Summer Drought in Northern Midlatitudes in a Time-Dependent CO₂ Climate Experiment

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ABSTRACT

A time-dependent climate-change experiment with a coupled ocean–atmosphere general circulation model has been used to study changes in the occurrence of drought in summer in southern Europe and central North America. In both regions, precipitation and soil moisture are reduced in a climate of greater atmospheric carbon dioxide. A detailed investigation of the hydrology of the model shows that the drying of the soil comes about through an increase in evaporation in winter and spring, caused by higher temperatures and reduced snow cover, and a decrease in the net input of water in summer. Evaporation is reduced in summer because of the drier soil, but the reduction in precipitation is larger. Three extreme statistics are used to define drought, namely the frequency of low summer precipitation, the occurrence of long dry spells, and the probability of dry soil. The last of these is arguably of the greatest practical importance, but since it is based on soil moisture, of which there are very few observations, the authors’ simulation of it has the least confidence. Furthermore, long time series for daily observed precipitation are not readily available from a sufficient number of stations to enable a thorough evaluation of the model simulation, especially for the frequency of long dry spells, and this increases the systematic uncertainty of the model predictions. All three drought statistics show marked increases owing to the sensitivity of extreme statistics to changes in their distributions. However, the greater likelihood of long dry spells is caused by a tendency in the character of daily rainfall toward fewer events, rather than by the reduction in mean precipitation. The results should not be taken as firm predictions because extreme statistics for small regions cannot be calculated reliably from the output of the current generation of GCMs, but they point to the possibility of large increases in the severity of drought conditions as a consequence of climate change caused by increased CO₂.

1. Introduction

Drought is one of the most serious problems arising for human societies and ecosystems from climate variability. Although its impact does not come through sudden events, such as floods and storms, drought is one of the most damaging types of natural disasters over long periods (Houghton 1994, 13 and 22). Hence, it is important to know what increases in the frequency or severity of droughts might be caused by climate change brought about by an increased atmospheric concentration of carbon dioxide.

In this paper, we use results from a climate-change experiment in which the CO₂ concentration is gradually increased

- to examine the nature, magnitude, and physical causes of simulated changes in the hydrologic cycle, and
- to make a quantitative assessment of the consequent changes in the frequency or severity of drought in northern summer [June–August (JJA)].

We concentrate on the regions of southern Europe and central North America, as defined by Mitchell et al. (1990) for studies presented by the Intergovernmental Panel on Climate Change, because conditions are fairly dry in the current climate in summer in northern mid-latitudes, and many model simulations, including ours, suggest that there will be further summer drying in Northern Hemispheric continental interiors in a climate of increased CO₂ (Manabe and Wetherald 1987; Mitchell et al. 1990; Kattenberg et al. 1995; Wetherald and Manabe 1995). Therefore, these regions are likely to show an increased incidence of drought, which is particularly relevant because summer is the main growing season and central North America in particular contains important agricultural areas.

Simulations including sulphate aerosols and greenhouse gases in global climate models have recently become available (e.g., Mitchell et al. 1995). By increasing the planetary albedo, sulphate aerosols cause a negative radiative forcing of climate, offsetting part of the global average greenhouse forcing. Unlike greenhouse gases,
sulphate aerosols have a short lifetime, so their
effect is mainly concentrated in regions near to or downstream
of the industrial areas where they are produced. In these
regions, climate change predictions may be altered con-
siderably. More analysis has yet to be done on simu-
lations including sulphate aerosols to clarify the find-
ings. The present work may have to be viewed more as
a sensitivity study than a climate prediction with respect
to regions strongly affected by sulphate aerosol forcing.
Long-term projections suggest that the effect of green-
house gases may increase considerably more than that
of sulphate aerosols. If this is so, CO₂-only simulations
retain a practical relevance.

The basic meaning of “drought” is an exceptional
lack of water. Possible quantitative definitions can be
framed in terms of lack of rain, dry soil, and an excess
of potential evapotranspiration (PET) over precipitation.
(PET is the rate of evaporation from a free water surface
and represents the atmospheric “demand” for water. It
usually exceeds actual evapotranspiration, which is the
sum of evaporation from the soil surface and transpi-
ration through plants.) Quantitative studies of historical
drought often use the Palmer drought severity index
(PDSI), described, for instance, by Briffa et al. (1994)
and references therein. This statistic is based on the
monthly anomaly in the excess of the supply of water
(precipitation) over the demand (evapotranspiration and
runoff). Evapotranspiration is calculated by the method
of Thornthwaite (1948) and runoff by using a simple
soil model. Calculation of PDSI also involves some em-
pirically calibrated constants and includes a dependence
at each month on the past history. PDSI has been used
in many studies of historical drought in the United States
(e.g., Karl and Koscielny 1982) and more recently ap-
plied to Europe by Briffa et al. (1994). It is not appli-
cable outside the midlatitudes.

PDSI has also been applied to assess the simulation
of drought by general circulation models (GCMs). This
was done by Rind et al. (1990) for the simulation of
time-dependent future climate change in the United
States by the model of the Goddard Institute for Space
Studies and by Jones et al. (1996) for Europe for the
experiment described in this paper. The advantage of
using PDSI is that it is readily comparable to the same
statistic calculated from observational data (at least in
the case of the United States). The drawback is that it
is not directly related to quantities simulated by the
GCM. In particular, it can make use only of the simu-
lated temperature and precipitation. Computing PDSI
involves calibrating separate models for PET and soil
moisture, which are unrelated to the representation of
the same processes in the GCM. Because of this draw-
back, Rind et al. (1990) also calculated a simpler statistic
obtained directly from PET and precipitation simulated
by their GCM. The results were qualitatively unaffected.
Whetton et al. (1993), in their study of the effect of
climate change on drought in Australia, used simulated
changes in temperature and precipitation to drive an
offline soil moisture model. Misgivings about the re-
ality of GCM-simulated soil moisture led them to adopt
this approach, but it nonetheless does not completely
eliminate the GCM hydrology scheme, which is still
involved in deriving the input fields. Furthermore, the
offline model cannot include the feedback of changes
in soil moisture upon temperature and precipitation.

The hydrologic scheme of our model (described in
section 2) is fairly complex compared with some others
used in GCM experiments, and we consider it to be
adequate, given the uncertainties in modeling other
physical processes relevant to the regional scale. There-
fore, we have not used PET or PDSI in this paper, but
have assessed drought in terms of simulated precipita-
tion and soil moisture. This allows us to relate the oc-
currence of drought directly to the physical processes
of the climate model. Whereas PDSI is a monthly sta-
tistic, we have also looked at some seasonal and daily
quantities. PDSI is quite a complicated statistic, but
since the climate changes that occur when carbon di-
oxide is increased are large, we believe that it is suf-
ficient to use simpler statistics for our analysis, as was
also the experience of Rind et al. (1990).

Precipitation is the best observed quantity pertaining
to drought, as well as the most directly and reliably
simulated by climate models. Low precipitation or long
periods without precipitation are the most common pop-
ular definitions of drought. However, for many purposes,
it is not lack of precipitation that causes problems. Low
soil moisture has adverse effects on plant life and ag-
riculture, disturbs the foundations of buildings, and re-
stricts the supply of groundwater. Hence, low soil mois-
ture may be a better practical indicator than precipitation
of the severity of a drought. Unfortunately, there are
few observations of soil moisture that can be used to
verify model simulations. Runoff is the important quan-
tity for surface water levels (lakes and rivers), dependent
ecosystems, and public water resources (where not de-
rived from groundwater), and this depends on both pre-
cipitation and soil moisture. Precipitation and soil mois-
ture thus both have advantages and disadvantages as the
basis for computing drought statistics, and we have chos-
en to investigate both.

