Framework for Surveillance Temperature Data Integration

R.M. Hassanpour and Clayton V. Deutsch

Temperature is an important reservoir parameter in thermal enhanced oil recovery operations such as SAGD. The temperature of the reservoir is usually monitored during the process at some observation wells. However it is not common in practice to use temperature surveillance data for improvement of geological models. The feasibility of temperature data integration is discussed. The sequential self calibration (SSC) technique is adapted and the methodology demonstrated by a simple synthetic example.

Introduction

The SAGD process (Butler,1994) has emerged as an effective technology for the recovery of oil from oil sands deposits that are too deep to be produced by surface mining. In this process, two horizontal wells are drilled one well above the other and separated by a distance (usually 5m) near the bottom of oil bearing formation. The top well is used to inject steam into the oil sands, heating up the oil and allowing it to drain into the bottom well.

The performance of SAGD process highly relies on the development of steam chamber. Larger steam chamber leads to more oil production. This is always a main challenge in SAGD reservoir studies to define how the steam distributes in the formation. There are generally three different kinds of parameters that may have effect on the steam distribution within the reservoir in a SAGD operation; operational parameters, fluid properties parameters, geological parameters. Steam injection rate and temperature of injected steam are examples of operational parameters. Bitumen viscosity and density are examples of fluid parameters, and rock permeability and porosity are examples of geological parameters.

Temperature distribution is closely related to the steam distribution in formation and is dependent to operational parameters, fluid parameters and geological parameters. Temperature surveillance data is widely available in SAGD operations. The temperature is measured during the production at different depth at many observation wells. Although the measurement is mostly for monitoring the operation, however it can be considered as a valuable dynamic data and integrated in the reservoir model.

A common practice of reservoir modeling begins by modeling reservoir with static data (static model), and then the dynamic data are used to update the reservoir model (dynamic model). Integration of dynamic data requires flow simulation to be run on the static model multiple times. The static model is perturbed each time until the difference between the flow simulation response and actual dynamic data minimized. This generally requires inverse solution of the flow equation. Figure 1 shows a typical reservoir modeling workflow.

The main goal of this paper is to introduce the new idea of temperature data integration. This required a thorough understanding of the thermal flow simulation and the inverse modeling algorithms.

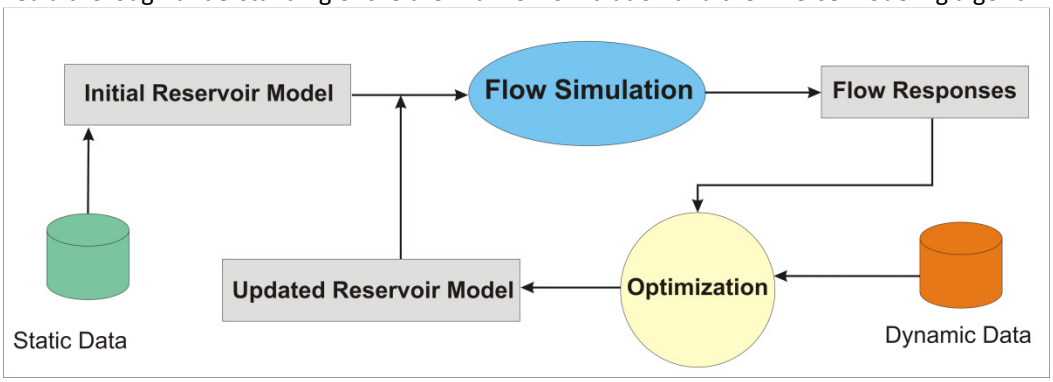

Figure 1. Typical Reservoir Modeling Workflow.

Thermal Flow Simulation

In thermal recovery process, such as SAGD, there are two mechanisms by which heat is transferred: thermal conduction through reservoir volume and thermal convection by fluid (Butler, 1997). When the hot fluid is injected, the in-place oil, water, or gas is displaced and heat is carried into the pore space. The in-place fluids are heated by conduction and the displaced fluids are heated by both conduction and convection (Ali, 2003).

Thermal conduction process is very slow and is not the dominant process of heat transfer within large reservoir volume. However it is effective in transferring heat over relatively short distance. The theory of heat conduction assumes that the direction of heat flux and the temperature gradient are the same and is proportional to the magnitude of the gradient. The proportionality constant is defined as the thermal conductivity of the material and assumed to be the same in each direction. Considering the transfer of heat by conduction, the heat flow equation in three dimensions is defined as:

$$\vec{u} = -K.\nabla T \tag{1}$$

Where $\vec{u}$ is the heat flux vector, K is the thermal conductivity, and $\nabla T = \frac{\partial T}{\partial x}\vec{i} + \frac{\partial T}{\partial y}\vec{j} + \frac{\partial T}{\partial z}\vec{k}$.

