Probabilistic downscaling of GCM scenarios over southern India

Nicolas Vigaud, M. Vrac, Yvan Caballero

[b] *Laboratoire des Sciences du Climat et de l'Environnement (LSCE-IPSL), CEA/CNRS/UVSQ, Gif-sur-Yvette, France*
[c] *Service Géologique Régional, Bureau de Recherches Géologiques et Minières (BRGM), Montpellier, France*

ABSTRACT: The cumulative distribution function transform (CDF-t) is used to downscale daily precipitation and surf temperatures from a set of Global climate model (GCM) climatic projections over southern India. To deal with the annual cycle, the approach has been applied by months, allowing downscaled projections for all seasons. First, CDF- validated over a historical period using observation from the Indian Meteorological Department (IMD). Resulting h resolution fields show substantial improvements compared to original GCM outputs in terms of distribution, seasonal cy and monsoon means for arid, semi-arid and wetter regions of the subcontinent. Then, CDF-t is applied to GCM large-sc fields to project rainfall and surface temperature changes for the 21st century under the IPCC SRES A2 scenario. T results obtained show an increase of rainfall, mostly during the monsoon season, while winter precipitation is reduced, a suggest a widespread warming especially in the winter and post-monsoon season. Copyright © 2012 Royal Meteorolog Society

KEY WORDS downscaling; climatic scenarios; southern India

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1. Introduction

Associated with fast social and economic growth locally, climate changes are likely to seriously impact India. As noted by Kundzewicz *et al.* (2007), southern India is already a water-stressed region. Climate changes have already been observed over the subcontinent, where increases of 0.4–0.6 °C have occurred over the past century together with the annual mean temperature warming most pronounced during post-monsoon and winter periods (Rupa Kumar *et al.*, 2006; Bhattacharya, 2007). In terms of precipitation, Cruz *et al.* (2007) have observed for the last decades that extreme summer monsoon rains increase over northwest India and the number of rainy days decrease along the east coast. While these projections are subject to large uncertainties (Paeth *et al.*, 2008), the potential impacts on water resources in India still need to be assessed depending on their location.

Global climate models (GCMs) are nowadays the only tool at disposal to investigate future climate variability. However, GCM projections cannot be used directly for impact studies due to the coarse resolution of GCM outputs which are not suited for regional assessments (Wilby *et al.*, 2004). Therefore, downscaling methods have been developed to go from large-scale data to local-scale data. The dynamical approach consists of using regional climate models (RCMs) to resolve physical equ of atmospheric regional dynamics (Wood *et al.*, 2 RCMs are, however, domain dependant and comput ally expensive, which restricts their use for many ap tions. The statistical approach, on the other hand, re statistical relationships between large-scale GCM fe and local-scale climatic variables (such as precipitat temperature, for instance). Statistical downscaling ods (SDMs) are quite flexible and generally requir computational costs. Such advantages make them p ularly attractive for regional impact studies. SDM be classified into three major categories: transfer tions, weather typing and weather generators. Tr functions are based on direct quantitative relatio between predictand and predictors through regre like methods (Prudhomme *et al.*, 2002). Weather t approaches consist in the grouping (or clusterin atmospheric circulations in relation to local meteo ical variables (Vrac *et al.*, 2007), while weather g tors are stochastic models simulating local-scale var based on their probability density function, whose p eters depend on large-scale information (Hughes 1999; Wilks and Wilby, 1999; Vrac and Naveau, 2 Worthnotingly, a common assumption to all SDMs the physical relationships underlying the statistical tionships identified over a historical period remain for the future climate scenarios to be downscaled.

Several SDMs have already been used for dow ing rainfall over India, such as relevance (Ghos

* Correspondence to: N. Vigaud, Service EAU, Bureau de Recherches Géologiques et Minières (BRGM), Montpellier, France.
E-mail: nicolas.vigaud@gmail.com

SDMs can also be used to model relationships between large-scale and local-scale statistical characteristics and can be referred in this context as probabilistic downscaling methods (PDMs). The cumulative distribution function transform (CDF-t) presented in Michelangeli *et al.* (2009) has the advantage of directly dealing with and providing CDFs. This method is used in this paper to downscale GCM projections from the Intergovernmental Panel on Climate Change Fourth Assessment Report (IPCC AR4) in order to investigate projected changes in both rainfall and surface temperatures over southern India. The purpose of this study is to document the use of CDF-t for providing regional precipitation and surface temperature changes as derived from several medium-term GCM projections under the Special Report on Emission Scenarios (SRES published by the IPCC) A2 scenario (horizons 2040–2060). Most of the recent statistical downscaling studies of future climate scenarios over India were restrained to the monsoon season (Tripathi *et al.*, 2006; Mujumdar and Ghosh, 2008) or to specific watersheds (Ghosh and Mujumdar, 2007; Anandhi *et al.*, 2008, 2009). This paper aims to present results from the CDF-t probabilistic downscaling method applied not only to the June–September (JJAS) monsoon period alone but to the full annual cycle, and for a domain covering the whole of southern India. In the next section, the data used and the downscaling method are presented. Then, the CDF-t approach is validated on a historical period in Section 3, prior to applying the method to downscale future scenarios from IPCC AR4 experiments in Section

seven GCMs as most reliable regarding Indian r
rainfall based on their representation of the mo
sonal cycle in phase and amplitude. Regarding th
ability of daily standard outputs from the Prog
Climate Model Diagnosis and Intercomparison (
database, five GCMs have been retained (see
However, at the time of this study MIROCM
surface temperatures for the SRES A2 scenar
not available from the PCMDI archives. Conse
only four GCMs will be used for the downsc
surface temperatures. Except for CGCM3, whic
porates heat and water fluxes adjustments, the
generation GCMs do not use surface flux corre
maintain a stable climate in their control run
details about the model components can be f
http://www.pcmdi.llnl.gov/ipcc/model-documenta

For the purpose of this study, simulated daily
and surface temperatures have been considered fr
historical experiments (run 20cm^3 for the 197
period) and future projections under the gre
gas emission scenario A2 (run A2 for the 204
period). The A2 storyline, based on high popula
regionally oriented economic growth with signifi
widespread decline in fertility (Nakicenovic *et al*
actually describes a very homogeneous world wit
economic and technical changes than other scen

Local-scale observations from the Indian Met
ical Department (IMD) are also used in this stu
daily rainfall is available from 1971 to 2005 or
degree grid and surface temperatures from 1969

Table I. Climate models and their references participating in the IPCC AR4 experiments (adapted from Kripalani *et al.*
Abbreviated acronyms are used in the text to identify each GCM.

No.	Originating group	Country	IPCC ID	Abbreviation	Reference
1	Canadian centre for climate modelling	Canada	CGCM3.1 (t47)	CGCM3	Flato *et a*
2	Météo-France/Centre National de Recherches Météorologiques	France	CNRM-CM3	CNRM3	Salas-Me (2006)
3	Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM	ECHAM5	Jungelaus (2006)
4	Bjerknes Centre for Climate Research	Norway	BCCR-BCM2.0	BCCR2	Furevik *e* (2003)
5	Centre for Climate System Research (The University of Tokyo) National Institute for Environmental Studies and Frontier Research Centre for Global Change (JAMSTEC)	Japan	MIROC3.2 (medres)	MIROCMR	K-1 Mode Developer

2.2. CDF-t method

The downscaling approach chosen here is the CDF-t (Michelangeli *et al.* (2009)) which can be seen as an extension of the quantile-matching method. CDF-t offers the advantage to directly deal with and provide CDFs. In its non-parametric form it does not make any assumption on the shape or family of distribution and thus can be applied separately to both rainfall and surface temperatures in the context of this study. CDF-t has already been successfully used to downscale GCMs and reanalyse 10 m wind over France by Michelangeli *et al.* (2009).

Let F_h stand for the CDF of observed local data at a given weather station (or IMD grid cell) over a historical time period h, G_h the CDF of GCM outputs bi-linearly interpolated at the station location for the same period, F_f and G_f their equivalent for the future period considered. The method is based on the assumption that there exists a transformation T translating the CDF of a GCM variable (predictor) into the CDF representing the local-scale climate variable (predictand) at the given weather station, through the transformation T: [0, 1] $\rightarrow$ [0, 1]

$$T(G_h(x)) = F_h(x) \tag{1}$$

Replacing x by $G_h^{-1}(u)$ in Equation (1) with $u \in [0, 1]$ allows the following definition for the transform T:

$$T(u) = F_h(G_h^{-1}(u)) \tag{2}$$

Assuming that this later relationship remains valid in the future (i.e. $F_f = T\ (G_f)$), the researched CDF is given by:

$$F_f(x) = F_h(G_h^{-1}(G_f(x))) \tag{3}$$

Following Michelangeli *et al.* (2009), the CDF-t is then defined in two steps. First, estimates of (F_h, G_h^{-1}, G_f) are non-parametrically modelled. Then, their combination using Equation (3) provides an estimate of F_f. Unlike the classical quantile-matching approach which projects the simulated future large-scale values on the historical CDF to compute and match quantiles, CDF-t takes into account the change in the large-scale CDF from the historical to the future period. To downscale rainfall/surface temperatures over the full annual cycle, CDF-t is applied at each grid point to multiannual chronicles consisting of daily rainfall/surface temperatures for each month of the calendar year (all January months, February months, etc.). The resulting local-scale daily chronicles of each month

calibration and 1986–1999 for which downscaled r
are evaluated regarding local observations from
The resulting downscaled CDFs are evaluated at
grid point against IMD data using Kolmogorov–Sm
(KS) statistics providing an estimate of the max
difference between downscaled and observed local
(Darling, 1957). The results for both rainfall and su
temperatures over southern India are presented. Hov
because rainfall has a discontinuity in zero, KS s
have also been computed after removal of days
no precipitation, this analysis is further discuss
Section 3.1. In addition, dedicated diagnostics are
for three watersheds ranging from arid (Pandam
semi-arid (Kudaliar) to wetter conditions (South Gu
These locations are chosen to illustrate and d
the performance of the method for different cli
environments.

