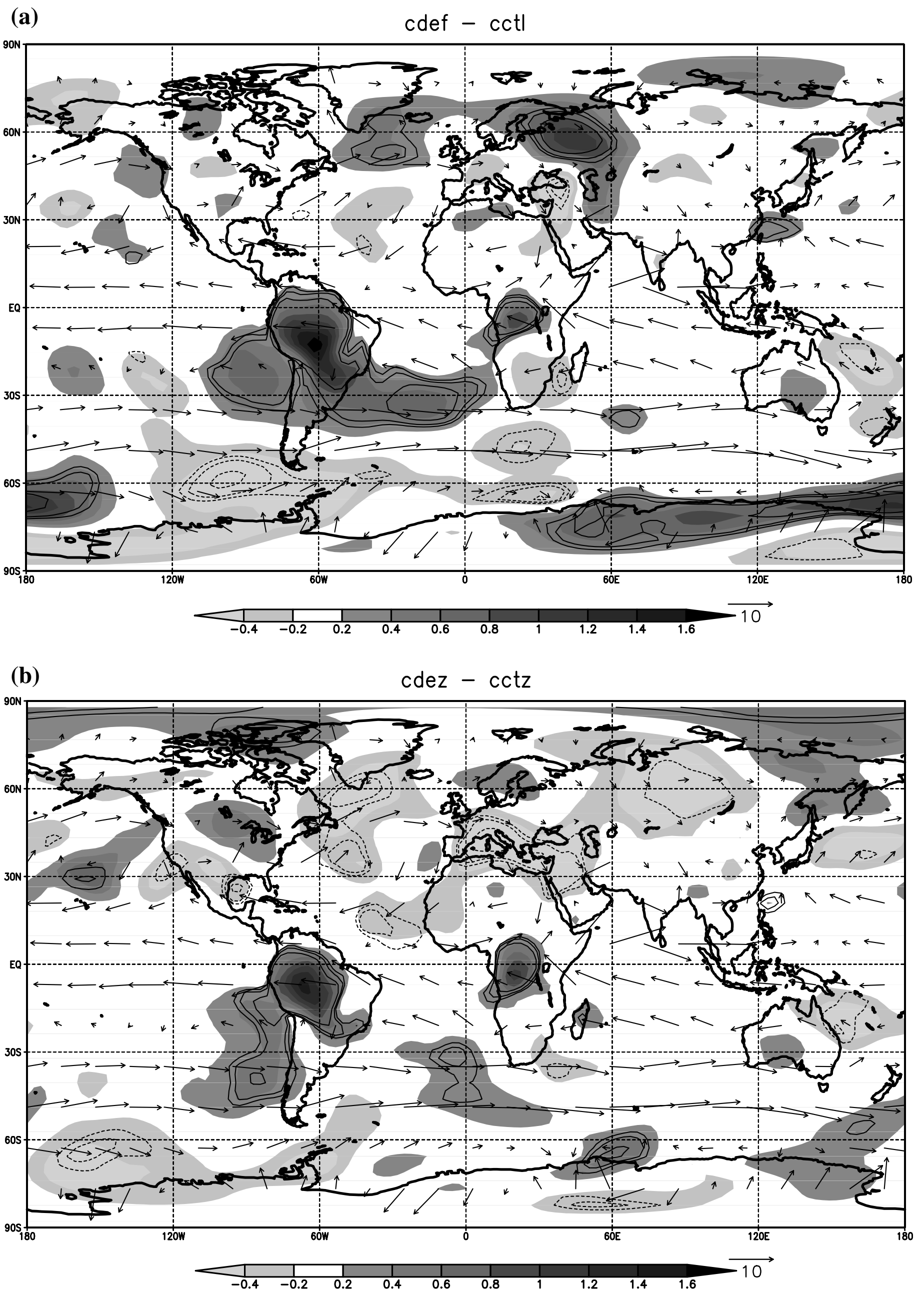


Fig. 11 Same as Fig. 9 for atmospheric temperature at 850 hPa in JJA with the control simulation wind vectors at 850 hPa superimposed