In convection heat transfer, heat is moved into reservoir by injected fluid. As the fluid moves within the reservoir, heat is given to the cooler surrounding and this transfer of heat produces temperature gradient. In SAGD process, convection is the major heat transfer mechanism inside the steam chamber while the thermal conduction plays an important role in the transition zone of steam chamber and the cooler reservoir. So considering heat convection within the steam chamber and heat loss by the heat conduction, the energy balance equation can be written as:

$$\nabla\left(K\nabla T + \sum_{i=o,w,g} \rho_i H_i \lambda_i \nabla P_i \right) + q_H = \frac{\partial}{\partial t}\left((1-\phi)\rho_f c_f T + \phi \sum_{i=o,w,g} \rho_i S_i U_i \right) \tag{2}$$

Where K is the thermal conductivity of rock and contained fluid, T is temperature gradient, H is the specific enthalpy, U is the specific internal energy, ρ_f is rock density, C_f is the heat capacity of rock, q_H is the injection rate, $\lambda = \frac{kk_r}{\mu}$ is the phase mobility, and P_i and S_i are pressure and saturation for oil, water, or gas phases that are calculated from the flow equation:

$$\nabla.\left(\rho_i \lambda_i \nabla P_i\right) + q_i = \frac{\partial}{\partial t}\left(\phi \rho_i S_i\right) \quad , \quad i = o, w, g \tag{3}$$

In thermal flow simulation, both the pressure equation and the energy equations need to be solved for each time step. The pressure equation is solved first for a time step and then the calculated pressures and saturations are substitute into the energy equation to get the temperature at each grid.

General Inverse Problem

Considering equations (2) and (3), the forward problem is to predict the flow responses (pressure, saturations, and temperature) when the model parameters (e.g. porosity, permeability) are defined. The inverse problem is to estimate the value of model parameters using some field measured value of flow responses. The main idea is to perturb the initial reservoir properties models to minimize the difference between the observed and calculated production data such as pressure and flowrates at well location.

The inverse problem has been studied by numbers of different authors. A complete review of inverse problem techniques is provided by Wen et al. (2005) and Reza (2003). Most of the available inverse modeling techniques is utilized for inversion of flow model and updating the permeability and porosity model. A very simple and naive solution for inverse modeling is trial and error method which is widely used in industry practices. The reservoir model perturbation is usually done with trial and error method. This may be very time consuming and requires extensive experiences. A more smart approach is to calculate the gradients or sensitivity of flow response to incremental change of input parameters and find the most effective parameters. Perturbation method, rigorous finite differencing of flow equation (Anterion et al., 1990; Bissell et al., 1992), convolution integral technique (Carter et al., 1974; Jacquard and Jain, 1965), are examples of methods that have been used for calculation of sensitivity coefficients. In

perturbation based methods, the sensitivity coefficients are calculated by first setting up an initial simulator base run and then perturbing each parameter and re-run the simulator several times.

The sequential self-calibration method (SSC) is an iterative geostatistical based method which was introduced by Gomez-Hernandez and Wen (1998) and Capilla et al. (1998). In this technique multiple realizations of permeability are generated conditioning to different type of static and dynamic field data. The perturbation mechanism is based on kriging that accounts for spatial correlation of parameters. The procedure begins by generating initial permeability realizations conditioned to static data (well logs and seismic). The flow equation is then solved for each realization at a time and the difference in observed and calculated pressure values at well locations are computed. If the mismatch is less than a pre-specified tolerance, the permeability realization is considered to honor both static and dynamic data. Otherwise, some master points are randomly selected inside the field. All the well locations with the permeability value is also considered as the master point. An optimization problem is then solved to find the optimal perturbations of permeability at master points. This optimal perturbation of master points is performed by kriging. The permeability realization is updated by adding the smooth perturbation model to the previous permeability model. The SSC method is flexible, robust and computationally efficient. Figure 2 shows the flowchart of the SSC technique.