3.1. Precipitation regimes

Figure 1 presents KS statistics between CDFs
original GCMs rainfall (bi-linearly interpolated c
0.5° IMD grid) as well as from downscaled GCM
and IMD observed precipitation for 1986–1999
calibration of the CDF-t over the 1971–1985 p
As mentioned previously, this KS test is performe
each grid point; therefore, the box-plots display
Figure 1 represent the spatial dispersion of the KS s
for the whole of the South India domain. For
periods, the different GCMs downscaled rainfall
are characterized by a spatial dispersion compara
original GCM outputs. For the full year (top p
and for all GCMs, even if they stay above the
of statistical significance (0.019 at 0.05 signifi
level, not plotted), KS scores are substantially imp
for downscaled daily rainfall compared to raw G
data. Similar results are found for the monsoon p
Maximum KS scores computed in Figure 1 actually
at the discontinuity of rainfall in zero, and the
results thus show that dry days are better represen
downscaled fields than in original GCM outputs
compared to observation. This is consistent wit
fact that dry days are generally rare in GCMs
Consequently, similar KS scores have been plott
Figure 2 after removal of days with no rainfall
values) in all precipitation dataset. For the whole ye
results are very contrasted depending on GCMs.
t seems to perform best in the case of ECHAM
which downscaled rainfall are closer to observation
original GCM outputs. While there is no improv

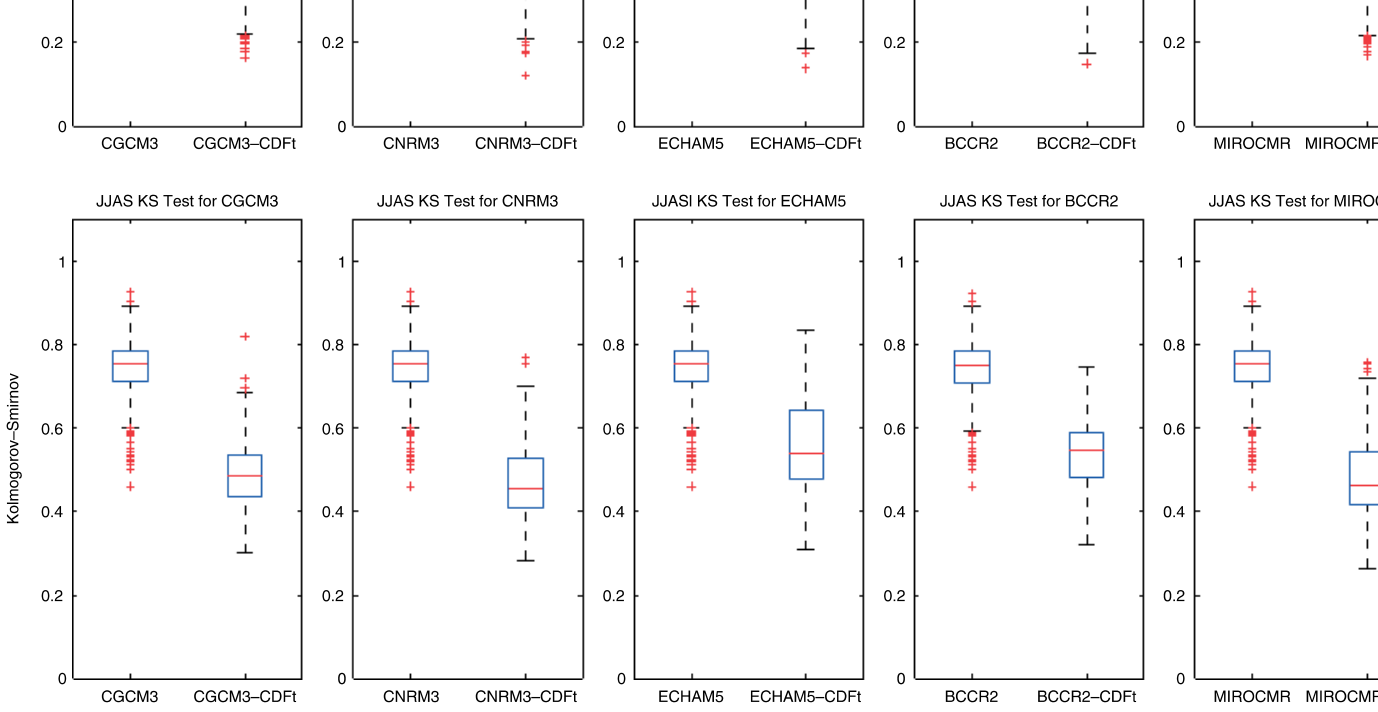

Figure 1. Kolmogorov–Smirnov statistics for original (left box-plots) and downscaled (right box-plots) GCMs rainfall when compare observation data over the 1986–1999 period for the whole of southern India, with calibration of the CDF-t over 1971–1985. Statisti for the full year and the JJAS period are presented in the top and bottom panels, respectively.

for CNRM3, the performance of the method is mitigated in the case of BCCR2, MIROCMR and CGCM3. For the JJAS period however, downscaled rainfall using CDF-t are all closer to observation than original GCMs data, witnessing of a good performance of CDF-t over the monsoon season.

In addition, downscaled GCMs daily rainfall fields are evaluated in regards to the seasonal cycle and mean monsoon precipitation rate over the validation period 1986–1999. Mean rainfall seasonal cycles shown in Figure 3 for Pandam Eru, Kudaliar and South Gundal locations (referenced in Figure 4) suggest for all GCMs, substantial improvements for downscaled data compared to large-scale outputs. The gain appears to be better for humid (South Gundal) and semi-arid (Kudaliar) regions than for arid areas (Pandam Eru), illustrating the varying performance of the method depending on climatic environments.

The mean JJAS pattern from IMD observed rainfall (Figure 4 upper right panel) shows maximum rainfall rates over the northeastern regions and along the west coast, while minimum values over central southern India separate these two regions. Clearly, such a structure is not found accurately in any of the GCMs used in this study. Nevertheless, these gradients are well reproduced in downscaled rainfall fields for all GCMs. The main differences between downscaled GCMs data are terized by the amplitudes of the above extreme the monsoon season: for instance, greatest maxim ues over northeast India are found for CNRM scaled rainfall while central regions of southern I the least dry for BCCR2 resulting local-scale da

Dry spells lengths PDFs at Pandam Eru, Kuda South Gundal locations are shown for original an scaled GCMs together with IMD observation in F The different climatic conditions over these wa are well represented from observed rainfall with ing slopes from arid to wetter climate. Inflexio within short dry spells lengths suggest that mos dry spells have a duration below five days bu varying proportion over all watersheds, short d being less prevalent for arid and semi-arid region 60–70%) than for wetter climate (almost 80% differences are less clear for the original GC (dashed coloured lines): large biases are found ing both slopes and proportion of short and lo spells. Nevertheless, downscaled fields (thick lines) systematically exhibit a better represent dry spells lengths compared to raw GCMs rai arid (Pandam Eru) and semi-arid (Kudaliar) reg these locations out of the five GCMs dataset, E appears to be the closest to observed dry spells

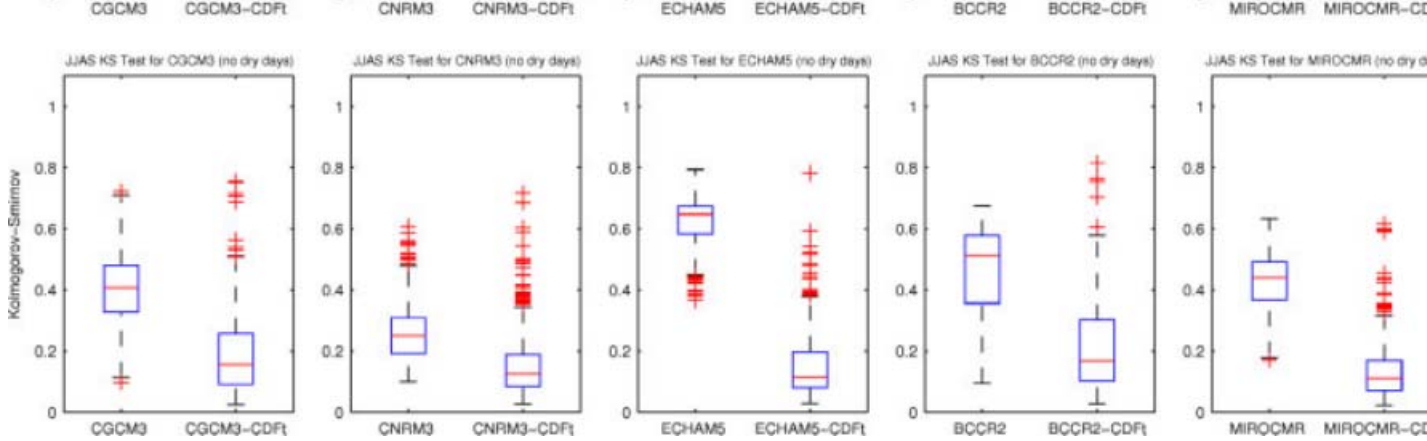

Figure 2. Similar to Figure 1 but after removal of days with no rainfall.

from IMD data, similarly for downscaled fields, downscaled ECHAM5 rainfall provide the best results. The remaining four GCMs display larger biases while substantial gains in dry spells representation characterize their corresponding downscaled rainfall fields. For wetter climatic conditions (South Gundal), similar but less efficient improvements are noticeable between original and downscaled GCMs precipitation except in the case of ECHAM5 for which dry spells lengths PDF from original GCM outputs seems closer to IMD observation than the resulting downscaled data. This could indicate a lesser performance of the CDF-t method for wetter climatic regions in terms of dry spells lengths.

