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Spatial and Temporal Variance of Soil and Meteorological Properties Affecting Sensor Performance—Phase 2

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August 2021

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Final Report

Approved for public release; distribution is unlimited.

Prepared for U.S. Army Corps of Engineers
Washington, DC 20314-1000

Under PE 06027121A, Project 468349, Task A1010, "Analysis of
Multimodal Sensors"

Abstract

An approach to increasing sensor performance and detection reliability for buried objects is to better understand which physical processes are dominant under certain environmental conditions. The present effort (Phase 2) builds on our previously published prior effort (Phase 1), which examined methods of determining the probability of detection and false alarm rates using thermal infrared for buried-object detection.

The study utilized a 3.05×3.05 m test plot in Hanover, New Hampshire. Unlike Phase 1, the current effort involved removing the soil from the test plot area, homogenizing the material, then reapplying it into eight discrete layers along with buried sensors and objects representing targets of interest. Each layer was compacted to a uniform density consistent with the background undisturbed density. Homogenization greatly reduced the microscale soil temperature variability, simplifying data analysis.

The Phase 2 study spanned May–November 2018. Simultaneous measurements of soil temperature and moisture (as well as air temperature and humidity, cloud cover, and incoming solar radiation) were obtained daily and recorded at 15-minute intervals and coupled with thermal infrared and electro-optical image collection at 5-minute intervals.

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Contents

Abstract	ii
Figures and Tables	iv
Preface	vi
Acronyms and Abbreviations	vii
Unit Conversion Factors	ix
1 Introduction	1
1.1 Background	3
1.2 Objectives	7
1.3 Approach	7
2 Methods	8
2.1 Site layout	8
2.2 Instrumentation	10
2.3 Object emplacement	13
2.4 Soil properties	15
3 Discussion of Results	18
3.1 FLIR camera performance	18
3.2 Homogenization effects	19
3.3 Pre- and post-object-emplacement disturbance comparison	23
3.4 Object-visibility parameterization	26
3.5 Significant factors	34
3.5.1 Incoming solar radiation	36
3.5.2 Air temperature, precipitation, and wind speed	40
4 Findings and Conclusions	41
References	44
Appendix A: Solar Noon for Hanover, New Hampshire	47
Report Documentation Page	48

Figures and Tables

Figures

1	CRREL Phase 2 test plot layout.....	8
2	Final plot setup with overhead infrared cameras.....	9
3	FLIR camera mounting with Model A300 on the <i>right</i> (south), closer to the center of the plot, and Model A310F 90 on the <i>left</i>	11
4	Plot layout and instrumentation at the following depths: (a) 5 cm, (b) 15 cm, (c) 25 cm, (d) 35 cm, (e) 45 cm, (f) 55 cm, and (g) 65 cm.....	12
5	Lidar image of the instrumentation layout at the 35 cm depth	13
6	Emplacement process: (a) test plot with empty excavated holes, (b) objects in holes (dark items are metal and upper two are at 25 cm depth), (c) postemplacement	14
7	Phase 2 test plot water-retention curve	17
8	Hot plate versus the average thermal IR image temperature	19
9	Comparison of Phase 1 and 2 thermal IR images of the plot prior to object emplacement under similar solar loading conditions: (a) Phase 1, 1530 on 13 September 2016, and (b) Phase 2, 1515 on 12 June 2018	20
10	Effects of homogenization for a dry and wet instance for Phase 1 (p1) and Phase 2 (p2): (a) surface thermal IR temperature of the plot, (b) histogram of IRT*, (c) omnidirectional semivariance (<i>red solid</i>), best-fit linear (<i>blue dashed</i>), and exponential (<i>black dashed</i>) curves. The rows from top to bottom are p1_dry, p1_wet, p2_dry, and p2_wet	22
11	Standard deviation of the IR image surface temperatures during pre- (<i>red</i>) and post- (<i>blue</i>) emplacement time periods for (a) the AOI, (b) the deep plastic box, (c) the deep metal box, (d) the background, (e) the shallow metal box, and (f) the shallow plastic box	24
12	Phase 2 monthly diurnal air-temperature trends	25
13	Difference between average FLIR surface temperature over the objects and the surrounding background as a function of the weather parameter: (a) time of day (hr), (b) incoming solar radiation (W/m ²), (c) air temperature (°C), (d) precipitation (mm), and (e) wind speed (m/s)	27
14	Instance of thermal IR temperature images: (a) 16 July 2018 at 1230, (b) 18 July 2018 at 1400, (c) 17 July 2018 at 1455, and (d) 24 July 2018 at 1235.....	30
15	Box plot of visibility metrics $V_1(y)$ to $V_4(y)$ and $V_1(\sigma)$ to $V_4(\sigma)$	33
16	Visualization metrics for 16 July 2018 at 1230, 18 July 2018 at 1400, 17 July 2018 at 1455, and 24 July 2018 at 1235	34
17	Average visibility metrics V_1 to V_4 calculated using the SD, semivariogram sill, and mean as a function of 300 W/m ² binned incoming shortwave radiation: (a) V_1 , (b) V_2 , (c) V_3 , and (d) V_4	37
18	Mean of the time-differenced visibility metrics $V_1(\sigma)$ to $V_4(\sigma)$ for 300 W/m ² incoming-solar-radiation bins: (a) V_1 , (b) V_2 , (c) V_3 , and (d) V_4	38

19	Mean of the time-differenced visibility metrics $V_1(\gamma)$ to $V_4(\gamma)$ for 300 W/m ² incoming-solar-radiation bins: (a) V_1 , (b) V_2 , (c) V_3 , (d) V_4	39
20	Mean of the time-differenced visibility metrics $V_1(\mu)$ to $V_4(\mu)$ for 300 W/m ² incoming-solar-radiation bins: (a) V_1 , (b) V_2 , (c) V_3 , (d) V_4	40

Tables

1	Grain-size distribution of Phase 2 plot soil	15
2	Homogenized soil pH, electrical conductivity, and color characteristics.....	16
3	Homogenized soil thermal conductivity	17
4	Image minimum and maximum thermal temperature, uniformity, variance, and standard deviation comparisons of Phase 1 and Phase 2 wet and dry instances for the region over the plot (AOI)	21
5	Image variogram statistics for both linear (lin) and exponential (exp).....	23
6	Meteorological conditions at the time of the images in Fig. 14. The colors indicate when objects are hotter (<i>red</i>) or colder (<i>blue</i>) than the background.....	31
7	Mean visibility metrics V_1 to V_4 for the SD and semivariogram sill for time differences of 15, 30, 60, and 120 minutes	35

Preface

This study was conducted for the U.S. Army Corps of Engineers and the U.S. Army Combat Capabilities Development Command (CCDC) C5ISR (Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance, and Reconnaissance) Center, formerly known as the U.S. Army Communications-Electronics Research, Development, and Engineering Center (CERDEC), Night Vision and Electronic Sensors Directorate (NVESD), under PE 06027121A, Project 468349, Task A1010, “Analysis of Multimodal Sensors.” The program monitor was Mr. Peter Brigham.

The work was performed by the Biogeochemical Sciences Branch (Mr. Nathan Lamie, Chief), the Terrestrial and Cryospheric Sciences Branch (Dr. John W. Weatherly, Chief), the Engineering Resources Branch (Dr. Caitlin Callaghan, Chief), the Force Projection and Sustainment Branch (Dr. Dorothea Lundberg, Chief), and the Signature Physics Branch (Dr. Marino A. Niccolai, Chief) of the Research and Engineering Division (Dr. George Calfas, Chief) and the Terrain and Ice Engineering Group (Ms. Meghan Quinn, group lead) of the Remote Sensing / GIS Center of Expertise (Mr. David C. Finnegan, Chief), U.S. Army Engineer Research and Development Center (ERDC), Cold Regions Research and Engineering Laboratory (CRREL). At the time of publication, Dr. Robert Davis was the Technical Director for Army Programs at CRREL and Chief Scientist for Geospatial Research and Engineering. The Deputy Director of ERDC-CRREL was Mr. David B. Ringelberg, and the Director was Dr. Joseph L. Corriveau.

COL Teresa A. Schlosser was Commander of ERDC, and Dr. David W. Pittman was the Director.

Acronyms and Abbreviations

AOI	Area of Interest
bgs	Below Ground Surface
CCDC	Combat Capabilities Development Command
CERDEC	Communications-Electronics Research, Development, and Engineering Center
CRREL	Cold Regions Research and Engineering Laboratory
C5ISR	Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance, and Reconnaissance
dp	Deep Plastic
dm	Deep Metal
ERDC	U.S. Army Engineer Research and Development Center
FAR	False Alarm Rate
GWC	Gravimetric Water Content
IR	Infrared
IRT	Thermal IR–Derived Temperature
LWIR	Longwave Infrared
NVESD	Night Vision and Electronic Sensors Directorate
PD	Probability of Detection
RGB	Red, Green, Blue
SD	Standard Deviation
sm	Shallow Metal
SM	Soil-Moisture Probe
sp	Shallow Plastic

TC	Thermocouples
USCS	Unified Soil Classification System
VWC	Volumetric Water Content
YPG	Yuma Proving Ground

Unit Conversion Factors

Multiply	By	To Obtain
cubic feet	0.02831685	cubic meters
feet	0.3048	meters
inches	0.0254	meters
microns	1.0 E-06	meters
pounds (force)	4.448222	newtons
pounds (mass)	0.45359237	kilograms

1 Introduction

The environmental phenomenological properties responsible for generating significant noise, or observation variability, in sensor systems monitoring the infrared (IR, wavelengths between 0.7 and 15 μm *) bands of the electromagnetic spectrum are complicated. The shorter IR wavelengths are influenced by aerosol loading in the atmosphere as well as absorption of energy by water vapor. Monitoring the thermal IR region of the spectrum at wavelengths between 3 and 15 μm can eliminate these effects. Unlike visible light sensors, which require illumination by the sun and scattering by objects, energy at the thermal IR wavelengths is emitted from different bodies based on their temperature and each substance's emissivity properties. That each object above absolute zero is an emitter permits the use of passive sensors such as thermal IR.