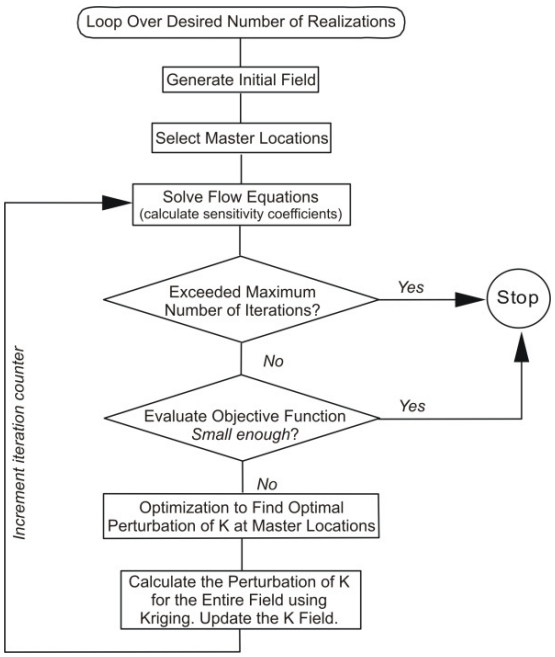

Figure 2. Flowchart of the Sequential Self Calibration (SSC) Method (Wen at al., 2005).

Temperature Inverse Modeling

The forward problem of thermal flow model can be solved by applying appropriate boundary conditions and using the finite-difference approximation on discretization grids. However, the thermal flow model is too complex and the analytical inversion of the model seems not to be practical.

The main goal of temperature inverse modeling is to find a set of permeability values for reservoir model that matches the measured temperature data. The SSC method can be adapted to generate permeability realizations that honor the observed temperature data.

To match the measured temperature data and the calculated temperature, the thermal flow simulation should be run. The mismatch is then calculated by the following objective function:

$$O = \sum_{t=1}^{nstep} \sum_{i=1}^{nw} \left(T^{obs}\left(u_i, t\right) - T^{cal}\left(u_i, t\right) \right)^2 \tag{4}$$

where $T^{obs}\left(u_i, t\right)$ is the observed temperature and $T^{cal}\left(u_i, t\right)$ is the calculated temperature at location u_i and time t, $nstep$ is the number of time steps, and nw is number of observation points.

The idea of using master points which has been used in SSC is to reduce the parameter dimension. The optimization is parameterized as a function of the perturbation of permeability at the selected master points. The perturbation values at the master points are calculated by minimizing the objective function constrained to the first order Taylor expansion approximation of the temperature data.

$$\left\{T^{cal}\left(u,t\right)\right\}' = \left\{T^{cal}\left(u,t\right)\right\} + \frac{\partial\left\{T\left(u,t\right)\right\}}{\partial\left\{\Delta k\right\}} \cdot \left\{\Delta k\right\} \tag{5}$$

where $\{T^{cal}(u,t)\}'$ and $\{T^{cal}(u,t)\}$ are temperature at location u and time t after and before introducing a permeability perturbation at master point locations, and the terms $\{S\}_t = \partial\{T(u,t)\}/\partial\{\Delta k\}$ is the sensitivity vector of temperature to the permeability perturbation at time t.

For solving the optimization problem, the sensitivity coefficients are needed at all master point locations and all time steps. As discussed earlier, there are different methods for calculation of sensitivity coefficients. In SSC technique, the sensitivity coefficients formula is derived directly from the finite difference form of the physical flow equations. The perturbation method can also be considered for the cases where the parameter dimension is small.

Substituting Equation (5) into Equation (4), the objective function can be presented as:

$$O\left(\{T^{cal}(u,t)\}'\right) = O\left(\{T^{cal}(u,t)\}\right) + \sum_{t=1}^{nstep}\{D\}_t^{tr}\{\Delta k\} + \sum_{t=1}^{nstep}\{\Delta k\}^{tr}[C]_t\{\Delta k\} \quad (6)$$

where the vector $\{D\}_t$ and the matrix $[C]_t$ are defined as:

$$\{D\}_t = 2\left(T^{obs}(u,t) - T^{cal}(u,t)\right)^{tr}[W]_t\{S\}_t \quad (7)$$

$$[C]_t = \left(\{S\}_t\right)^{tr}[W]_t\{S\}_t \quad (8)$$

where $[W]_t$ is the inverse covariance matrix of observation error at time t.

The optimization problem is solved with the constrained on the possible minimum and maximum perturbation values. To illustrate the feasibility of the methodology of temperature data integration, a synthetic example is presented.

Synthetic Example

A 2D SAGD single well pair model was considered with 13 grids of 10*m* in Easting direction, and 10 grids of 2*m* in vertical direction. The size of grid in the direction of horizontal well pairs was set as 100*m*. A base case simulation was run with permeability model that contains high value (1000.0 md) in one half of the model including the well pair and low values (10.0 md) in the other half. The porosity model was generated based on the permeability model as the porosity values were set to 0.25 and 0.10 for the high permeability and low permeability regions, respectively. The thermal flow simulation is run by CMG STARS for 10 years and the output temperature models were exported for 5 time steps of 720, 1440, 2160, 2880, 3600 days. Figure 5 shows the base case permeability model and the base case temperature models at five time steps.