Finally, JJAS anomalies over the 1986–1999 period for original and downscaled GCMs rainfall at the different watersheds (not shown) suggest that interannual variability within the resulting local-scale data is driven by the GCM outputs. Compared to IMD observations, no GCM seems able to reproduce the observed year to year monsoon rainfall variability, and such is the case regarding their corresponding downscaled fields.

3.2. Surface temperatures

Regarding annual fields, even though some scores are still above significance level (not plotted), KS statistics shown in Figure 6 (top panels) exhibit systematic improvements for downscaled GCMs surface temperatures when compared to observation. Interestingly, the spatial dispersion of the KS is much smaller for the resulting high resolution fields than for original GCMs data. Concerning the monsoon period, no such gain is found for JJAS KS diagnostics (Figure 6 bottom panels): except from CNRM3, statistical scores are similar to those obtained for original GCMs data.

Mean surface temperatures seasonal cycle at Pa
Eru, Kudaliar and South Gundal locations are pres
in Figure 7 for the 1986–1999 period. For all water
in dry or more humid conditions, downscaled fiel
systematically improved compared to original G
surface temperatures and are fitting closely the
observations over this historical period.

All mean JJAS GCMs downscaled surface tem
tures (Figure 8) display patterns close to what is obs
for IMD data while fields from original GCMs
presenting substantial biases. In particular, the la
nal gradient along the west coast which is subj
marked discrepancies in large-scale GCM outputs, i
represented in all downscaled data. The meridiona
dient from western to eastern parts of the subcon
is also better reproduced in resulting local-scale su
temperatures, with a more or less marked minimun
northeastern regions, as found in IMD observation

Mean JJAS surface temperatures differences be
the validation (1986–1999) and calibration (1971–
periods are plotted in Figure 9 for raw GCM outpu
IMD observations. Noteworthingly, no much diffe
is found for IMD observations but also for CNRM
while other GCMs are characterized by more o
marked variations. Given that CDF-t downscaled
are strongly driven by the evolution of the original
outputs, this could explain the poor JJAS KS sco
Figure 6 for CGCM3, ECHAM5, and BCCR2 res
local-scale data.

In addition, JJAS surface temperature anomalies
different watersheds locations for the 1986–1999 p
(not shown) exhibit substantial discrepancies in
of interannual variability for raw GCM outputs
compared to observations. Here again, these differ
remain in the downscaled data.

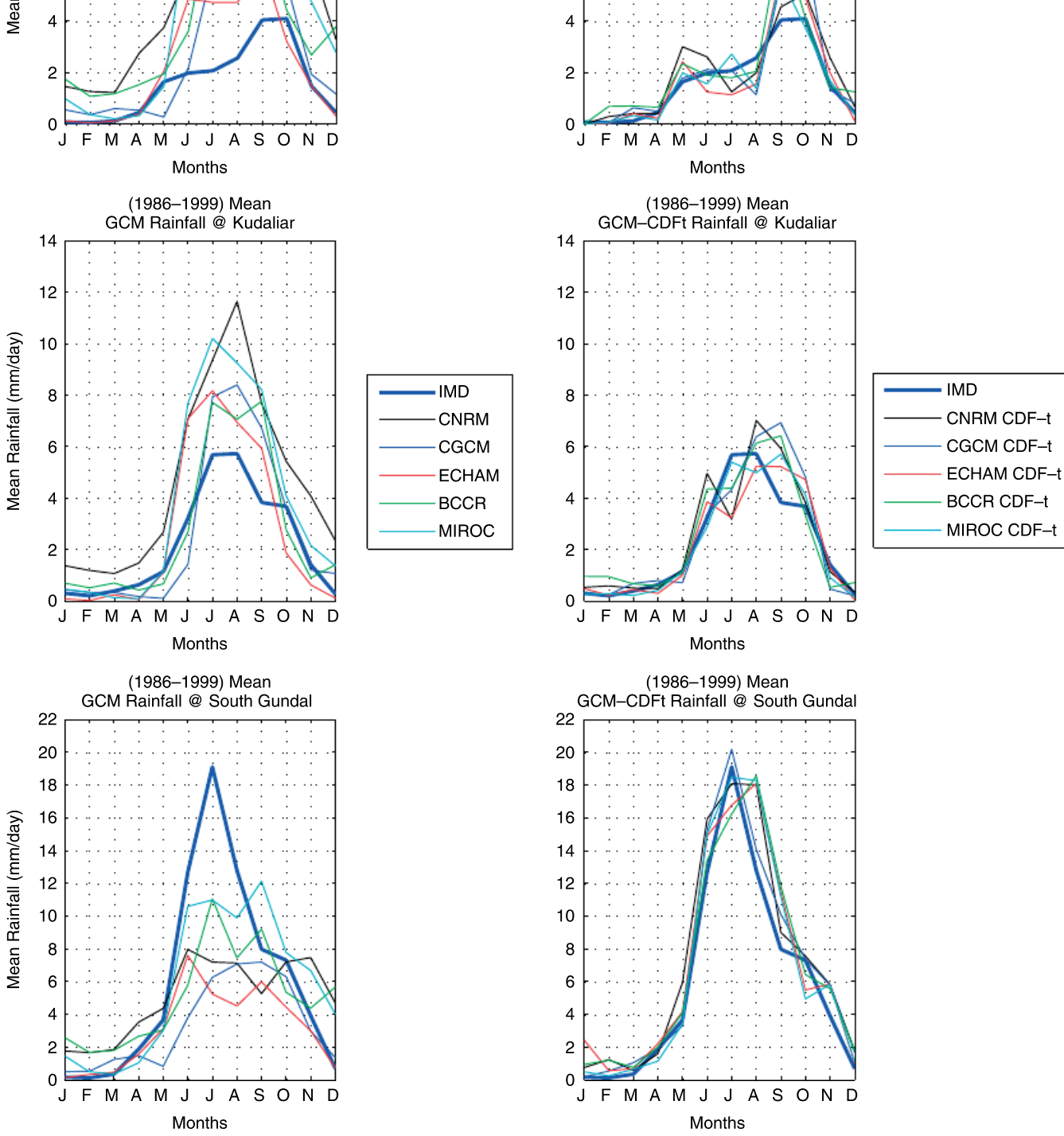

Figure 3. Mean seasonal cycle (in mm d^{-1}) at Pandam Eru (top panel), Kudaliar (middle panel) and South Gundal (bottom panel) loc original (left) and downscaled (right) GCMs rainfall together with IMD observation (thick blue line) over the 1986–1999 period, with c of the CDF-t over 1971–1985.

4. Application to projected GCM A2 scenarios

The CDF-t method is now applied to downscale large-scale precipitation and surface temperature projections from IPCC AR4 experiments under the greenhouse gas emission scenario A2 over southern India. As for the historical period, resulting high resolution fields are generated by applying CDF-t by months c GCM outputs. Regarding the availability of daily for the GCMs selected within the PCMDI 2046–2065 (hereafter A2 period) is the period for downscaling future A2 scenarios at mediu The 1971–1999 period is used for calibration t in order to take advantage of the longest pe

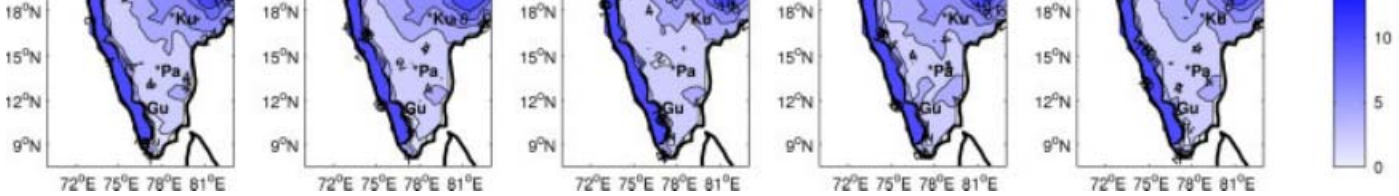

Figure 4. Mean June to September rainfall (in mm d^{-1}) for original (top panels) and downscaled (bottom panels) GCMs data together wi observation (top right) over the 1986–1999 period for the whole of southern India, with calibration of the CDF-t over 1971–1985. Pand (Pa), Kudaliar (Ku) and South Gundal (Gu) locations are referenced on the maps for indication.

observation available from IMD. It is worth noting that the aim of this paper is not to fully investigate the potential impacts of climate change over southern India but rather to document the use of the CDF-t method for statistical downscaling of a future climatic scenario over the full year cycle.

