Subsurface thermal effects of land use changes
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The International Heat Flow Commission global geothermal data set contains over 10,000 borehole temperature logs worldwide. Only about 10% of these data are currently used for climate studies because a number of known nonclimatic energy perturbations are superimposed on the climatic signal. Here we propose a first-order approach in terms of ground surface temperatures (GSTs) to attempt to correct borehole temperature data for the effects of one of these nonclimatic energy perturbations: deforestation. We simulate the ground surface temperature changes following deforestation using a combined power-exponential function describing the organic matter decay and recovery of the forest floor after a clear-cut. Application of this correction could allow many borehole data to be incorporated into the borehole climatology database and, at the same time, may allow land surface models to use geothermal data in regions of known land disruption in order to optimize land surface energy exchange parameterizations.


1. Introduction

[2] Solar energy is a fundamental factor determining climate. Almost half of that reaching the top of the atmosphere is absorbed by the terrestrial system [Oke, 1987; Schneider, 1990] and even an increase of 1% can influence the average global surface temperature by 0.5°–1.0°C [Schneider, 1995]. However, precisely determining such a small but important quantity of energy is difficult from meteorological data because of the uncertainties associated with the measurements of atmospheric variables [Karl et al., 1989].

[1] In a forest ecosystem, only 5–20% of the short-wave solar radiation incident on the forest canopy reaches the land surface [Oke, 1987; Beltrami, 2001a]. Therefore any removal of trees results in a substantial increase in solar radiation reaching the land surface, a reduction of the leaf area involved in transpiration [Aber, 1995], and in general, a rearrangement of the energy budget at the air-ground interface [Geiger et al., 1995].

[4] Feedback effects of large-scale deforestation are important and extend beyond the limits of the area undergoing land use change, influencing the global climate [Bonan et al., 1992; Pielke et al., 1998; Chase et al., 2000]. Hansen et al. [1998] and Betts [2001] compared the radiative forcing caused by land use changes, by greenhouse gases, aerosols and stratospheric ozone, and found them to be of comparable magnitudes. There is also clear evidence that land use induced subsurface thermal changes alter biogeochemical feedbacks including the CO2 exchange between land and the atmosphere, further influencing the climate [Risk et al., 2002a, 2002b].

[3] The organic matter layer covering the forest floor is an important thermal insulator [Yoshikawa et al., 2003]. Its variability after deforestation has been described by Covington [1981] using a chronosequence study in northern hardwood forest stands. The study found a decrease of almost 50% of forest floor mass during the first 20 years after deforestation, followed by a slow recovery with a return to precutting levels after almost 100 years (see Figure 1). The rapid loss of the forest floor organic mass was initially explained by the increased moisture and soil temperature following clear-cutting that accelerated the rate of decomposition and by the decrease in the woody litter inputs [Covington, 1981]. The subsequent increase of forest floor organic matter mass is thought to be due to the increase in woody litter inputs after the forest regrowth. Although not all the processes governing Covington’s curve are well understood or explained [Fedderer, 1984; Johnson et al., 1985; Yanai et al., 2003], several studies have made use of this function to address a variety of subjects. Mattson and Smith [1993] found that forest floor mass changes after deforestation in northern West Virginia obey Covington’s model. Houghton et al. [1983, 1987] used this model to estimate the carbon loss through deforestation of temperate forest soils. Hornbeck et al. [1986] and Yanai [1992] applied Covington’s model to estimate nutrient release and phosphorus accumulation in postharvest hardwood forest floors in New Hampshire. Brais et al. [1995] confirmed Covington’s observations in northwestern Quebec. In tropical regions, Lugo and Brown [1986] estimated the effects of deforestation on soil carbon content using the chronosequence approach. Some studies [Yanai et al., 2003] claim that discrepancies between recent observations and Covington’s model may be due to the differences in physical disturbances of the sites caused by recent, more disruptive stand harvest methods [Johnson et al., 1995].
Processes such as deforestation modify the surface energy balance and change the boundary conditions of the climate system [Zeng and Neelin, 1999]. The ground surface is the lower boundary for almost 30% of the atmosphere, and the ground/atmosphere interaction involves exchanges of heat, moisture and momentum. It is thus important to have a robust parameterization of the energy balance at the surface of the Earth. Precise information may then be obtained from borehole temperature data since the ground is very sensitive to small energy changes at its surface and continuously records these imbalances [Lachenbruch and Marshall, 1986]. While the amplitude of daily variations of the surface heat flux are much higher than the changes caused by events such as deforestation or snow cover variations, over the long-term, small energy imbalances become important, and since the ground acts as a high-frequency filter of energy fluctuations [Vasseur et al., 1983; Beltrami et al., 2000; Baker and Baker, 2002], it records these long-term trends as temperature perturbations superimposed on the equilibrium state. Energy imbalances at the ground surface as small as 17 m Wm$^{-2}$, persistent over 200 years, can be easily detected from borehole temperature data [Beltrami et al., 2000]. Since Lane [1923] recognized that the energy imbalances at the surface of the Earth are propagated and recorded into the ground, much work has been done to reconstruct the ground surface temperature history (GSTH) [Beltrami and Harris, 2001, and references therein; Beltrami et al., 2003] and the energy balance at the Earth’s surface [Beltrami et al., 2000; Beltrami, 2002] from borehole temperature data.