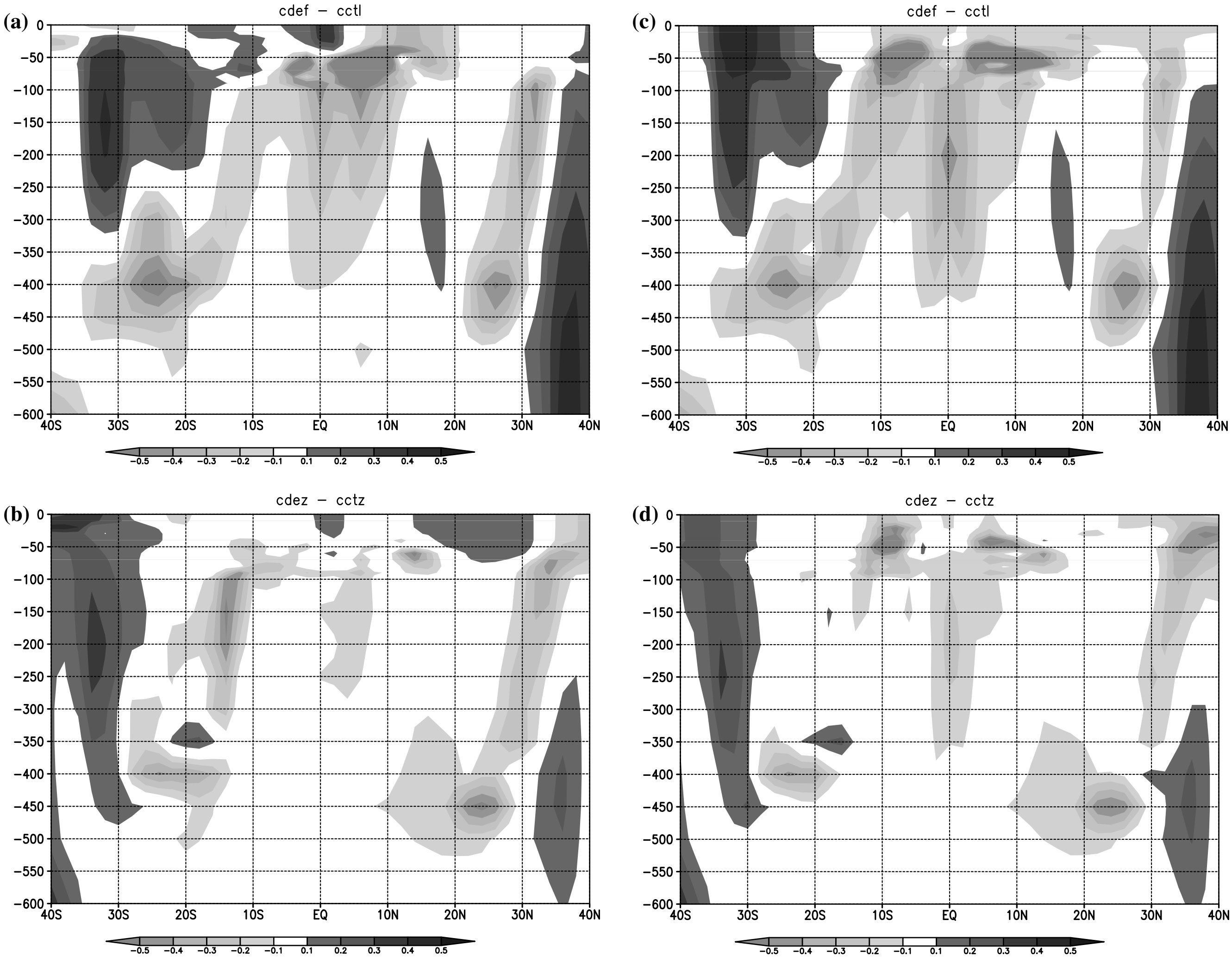


Fig. 12 Meridional section of the sea temperature (°C) averaged anomaly over (40°W–20°W) in DJF (**a, b**) and JJA (**c, d**) for the deforested experiment CDEF (*top*) and CDEZ (*bottom*)

For most diagnostics, the value of Δ is quasi-constant for n larger than 5 years (Fig. 7). This suggests that the length of simulation needed to reach a given significance level only depends on the amplitude of the signal as compared to the variability of the model. The function Δ has been recalculated with s' taken as a constant (the value for n maximum) to detect the influence of the estimate of the variance in the signal. For all parameters, the curves are similar with or without the variance taken as constant. With more than 5 years they are rather equivalent. This indicates that the problem of sampling the variance is reduced with 5 years of simulation. This also suggests that there is no trend in the difference of means. This shows that there is no amplification effect (or positive feedback) that would increase the signal magnitude with time. This figure is therefore an indicator of the strength of the impact of deforestation in our model. For maximum temperatures, apart from the FDF experiment over Amazonia, the signal reaches the significance level over at least 15 years of simulation. On the contrary, for minimum temperatures, the signal is much stronger and reaches a high level of significance over only 10 years of simulation. The mean surface temperature signal is less consistent between the experiments. It seems to be zero for all experiments over Amazonia. However, the CDEZ experiment curve indicates an increase in the signal with the number of years considered. Over Africa, there is no signal for FDF, while for the other experiments there is a tendency for the signal to increase. The tendency observed here could be attributed to an increase in the difference in mean or to a decreasing estimate of the variance while increasing the number of years.