4.1. Projected rainfall changes

Projected large-scale as well as downscaled GCM outputs are now compared to their corresponding 1971–1999 fields using KS tests (Figure 10). For both the annual cycle and the monsoon period, systematic higher KS scores, are found for downscaled data. In the light of Section 3.1 the medians (red lines) would indicate more dry days for A2 scenario projections than for the contemporary period. When computing KS after removal of days with no rainfall (zero values) very similar plots were obtained (not shown), suggesting more pronounced projected climate changes in local-scale precipitation than for raw GCM outputs. The results obtained also exhibit a greater spatial dispersion for downscaled fields relatively to original large-scale GCM outputs, suggesting that resulting changes linked to climate change are more contrasted geographically at local-scale for all GCMs.

Mean seasonal rainfall changes are shown in Figure 11 at Pandam Eru (left), Kudaliar (centre) and South Gundal (right) locations for all downscaled GCMs individually. In order to have a benchmark to which CDF-t downscaled fields could be compared, the differences of GCMs seasonal cycles between two 20 year periods have been computed to represent the climate change signal as depicted in the raw GCMs data. Hereafter, rainfall changes are calculated relative to the historical 1980–1999 period (XX period in the following).

The dispersion within the different GCMs projected changes illustrates clearly the need to consider a panel of GCMs for climate change impact studies over southern India. In terms of mean GCMs ensemble, the CDF-t method gives similar results to original GCM outputs: most pronounced changes are found during the soon season over all watersheds with maximum vari during May–June and August. Nevertheless, as in from JJAS KS scores discussed previously, chang precipitation between the A2 and XX periods to differ in magnitude from one location to an For the arid Pandam Eru basin, maximum change just below 1 mm d^{-1} in June and August (represe approximately a 15% increase of the monthly mea cipitated amount) with very small differences be CDF-t results and original GCM fields. At Kud raw GCMs data exhibit similar changes (below d^{-1}) while the CDF-t method shows variations of a 2 mm d^{-1} (about 50% increase) in June. For the ter South Gundal location, differences increase be CDF-t downscaled fields and original GCM ou Maximum downscaled precipitation changes are ra from about 1 mm d^{-1} (1.5 mm d^{-1} for raw GCM puts) in May–June to 1.5 mm d^{-1} (2.8 mm d^{-1} for inal GCMs data) in August (about 10% to 15% incr While differences in CDF-t projected and GCMs or rainfall changes seem to increase from arid to wett matic regions of southern India, noteworthingly th persion within downscaled GCMs climate change s also becomes more pronounced. In addition, weak tive changes are found during the dry season, mos ticularly from October to April, from the CDF-t m as well as from raw GCMs data. At Pandam Eru tion, both the CDF-t approach and original GCMs fall exhibit variations just below zero from Octob December while no substantial changes seem to p from January to April. Similar results are found raw GCM outputs at Kudaliar while negative ch are slightly more pronounced for CDF-t estimates (0.5 mm d^{-1} corresponding to a 50% decrease). Fi more substantial negative changes are characteris the South Gundal basin: the CDF-t approach and or GCMs data suggest most pronounced rainfall dec from October/November to December (up to 1 mm

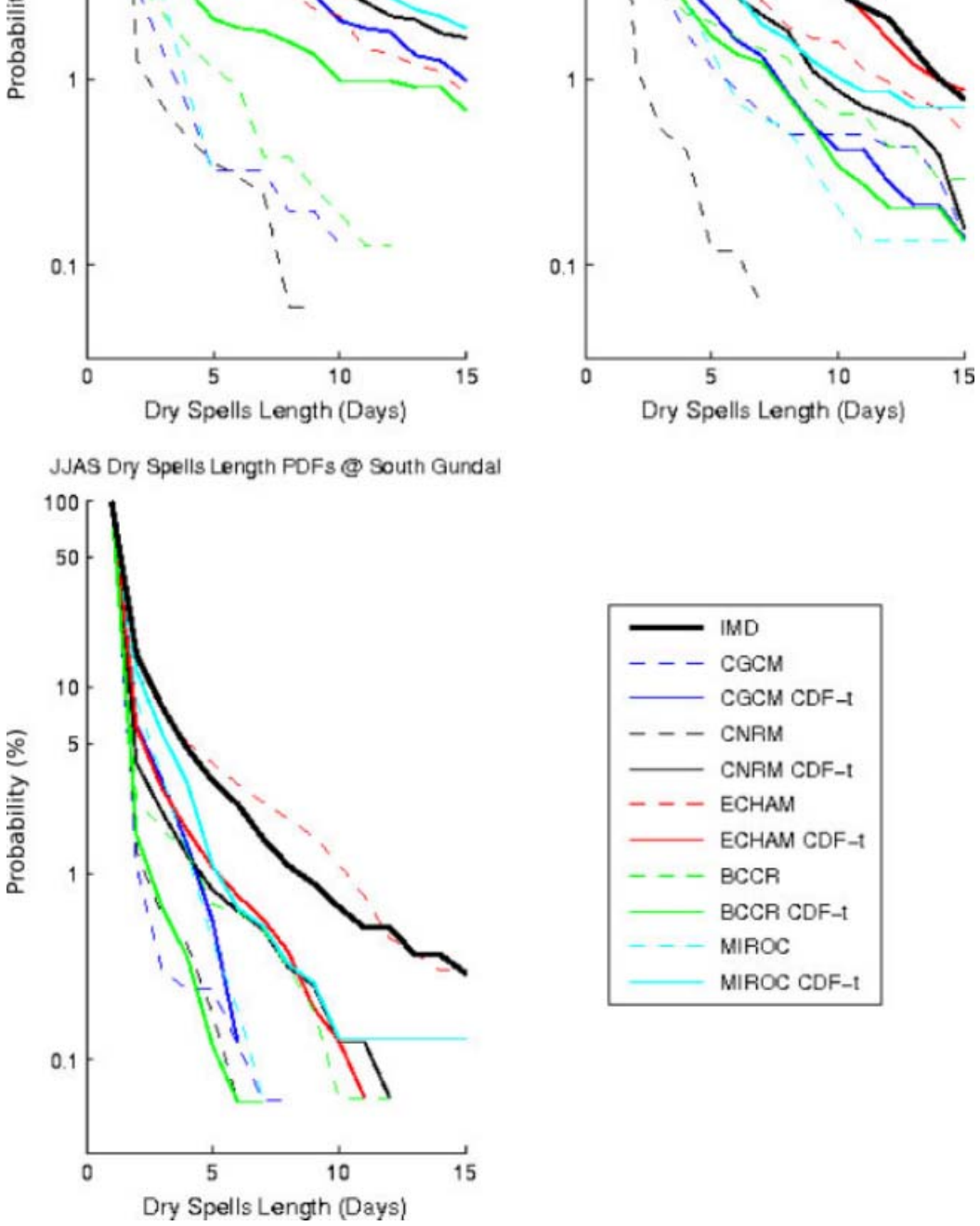

Figure 5. Dry spells length PDFs (in %) at Pandam Eru (top left), Kudaliar (top right) and South Gundal (bottom) locations for origina coloured lines) and downscaled (thick coloured lines) GCMs data together with IMD observations (black thick line) over the 1986–19 with calibration of the CDF-t over 1971–1985.

about 80% of precipitated amounts) respectively while negative variations from January to April are less substantial (maximum about 0.5 mm d^{-1} in March, about 50% decrease). Overall, these results corroborate findings from previous studies emphasizing enhanced precipitation over southern India, mostly during the monsoon season (Rupa Kumar *et al*., 2006; Tripathi *et al*., 2006; Kripalani *et al*., 2007; Anandhi *et al*., 2008).

Regarding JJAS rainfall means (Figure 12 two top panels), downscaled fields are more coherent with the known climatology from IMD data for the historical per Figure 4) than raw GCMs. In particular, maxim cipitated amounts along the west coast and n regions of the subcontinent as well as the cen terns associated to more arid regions, are well rep in the resulting downscaled fields from all GC course, there is no benchmark to compare futu jections, nevertheless these regional variations more realistic for downscaled rainfall than for t inal GCM projections. Moreover, the spatial cha