Several gases are strong absorbers of electromagnetic energy in the thermal IR spectral bands (Hudson and Hudson 1975). These gases include ozone, methane, carbon dioxide, ammonia, and water vapor. The amount of total energy absorbed is a function of the highly variable, both in space and time, concentration of the gases. However, despite the tendency of these gases to absorb a significant amount of thermal IR energy, a region of low absorption exists in the electromagnetic spectrum between 8 and 14 μm . In this window, absorbing gases weakly reduce the energy transmitted in the electromagnetic spectrum. This window is then useful for sensors seeking to detect land-based objects with minimal effects from atmospheric gases. However, as discussed in the scientific literature (e.g., Koh and Wakeley 2009), the surface-emitted thermal IR energy is subject to not only atmospheric effects but also varying soil surface temperature and emissivity. Terrain emissivity is dependent on heterogeneity of land surface material (e.g., soil type and texture, vegetation, soil moisture, etc.; Khanafer and Vafai 2002; Van De Griend et al. 1985), which yields a highly variable detected signal from the environment, or what is referred to as background noise. Superimposed on the background noise is the actual signal from the target, which we are interested in. In our case, we are interested specifically in objects buried beneath the soil surface. When the

* For a full list of the spelled-out forms of the units of measure used in this document, please refer to U.S. Government Publishing Office Style Manual, 31st ed. (Washington, DC: U.S. Government Publishing Office, 2016), 248–252, <https://www.govinfo.gov/content/pkg/GPO-STYLEMANUAL-2016/pdf/GPO-STYLEMANUAL-2016.pdf>.

ratio of signal (object) to noise (background) is low, it can be difficult to distinguish the object from the background noise.

The inability to account for environmental effects manifests in a poor probability of detection (PD) and elevated false alarm rate (FAR) when using thermal IR for buried-object detection. We conducted a pilot study in 2016 (Phase 1) to investigate the sensitivity of thermal IR sensor performance to various soil properties and atmospheric forcing and their impact on buried-object detection (Clausen et al. 2020). This included examining the environmental properties as categorical variables; estimating soil parameters, chemistry, and particle size; calibrating thermal IR sensors; and managing meteorological station data. The hypothesis was that the thermal behavior of a soil is a function of several interdependent variables, such as material density, moisture content, reflectance, surface texture, and solar thermal loading.

The research objective of this effort (Phase 2) was to continue to enhance our understanding of the environmental (soil and atmospheric) phenomenological properties affecting the temporal and spatial thermal variance of soils. The primary question being addressed is how to quantify the natural variance, or background noise, such that it can be subtracted from a disturbed area or object “signal” by accounting for the physical phenomenological material and atmospheric properties. Phase 2 used buried objects to help understand the underlying phenomenology. This follow-on study investigated more in depth the variables identified as statistically significant and correlated them to variations in thermal irradiation measures of thermal IR sensors. Our hypothesis focuses on the interplay of variables and the thermal behavior of a homogeneous soil. As with the Phase 1 pilot study, this investigation used the Engineer Research and Development Center (ERDC) and Combat Capabilities Development Command (CCDC) C5ISR (Command, Control, Communications, Computers, Cyber, Intelligence, Surveillance, and Reconnaissance) Center Test Bed located at the Cold Regions Research and Engineering Laboratory (CRREL) in Hanover, New Hampshire, to further test and validate our understanding of the physical and atmospheric properties responsible for temporal and spatial thermal variance. Results from this study led to insights and a deeper understanding of the physical variables influencing background noise and hindering thermal IR sensor performance. This document focuses on the design of the Phase 2 test plot and initial observations.

1.1 Background

The U.S. Army has been testing a variety of sensor systems (e.g., thermal IR, seismic, acoustic, and radar) to detect buried objects at the test site at Yuma Proving Ground (YPG) in Arizona and at other locations globally and has amassed a significant warehouse of data. The U.S. Army has spent the last several years developing and testing computer algorithms to improve the PD of buried objects. However, these efforts have resulted in only modest improvements in PD and reduction in FAR and have not achieved the necessary objectives for a high-confidence system. Our investigation hypothesizes that one reason is the lack of consideration as to the amount and structure from background noise produced by soil and atmospheric phenomenological properties.

The Army needs techniques for rapidly assessing within a large spatial area the location of soils disturbed by buried-object emplacement or other elicit activities. Our investigation hypothesizes that various environmental phenomenologies are responsible for elevated background noise and degraded target detection. Our approach exploits long-wave IR (LWIR) imagery for identifying buried objects while exploring the impacts of environmental phenomenology on target visibility. For example, modern thermal sensors can detect thermal differences at a fraction of a degree. However, the common problem for practical use of this technology is the high degree of soil thermal variability and trying to differentiate a signal indicative of a buried object from one associated with background noise. The undesirable outcome is an elevated rate of false positive detections, requiring substantial human intervention to assess the data and confirm the presence or absence of an object.

Historically, electromagnetic sensor systems have been used to detect buried ferrous objects. However, buried objects are made out of nonferrous materials such as wood and plastic as well. Consequently, since the start of the century, there has been increasing interest in the use of additional sections of the electromagnetic spectrum that permit sensing of nonferrous objects. Studies are exploring the use of sensed input from different parts of the electromagnetic spectrum or other physical properties, which are referred to as sensor modalities (e.g., IR, hyperspectral imagery, seismic and acoustic methods, and ground-penetrating radar), to determine if they are capable of detecting buried objects regardless of material composition. These alternative sensor modalities can be operated independently; or increasingly, there is interest in fusion of multiple sensor outputs into a

single comprehensive interpretation, allowing for complimentary integrative analysis (Chair and Varshney 1986). Additionally, there is interest in using autonomous unattended airborne vehicles or ground platforms for quickly characterizing an area at standoff distances prior to or during military patrols, convoys, or combat operations.

Various forms of sensor modalities have existed throughout the ages, with the first metal detector invented in the late nineteenth century, not long after Maxwell's equations of electromagnetism were published. It was not until the Second World War that the technology finally made it to the front lines, and it has been an invaluable asset to militaries worldwide since. But in an ever-changing global climate, the sophistication of explosive devices has somewhat regressed, taking on various forms, including plastic and wood in addition to electromagnetically sensitive ferrous metals. This has led to an increased interest in a sensor modality with a high PD and low FAR, capable of detecting buried objects regardless of their material composition.

The ability to accurately detect buried and surface objects at a stand-off distance by using remote sensors is important to the Army, and interest in IR as a sensor modality has increased in the past decade (Kylili et al. 2014). Although the Earth's atmosphere is not a favorable transmission medium for IR (as opposed to the radio wave electromagnetic band for radar applications), there exist within a small atmospheric window from 7.5 to 14 μm where attenuation is minimal (Hudson and Hudson 1975). This region is defined as the LWIR, or "thermal-imaging," region of the electromagnetic spectrum. Sensors used in our investigation, a FLIR Systems Inc. camera (model A300 with a Scout III 240 lens and model A310F), operate at 7.5–13 μm , well within the thermal-imaging band. The use of thermal IR as a detection mechanism is based on the concept that objects buried at shallow depths (Moukalled et al. 2006) or disturbance of the soil may alter the thermal signature of soil. Materials differ in thermal capacities, resulting in different heating and cooling rates and associated IR radiation emissions (Simard 1996). This variability is IR sensitive and has been exploited since the mid-1800s, with the first thermographic camera used in 1929 for anti-aircraft defense over Britain.

Thermal IR has seen a renewed interest as a sensor modality for buried-object detection since the early 2000s. However, a host of environmental factors that affect PD and generate FAR are soil grain size, composition,

texture, soil disturbance, moisture content and its migration and surface evaporation, and terrestrial radiant reflection and emittance. Diurnal thermal fluctuations from changing solar (shortwave radiation) input throughout the day give rise to thermal contrasts at the soil surface (Khanafar and Vafai 2002; Van De Griend et al. 1985). Adding to this complexity is the additional influence of a buried object on both heat, or long-wave radiation, and moisture transfer to the atmosphere (Pan and Mahrt 1987). Understanding how and why, along with the magnitude of the interference from environmental features, helps in quantifying these affects and thus improving current detection algorithms through a process of strategic elimination (Howington 2019).

However, at the opposite end of the spectrum, the sensor application community has been exploring “active” ways to increase PD of buried objects by utilizing a multisensor approach, sometimes referred to as sensor fusion. Abbott et al. (2020) showed that the resolution and contrast of thermal imaging improve significantly by utilizing polarized thermal IR sensors, which have the potential to simultaneously decrease background clutter while increasing contrast and producing highly resolved fused images (Baur 2018). Similarly, Abbott et al. (2020) created an effective detection algorithm by using RGB (red, green, blue) imagery for translating noncorresponding LWIR/RGB. Active systems such as ground-penetrating radar (Hendrickx 2006), microwave generators (Deans 2001), and IR heating (Yao et al. 2019) utilized simultaneously with the passive thermal sensor complement and stimulate thermal variability. Yao’s team used an IR lamp adjusted to 800 W/m^2 to mimic the natural diurnal cycle of Earth in a controlled indoor environment. Li et al. (2020) took a different approach by looking at acoustic impedance to observe how buried objects impacted the acoustic-to-seismic coupling efficiency.

The trend in using active systems in thermal IR imagery does present some drawbacks as well. The potential scattering mechanisms that exist in the environment must be considered. When airborne particles are within a similar size as the wavelength, scattering efficiency increases. The particles in fogs, mists, and clouds range from 2 to $20 \text{ }\mu\text{m}$, making them an effective scatterer for LWIR (Hudson and Hudson 1975). Furthermore, rainfall affects the physical and spectral properties of soils by changing the surface particle-size distribution caused by the separation of the silt particles from the larger sand particles in sand-silt soil mixture (Ballard et al. 2013). Ballard discovered that the reflectance was most profound in the $8.1\text{--}9.2 \text{ }\mu\text{m}$

spectral band (part of the thermal IR window). Ewing et al. (2020) went further in exploring the increase in the Reststrahlen band with increasing sand-silt ratio with the maximum occurring at 80% sand but also demonstrated that mixed soil gives a reproducible decrease in reflectivity.