The limitations of computing resources determine the
spatial resolution that can be employed for a global
climate model. The use of a fairly coarse grid, as in this
model, is a particular problem for simulation of ex-
tremes occurring on short timescales, such as heavy pre-
cipitation, because these often have limited spatial ex-
tent. Drought, however, is an extreme with a long time-
scale, which typically afflicts a large area. For a study
of drought, the low resolution of the model is less of a
drawback.

2. Model and experiment

This paper is based on an analysis of results from the
first Hadley Centre time-dependent climate-change ex-
experiment, described by Murphy (1995a), Murphy and Mitchell (1995), and Murphy (1995b). The climate model used for the experiment comprises coupled oceanic and atmospheric GCMs. The atmospheric GCM is a finite-difference gridpoint model in which the primitive equations are solved on 11 irregularly spaced $\sigma$ levels using finite-difference techniques (see Slingo 1985). The oceanic GCM is also a finite-difference gridpoint model, derived from ocean code developed by Cox (1984) at the Geophysical Fluid Dynamics Laboratory and having 17 levels, with maximum resolution near the surface. Both components employ a horizontal grid with a spacing of 2 1/2° in latitude and 3 3/4° in longitude, with realistic geography, orography, and bathymetry. The atmospheric and oceanic GCMs are run alternately, with coupling fields being exchanged at 5-day intervals.

The climate model includes parameterizations for the following:

- Gravity wave drag (Palmer et al. 1986).
- Radiative fluxes, which include seasonal and diurnal cycles, and depend on temperature and the concentrations of water vapor, cloud amount, carbon dioxide, and ozone (Slingo and Wilderspin 1986).
- Clouds and convection. Cloud amounts, ice content, and water content are calculated by the model (Smith 1990). Cloud radiative properties are prescribed. A penetrative convection scheme is used (Gregory and Rowntree 1990), and the convective cloud amount is determined from the convective mass flux. Over the ocean, subgrid-scale gustiness associated with convection is accounted for by increasing the surface wind (Gordon 1989).
- Atmospheric boundary layer and surface. Both the mixing in the boundary layer (see Mitchell and Slingo 1988) and the surface exchanges are dependent on stability. Snow depth is computed. A four-layer soil temperature scheme is used. The surface hydrology parameterization is as described by Warrilow et al. (1986) and Warrilow and Buckley (1989). Soil and vegetation type and related surface parameters are geographically prescribed and derived from empirical datasets. They include roughness length, snow-free albedo, deep snow albedo, saturation soil moisture, critical soil moisture, wilting point, and the other parameters of the hydrology scheme (see also below).
- Oceanic isopycnal diffusion of heat and salt (Redi 1982).
- Enhancement of vertical mixing in the ocean due to current shear (Pacanowski and Philander 1981).
- Oceanic mixed layer (Kraus and Turner 1967).
- Sea ice, which is modeled using a “zero-layer” thermodynamic model (Semtner 1976) modified to allow variable lead fraction and to incorporate brine rejection during freezing.

The surface scheme is depicted in Fig. 1. The vegetative canopy has a small water holding capacity, but allows evaporation at the potential rate and makes an important contribution to total evaporation. Water input to the soil is derived from snowmelt and precipitation falling through the canopy. The water supplied does not all enter the soil because there is a maximum infiltration rate; the remainder runs off at the surface. No more water can be taken up by the soil once it saturates, but this condition is rare because there is continuous sub-surface runoff while the soil is not dry. Evapotranspiration from the soil occurs at a rate depending on water vapor pressure deficit, aerodynamic resistance, and stomatal resistance while soil moisture is above the “critical” level. Below this level, it is reduced by a fraction that decreases linearly with soil moisture to zero at the “wilting” point, which is so called because the remaining moisture cannot be removed by plants.

Model surface temperature is used to calculate the rate of evaporation (rather than the lower temperature applicable to the surface of a body of water evaporating freely). This is criticized by Milly (1992), who argues that it may lead to an overestimate of evaporation and hence excessive drying of the soil. However, evaporation in the model is restricted by stomatal resistance, which has been adjusted in order to give reasonable rates (Warrilow et al. 1986; Warrilow and Buckley 1989).

A few of the quantities used in this analysis require explicit definition.

- The soil moisture content is the excess of soil moisture over the wilting point. We most often express it as fractional soil saturation, which is the soil moisture content divided by its value at saturation.
- Precipitation is partitioned into large-scale rain, con-
 vective rain, and snowfall. Large-scale and convective precipitation arise from distinct physical processes in the model, but for snowfall we are not able to distinguish them in the analysis.

- **Evaporation** is the total of evaporation from bare earth, transpiration through vegetation, free evaporation from the plant canopy, and sublimation of lying snow.

- **Runoff** is the total of surface runoff and subsurface runoff. We are not able to distinguish these in the analysis.

- **Cloud fraction** is the total fraction of the sky that is obscured by clouds at any level.

The experiment consisted of two 75-yr integrations, serving as control and anomaly, from the same initial state (Murphy and Mitchell 1995). The atmospheric CO$_2$ concentration remained constant throughout the control and increased at 1% yr$^{-1}$ compound in the anomaly. During the final decade, an interval centered around the time at which CO$_2$ reached double its initial concentration, the global average temperature rise (anomaly − control) was −1.7°C. This is less than the climate sensitivity of the coupled model (equilibrium temperature change for a doubling of atmospheric CO$_2$), estimated at +2.7°C (Murphy 1995b), owing to the thermal inertia of the oceans. The climate of the control simulation also warmed slightly through the course of the experiment (Murphy 1995a), mainly in the Southern Hemisphere. The effect was small in the Northern Hemisphere, where this analysis is concentrated. To eliminate the influence of this drift as far as possible, we consider differences between the anomaly integration and corresponding periods of the control simulation, instead of using the full length of the control. Several other aspects of the experiment have been analyzed, including changes in sea level (Gregory 1993), tropical variability (Tett 1994), surface variables (Murphy and Mitchell 1995), energy balance (Murphy 1995b), the Asian summer monsoon (Bhaskaran et al. 1995), and storm tracks (Carnell et al. 1995).

For the final 10 yr of both integrations, simulated daily data were archived, enabling us to examine the structure of daily precipitation and other quantities, as well as means over months and longer periods. This study analyzes that decade for the two climates. Note that the phrase “2 × CO$_2$ climate” is often employed to describe the equilibrium for doubled carbon dioxide. Here, we are looking at the response around the time of doubling in a time-dependent experiment.

### 3. Simulation of the current precipitation climatology

A good simulation of the current climate is a necessary (though not sufficient) requirement for making credible predictions about climate change. We compare the model’s precipitation with two observational climatologies. The first is that of Shea (1986). This is a climatology of monthly, seasonal, and annual fields, derived from observations of 1950–79, gridded at 2.5°, with no data south of 45°S. It contains fields of interannual standard deviation as well as means. The second is that of Hulme (1994), which is a land-only dataset of precipitation fields for each month this century on the same grid as the climate model. We use the period 1951–80. The dataset has substantial areas of missing data where there were no available or satisfactory observational records, but Europe and the United States are not affected by this.

The agreement between the simulated and climatological values is good (Fig. 2a). The most serious errors are in the subtropics; in particular, the model is too dry in the Indian monsoon area.