It has long been known that alterations of the surface conditions (i.e., deforestation, snow cover variations) can have a significant effect on the subsurface thermal regime [Lewis and Wang, 1998; Geiger et al., 1995]. Indeed, many borehole temperature-depth data from around the world have been excluded from the global data set dedicated to borehole climatology because they are located in areas subjected to land use changes including deforestation [Guillon-Frottier et al., 1998]. For areas where the deforestation can be dated, we propose to use a first-order approach, presented here, to correct borehole temperature data by removing the nonclimatic temperature perturbations from the measured temperature-depth profiles. This would allow a significant enlargement of the present data set. We demonstrate that correcting these “contaminated” data may be possible if the time and the character of the land use change is known. The application of the correction method to one temperature-depth profile from central Canada affected by deforestation, shows that the effects of the disturbance are removed and the GSTH obtained represents the actual climate signal: a ground surface warming that is in good agreement with the warming trends revealed by other studies in the same region.

2. Theory

Reconstruction of ground surface temperature histories from geothermal data assumes that the thermal regime of the ground is dominated by conduction and that there is no lateral propagation of the heat; thus surface temperature...
variations propagate into the subsurface following the one-
dimensional time-dependent heat conduction equation
[Carlsow and Jaeger, 1959]
\[
\frac{\partial T}{\partial t} = \kappa \frac{\partial^2 T}{\partial z^2}, \tag{1}
\]
where \(\kappa(z)\) is the thermal diffusivity, \(z\) is the depth, and \(T\) is
the temperature.

[13] When the subsurface temperatures are not disturbed
by nonclimatic factors like topography, ground water flow
or variations in thermal properties, the temperature at depth
\(z\) is given, at any time, by the quasi steady state surface
temperature \(T_0\), and the temperature perturbation \(T(z)\)
caused by the time varying ground surface temperature
according to
\[
T(z) = T_0 + q_0 R(z) + T_i(z), \tag{2}
\]
where \(q_0\) is the quasi steady state surface heat flow density
and \(R(z)\) is the thermal depth:
\[
R(z) = \sum_{i=1}^{N} \frac{\Delta z_i}{\lambda_i}, \tag{3}
\]
where \(\lambda_i\) is the thermal conductivity over the depth interval
\(\Delta z_i\).