Adding to the complexity of the problem, water molecules tend to absorb IR energy; thus, atmospheric transmissions in the thermal IR band are degraded by molecular rotational transitions from water vapor, or broadening affects from hydrogen-bonding interactions in the case of liquid water (Gorman 1957; Raqueno et al. 2008). Water content does indeed affect thermal signatures, though the correlation does not have a quantifiable linear relationship (van Dam et al. 2005). Instead, accounting for the properties of disturbed and undisturbed soil can help to better detect buried objects (Koenig et al. 2008). The presence of a buried object disturbs the heat and diffusion parameters of the soil, enabling anomaly detection (Frost 2006). However, it now is generally believed that disturbance of the soil and alteration of the soil properties also gives rise to the thermal signature. Thermal contrasts are manifested as a result of three effects: (1) the object itself likely has different thermal properties than the soil it has replaced, which may result in differential heat transport and a thermal expression at the surface; (2) disturbing a soil normally changes its density and thermal properties, also leading to a surface expression of physical temperature; and (3) disturbing a soil redistributes finer particles to the ground surface, which, for some soil compositions, changes their spectral reflectance (S. Howington, pers. comm., February 2020). Interestingly, the surface effect remains for weeks after the disturbance and enhances the contrast induced by the buried object.

Waldemar et al. (2012) extended the work of Hong et al. (2002) and van Dam et al. (2003). They used physical measurements and numerical modeling techniques to observe the effects that varying moisture levels and the density of soil have on buried-object detection. Predicting expected surface-soil temperatures is complicated by the nonlinear movement of water within soil and changes in surface temperature during the drying process (Frost 2006). Understanding the relationship between meteorological conditions and soil properties is paramount to detect objects buried in soil and to predict sensor performance. However, an in-depth review of the soil science, agricultural, and atmospheric literature may shed more light on understanding the near-surface processes. An analytical solution requires extensive knowledge of the buried material, the surface

composition, and the water content and the humidity of the environment. This multivariate and multilayered problem is thus limited without quantifying the environment absolutely. As van Dam et al. (2005) stated, without knowing all of the parameters involved, it is impossible to predict the thermal signatures accurately.

1.2 Objectives

The goal of this investigation is to improve the understanding of the environmental (soil and atmospheric) phenomenological properties affecting temporal and spatial thermal variance of soils such that this knowledge can be applied toward improving the detection capability, PD, and FAR of thermal IR sensors. Specifically, this effort focuses on identifying, for a given soil and meteorological state, the physical variables that significantly contribute to soil temperature variations between disturbed and undisturbed soil. We subsequently use this understanding to calculate the natural surface-soil variance so that the background noise can be quantified and subtracted from an object-derived thermal IR sensor signal.

1.3 Approach

Our approach towards meeting the research objective involved constructing a new CRREL/C5ISR Test Bed to test and validate our understanding of the physical properties responsible for soil temporal and spatial variance. The test bed consisted of a homogenized volume of soil containing thermocouple and moisture sensors along with four equal-sized buried objects, two plastic and two aluminum, emplaced at two different depths. The data from the emplaced soil sensors and nearby meteorological station were collected continuously at a 15-minute interval along with thermal IR and electro-optical imagery. Much of the effort of the present study focused on constructing a new test plot, collecting data, and identifying and developing tools for data analysis. Section 2 details the test bed construction and the homogenous soil properties. Section 3 presents the data collected from the site, and section 4 present initial findings and conclusions drawn from this study. A follow-on report for Phase 3 will provide a more detailed analysis of the Phase 2 data.

2 Methods

2.1 Site layout

The experimental site is located in Hanover, NH, at CRREL (43°43′24″ N, 72°16′24″ W) in an open area with no permanent physical shading caused by structures or vegetation (Figure 1). The photograph of the CRREL Phase 2 test plot layout was taken on September 2018 facing north-north-west. Pins and white balls mark the corners of the homogenized area. The camera tower and the shack are located on the north side of the plot to minimize the shading effects on the plot and are far enough away to minimize reflected shortwave radiation.

Figure 1. CRREL Phase 2 test plot layout.

The first phase of the experiment, conducted from September through November 2016 (referred to as “Phase 1” hereafter), was a proof-of-concept study. The second phase of the experiment (referred to as “Phase 2” hereafter) was conducted from May through November 2018. During Phase 2, any grass and similar short vegetation, was removed from the surface of the test area, and the surface remained bare for the duration of the study. For both phases, the test plot consisted of a 3.05×3.05 m area. In Phase 1, the plot was subdivided into twenty-five 0.61 by 0.61 m cells while for Phase 2 it was subdivided into nine 1.0×1.0 m cells. Clausen et al. (2020) discusses the Phase 1 results in detail.

Unlike the Phase 1 plot, the soil in the Phase 2 plot was homogenized to a depth of 65 cm in an effort to eliminate effects from near-surface soil variability. One of the issues during Phase 1 was the unexpected high degree of

surface-temperature spatial variability across the plot, which made data analysis and interpretation difficult. Consequently, the project team decided that homogenization of the test plot soil should reduce the surface-temperature spatial variability. Homogenization involved excavating the entire volume of test plot soil, removing large rocks, and mixing. The mixed soil was replaced in a series of eight lifts along with the associated soil sensors. Each lift was compressed with a vibratory compactor to the predisturbed soil density. Section 2.4 provides additional details.

In both study phases, a variety of instruments monitored the below- and aboveground meteorological and soil temperature and moisture conditions, and the observations were continuously automatically downloaded to a datalogger and then saved to a computer server. Soil properties such as the soil type and density were characterized to support the phenomenology analysis. IR cameras were mounted 4.27 m above the surface. Figure 2 shows the final test configuration with overhead IR cameras. An electro-optical camera was also installed at the test plot at a distance of 4.37 m above the ground. The following section discusses the instrumentation specifics, and section 2.3 describes the buried objects. Note that the objects were not emplaced until the test plot had reached equilibrium.

Figure 2. Final plot setup with overhead infrared cameras.

2.2 Instrumentation

Instrumentation was installed to monitor both above- and below-ground conditions. Full meteorological forcing was measured approximately 1 m above the ground for both experimental periods and included air temperature, relative humidity, precipitation, solar angle, and incoming and reflected short- and long-wave solar radiation. Table 9 of Clausen et al. (2020) provides details. We relocated the meteorological station from its Phase 1 location to the current location approximately 13 m northeast of the experimentation site. The meteorological data was continuously collected at 0.067 Hz, averaged, and stored at 15-minute intervals while the buried sensors were sampled once every 15 minutes. All data was stored on a Campbell Scientific CR1000 datalogger.

This study used two different thermal camera systems (Figure 3). The model A300 FLIR Systems Inc. camera with a Scout III 240 lens was used for both study phases. The FLIR Systems Inc. A310F 90 camera was used for only Phase 2. Clausen et al. (2020) gives details for the A300. The A310F 90 specifications are (FLIR Systems Inc. 2014)

- $90^{\circ} \times 73^{\circ}$ field of view,
- 320×240 pixel resolution,
- $<0.05^{\circ}\text{C}$ at 30°C per 50 mK thermal sensitivity,
- -20°C to 120°C temperature range,
- $\pm 4^{\circ}\text{C}$ or $\pm 4\%$ of reading, and
- $7.3\text{--}13\text{ }\mu\text{m}$ spectral range.

Camera radiance values and their associated metadata were registered every 5 minutes using FLIR software and a laptop computer and represent the actual instance. Occasional power losses and shut down of the on-site computer, data logger, or cameras resulted in data losses.

An electro-optical Netcam XL 3MP camera with 8 mm lens was used for this study. Image resolution is 2048×1536 pixels with a maximum transfer speed of 225 frames/second. The camera has a Sony $1/2$ in. charge-coupled device sensor with an exposure range of $1/100,000$ to 1.3 seconds.

Our primary approach was to work with nongeoreferenced thermal IR image data so that the photographic quality was not unnecessarily degraded. Georeferencing of the images was conducted for only those instances where the thermal IR imagery at the pixel scale was being directly compared to

rasterized datasets such as lidar, which was used for characterizing surface roughness. Section 2.4 of the Phase 1 report (Clausen et al. 2020) provides details on the lidar scan. The same process was used for Phase 2.

Figure 3. FLIR camera mounting with Model A300 on the *right* (south), closer to the center of the plot, and Model A310F 90 on the *left*.

In Phase 2, the soil temperature was measured at 158 locations, both within and adjacent to the test plot, by using thermocouple strings fabricated and calibrated at CRREL. The thermocouples were installed at depths of 0, 5, 15, 25, 35, 45, 55, and 65 cm below ground surface (bgs).

In addition, we installed 26 calibrated Campbell Scientific CS655 sensors at three different depths. Thirteen are at 15 cm, six are at 35 cm, and the remaining seven are at 55 cm bgs. These sensors measure soil temperature, volumetric water content, bulk electrical conductivity, and relative dielectric permittivity. Refer to Table 9 of Clausen et al. (2020) for additional details regarding the sensors.

Two heat plates were outside of the test plot but within the FLIR camera field of view for image comparison and calibration. Plate 1 was placed on the surface (0 cm bgs) approximately 40 cm northeast of the test plot. The

temperature was set to 24°C, turning on at 2300 and off at 0600. Plate 2 was installed 5 cm bgs about the same distance northwest of the test plot and set at 35°C following the same schedule.

Data collection between the sensors and cameras was synchronized between the two acquisition systems. Figure 4 shows subsurface instrument locations. All sensors were emplaced in one of eight lifts.

Figure 4. Plot layout and instrumentation at the following depths: (a) 5 cm, (b) 15 cm, (c) 25 cm, (d) 35 cm, (e) 45 cm, (f) 55 cm, and (g) 65 cm.

Figure 5 provides a view of the layout at the 35 cm depth. First, the sensors were laid out using a template created at CRREL to locate all of the sensors, then a lidar survey was conducted to record the location of each sensor after the sensors were placed in the appropriate soil lift. Then, the sensors were covered with 10 cm of soil, which was then compacted using a Northern Industrial model JPC-80 walk-behind plate compactor to the measured dry density of the soil prior to removal, approximately 1880 kg/m³. In situ density was measured using a Troxler Model 4590 Surface Density Gauge (eGauge). Subsequent lifts were emplaced in the same manner working towards the surface.

Figure 5. Lidar image of the instrumentation layout at the 35 cm depth.

TC = thermocouples

SM = soil-moisture probe

2.3 Object emplacement

In Phase 2, we buried four equal-sized (40 cm sides, 20 cm height) rectangular objects, two plastic and two metal. The burial process began on 11 July and ended on 12 July at 1600. The bottoms of the objects were at 45 cm and 25 cm with one item of each type at both depths as shown in Figure 4. Excess soil was spread around the emplacement location so there was no obvious surface mounding. Figure 6 shows the plot with excavated holes empty and object filled.

