Implementing an anisotropic and spatially varying Matérn model covariance with smoothing filters

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Figure 1. A horizon slice of a 3D seismic image (a) provides a model of spatial correlation (b) for an anisotropic and spatially varying Matérn model covariance used here in a geostatistical simulation of porosities (c). The model covariance is implemented with smoothing filters.

ABSTRACT
While known to be an important aspect of geostatistical simulations and inverse problems, an a priori model covariance can be difficult to specify and implement, especially where that model covariance is both anisotropic and spatially varying. The popular Matérn covariance function is extended to handle such complications, and is implemented as a cascade of numerical solutions to partial differential equations. In effect, each solution is equivalent to application of an anisotropic and spatially varying smoothing filter. Suitable filter coefficients can be obtained from auxiliary data, such as seismic images. An example with simulated porosities demonstrates the effective use of a Matérn model covariance implemented in this way.

Key words: inversion model covariance

1 INTRODUCTION
The solution of many inverse problems in geophysics is facilitated by a priori information about the desired solution. In least-squares inverse theory this information is provided in the form of an initial model estimate \( m_0 \) and a covariance matrix \( C_M \), which can be used to compute a better (a posteriori) model estimate \( \tilde{m} \) as follows (Tarantola, 2005):

\[
\tilde{m} = m_0 + C_M G^T (G C_M G^T + C_D)^{-1} (d - G m_0).
\]

Here, \( d \) denotes observed data, which are assumed to be approximately related to the true model \( m \) by \( d \approx G m \), for some linear operator \( G \). The data covariance matrix \( C_D \) quantifies uncertainties due to errors (e.g., measurement errors or ambient noise) in this approximation, while the model covariance \( C_M \) quantifies spatial correlation of the model \( m \).

The matrices in equation 1 can be viewed more generally as linear operators, and this view is especially useful for the model covariance matrix \( C_M \). For a model \( m \) with \( M \) parameters, the matrix \( C_M \) would contain \( M^2 \)
elements, which for large $M$ cannot be stored in computer memory. Moreover, analytical expressions for the elements of $C_M$ may be unavailable, as when $m$ is a sampled function of space with covariance that is both anisotropic and spatially varying. We are therefore motivated to implement multiplication by $C_M$ in equation 1 as an algorithm that applies the linear operator $C_M$ without explicitly constructing and storing a matrix.

Although we might avoid computing and storing the matrix $C_M$, we must still specify parameters that describe this linear operator. This task can be especially difficult for anisotropic and spatially varying models of spatial correlation.

Figure 1 illustrates one way to parameterize the linear operator $C_M$ using additional information. The spatial correlation of seismic amplitudes displayed in Figure 1a is clearly anisotropic and spatially varying. A quantitative measure of this spatial correlation is obtained from structure tensors (Weickert, 1999; Fehmers and Höcker, 2003) computed for every sample in the seismic image. In Figure 1b, a small subset of these structure tensors are represented by ellipses. Spatial correlation of seismic amplitudes is high at locations where ellipses are large and in directions in which they are elongated. In this paper I show how this tensor field can almost completely parameterize an anisotropic and spatially varying model covariance operator $C_M$.

Moreover, if the model covariance operator can be factored such that $C_M = FF^\top$, then we can easily simulate models $m$ with covariance $C_M$ by applying the operator $F$ (or $F^\top$) to an image of random numbers (Cressie, 1993). Figure 1c displays a simulated model $m$ of porosities computed in this way. In this example, porosity is not directly correlated with seismic amplitude. In other words, we cannot accurately predict porosity at some location from the seismic amplitude at that location. However, the spatial correlation of porosities mimics that of seismic amplitudes, because the model covariance operator $C_M$ used in this simulation was derived from the seismic image.

In this paper I describe a method for using tensor-guided smoothing filters to implement a linear operator $C_M$ that approximates the Matérn covariance, which is widely used in geostatistics (Stein, 1999). My implementation of $C_M$ is an approximation that extends the Matérn covariance to be both anisotropic and spatially varying. I illustrate the use of this $C_M$ in a tensor-guided kriging method for gridding data sampled at scattered locations.