[14] If the past variations of ground surface temperature
are modeled as a series of \(K\) step changes in temperature,
then the subsurface temperature signatures from each step
change are superimposed and the temperature perturbation
at depth \(z\) is given by [Mareschal and Beltrami, 1992]
\[
T_i(z) = \sum_{k=1}^{K} T_k \left[ \text{erfc} \left( \frac{z}{\sqrt{2 \kappa k t_{k-1}}} \right) \right]. \tag{4}
\]
where \(T_k\) is the ground surface temperature, each value
representing an average over a time \(t_k - t_{k-1}\), and \(\text{erfc}\) is
the complementary error function.

[15] The inverse problem determines \(T_0\), \(q_0\) and the
ground surface temperature history (GSTH), represented
through \(T_1, \ldots, T_K\), from \(T(z)\). Alternatively, \(T_0\) and \(q_0\)
can be estimated independently from the upward continuation
from the deepest part of the profile, least affected by recent
ground surface temperature changes.

[16] The solution for \(T(z)\) requires equation (2) to be
evaluated at every depth where data exist, forming a system
of linear equations with \(k + 2\) unknowns which can be
written as
\[
\Theta_j = A_j \Xi_j, \tag{5}
\]
where \(\Theta_j\) is a column vector containing the \(j\) values of
temperature \((\Theta_1, \ldots, \Theta_J)\) measured at depth \(z_j\), \(\Xi_j\) is
a column vector containing the \(i + 2\) unknown model parameters \((T_0, q_0, T_1, \ldots, T_K)\); \(A_j\) is a \((j \times i)\) matrix which contains 1 in the
first column, the thermal resistance at depth \(z_j\), \(R(z)\), in the
second column, and the differences between complementary
error functions at times \(t_{k-1}\) and \(t_k\) for depth \(z_j\) in columns 3
to \(k + 2\):
\[
\begin{pmatrix}
\Theta_1 \\
\Theta_2 \\
\vdots \\
\Theta_j \\
\end{pmatrix} =
\begin{pmatrix}
1 & R_1 & A_{1,3} & A_{1,4} & \ldots & A_{1,k+2} \\
1 & R_2 & A_{2,3} & A_{2,4} & \ldots & A_{2,k+2} \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
1 & R_j & A_{j,3} & A_{j,4} & \ldots & A_{j,k+2} \\
\end{pmatrix}
\begin{pmatrix}
T_0 \\
q_0 \\
T_1 \\
\vdots \\
T_k \\
\end{pmatrix}
\]
\[
\begin{pmatrix}
A_{j,k+2} = \text{erfc} \left( \frac{z_j}{\sqrt{2 \kappa k t_{k-1}}} \right) - \text{erfc} \left( \frac{z_j}{\sqrt{2 \kappa k t_k}} \right) \\
\end{pmatrix}. \tag{6}
\]

[17] The system of linear equations (5) can be solved for
a GSTH, using Singular Value Decomposition (SVD)
[Lanczos, 1961; Jackson, 1972; Menke, 1989]. Any matrix
\(A(\times i)\) can be decomposed as \(A = U \Lambda V^T\),
where \(\Lambda\) is a \(j \times j\) diagonal matrix which contains on the
diagonal entries the nonzero singular values \(\lambda_{r(e)}\) of matrix \(A\), \(r = 1, \ldots, R\). \(R\) is the rank of \(A\); \(\lambda_{r(e)}\) are the square roots of
the eigenvalues of the symmetric matrix \(A^T A\). \(U\) is an \(i \times j\)
column orthogonal matrix, each column forming a vector,
and all \(i\) normed vectors \((u_j)\) forming an orthonormal basis
spanning the data space (i.e., they are dependent and are
generated solely from data). \(V\) is an \(i \times i\) orthogonal
matrix, each column forming a vector, and all \(i\) normed
vectors \((v_i)\) forming an orthonormal basis spanning the
model space (i.e., they are dependent on model geometry
and physics of heat diffusion). Also, the rows of matrix \(V\)
are \(i\) normed vectors forming an orthonormal basis. The
column vectors \(v_i\) are eigenvectors corresponding to
the eigenvalues of \(A^T A\). The normed eigenvectors that
span the model space, \(v_i\), could be interpreted as the effect
on the subsurface of a GSTH given by the normed
eigenvectors that span the data space, \(u_j\) [Vasseur et al.,
1983]. A general solution is given by Lanczos [1961]:
\[
X = V \Lambda^{-1} U^T \Theta. \tag{8}
\]

