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Measuring UCG cavity development with InSAR

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Introduction

Underground coal gasification (UCG) produces gas in situ from underground coal deposits. It is useful in extracting energy from inaccessible coal deposits and with less environmental impact than other methods. For a review of UCG history and uses, see *Couch*, [2009]; *Shafirovich and Varma*, [2009]. One difficulty with UCG is in monitoring the development of the underground cavity, which, due to uncertainties in the sub-surface structure, may progress in unanticipated ways. One example is roof collapse, which decreases the efficiency of the gasification and may allow UCG gases into shallower layers. Therefore, it is necessary to track the sub-surface burn front carefully and in a cost effective way. In this paper we show that satellite remote sensing is capable of detecting and monitoring surface subsidence caused by UCG activities.

Detection

The method we use to measure the surface subsidence is Interferometric Synthetic Aperture Radar, or InSAR. This technique measures surface subsidence using satellite-based radar. See *Curlander and McDonough*, [1988] for a review of SAR and

Inversion Methodology

For this work, we have adopted a linear, deterministic inversion methodology. The first ingredient is a forward model that gives the surface displacements due to extracting a certain volume of rock (or coal) at depth. We can then use this forward model to invert for the extracted volume given a known surface displacement field as measured by InSAR.

In this work, we assume that the extraction of an infinitesimal volume dV of rock will lead to a (vertical) displacement dS at the surface following the linear approximation

$$dS = K_z dV$$

where K_z is a specified influence kernel. Here, we adopt the empirical kernel,

$$K_z = -\frac{1}{R^2}\exp\left(\frac{-\pi r^2}{R^2}\right)$$

where $r = d(x, y)$ is the horizontal distance from an extraction point y to a displacement point x, and R is a maximum influence radius (Figure 1). The extraction a volume of rock leads to a trough at the surface, as expected from physical considerations. Further detail on several alternative kernels is described in Ren et al. [1987].

The single free parameter R lumps all of the site-specific material information about the overburden response. At a given site, we calculate R using the depth to extraction H and the estimated draw angle θ as

$$R = H \tan \theta$$

In the absence of better site-specific information, the approximation $R = 0.7H$ is often adopted (using a draw angle of 35 degrees).

This differential relationship may then be integrated over the total extracted volume V to determine the vertical displacement at any given point,

$$U_z(x) = \int K_z(x, y) dV$$

To develop a numerical approximation, the modeled system is discretized into a grid of surface displacement points and a grid of extraction points at depth H. After introducing a numerical quadrature rule and some simple manipulations, we may write the response of the discretized system as a simple algebraic equation

$$u = Kv$$

where u is a vector of displacements at every surface point (with size m), v is a vector of extracted volumes at each extraction point (with size n), and K is a $m \times n$ system of influence coefficients. This discretization leads to a complicated surface deformation profile being modeled as the sum of several elementary troughs corresponding to extraction point sources of different weights. Due to the nature of the formulation, K is a dense matrix, though the density of non-zero entries for a particular problem depends on the influence radius R.

We are then in a position to solve the inverse problem. Note that the system of equations is underdetermined. A common approach to solving this problem is via a regularized least squares formulation,

$$v = (K^T K + \lambda L)^{-1} (K^T u)$$

where L is a regularization operator and λ is the regularization constant. For example, a Laplacian matrix can be used to selectively penalize non-smooth solutions.

In this work, we add a small modification to the standard procedure. In the previous formulation, negative volume source solutions are allowed, but this would be physically unacceptable. A negative volume source implies a subsurface expansion due to adding, rather than extracting, material. We therefore need to solve the inverse problem with an added constraint that $v > 0$. We solve the resulting non-negative least squares problem using the procedure described by Lawson and Hanson [1974].

A challenge in all regularized formulations is how to best choose the parameter λ. Choosing λ too large will overly smooth the solution, while a certain mimimum value is required to eliminate numerical noise. Here, we adopt a Generalized Cross Validation (GCV) procedure to appropriately choose the regularization parameter [Golub et al., 1979].

At present, we have not included any covariance terms to account for prior model information or data error estimates. This additional complexity will be explored in the next iteration of the model.