For precipitation, the signal reaches a significance level for all experiments within 15 years over Amazonia, but is still not significant after 20 years over Africa. As was suggested by the analysis of annual means, there is no impact on precipitation over Africa in the CDEF experiment and the evolution of Δ confirms this. For evaporation, the signal is strong and can be detected

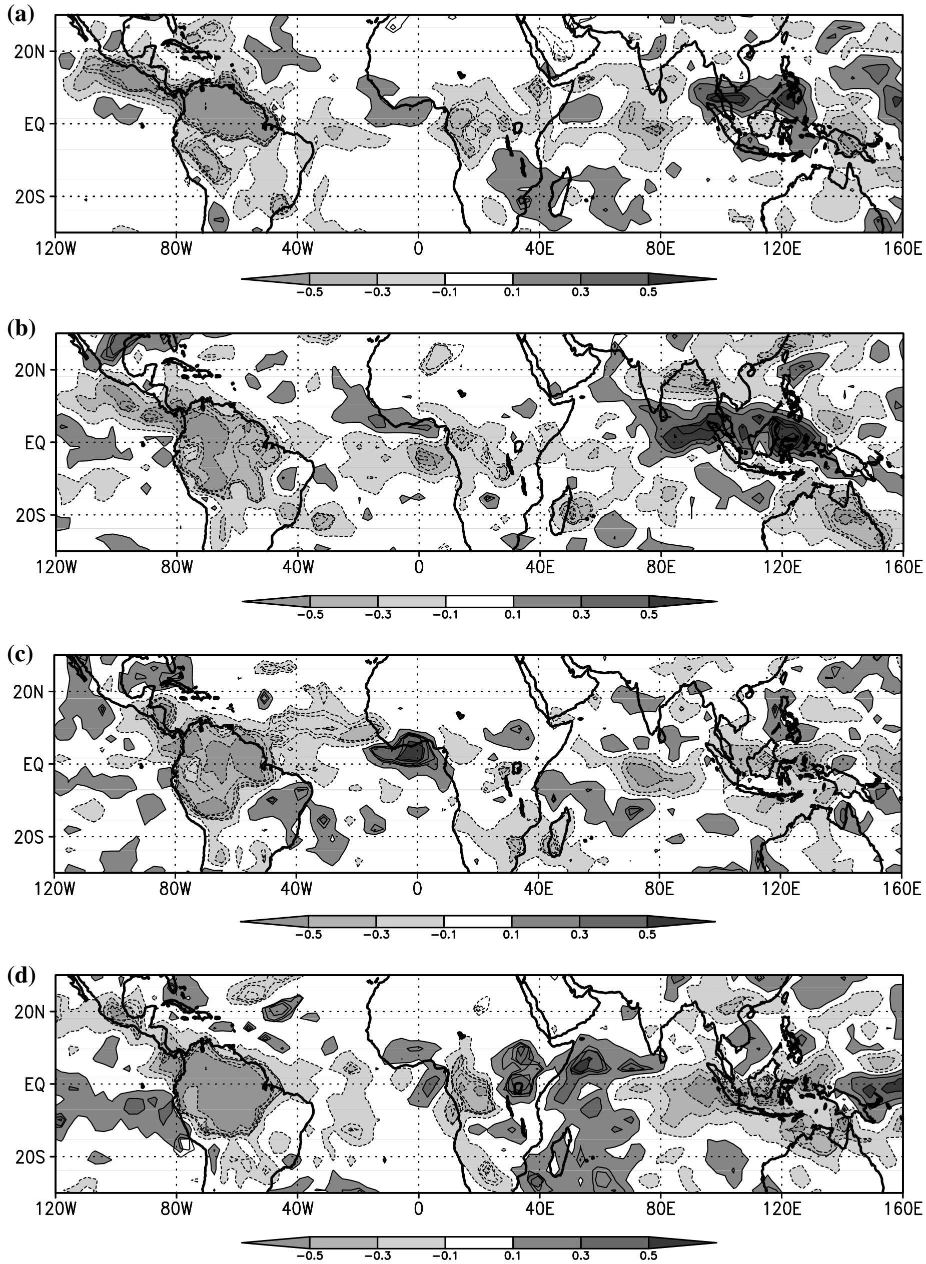


Fig. 13 Annual mean precipitation anomaly (mm day^{-1}) in **a** FDF, **b** FDEF, **c** CDEF and **d** CDEZ as compared to their respective control simulations (FCL, FCTL, CCTL and CCTZ)

