Sensitivity of airborne geophysical data to sublacustrine and near-surface permafrost thaw

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Abstract

A coupled hydrogeophysical forward and inverse modeling approach is developed to illustrate the ability of frequency-domain airborne electromagnetic (AEM) data to characterize subsurface physical properties associated with sublacustrine permafrost thaw during lake talik formation. Numerical modeling scenarios are evaluated that consider non-isothermal hydrologic responses to variable forcing from different lake depths and for different hydrologic gradients. A novel physical property relationship connects the dynamic distribution of electrical resistivity to ice-saturation and temperature outputs from the SUTRA groundwater simulator with freeze/thaw physics. The influence of lithology on electrical resistivity is controlled by a surface conduction term in the physical property relationship. Resistivity models, which reflect changes in subsurface conditions, are used as inputs to simulate AEM data in order to explore the sensitivity of geophysical observations to permafrost thaw. Simulations of sublacustrine talik formation over a 1,000-year period are modeled after conditions found in the Yukon Flats, Alaska. Synthetic AEM data are analyzed with a Bayesian Markov chain Monte Carlo algorithm that quantifies geophysical parameter uncertainty and resolution. Major lithological and permafrost features are well resolved by AEM data in the examples considered. The subtle geometry of partial ice-saturation beneath lakes during talik formation cannot be resolved using AEM data, but the gross characteristics of sub-lake resistivity models reflect bulk changes in ice content and can identify the presence of a talik. A final synthetic example compares AEM and ground-based electromagnetic responses for their ability to resolve shallow permafrost and thaw features in the upper 1-2 m below ground outside the lake margin.
Introduction

Permafrost thaw can have important consequences for the distribution of surface water
(Roach et al., 2011; Rover et al., 2012), stream discharge and chemistry (O’Donnell et
al., 2012; Petrone et al., 2007; Striegl et al., 2005; Walvoord and Striegl, 2007), and
exchange between groundwater and surface water systems (Bense et al., 2009; Callegary
et al., 2013; Walvoord et al., 2012). Likewise, hydrologic changes that alter the thermal
forcing supplied by surface water or groundwater systems can modify the distribution of
permafrost, illustrating the strong feedbacks between permafrost and hydrology. In
addition to hydrologic processes, permafrost is affected by climate warming in Arctic and
sub-Arctic regions (Hinzman et al., 2005; Jorgenson et al., 2001), as well as disturbance
by fire (Yoshikawa et al., 2002). Climate feedbacks associated with permafrost thaw
include changes in the amount of organic carbon stored in soils that is vulnerable to
decomposition (Koven et al., 2011; O’Donnell et al., 2011) and subsequent methane and
carbon dioxide released from soils by the degradation of organic material previously
sequestered in frozen ground (Anthony et al., 2012). Permafrost thaw also has significant
implications for land management and infrastructure, including the potential to damage
buildings, roadways, or pipelines due to ground settling, and thermal erosion that can
alter coastlines and landscape stability (Larsen et al., 2008; Nelson et al., 2002).

Several investigations have shown the significance of climate and advective heat
transport in controlling the distribution of permafrost in hydrologic systems (Bense et al.,
2009; Rowland et al., 2011; Wellman et al., 2013). These results yield important insight
into the mechanistic behavior of coupled thermal-hydrologic systems, and are a means
for predicting the impact on permafrost from a wide range of climate and hydrologic
conditions. However, few techniques are capable of assessing the distribution of
permafrost, and most approaches only capture a single snapshot in time.

Satellite remote-sensing techniques have proven useful in detecting the distribution and
changes in shallow permafrost, vegetation, and active layer thickness over large areas
(Liu et al., 2012; Panda et al., 2010; Pastick et al., 2014), but are only sensitive to very
near-surface properties. Borehole cores and downhole temperature or geophysical logs
provide direct information about permafrost and geologic structures, but tend to be
sparsely located and are not always feasible in remote areas. Geophysical methods are necessary for investigating subsurface physical properties over large and/or remote areas. Recent examples of geophysical surveys aimed at characterizing permafrost in Alaska include: an airborne electromagnetic (AEM) survey used to delineate geologic and permafrost distributions in an area of discontinuous permafrost (Minsley et al., 2012a), ground-based electrical measurements used to assess shallow permafrost aggradation near recently receded lakes (Briggs et al., 2014), electrical and electromagnetic surveys used to characterize shallow active layer thickness and subsurface salinity (Hubbard et al., 2013), and surface nuclear magnetic resonance (sNMR) soundings used to infer the thickness of unfrozen sediments beneath lakes (Parsekian et al., 2013). A challenge with geophysical methods, however, is that geophysical properties (e.g. electrical resistivity) are only indirectly sensitive to physical properties of interest (e.g. lithology, water content, thermal state). In addition, various physical properties can produce similar electrical resistivity values. Therefore, it is critically important to understand the relationship between geophysical properties and the ultimate physical properties and processes of interest (Minsley et al., 2011; Rinaldi et al., 2011).