### 2 THE MATÉRN COVARIANCE

In its simplest form, the Matérn covariance function is defined by

$$c(r) = \frac{2^{1-\nu}}{\Gamma(\nu)} r^\nu K_\nu(r),$$

where $r$ is the Euclidean distance between two points in space, $\nu$ is a positive real number that controls the function’s shape, and $K_\nu(r)$ denotes the modified Bessel function of the second kind with order $\nu$. The function $c(r)$ is normalized to have unit variance $c(0) = 1$, but may easily be scaled to have any variance $\sigma^2$.

Figure 2 displays the Matérn covariance function $c(r)$ for four different choices of the shape parameter $\nu$. For any value of $\nu$, this function decays smoothly and monotonically with increasing distance $r$. For $\nu = 0.5$, the Matérn covariance is simply the exponential function $c(r) = e^{-r}$.

Despite its somewhat complex definition in terms of special functions, the Matérn covariance function is widely used in spatial statistics (Stein, 1999), partly because of the flexibility provided by the shape parameter $\nu$. Indeed, equation 2 is sometimes described as defining the Matérn family of covariance functions, because for any $\nu > 0$ yields a valid (positive definite) covariance function, for any number of spatial dimensions.

For $d$ spatial dimensions, the Fourier transform of $c(r)$ is

$$C(k) = \frac{\Gamma\left(\frac{d}{2} + \nu\right)}{\Gamma(\nu)} \frac{(2\sqrt{\pi})^d}{(1 + k^2)^{d/2 + \nu}},$$

where $k$ is the magnitude of the wavenumber vector $k$. Because the covariance function $c(r)$ is real and symmetric about the origin, its Fourier transform $C(k)$ is real and symmetric as well. Because $C(k)$ decays monotonically with increasing $k$, we may view the Matérn covariance function $c(r)$ as the impulse response of a smoothing filter that attenuates high spatial frequencies.

#### 2.1 Range scaling

Figure 2 illustrates that the effective width or range of the Matérn covariance function increases as the shape parameter $\nu$ increases. In practice, we wish to specify both the shape and the range of this function, indepen-
To keep these factors separate, so that we can adjust
definite

Here $D$ with Fourier transform

Anisotropic covariance functions can be obtained by us-

correlation varies only with distance, not with direction.

The scaling in equations 4 and 5 is isotropic; corre-

Anisotropic covariance functions can be obtained by us-

The effect on covariance shape caused by varying the

In anisotropic spatial contexts, correlation is highest in

For simplicity in equations 6 and 7 and below, I let

In both of these expressions the parameter $a$ is the ef-

dependently. To do this, we make the following substi-

corresponding to its largest eigenvalue.

To simplify the discussion below, let us consider only the

The problem addressed in this paper is that nei-

Equivalently, and perhaps more efficiently, we can

(i) Fourier transform $p(x)$ to obtain $P(k)$,

(ii) compute $Q(k) = C\left(\sqrt{k^2 Dk}\right)P(k)$, and

(iii) inverse Fourier transform $Q(k)$ to obtain $q(x)$.

Note that, for either convolution with $c(r)$ or multipli-

tion by $C(k)$, we need not construct and store a matrix

2.2 Partial differential equations

To simplify the discussion below, let us consider only the

2D case for which $d = 2$, although the methods proposed

in this paper can be extended to any number of spatial

dimensions. In 2D, the (unscaled) Fourier transform of

the Matérn covariance is simply

$$ C(k) = \frac{4\pi \nu}{(1 + k^2)^{1+\nu}}. \quad (9) $$

This simple form for $C(k)$ follows from equation 3 and

the identity $\Gamma(1 + \nu) = \pi \Gamma(\nu)$.

Multiplication by the Fourier transform $C(k)$ of the

2D Matérn covariance function has been shown (Whit-

tle, 1954; Guttorp and Gneiting, 2006) to be equivalent to

solving the following partial differential equation (PDE):

$$ (1 - \nabla \cdot \nabla)^{1+\nu} q(x) = 4\pi \nu p(x). \quad (10) $$

This equivalence results from the fact that multiplication

by $k^2$ in the wavenumber domain is equivalent to

applying the differential operator $-\nabla \cdot \nabla$ in the space

domain.