The simulation of interannual variability is mostly reasonable (Fig. 2b), although not as good as the mean. Estimates of variability are more uncertain, as reflected in the differences between the climatologies. The model has too little variability in the midlatitudes. The large deficiency in the southern midlatitudes may be an artifact of the small area of data included in the plots south of 30°S.

In Europe and North America, the model precipitation mostly differs from observations (Hulme 1994) by less than 50% (Fig. 3). This is fairly good agreement, given the large spatial variability of the precipitation field. (Over southern Europe, the spatial standard deviation is 75% of the mean. The boundaries of southern Europe and central North America, the regions of detailed study, are shown on the maps.) The area average modeled precipitation is 16% too large in southern Europe and 11% too large in central North America. These regions, although large in terms of a GCM, are large enough in the real world to encompass a range of hydrologic regimes. This range is neglected in this study because the relatively coarse spatial resolution of the model does not allow us to represent this heterogeneity properly or to attach high confidence to the simulation of an individual small region.

The soil moisture at any point in the year results from the integrated effect of precipitation and other water fluxes over preceding months, so in order to explain or predict summer soil moisture we need a reliable simulation of the whole seasonal cycle of precipitation. Considering the very variable character of precipitation in space and time, and bearing in mind the uncertainties in the observations, the agreement is good (Fig. 4) between the model’s monthly mean area average precipitation in our two regions and the 1951–80 monthly climatology from Hulme (1994). Note that the maximum occurs in spring and summer in central North America, but in winter in southern Europe. The timing of the extremes in the model is at most 2 months in error, and the range of values is well reproduced.
From these comparisons, we conclude that the model captures the main features of the variation of precipitation in the regions of interest.

4. Change in the annual-mean water budget

Comparisons of the mean climates in the last decade of the two integrations are described by Murphy and Mitchell (1995). By the end of the experiment, there was a statistically significant rise in the surface temperature over almost the entire globe. On the global and annual average, precipitation increases by 3%. Local precipitation changes are larger and of both signs, but their statistical significance is harder to establish, owing to greater variability. Nonetheless, there are some features that develop early in the experiment and persist, and can be correlated with changes in soil moisture. These include an increase in precipitation in winter in...
mid-to-high latitudes, and a marked reduction in summer over North America and Eurasia.

On the annual average, precipitation $P$ over southern Europe and central North America decreases by 7% and 4%, respectively. Evaporation $E$ is 3% less in southern Europe and little changed in central North America. This means that in both cases $P - E$ is smaller in the anomaly climate, by 11% and 20%. The proportions are higher than for precipitation and evaporation individually since $P$ and $E$ largely balance each other, the difference being accounted for by runoff. The soil moisture is reduced by 12% and 15%, respectively, in the anomaly climate.

It is instructive to examine how a reduction in $P - E$ is related to a fall in soil moisture. Very crudely, we can consider the soil to be a reservoir containing a mass $M$ of water, which is increased by the flux of precipitation applied (neglecting the time delay between snowfall and snowmelt) and reduced by the evaporative flux extracted. Subsurface runoff is a monotonic increasing function $G(M)$ of soil moisture. Surface runoff diminishes $P$ by an amount that depends on the distribution of $P$ over time. If we neglect this dependence, we need not distinguish surface runoff from $P$. The simplified water budget can be written as

$$\frac{dM}{dt} = P - E - G(M), \quad (1)$$

where $t$ is time. In a steady-state climate, soil moisture is not changing on the annual average, so water input and output sum to zero when averaged over the seasonal cycle; thus
Fig. 4. Mean seasonal cycle from the dataset of Hulme (1994) and the control simulation of the total and components of precipitation in (a) southern Europe and (b) central North America. In this and subsequent figures showing the seasonal cycle, the position of each month initial on the time axis marks the beginning of the month.

\[
\frac{dM}{dt} = 0 = \langle P \rangle - \langle E \rangle - \langle G(M) \rangle.
\]

If more \( P \) is supplied on the annual average but \( E \) is unchanged (because evaporation is proceeding at the potential rate and other factors are unaltered), the balance is preserved by increasing \( G(M) \), which requires the soil to become wetter. If \( E \) is increased (by higher temperature, for instance) and \( P \) unaltered, \( G(M) \) must respond with a decrease, which means the soil becomes drier.

If \( G \) were constant (or zero), any seasonal cycle having \( \langle P - E \rangle = G \) would be consistent with any value of \( \langle M \rangle \). But since \( G \) increases with \( M \), an increase or
decrease in \((P - E)\) must be accompanied by a corresponding change in soil moisture \((M)\). This is the basic reason why the reduction in \(P - E\) in the anomaly climate is associated with drier soil.

5. Seasonal hydrologic cycle in the current climate

Changes in annual averages alone do not give an adequate picture of the effect of climate change on the hydrology of the two climates because of the strong seasonal cycle in both precipitation and soil moisture. In order to account for the summer dryness of the current climate and the changes that occur as a consequence of climate change, we have to examine the hydrologic cycle throughout the year. In this section, we look at the current climate. (Note that because of missing monthly data in some quantities, the seasonal cycles shown in figures are made from the last 9 yr of the integrations only. They are consistent with one another, but are not exactly consistent with the numbers we quote, which are generally based on the last 10 yr.)

First, we describe the seasonal cycle of precipitation, which is different in the two regions.

In southern Europe in winter, the ridge of high pressure from the Azores anticyclone shifts southward, allowing penetration of moist westerly air from the Atlantic into the Mediterranean (e.g., Shea 1986). A comparison of the observed and simulated flow (Murphy 1995a, his Fig. 25) shows that the model captures this transition, although the westerly flow in the model over the Mediterranean becomes excessive. The seasonal shift is accompanied by an increase in synoptic activity, as indicated by a near doubling of the bandpass (2.5–6-day) filtered variance of 50-kPa heights between winter and summer in both observations and simulation (Murphy 1995a, his Fig. 26). Large-scale rainfall reaches a maximum in the model in January (Fig. 4a), consistent with this increase in synoptic activity.

In summer the Azores ridge shifts northwestward in both observations and the model (Murphy 1995a, his Fig. 25), leading to a minimum in total rainfall (Fig. 4a), presumably because the change to easterly flow over southern Europe replaces moist Atlantic air with warm dry air from the interior of Eurasia. In the model, large-scale rainfall decreases, consistent with the decrease in synoptic activity in the observations and model noted above, but convective precipitation reaches a maximum in summer (Fig. 4a), as solar heating of the surface, which tends to destabilize the atmosphere, reaches a maximum (see later).

Since simulated precipitation peaks in winter and a large fraction of the snowfall melts quickly (compare Fig. 4a to Fig. 5a), there is plentiful input of water to the soil from rain and snowmelt throughout the autumn, winter, and early spring. Fractional soil saturation rises to a value of about 0.5 in January and does not decline very much until March (Fig. 5a).

The second region is central North America. This region has a continental climate, with winter low temperatures and high pressure associated with subsiding dry cold air (see, e.g., Shea 1986). In spring, the pressure declines over the continent, and the circulation around the intensifying Atlantic anticyclone brings a moist southeasterly flow from the Caribbean (Shea 1986), contributing to the increase in precipitation in spring (Fig. 4b). During the summer, there is a continental heat low, which tends to steer flow away from the interior. The model again reproduces the main features of the seasonal cycle in circulation (Murphy 1995a) and precipitation (Fig. 4b). Total precipitation reaches a maximum in June in observations and May in the model. In the model the large-scale precipitation peaks in March or April and falls to a minimum in summer (Fig. 4b), consistent with the decline in synoptic activity both in the observations and simulations (Murphy 1995a, his Fig. 26). The peak in simulated convective precipitation is stronger than in southern Europe and dominates the cycle of total precipitation.