The thickness of the extraction zone is often known a-priori. In this formulation we solve for volumetric sources, but these may be readily converted to an areal extent by dividing by the seam thickness. Alternatively, the results may be expressed as an extraction height by dividing by the patch area associated with each grid point. We adopt this latter approach for presenting results, as it makes it easier to compare solutions at different grid resolutions.

Also, the formulation assumes perfect collapse of the volume. In reality, cavities may remain partially open, or may be partially supported due to bulked rubble. To connect the computed extraction volume v to the actual extraction volume $\tilde{v}$, another material coefficient $\alpha < 1$ may be introduced such that $v = \alpha\tilde{v}$. For example, $\alpha = 0.9$ could be assumed for longwall mine models, in which a moderate level of bulking occurs. In the UCG case it is conceivable that α may be much less, as the relatively small cavities are sufficiently strong to remain open. In the following results we only present computed extraction volumes, but note that care should be taken in interpreting what the volumetric values imply about the true extracted volume. For these UCG solutions, the true extracted volumes are likely larger and we are merely estimating the loss of material volume associated with partially closed cavities.

Inversion Results

Our first test case is a surface depression observed via InSAR at the Angren site. The extraction grid is 600×600 meters, with 64 extraction grid points in each direction. Each extraction cell therefore has a spacing of ~9 meters. We assume an approximate depth to the coal seam as 150 meters, and take the influence radius $R = 100$ meters.

The results of the GCV analysis are presented in Figure 2. The optimal parameter regularization parameter occurs at the minimum of the GCV curve, at lambda=1e-13. Extraction height solutions at several values of the regularization parameters are presented in Figure 3. Note that the color bar range changes between each figure. A comparison of the observed and modeled displacements at the surface are presented in Figure 4.

We observe that results at different regularization values are consistent with one another, and display a series of long subsurface cavities that appear to connect with one another. At high λ, these cavities are diffused over several extraction grid points, while at low lambda they reduce to a single grid point in width. While the extraction height changes, the approximate extraction volume for each cavity remains roughly constant. The height merely decreases as the cavity volume is diffused over more grid points. The typical seam thickness at Angren varies between 4 and 24 meters. The typical cavity width is expected to be less than 16m in width, while the extraction grid spacing is ~9 meters. It is therefore unlikely that we have more than a few grid points across the true cavity widths, and the inversion model is right at the limit of resolving these features.

Unfortunately, we have little knowledge of the true cavity geometry at Angren, and therefore are unable to validate whether the computed solution is realistic or simply a numerical artifact. To address this issue, current work is focused on applying the same technique to other case studies for which we have detailed understanding of the true subsurface geometry. Once validated on these other case studies, we intend to return to the Angren analysis.

References

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2. G.H. Golub, M. Heath, and G. Wahba (1979). Generalized Cross-Validation as a method for choosing a good ridge parameter. Technometrics (21) 215-223.
3. C.L. Lawson and R.J. Hanson (1974). *Solving Least Squares Problems*, Prentice-Hall, p. 161.

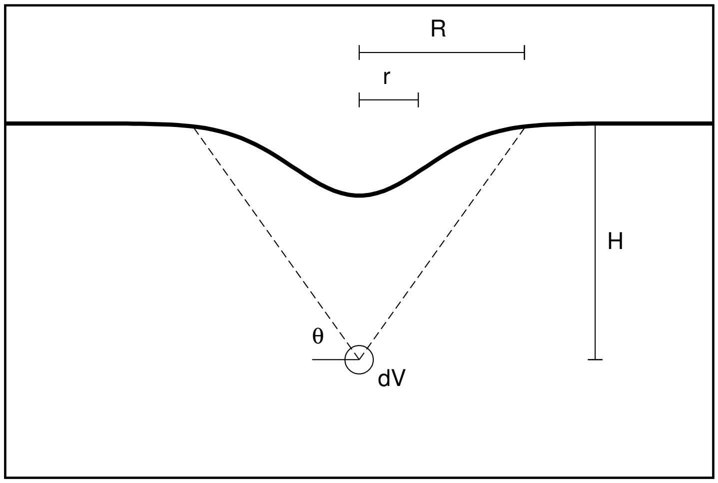


Figure 1: Empirical influence kernel. Extraction of an infinitesimal volume dV at depth leads to a subsidence trough at the ground surface.