with a high confidence level within less than 10 years of simulation.

We also note that the signal amplitude is comparable between the experiments. There is no clear difference between forced SSTs and coupled ocean simulations. This allows us to consider them as an ensemble of deforestation experiments for which we can calculate an averaged signal. If we consider that we know a reliable estimate of the variance σ^2 then we can calculate the number of years needed to discriminate the signal from natural variability with the equation:

$$n_l > 2t_{95}^2 \frac{\sigma^2}{(\bar{x}_{\mathrm{DEF}} - \bar{x}_{\mathrm{CTL}})^2} \quad (4)$$

where $(\bar{x}_{\mathrm{DEF}} - \bar{x}_{\mathrm{CTL}})$ is the averaged signal calculated by averaging the anomalies between all deforested experiments and their respective control simulation.

To estimate the variance of our coupled model, we have used a 150-year integration, which has been used as a control experiment for scenario simulations of the twenty-first century (Royer et al. 2002). This simulation used constant forcings for boundary conditions and GHG concentrations. Values of n_l have been calculated for each domain and different parameters and are shown in Fig. 8. Notice that the vertical axis is limited to 150 years to obtain readable and comparable figures between different parameters. However, for surface temperature, in most cases, the number of years evaluated is higher (of the order of few centuries). For this parameter, as the sign of the impact is different depending on the experiment, aggregating all experiments does not increase the signal. The fact that the number of years is so important indicates that on average there is no signal. Two conclusions are thus possible: there is no impact on this parameter or the different experiments obtained different impacts in sign which could be significant but which are different because of the different ocean forcing. In the latter case, the chosen method to evaluate the number of years is not appropriate.

For the other diagnostics, the estimated sample size needed strongly depends on the parameter considered. For daily maximum temperature, it is of an order of 20 years for seasonal means and can be reduced to 10 years for annual means. For minimum temperatures and evaporation, it is less than 10 years. However, for precipitation it is estimated to be between 50 years and 100 years depending on the domain considered. This estimate depends on the amplitude of the response to deforestation, and is therefore model-dependent. Nonetheless, this provides a general idea of the required size of simulations needed to detect such a signal. It is not surprising that we obtain an evaporation signal quickly as this variable is affected immediately by the changes in biophysical parameters. Temperature is a second order parameter that reflects change in available energy and its partitioning. Precipitation is obviously a third order parameter, which is impacted through modification of the atmospheric circulation and/or properties.

This diagnostic could be considered as a good indicator of the strength of the coupling between land and atmosphere in different models. For instance, the length of time needed to detect the impact on precipitation could be a good indicator of the strength of the coupling in inter-comparison studies.

5 Remote impacts

5.1 Impact on sea surface temperatures

If the ocean plays a role in the deforestation experiment, we should observe differences in the SSTs between experiments CCTL and CDEF, CCTZ and CDEZ. The Student *t*-test has been calculated for seasonal mean anomalies of SSTs and is shown in Figs. 9 and 10. Note that this test is not reliable outside tropical regions. As the auto-correlation of the seasonal mean SSTs can be important in middle and high latitudes, we cannot consider that each year of the experiments is independent from the others and the equivalent sample size would be very small. In the Tropics, the auto-correlation is generally weaker (except in the eastern Pacific). The equivalent sample size necessary to account for the non-independence of years is therefore rather large and the *t*-test can be considered as a broad indicator of the significance of anomalies. The level of significance is thus only indicated between 40°S and 40°N on Figs. 9 and 10.