Our reason for considering solution of partial dif-

ferential equations like equation 10 is the need to apply

the Matérn model covariance operator in contexts where

the direction and extent of correlation are described by

a spatially varying tensor field $D(x)$. In such contexts

equation 10 should be rewritten as

$$ |D|^{-\frac{1}{2}}(x) (1 - \nabla \cdot D(x) \cdot \nabla)^{1+\nu} |D|^{-\frac{1}{2}}(x)q(x) $$

$$ = 4\pi \nu p(x). \quad (11) $$


Figure 3. Matérn covariance functions $c(r)$ after range scal-

ing, so that all functions shown here have an effective range

$\nu = 1$ that is independent of the shape parameter $\nu$.

$$ c(r) \rightarrow c\left(2\sqrt{\frac{\nu}{a}} r\right), \quad (4) $$

with a corresponding change to the Fourier transform

$$ C(k) \rightarrow \left(\frac{a}{2\sqrt{\nu}}\right)^d C\left(\frac{a}{2\sqrt{\nu}} k\right). \quad (5) $$

In both of these expressions the parameter $a$ is the ef-

cective range of the covariance function $c(r)$; the addi-

tional factor $2\sqrt{\nu}$ compensates for the increase in range with

increasing $\nu$ apparent in Figure 2.

Figure 3 displays unit range ($a = 1$) Matérn co-

variance functions with this range scaling substitution.

The effect on covariance shape caused by varying the

parameter $\nu$ is more apparent in Figure 3 than in Fig-

ure 2. Note that the effect of varying $\nu$ is greatest for

distances $r < 1$ or, more generally, $r < a$.

The scaling in equations 4 and 5 is isotropic; corre-

lation varies only with distance, not with direction.

Anisotropic covariance functions can be obtained by us-

ing a more general definition of distance $r$ between two

points $x$ and $y$, with the following substitution:

$$ c(r) \rightarrow c\left(\sqrt{(x - y)^\top D^{-1}(x - y)}\right), \quad (6) $$

with Fourier transform

$$ C(k) \rightarrow |D|^{-\frac{1}{2}} C\left(\sqrt{k^\top Dk}\right). \quad (7) $$

Here $D$ denotes a metric tensor and $|D|$ its determi-

nant. In $d$ spatial dimensions $D$ is a symmetric positive

definite $d \times d$ matrix. With these substitutions, corre-

lation is highest in the direction of the eigenvector of $D$

corresponding to its largest eigenvalue.

For simplicity in equations 6 and 7 and below, I let

the range scaling factor $2\sqrt{\nu}/a$ in equations 4 and 5 be

included in the tensor $D$. In practice, where $D$ varies

spatially, such that $D = D(x)$, it is most convenient to

keep these factors separate, so that we can adjust

the shape $\nu$ or effective range $a$ without modifying the

tensor field $D(x)$.

Where the tensor $D$ is spatially invariant, we can

apply the Matérn model covariance operator $C_M$ by

convolution with the function $c(r)$. Let $p(x)$ denote the

input to the function that applies the operator $C_M$ to

obtain an output $q(x)$. Then

$$ q(x) = \int p(y) c\left(\sqrt{(x - y)^\top D^{-1}(x - y)}\right) \, dy. \quad (8) $$

Equivalently, and perhaps more efficiently, we can

(i) Fourier transform $p(x)$ to obtain $P(k)$,

(ii) compute $Q(k) = C\left(\sqrt{k^2 Dk}\right)P(k)$, and

(iii) inverse Fourier transform $Q(k)$ to obtain $q(x)$.

Note that, for either convolution with $c(r)$ or multipli-

cation by $C(k)$, we need not construct and store a matrix

representing $C_M$.

Model covariance with smoothing filters

...
This equation is analogous to equation 10, with the anisotropic range scaling of equation 7. Note that we must move the factor $|D|^{\frac{1}{2}}$ in equation 7 to the left-hand side of equation 11 and split it into two parts, to ensure that the product of symmetric positive definite (SPD) operators on the left-hand side remains symmetric. That product is proportional to the inverse of the desired Matérn model covariance operator $C_M$, and so must be SPD.

For any tensor field $D(x)$, solution of equation 11 is straightforward when the shape parameter $\nu$ is an integer. This is one reason that Whittle (1954) considered the integer shape $\nu = 1$ to be most natural for 2D problems. In a similar but more recent context, Fuglstad (2011) and Lindgren et al. (2011) have likewise assumed problems. In a similar but more recent context, Fuglstad (2011) and Lindgren et al. (2011) have likewise assumed integer $\nu$ and thereby avoided the complexities of fractional PDEs.