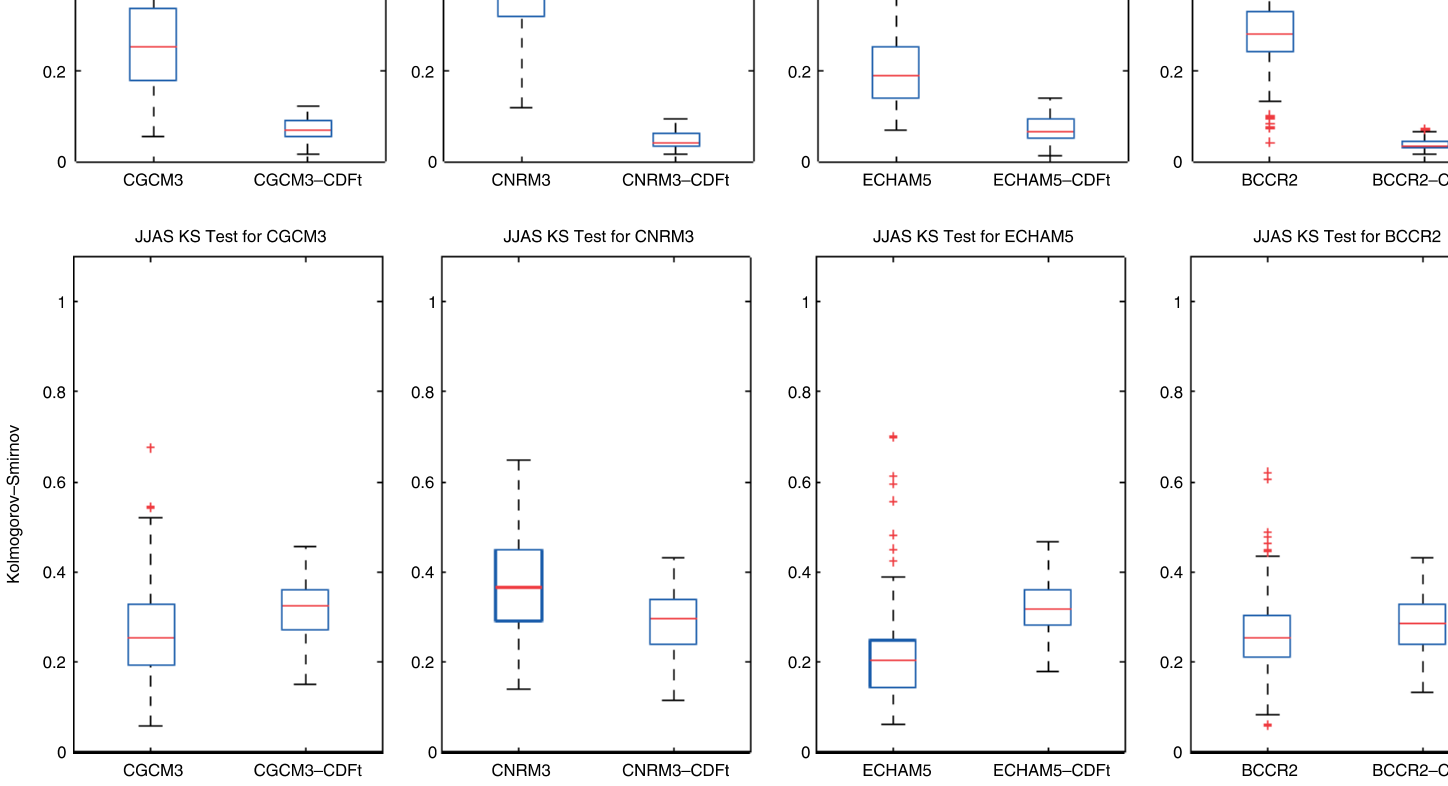

Figure 6. Kolmogorov–Smirnov statistics for original (left box-plots) and downscaled (right box-plots) GCMs surface temperature compared to IMD observation data over the 1986–1999 period for the whole of southern India, with calibration of the CDF-t over 1971 Statistical scores for the full year and the JJAS period are presented in the top and bottom panels, respectively.

JJAS rainfall obtained for individual GCM downscaled data (Figure 12 bottom panels) are systematically comparable to these from their corresponding raw GCM outputs. The amplitudes of these variations however appear to be enhanced for the resulting high resolution fields, corroborating findings from JJAS KS scores (Figure 10), with most pronounced differences over western coastal areas and northeastern regions of the subcontinent.

Differences in dry spells lengths PDFs between the A2 and XX periods are presented for the three watersheds in Figure 13. At all locations, maximum changes are found for short dry spells lengths (below 5 d) with enhanced variations for the downscaled fields when compared to raw GCM outputs. At Pandam Eru and Kudaliar, the mean GCM A2 projections in JJAS are characterized by a reduction of very short dry spells (below 2 d), while dry spells with a duration above 2 d are likely to increase. The reverse is found for the wetter South Gundal basin with enhanced very short dry spells occurrences and a reduction of longer periods without rain (above two days) during the monsoon season. Interestingly similar results are found from mean raw GCM projections at Kudaliar and South Gundal locations with some differences in terms of magnitude of these changes. However, original GCMs data would rather suggest a slight increa very short dry spells at Pandam Eru contrasting wi reduction suggested by the resulting high resolution

4.2. Projected surface temperatures

Surface temperature variations associated with rainfall regime changes are examined here in order t further description of A2 scenario projections consi in this study. As mentioned in Section 2.1, due availability of daily surface temperatures data fo 2046–2065 period, only four GCMs will be us this part (MIROCMR daily surface temperatures unavailable from PCMDI archives at the time o study).

Similarly to Figure 10, KS diagnostics charac surface temperatures evolution for both the full a cycle and the monsoon season for all GCMs (Figur As shown by their respective median, a signal v similar amplitude is recovered from the origina downscaled GCMs data between the contemporary p and the projected A2 scenario, downscaled median v being a little lower than for raw GCMs excep ECHAM5. A slightly higher spatial dispersion is for CGCM3, ECHAM5 and BCCR2 downscaled

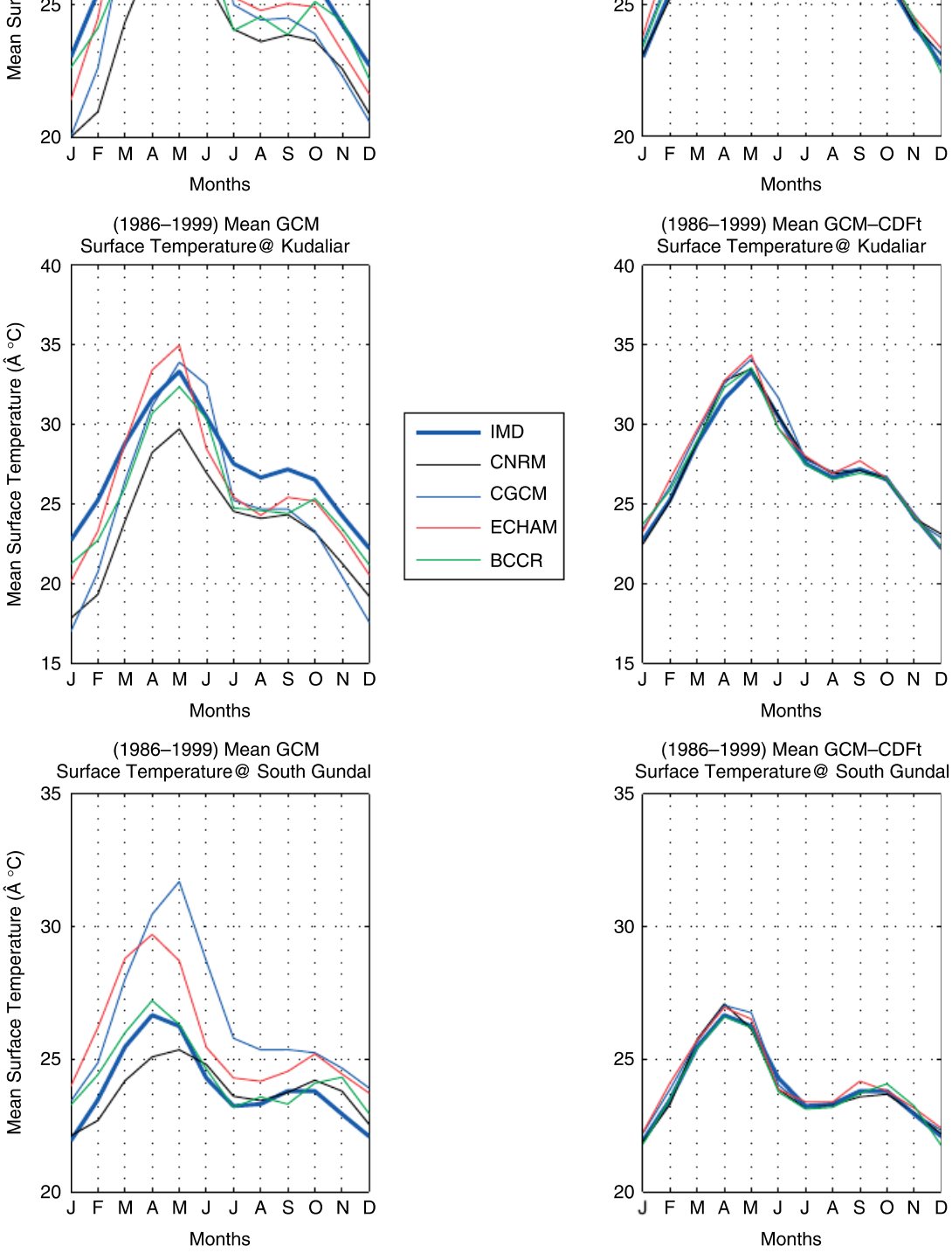

Figure 7. Mean seasonal cycle (in °C) at Pandam Eru (top panels), Kudaliar (middle panels) and South Gundal (bottom panels) loc
original (left) and downscaled (right) GCMs surface temperatures together with IMD observation (thick blue line) over the 1986–19
with calibration of the CDF-t over 1971–1985.

compared to GCM outputs, but overall the KS scores are roughly of the same order for both the full year and the monsoon season. Such results would suggest very similar evolutions between the A2 and XX periods for large-scale GCMs and downscaled surface temperatures.