The non-isothermal hydrologic simulations of Wellman et al. (2013) predict the evolution of lake taliks (unfrozen sub-lacustrine areas in permafrost regions) in a two-dimensional axis-symmetric model under different environmental scenarios (e.g. lake size, climate, groundwater flow regime). Here, we investigate the ability of geophysical measurements to recover information about the underlying spatial distribution of permafrost and hydrologic properties. This is accomplished in three steps: (1) development of a physical property relation that connects permafrost and hydrologic properties to geophysical properties; (2) generation of synthetic geophysical data that would be expected for various permafrost hydrologic conditions that occur during simulated lake talik formation; and (3) inversion of the synthetic geophysical data using realistic levels of noise to investigate the ability to resolve specific physical features of interest. Our focus is on electromagnetic geophysical methods as these types of data have previously been acquired near Twelvemile Lake in the Yukon Flats, Alaska (Ball et al., 2011; Minsley et al., 2012a); a lake that is also the basis for the lake simulations discussed by Wellman et al. (2013).
2 Methods

2.1 Coupled Thermal-hydrologic Simulations

Wellman et al. (2013) describe numerical simulations of lake-talik formation in watersheds modeled after those found in the lake-rich Yukon Flats of interior Alaska. Modeling experiments used the SUTRA groundwater modeling code (Voss and Provost, 2002) enhanced with capabilities to simulate freeze-thaw processes (McKenzie and Voss, 2013). The phase change between ice and liquid water occurs over a specified temperature range, and accounts for latent heat of fusion as well as changes in thermal conductivity and heat capacity for ice-water mixtures. Ice content also changes the effective permeability, thereby altering subsurface flowpaths and enforcing a strong coupling between hydraulic and thermal processes. The modeling domain, which is adapted for this study, is axis-symmetric with a central lake and upwards-sloping ground surface that rises from an elevation of 500 m at \( r = 0 \) m to 520 m at the outer extent of the model, \( r = 1800 \) m (Figure 1). The model uses a layered-geology consistent with the Yukon Flats (Minsley et al., 2012a; Williams, 1962), with defined hydrologic and geophysical parameters for each layer summarized in Table 1. Initial permafrost conditions prior to lake formation were established by running the model to steady state under hydrostatic conditions with a constant temperature of \(-2.25 \, ^\circ\text{C}\) applied to the land surface, which produces a laterally continuous permafrost layer extending to a depth of about 90 m.

Subsequent hydrologic simulations assume fully saturated conditions, and are performed over a 1,000-year period under 36 different scenarios of climate (warmer than, colder than, and similar-to present conditions); hydrologic gradient (hydrostatic, gaining, and losing lake conditions); and lake depth/extent (3-, 6-, 9-, and 12-m-deep lakes that intersect the ground surface at increasing distance, as shown in Figure 1). Complete details and results of the hydrologic simulations can be found in Wellman et al. (2013). At each simulation time step, the SUTRA model outputs temperature, pressure, and ice saturation. Conversion of these hydrologic variables to electrical resistivity-the geophysical property needed to simulate electromagnetic data considered here-is described below.
2.2 A physical property relationship

Electrical resistivity is the primary geophysical property of interest for the electromagnetic geophysical methods used in this study. It is well-established that resistivity is sensitive to basic physical properties such as unfrozen water content, soil or rock texture, and salinity (Palacky, 1987). Here, we build on earlier efforts to simulate the electrical properties of ice-saturated media (Hauck et al., 2011) by using a modified form of Archie’s Law (Archie, 1942) that also incorporates surface conduction effects (Revil, 2012) to predict the dynamic electrical resistivity structure for the evolving state of temperature and ice saturation ($S_i$) in the talik simulations. Bulk electrical conductivity is described by Revil (2012) as

$$\sigma = \frac{S_w^n}{F} \left[ \sigma_f + m(S_w^n F - 1) \sigma_s \right], \quad (1)$$

where $\sigma$ is the bulk electrical conductivity [S/m]; $S_w$ is the fractional water saturation [-] in the pore space, where $S_w = 1 - S_i$; $\sigma_f$ is the conductivity of the saturating pore fluid [S/m]; $m$ is the Archie cementation exponent [-]; $n$ is the Archie saturation exponent [-]; $F$ is the formation factor [-], where $F = \phi^{-m}$ and $\phi$ is the matrix porosity [-]; and $\sigma_s$ is the conductivity [S/m] associated with grain surfaces. The Archie exponents $m$ and $n$ are known to vary as a function of pore geometry; here, we use $m = n = 1.5$, which is appropriate for unconsolidated sediments (Sen et al., 1981). Simulation results are presented as electrical resistivity [ohm-m], which is the inverse of the conductivity, i.e. $\rho = 1/\sigma$.

The first term in Eq. (1) describes electrical conduction within the pore fluid, where fluid conductivity is defined as

$$\sigma_f = F \sum_i \beta_i |z_i| C_i. \quad (2)$$

The summation in Eq. (2) is over all dissolved ionic species ($\text{Na}^+$ and $\text{Cl}^-$ are assumed to be the primary constituents in this study), where $F_c$ is Faraday’s constant [C/mol] and $C_i$, $\beta_i$, and $z_i$ are the concentration [mol/L], ionic mobility $[\text{m}^2/\text{V}s]$, and valence of the $i^{th}$ species, respectively.
Surface conduction effects, described by the second term in Eq. (1), are related to the chemistry at the pore-water interface, and can be important in fresh water (low conductivity) systems at low porosity (high ice saturation). Additionally, the surface conduction term provides a means for describing the conductivity behavior for different lithologies, as will be described below. The surface conductivity is given by

\[ \sigma_s = \frac{2}{3} \left( \frac{\phi}{1 - \phi} \right) \beta_s Q_v, \]  

(3)

where \( \beta_s \) is the cation mobility \([\text{m}^2/\text{Vs}]\) for counterions in the electrical double layer at the grain-water interface (Revil et al., 1998) and \( Q_v \) is the excess electrical charge density \([\text{C/m}^3]\) in the pore volume,

\[ Q_v = S_w^{-1} \rho_g \left( \frac{1 - \phi}{\phi} \right) \chi, \]  

(4)

where \( \rho_g \) is the mass density of the grains \([\text{kg/m}^3]\) and \( \chi \) is the cation exchange capacity \([\text{C/kg}]\). Changes in \( \chi \), representative of bulk differences in clay mineral content, are used to differentiate the electrical signatures of the lithologic units in this study (Table 1).