The perturbation method was used for calculation of sensitivity coefficients. So, for all grids in the model the permeability value was perturbed and the perturbation was propagated to the model with kriging. An isotropic spherical variogram with range of 100*m* was considered for kriging. Then, the thermal flow simulation with the same set up as the base case model was run. The sensitivity coefficients for the perturbed location was then calculated as the temperature variation at all location and all time steps respect to the permeability perturbation value. This step was reaped 130 times to get the sensitivity coefficients for all locations in the model. The computer time for calculation of sensitivity coefficients on a machin with dual core CPU(2.41 GHz) and 2.5 GB of RAM was about 25 minutes.

Twelve master point locations were considered for perturbation. In order to find the locations of master points in the model, the sensitivity coefficients for all locations were averaged and the most sensitive locations were defined. Figure 3 shows the map of average sensitivity coefficients in the model that shows the most sensitive locations and the master points. The boundary between two high value and low value permeability zones is the most sensitive location in the model.

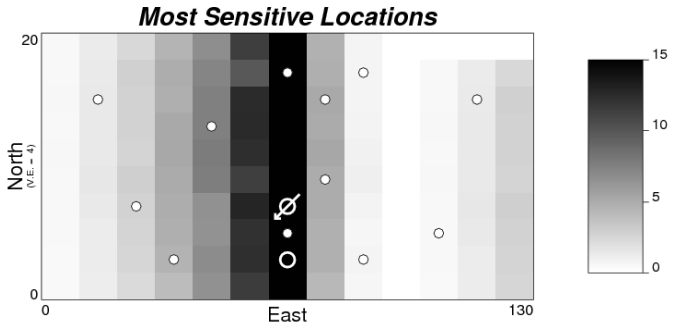

Figure 3. Map of average sensitivity coefficient and location of 12 selected master points (white dots).

The methodology was applied for inverse modeling of temperature responses. An initial homogeneous permeability model with permeability of 100 md was assumed. For this example, all grids were considered as the observation locations. The relative objective function was dropped to almost zero after 40 iterations. Figure 4 shows the value of relative objective function for each iterations. The computer time for 40 iterations on a computer with dual core CPU (2.41 GH) and 2.5 GB of RAM was about 8 minutes. The updated permeability models after each iteration are shown in Figure 6. The high and low permeability zones are clearly reproduced in the updated permeability models. The updated permeability model after 40 iterations and the corresponding temperature responses for five time steps are shown in the Figure 7. The results show that the steam chamber is fairly developed as the base case simulation run after 10 years. The expansion of steam chamber in the higher permeability zone is obvious.

To better investigate the temperature reproduction, six observation points were randomly selected and the temperature responses and the base case temperature were extracted and plotted. Figure 8 shows the locations of the selected observation points and the temperature responses at the observation points for different time steps. The temperature responses were reproduced very well at all random observation points.

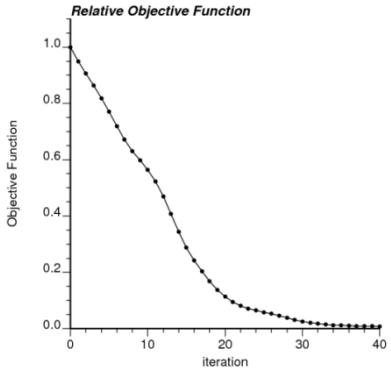

Figure 4. Relative Objective Function.

Conclusion

The sequential self calibration method was adapted for temperature inverse modeling. A simple synthetic example was illustrated. The sensitivity coefficients were calculated by perturbation method. The result of synthetic example shows that temperature surveillance data can be effectively used to improve the geological models. However, a more accurate result can be achieved by adding non-linear sensitivity coefficients terms into Equation (5). Another future work would be to consider couple Temperature and Pressure inverse modeling.

Appendix: Calling CMG STARS from Fortran

The computer codes required for implementation of the methodology in this paper were written in Frotran. The inverse modeling of temperature data needs the thermal flow simulation to be run several times. CMG STARS thermal flow simulator was used. For each outer iteration in the inverse modeling (see Figure 2) the flow simulator should be called from the Fortran code. This has been utilized by calling the

STARS executable file using the SYSTEMQQ function. This function executes a system command by passing a command string to the operating system's command interpreter (Compaq Visual Fortran). The general form of this function is:

result = SYSTEMQQ(*commandline*)

where *result* type is logical and *commandline* type is character.

