

MINIMUM DETECTABLE CONCENTRATION FOR CONTINUOUSLY COLLECTED DATA

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Table of Contents

1	Introduction	1
	1.1 Detector Signal Processing	4
	1.2 Accumulation Time Interval	4
	1.3 Detector Response to Spatial Variability	5
2	Key Statistical Foundations	6
3	Lag- k Differencing Methods	7
	3.1 Values for k	8
	Dependence Cutoff Optimization Procedure	9
	3.2 Generalized Midpoint Lag- k Differencing (Arbitrary k)	10
	Statistical Properties	11
	Expected Value	11
	Variance	11
	Strengths and Limitations	12
	3.3 Differencing with a Centered Moving Average	12
	Statistical Properties Under Background-Only Conditions	13
	Expected Value	13
	Variance	13
	Implications for Detection Limit Calculation	13
	Strengths and Limitations	14
	3.4 Differencing with Centered Exponentially Weighted Moving Average Smoothing	14
	Value for λ	15
	Statistical Properties Under Background-Only Conditions	15
	Expected Value	15
	Variance of the Centered EWMA-Differenced Signal	15
	Detection Limit for Centered EWMA Differencing	16
	Strengths and Limitations	16
	3.5 Summary of Differencing Methods and Comparison to Currie's Approach	17
	3.6 Choosing the Appropriate Detection Method	18
	3.7 Bias and Precision Checks on Detection Limit	19
	3.8 Bootstrap Technique	19
	Assessing Bias in the Estimated Detection Limit	20
	Bootstrap Precision Intervals for the Detection Limit	20
	3.9 Simulation Example	21
	Constant-Background Scenario ($A = 0$)	23
	Nonconstant-Background Scenario ($A = 50$)	25
	Nonconstant-Background Scenario ($A = 100$)	29
	3.10 Field Survey Example	32
4	Impacts of Varying Radiological Background Within an Area	37
5	Approach for Selecting Statistical Method	47
6	Scanning with an Energy Window or Spectroscopy for Gamma-Emitting Radionuclides	48
	6.1 Benchtop Testing	49
7	Comparing Gross Gamma, Energy Window, and Spectroscopic Continuously Collected Data for a Common Reference Area	54
	7.1 Gross Gamma Evaluation	54
	7.2 Energy Window Gamma Evaluation	57
	7.3 Spectral Gamma Evaluation	59
8	Determining Minimum Detectable Concentrations from the Minimum Detectable Count Rate	60

	8.1	Background	60
	8.2	Beta Detector Efficiency	61
	8.3	Gamma Detector Efficiency	62
9		Bench Testing Detector Response Accumulation Time	62
10		Scanning Localized Versus Wide Elevated Areas: Techniques, Considerations, and Effect on Minimum Detectable Concentration	69
	10.1	Serpentine Path.....	70
	10.2	Towed Array Example	70
	10.3	Modeling of a Small Elevated Area	73
	10.4	Modeling of a Larger Elevated Area	76
11		Additional Variables Affecting Minimum Detectable Concentrations.....	81
	11.1	Aspects to Consider	81
	11.2	Good Practices for Continuously Collected Data	82
12		References	83
13		Bibliography	83

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1 Introduction

The calculation of an a priori minimum detectable concentration (MDC) for continuously collected data (CCD) requires considerations and evaluations different from those assumed for the two-stage scanning process, as described in Section 3 of NUREG-1507, "Minimum Detectable Concentrations with Typical Radiation Survey for Instruments for Various Contaminants and Field Conditions," for surveys with vigilance. As described in NUREG-1575, Revision 2, "Multi-Agency Radiation Survey and Site Investigation Manual (MARSSIM)" (NRC 2026), a two-stage scan survey with vigilance calls for "pausing or stopping to investigate further when audio click data from a ratemeter indicate potential areas of concern." CCD can be described as data collected in real time at designated, nearly regular time intervals and geospatial distances. As applied for radiation scanning measurements, the geospatial (location) and temporal (date and time) information accompanies each recorded measurement. For CCD, there is no assumed surveyor vigilance. Without surveyor vigilance, there is no possibility of responding to increased "clicks," of stopping to count longer to ensure full-scale response, or of further scanning to identify the areas with the highest measurements. The recorded data alone are the basis for determining the scan MDC.