At least two reasons contribute to the very different annual cycle of precipitation in the two regions. First, winter temperatures are about 8 K warmer over southern Europe (see, e.g., Shea 1986), so specific humidity, moisture convergence, and, hence, precipitation can be stronger than in southern Europe and dominates the cycle of total precipitation.

Since rainfall over central North America is limited in winter and there is little snowmelt on account of the low temperatures, soil moisture rises rather slowly through autumn and winter, but more quickly in spring as the snow begins to melt and rainfall increases. The maximum fractional saturation of around 0.4 is attained in April.

In both regions, the runoff is large at the time of maximum soil moisture. In experiments with a later version of the model, in which we use the same hydrologic scheme and for which we have information on the separate components of runoff (Johns et al. 1997), the subsurface component \(G\) (drainage from the wet soil) dominates. It is likely, because of the similarity of the models, that this is true in the present analysis as well. In the simpler hydrology of Manabe and Wetherald (1987), the soil completely saturates in winter, so the maximum \(M\) is the prescribed saturation value. While the soil is saturated in their model, positive \(P - E\) is balanced by surface runoff. In our model, on the other hand, the maximum \(M\) is determined by a balance between \(P - E\) and \(G\). The dependence of \(G\) on \(M\) is important, as in the annual-mean case. If we represent it by a linear relation \(G = gM\), \(M\) develops according to

\[
\frac{dM}{dt} = P - E - gM, \tag{3}
\]
so will have a turning point when $\frac{dM}{dt} = 0 \Rightarrow M = \frac{(P - E)}{g}$, which is obviously an acceptable solution provided that $P > E$. (In fact, the relation is not linear, but involves a higher power of $M$. The dependence is not important to this qualitative argument, except for the fact that $G$ increases monotonically with $M$.)

After the winter or spring maximum, soil moisture begins to decline as evaporation increases. There are two main factors influencing the seasonal cycle of evaporation (Fig. 5).

First, solar heating at the surface determines how much energy is available for latent heat of evaporation. This is the basic reason why the latent heat flux peaks in June (Fig. 6). Provided that there is an unlimited supply of water, the rate of heat loss from the surface by evaporation rises much more strongly with temperature than sensible or radiative heat loss. Thus, the latent heat flux is the largest heat loss term for some of the late spring and summer: May and June in southern Europe, and April to August in central North America. Latent heat flux is a more important term through these months in central North America because the surface temperature is higher there. Throughout the summer and into September, convective rain is the largest part of
precipitation. Its seasonal cycle is similar to that of latent heat, and it also peaks in June. It is probable that convective precipitation is largely derived from local evaporation.

Second, as described above (section 2), evaporation is restricted when soil moisture falls below the critical level. The critical fractional saturation is about 0.18 in both regions, and the area average does not fall to this level until July. However, there is variation within the regions, and the areal fraction with soil moisture below the critical level is 0.35 in southern Europe and 0.22 in central North America in June. After June, evaporation declines. The restriction on evaporation is the reason why the soil cannot dry out completely during the summer. Above, we saw that a steady state requires that $M = (P - E)/g$. In summer, with moist soil, $E$ exceeds $P$, implying that $M$ should decline to zero before reaching a steady state. To understand the effect of the restriction on evaporation by dry soil, let $E = \gamma M$, assuming $E$ is less than the critical value. (A simple linear dependence is a simplification, as for subsurface runoff. The important fact, which correctly represents the model formulation, is that $E$ declines with $M$.) The water balance then becomes

$$M = \frac{(P - E)}{g}$$
\[
\frac{dM}{dt} = P - \gamma M - gM, \tag{4}
\]
which has the same form as before, with the replacement of \( P - E \) by \( P \) and \( g \) by \( \gamma + g \). The equilibrium \( M \) is now
\[ M_{eq} = P(\gamma + g). \tag{5} \]
Unlike before, a steady state with nonzero \( M \) can be achieved since \( P > 0 \).

The latent heat flux, with evaporation, declines after June in both regions. This causes an increase in surface temperature, so that sensible heat and net upward long-wave radiation increase to compensate for the loss of evaporative cooling. Net upward longwave radiation peaks in August, with the surface temperature. The maximum net downward shortwave radiation occurs in July, although the maximum incoming radiation at the top of the atmosphere is at the solstice in June. This is because cloud amount and, hence, planetary albedo are declining through the summer. Soil moisture continues to decline through July and August, reaching a minimum fractional saturation in September of about 0.12, when 0.61 and 0.72, respectively, of the areas of the two regions have soil moisture below the critical level.

The simultaneous decline of soil moisture content and cloud amount through the summer are connected because the reduction of soil moisture restricts evaporation and raises temperatures, leading to lower relative humidity and less condensation. The effect is that \( E \) is increased for a given \( M \) because of reduced cloud and higher temperatures, which in terms of the above formalism is represented by an increase to \( \gamma \) and, hence, a lower, but still nonzero, final \( M \).

Since the reduction of cloud and rise in temperature are associated with the drying soil, it is tempting to think of them as constituting a positive feedback upon further drying. This is misleading. It is evident that the reasoning is confused when it is set out in full as follows: drier soil \( \Rightarrow \) less evaporation \( \Rightarrow \) less cloud \( \Rightarrow \) more surface heating \( \Rightarrow \) more evaporation \( \Rightarrow \) drier soil. This description involves evaporation twice, with opposite changes, and it is simpler to regard the relationships as two separate negative feedbacks on changes in evaporation. The first of these involves cloud cover—when evaporation declines (for whatever reason), the reduction in cloud acts against the change. A fall in soil moisture is one possible initial cause of a reduction in evaporation. Soil moisture itself provides the other negative feedback on changes in evaporation. When evaporation increases (for whatever reason), it has a tendency to reduce soil moisture (precipitation and runoff have also to be taken into account) and, hence, leads to a greater restriction on evaporation, thus offsetting part of the initial change.

The most important points from this section are as follows.

1) A maximum of soil moisture occurs in January in southern Europe and April in central North America, at the time when the net input of water to the soil balances the subsurface runoff.

2) This time is different in the two regions because winter large-scale precipitation is more important in the European region and spring convective rainfall in the American.

3) Soil moisture declines rapidly in early summer, while solar heating is balanced by the latent heat flux.

4) Evaporation is restricted when the soil moisture falls below a critical value. The restriction is partly countered by the lessened cloud cover and rise in temperature, which result from the reduction in evaporation, but evaporation is nonetheless limited by soil moisture.

5) For this reason the soil does not dry out completely, but reaches a minimum at the end of the summer.

6. Climate change in the seasonal cycle

We now turn to examine the effect of climate change on the seasonal hydrologic cycle. In southern Europe there is negligible change in winter mean precipitation and a 22% decrease in summer, while in central North America there is an increase of 9% in winter and a reduction of 12% in summer (Table 1 and Fig. 7). (As noted above, Table 1 was made from 10 yr of data, but Fig. 7 from only 9 yr. This is the reason for small discrepancies between the two.) Other seasons show intermediate changes. Soil moisture is lower, not only in the annual average, but throughout the year, and especially in summer, when it is down by 28% and 25% in the two regions (Table 2 and Fig. 8). These reductions are about twice those in the annual average. Nonetheless, changes in precipitation, soil moisture, and other quantities are considerably smaller in magnitude than the seasonal cycle of the same quantities in either climate and so may be regarded as a small perturbation. Here, we document the changes and speculate on the underlying mechanisms. The two regions are qualitatively more similar regarding the changes in the hydrologic cycle than they are in respect of the control climate, so we do not generally need to consider them separately.