The temperature, \( T \) \([\text{C}]\), dependence of ionic mobility affects both the fluid conductivity (Eq. (2)) and surface conductivity (Eq. (3)), where mobility is approximated as a linear function of temperature (Keller and Frischknecht, 1966; Sen and Goode, 1992) as

\[ \beta(T) = \beta_{T=25C} \left[ 1 + 0.019(T - 25) \right]. \]  

(5)

Finally, we consider the effect of increasing ice saturation on salinity. Because salts are generally excluded as freezing occurs, salinity of the remaining unfrozen pore water is expected to increase with increasing ice content (Marion, 1995), leading to a corresponding increase in fluid conductivity according to Eq. (2). To describe this dependence of salinity on ice saturation, \( C(S_i) \), we use the expression

\[ C(S_i) = C_{S_i=0} S_w^{-\alpha}, \]  

(6)

where \( \alpha \sim 0.8 \) accounts for loss of solute from the pore space due to diffusion or other transport processes, and \( S_i = 1 - S_w \).
Information about the different lithologic units described by Wellman et al. (2013) that are also summarized in Table 1 are used to define static model properties such as porosity, grain mass density, cation exchange capacity, and Archie’s exponents.

Dynamic outputs from the SUTRA simulations, including temperature and ice saturation, are combined with the static variables in Eqs. (1) - (6) to predict the evolving electrical resistivity structure.

2.3 Geophysical Forward Simulations

Synthetic airborne electromagnetic (AEM) data are simulated for each snapshot of predicted bulk resistivity values using nominal system parameters based on the Fugro RESOLVE\(^1\) frequency-domain AEM system that was used in the Yukon Flats survey (Minsley et al., 2012a). The RESOLVE system consists of five horizontal coplanar (HCP) transmitter-receiver coil pairs separated by approximately 7.9 m that operate at frequencies 0.378 kHz, 1.843 kHz, 8.180 kHz, 40.650 kHz, and 128.510 kHz; and one vertical coaxial (VCX) coil pair with 9-m separation that operates at 3.260 kHz.

Oscillating currents and associated magnetic fields created by the transmitter coils induce electrical currents in the subsurface that, in turn, generate secondary magnetic fields that are recorded by the receiver coils (Siemon, 2006; Ward and Hohmann, 1988). Data are reported as in-phase and quadrature components of the secondary field in parts-per-million (ppm) of the primary field, and responses as a function of frequency can be converted through mathematical inversion to estimates of electrical resistivity as a function of depth (e.g., Farquharson et al., 2003). Data are simulated at the nominal survey elevation of 30 m above ground surface using the one-dimensional modeling algorithm described in Minsley (2011), which follows the standard electromagnetic theory presented by Ward and Hohmann (1988).

The vertical profile of resistivity as a function of depth is extracted at each survey location and is used to simulate forward geophysical responses. There are 181 sounding locations for each axis-symmetric model, starting at the center of the lake \((r = 0 \text{ m})\) to the edge of the model domain \((r = 1,800 \text{ m})\) in 10-m increments. Each vertical resistivity

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\(^1\) Any use of trade, product, or firm names is for descriptive purposes only and does not imply endorsement by the U.S. Government
profile extends to 200 m depth, which is well beyond the depth to which we expect to
recover parameters in the geophysical inversion step. A center-weighted 5-point filter
with weights equal to [0.0625, 0.25, 0.375, 0.25, 0.0625] is used to average neighboring
bulk resistivity values at each depth before modeling in order to partly account for the
lateral sensitivity of AEM systems (Beamish, 2003). Forward simulations are repeated
for each of the 50 simulation times between 0 and 1,000 years output from SUTRA,
resulting in 9,050 data locations per modeling scenario.

Synthetic ground-based electromagnetic data presented in Section 3.3 are simulated using
nominal system parameters based on the GEM-2 instrument (Huang and Won, 2003).
The GEM-2 has a single HCP transmitter-receiver pair separated by 1.66 m, and data are
simulated at six frequencies: 1.5 kHz, 3.5 kHz, 8.1 kHz, 19 kHz, 43 kHz, and 100 kHz.
A system elevation of 1 m above ground is assumed, which is typical for this hand-
carried instrument.