Figure 6. Emplacement process: (a) test plot with empty excavated holes, (b) objects in holes (dark items are metal and upper two are at 25 cm depth), (c) postemplacement.

2.4 Soil properties

As mentioned in section 2.1, the soil in the 3.05×3.05 m plot was excavated and homogenized. The surrounding soil outside of the subplot was left in its natural state and had the same soil properties as the Phase 1 experimental design (Clausen et al. 2020). Because the soil had the same composition, the chemical composition was unchanged from the surrounding soil. The average field dry density was 1883.47 kg/m^3 with a standard deviation of 38.95 kg/m^3 . In comparison, the natural soil has a density range of 1525 to 1825 kg/m^3 .

Prior to homogenization, we collected six soil samples at random from the test plot area for grain-size analysis. The soils were dried at 105°C for 24 hours, then 600–850 g of dry soil were added to a sieve stack composed of aperture sizes 19, 7.93, 4, 2, 0.84, 0.5, 0.25, 0.12, 0.062, and 0.044 mm. The sieve stack was placed on a shaker and agitated for 30 min. Soil fractions for each aperture were weighed and the values were used to calculate particle-size distribution. The percent fines needed to determine clay content was not measured. This was repeated for each of the six samples. The grain-size distribution corresponds to a silty sand, USCS (Unified Soil Classification System) soil SM similar to grid cell B21 from Phase 1 (Clausen et al. 2020). Table 1 shows the grain-size distributions for the six samples.

Table 1. Grain-size distribution of Phase 2 plot soil.

Sample Number	Gravel (%)	Sand (%)	Silt (%)
1	12.4	69.0	18.6
2	18.6	63.1	18.3
3	16.7	64.1	19.2
4	13.8	68.8	17.4
5	15.1	65.8	19.1
6	9.6	70.9	19.5
Mean	14.3	67.0	18.7
Homogenized Soil	14.3	67.0	18.7

To measure pH, electrical conductivity, and thermal conductivity, we removed several kilograms of homogenized soils and dried them at 105°C for 24 hours. Electrical conductivity and pH readings were collected for six replicates by using a Fisherbrand Accumet AB200 pH/conductivity probe (Thermo Fisher Scientific). Each sample consisted of three grams of dried soil and 10 mL of deionized water, which were mixed at 200 rpm for 30 minutes. The mean pH of the homogenized soil was 7.59, and mean

electrical conductivity was 187.2 $\mu\text{S}/\text{cm}$ (Table 2). Soil color classification was assessed by visually comparing samples to a Munsell Soil Color Chart (Munsell Color 2009). The soil is light gray with a hue of 10YR, 7/2.

Table 2. Homogenized soil pH, electrical conductivity, and color characteristics.

Sample Number	pH	Conductivity ($\mu\text{S}/\text{cm}$)	Munsell Color
1	7.48	183.5	Hue 10YR, 7/2, Light Gray
2	7.54	181.3	Hue 10YR, 7/2, Light Gray
3	7.55	182.2	Hue 10YR, 7/2, Light Gray
4	7.66	190.2	Hue 10YR, 7/2, Light Gray
5	7.71	198.6	Hue 10YR, 7/2, Light Gray
6	7.56	178.6	Hue 10YR, 7/2, Light Gray
Mean	7.59	187.2	Hue 10YR, 7/2, Light Gray

To measure thermal conductivity, we combined the 5376 g of homogenized dried soil with 624 mL deionized water and mixed for 10 minutes. After mixing, three replicate soil samples were taken to determine the gravimetric water content (GWC, water content by weight). The average GWC of the three samples was 0.092. The target GWC was 0.104 (0.196 VWC, volumetric water content), corresponding to the field average at 15, 35, and 55 cm bgs from 1 August to 24 September 2018. Next, 5174.6 g of the moist soil was folded into a 2301.9 cm^3 thermal conductivity plate. The soil was tamped into the plate to yield a wet density of 2248 kg/m^3 . Unfortunately, an error was made in calculating the wet density for the target moisture and plot dry density (1183.47 kg/m^3) such that the actual moisture content of the sample was 0.196 GWC (0.364 VWC). To prevent drying, the plate was covered with polyethylene wrap and placed in a LaserComp heat flow meter for analysis. To yield a mean target temperature of 23.5°C, the lower and upper temperatures were set to 20.0°C and 27.0°C, respectively. The target temperature equals the mean soil temperature for the field site over the period of interest. The thermal conductivity data was analyzed using WinTherm32 software (LaserComp, Inc., 2007). The mean measured thermal conductivity of the soil at the given wetness was 0.773 W/mK (Table 3).

Figure 7 shows the water retention curve for the Phase 2 plot. These measurements were performed in an adjacent area referred to as the microbiology testbed (Barbato et al. 2018), which is located just beyond the FLIR camera field of view. We believe the results for the microbiology testbed area are likely to be comparable to our study area due to similarity of soil

and proximity. To create this curve, soil samples were saturated, placed on a porous disc, and held at particular pressures, or matric potentials, using a pressure-kettle device. At the end of the test, the gravimetric water content for the four replicate sample was measured and correlated to the pressures by utilizing the average value (Barbato et al. 2018).

Table 3. Homogenized soil thermal conductivity.

Sample Number	Thermal Conductivity (W/mK)	Resistance (m ² K/W)	Resistance/unit Average (mK/W)
1	0.749	0.044	1.335
2	0.854	0.039	1.172
3	0.715	0.046	1.399
Mean	0.773	0.043	1.302

Figure 7. Phase 2 test plot water-retention curve.

3 Discussion of Results

The focus of this report is on the construction details of the Phase 2 test plot, initial summary of the thermal IR imagery results, and preliminary discussion of observations. A detailed analysis and discussion of the data will follow in subsequent reports.

The presentation of results is separated into pre- and post-soil-disturbance categories. The predisturbance time period is from 20 May to 10 July 2018 and represents conditions prior to object emplacement. The postdisturbance results span from 1500 13 July to 1000 15 November 2018 after the objects representing targets were buried inside the experimental site on 11–13 July 2018.

The field of view of the FLIR camera is larger than the test area. Since the study focused on the effects of homogenization and seasonality on detecting buried objects, the analyses and following discussions used only a subset of the full 240×320 pixels, ignoring the rest. To distinguish this subset from the whole image, and following military practices, this region is referred to as the area of interest (AOI).

3.1 FLIR camera performance

Before any analysis, the FLIR camera needed to be calibrated. The camera measures thermal radiance, which is then converted to surface temperature using FLIR-provided MATLAB functions and camera default parameters. Calibration involved installing two hotplates, as noted in section 2.2, outside of the AOI but within the camera field of view, northeast and southwest of the test plot. Figure 8 compares the northeast hot plate and the average thermal IR image temperature corresponding to the hotplate ($\sim 5 \times 5$ pixels). All images were taken at 2300 local time between 22 May and 20 November 2018. The slope of the line is linear with an R^2 of 0.9988, indicating a nearly 1:1 relationship between the FLIR-derived image temperature and the actual object temperature. Consequently, we have confidence that the thermal IR image temperature is representative of the true temperature, and thus the camera is correctly calibrated.

Figure 8. Hot plate versus the average thermal IR image temperature.

Another potential error source was the contribution of thermal noise as a function of LWIR reflection from the soil surface. CCDC-C5ISR performed tests on soil from the test plot to measure the surface differential reflectivity, directional reflectance, and hemispherical directional reflectance as a function of wavelength at low angles. The results indicated no significant noise directed at the thermal IR camera as a function of LWIR reflection between the 7.5 and 13.5 μm wavelength.

3.2 Homogenization effects

The primary interest in the predisturbance time period of Phase 2 is the effect of homogenization on the interpretation of IR camera images. Mainly, does homogenizing the soil reduce background noise (i.e., reduce spatial variability of the sensed surface temperature), aiding data analysis? Initial subjective comparisons of thermal IR images of the Phase 1 and 2 plots prior to object emplacement indicate this objective was achieved (Figure 9).

Figure 9. Comparison of Phase 1 and 2 thermal IR images of the plot prior to object emplacement under similar solar loading conditions: (a) Phase 1, 1530 on 13 September 2016, and (b) Phase 2, 1515 on 12 June 2018.

To quantify the impact on thermal IR imagery through a standardized metric, we compared several days with similar temperature and wetness in Phases 1 and 2. The brightness temperatures obtained by the FLIR sensor were normalized using the formulation

$$IRT^* = \frac{IRT - \mu(IRT)}{\sigma(IRT)}, \quad (1)$$

where

IRT = the thermal IR-derived temperature, using the FLIR default parameters;

$\mu(IRT)$ = the mean IRT of the plot;

$\sigma(IRT)$ = the standard deviation of the IRT over the plot; and

IRT^* = the normalized value.

We used several statistical methods to compare the effects of homogenization for both wet and dry conditions, including the variance, uniformity, semivariogram, and standard deviation (SD). Figure 10 and Table 4 present the results as well as the image minimum and maximum temperatures for reference. Uniformity is a measure of the number of different radiance values in a given image while the variance quantifies the spread of the data from their mean. The variogram is a measure of spatial correlation. For a set of observations at locations $s = (s_1, s_2, \dots, s_n)$, the variogram, $2\gamma(s_i, s_j)$, is defined as the variance of the difference between the field values at two locations across all realizations of the field, given by

$$2\gamma(s_i, s_j) = \text{var}(Z(s_i), Z(s_j)), \quad (2)$$

Where $Z(s_i)$ is the observation, in this case FLIR-derived surface temperature, at spatial location s_i . The semivariogram is simply one half of the variogram.

Table 4. Image minimum and maximum thermal temperature, uniformity, variance, and standard deviation comparisons of Phase 1 and Phase 2 wet and dry instances for the region over the plot (AOI).