This document describes the process for establishing an a priori MDC for CCD, based on surveys performed in areas with characteristics similar to those of the areas for which the evaluation or investigation is being planned. Establishing an a priori MDC ensures that the design and conduct of scanning surveys using CCD will meet the defined objectives (i.e., the surveys will be able to detect levels of contamination above background levels at an acceptable fraction of identified limits or regulatory criteria).

Postprocessing CCD scan measurements for a survey area, as opposed to a reference area, serves as the primary method for identifying areas for followup investigation. Section 6.3 of NUREG-1507 describes different statistical methods that may be used for this survey unit postprocessing. However, if instrumentation and methods are not capable of achieving a suitable MDC for CCD, then survey results may be inadequate. To this end, the a priori MDC is primarily a planning tool—a Data Quality Objective (DQO) to ensure that the selection of scanning instrumentation and the determination of scanning methods will provide appropriate detection capability to support the final status survey and dose compliance evaluations as required for license termination.

In the two-stage scanning process described in Section 6 of NUREG-1507 for surveys conducted with surveyor vigilance, the surveyor (1) listens to audible click data, and (2) pauses to count longer if an audible increase in counts occurs. This two-stage technique enables the surveyor to identify a finite area of elevated activity by audio response, with followup focused scanning measurements to identify and quantify a steady-state detector response in standard units of measurement, such as counts per minute (cpm). For CCD, however, there is no assumption of surveyor attention to identify contamination in the environment using a detector's audio response (i.e., audible clicks).

With automated or semiautomated scanning systems, the time sequencing and geospatial distances can be reasonably controlled. When the surveyor manually controls the movement, scanning speed is likely to vary as a result of normal human reactions. Although the method of survey with vigilance may have some advantage for characterization and remediation surveys, it

should be avoided when performing background reference area surveys for the purpose of determining an a priori MDC. Reasonable surveyor attention is needed to avoid overly biasing the data and statistical analysis. It is generally assumed that postprocessing and evaluation of the CCD will be used to determine the need for followup investigations (discussed in Section 6.3 of NUREG-1507). Data collection frequency should be automated, with no surveyor attention needed other than to initiate and terminate. In other words, the determination of the a priori scan MDC should be made with a constant scan speed to the extent practical. This is not to imply that surveyor vigilance cannot be incorporated when performing CCD surveys for areas being evaluated.

Each recorded measurement must stand on its own—its recorded value must be accompanied by pertinent temporal and spatial information. Postprocessing of the CCD, during which geospatial methods can be used to identify anomalies and spatial variations, may reveal the need for resurveys or investigations. The design of the survey, including the selection of instruments and scan method (scan height and speed), is important in ensuring an acceptable MDC that meets the MARSSIM criteria. However, MARSSIM does not address MDC for CCD. Section 6.3.3.1 of MARSSIM Revision 2 states the following:

The scan MDC calculations include an index of sensitivity, surveyor efficiency, and observation interval for an assumed elevated area size and scan speed. These equations do not necessarily apply to the CCD data collected without audible surveyor vigilance, and depending on the elevated area size and scan speed, the detector output may not pick up the full response rate....

...Marianno et al. 2003 studied the impact of scan speed, depth of residual radioactivity, and selected response time on efficiency, with faster scan speeds, depth of residual radioactivity, and longer response times leading to lower efficiencies. Falkner and Marianno 2019 went on to develop a well-defined relationship between MDA [minimum detectable activity] and detector speed based on Monte Carlo N-Particle [MCNP®] and model fits to modified four-parameter logistic function. Scan parameters and detector response time should be carefully selected as part of the DQO process and considered when calculating scan MDC.