2.4 Parameter Estimation and Uncertainty Quantification

The inverse problem involves estimating subsurface resistivity values given the simulated
forward responses and realistic assumptions about data errors. Geophysical inversion is
inherently uncertain; there are many plausible resistivity models that are consistent with
the measured data. In addition, the ability to resolve true resistivity values is limited both
by the physics of the AEM method and the level of noise in the data. Here, we use a
Bayesian Markov chain Monte Carlo (McMC) algorithm developed for frequency-
domain EM data (Minsley, 2011) to explore the ability of simulated AEM data to recover
the true distribution of subsurface resistivity values at 20-year intervals within the 1,000-
year lake talik simulations. This McMC approach is an alternative to traditional
inversion methods that find a single ‘optimal’ model that minimizes a combined measure
of data fit and model regularization (Aster et al., 2005). Although computationally more
demanding, McMC methods allow for comprehensive model appraisal and uncertainty
quantification. AEM-derived resistivity estimates for the simulations considered here
will help guide interpretations of future field datasets, identifying the characteristics of
relatively young versus established thaw under different hydrologic conditions.
The McMC algorithm provides comprehensive model assessment and uncertainty analysis, and is useful in diagnosing the ability to resolve various features of interest. At every data location along the survey profile, an ensemble of 100,000 resistivity models is generated according to the Metropolis-Hastings algorithm (Hastings, 1970; Metropolis et al., 1953). According to Bayes’ theorem, each model is assigned a posterior probability that is a measure of (1) its prior probability which, in this case, is used to penalize models with unrealistically large contrasts in resistivity over thin layers; and (2) its data likelihood, which is a measure of how well the predicted data for a given resistivity model match the observed data within data errors. A unique aspect of this algorithm is that it does not presuppose the number of layers needed to fit the observed data, which helps avoid biases due to assumptions about model parameterization. Instead, transdimensional sampling rules (Green, 1995; Sambridge et al., 2013) are used to allow the number of unknown layers to be one of the unknowns. That is, the unknown parameters for each model include the number of layers, layer interface depths, and resistivity values for each layer.

Numerous measures and statistics are generated from the ensemble of plausible resistivity models, such as: the single most-probable model, the probability distribution of resistivity values at any depth, the probability distribution of where layer interfaces occur as a function of depth, and the probability distribution of the number of layers (model complexity) needed to fit the measured data. A detailed description of the McMC algorithm can be found in Minsley (2011). Finally, probability distributions of resistivity are combined with assumptions about the distribution of resistivity values for any lithology and/or ice content in order to make a probabilistic assessment of lithology or ice content, as illustrated below.

3 Results

3.1 Electrical resistivity model development

Information about the different lithologic units described by Wellman et al. (2013) that are also summarized in Table 1 are used to define static model properties such as porosity, grain mass density, cation exchange capacity, and Archie’s exponents. Dynamic outputs from the SUTRA simulations, including temperature and ice saturation,
are combined with the static variables in Eqs. (1) - (6) to predict the evolving electrical resistivity structure. The behavior of bulk resistivity as a function of ice saturation is shown in Figure 2. Separate curves are shown for a range of $\chi$ (cation exchange capacity) values, which are the primary control in defining offset resistivity curves for different lithologies, where increasing $\chi$ is generally associated with more fine-grained material such as silt or clay.

For each of the 1,000-year simulations, the static variables summarized in Table 1 are combined with the spatially and temporally variable state variables $T$ and $S_i$ output by SUTRA to predict the distribution of bulk resistivity at each time step using Eqs. (1) - (6). An example of SUTRA output variables for the 6 m-deep gaining lake scenario at 240 years (the approximate sub-lake talik breakthrough time for that scenario) is shown in Figure 3A-B, and the predicted resistivity for this simulation step is shown in Figure 3C. The influence of different lithologic units is clearly manifested in the predicted resistivity values, whereas lithology is not overly evident in the SUTRA state variables. For a single unit, there is a clear difference in resistivity for frozen versus unfrozen conditions. Across different units, there is a contrast in resistivity when both units are frozen or unfrozen. Resistivity can therefore be a valuable indicator of both geologic and ice content variability. However, there is also ambiguity in resistivity values as both unfrozen Unit 2 and frozen Unit 3 appear to have intermediate resistivity values of approximately 100-300 ohm-m (Figure 3C) and cannot be characterized by their resistivity values alone. This ambiguity in resistivity can only be overcome by additional information such as borehole data or prior knowledge of geologic structure. Synthetic bulk resistivity values according to Eq. (1) are shown in Figure 4 for the four different lake depths (3, 6, 9, and 12 m) at three different simulation times (100, 240, and 1,000 years) output from the hydrostatic/current climate condition simulations.

Lithology and ice saturation are the primary factors that control simulated resistivity values (Figure 2), though ice saturation is a function of temperature. The empirical relation between temperature and bulk resistivity is shown in Figure 3D by cross-plotting values from Figure 3B-C. Within each lithology resistivity is relatively constant above zero degrees, with a rapid increase in resistivity for temperatures below zero degrees. This result is very similar to the temperature-resistivity relationships illustrated by
Hoekstra (1975, Fig. 1), lending confidence to our physical property definitions described earlier. Above zero degrees, the slight decrease in resistivity is due to the temperature-dependence of fluid resistivity. The rapid increase in resistivity below zero degrees is primarily caused by reductions in effective porosity due to increasing ice saturation, though changes in surface conductivity and salinity at increasing ice saturation are also contributing factors. Below -1°C, the change in resistivity values as a function of temperature rapidly decreases. This is an artifact caused by the imposed temperature-ice saturation relationship defined in SUTRA that, for these examples, enforces 99% ice saturation at -1°C. It is more likely that ice saturation continues to increase asymptotically over a larger range of temperatures below zero degrees, with corresponding increases in electrical resistivity. However, because AEM methods are limited in their ability to discern differences among very high resistivity values, as discussed later, this artifact does not significantly impact the results presented here.

3.2 Parameter Estimation and Uncertainty Quantification

AEM data (not shown) are simulated for each of the electrical resistivity models (e.g. Figure 4) using the methods described in Section 2.3. The simulated data are then used to recover estimates of the original resistivity values according to the approach outlined in Section 2.4, assuming 4% data error with an absolute error floor of 5 ppm. Resistivity parameter estimation results for the 6 m-deep hydrostatic lake scenario (Figure 4, D-F) are shown in Figure 5. At each location along the profile, the average resistivity model as a function of depth is calculated from the McMC ensemble of 100,000 plausible models. The overall pattern of different lithologic units and frozen/unfrozen regions is accurately depicted in Figure 5, with two exceptions that will be discussed in greater detail: (1) the specific distribution of partial ice saturation beneath the lake before thaw has equilibrated (Figure 5A-B); and (2) the shallow sand layer (Unit 1) that is generally too thin to be resolved using AEM data.