Image	Minimum/ Maximum (°C)	Uniformity (No. of unique intensity levels)	Variance	Standard Deviation
p1_dry, 13 Sep 1530	29.93/47.79	4.44×10^{-4} (3231)	11.14	3.34
p2_dry, 12 Jun 1515	40.89/47.47	2.03×10^{-3} (881)	0.51	0.71
p1_wet, 19 Sep 0445	23.68/25.11	8.30×10^{-3} (225)	0.04	0.19
p2_wet, 28 Jun 0915	20.43/21.71	1.44×10^{-2} (160)	0.01	0.12

Initial visual inspection of the images (IRT, Figure 10a) indicates that for dry conditions there is less variability in the homogenized (Phase 2) than the nonhomogenized (Phase 1) soil. In both situations, image variability decreases when the soil is wet. In these situations, the temperature variation is nearly identical between the homogenized and natural soil plots. These visual observations are reinforced by the range between minimum and maximum thermal temperatures presented in Table 4. We believe this is due to two reasons. First, a precipitation event delivers moisture evenly across the test bed at the scale of the study area. The precipitation has a uniform temperature. The interaction of the precipitation with the soil surface decreases the surface-soil temperature contrasts. Second, movement of precipitation vertically, and subsequently laterally, into the soil aids in spatially decreasing soil temperatures.

To calculate the uniformity (0–1), a histogram of IRT* is first produced where the number of bins equals the number of unique IRT* values. Next, the normalized sum of (values/bin)² is determined. Maximum uniformity is achieved if all of the values reside in a single bin. Figure 10b shows the resulting histograms for the wet and dry days. Even though the Phase 2 soil is homogenized, both the wet and dry histograms have tails whereas the Phase 1 images are more compact (Figure 10b). The Phase 1 histograms appear to be bimodal with a slight skewness to the right, especially the dry image, while the Phase 2 ones are more bell shaped. Table 4 gives

the uniformity and the number of bins for each. The number of unique values for the dry natural soil image are an order of magnitude greater than for the dry homogenized and both of the Phase 1 and 2 wet images. As expected from the visual inspection of the images, there is little difference between the two wet images and the Phase 2 dry image uniformity, with the wet images being more uniform than the dry ones.

Figure 10. Effects of homogenization for a dry and wet instance for Phase 1 (p1) and Phase 2 (p2): (a) surface thermal IR temperature of the plot, (b) histogram of IRT*, (c) omnidirectional semivariance (*red solid*), best-fit linear (*blue dashed*), and exponential (*black dashed*) curves. The rows from top to bottom are p1_dry, p1_wet, p2_dry, and p2_wet.

The variance and SD (Table 4) reinforce the findings discussed in the previous paragraph in that there is a greater spread in the intensity levels in Phase 1 compared to Phase 2 for the dry scenarios while the wet cases are more evenly distributed. In Phase 1 (Clausen et al. 2020), it was found that increased soil moisture dampened the camera response. The same was true for the homogenized soil. This is most likely due to the smoothing of the soil surface microroughness as a result of the rain.

Finally, Figure 10c presents the omnidirectional variance, or variogram, along with the best-fit lines for linear (blue dashed) and exponential (black dashed) behavior. Table 5 includes the associated statistics. The nugget represents random behavior and measurement errors, the range is the distance at which the data are no longer correlated, and the sill is the variance of the random field. The normalized range is the actual value divided by the total number of pixels in a given direction. Linear variograms indicate that there is a trend in the data that cannot be interpreted using deterministic approaches.

Table 5. Image variogram statistics for both linear (lin) and exponential (exp).

Variable	p1_dry	p1_wet	p2_dry	p2_wet
Nugget	0.083 (lin) 0.043 (exp)	-0.044 (lin) 0.000 (exp)	0.41 (lin) 0.38 (exp)	0.60 (lin) 0.38 (exp)
Sill (exp)	1.49	1.62	1.59	0.97
Normalized range (exp)	0.64	0.55	1.26	0.27
R^2	0.99 (lin) 0.91 (exp)	0.98 (lin) 0.91 (exp)	0.77 (lin) 0.66 (exp)	0.79 (lin) 0.96 (exp)

3.3 Pre- and post-object-emplacement disturbance comparison

Phase 2 collection of imagery, meteorological information, and in-ground sensor data occurred from 20 May through 15 November 2018. Except for occasional disruptions, data from the test plot continue to be collected as of the time of publication. Section 2 discusses data collection specifics and types.

To try and gain a high-level overview of the effects of object emplacement on the thermal IR measurements, the SD, minimum, maximum, and average of the total AOI for the areas over the four boxes and the remaining region of the AOI not over the objects (referred to hereon as the background), we calculated for each image from 20 May through 15 November 2018. This resulted in 14,409 preemplacement images and 30,599 postemplacement images. Although these statistical measures do not provide any spatial information, they do provide valuable insights. The SD, which equals the square root of the variance, is related to the sill of the semivariogram of an image. As Pacific Northwest National Laboratory (n.d.) explains, “The sill is the total variance where the empirical variogram appears to level off, and is the sum of the nugget plus the sills of each nested structure. Variogram points above the sill indicate negative spatial correlation, while points below the sill indicate positive correlation.” Both the SD and sill are a measure of the data spread.

Figure 11 shows the SD for each of the six regions mentioned above. As apparent when comparing Figure 11a and Figure 11d, there is essentially no difference in the variability of the surface temperature as measured with the IR thermal camera between the whole AOI and background region. The SD from both of these areas appears nearly the same for the pre- and postemplacement periods. This indicates that the combined impact of the four buried objects is insufficient to affect the entire AOI. This is not

surprising considering the impacted area of the buried objects represents approximately 10% of the total test area.

Figure 11. Standard deviation of the IR image surface temperatures during pre- (*red*) and post- (*blue*) emplacement time periods for (a) the AOI, (b) the deep plastic box, (c) the deep metal box, (d) the background, (e) the shallow metal box, and (f) the shallow plastic box.

However, there is a difference in the pre- and postemplacement period for these areas, which must be weather related. In general, there is a small increase in SD as the air temperature increases followed by a decrease as cooling begins in later fall. During the preemplacement period, there is more consistency in air temperature from day to day. In August of the postemplacement period, there was less variability in the day and night air temperatures (Figure 12), which is reflected by a decrease in the SD. In September, the range of day and night air temperatures increased and is reflected by a corresponding increase in SD. Daytime is defined as periods when the incoming solar radiation is positive. Most of the differences are due to variability in the maximum temperatures as the day and night minimum monthly air temperatures are nearly the same. The day and night minimum temperatures typically occur just before and after sunrise.

Figure 12. Phase 2 monthly diurnal air-temperature trends.

The comparatively high SD over the deep plastic box (Figure 11b) is a result of camera shadowing over this area starting just before and ending just after local solar noon. This is negated by the presence of the object after emplacement.

There is a notable difference in the surface-temperature variation over the four boxes between the pre- and postemplacement time periods (Figure 11b, c, e, and f). In general, the SD is greater for the postemplacement period, especially for the shallow objects (Figure 11e and f). The plastic and metal boxes have different thermal conductivities than the surrounding soil. The plastic requires less energy than the metal to heat, resulting in it becoming hotter faster and thus, for the CRREL location, more discernable compared to the background.

The burial depth of an object also has an impact on the postemplacement SD. The shallow buried objects are more responsive to changes in solar energy input as reflected by higher relative SDs than the background location. The surface temperature over the deep metal box (Figure 11c) behaves like the background although the magnitude of variation is slightly greater due to the increased thermal conductivity of the object.

3.4 Object-visibility parameterization

In Phase 1, it was found that certain meteorological phenomena, such as incoming solar radiation, significantly affected the spatial variance of the thermal IR image intensity. The main takeaway was that the thermal signature depended on an interplay of multiple meteorological and physical properties, such as the structure and consistency of the soil and the radiative fluxes at the surface, rather than depending on a single parameter such as near-surface air temperature. The list narrowing and cataloguing weather-related variables deemed important to characterizing thermal IR signal intensity in Phase 1 enabled a more specialized and focused investigation into environmental effects for Phase 2. Before investigating the interplay of multiple meteorological forcing's on the thermal identification of buried objects, this report examines in greater detail the dependence of the thermal signature on the parameters identified in Phase 1. Since the weather observations and thermal IR images are not obtained at the same time interval, the meteorological conditions at the time that the IR image was collected were calculated through linear interpolation based on the image and meteorological time stamps.

After the meteorological parameters were determined for the image time stamp, a simple differencing scheme ($|\mu_i - \mu_b|$) between the mean IR temperature over the buried objects (μ_i) and the background (μ_b) for the postemplacement time period was examined. Two different cut-off temperatures for this simple difference were investigated, 0.25°C and 0.5°C, after a trial-and-error period of testing (the 0.5°C level is shown as the red line in Figure 13). These are not definitive values but represent starting points for the investigation.

A well-known phenomenon in the detection of objects by using thermal imagery is the crossover period. During this time, the temperature of the object cools or warms relative to its surroundings, which correspond to periods of poor detection. The crossover period is not fixed but will change depending on time of year and meteorological conditions. Figure 13a shows the average temperature differences as a function of time of day for the postemplacement period of Phase 2. For all four objects, the greatest thermal contrast between the boxes and their surroundings occurs during the middle of the day. For these conditions and time of year, the crossover occurs near sunrise and sunset. Unlike the other buried boxes, the shallow plastic one is discernable at night as well as during the day. While the shallow plastic object heats up faster, there are times when enough energy

penetrates into the soil to heat the deeper metal box. Once warmed, metal retains its heat longer and is hotter than plastic at the same depth. The shallow metal box is more susceptible to surface forcing and as a result loses its heat faster than the deeper one, resulting in a smaller difference with the background.

Figure 13. Difference between average FLIR surface temperature over the objects and the surrounding background as a function of the weather parameter: (a) time of day (hr), (b) incoming solar radiation (W/m^2), (c) air temperature ($^{\circ}\text{C}$), (d) precipitation (mm), and (e) wind speed (m/s).

Phase 1 found object visibility was best on clear sunny days, poorer on cloudy, and limited to not possible on rainy days. It was found in Phase 1 that solar radiation, air temperature, and soil moisture were the most important factors governing object identifiability. In fact, no objects were detectable below 500 W/m^2 (Clausen et al. 2020). Although cloud cover is not measured, daylight values can be inferred using the incoming solar radiation. In Figure 13b, the difference between the average object and background temperatures in our Phase 2 test increases as the incoming solar radiation increases. For the shallow plastic box (sp), there is a notable difference even for very small solar loadings unlike in the Phase 1 findings.