Figure A1 shows part of a Fortran code that calls the STARS. "*st200910.exe*" is the STARS executable file (version 2009) that available on the "**..\CMG2009\STARS\2009.10\Win32\EXE**" under the installation directory root and "*Run-ssct.dat*" is the input parameter file for STARS.

```
c
c Run Thermal Flow Simulator (CMG STARS)
c
      r=SYSTEMQQ('echo Run-ssct.dat | st200910.exe')
```

Figure A1. Part of the Fortran code that calls the CMG STARS.

Reference

Anterion, F., Eymard, R., and Karcher, B (1990). Use of parameter gradients for reservoir history matching. In 10th SPE Symposium on Reservoir Simulation, Houston, TX. Society of Petroleum Engineers. SPE Paper 18433, pages 339-354.

Bissell, R. C., Killough, J. E., and Sharma, Y. (1992). Reservoir history matching using the methods of gradients on a workstation. In European Petroleum Computer Conference, Stavanger, Norway. Society of Petroleum Engineers. SPE Paper 24265.

Butler, R.M. (1997). *Thermal recovery of oil and bitumen.* Prentice-Hall Inc..

Carter, R. D., Kemp, L., Pierce, A., and Williams, D. (1974). Performance matching with constraints. SPE Journal, pages 187-196.

Capilla, J.E., Gomez-Hernandez, J.J. and Sahuquillo, A. (1998). Stochastic simulation of transmissivity fields conditioning to both transmissivity and piezometric data, 2. Demonstration in a synthetic case. *Journal of Hydrology*, 302:175-188.

Gomez-Hernandez, J.J. and Wen,X.H. (1998). To be or not to be MultiGaussian: A reflection on stochastic hydrology. *Adv. Of Water Resources*, 21(1):47-61.

Reza, Z. (2003). *Some aspects of production data integration in reservoir modeling*. Ph.D. Thesis, University of Alberta, Edmonton, Canada.

Wen, X.H., Deutsch, C.V., Cullick, A.S. and Reza, Z.A. (2005). *Integration of production data in generating reservoir models*. Centre for Computational Geostatistics, University of Alberta, Edmonton, Canada.

Jacquard, P., and Jain, C. (1965). Permeability distribution from field pressure data. SPE Journal, pages 281-294.