A point-by-point comparison of true (Figure 4F) versus predicted (Figure 5C) resistivity values for the hydrostatic 6 m-deep lake scenario at the simulation time 1,000 years is shown in Figure 6A. The cross-plot of true versus estimated resistivity values generally fall along the 1:1 line, providing a more quantitative indication of the ability to estimate
the subsurface resistivity structure. Estimates of the true resistivity values for each
lithology and freeze/thaw state (Figure 6B) tend to be indistinct; appearing as a vertical
range of possible values in Figure 6A due to the inherent resolution limitations of inverse
methods and parameter tradeoffs (Day-Lewis, F. D. et al., 2005; Oldenborger and Routh,
2009). Although the greatest point density for both frozen and unfrozen silts (Unit 3)
falls along the 1:1 line, resistivity values for these components of the model are also often
overestimated; this is likely due to uncertainties in the location of the interface between
the silt and gravel units. This is in contrast with the systematic underestimation of frozen
gravel resistivity values due to the inability to discriminate very high resistivity values
using EM methods (Ward and Hohmann, 1988). Frozen sands (true log resistivity ~2.8
in Figure 6B) are also systematically overestimated in Figure 6A; in this case, due to the
inability to resolve this relatively thin resistive layer.

While useful, single ‘best’ estimates of resistivity values at any location (Figure 6) are
not fully representative of the information contained in the AEM data and associated
model uncertainty. From the McMC analysis of 100,000 models at each data location,
estimates of the posterior probability density function (pdf) of resistivity are generated for
each point in the model. Probability distributions are extracted from a depth of 15 m,
within the gravel layer (Unit 2), at one location where unfrozen conditions exist ($r = 0$
m), and a second location outside the lake extent ($r = 750$ m) where the ground remains
frozen (Figure 7A). Results from a depth of 50 m, within the silt layer (Unit 3), are
shown in Figure 7B. With the exception of the frozen gravels, whose resistivity tends to
be underestimated, the peak of each pdf is a good estimate of the true resistivity value at
that location.

Resistivity values are translated to estimates of ice saturation, which is displayed on the
upper axis of each panel in Figure 7, using the appropriate lithology curve from Figure 2.
Using the ice saturation-transformed pdfs, quantitative inferences can be made about the
probability of the presence or absence of permafrost. For example, the probability of ice
content being less than 50% is estimated by calculating the fractional area under each
distribution for ice-content values less than 0.5. Probability estimates of ice content less
than 50% and greater than 95% for the four distributions shown in Figure 7 are
summarized in Table 2. High probabilities of ice content exceeding 95% are associated
with the $r = 750$ m location outside the lake extent, whereas high probability of ice
content below the 50% threshold are observed at $r = 0$ beneath the center of the lake. The
pdfs for each lithology shown in Figure 7 are end-member examples of frozen and
unfrozen conditions. Within a given lithology, a smooth transition from the frozen-state
pdf to the unfrozen-state pdf is observed as thaw occurs, with corresponding transitions in
the calculated ice threshold probabilities.

Further illustration of the spatial and temporal changes in resistivity pdfs are shown in
Figure 8. The resistivity pdf is displayed as a function of distance from the lake center at
the same depths (15 m and 50 m) shown in Figure 7, corresponding to gravel (Figure
8A,C, and E) and silt (Figure 8B, D, and F) locations. High probabilities, i.e. the peaks in
Figure 7, correspond to dark-shaded areas in Figure 8. Images are shown for three
different time steps in the SUTRA simulation for the hydrostatic 6 m-deep lake scenario:
100 years (Figure 8A-B), 240 years (Figure 8C-D), and 1,000 years (Figure 8E-F).

Approximate ice-saturation values, translated from the ice versus resistivity relationships
for each lithology shown in Figure 2, are displayed on the right axis of each panel in
Figure 8, and true resistivity values are plotted as a dashed line. Observations from
Figure 8 include:

(1) Outside the lake boundary, pdfs are significantly more sharply peaked (darker
shading) for the gravel unit than the silt unit, suggesting better resolution of shallower
resistivity values within the gravel layer. It should be noted however, that this improved
resolution does not imply improved model accuracy; in fact, the highest probability
region slightly underestimates the true resistivity value. (2) Probability distributions for
the silt layer track the true values, but with greater uncertainty. (3) Inside the lake
boundary, gravel resistivity values are not as well resolved compared with locations
outside the lake boundary due to the loss of signal associated with the relatively
conductive lake water. (4) Increasing trends in resistivity/ice saturation towards the outer
extents of the lake are captured in the pdfs, but are subtle. (5) Within the silt layer at
early times before the talik is fully through-going (Figure 8B, D), the AEM data are
insensitive to which layer is present, hence the bi-modal resistivity distribution with
peaks associated with characteristic silt and gravel values. This ambiguity disappears at
later times when the low-resistivity unfrozen silt layer extends to the base of the unfrozen gravels, which is a more resolvable target (Figure 8F).