The unknowns given by the generalized solution (7) can be
written explicitly as
\[
X_i = \Theta_j \left( \frac{v_i u_j}{\lambda_{r(e)}} \right). \tag{9}
\]

[18] Since the variance of the estimated model parameters
can be written as
\[
\sigma^2 = \sum_{i=1}^{K} \frac{v_i^2}{\lambda_{r(e)}}. \tag{10}
\]

it can be seen that any error in the data will be multiplied by
\(1/\lambda_{r(e)}\) and will be amplified for the very small singular
values. The square root of the ratio of the largest to the
smallest eigenvalue measures the amplification of the noise
in the direction of the smallest eigenvalue. So, it is
necessary to eliminate the singular values which are smaller
than a cut-off value. The solution consists of linear
combinations of model parameters corresponding only to
the highest eigenvalues, and thus it differs from the “true” solution but it has a small variance. However, for noise free data or with a low noise level, the resolution can be improved by including more singular values in the inversion [Beltrami and Mareschal, 1995], that is, reconstructing the GSTH with a larger number of principal components.

3. Analysis

[19] Since the energy balance at the forest floor and thus the ground surface temperature are affected by the removal of vegetation and by the variations of the thickness of the forest floor organic matter layer [Yoshikawa et al., 2003], we propose a model based on Covington’s curve to describe the pattern of the ground surface temperature (GST) variation after deforestation:

$$T_g = At^B e^{Ct} + T_0,$$

where $T_g$ represents the GST, $t$ is the time in years since deforestation, and $A = 5.25$, $B = 1.24$, $C = -0.0649$, $D = 1.063$, and $T_0$ are regression coefficients [Covington, 1981].

[20] We assume that in the first years after deforestation, when the surface is covered by debris and small-size sparse vegetation, the shape of the GST variation is governed by the function $At^B$, with $A$ and $B$ positive values, and the temperature increases to a maximum of $2\degree K$ [de Souza et al., 1996; Beltrami, 2001a; Beltrami and Kellman, 2003; Yoshikawa et al., 2003]. As the forest floor organic matter recovers, we assume that the temperature decreases to its original value, $T_0$.

3.1. Synthetic Example

[21] In order to illustrate the procedure we generated a synthetic, base GSTH consisting of two temperature step increases, of $2\degree K$ and of $1\degree K$, occurring at 150 and 100 years before present (ybp) respectively. To examine how the time of deforestation affects the ground surface and subsurface temperatures, we assumed two cases of deforestation: in the first case the deforestation event occurred 100 ybp and, in the second case, 50 ybp. Following equation (10), deforestation-induced GST variations were generated for both cases. These and the base GSTH are shown in Figure 2. Figure 3 shows the subsurface temperature perturbation profiles, from the surface to 500 m, at 10 m intervals, generated as a forward problem from the deforestation models shown in Figure 2. The shallowest 20 m reflect the annual variation of the ground surface temperature and were eliminated to simulate typical borehole temperature data. We assumed constant thermal conductivity ($\lambda = 3.0 \text{ W m}^{-1} \text{ K}^{-1}$) and thermal diffusivity ($\kappa = 10^{-6} \text{ m}^2 \text{ s}^{-1}$) [Cermak and Rybach, 1982]. The deforestation event that took place 50 ybp caused a subsurface thermal signal that was propagated to almost 150 m with a maximum perturbation of the upper part of the profile. The subsurface temperature perturbations caused by the deforestation that occurred 100 ybp were propagated deeper into the ground (i.e., almost 200 m) but with a maximum disturbance of the profile at 60 m. The amplitude of the perturbations caused by older deforestation events were smoothed out by the diffusion process. Subtracting the nonclimatic temperature perturbations from the base temperature-depth profile completes the correction. The uncorrected and the corrected profile for both modeled cases of deforestation are shown in Figure 4.