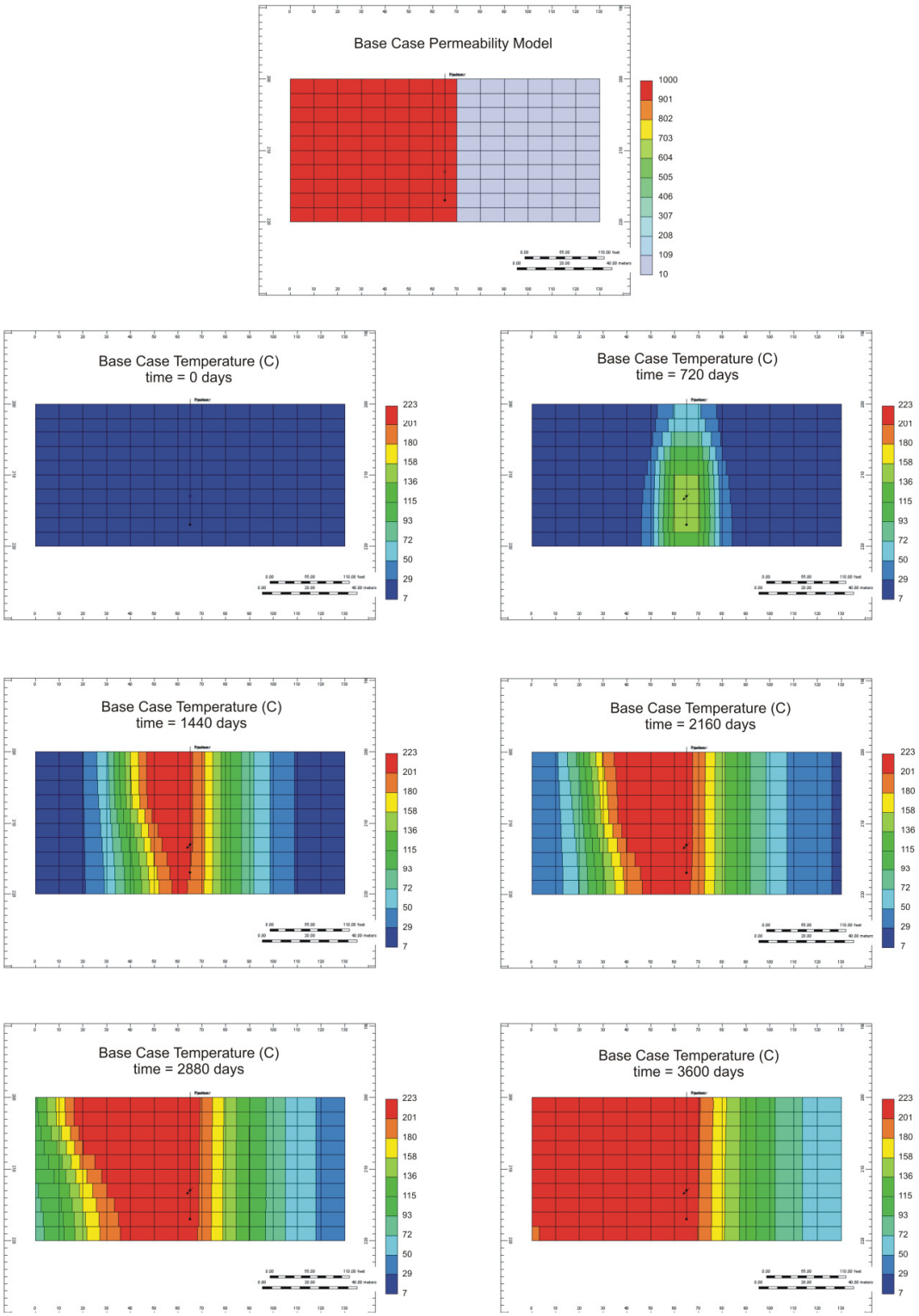

Figure 5. Base Case Permeability Model (top) and the Temperature Responses at Five Time Steps.