A more detailed analysis of the changes in resistivity and ice-saturation as a function of time, and for the differences between hydrostatic and gaining lake conditions, is presented in Figure 9. Average values of resistivity/ice-saturation within 100 m of the lake center are shown within the gravel layer at a depth of 15 m (Figure 9A) and a depth of 50 m within the silt layer (Figure 9B) at 20 year time intervals. Outputs are displayed for both 6 m-deep hydrostatic and gaining lake scenarios. Thawing due to conduction occurs over the first ~200 years within the gravel layer (Figure 9A), with similar trends for both the hydrostatic and gaining lake conditions and no clear relationship to the talik formation times indicated as vertical lines. Conduction-dominated thaw is observed for the gravel layer in the gaining lake scenario because significant advection does not occur until after the thaw bulb has extended beneath the gravel layer. In the deeper silt layer (Figure 9B), however, very different trends are observed for the hydrostatic and gaining lake conditions. Ice content decreases gradually as thawing occurs in the hydrostatic scenario, consistent with conduction-dominated thaw, reaching a minimum near the time of talik formation at 687 years (Wellman et al., 2013, Table 3). In contrast, there is a rapid loss in ice content in the gaining lake scenario resulting from the influence of advective heat transport as groundwater is able to move upwards through the evolving talik beneath the lake. This rapid loss in ice content begins after the gravel layer thaws, and reaches a minimum near the 258-year time of talik formation for this scenario. These trends, captured by the AEM-derived resistivity models, are consistent with the plots of change in ice volume output from the SUTRA simulations reported by Wellman et al. (2013, Figure 3).

3.3 Near-Surface Resolution

Finally, we focus on the upper sand layer (Unit 1), which is generally too thin (2 m) and resistive (> 600 ohm-m) to be resolved using AEM data; though may be imaged using other ground-based electrical or electromagnetic geophysical methods. Seasonal thaw and surface runoff causes locally reduced resistivity values in the upper 1 m, which is still too shallow to resolve adequately using AEM data. In practice, shallow thaw and sporadic permafrost trends are observed to greater depths in many locations, including
inactive or abandoned channels (Jepsen et al., 2013b). To simulate these types of features, the shallow resistivity structure of the 6 m-deep hydrostatic lake scenario at 1,000 years is manually modified to include three synthetic ‘channels’. These channels are not intended to represent realistic pathways relative to the lake and the hydrologic simulations; they are solely for the purpose of illustrating the ability to resolve shallow resistivity features.

Figure 10A shows the three channels in a zoomed-in view of the uppermost portion of the model outside the lake extent. Each channel is 100 m wide, but with different depths: 1 m (half the Unit 1 thickness), 2 m (full Unit 1 thickness) and 3 m (extending into the top of Unit 2). Analysis of AEM data simulated for this model, presented as the McMC average model, are shown in Figure 10B. All three channels are clearly identified, but their thicknesses and resistivity values are overestimated and cannot be distinguished from one another. To explore the possibility of better resolving these shallow features, synthetic EM data are simulated using the characteristics of a ground-based multi-frequency EM tool (the GEM-2 instrument) that can be hand carried or towed behind a vehicle, and is commonly used for shallow investigations. The McMC average model result for the simulated shallow EM data is shown in Figure 10C. An error model with 4% relative data errors and an absolute error floor of 75 ppm was used for the GEM-2 data. Channel thicknesses and resistivity values are better resolved compared with the AEM result, though the 1 m-deep channel near $r = 800$ m appears both too thick and too resistive. In addition, the shallow EM data show some sensitivity to the interface at 2-m depth between frozen silty sands and frozen gravels, though the depth of this interface is over-estimated due to the limited sensitivity to these very resistive features.

4 Discussion

Understanding the hydrogeophysical responses to permafrost dynamics under different hydrologic and climatic conditions, and in different geological settings, is important for guiding the interpretation of existing geophysical datasets and also for planning future surveys. Geophysical models are inherently uncertain and ambiguous because of (1) the resolution limitations of any geophysical method and (2) the weak or non-unique relationship between hydrologic properties and geophysical properties. We have presented a general framework for coupling airborne and ground-based electromagnetic
predictions to hydrologic simulations of permafrost evolution, including a novel physical property relationship that accounts for the electrical response to changes in lithology, temperature, and ice content, as well as a rigorous analysis of geophysical parameter uncertainty. Although the focus here is on AEM data, other types of electrical or electromagnetic measurements could be readily simulated using the same resistivity model. Future efforts will focus on the simulation of other types of geophysical data (e.g. nuclear magnetic resonance or ground penetrating radar) using the same basic modeling approach.

In the specific examples of lake talik evolution presented here, which are modeled after the physical setting of the Yukon Flats, Alaska (Minsley et al., 2012b), AEM data are shown to be generally capable of resolving large-scale permafrost and geological features (Figure 5), as well as thermally and hydrologically induced changes in permafrost (Figure 8, Figure 9). The Bayesian McMC analysis provides useful details about model resolution and uncertainty that cannot be assessed using traditional inversion methods that produce a single ‘best’ model. A fortuitous aspect of the Yukon Flats model is the fact that the silt layer (Unit 3) is relatively conductive compared with the overlying gravels (Unit 2), making it a good target for electromagnetic methods. If the order of these layers were reversed, if the base of permafrost were hosted in a relatively resistive lithology, or if the base of permafrost was significantly deeper, AEM data would not likely resolve the overall structure with such good fidelity. In addition, knowledge of the stratigraphy helps to remove the ambiguity between unfrozen gravels and frozen silts, which have similar intermediate resistivity values (Figure 4, Figure 5). The methods developed here that use a physical property model to link hydrologic and geophysical properties provide the necessary framework to test other more challenging hydrogeological scenarios.