[22] In order to assess qualitatively and quantitatively the effects of the correction on the typical GSTH recovered by inversion, we inverted the profiles shown in Figure 4 using a model consisting of a series of 25 surface temperature changes, each representing a temperature averaged over 20 years [Mareschal and Beltrami, 1992]. The GSTHs

Figure 2. Synthetic ground surface temperature history (GSTH) (squares) and the ground surface temperature (GST) model variations due to deforestation events taking place 100 years before present (ybp) (triangles) and 50 ybp (line).

Figure 3. Subsurface temperature perturbation profiles generated from the GST model variations, as a forward solution, due to deforestation taking place 100 ybp (triangles) and 50 ybp (squares).
recovered from inversion are shown in Figure 5. The inversion of the corrected temperature perturbations profiles shows that the effects of deforestation were removed for both models and that the greatest perturbation of the GST was caused by the more recent deforestation event, at 50 ybp.

[23] A clear-cut event taking place 100 years ago which is followed by a total recovery of the initial forest, will have a subsurface signature increasing the ground temperatures as a function of depth. However, if at the time of the observation, the forest recovery is complete and the GST has reached the precutting value, the differences between the synthetic and the corrected GSTHs (Figure 5) for the most recent 20 years, are almost nonexistent. For the second case, when the deforestation event takes place in more recent times (i.e., 50 ybp), the corrected GSTH shows the removal of the 2°K difference between forested and open areas, and since the forest is still recovering, the GST does not reach the precutting value, as it does for the 100 ybp event model.

3.2. Application to Field Data

[24] Many borehole temperature data have been excluded from studies of recent climate changes because of different anthropogenic influences such as deforestation and forest fires. Guillou-Frottier et al. [1998] rejected data from the Pipe Mine site, central Canada, because of the great warming indicated by these profiles, more than 3°K, attributed to land clearing. Gosselin and Mareschal [2003] suggested that the great warming recorded at the Pipe Mine site after 1960 might be caused by deforestation.

[25] To illustrate the correction method on real borehole temperature data, one temperature profile from central Canada was analyzed: The Pipe Mine 9411 log is located 55°29′10″ N, 98°07′54″ W, 32 km southwest of Thompson, Manitoba. The borehole site was deforested around 1960 when a highway and power line were built and when the first mine in Thompson opened in 1961 [Gosselin and Mareschal, 2003]. In 1994 when the temperature-depth profile was measured the site was covered by vegetation.

[26] We applied the correction to these data in the same fashion as for the synthetic data shown above, by subtracting the subsurface temperature perturbations caused by the deforestation event 34 ybp from the measured temperature-depth profile. The uncorrected and the corrected profiles are shown in Figure 6. The reconstruction of the GSTHs, from both corrected and uncorrected profiles, was performed for a series of 50 step temperature changes, each representing an average surface temperature over 20 years. The results for the last 500 years are shown in Figure 7. The inversion of the uncorrected profile reveals a GST increase of almost 1.5°K in the recent 40 years when the deforestation event took place, superimposed on a long-term increase that started around 200 ybp. After correction, the GSTH at the Pipe Mine 9411 site shows a warming of 1.7°K over the last two centuries which is good agreement with the
warming trends found in the region [Beltrami et al., 1992; Guillou-Frottier et al., 1998; Gosselin and Mareschal, 2003].