Mean surface temperatures seasonal differences from the XX to the A2 periods with the CDF-t method are compared in Figure 15 with raw GCMs. Bot
t downscaled fields and raw GCMs data lead
similar conclusions in terms of GCMs ensembl
at least. Despite the dispersion within all GCM
tions, GCMs ensemble mean surface temperature
appear to be more pronounced over arid an
arid basins (Pandam Eru and Kudaliar respective

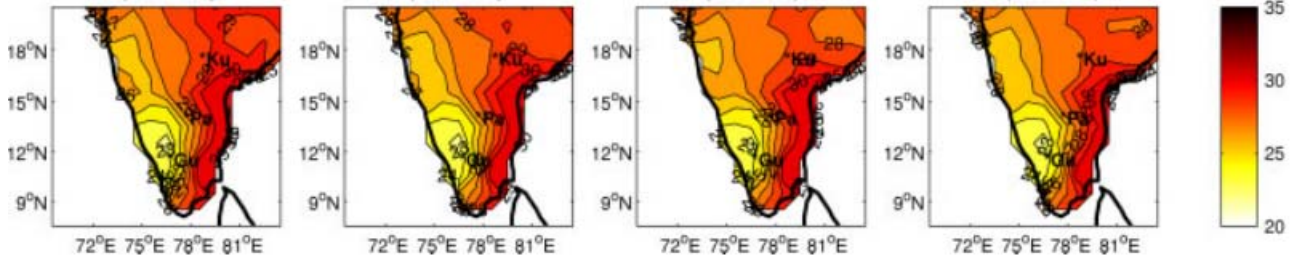

Figure 8. Mean June to September surface temperatures (in °C) for original (top panels) and downscaled (bottom panels) GCMs data t with IMD observation (top right) over the 1986–1999 period for the whole of southern India, with calibration of the CDF-t over 1971-

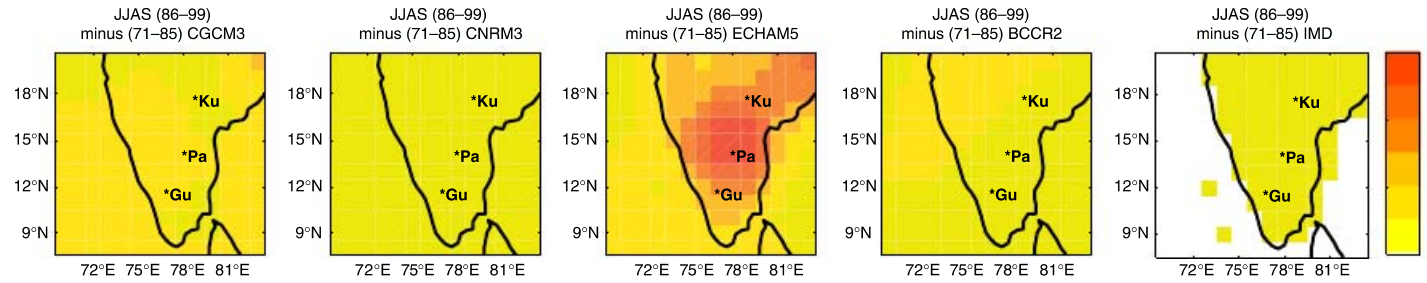

Figure 9. Mean JJAS surface temperatures differences (in °C) between the validation (1986–1999) and calibration (1971–1985) periods GCMs and IMD observations.

for wetter environment (South Gundal). Nevertheless, maximum surface temperature changes for all watersheds are found during the dry season, most particularly in February–March (about 2.5 °C at Pandam Eru and Kudaliar, and 2.2 °C at South Gundal). Smaller variations are found during the monsoon season with minimum changes in August (about 1.5 °C for all watersheds). These findings are in agreement with other studies emphasizing an increasing trend in mean annual surface temperatures with a more pronounced warming during the post-monsoon and winter seasons (Bhattacharya, 2007). Moreover, it appears that arid and semi-arid areas are where the seasonal amplitude of surface temperatures projected changes would be maximum.

In Figure 16 are shown mean JJAS surface temperatures for original/downscaled (top panels/2nd line from top) GCM outputs under the A2 scenario (2046–2065) and their respective differences (3rd/4th lines) with original/downscaled GCMs data for the historical period (1980–1999). Again, there is no reference to which downscaled fields can be compared to for the projected scenario. Nevertheless, in regards to the mean JJAS climatology from IMD observations over the contemporary period (see Figure 8), the patterns found in all GCMs downscaled data is far more coherent than raw GCMs surface temperatures, in particular regarding the latitudinal gradient along the west coast and the r ional gradient inland. Concerning surface tempe changes between the A2 and XX periods, simila terns characterize both original and downscaled The amplitude of these projected changes are c rable between large-scale and downscaled data, e for ECHAM5 for which downscaled changes are sl greater, agreeing with the findings from Figure 1 cussed previously. ECHAM5 projections depict mos nounced changes (up to 3 °C) over northern regio the subcontinent while the other GCMs suggest mum surface temperature increases (from 1 to 2 ° southern regions. Interestingly, for CGCM3 and BC regions of maximum surface temperatures chang JJAS correspond approximately to areas of max monsoon rainfall increases. Recent studies have e sized, from multi-model projections, the intensifi of different pressure systems at play over the r and enhanced moisture advection from the oceans (Kripalani *et al.*, 2007). This could suggest a po increase of local convection in these two GCM jections. However, the possible linkages between fall and surface temperatures changes for CNRM ECHAM5 are less clear from the short diagnostics in this paper and deeper research is needed in or give further elements of description relative to th cesses at play.

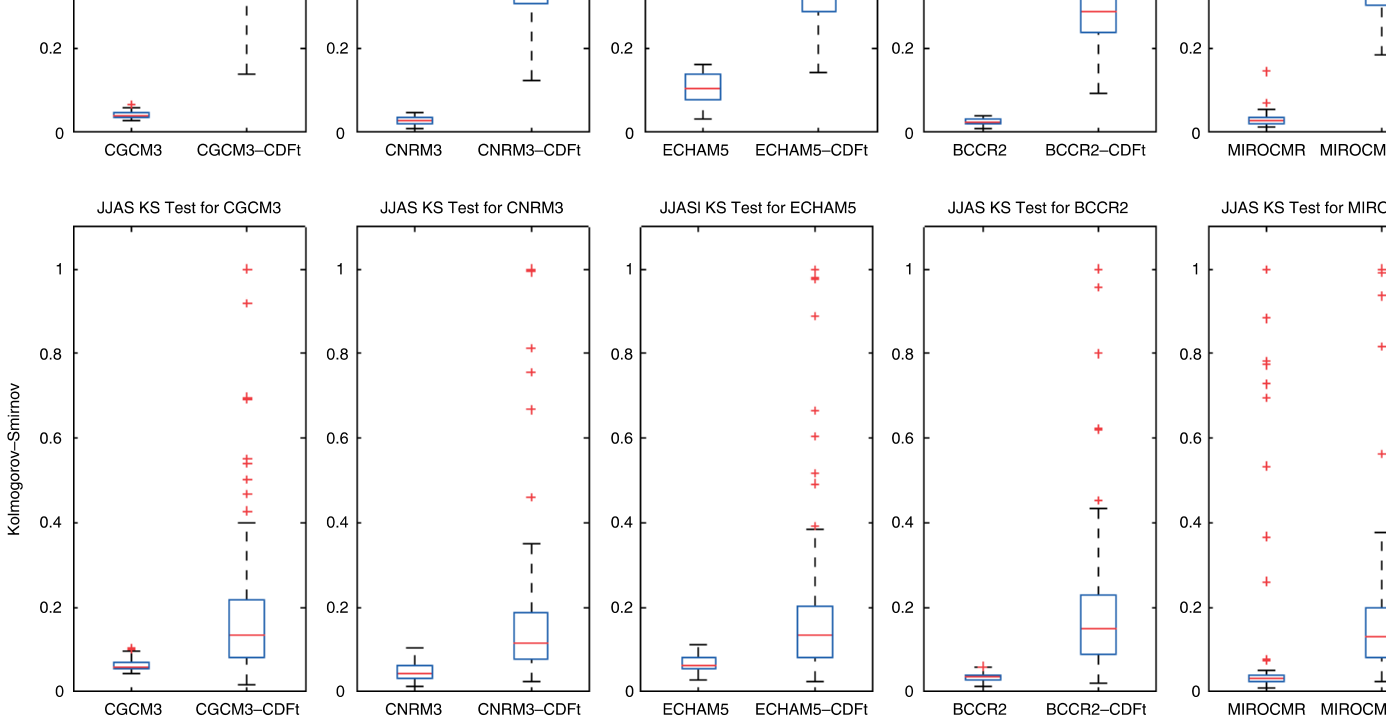

Figure 10. Kolmogorov–Smirnov statistics between original (left box-plots) and downscaled (right box-plots) GCMs rainfall for the A (2046–2065) and the 1971–1999 calibration period for the whole of southern India. Scores for the full year and the JJAS period are in the top and bottom panels, respectively.

5. Discussion and conclusions

In order to downscale GCM projections over southern India for the whole annual cycle, the CDF-t method (Michelangeli *et al*., 2009) has been applied to monthly chronicles of daily large-scale rainfall and surface temperatures. First, CDF-t has been validated on the 1986–1999 period and compared to historical IMD observations. In terms of KS statistics, resulting local-scale fields exhibit substantial improvements in comparison to original GCM outputs regarding distribution characteristics but also mean seasonal cycle and monsoon means for both precipitation and surface temperatures. Then, the CDF-t method has been applied to GCMs climate simulations of the 21st century under the SRES A2 scenario. Resulting high resolution fields have been compared to original GCM outputs at different locations (arid, semi-arid and wetter environment) where both lead to similar conclusions. Concerning precipitation, the results show a substantial increase of rainfall in particular during the monsoon season and for semi-arid and wetter climatic zones (from about 15 to 50%) while winter precipitation are generally reduced (maximum decrease of about 50–80% for wetter climatic regions) in accordance with previous findings (Rupa Kumar *et al*., 2006; Kripalani *et al*., 2007; Raje and Mujumdar, 2009). These changes are accompanied by increases in surface temp most pronounced during the post-monsoon (up t and winter season at all locations also agreei earlier studies (Rupa Kumar *et al*., 2006; Bhatt 2007).