In MARSSIM, the methods for calculating an MDC for scan surveys with vigilance make certain assumptions regarding the statistical characteristics of the scan data (from Pacific Northwest National Laboratory [PNNL] 2023):

Data distributions associated with each hypothesis are determined by making the following assumptions (NUREG-1507 [Revision 1]).

- Data are assumed to follow Poisson distributions, which are generally approximated by normal distributions in both the null and alternative hypotheses for adequate counts.
- The data distribution under the null hypothesis (H_0) is normal and centered at zero, representing the net noise distribution when no net activity is present.
- The data distribution under the alternative hypothesis (H_A) is normal and centered at a point greater than zero, representing the net signal distribution when net activity is present.

Both distributions described above are distributions of the net signal, that is, of the measurement remaining after the background estimate has been subtracted. Under the null hypothesis, the subtraction is what places the distribution at zero: centering a measurement on its own background produces a distribution with a mean of zero by construction. Under the alternative hypothesis, the mean must be strictly greater than zero, because the contribution of the source is a count and cannot be negative. This is also why the same framework carries over unchanged to the differenced signals developed in Section 3. Each of the lag- k methods is a centering operation, so under background-only conditions the expected value of the difference is zero (Equations 5, 13 and 22), and the critical and detection limits follow directly from Equations 1 through 3 with the background standard deviation replaced by the standard deviation of the differences.

As discussed in Section 3.1 of NUREG-1507, the application of MARSSIM, Revision 2, Equation 62, for calculating the a priori scan MDC for surveys with vigilance assumes that the measurements can be represented as a Poisson distribution, which at counts above about 70 can be represented as a normal distribution. For most environmental conditions, it may not be reasonable to assume that the recorded CCD measurements themselves follow a normal distribution. The methods developed in this report do not require that they do. The critical and detection limits are computed from the differences between each measurement and an estimate of the local background, and those differences are linear combinations of many observations; they approach normality by the central limit theorem even where the measurements are skewed, and the approximation improves as the lag distance increases. The bootstrap check described in Section 3.8 provides a distribution-free verification for cases in which that approximation is in doubt. Because of variation in material composition or geological conditions, the spatial distribution may be more random, with potentially significant variation. Hence, to calculate a suitable a priori MDC for CCD, one first needs to select a suitable reference area with representative characteristics (i.e., geology and background radiation).

As described in Section 6.2 of NUREG-1507, the a priori scan MDC for surveys with vigilance is determined by (1) estimating the net minimum detectable count rate (MDCR) that a surveyor can distinguish from the background detector response, and (2) applying efficiency factors related to the surveyor, instrumentation, and source of radiation. As shown in Equation 6.2 of NUREG-1507, this method includes consideration of an “observation interval.” As defined in Section 6.2.3 of NUREG-1507, “The observation interval during scanning is the actual time that the detector can respond to the contamination source. It depends on the scan speed, detector orientation, and size of the hotspot.” A value of 0.25 square meter (m^2) serves as a nominal area of concern for this evaluation. Because there are no data to characterize the variation in count rate across an area, the square root of an assumed mean background count is taken as representative of the standard deviation. This assumption is based on the Poisson distribution, for which the variance equals the mean. The normal distribution enters separately, as an approximation to the Poisson distribution that is adequate when counts are sufficiently large, and it is what justifies the use of the z-based critical and detection limits.

For CCD, the same process applies, except that the standard deviation of the background need not be assumed—it is calculated directly from the data collected for the background reference area. The first step is to calculate the MDCR, and the second is to correlate the MDCR to an MDC. For the latter task, essentially the same steps as described in Section 4 of NUREG-1507 can be applied to CCD. The primary difference is that in a survey with vigilance, the surveyor is able to respond to an audible or visual increase by performing immediate followup scanning to identify an area of elevated activity (or “hotspot”). An observation time is included, representing the time that the source is detectable, that is, the time the detector is located over the 0.25 m^2

area. For CCD, there is no surveyor vigilance and no observation time; instead, there is an accumulation time, as described in Section 1.2 below.