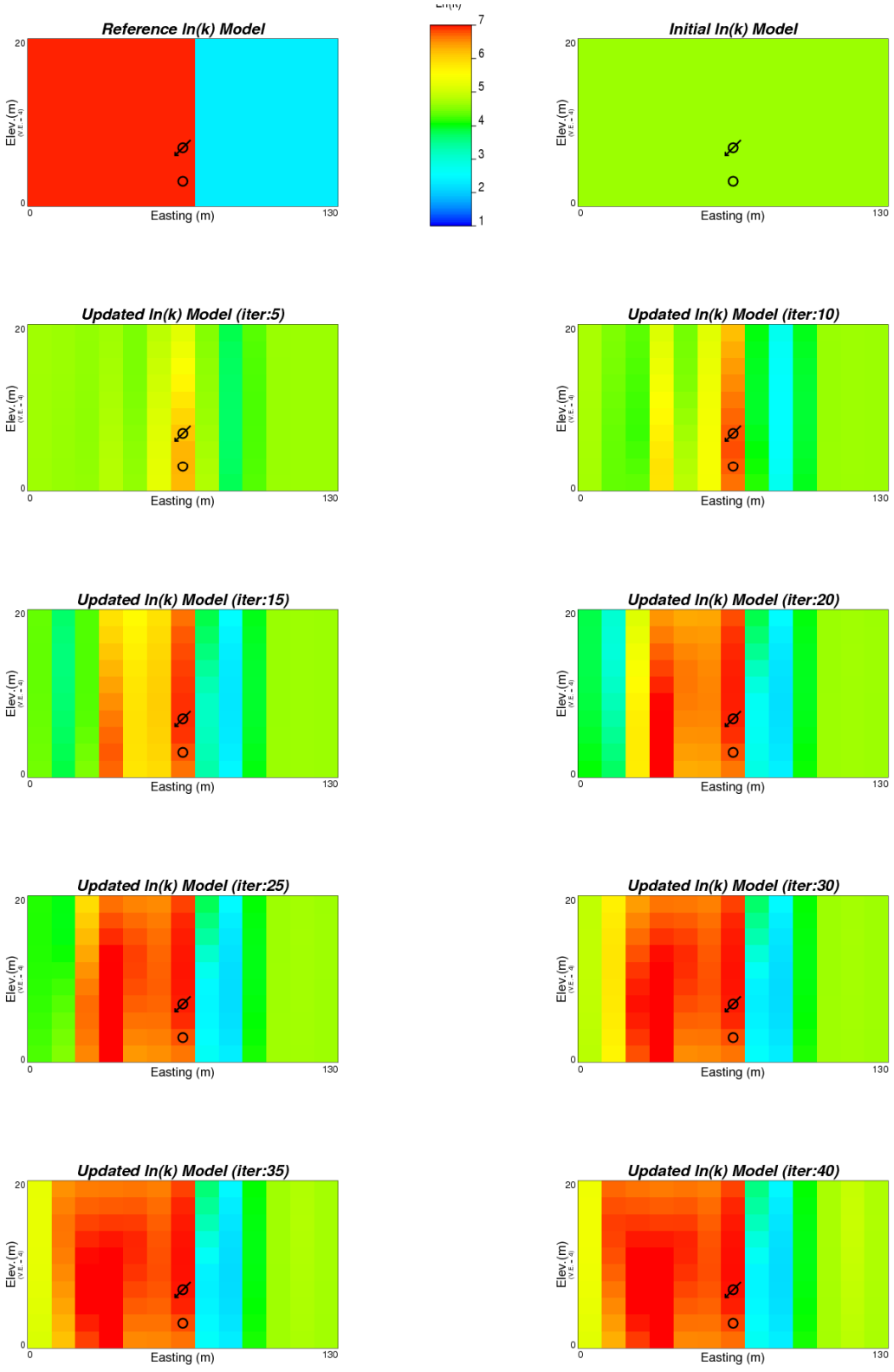

Figure 6. Reference Permeability Model (top left), Initial Permeability Model (top right) and Eight Updated Permeability Models.

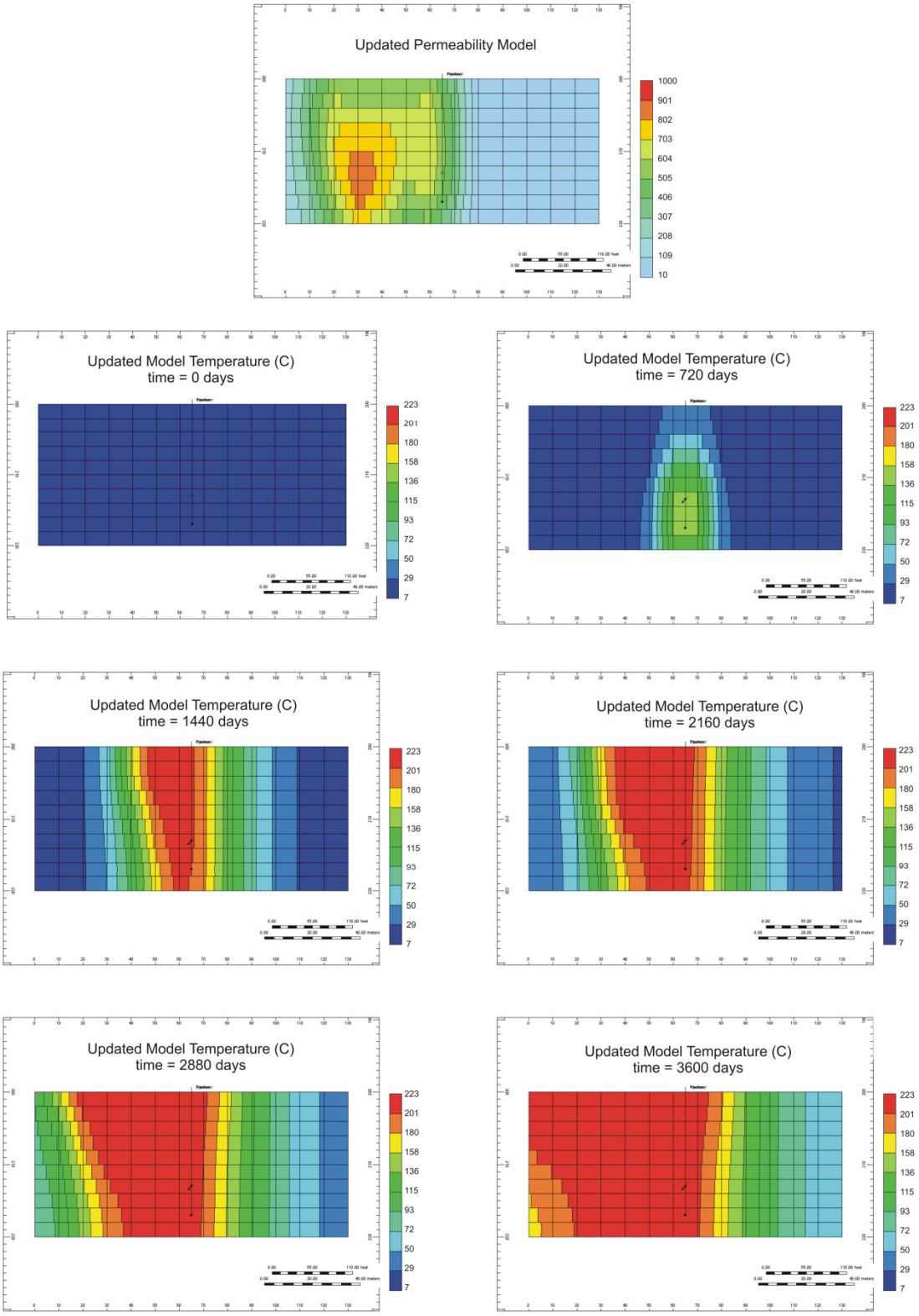

Figure 7. Updated Permeability Model (top) and Temperature Responses at Five Time Steps.