This method was used to provide local-scale variables for impact studies (hydrological an economical) at basin scale over southern India, stressed region where the impacts of global cha due to increase significantly (Kundzewicz *et al*. Most statistical downscaling studies generally f a single season (for example JJAS) and dow projections from different GCMs for the full rarely documented. The monthly approach chos gave better results than for the full year (not and supports findings from other studies regar need to seasonalize SDMs for better projected lo estimates (Tripathi *et al*., 2006).

The same non-parametric approach was chose study to downscale separately rainfall and surfa peratures. However, in the case of rainfall, the cipitation' occurrences (which are particularly i during the dry season) may need more develo Days without precipitation are generally not ad represented in GCM outputs, and this could af

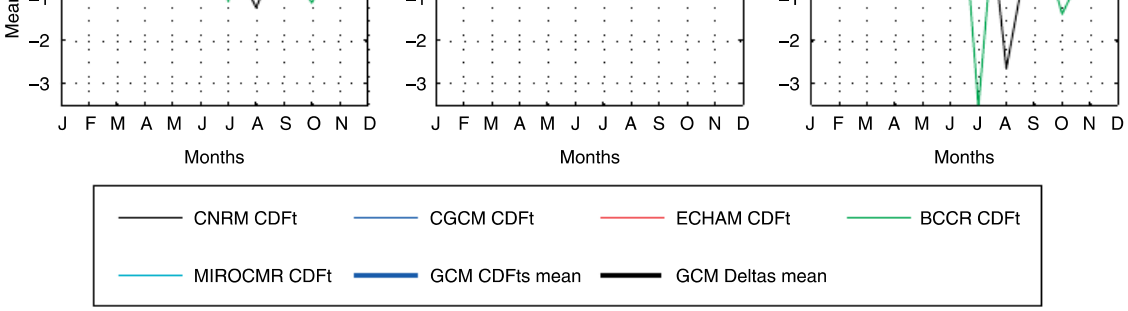

Figure 11. Mean seasonal rainfall cycle changes (in mm d^{-1}) at Pandam Eru (left panel), Kudaliar (middle panel) and South Gundal (right locations between the A2 (2046–2065) and XX (1980–1999) periods seen by CDF-t compared to results from raw GCMs outputs

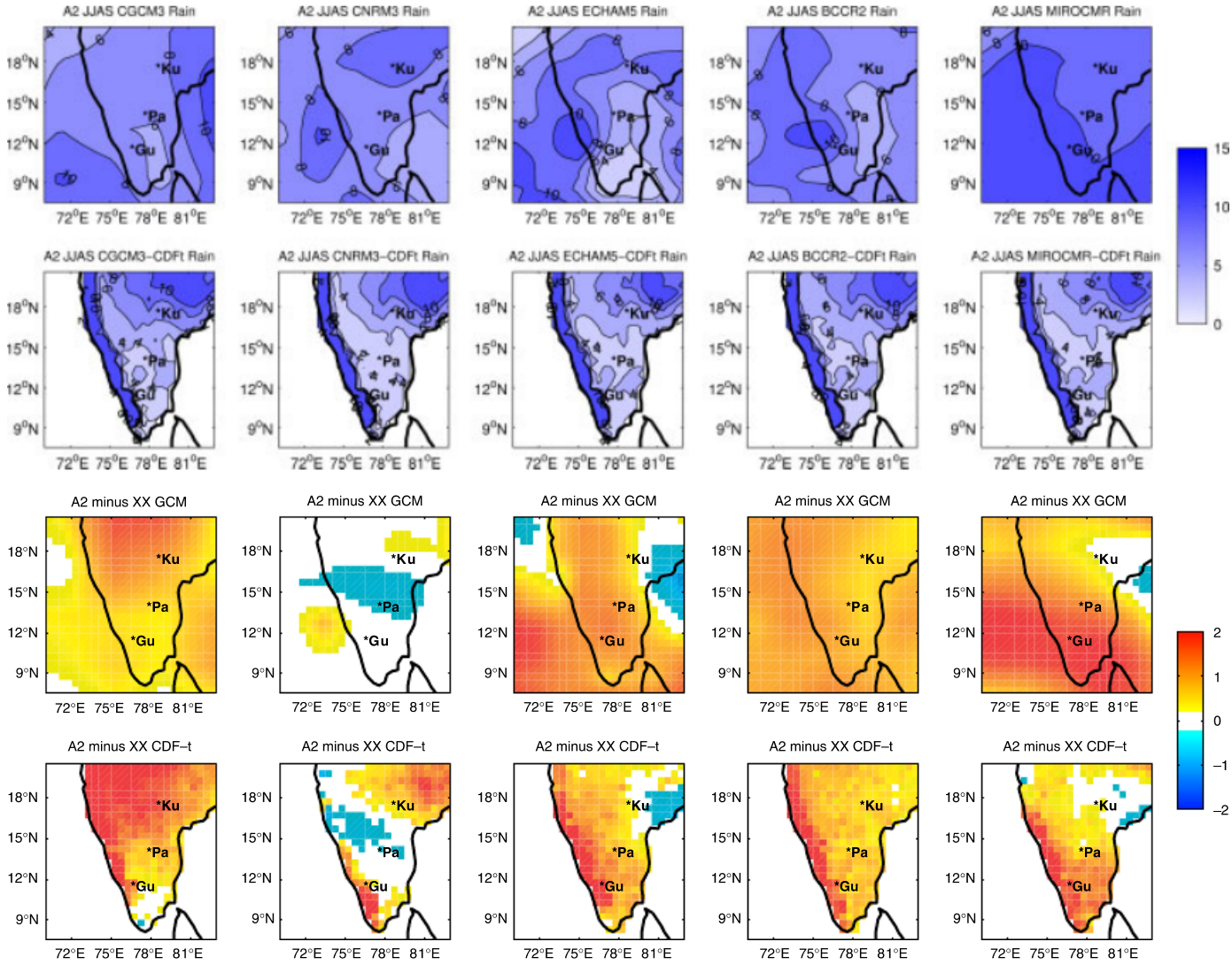

Figure 12. Mean June to September original (top panels) and downscaled (second line) GCMs rainfall for the A2 scenario (2046–206 southern India as well as the original GCMs (third line) and CDF-t projected (bottom panels) changes (in mm d^{-1}) when compared historical XX period (1980–1999).

CDF-t formulation used for downscaling rainfall. As shown in Section 3.1, dry days are better represented in downscaled precipitation than in GCMs data when compared to observation. Nevertheless, for all GCMs CDF-t seems to perform better, in terms of dry day precipitated amount, during the monsoon season wit 'no-precipitation' occurrences, than for the whole To address this issue, a next step would be to use

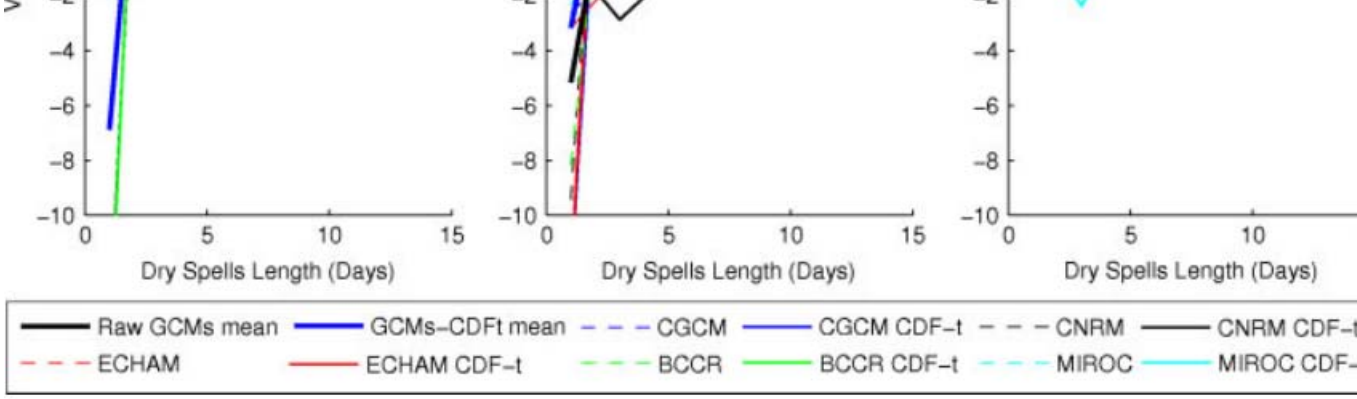

Figure 13. Differences in dry spells length PDFs (in %) at Pandam Eru (left), Kudaliar (centre) and South Gundal (right) locations fo (dashed coloured lines) and downscaled (thick coloured lines) GCMs data between the A2 (2046–2065) and XX (1981–1999) 20 yea