The use of CCD does not rely on this two-stage scanning (although it is not necessarily excluded from the scan technique). The surveyor can still view the data as they are collected and make observations to further inform the survey process.

The determination of the MDCR requires consideration of three main characteristics of the CCD process:

- (1) the detector's signal processing capabilities, or instrument response characteristics for the recorded value
- (2) the accumulation time interval (i.e., the time interval between recorded measurements) and the corresponding area of coverage
- (3) the detector's response (and the resulting properties of the recorded measurements) as a function of the spatial characteristics of potential elevated areas

Each of these three characteristics is discussed further below.

1.1 Detector Signal Processing

For CCD, the recorded measurement is a single value, typically in units of counts or count rate, such as cpm. This value also reflects how the instrument processes the signal (e.g., a pulse) from the detector to produce the output, which is the recorded measurement. Ideally, the output, as recorded, should reflect the detector interactions (counts) over the defined time interval for recording the measurements (in seconds). However, some instruments may express outputs in different units, such as cpm, or may produce an equivalent exposure rate in units of microrentgen (μR) per hour (h).

When data are collected without pausing, and depending on the signal processing capabilities of the instrumentation, the electronically captured count (or count rate) data may not accurately reflect a representative measurement of the area, as the instrument may not capture the maximum or full-scale response.

With CCD, another consideration is instrument dead time, meaning that the instrument may not be capable of processing further signals from the detector during signal processing and data transfer. This is analogous to the increased dead time created by increased count rate.

1.2 Accumulation Time Interval

As discussed in Section 6.2.3 of NUREG-1507, for surveys with vigilance, the actual length of time when the detector can respond to the contamination source during scanning is referred to as the observation interval. For CCD, the corresponding concept is better characterized as an accumulation time interval. It is defined simply as the time interval between the recorded scan measurements, and is typically specified by an instrument setting established before the survey is conducted.

The accumulation time interval is thus independent of the scan speed and of the size of any area of contamination. However, the recorded count data themselves may depend on both the scan speed and the sizes of contaminated areas. These two factors, combined, determine how

long the detector spends over a contaminated area. As a result, the MDCR for CCD (unlike the MDCR for two-stage scanning with vigilance) is independent of the scan speed but dependent on the accumulation time.

The combination of scan speed and accumulation time interval determines the scan measurement for a given scanned area. Without vigilance, there is no pausing to ensure full-scale meter response; hence, the CCD for the area covered in a given time interval reflect an average value for the area. When the time interval is too long (and hence the area covered is relatively large), this averaging can compromise the ability to identify small areas of elevated activity. On the other hand, a short accumulation time (e.g., 1 second) could hinder detection, as the number of counts recorded would likewise be lower. Falkner and Marianno (2019) investigated the effect of increased scan speeds on the geometric efficiency of a typical 2"x2" sodium iodide (NaI) gamma scintillation detector. In that investigation, MCNP® was used to model the solid angle subtended by a cylindrical detector from a cesium (Cs)-137 source, as the scan speed increased, to determine the detector efficiency. The study clearly demonstrated that the calculated minimum detectable activity increases as scan speed increases, because of the corresponding decrease in the geometric efficiency of the detector. It also showed that slight variations in scan speed can affect the detector's ability to achieve the desired minimum detectable activity, highlighting the need to ensure a consistent scan speed during surveys.

For widespread elevated areas, increasing the accumulation time interval can improve detection by increasing the total number of accumulated counts (detections above background) and reducing variability in the data. The accumulation time interval can be increased either as a part of the survey (i.e., by increasing the actual time between recorded measurements) or during postprocessing, by combining survey measurements across multiple time intervals (binning). Section 9 examines in more detail the tradeoff between the statistical benefits of increasing the accumulation time interval and the risk of masking small elevated areas by doing so.

1.3 Detector Response to Spatial Variability

"Field of view" is a common term for describing a detector's response to a source—in this case, a contaminated area. The field of view refers to the area or region that can be observed or captured by a particular instrument or sensor (i.e., the extent of the observable space or landscape within the range of a specific device or equipment). The concept of a field of view is described in more detail in Section 7.2 of NUREG-1507 for a collimated gamma detector, such as an NaI detector. For most alpha and beta detectors, owing to the limited penetration and path lengths for these particles, the field of view can be approximated as the active detection surface area of the detector.