Two key challenges for the lake talik scenarios were identified: (1) resolving the details of partial ice saturation beneath the lake during talik formation, and (2) resolving near-surface details associated with shallow thaw. The first challenge is confirmed by Figure 5 and Figure 8, which show that AEM data cannot resolve the details of partial ice saturation beneath a forming talik. However, there is clearly a change in the overall characteristics of the sub-lake resistivity structure as thaw increases (Figure 9). One
A notable feature is the steadily decreasing depth to the top of the low-resistivity unfrozen silt (red) beneath the lake (Figure 5A-B) as thaw increases, ultimately terminating at the depth of the gravel-silt interface when fully unfrozen conditions exist (Figure 5C).

Measurements of the difference in elevation between the interpreted top of unfrozen silt and the base of nearby frozen gravels were used by Jepsen et al. (2013a) to classify whether or not fully thawed conditions existed beneath lakes in the Yukon Flats AEM survey described by Minsley et al. (2012a). The simulations presented here support use of this metric to distinguish full versus partial thaw beneath lakes. However, without the presence of a lithological boundary, the shallowing base of permafrost associated with talik development beneath lakes would be much more difficult to distinguish. Finally, it is important to note that resistivity is sensitive primarily to unfrozen water content, and that significant unfrozen water can remain in relatively warm permafrost that is near 0°C, particularly in fine-grained sediments. Resistivity-derived estimates of talik boundaries defined by water content may therefore differ from the thermal boundary defined at 0°C.

The second challenge, to resolve near-surface details associated with supra-permafrost thaw, is addressed in Figure 10. For the scenarios considered here, AEM data can identify shallow thaw features, but have difficulty in discriminating their specific details. There are many combinations of resistivity and thickness that produce the same EM response; therefore, without additional information it is not possible to uniquely characterize both thaw depth and resistivity. Ground-based EM data show improved sensitivity to the shallow channels, and also limited sensitivity to the interface between resistive frozen gravels and frozen silty sands (Figure 5). By restricting the possible values of resistivity and/or thickness for one or more layers based on prior assumptions, Dafflon et al. (2013) showed that improved estimates of active layer and permafrost properties can be obtained. The quality of these estimates, of course, depends on the accuracy of prior constraints used. In many instances, it may be possible to auger into this shallow layer to provide direct observations that can be used as constraints. This approach could be readily applied to the ensemble of McMC models. For example, if the resistivity of the channels in Figure 10A were known, the thickness of the channels could be estimated more accurately by selecting only the set of McMC models with channel...
resistivity close to the true value, thereby removing some of the ambiguity due to equivalences between layer resistivity and thickness.

AEM data are most likely to be useful for baseline characterization of subsurface properties as opposed to monitoring changes in permafrost. Although there are some cases of rapid change associated with near-surface freeze/thaw processes (Koch et al., 2013) or in the case of catastrophic loss of ice in the gaining lake scenario (Figure 9B) that may be of interest, large-scale changes in permafrost generally occur over much longer time periods than is practical for repeat AEM surveys. One exception could be related to infrastructure projects such as water reservoirs or mine tailing impoundments behind dams, where AEM could be useful for baseline characterization and repeat monitoring of the impact caused by human-induced permafrost change. Geophysical modeling, thermophysical hydrologic modeling, and field observations create a synergy that provides greater insight than any individual approach, and can be useful for future characterization of coupled permafrost and hydrologic processes.

5 Summary

Analysis of AEM surveys provide a means for remotely detecting subsurface electrical resistivity associated with the co-evolution of permafrost and hydrologic systems over areas relevant to catchment-scale and larger processes. Coupled hydrogeophysical simulations using a novel physical property relationship that accounts for the effects of lithology, ice saturation, and temperature on electrical resistivity provide a systematic framework for exploring the geophysical response to various scenarios of permafrost evolution under different hydrological forcing. This modeling approach provides a means of robustly testing the interpretation of AEM data given the paucity of deep boreholes and other ground truth data that are needed to characterize subsurface permafrost. A robust uncertainty analysis of the geophysical simulations provides important new quantitative information about the types of features that can be resolved using AEM data given the inherent resolution limitations of geophysical measurements and ambiguities in the physical property relationships. In the scenarios considered here, we have shown that large-scale geologic and permafrost structure is accurately estimated. Sublacustrine thaw can also be identified, but the specific geometry of partial ice
saturation beneath lakes can be poorly resolved by AEM data. Understanding the
geophysical response to known simulations is helpful both for guiding the interpretation
of existing AEM data, and also to plan future surveys and other ground-based data
acquisition efforts.

Author contribution

B. M. carried out the geophysical forward and inverse simulations, and prepared the
manuscript with contributions from all co-authors. T. W. and M. W. provided SUTRA
simulation results and hydrologic modeling expertise. A. R. helped to establish the
petrophysical relationships used to define the electrical resistivity model used in this
study.

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acknowledge additional support from the USGS National Research Program and the
USGS Geophysical Methods Development Project. USGS reviews provided by Josh
Koch and Marty Briggs have greatly improved this manuscript.
References


Table 1. Description of geologic units and physical properties used in numerical simulations. Entries separated by commas represent parameters with different values for each of the lithologic units.