In practical applications with spatially invariant 2D Matérn model covariances, commonly used values for the shape parameter $\nu$ lie in the interval $[0.5, 1.5]$, which includes only the one integer value $\nu = 1$. In practice, permitting only integer $\nu$ may reduce the Matérn family of covariance functions to just one function.

### 3 A SMOOTHING COVARIANCE

To facilitate more general (non-integer $\nu$) shapes of covariance functions in the Matérn family, let us consider approximations to the fractional partial differential equation 11. For simplicity in developing these approximations, I temporarily omit the tensor field $D(x)$ and use the Fourier transform $C(k)$ in equation 9 as a convenient shorthand for equations 10 and 11.

The approximation to $C(k)$ proposed here is of the form

$$\tilde{C}(k) = \frac{\gamma}{(1 + \alpha k^2)^\frac{\alpha}{2}(1 + \beta k^2)^\frac{\beta}{2}}, \quad (12)$$

where $\alpha$, $\beta$, $\gamma$, and $l$ are constants computed from the shape $\nu$ of the desired Matérn covariance function. Computation of the constant integer $l$ is easy: $l = \lfloor 1 + \nu \rfloor$. For example, if $\nu = \frac{1}{2}$, then $l = 1$; if $\nu = 1$, then $l = 2$.

If $\nu$ is an integer, then $l = 1 + \nu$, $\alpha = 1$, $\beta = 0$, and $\gamma = 4\pi\nu$ yields an exact match to the Matérn covariance function. In this case $\tilde{C}(k)$ in equation 12 exactly equals $C(k)$ in equation 9, and no approximation is required.

Otherwise, after computing $l$, I compute the three non-negative constants $\alpha$, $\beta$, and $\gamma$ so that the approximate covariance function $\tilde{c}(r)$ corresponding to $\tilde{C}(k)$ matches exactly three values of the Matérn covariance function $c(r)$ given by equation 2. To obtain an approximation that is accurate for both large and small distances $r$, I choose to match the values 0.1, 0.9 and 1.0.

I first express the scale factor $\gamma$ in terms of $\alpha$ and $\beta$ so that $\tilde{c}(0) = 1$, which is one of the three values to be matched. Recall that $\tilde{c}(0)$ is just the 2D inverse Fourier transform of $\tilde{C}(k)$ evaluated at $r = 0$ which, turn, equals the 2D integral of $\tilde{C}(k)$ divided by $4\pi^2$. By analytically performing this integration I obtained the expressions for $\gamma$ listed in Table 1.

<table>
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<th>$l$</th>
<th>$\gamma$</th>
</tr>
</thead>
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<td>1</td>
<td>$4\pi(\alpha - \beta)/\log(\alpha/\beta)$</td>
</tr>
<tr>
<td>2</td>
<td>$4\pi(\alpha - \beta)^2/\alpha - \beta/2\log(\alpha/\beta)$</td>
</tr>
<tr>
<td>3</td>
<td>$8\pi(\alpha - \beta)^3/[(\alpha - 3\beta)(\alpha - \beta) + 3\beta^2\log(\alpha/\beta)]$</td>
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</table>

In practical applications with spatially invariant 2D Matérn model covariances, commonly used values for the shape parameter $\nu$ lie in the interval $[0.5, 1.5]$, which includes only the one integer value $\nu = 1$. In practice, permitting only integer $\nu$ may reduce the Matérn family of covariance functions to just one function.

I begin the Newton-Raphson iterations with initial values $\alpha = 1$ and $\beta = 0$. The results of the fitting process are listed in Table 3. In practical applications we might use these tabulated values directly to obtain adequate approximations to $\tilde{c}(r)$ or $\tilde{C}(k)$. Note that for integer shapes $\nu$, no approximation is required.

Figure 4 displays approximations to Matérn covariance functions computed in this way. All of these approximations match the Matérn covariance for at least three values of distance $r$, those with covariance values 0.1, 0.9 and 1.0. For shape $\nu = 1$, no approximation is necessary, since for this case we have simply $l = 2$, $\alpha = 1$, $\beta = 0$, and $\gamma = 4\pi$. For shape $\nu = 1.5$, the approximate covariance is almost indistinguishable from the Matérn covariance. The approximations are worse for $\nu < 1$, but even for $\nu = 0.5$ may be adequate.