First, winter will be examined. Since the warmer tem-
temperatures of the anomaly climate lead to higher specific humidity, one might expect an increase in precipitation. Precipitation does indeed increase in central North America (Fig. 7b), but there is little change in southern Europe (Fig. 7a). This may be because in this region the circulation becomes more northerly and anticyclonic (Murphy and Mitchell 1995), tending to suppress precipitation. Changes in flow over central North America are weaker than over southern Europe.

In the warmer climate, much of the winter snowfall

**TABLE 2.** Seasonal soil moisture content in the two climates. Figures are fractions of saturated moisture capacity. Seasons are labelled by their constituent months.

<table>
<thead>
<tr>
<th>Season</th>
<th>Southern Europe</th>
<th>Central North America</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C</td>
<td>A</td>
</tr>
<tr>
<td>SON</td>
<td>4.54</td>
<td>3.38</td>
</tr>
<tr>
<td>DJF</td>
<td>10.60</td>
<td>10.14</td>
</tr>
<tr>
<td>MAM</td>
<td>9.60</td>
<td>8.90</td>
</tr>
<tr>
<td>JJA</td>
<td>4.35</td>
<td>3.15</td>
</tr>
</tbody>
</table>
is replaced by rain. Furthermore, the snow that falls melts more quickly. Consequently, the input of water to the soil in autumn and winter is greater than in the control, while in spring there is less snow to melt and reduced water input. This is merely a redistribution of the soil water supply, leading to a more rapid replenishment in autumn, following the summer drying. Another, smaller, effect that influences the recovery of the soil moisture in southern Europe is that runoff is reduced in the early autumn because of lessened gravitational drainage out of the drier soil. The effect is not present in central North America, as autumn runoff is negligible even in the control climate.

A second consequence of reduced snowfall and snow cover is a decreased surface albedo, which leads to a small increase to surface solar heating in winter. This amounts to about 10 W m\(^{-2}\) in central North America and 5 W m\(^{-2}\) in southern Europe. Evaporation is not generally limited by soil moisture in winter in either simulation and increases on account of several factors. First, the increase in surface temperature, resulting directly from the enhanced greenhouse effect, implies a higher saturation vapor pressure and, hence, a greater rate of evaporation. Second, increased solar heating (see above) means there is more energy available for evaporation. (Both latent and sen-
sible heat loss are increased.) Third, the reduction of snow cover increases total evaporation because evapotranspiration from soil proceeds at a higher rate than sublimation from snow.

In winter, in conclusion, we find that there is an increase in water input to the soil, but it is restricted because the increases in precipitation are small and there is greater evaporation. There is also a tendency for water input to occur earlier in winter on average.

The increases in precipitation dwindle on, passing from winter into spring. Evaporation is greater in the anomaly in early spring because of higher temperatures, but this effect is counteracted by the restriction on evaporation from low soil moisture, which becomes important earlier in the year in the anomaly, as the soil is always drier. Therefore, the increases in evaporation reach a maximum in March in southern Europe and May in central North America, in both cases shortly after the time of maximum soil moisture. After June, evaporation in the anomaly climate is less than in the control, but soil moisture continues to decline throughout the summer, bottoming out in August and September at a fractional saturation of about 0.05 in both regions, which is roughly half the minimum value in the control climate.

Summer drying over southern Europe is a feature of almost all experiments with increased CO₂ (Kattenberg et al. 1995). This suggests that its occurrence is not dependent on the details of individual parameterization schemes, but results from robust features of the simulated climate in that region. Increases in temperature and water vapor generally tend to cool the atmosphere radiatively and warm the surface, leading to increased convection (Mitchell et al. 1990). (Note that convective rain is greater in spring and early summer in the anomaly climate, until evaporation becomes limited.) Convection tends to warm up and dry out the lower troposphere, further increasing evaporation. All these factors combine to produce marked increases in evaporation, as long as it is not limited by low soil moisture.

We speculate that the presence of the Azores high pressure ridge damps any tendency for increased precipitation in summer over southern Europe. Indeed, if there is predominantly large-scale subsidence in the region, then this will tend to dry the atmosphere. In addition, M. Rodwell and B. Hoskins (1996) have demonstrated in idealized experiments that increased latent heat release over Southeast Asia (another feature common to most simulations of the climate change response to increased CO₂) is associated with enhanced descent over the eastern Mediterranean. The summer circulation over North America is not as conducive to subsidence as that over southern Europe, which may explain the greater intermodel differences in the response of summer soil moisture levels to increased CO₂ in this region. Nonetheless, the relevant quantities in this experiment show similar kinds of changes in the two regions. In the absence of increased moisture convergence, the factors mentioned above will continue to dry the atmosphere in summer, which would account for the decrease in large-scale precipitation.

There is a close similarity between decreases in evaporation and in convective rain after June, suggesting that the main supply of moisture to the atmosphere in summer is from the surface. (Large-scale precipitation requires ascent and grid-box humidities close to saturation, whereas convective precipitation can occur with relatively low humidities.) Including the decrease in large-scale precipitation, \( P \) decreases more than \( E \), so the soil dries out.

The difference in water budget in the period when evaporation is limited can be derived from Eq. (4) as

\[
\frac{dM}{dt} = \Delta P - \Delta (\gamma M) - g \Delta M, \tag{6}
\]

where \( \Delta \) indicates the difference (anomaly − control) between the integrations. The change in evaporation \( \Delta E \) has two terms:

\[
\Delta E = \Delta (\gamma M) = M \Delta \gamma + \gamma \Delta M. \tag{7}
\]

Overall, evaporation is reduced because of the decrease in \( M \). However, this leads to higher surface temperature and less cloud cover, and, hence, to greater \( \gamma \), which offsets part of the reduction. This is one of the negative feedbacks on evaporation discussed earlier. In an idealized experiment, Wetherald and Manabe (1995) isolate this effect by imposing the control cloud cover on the anomaly experiment, in order to suppress the feedback. During the summer, the net water balance of the soil is negative and it dries out, thus restricting evaporation. The reduction of evaporation is greater without the negative feedback of interactive cloud, so evaporation is less and the drying of the soil is less than in the anomaly experiment with interactive cloud.

The lower minimum \( M \) at the end of the summer can be explained by Eq. (5) as a consequence of the larger \( \gamma \). However, in the latter part of the summer, both \( \Delta M \) and \( d(\Delta M)/dt \) are negative—not only is the soil drier, but it dries out more, in the anomaly climate. Since \(-g \Delta M\) is positive, the negative \( d(\Delta M)/dt\) can only occur with reduced precipitation \( P \) under the simplifying assumptions of this formalism.

As we have remarked before, evaporation and convective rain appear to be related. We can show the effect of the hypothesis that convective rain is derived from local evaporation by replacing \( P \) with two terms: \( P = L + cE = L + c \gamma M \), where \( L \) is large-scale rain and \( c \) the fraction of evaporation returned as convective rain.