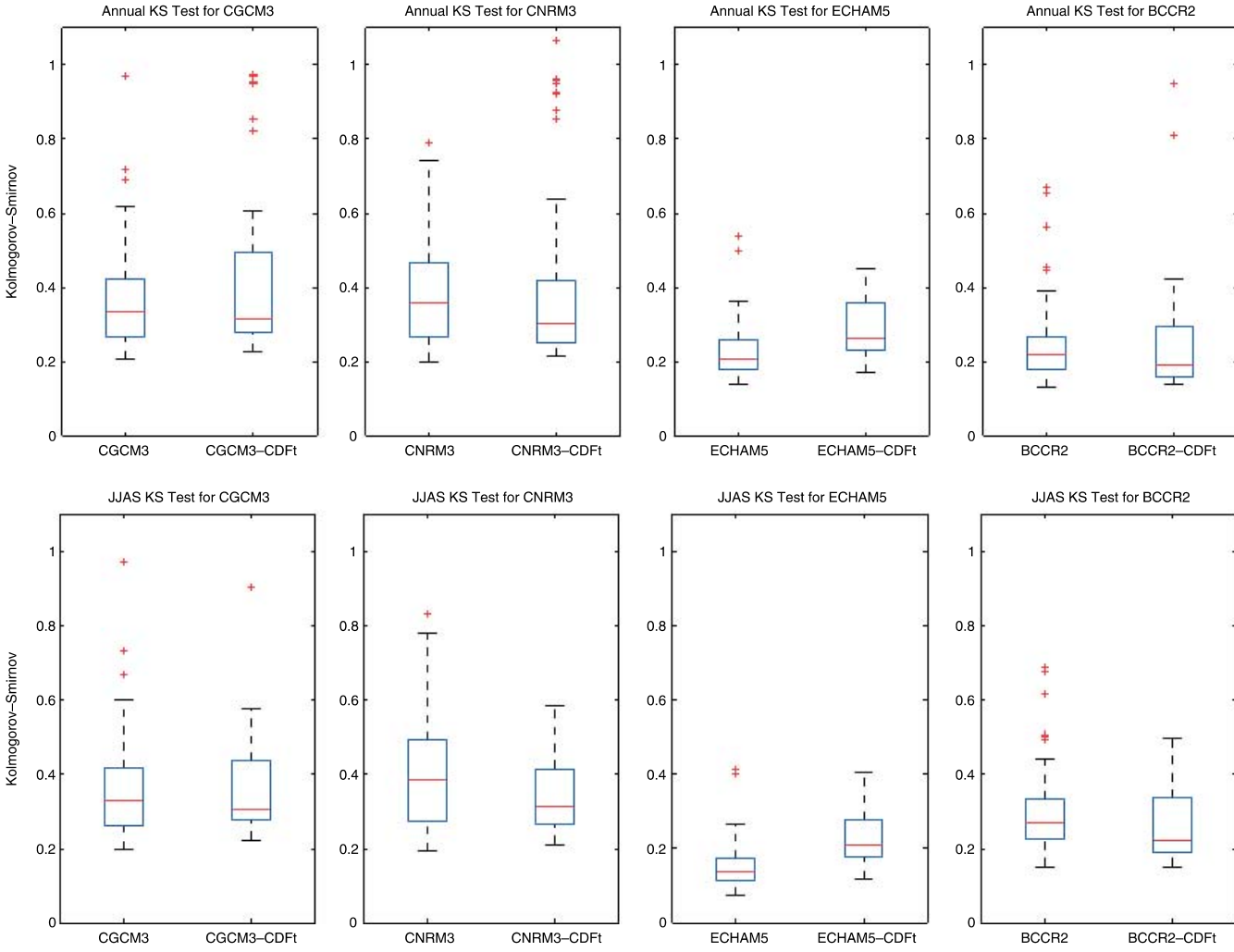

Figure 14. Same as Figure 10 but for surface temperatures.

relevant distribution models for precipitation through a parametric approach as it has been done with other SDMs using Gamma or mixed distributions for example (Vrac and Naveau, 2007).

Nevertheless, CDF-t proved to be an interes efficient statistical tool, offering substantial pers in terms of downscaling and climate change studies at local-scale, with the low computatio

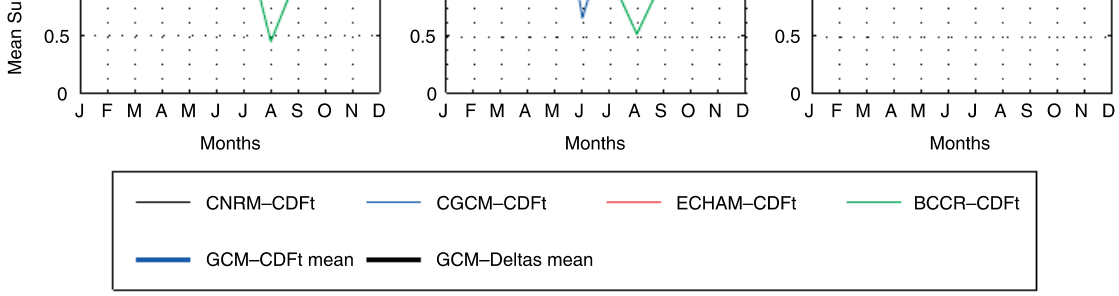

Figure 15. Same as Figure 11 but for surface temperatures (in °C).

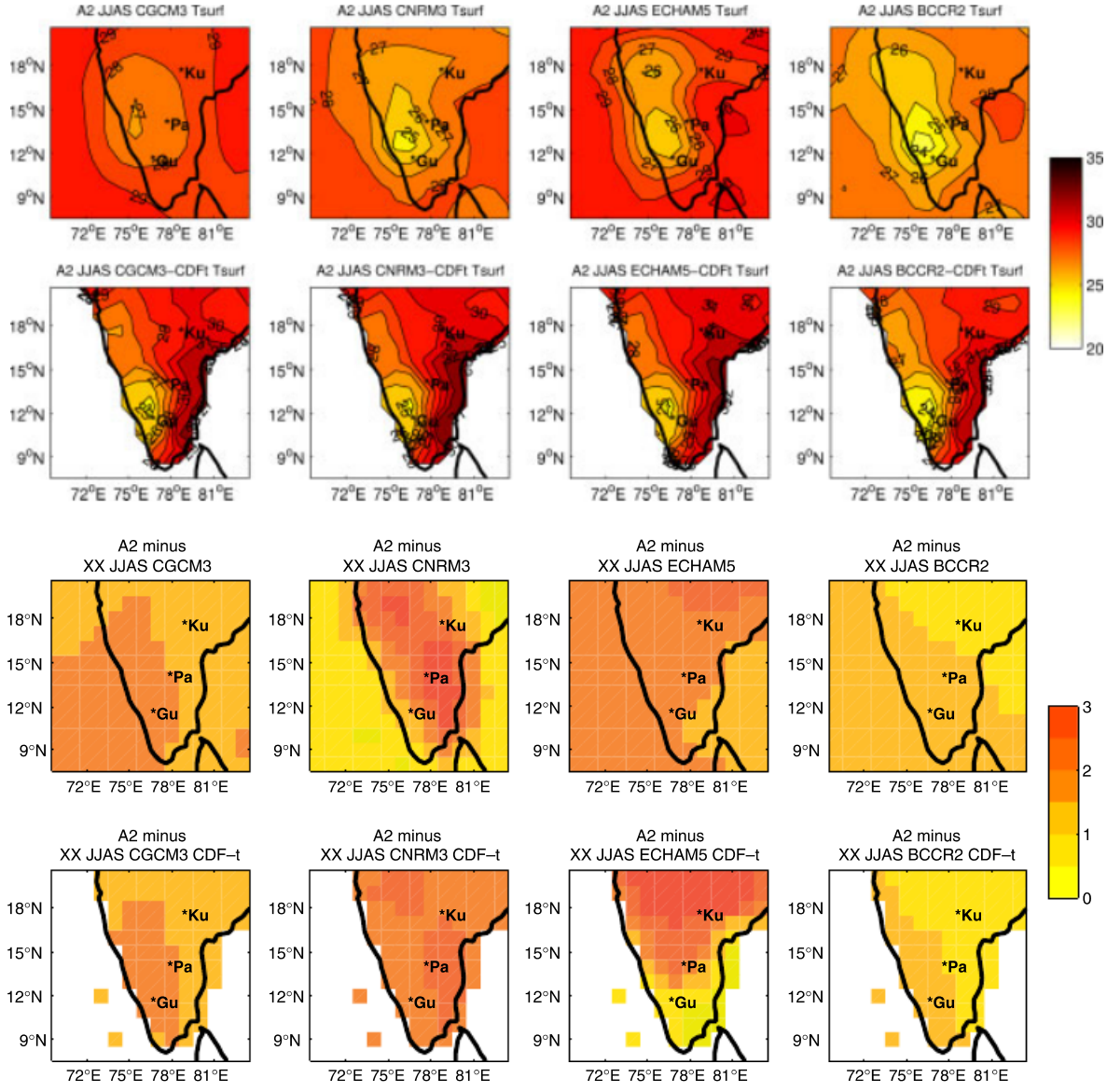

Figure 16. Same as Figure 12 but for surface temperatures (in °C).

and flexibility of this approach making it even more attractive.

Finally, deeper research is needed to give further elements of description regarding future climatic projections over southern India and the processes involved. First the period of study regarding these projecti limited to 20 years and could be extended. It also be relevant to compare our results to pro fields obtained through numerous statistical downs approaches (other than the single delta method) in

However, this paper corresponds to one more step in that direction helping to document medium-range future climatic scenarios (2040–2060), these horizons being crucial for local adaptation strategies.

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