Although I derived the covariance functions $\tilde{c}(r)$ displayed in Figure 4 as approximations, we may consider them to be a practical alternative to the Matérn family of covariance functions $c(r)$ displayed in Figure 2. We can control the shape of a function in this alternative family using a single parameter $\nu$, just as we might do for the Matérn family. A key advantage of the alternative covariance functions $\tilde{c}(r)$ is that corresponding model covariance operators can be easily applied by solving partial differential equations.
Table 2. Covariance functions \(\tilde{c}(r)\) for \(\beta > 0\), which correspond to non-integer values of the shape parameter \(\nu\).

<table>
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<th>(\beta)</th>
<th>(\gamma)</th>
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<td>0.0</td>
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<td>2.0</td>
<td>1.0</td>
<td>0.0</td>
</tr>
<tr>
<td>4</td>
<td>3.0</td>
<td>1.0</td>
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Table 3. Parameters for covariance functions \(\tilde{c}(r)\).

<table>
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<th>(l)</th>
<th>(\alpha)</th>
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3.1 PDE implementations

Recall that the motive for an alternative family of covariance functions \(\tilde{c}(r)\) is that factors in their Fourier transforms \(\tilde{C}(k)\) have only integer exponents, which greatly simplifies PDE implementations of the corresponding model covariance operators \(C_M\). The PDE corresponding to \(\tilde{C}(k)\) in equation 12 is

\[
(1 - \alpha \nabla \cdot \nabla)^l (1 - \beta \nabla \cdot \nabla) p(x) = \gamma p(x).
\]
sequence of equations:
\[ q_0(x) = |\gamma^2 D(x)|^{\frac{1}{2}} p(x) \]
\[
(1 - \alpha \nabla \cdot D(x) \cdot \nabla) q_1(x) = q_0(x)
\]
\[
(1 - \alpha \nabla \cdot D(x) \cdot \nabla) q_2(x) = q_1(x)
\]
\[
\ldots
\]
\[
(1 - \beta \nabla \cdot D(x) \cdot \nabla) q_L(x) = q_{L-1}(x)
\]
\[ q(x) = |\gamma^2 D(x)|^{\frac{1}{2}} q_L(x). \quad (15) \]

In the special case where \( \beta = 0 \) (\( \nu \) is an integer), solution of the last PDE for \( q_L(x) \) is unnecessary. In any case, the total number of conjugate-gradient iterations grows only linearly, not exponentially, with the number of equations 15.

The solution of each PDE in the sequence of equations 15 is equivalent to applying a smoothing filter to a function \( q_i(x) \) on the right-hand side. Tensor coefficients \( D(x) \) can be specified so that this smoothing is both anisotropic and spatially varying. At each location \( x \) the extent of smoothing is greatest in directions of eigenvectors corresponding to the largest eigenvalues of \( D(x) \). The cascade of tensor-guided smoothing filters in equations 15 approximates the application of a Matérn covariance operator \( C_m \) in which covariance is both anisotropic and spatially varying.

Because this approximation is implemented with smoothing filters, it is henceforth referred to as a smoothing covariance.

4 TENSOR-GUIDED KRIGING

A simple and common use of a model covariance operator \( C_M \) is in the interpolation of measurements acquired at locations scattered in space. In this application, the linear operator \( G \) in equation 1 is simply a model-sampling operator \( K \) that extracts values of the model \( m \) at scattered locations to obtain data \( d \approx K m \). Here, the approximation is due to measurement errors that may be non-zero. Substituting the model-sampling operator \( K \) for \( G \) in equation 1, we obtain
\[
\tilde{m} = m_0 + C_M K^\top (K C_M K^\top + C_D)^{-1} (d - K m_0). \quad (16)
\]

As noted by Hansen et al. (2006), the process of computing a model estimate \( \tilde{m} \) with equation 16 is equivalent to gridding with simple kriging, a process well known in geostatistics. In this process, we estimate the model \( m \) at locations on a uniform and dense sampling grid. The number of gridded-model samples in \( m \) is typically much larger than the number of scattered-data samples in \( d \). The operator \( K \) gathers values from a small subset of locations in the uniform grid, the scattered locations where data are available, and the operator \( K^\top \) scatters values into those same locations.