The water balance [Eq. (4)] becomes

\[
\frac{dM}{dt} = L + c \gamma M - (\gamma + g)M = L - [((1 - c) \gamma + g)M. \tag{8}
\]

The corresponding steady-state value of \( M \) is
This has just the same form as $M_\gamma$ of Eq. (5) with $L$ and $(1 - c)\gamma$ substituted for $P$ and $\gamma$. Thus, the possible relationship between convective precipitation and evaporation does not alter the conclusion that the lower minimum of $M$ in the anomaly climate can be accounted for in terms of this formula by reduced precipitation (now $L$ instead of $P$) and increased $\gamma$.

In summary, we have identified the following main factors influencing the change in the seasonal cycle of soil moisture:

1) a shift in water input to the soil from spring to autumn, on average;
2) a small increase in net input during the winter months;
3) greater evaporation in winter and spring; and
4) reduced $P - E$ in summer.

Items 2–4 account for the net reduction in $\langle P - E \rangle$, and, hence, the reduced $\langle M \rangle$ and the lower summer soil moisture. Item 1 results in a faster rise of $M$ in autumn in the anomaly and, hence, a smaller decrease in $M$ in the winter months than would otherwise have been the case.

7. Extreme events

Having examined the effect of climate change on the mean hydrologic cycle in our two regions, we now turn to the statistical analysis of the consequent changes in the occurrence of drought. At the outset, we defined drought as an exceptional lack of water. This is an extreme event, so we must bear in mind some general points about extremes.

Even though they are based on physical principles, the parameterization schemes employed in a GCM inevitably contain constants and other adjustable properties that cannot be determined exactly from theory or detailed measurements on small scales. These are chosen so that the model reproduces as nearly as possible the large-scale observations it is intended to simulate. When a parameterization scheme is calibrated in this way, the mean of a quantity is generally the statistic whose faithful reproduction is given first priority. The mean contains the most important information for characterizing the quantity, and in some cases its value has a strong influence on the sensitivity to climate change. Also, the mean is generally the most reliable (and sometimes the only) statistic available from observations. Because of the attention given to it, the mean of a quantity simulated by the model is likely to be more accurate than higher-order statistics such as the variance (on whatever timescale is of relevance). Extremes are the tails of a distribution and, hence, depend on its mean, variance, and shape. The correct simulation of extremes, therefore, makes very exacting requirements on a model’s representation of the current climate.

Note that the uncertainty of estimation of an extreme statistic will generally be greater than the uncertainty in the standard deviation or the mean, for a given sample. (This problem can sometimes be tackled by calculating extremes from better-estimated parameters, assuming a particular statistical model.) Observational datasets are often rather small for computing extreme statistics, and model-generated datasets are typically even smaller. This is another reason why the study of extremes is a relatively difficult area in which to draw reliable conclusions.

An important and well-known statistical point regarding extremes is that a change in an extreme statistic can be large even when the change in the mean of the distribution is small (Mitchell et al. 1990, 152, and references given therein). We illustrate this with the simple example of the standard normal probability distribution function, which has a mean of zero and a standard deviation of unity. Fifty percent of the distribution lies below the mean. Consider a shift of the distribution, decreasing the mean but not altering the standard deviation, such that 75% of it lies below the old mean of zero. This decrease in the mean is only 0.67 of the standard deviation, so it is fairly small. However, the lower 1% level of the old distribution has a probability of 4.9% with the new mean. If the 1% level represents an event that causes severe disruption or stress to society or the ecosystem, a fivefold increase in its probability is a serious matter. Changes in the variability of the quantity also influence the probability of extremes; in some cases, changes in the variability are more important than changes in the mean (Katz and Brown 1992). The second main purpose of this paper is to provide a practical illustration of results of this kind.

8. Occurrence of dry summers

The first and most straightforward statistic we have analyzed is the occurrence of summers with a low seasonal average precipitation. Since we have only 10 yr of data in each integration, we look at the frequency of dry summers that have a return period of 10 yr. We describe three possible methods for doing this.

a. No statistical model

An approach that is independent of the choice of any statistical model is, for each point, to

1) find the smallest seasonal average value $Y_i$ that occurs in any of the 10 yr of the control integration, and
2) count the number of times $n_a$ that the seasonal average value in the anomaly integration is less than or equal to $Y_i$ and use this to estimate the probability that the seasonal mean precipitation is equal to or
less than this value in the anomaly climate, using 

\[ P_a(S \leq Y_1) = n_a/10 \]

where \( S \) is the seasonal-mean precipitation.

The drawback of this approach is that \( Y_1 \) is not the quantity we really want. We would like an estimate of \( R_1 \), the low value that has a return period of 10 yr—that is, \( R_1 \) such that \( P_c(S \leq R_1) = 0.1 \). In fact, \( Y_1 \) is biased to values smaller than \( R_1 \), but, as we shall see shortly, the difference is not very great.

The results for \( P_a(S \leq Y_1) \) are shown in Fig. 9. In southern Europe and central North America, there are many grid boxes where \( n_a \) is 2 or more \( \Rightarrow P_a \approx 0.2 \), meaning that the minimum dry level in the control occurs in 2 or more years in the anomaly. The area-averaged probabilities are 0.27 and 0.22 in the two regions. This is an increase of a factor of around 2.5 in probability, whereas the decrease in precipitation was only 10%–20%.

b. Order statistics from the normal distribution

If we adopt a statistical model for \( S \), we can calculate probabilities from parameters of the distribution. The most obvious choice for the distribution of seasonal precipitation totals is the normal. A sample of only 10 is too small to give a reasonable idea of the shape, so on the assumption that the distribution is indeed normal everywhere, we show in Fig. 10 the aggregate of the distributions at all points, standardized at each one by its sample mean and standard deviation. This looks fairly symmetrical; certainly it would be hard to justify the use of any more elaborate function. The figure shows...
the distributions for the perturbed climate as well, standardized by the parameters of the control climate at each point, and we note that it spreads out in both tails, meaning there are more very wet summers as well as more very dry summers.

We now take the probability density functions $f_c$ and $f_a$ of seasonal average precipitation in the two climates to be normal, with parameters given by the sample mean and standard deviation in each case. Then, if $y_1$ is the probability density function of $Y_1$ in the control climate, we have

$$P_c(S \leq Y_1) = \mathcal{N}(0,1) \int_0^\infty y_1(y) f_c(s) ds dy.$$

The asymptotic form of the order statistic $y_1$ for large samples from the normal distribution is the double exponential (e.g., Gumbel 1958). Our samples of 10 are quite small, and we can be more accurate if we obtain the approximate distribution by generating normally distributed random samples of 10 and finding the minimum of each sample. We do this for the standard normal $\mathcal{N}(0,1)$.
The resulting distribution is converted to \( y_1 \) by shifting and rescaling it with the mean and standard deviation of \( f_c \).

We then use \( y_1 \) to calculate \( P_a(S \leq Y_1) \) for each point. This gives maps that look very similar to those of Fig. 9, suggesting that the normal approximation is adequate. The area-averaged probabilities are 0.25 and 0.24 by this method.

c. Normal deviates for chosen probabilities

Finally, again on the assumption that the distributions are normal and using sample estimates of the parameters, we calculate \( R_1 = F^{-1}(0.1) \) and \( P_a(S \leq R_1) = F_a(R_1) \), where \( F_a \) and \( F_c \) are the cumulative distribution functions corresponding to \( f_a \) and \( f_c \). This is dependent on the particular statistical model, but it gives a more easily comprehensible result, namely the probability of occurrence in the anomaly climate of the dry summer that has a return period of 10 yr in the control. This is not very different from the previous statistics, in practice. The mean of \( Y_1 \) from the random samples is \(-1.537\), while \( R_1 \) for \( N(0, 1) \) is \(-1.282\). Again, maps of \( P_a(S \leq R_1) \) are similar in character to those from the other two methods, and the area averages are both 0.22.