4. Discussion and Conclusions

[27] Vegetation is an important factor affecting the surface temperature. Recent studies [Kaufmann et al., 2003] showed that the increased vegetation cover during the summer time in North America and Eurasia, have slowed down the temperature increase during the last 20 years. Clearing by deforestation or by forest fire increases the energy reaching the land surface. The increase in albedo is compensated by the decrease in evapotranspiration, and the net energy transfer into the ground increases the surface temperature in the first years after land clearing [Dickinson and Henderson-Sellers, 1988; Shukla et al., 1990; Dickinson and Kennedy, 1992; Zhang et al., 1996]. As a new forest grows, the ground surface temperature decreases to near its original value.

[28] In the method described here we assumed that after deforestation the forest regrows to the preharvest state. Given that the time necessary for the GST (and organic matter layer) to return to the undisturbed value is almost 100 years [Covington, 1981], it is clear that the subsurface temperature perturbations due to a more recent clear-cut event (50 ybp) are still important. Although the shapes of the GST variation for both deforestation models (Figure 2) are quite similar, the effects on the subsurface temperatures (Figures 3 and 4) are larger for the more recent event. Subsurface disturbances caused by older deforestation events propagate to larger depths, but much of their magnitude has decayed because of the character of the heat diffusion in the subsurface. This behavior is accentuated for a model consisting of a rapid GST increase followed by a slower decrease to the preharvest value, because the applied disturbance is present only for a limited time and the subsurface temperature perturbations dissipate with time.

[29] There are several situations that can be incorporated into this first-order model. Complete forest regeneration to a preharvest state (Figure 8, line 4) is not common and in most cases the new growth forest will be different in density and species. Thus the GST will settle to a different value (perhaps higher) than the preharvest GST (Figure 8, line 3). The GST variation post clear-cut could be still described by this model, but with a new end-point GST corresponding to the new equilibrium state.

[30] If the forest is transformed into grassland, or bare ground, then the GST model might be described as lines 2 and 1 in Figure 8, respectively. However, in the case of a bare ground end point, the GST increase may be much higher than 2°C [Geiger et al., 1995].

[31] The subsurface thermal effects due to a series of deforestation events could also be estimated with this model. A sequence of deforestation events is typical for today’s forests lands in Canada, where maximization of yield calls for harvest at 50 year intervals [McGrath, 1999; Erdle, 1999]. Since the subsurface temperature perturbation caused by a deforestation event that occurred 50 ypb are quite large in the upper 100 m, borehole temperature data located in present-day forested areas that might have such a land cover history should be corrected for these effects.

[32] The practice of partial harvesting is more difficult to model, but is probably negligible as a correction for geothermal data since this practice is too recent, although this type of process may also be included in this method by decreasing the GST rate of change after deforestation. The adjustments in the correction model can be easily made once the type of regrowth is known. Work on modeling the effects of different harvesting practices is in progress.

[33] We have shown that subsurface temperatures are affected by disturbances (especially for events in the recent past) but these effects can be removed if the time when the disturbance occurred is known. The application of this correction method to the “contaminated” borehole temperature data from the global geothermal data set would allow inclusion of data from “contaminated” sites in the borehole climatology database and enhance the GSTH.
reconstructions from geothermal data for the last millennium. A full energy balance, vegetation, and soil process model would be the desired method of correction of geothermal data, but the characterization of surface conditions at each of the 10,000 borehole sites for inclusion in a full model, seems unattainable at least in the near future. [34] The results from this work may be useful for land surface models where the long-term energy storage in the subsurface has generally been neglected [Baker and Baker, 2002]. Furthermore, evaluation of the surface energy balance history from geothermal data could provide the boundary conditions needed for land surface and general circulation model improvements [Beltrami et al., 2000; Beltrami, 2001b; Baker and Baker, 2002] and, perhaps more importantly, subsurface temperature data may provide a way to discriminate between rival land surface energy partition subroutines and optimize land surface energy exchange parameterizations.

in recent clearcut forest ecosystems, Ph.D. dissertation, Univ. of Maine, Orono.


Lane, E. C. (1923), Geotherms of the Lake Superior Copper County, J. Geol., 42, 113–122.


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