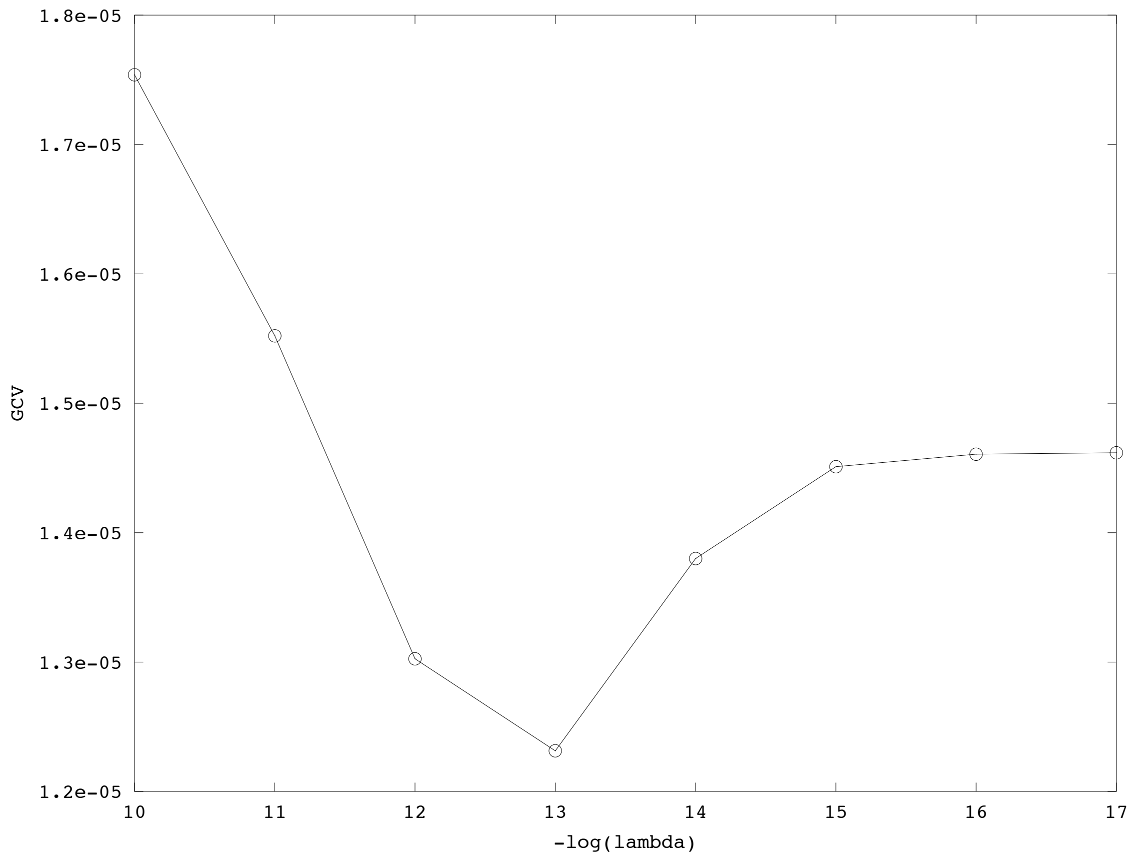
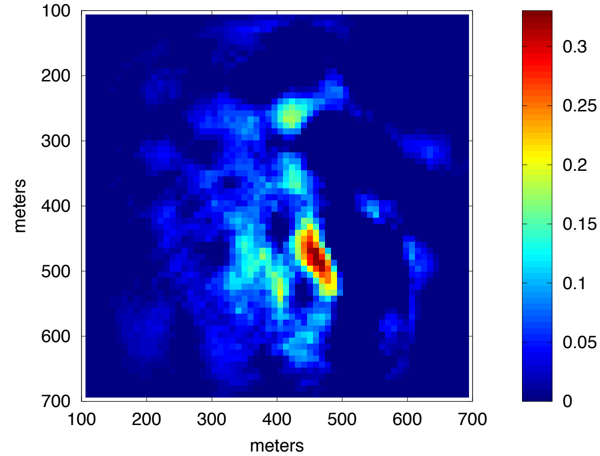
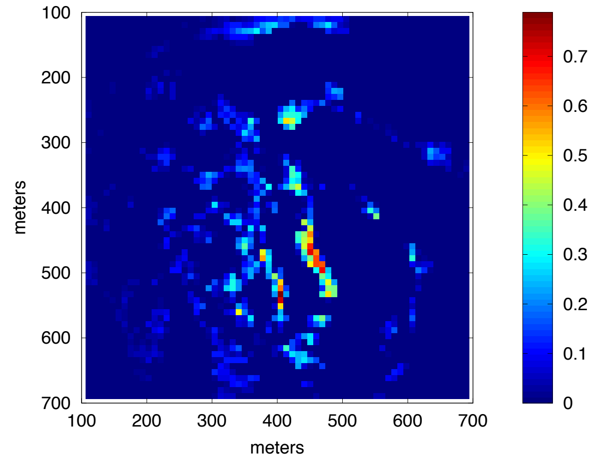