Analysis of the distribution of seasonal-mean precipitation, then, shows us that exceptionally dry summers that happen once in 10 yr on average in the control climate become 2–2.5 times more frequent in the anomaly. Two of the methods assume a statistical model for the distribution, but results appear to uphold this assumption as sufficiently good.

9. Lengths of dry spells

a. Importance and definition of dry spells

Another description of the character of precipitation is in terms of wet and dry spells—runs of consecutive days during which there is, or is not, precipitation. A common definition of drought is as a long period when there has been no precipitation. Labeling days as “wet” or “dry” is the best summary of the weather (at least in the midlatitudes) that can be made with a yes–no classification. This is not only a popular perception, but also the basis for several practical stochastic weather generating computer programs (Richardson 1981; Wal- lis 1995).

We have used the length of dry spells as a second statistic to quantify the occurrence of drought. A dry day is defined as one in which the accumulated precipitation is less than 0.05 mm. A dry spell is a run of consecutive dry days, preceded and followed by a wet day. At each grid box, we counted all dry spells that began, ended, or both began and ended, within the summer months. A very long dry spell—more than a month long, say—is a significant fraction of a year, and might not be entirely “during the summer.” However, spells of this length are uncommon in the regions considered.

b. Comparison of the GCM, observations, and the Markov model

To illustrate the character of the distribution of summer dry spell lengths, we compare observed and simulated data for northern Italy in Fig. 11, which shows...
the distributions for the daily precipitation time series formed by averaging the records covering 1958–77 from Pisa, Ancona, and Pescara, Italy, and for the model grid box containing these places. Since the observed time series cover more years (20 rather than 10), they provide information about less frequent (i.e., longer) dry spells. The choice of a three-site average is rather arbitrary. How best to compare observed daily time series to GCM grid-box time series is a subject in itself, which is not within the remit of this paper to address. Other work, such as that by Reed (1986) and Gregory and Mitchell (1995), suggests that an average of several sites is preferable to a single site, but the relation is not well quantified.

The lines in Fig. 11 are predictions of the distribution obtained by assuming that occurrence or nonoccurrence of precipitation can be modeled by a two-state Markov chain. The essence of this assumption, often made in the hydrologic literature (Gabriel and Neumann 1962; Todorovic and Woolhiser 1975; Richardson 1981; Wallis 1995), is that the probability that tomorrow will be dry, given that today is dry, is a constant $p_{dd}$ irrespective of how long the dry spell has lasted so far. With this assumption, the probability that a dry spell, once started, will be exactly $n$ days long is $p_{dd}^{n-1}(1 - p_{dd})$, the sum of which to all lengths is

$$\sum_{n=1}^{\infty} p_{dd}^{n-1}(1 - p_{dd}) = 1.$$  \hspace{1cm} (11)

In a time series containing $n_d$ dry days, there will be $n_d(1 - p_{dd})$ dry spells (this is the expected number of occasions on which a dry day is followed by a wet day, which is the definition of the end of a dry spell). Hence, the expected number of dry spells of exactly length $n$ is

$$n_d(1 - p_{dd})p_{dd}^{n-1},$$  \hspace{1cm} (12)

which is what is plotted in the figure, $n_d$ being the actual number of dry days in the time series and $p_{dd}$ estimated as $n_d/n_p$, where $n_d$ is the number of dry days followed by a dry day.

For short dry spell lengths, the Markov chain fit describes the observed data quite well. There are more dry spells of longer than about 15 days, however, than the fit predicts. This indicates that the assumption of constancy of $p_{dd}$ is inadequate. In nature, there is variability that affects the likelihood of precipitation and has a timescale of more than 1 day. This arises, for instance, from dynamic processes such as blocking, when an anticyclone persists for several days and disrupts the normal westerly flow that brings the weather fronts. Different regimes have different probabilities of precipitation. When a day is picked from a dry spell at random, the longer the dry spell has lasted up to that point, the more likely it is to be from a period having a lower probability of precipitation. There are also physical processes, such as the feedback, whereby rainfall is reduced as the soil dries, which cause dry spells to persist. For these reasons $p_{dd}$ increases with $n$ in nature.

Unlike a stochastic model based on a Markov chain, the GCM should represent the processes that lead to the persistence of dry spells. It is, therefore, encouraging that $p_{dd}$ increases with $n$ in the model, as in the observations. But given the sparseness of data for long dry spells, it is not possible to draw precise conclusions about the realism of the model. It is also obvious that a study of only one grid box is not a comprehensive evaluation of the model’s performance. The main difficulty in this regard is the lack of readily available long-period quality-controlled daily observational time series. We would require several stations for each grid box for a satisfactory investigation. In the absence of this, our results for climate change for daily statistics should be regarded as having greater systematic uncertainty than those for seasonal statistics.

c. Climate change

For spells of 1–30 day length, we find the area average of the number of occurrences in the data. This gives us an estimate of the number of spells of that length occurring per year on average. By taking an area average, we are aggregating points rather different precipitation regimes. This is especially true in the southern European area, in which there is a large north–south precipitation gradient. In a sample of only 10 yr, we have to use this approach in order to obtain sufficient statistics for long dry spells. The area average results can be taken to indicate only the character of dry spell distributions and the changes that occur.

From the frequency distribution $N(n)$ (occurrences per year) of dry spells of exactly length $n$ we obtain the return period of a spell of at least $n$ days as $[\sum_{i=n}^{\infty} N(i)]^{-1}$. This is plotted in Fig. 12. The feature that is immediately obvious is that the return period for a given $n$ decreases in the anomaly climate, or, equivalently, the $n$ for a given return period is greater. This is true for all $n$ except the very smallest and becomes more pronounced the longer the spell. (It is not true for spells of a single dry day because the number of these is less in the anomaly climate, as a result of all other dry spells becoming longer on average.) That is to say, long dry spells become more frequent.

For instance (Table 3), the return periods for a dry spell of at least 30 days decrease by one-third in southern Europe and by two-thirds in central North America, in the latter case from 48 to 17 yr. These are equivalent to probability increases by factors of 1.5 and 2.8, respectively. For central North America, a dry spell of this length is a rare and extreme event, and such a marked increase in its likelihood would be a serious impact of climate change.

This marked change in the distribution of dry spell lengths is not necessarily caused by the reduction in mean precipitation, however. The probability of long
Fig. 12. Return periods for dry spells of various lengths in the control and anomaly simulations in (a) southern Europe (b) central North America.

Dry spells could be increased if precipitation tended to arrive in less frequent but more intense events, without alteration to the average. Such a change in the character of daily precipitation is found by Gregory and Mitchell (1995) and K. Hennessy and J. M. Gregory (1996, personal communication) in an equilibrium climate-change experiment with an earlier version of this model (see also Whetton et al. 1993). A possible explanation is that longwave cooling increases less strongly with temperature than the saturation vapor pressure. Hence, in a warmer climate it requires fewer convective events to transport the required amount of moisture to upper levels in the atmosphere, where the release of latent heat balances the radiative cooling.

We can test whether the increase in probability of long dry spells is caused by a reduction or by a redistribution of precipitation by performing the same cal-

Table 3. Return periods for dry spells of at least a given length. Return periods are in years.