Tarantola (2005) shows that simple kriging can also be performed in a different but equivalent way:
\[
\tilde{m} = m_0 + (C_M^{-1} + K^\top C_D^{-1} K)^{-1} K^\top C_D^{-1} (d - K m_0). \quad (17)
\]

This alternative is appealing because finite-difference approximations to \( C_M^{-1} \) are compact and can be applied more efficiently than those for \( C_M \), which requires solution of partial differential equations 15. However, equations 16 and 17 are equivalent only when the inverses of matrices in these equations exist. If measurement errors are negligible, so that \( C_D \approx 0 \), then \( C_D \) is nearly singular and equation 17 is ill-conditioned. The fact that equation 17 is invalid without measurement error is just one reason to favor gridding with equation 16.

Another reason is that the size of the matrix \( C_M K^\top + C_D \) equals the number of scattered data samples, which is often small enough to enable efficient direct solution of the kriging equations 16. In contrast, the size of the matrix \( C_M^{-1} + K^\top C_D^{-1} K \) equals the (typically) much larger number of gridded model samples, so that iterative solution of equation 17 is required. When \( C_D \approx 0 \), and without a good preconditioner, convergence of iterative methods is slow.

For these reasons I choose to use equation 16 to implement gridding with an anisotropic and spatially varying model covariance. However, even with this choice, an iterative solution is required, because we lack analytic expressions for elements of the smoothing covariance matrix \( C_M \) and, hence, the composite matrix \( A_M \equiv K C_M K^\top + C_D \). The smoothing equations 15 provide only a method for applying (performing multiplication by) \( C_M \). Nevertheless, that method is sufficient for iterative conjugate-gradient solution of equation 16.

4.1 Paciorek’s approximation

Convergence of conjugate-gradient iterations is greatly accelerated by a good preconditioning operator \( P \approx A_M^{-1} \), one that can be computed and applied more quickly than \( A_M \) itself. Recalling that \( A_M \equiv K C_M K^\top + C_D \), one way to obtain such a preconditioner is to find a good approximation to the smoothing covariance operator \( C_M \).

Paciorek (2003) and Paciorek and Schervish (2006) propose an approximation \( C_P \approx C_M \) whose elements can be computed quickly by the following modification of equation 6:
\[
c(r) \to a(x, y) c \left( \sqrt{(x - y)^\top D^{-1} (x - y)} \right), \quad (18)
\]
where
\[
D(x, y) \equiv \frac{D(x) + D(y)}{2}, \quad (19)
\]
and
\[
a(x, y) \equiv \frac{|D(x)|^{\frac{1}{2}} |D(y)|^{\frac{1}{2}} |D(x, y)|^{\frac{1}{2}}}. \quad (20)
\]
In effect, these expressions approximate the covariance of the model at location \( x \) and the model at location \( y \) using averages of tensors \( D(x) \) and \( D(y) \) at only those two locations. The approximation is best where \( D(x) \) varies slowly within the effective range of that function.

Assuming that the number of scattered measurements in \( d \) is sufficiently small, say, less than 1000, we can use Paciorek’s approximation to quickly compute and store the elements of the approximate composite matrix \( A_P \equiv KC_PK^\top + C_D \). We can then use Cholesky decomposition to compute the preconditioner \( P = A_P^{-1} \), for use in a conjugate-gradient solution of equation 16. The resulting process is a method for performing simple kriging with an anisotropic and spatially varying Matérn model covariance or, more simply, tensor-guided kriging.

4.2 Simulated model and data

To test the process, I synthesized data by sampling a known gridded model at 256 random locations. Figure 5a shows the known model porosities \( m \), while Figure 5b shows the sampled data porosities \( d \). The data were sampled without error; i.e., the data covariance \( C_D = 0 \).

The model has a known covariance \( C_M \) that I derived from seismic amplitudes, also shown in Figure 5. (The images in Figures 1a and 1c are identical to those in Figures 5c and 5a, respectively.) These amplitudes were extracted from a 3D seismic image at depths corresponding to a seismic horizon. Stratigraphic features apparent in this image suggest an anisotropic and spatially varying model covariance \( C_M \).

I computed the known model \( m \equiv m(x) \) displayed in Figure 5a by smoothing an image \( r \equiv r(x) \) of pseudo-random values independently generated for a normal distribution \( N(0.25, 0.02) \). The smoothing was performed by solving a finite-difference approximation to the following partial differential equation:

\[
(1 - \nabla \cdot D(x) \cdot \nabla) m(x) = |\gamma^2D(x)|^{\frac{1}{4}} r(x), \tag{21}
\]

where \( D(x) \) are structure tensors computed from the seismic image displayed in Figure 5c.