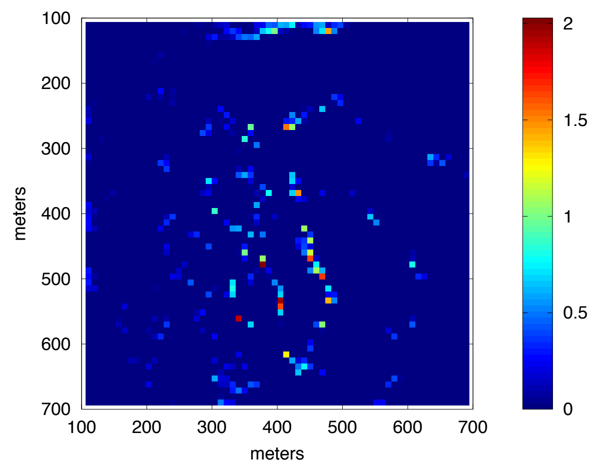
Figure 2: Generalized Cross Validation analysis of the regularization parameter lambda. The optimal parameter is chosen as the minimum of the GCV function, at 1e-13.



(a) Lambda=1e-11

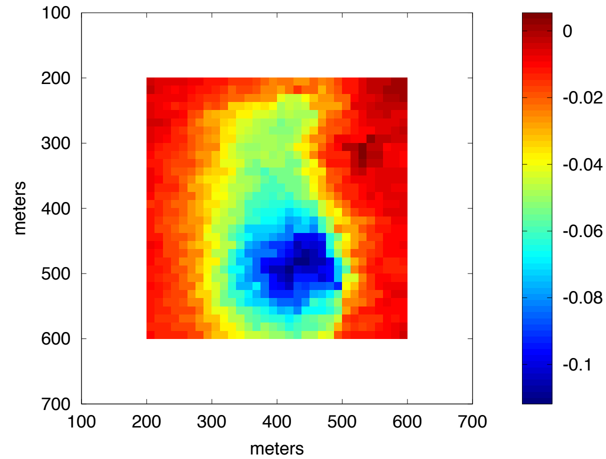


(b) Lambda=1e-12

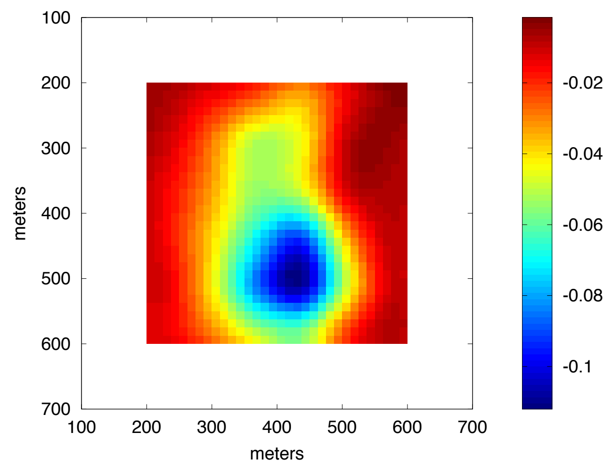


(c) Lambda=1e-13

Figure 3: Extraction height solution (m) at three values of regularization parameter lambda. Note that cavity volumes are consistent across all figures, but cavity height changes as the cavities diffuse across more grid points.



(a) Observation



(b) Prediction

Figure 4: Comparison of observed and predicted surface displacements (meters).