<table>
<thead>
<tr>
<th>Spell/day</th>
<th>Southern Europe</th>
<th>Central North America</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C</td>
<td>A</td>
</tr>
<tr>
<td>10</td>
<td>0.79</td>
<td>0.61</td>
</tr>
<tr>
<td>20</td>
<td>1.51</td>
<td>1.06</td>
</tr>
<tr>
<td>30</td>
<td>2.53</td>
<td>1.68</td>
</tr>
</tbody>
</table>
culation of spell lengths using daily rainfall time series from the anomaly integration, which have been scaled up to have the same mean as the corresponding time series of the control integration. The results of this procedure are very similar to the results described above. This indicates that the increased likelihood of long dry spells arises from a change in the character of summer rainfall, rather than a reduction in its amount. It is, therefore, not directly related to the change in the probability of dry summers calculated in the previous section.

10. Probability of dry soil

The third and simplest statistic we use to quantify drought is the probability of the soil drying out. As discussed in section 1, this is for some purposes the statistic of most direct practical importance, but also the most model dependent.

The way in which precipitation is distributed over time has an effect on the soil moisture. If it arrives episodically, there will be long dry spells during which the soil moisture may fall to levels much lower than the average, whereas continual input of water would keep the moisture at a higher value. The most important characteristic is the length of dry spells, considered in the last section, but the distribution of daily precipitation amounts also has an influence. Furthermore, because of the maximum limit on infiltration, the proportion of precipitation taken up by the soil will be smaller if it arrives in larger amounts. In this model, however, this effect is probably minor; we believe surface runoff to be relatively small (see section 5). A comparison of the distribution of daily precipitation amounts in the model and in observations (Fig. 13) for the grid box studied in the previous section reveals that the model's performance is fairly good. Its main error is a tendency to simulate too many moderate events and too few heavy events, as was also noted by Gregory and Mitchell (1995) for an earlier version. We judge that the error is not serious for this purpose.

At a given grid box, what we define as the “probability of dry soil” is the chance of the soil being dry on a randomly chosen day; we estimate it simply as the fraction of days that have dry soil. “Dry soil” means values of soil moisture below a particular threshold; we used three different thresholds, namely 1 and 10 mm water (excess over the wilting point) and the critical level (which is geographically varying but always larger than 10 mm). A lower threshold defines a more extreme event. The probability of soil moisture being below the critical level was considered in section 5 in connection with restriction on evaporation, and the seasonal cycle of its area average is shown in Fig. 5.

Changes in the probability of dry soil in summer are more marked for the 1-mm threshold than for the critical level (Table 4), with 10 mm being intermediate; that is, the increase in likelihood of the most extreme event is largest, as we might expect. The increases in the prob-
ability of 1 mm of soil moisture, of 52% and 88% for southern Europe and central North America, respectively, should be compared with the decreases of 22% and 12% in precipitation and 28% and 25% in soil moisture. The proportional increases in probability for these extreme events are fairly large, but the effect is not as marked as for other statistics we have considered. The main reason for this is that normal variations of soil moisture take it near to its minimum value of zero, so the size of possible change is limited.

Whereas shortage of simulated data restricts us to area average statistics in the previous two sections, we are able to examine geographic variation for the probability of dry soil, which is a daily statistic. The largest increases in the probability of dry soil (Fig. 14 for the threshold of 10 mm) are, unsurprisingly, in the areas of the greatest reduction of precipitation.

At a given location, it is of interest to know not only whether the soil moisture will fall below a particular threshold, but how long it will spend below that threshold. We characterize dry soil conditions in terms of two variables, such that the soil moisture is below a given threshold for at least a given fraction of the summer (for instance, below 10 mm for at least half of the time). We can then calculate the proportions of the areas of our regions affected by dry soil conditions described in this way (shown in Fig. 15 for central North America). We also look at changes in these areal proportions (shown in Fig. 16 for central North America). The largest increases in affected areas occur for low thresholds (below 20 mm) and relatively infrequent states (less than half the time). For instance, in the control climate, the areal proportions of southern Europe and central North America where the soil moisture is below 10 mm for at least half of the summer on average are 0.35 and 0.18. In the anomaly climate, these increase to 0.61 and

Fig. 14. Change in probability (anomaly – control) of soil moisture on an individual day being less than 10 mm in (a) Europe and (b) North America.
0.33—that is, by around 75% in both cases. The expansion of the area affected by such an extreme event could obviously have serious consequences.

11. Conclusions

Our object in this paper has been to use a coupled GCM climate-change experiment to investigate the mechanisms and magnitude of changes in drought. Previous studies of this subject have applied offline models and empirical relationships to GCM output, rather than using the GCM-simulated quantities themselves to assess drought, because of reservations about the realism of parameterization schemes used in the models. While being aware of the coarseness of the spatial scale and the systematic uncertainty arising from the need for parameterization, we have chosen to base our investigation solely on GCM output. This gives us the advantage of simplicity, since we are using only one model, and allows us to relate the statistics we calculate directly to processes in the model.

We have focused on changes in southern Europe and central North America in summer, both being regions of likely vulnerability to increased incidence of drought. In both cases, there are reductions in precipitation and soil moisture in the summer of 10%–30%. Possible rea-
sons for the reduction in precipitation include the restriction of evaporation by the lower soil moisture in summer and a greater drying of the troposphere by increased convective activity. Increased evaporation in winter and spring, resulting from reduced snow cover and higher temperatures, contributes to the reduction of summer soil moisture. Increases in winter precipitation are relatively small. Further investigation of the factors behind these changes is not possible with the data available from this experiment, but could form a subject for analysis of experiments now in progress with a later version of the model.

Drought has various definitions and impacts, so we have quantified it using three different statistics: the occurrence of summers with low precipitation, the length of dry spells, and the likelihood of dry soil. Although the changes in average precipitation and soil moisture are modest, the changes in all these statistics, which quantify extreme events, are considerable. In percentage terms, they are many times larger than the changes in the averages. This is to be expected on statistical grounds, since the likelihood of an extreme event is very sensitive to changes in the mean and variability of the distribution.

Precipitation is a well-observed quantity, and the model simulation compares well with observations. The increase in probability of low summer precipitation is the simplest and likely to be the most reliable of our results. The increase in likelihood of long dry spells arises from a tendency for rainfall to occur in fewer but heavier events, rather than from the reduction in mean precipitation. This is a demonstration of the importance of looking at statistics other than the mean when evaluating the effect of climate change. An exceptionally long dry spell is a popular definition of drought, but the main reason for this is its effect on soil moisture. Probability of dry soil is the most model-dependent of the statistics we have calculated and the least well evaluated against observation. Nonetheless, it is valuable to consider it because of its significance to studies of the impacts of climate change. Changes in this quantity are proportionately smaller. The most notable effect is the considerable expansion of the area that experiences low soil moisture levels. Even though the changes in these statistics are not as marked as those for precipitation, the impact of such changes may be considerable.

Since GCM results for small regions and extreme statistics are, as yet, not as reliable as results for large regions and means, we think that the statistics we have calculated should be regarded as indicative, rather than as firm predictions. Nevertheless, we believe that the conclusion or the possibility of large changes in the severity of frequency of drought should be taken seriously, since it is through such extreme events that climate change will have its most important impact. Further studies in this area will be required as climate model development continues. Readily available long-period, high-quality, daily observational time series of precipitation and other quantities would be of great value to the evaluation and improvement of model output. Greater computing power in the future will enable longer integrations (providing more data) and permit the use of higher spatial resolution. Improvements in these areas will be particularly beneficial for the investigation of extremes.

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