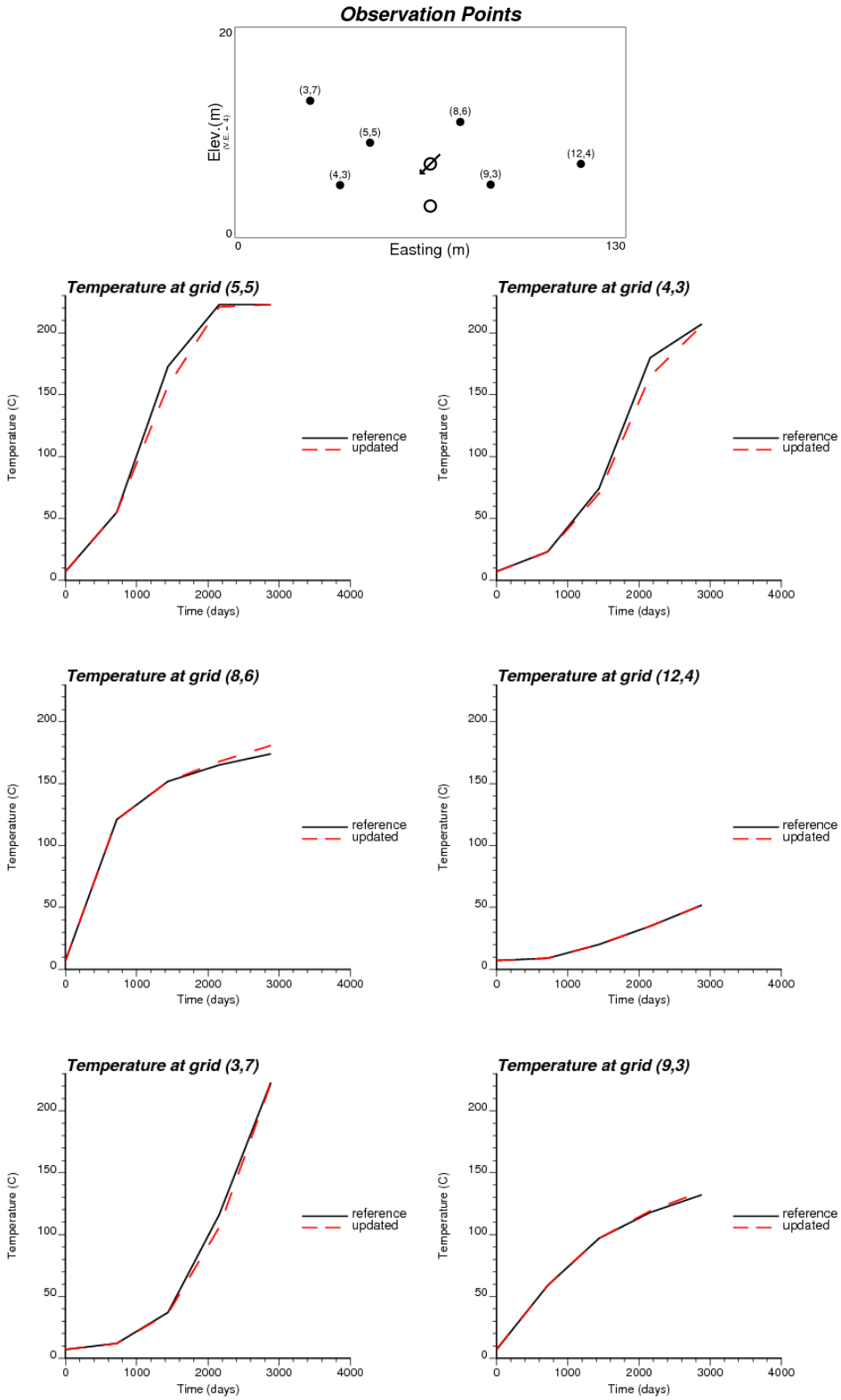

Figure 8. Location of observation points (top) and the temperature responses computed from the updated permeability model (dash line) and reference temperature response (solid line) at observation points.