This difference is due to the volume of the objects, which were smaller in Phase 1 and larger in Phase 2. The larger-volume objects of Phase 2 have greater thermal mass, resulting in increased differences in thermal response as compared to the surrounding soil. During the heating phase (following sunrise) the objects heat faster than the surrounding soil. During the cooling phase (after sunset) the objects cool faster than the surrounding soil. However, the objects and soil start at different temperatures at the start of the thermal cycle (sunrise) as the objects are cooler than the surrounding soil. The objects rapidly heat, and their temperature catches up to the surrounding soil temperatures (crossover). Crossover typically occurs midmorning. During the crossover period, the objects are at the same temperature as the surrounding soil and are thus invisible. This crossover period can vary from a few tens of minutes to several hours, depending on the meteorological conditions and soil properties. Then, the objects become warmer than surrounding soil and visible again. At sunset the soil appears initially cooler than the objects. However, the objects cool faster than the surrounding soil and reach a crossover point in late evening whereupon the objects are cooler than the surrounding soil. The greatest temperature contrast occurs just before sunrise. In phase II, we found that plastic objects were more thermally responsive than metal objects.

We also found in Phase 1 that, on a diurnal cycle, objects were easier to find when the air temperature was higher. There is a corresponding relationship between air temperature and the surface-soil temperature. The same was found in Phase 2. Air temperature is related to solar loading with higher values occurring on sunnier days. More energy is transmitted into the soil in these instances, resulting in increased surface-soil temperature differences, especially for the shallow objects as Figure 13c shows.

From Figure 13*d*, it is clear that the buried objects are not visible during precipitation events as the differential temperature is consistently below the 0.5°C cutoff. The Phase 1 study (Clausen et al. 2020) found that the objects could not be detected when the soil moisture content was elevated. The thermal conductivity of the soil increases as the pores fill with water. This results in a smaller thermal contrast between the background and the objects. Also, the rain will wet the surface before it penetrates into the soil. Because the rain is of uniform temperature, it decreases the variability of the surface-soil temperature (i.e., background noise). Unfortunately, even though the background noise is lower during rain events, the lack of thermal contrast between the object and surrounding soil precludes detection. During Phase 2, the rain was typically colder than the near-surface air temperature. With time, the surface-soil temperature became colder than the air temperature.

It is hard to see a pattern in Figure 13*e* between temperature difference and wind speed except that perhaps the objects are easier to find at lower wind speeds. The wind convects latent and sensible energy away from the surface, resulting in reduced thermal forcing reaching the buried objects. Like with the other meteorological parameters, the shallow plastic box is the least affected.

Summarizing, as was found in the unhomogenized soil of Phase 1, there is more thermal difference between the objects and the background on calm, sunny days and almost no contrast during rain events.

Before assessing which properties statistically affect object visibility in thermal images, a numerical representation of object visibility is needed. Many such metrics have been tried with varied success (F. Pantuso, C5ISR Night Vision and Electronic Sensors Directorate, pers. comm., 2016–2021). Once a numerical representation of visibility is established, statistical tests can be used to compare the numerical outputs instead of relying on anecdotal evidence. Detectability is defined by how easy it is to determine unnatural or abnormal changes in surface temperature (often represented as color). For instance, in Figure 14*a* and *b*, it is evident that there is something different about the four corners of the image, such as buried objects, while in Figure 14*c* and *d*, the image is relatively uniform, and it is hard to distinguish any irregularities. Note that the temperature scales are not the same for the four images in Figure 14*a–d*. Although not shown, if the same scale is used, in this case 25–60°C, the objects are still visible

when they are warmer than their surroundings (Figure 14*a*) but are much harder to distinguish when they are relatively colder (Figure 14*b*). Thus, the visibility metric must have greater magnitudes for Figure 14*a* and *b* and lower ones for Figure 14*c* and *d*. Of note, the colder region in the upper left corner of Figure 14*a* and *d* is caused by the camera shadow.

Figure 14. Instance of thermal IR temperature images: (*a*) 16 July 2018 at 1230, (*b*) 18 July 2018 at 1400, (*c*) 17 July 2018 at 1455, and (*d*) 24 July 2018 at 1235.

The goal is to make the visibility criteria as simple as possible to calculate. Because weather conditions influence the surface temperature and, hence, the thermal IR camera image, Table 6 lists the meteorological conditions at the time that the images in Figure 14 were taken. The colors in Table 6 indicate when objects are hotter (red) or colder (blue) than the background. Figure 14*a* and *d* have similar solar radiation and temperatures, but it is considerably windier on 24 July. However, it is also windier on 18 July (Figure 14*b*) when the objects appear colder than their surroundings even though the solar radiation forcing is greater. Cloud cover is affecting the camera's ability to identify the objects on 17 July (Figure 14*c*). These results agree with trends noted in Figure 13.

Table 6. Meteorological conditions at the time of the images in Fig. 14. The colors indicate when objects are hotter (*red*) or colder (*blue*) than the background.

Date_Time	Solar Radiation (W/m ²)	Air Temperature (°C)	Precipitation (mm)	Wind Speed (m/s)
20180716_1230 (Figure 14a)	868	29.5	0	0.87
20180718_1400 (Figure 14b)	945	23.1	0	2.16
20180717_1455 (Figure 14c)	237	23.2	0	1.28
20180724_1235 (Figure 14d)	864	28.9	0	3.32

The purpose of developing a visibility parameterization is to provide a simple metric that can determine whether the object is visible or not in the imagery. The procedure should be automatable to process a large number of images quickly as it is impractical to manually scan tens of thousands of images for objects of interest. Once the imagery visibility criterion was developed, we investigated its sensitivity to meteorological forcing and soil properties and made statistical comparisons.

The majority of the visibility criteria in use employ some combination of the mean or the SD of the target and background (F. Pantuso, pers. comm.). For this study, the SD of each of the buried objects relative to the background as well as the semivariogram sill values (equation [2]) were used to construct four visibility metrics, V_1 to V_4 :

$$V_1(X_i) = \frac{X_i - X_b}{X_i + X_b}, \quad (3)$$

$$V_2(X_{i,b}) = \frac{X_{i,b} - X_{all}}{X_{i,b} + X_{all}}, \quad (4)$$

$$V_3(X_i) = \frac{X_i}{X_i + X_b}, \quad (5)$$

$$V_4(X_{i,b}) = \frac{X_{i,b}}{X_{i,b} + X_{all}}, \quad (6)$$

where X represents any parameter of interest, in this case the SD (σ), semivariogram sill (γ), or mean (μ).

If the mean is used, V_1 is equivalent to the Michaelson contrast (Michaelson 1927). The form of V_1 is also similar to the polarization ratio used by the sea-ice community to determine ice concentrations from microwave passive satellite images (Cavalieri et al. 1984), which compares either the

vertical and horizontal signals at a given frequency or compares the signal at two different wavelengths but in the same direction.

Notched box plots were used to compare the different proposed visibility metrics, and Figure 15 shows the results. The center line is at the median value, the notches represent the 95% confidence limits, the box extents are at the 25th and 75th percentiles (first and third quartiles), the whiskers encompass 99.3% of the data, and the individual points (red x's) are outliers. If the data are normally distributed, the box plot is evenly distributed vertically. The visibility metrics calculated using the semivariogram ($V_1(\gamma)$ to $V_4(\gamma)$) are skewed upward for all but the shallow plastic object, which is skewed downwards. $V_1(\sigma)$ to $V_4(\sigma)$ are more evenly distributed for the two deep objects, upward skewed for the shallow metal box, and downward skewed for the shallow plastic object. In all instances, there is a larger spread in the calculated semivariogram-visibility metrics than in the SD as evidenced by the distance between the 25th and 75th percentiles. Most notable are the large number of outliers in the visibility metric regardless of which parameter is used, except for the shallow plastic object. For $V_1(\sigma)$ to $V_4(\sigma)$, the outliers occur both below and above the 99th percentile while for $V_1(\gamma)$ to $V_4(\gamma)$ they are all above. Interestingly, all of the background visibility metrics are equal when the sill values are used ($V_2(\gamma)$, $V_4(\gamma)$) but are downward skewed for the SD ($V_2(\sigma)$, $V_4(\sigma)$). Finally, the median value and extent of the first and third quartiles for the shallow plastic object are measurably higher than the other boxes regardless of which parameter or visibility metric is used. Based on the above observations, all of the variogram methods are preferable for distinguishing shallow plastic objects compared to the SD metrics, with $V_3(\gamma)$ and $V_4(\gamma)$ preferable due to their higher values. For the other buried objects, $V_1(\gamma)$ and $V_2(\gamma)$ are most promising also due to the magnitude of the visualization metric being greatest.

The next step was to investigate how the above visibility metrics worked for the four images shown in Figure 14. Figure 16 presents the results. On 16 July 2018 at 1230, all objects are visible and warmer than their surroundings. Thus, the visibility index should be positive for all four boxes. This eliminates $V_1(\sigma)$ and $V_2(\sigma)$ as seen in Figure 16. The comparative magnitude of $V_3(\sigma)$, $V_4(\sigma)$, $V_3(\gamma)$, and $V_4(\gamma)$ compared to $V_1(\gamma)$ and $V_2(\gamma)$ suggests that one of these is the appropriate visibility metric. On 18 July 2018 at 1400, all of the boxes were colder than the background, so visibility metrics $V_1(\sigma)$, $V_2(\sigma)$, $V_1(\gamma)$, and $V_2(\gamma)$ must be negative. Unlike the previous image, $V_1(\gamma)$, and $V_2(\gamma)$ have a larger magnitude than $V_3(\sigma)$,

$V_4(\sigma)$, $V_3(\gamma)$, and $V_4(\gamma)$. On both 17 July 2018 at 1455 and 24 July 2018 at 1235, none of the buried objects were visible in the images displayed in Figure 14. Therefore, the visibility metrics based on difference, or contrast, based should be close to zero; and the other ones should have a lower magnitude than when the objects can be seen. Although closer to zero on the 17th than on the 24th, $V_1(\sigma)$, $V_2(\sigma)$, $V_1(\gamma)$, and $V_2(\gamma)$ are relatively large, especially on the 24th. Based on the above discussion, the noncontrasting metrics— $V_3(\sigma)$, $V_4(\sigma)$, $V_3(\gamma)$, $V_4(\gamma)$ —seem to be the most promising and warrant further investigation.