Equation 21 is comparable to the “stochastic Laplace equation” described by Whittle (1954), but here with anisotropic and spatially varying coefficients \( D(x) \). Equation 21 is also equivalent to the first two equations in the sequence of equations 15, for the special case where the Matérn shape is \( \nu = 1 \) (\( l = 2, \alpha = 1, \beta = 0 \)). In this case, if we define this first half of equations 15 as a linear operator \( F \), then the second half of those same equations is its transpose \( F^\top \). In summary, I used the factor \( F \) in \( C_M = FF^\top \) to generate a known porosity model \( m \) with model covariance \( C_M \)(Cressie, 1993).

It is important to emphasize that I did not assume any direct correlation between seismic amplitudes and porosities. Instead, I used the seismic image only to construct an anisotropic and spatially varying model covariance for porosity. Structure tensors \( D(x) \) computed from the seismic image enable the effective range of the model covariance \( C_M \) to be both anisotropic and...
spatially varying. For this example I set the maximum range to be 1 km.

4.3 Gridding with kriging

Figure 6 displays model estimates $\tilde{m}$ obtained by kriging via equation 16 the simulated data $d$ for three different model covariances. In all three cases, I used the correct model mean $m_0 \equiv m_0(x) = 0.25$.

For Figure 6a, I used the correct smoothing covariance $C_M$ (and $C_D = 0$) in tensor-guided kriging with equation 16 to estimate the model $\tilde{m}$. This model estimate $\tilde{m}$ is most accurate because it is most consistent with the method (described above) used to synthesize the data $d$. In the iterative conjugate-gradient solution of equation 16 I used a preconditioner based on Paciorek's approximation. The model estimate shown here was obtained after 16 iterations.

For Figure 6b, I replaced $C_M$ in equation 16 with Paciorek’s approximate model covariance $C_P$, for which the matrix $A_P = KC_PK^T + C_D$ can be efficiently computed and factored directly. In this example, the resulting model estimate $\tilde{m}$ differs significantly from that obtained using the correct model covariance $C_M$ (Figure 6a), because the tensors $D(x)$ vary significantly within the maximum range (1 km) of the covariance function. This result indicates that, while Paciorek’s approximation may provide a useful preconditioner for tensor-guided kriging, it may not be an adequate substitute for the correct smoothing covariance $C_M$.

To estimate the model displayed in Figure 6c, I replaced $C_M$ with a simple isotropic and spatially invariant model covariance. The resulting model estimate $\tilde{m}$ is least accurate of those displayed in Figure 6, because the correct model covariance $C_M$ is both anisotropic and spatially varying.

The implementation of tensor-guided kriging demonstrated with this simple 2D example has a significant shortcoming not addressed in this paper. Recall that the number of scattered measurements in the data vector $d$ in this example is 256. As that number increases to, say, 10,000 or more, the computational cost of the Paciorek preconditioner becomes prohibitive; this cost is mostly that of Cholesky decomposition of the matrix $A_P$, which grows with the cube of the number of data samples.

This high cost makes the implementation of tensor-guided kriging proposed in this paper infeasible for 3D gridding of scattered borehole data. For such large 3D subsurface gridding problems, we might exploit the fact that the range for vertical correlation of subsurface properties is typically much smaller than that for lateral correlation, and solve the large problem with a sequence of solutions to overlapping smaller problems.

5 CONCLUSION

By solving a cascade of partial differential equations with tensor coefficients, we effectively implement an anisotropic and spatially varying Matérn model covariance $C_M$. In addition to the tensor coefficients $D(x)$, this model covariance requires only a few additional pa-
parameters: variance $\sigma^2$, maximum effective range $a$, and shape $\nu$. The latter parameters are well-known to those familiar with the popular Matérn covariance function.

For some inverse problems, the necessary tensor field $D(x)$ can be obtained directly from auxiliary data, such as seismic images. For other problems, a necessary first step might be for experts to specify this tensor field, perhaps using new interactive software tools developed for this purpose. In any case, it is difficult to imagine a geophysical inverse problem for which an isotropic or spatially invariant model covariance is appropriate.

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