There are only a few regions where anomalies of SSTs between two experiments are significant (Fig. 9). Over the tropical Atlantic, we observe a significant warming along the Equator in DJF both in CDEF and CDEZ. In CDEF, there is also a cooling along the west coast of Africa, which is not reproduced in CDEZ. In JJA, a strong warming occurs in both experiments in the south Atlantic and south Pacific close to the South American continent (Fig. 10). This warming is more intense in the CDEF experiment but it is still significant at the 99% level in CDEZ. This warming is associated with a warming of low-level atmospheric temperature (Fig. 11). The similarity of the patterns of SST and atmospheric temperature anomalies is noticeable. However, for the experiment CDEF the increase in atmospheric temperature over Amazonia seems to spread over the ocean on both coasts. This experiment suggests that the ocean anomaly could be generated by the atmospheric impact of deforestation over Amazonia. On the other hand, for the CDEZ experiment, the warming over the south Atlantic does not seem to be related to the South American coast. It is thus unclear whether the atmospheric anomaly above the ocean is the cause or the consequence of the SST anomaly. Nevertheless, the similarity of the response over the Pacific could indicate that the SST anomaly is due to the atmospheric warming induced by deforestation.

Figure 12 illustrates how deep these temperature anomalies extend into the Atlantic Ocean. Temperature anomalies are not limited to the surface. Associated with the large positive SST anomaly observed over southern Atlantic in JJA, there is a warming up to a depth of 350 m. This pattern is observed in both experiments, but the signal is stronger in CDEF. It is also observed in DJF but it has disappeared from the surface in the CDEF experiment. There is also a cooling in the equatorial Atlantic. In DJF, the cold anomaly does not reach the surface where a significant warming is observed. The cooling is more intense in the CDEF experiment, however the pattern is quite similar in the two experiments in JJA with a 50-m deep core under the surface at 8°S and 8°N.

We thus observe an impact in ocean temperature over a depth of a few hundred meters, which is quite consistent between experiments CDEF and CDEZ. Nevertheless, the local impact of deforestation is stronger in CDEZ whereas the impact on oceanic temperatures is weaker.

5.2 Impact on precipitation

The impact of deforestation on precipitation is generally weak (Fig. 13). Except over the deforested regions, there are only one or two regions where anomalies are significant but there is no consistency between the experiments. In CDEF, there is a significant decrease in precipitation at 10°N over the Atlantic, but this anomaly is not reproduced in other simulations. One might conclude that it is a consequence of the use of an ocean model, but this has yet to be proved. Moreover, the fact that we do not observe the same impact on CDEZ raises more doubts. There is also an increase in rainfall along the Guinean coast. This increase is not significant except for CDEF, but it is consistently observed in all simulations. The analysis of the signal-to-noise ratio over deforested regions has shown that the precipitation signal was weak compared to natural variability and required large sample sizes to be statistically significant. As remote impacts on precipitation are smaller than local impacts, this suggests that the sample size of 20 years for CDEF and CDEZ is still too small to study remote effects on precipitation as well.

6 Conclusion

A thorough tropical deforestation experiment has been performed in a coupled atmosphere-ocean GCM in order to compare the impact with that found in a forced AGCM. An analysis of the signal-to-noise ratio has shown that the inclusion of the ocean component has not greatly modified this ratio. Hence, the length of simulation needed to detect the impact of land cover change is not increased when using the coupled AOGCM. It has been shown that impacts on fluxes are almost immediately statistically significant since they directly reflect the changes in biophysical parameters. The impacts on the surface energy balance need a longer integration period in order to be detected, while the impacts on the atmospheric circulation and precipitation need even longer periods of integration, of the order of a century. The time evaluated here is obviously model dependent, however the broad time-scale might not be greatly modified with other GCMs. We suggest that differences in simulation length needed to detect the land cover change signal between models could reflect the strength of their coupling between land and atmosphere.

With the ocean system, the control climates deteriorated to some extent, thus the simulated impacts to deforestation are less realistic than when using observed SSTs. On the other hand, we have shown that there were some impacts on the upper ocean in both coupled simulations. This indicates that neglecting the ocean component in such studies might also not be completely realistic. Here, as the oceanic impacts are limited to the first hundred meters, this suggests that most aspects of the remote response could be realistically simulated with an AGCM coupled to a mixed-layer ocean model. A similar experiment comparing the effect with an ocean GCM and a mixed-layer model could be proposed. The use of a mixed-layer ocean model would have another advantage: the simulated control climate would be more realistic than with an ocean GCM since the system is more constrained.

The indirect effect of ocean changes on the atmosphere could hardly be detected. Even when increasing the land cover perturbation, the oceanic impacts were not enhanced. These indirect effects are of second order and their detection would require larger ensembles of experiments.

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