Figure 15. Box plot of visibility metrics $V_1(\gamma)$ to $V_4(\gamma)$ and $V_1(\sigma)$ to $V_4(\sigma)$.

Figure 16. Visualization metrics for 16 July 2018 at 1230, 18 July 2018 at 1400, 17 July 2018 at 1455, and 24 July 2018 at 1235.

To investigate the findings of the boxplots and the four individual images further, we will next discuss the effects of time of day and various meteorological forcings on these metrics.

3.5 Significant factors

Phase 1 showed that time differencing of images could enhance features, making it possible to find objects not visible in a single frame (Clausen et al. 2020). The effect of differencing on the visibility metrics was investigated as part of the Phase 2 analysis. To do this, time differences (dt) of image-derived surface temperature at 15-, 30-, 60-, and 120-minute intervals were calculated. From these differences, the visibility metrics V_1 to V_4 were calculated using the semivariogram sill, SD, and mean over the four buried objects, the remaining background, and the whole AOI. We found that there is no difference between the background and total AOI values for all three statistical measures regardless of the time step, resulting in $V_1 = V_2$ and $V_3 = V_4$. When the mean is used to calculate the visibility metrics,

the average values for $(V_1(\sigma) = V_2(\sigma) = V_1(\gamma) = V_2(\gamma)) = 0$ and $(V_3(\sigma) = V_4(\sigma) = V_3(\gamma) = V_4(\gamma)) = 0.5$. For the other two statistical parameters, the differences over the boxes for the four time steps is nearly identical and too small to discern visually. Therefore, Table 7 presents the means of $V_1(\sigma)$ to $V_4(\sigma)$ and $V_1(\gamma)$ to $V_4(\gamma)$ at each time step. For V_1 and V_2 the means decrease as the time step increases for all but the shallow plastic box for both the semivariogram sill and SD methods. For the shallow plastic object, the means increase as the time step increases for all metrics. For all methods, there are many outliers at all time steps.

Table 7. Mean visibility metrics V_1 to V_4 for the SD and semivariogram sill for time differences of 15, 30, 60, and 120 minutes.

Visibility Metric		Mean dp	Mean dm	Mean sm	Mean sp
$V_1(\sigma)$	$dt = 15$	-0.039	-0.031	-0.027	-0.009
	$dt = 30$	-0.045	-0.036	-0.029	-0.006
	$dt = 60$	-0.054	-0.045	-0.032	0.004
	$dt = 120$	-0.072	-0.060	-0.038	0.025
$V_3(\sigma)$	$dt = 15$	0.481	0.484	0.487	0.495
	$dt = 30$	0.478	0.482	0.485	0.497
	$dt = 60$	0.473	0.477	0.484	0.502
	$dt = 120$	0.464	0.470	0.481	0.512
$V_1(\gamma)$	$dt = 15$	-0.096	-0.078	-0.073	-0.037
	$dt = 30$	-0.112	-0.091	-0.081	-0.034
	$dt = 60$	-0.136	-0.110	-0.092	-0.020
	$dt = 120$	-0.179	-0.145	-0.113	0.008
$V_3(\gamma)$	$dt = 15$	0.452	0.461	0.463	0.481
	$dt = 30$	0.444	0.454	0.459	0.483
	$dt = 60$	0.432	0.445	0.454	0.490
	$dt = 120$	0.411	0.427	0.443	0.504

Based on the above findings, the visibility metrics $V_1(\sigma)$, $V_2(\sigma)$, $V_1(\gamma)$, and $V_2(\gamma)$ do not provide enough information for finding buried objects. V_4 is also not suitable since the background values are nearly the same as those over the boxes. Thus, V_3 appears to be the visibility parameter of choice. More importantly, time differencing does not provide any additional information in regard to the proposed visibility metrics in this study. However, we did not identify if any information can be gleaned by investigating how they vary with meteorological forcings, such as the differences in means presented in Figure 13 show. The next section discusses this further.

3.5.1 Incoming solar radiation

Surface incident shortwave solar radiation should be maximum at solar noon, which occurs approximately 2 hours after local noon in Hanover, New Hampshire (see Appendix Table A-1). If clouds are present, the amount of incoming solar radiation at the surface is reduced. Consequently, depending on weather conditions, the solar maximum measured at the site can occur at times other than solar noon. Figure 13*b* shows that, on average, there is greater variability between the objects and background when more solar energy is reaching the surface. To further investigate the relationship between object visibility and surface incident shortwave solar radiation, the radiation was parsed into 300 W/m² bins, and the averages of the four visibility metrics were calculated using the three statistical parameters over the entirety of the Phase 2 postemplacement period for each bin calculated. Figure 17 shows the results. The visibility metrics, $V_1(\mu)$, $V_2(\mu)$, and $V_4(\mu)$, provide no useful information with which to identify the buried objects because there is a negligible difference between the surface temperature of the objects and background. $V_1(\sigma)$, $V_2(\sigma)$, $V_1(\gamma)$, and $V_2(\gamma)$ can be used to find the objects, especially if the semivariogram sill is used when radiation levels are low (0–300 W/m²). Visibility metric V_3 provides the greatest contrast between the buried objects and the background, as discussed previously.

The average of V_1 – V_4 for the four time differences was calculated using the SD (Figure 18), semivariogram sill (Figure 19), and mean (Figure 20) for the same 300 W/m² incoming-solar-radiation bins discussed above. Overall, the value of V_4 for the background is too close to those of the buried objects regardless of the statistical parameter used or the time-difference step and therefore is not suitable. Two notable exceptions are $V_4(\mu)$ at $dt = 15$ and $dt = 120$ minutes at high solar loadings (900–1200 W/m²). At $dt = 15$ minutes, the shallow plastic object can be found, while at 120 minutes, the deep plastic box signal is much larger than the background.

As with the non-time-differenced investigation, V_3 calculated using the time-offset images can reliably be used to find the buried objects at all radiation levels, especially if the mean temperature is used. The findings using V_1 and V_2 are less conclusive. $V_1(\sigma)$ and $V_2(\sigma)$ are small at all time steps. The shallow plastic metric is relatively large at all radiation levels using $V_1(\gamma)$ and $V_2(\gamma)$. At lower incoming-solar-radiation strengths, the deep metal and shallow metal $V_1(\gamma)$ can be found. The opposite is true for $V_2(\gamma)$, where they are more easily detected at high solar impingement. This

is also true for the deep plastic object. The results using $V_1(\mu)$ and $V_2(\mu)$ are less clear with the shallow plastic object signal strong under certain conditions. As with $V_4(\mu)$, the deep plastic object signal is very high at large solar radiation levels at $dt = 120$ minutes.

Based on the above discussion, the V_3 visibility metric is consistently large enough to differentiate between the buried objects and background in Phase 2 at all incoming-solar-radiation levels. Second, time-differentiating images do not provide additional insight. Air temperature, precipitation, and wind speed will be considered next.

Figure 17. Average visibility metrics V_1 to V_4 calculated using the SD, semivariogram sill, and mean as a function of 300 W/m² binned incoming shortwave radiation: (a) V_1 , (b) V_2 , (c) V_3 , and (d) V_4 .

Figure 18. Mean of the time-differenced visibility metrics $V_1(\sigma)$ to $V_4(\sigma)$ for 300 W/m² incoming-solar-radiation bins: (a) V_1 , (b) V_2 , (c) V_3 , and (d) V_4 .

Figure 19. Mean of the time-differenced visibility metrics $V_1(\gamma)$ to $V_4(\gamma)$ for 300 W/m² incoming-solar-radiation bins: (a) V_1 , (b) V_2 , (c) V_3 , (d) V_4 .

Figure 20. Mean of the time-differenced visibility metrics $V_1(\mu)$ to $V_4(\mu)$ for 300 W/m² incoming-solar-radiation bins: (a) V_1 , (b) V_2 , (c) V_3 , (d) V_4 .

3.5.2 Air temperature, precipitation, and wind speed

As the results are similar to the incoming-solar-radiation study in the previous section, this discussion includes no supporting figures. As with the incoming solar radiation, the V_3 metric consistently performs better than V_1 , V_2 , and V_4 regardless of which statistical parameter is used to calculate the visibility metrics as a function of air temperature, precipitation, or wind speed. As with the solar radiation (Figure 17), $V_1(\mu)$ and $V_2(\mu)$ are too small to find any buried objects with respect to the available meteorological forcings. After V_3 , $V_1(\gamma)$ and $V_2(\gamma)$ also provide useful information for finding buried objects although to a lesser extent. As with the solar radiation, no additional information is gained by time-differencing images.

4 Findings and Conclusions

The present study involved constructing a test plot consisting of soil that was removed, homogenized, replaced in lifts along with buried sensors, and compacted to ensure a uniform density with depth. The objective was to enhance the understanding of the environmental (soil and atmospheric) phenomenological properties affecting the temporal and spatial thermal variance of soils. It was evident that homogenizing the soil significantly decreased the soil thermal spatial variability (i.e., background noise), making analysis of the data easier than the Phase 1 tests. Phase 1 consisted of a test using nonhomogenized soil that exhibited significant spatial temperature variability. The noise reduction was evident both visually and statistically by analyzing images under dry and wet meteorological conditions from both Phase 1 and Phase 2.

Once the soil properties had equilibrated, we placed four equal-sized boxes, two metal and two plastic, at two different depths below the surface. The SD of the thermal IR temperature before and after emplacement was used to investigate the effects of the objects on the AOI (Figure 11). Except for the deep plastic box, where camera shadowing affected the thermal IR signal at certain times of the day, the SD increased after emplacement. Also, the variability of the SD as well as the magnitude was greatest for the shallow plastic object.

We examined the meteorological phenomenological effects of air temperature, incoming solar radiation, precipitation, wind speed and time of day for their influence on the detectability of the buried objects. The difference between the mean of the derived thermal IR temperature over the buried objects and the undisturbed background soil as a function of weather variability (Figure 13) indicated the buried objects were not significantly different than the neighboring regions (thermally invisible) during precipitation events. Conversely, the soil over the buried objects exhibited a much larger difference in derived thermal IR temperature (thermally visible), as compared to the background area, during sunny and warmer days near solar noon. Consequently, the best time for detecting the buried objects with thermal IR was during sunny days corresponding to high solar loading. Finally, the soil over buried objects exhibited less contrast in thermal IR images during windy days at the test site, implying the objects would be more difficult to identify as wind speed increased.