<table>
<thead>
<tr>
<th>Geologic unit properties</th>
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<tbody>
<tr>
<td>Lithology:</td>
<td></td>
</tr>
<tr>
<td>Unit 1</td>
<td>Sediment (silty sand)</td>
</tr>
<tr>
<td>Unit 2</td>
<td>Sediment (gravelly sand)</td>
</tr>
<tr>
<td>Unit 3</td>
<td>Lacustrine silt</td>
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<td>Unit depth range [m]</td>
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<tr>
<td>Porosity [-]</td>
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</table>

<table>
<thead>
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<tbody>
<tr>
<td>Archie cementation exponent (m) [-]</td>
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</tr>
<tr>
<td>Archie saturation exponent (n) [-]</td>
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</tr>
<tr>
<td>Water salinity (C) [ppm]</td>
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<tr>
<td>Na$^+$ ionic mobility ($\beta$) [m$^2$/Vs]</td>
<td>5.8 x $10^{-8}$ (25°C)</td>
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<tr>
<td>Cl$^-$ ionic mobility ($\beta$) [m$^2$/Vs]</td>
<td>7.9 x $10^{-8}$ (25°C)</td>
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<tr>
<td>Na$^+$ surface ionic mobility ($\beta_s$) [m$^2$/Vs]</td>
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</tr>
<tr>
<td>Grain mass density ($\rho_g$) [kg/m$^3$]</td>
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<tr>
<td>Cation exchange capacity ($\chi$) [C/kg]</td>
<td>200, 10, 500</td>
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<tr>
<td>Salinity exponent (a) [-]</td>
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Table 2. Probability of ice saturation falling above or below specified thresholds based on the McMC-derived resistivity probability distributions shown in Figure 7.

<table>
<thead>
<tr>
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<th>p(ice &lt; 0.5)</th>
<th>p(ice &gt; 0.95)</th>
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<tr>
<td>Unit 2 (gravel), r = 0 m</td>
<td>0.76</td>
<td>0.05</td>
</tr>
<tr>
<td>Unit 2 (gravel), r = 750 m</td>
<td>0.00</td>
<td>0.88</td>
</tr>
<tr>
<td>Unit 3 (silt), r = 0 m</td>
<td>0.76</td>
<td>0.05</td>
</tr>
<tr>
<td>Unit 3 (silt), r = 750 m</td>
<td>0.00</td>
<td>0.98</td>
</tr>
</tbody>
</table>
Figure 1. Axis-symmetric model geometry indicating different lithologic units and simulated lake depths/ extents.
Figure 2. Bulk resistivity as a function of ice saturation using the physical properties defined for each of the lithologic units described in Table 1.
Figure 3. SUTRA model outputs and geophysical transformations from the 6-m gaining lake simulation at 240 years. Ice saturation (A) and temperature (B) are converted to predictions of bulk resistivity (C). Variability in resistivity as a function of temperature is indicated in (D) for lithologic units 1-3.
Figure 4. Synthetic bulk resistivity images under hydrostatic flow and current climate conditions. Lake depths of 3 m (A-C), 6 m (D-F), 9 m (G-I), and 12 m (J-L) are illustrated at simulation times 100, 240, and 1,000 years.
Figure 5. Mean resistivity model extracted from McMC ensembles. Results are shown for the 6-m-deep hydrostatic lake scenario outputs at (A) 100 years, (B) 240 years, and (C) 1,000 years.
Figure 6. Performance of geophysical parameter estimation in recovering true parameter values. (A) True versus McMC-estimated resistivity values for the hydrostatic 6-m-deep lake scenario at simulation time 1,000 years, compared with the frequency distribution of true resistivity values (B). Estimated resistivity values generally fall along the dashed 1:1 line in (A), with exceptions being under-prediction of the resistive frozen gravels, over-prediction of the thin surficial frozen sand, and some over-prediction of the frozen silt where it is in contact with frozen gravel.
Figure 7. McMC-estimated resistivity posterior distributions within frozen and unfrozen unit #2 gravels (A) and frozen and unfrozen unit #3 silts (B) for the hydrostatic 6-m-deep lake scenario at 1,000 years. Unfrozen resistivity distributions are extracted beneath the center of the lake ($r = 0$) at depths of 15 m and 50 m for the gravels and silts, respectively. Frozen distributions are extracted at the same depths, but at $r = 750$ m. The upper x-axes labels indicate approximate ice saturation based on the lithology-dependent ice saturation versus resistivity curves shown in Figure 2.
Figure 8. Resistivity probability distributions for the hydrostatic 6-m-deep lake scenario at simulation times 100 years (A-B), 240 years (C-D), and 1,000 years (E-F). Shading in each image represents the probability distribution at depths of 15 m (A, C, E) and 50 m (B, D, F) from the lake center ($r = 0$ m) to the edge of the model ($r = 1800$ m). Dashed lines indicate the true resistivity values. Ice saturation is displayed on the right axis of each image, and is defined empirically for each lithology using the relationships in Figure 2.
Figure 9. Change in ice saturation and resistivity as a function of time. Results are shown for the 6-m-deep lake hydrostatic and gaining lake scenarios within (A) the gravel layer, unit #2, at a depth of 15 m and (B) the silt layer, unit #3, at a depth of 50 m.
Figure 10. Comparison of airborne and ground-based measurements for recovering shallow thaw features. (A) True shallow resistivity structure extracted from the hydrostatic 6-m-deep lake scenario at a simulation time of 1,000 years, shown outside of the lake extent (distance > 500 m). Three shallow low-resistivity channels with thicknesses 1 m, 2 m, and 3 m were added to the resistivity model to provide added contrast. McMC-derived results using simulated AEM data (B) and ground-based EM data (C) illustrate the capability of these systems to image shallow features.