The concept of a visibility metric was introduced to aid in the identification of buried objects. The four metrics (V_1 to V_4) were defined based on either a normalized value or the difference between basic descriptive statistically derived parameters of the thermal IR temperature over the buried objects as compared to the selected AOI. The descriptive statistical parameters utilized were the SD, semivariogram sill value, and arithmetic mean.

These descriptive statistically derived metrics were applied to four images chosen for in-depth analysis. The four images chosen included the following conditions: (1) surface soil above the buried objects appearing warmer than the surroundings, (2) surface soil above the objects appearing colder than the surroundings, 3) no surface-soil temperature difference between buried-object locations and background with the buried objects indistinguishable from background to the human eye, and (4) surface-soil temperature difference of over 7°C between buried-object locations and background with the buried objects indistinguishable from background to the human eye. We found that the normalized metrics, V_3 and V_4 , best quantified what was identified visually.

Phase 1 showed that time differencing of images could enhance features such as buried objects as compared to the background noise, making it possible to find objects not visible in a single image frame (Clausen et al. 2020). Therefore, in the present study we also investigated the effect of time differencing on the visibility metrics by using the visibility metric discussed above. Similar to the analysis of a single image, differencing of images indicated the normalized metrics for V_3 and V_4 were found to be most useful in distinguishing the buried objects. However, all metrics at all time steps had significant outliers.

Time differencing images before applying statistical analysis and then the visibility metrics improved the normalized difference metric (V_2) using the semivariogram sill. If the mean was used instead, at the largest time step, the deep plastic object became easily visible at high incoming solar radiation ($>900 \text{ W/m}^2$). While this study investigated the relationship of various metrics to individual weather parameters, the interrelationship of meteorological forcing variables requires further investigation, as do seasonal affects such as freezing and snow accumulation.

From these analyses, it appears that the use of a normalized contrast metric increases the likelihood of object detection as compared to direct visual

inspection of images. Time differencing is beneficial if differencing metrics are used. Contrast metrics are useful for analyzing thousands of images quickly and binning them into specific categories for computing statistical information for each condition.

Much of the effort of the Phase 2 study focused on constructing the new test plot, collecting data, and identifying and developing tools for analyzing the data. Further effort is needed for the interrelationship of weather parameters on the IR surface response. However, our initial analysis indicates that solar loading as a function of weather conditions (sunny versus cloudy) and soil moisture as a function of precipitation events have a direct role in buried-object visibility. We are presently exploring the details of these relationships to develop a quantifiable response matrix. While the ultimate goal is to be able to apply our findings to other scenarios, at this time it is unclear how broadly the findings observed at the Hanover test plot can be applied to other geographic locations with different environmental phenomenological conditions.

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Appendix A: Solar Noon for Hanover, New Hampshire

Table A-1. Solar noon for Hanover, New Hampshire, 43.7022° N, 72.2896° W.

Day	Month											
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	11:52:41	12:02:41	12:01:22	11:52:53	11:46:15	11:47:06	11:53:10	11:55:32	11:49:12	11:38:44	11:32:40	11:38:15
2	11:53:09	12:02:48	12:01:10	11:52:36	11:46:08	11:47:16	11:53:21	11:55:28	11:48:47	11:38:25	11:32:39	11:38:38
3	11:53:37	12:02:55	12:00:57	11:52:18	11:46:02	11:47:26	11:53:32	11:55:23	11:48:27	11:38:06	11:32:39	11:39:02
4	11:54:04	12:03:01	12:00:44	11:52:01	11:45:57	11:47:37	11:53:43	11:55:17	11:48:07	11:37:47	11:32:39	11:39:26
5	11:54:31	12:03:06	12:00:31	11:51:44	11:45:52	11:47:47	11:53:54	11:55:11	11:47:47	11:37:29	11:32:41	11:39:51
6	11:54:57	12:03:10	12:00:14	11:51:27	11:45:47	11:47:58	11:54:04	11:55:04	11:47:27	11:37:11	11:32:43	11:40:16
7	11:55:23	12:03:14	12:00:02	11:51:10	11:45:43	11:48:10	11:54:13	11:54:57	11:47:06	11:36:53	11:32:47	11:40:42
8	11:55:48	12:03:16	11:59:47	11:50:54	11:45:40	11:48:21	11:54:22	11:54:49	11:46:46	11:36:36	11:32:51	11:41:08
9	11:56:13	12:03:18	11:59:32	11:50:37	11:45:38	11:48:33	11:54:31	11:54:41	11:46:25	11:36:20	11:32:56	11:41:35
10	11:56:38	12:03:19	11:59:17	11:50:22	11:45:36	11:48:45	11:54:40	11:54:32	11:46:04	11:36:04	11:33:02	11:42:02
11	11:57:02	12:03:20	11:59:01	11:50:06	11:45:34	11:48:57	11:54:48	11:54:22	11:45:43	11:35:48	11:33:08	11:42:30
12	11:57:25	12:03:19	11:58:45	11:49:51	11:45:33	11:49:09	11:54:55	11:54:12	11:45:22	11:35:33	11:33:16	11:42:57
13	11:57:47	12:03:18	11:58:29	11:49:36	11:45:33	11:49:22	11:55:02	11:54:01	11:45:00	11:35:18	11:33:24	11:43:26
14	11:58:09	12:03:16	11:58:12	11:49:21	11:45:33	11:49:35	11:55:09	11:53:50	11:44:39	11:35:04	11:33:34	11:43:54
15	11:58:31	12:03:13	11:57:55	11:49:07	11:45:34	11:49:48	11:55:15	11:53:38	11:44:18	11:34:50	11:33:44	11:44:23
16	11:58:52	12:03:10	11:57:38	11:48:53	11:45:35	11:50:01	11:55:20	11:53:25	11:43:56	11:34:37	11:33:55	11:44:52
17	11:59:12	12:03:05	11:57:21	11:48:39	11:45:37	11:50:14	11:55:26	11:53:12	11:43:35	11:34:25	11:34:07	11:45:21
18	11:59:31	12:03:01	11:57:04	11:48:26	11:45:39	11:50:27	11:55:30	11:52:59	11:43:13	11:34:13	11:34:19	11:45:51
19	11:59:49	12:02:55	11:56:46	11:48:13	11:45:42	11:50:40	11:55:34	11:52:45	11:42:52	11:34:02	11:34:33	11:46:20
20	12:00:07	12:02:49	11:56:29	11:48:03	11:45:46	11:50:53	11:55:37	11:52:31	11:42:30	11:33:51	11:34:47	11:46:50
21	12:00:24	12:02:42	11:56:11	11:47:48	11:45:50	11:51:06	11:55:40	11:52:16	11:42:09	11:33:41	11:35:02	11:47:19
22	12:00:41	12:02:34	11:55:53	11:47:37	11:45:54	11:51:19	11:55:42	11:52:06	11:41:48	11:33:32	11:35:18	11:47:49
23	12:00:56	12:02:26	11:55:35	11:47:26	11:46:00	11:51:32	11:55:44	11:51:45	11:41:27	11:33:23	11:35:35	11:48:19
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26	12:01:39	12:01:58	11:54:41	11:46:55	11:46:18	11:52:10	11:55:46	11:50:55	11:40:24	11:33:02	11:36:30	11:49:48
27	12:01:51	12:01:48	11:54:23	11:46:46	11:46:25	11:52:22	11:55:45	11:50:38	11:40:04	11:32:56	11:36:49	11:50:17
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REPORT DOCUMENTATION PAGE				Form Approved OMB No. 0704-0188	
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1. REPORT DATE (DD-MM-YYYY) August 2021		2. REPORT TYPE Final Report		3. DATES COVERED (From - To) FY17-FY18	
4. TITLE AND SUBTITLE Spatial and Temporal Variance of Soil and Meteorological Properties Affecting Sensor Performance—Phase 2				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT 06027121A	
6. AUTHOR(S) Jay L. Clausen, Susan Frankenstein, Jason R. Dorvee, Austin Workman, Blaine F. Morriss, Keran J. Claffey, Terrance M. Sobacki, Christopher R. Williams, Stephen D. Newman, Brandon K. Booker, Rosa T. Affleck, Charles E. Smith, Michele L. Maxson, Andrew P. Bernier, and Bonnie J. Jones				5d. PROJECT NUMBER 468349	
				5e. TASK NUMBER A1010	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) U.S. Army Engineer Research and Development Center (ERDC) Cold Regions Research and Engineering Laboratory (CRREL) 72 Lyme Road Hanover, NH 03755-1290				8. PERFORMING ORGANIZATION REPORT NUMBER ERDC/CRREL TR-21-10	
9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES) U.S. Army Corps of Engineers Washington, DC 20314-1000				10. SPONSOR/MONITOR'S ACRONYM(S) USACE	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited.					
13. SUPPLEMENTARY NOTES					
14. ABSTRACT <p>An approach to increasing sensor performance and detection reliability for buried objects is to better understand which physical processes are dominant under certain environmental conditions. The present effort (Phase 2) builds on our previously published prior effort (Phase 1), which examined methods of determining the probability of detection and false alarm rates using thermal infrared for buried-object detection.</p> <p>The study utilized a 3.05 × 3.05 m test plot in Hanover, New Hampshire. Unlike Phase 1, the current effort involved removing the soil from the test plot area, homogenizing the material, then reapplying it into eight discrete layers along with buried sensors and objects representing targets of interest. Each layer was compacted to a uniform density consistent with the background undisturbed density. Homogenization greatly reduced the microscale soil temperature variability, simplifying data analysis.</p> <p>The Phase 2 study spanned May–November 2018. Simultaneous measurements of soil temperature and moisture (as well as air temperature and humidity, cloud cover, and incoming solar radiation) were obtained daily and recorded at 15-minute intervals and coupled with thermal infrared and electro-optical image collection at 5-minute intervals.</p>					
15. SUBJECT TERMS Detection, Detectors, Environmental, Infrared, Meteorology, Phenomenology, Sensors, Soil moisture, Soil temperature, Targets, Thermal					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT Unclassified	b. ABSTRACT Unclassified	c. THIS PAGE Unclassified			19b. TELEPHONE NUMBER (include area code)