For a typical background environment (common materials and natural conditions), the recorded CCD measurements can be expected to reflect a Poisson distribution, and a corresponding MDCR can be calculated to reflect a uniform radiation field (with expected variability). However, the ability to detect spatial variability (i.e., an elevated area) is a function of the size of the elevated area, as well as the scan speed and recording time. Therefore, for CCD, the MDCR is also inversely proportional to the size of the elevated area. In other words, as the dimensions of an elevated area decrease, the MDCR is likely to increase, depending on the observation interval for the elevated area.

Information collected during a historical site assessment may provide insight into the physical characteristics of likely areas of contamination. Scoping and characterization survey data can be used to better define these characteristics. These information sources should be used for

selecting scan survey instrumentation and survey methods, including whether a multidetector array is needed to identify and quantify small areas of elevated activity.

From an application standpoint, many of the instrument and source characteristics discussed in Sections 4 and 5 of NUREG-1507 remain applicable for determining the instrument response and the calculated scan MDC for CCD. Section 8 shows how the instrument efficiency and source efficiency can be used to calculate the MDC from the MDCR. Similarly, the findings discussed in Section 5 of NUREG-1507, related to source effects and signal degradation, can be applied to scan CCD measurements in converting the MDCR to MDC. Section 7 illustrates how the dimensions of an elevated area and the choice of scan methods, including observation interval, can affect the MDCR and the resulting MDC.

2 Key Statistical Foundations

For CCD, the accurate and defensible identification of radioactive contamination during scanning surveys relies fundamentally on the ability to distinguish an increased instrument response using rigorous statistical principles. Central to this process are two complementary frameworks: Currie's Classical Detection Theory and Signal Detection Theory (Currie, 1968). Together, these frameworks define how thresholds for detection are established, balancing the competing risks of false positives and false negatives in survey data interpretation.

As discussed in Section 3.1 of NUREG-1507, applying the seminal methodology in Currie (1968) to the quantification of detection thresholds in radiometric measurements provides a statistically rigorous way to define two critical decision points, assuming the data fit a Poisson distribution:

- critical level (L_C): the net signal that must be exceeded before contamination is declared possibly present. The threshold is set so that a background-only measurement exceeds it with probability α , the false positive (Type I) error rate.
- detection limit (L_D): the smallest true net signal that will produce a measurement exceeding L_C with probability $1 - \beta$, where β is the acceptable false negative (Type II) error rate.

In mathematical terms, the critical level (L_C) is defined as follows:

$$L_C = z_\alpha \times \sigma_B \quad (\text{Eq. 1})$$

where:

z_α = the critical value from the standard normal distribution corresponding to the desired Type I error rate

σ_B = the standard deviation of the background measurement distribution

The detection limit (L_D) is expressed as follows:

$$L_D = L_C + (z_\beta \times \sigma_D) \quad (\text{Eq. 2})$$

where:

z_β = the critical value from the standard normal distribution corresponding to the desired Type II error rate

σ_D = the standard deviation of the signal-plus-background distribution

In most practical radiological scanning scenarios, particularly under high-count conditions, it is reasonable to assume $\sigma_D \approx \sigma_B$. Under this assumption, the detection limit simplifies to the following:

$$L_D = (z_\alpha + z_\beta) \times \sigma_B \quad (\text{Eq. 3})$$

This form is especially practical in field conditions where measurements are numerous and rapid decisions about potential contamination are needed.

3 Lag-k Differencing Methods

Scanning with vigilance relies on the surveyor's ear: the audible count rate is judged, moment to moment, against the background the surveyor has just been hearing, and an increase that stands out prompts a pause and a closer look. Lag- k differencing performs the same comparison numerically on recorded data. Each measurement is compared not against a single global background value but against an estimate of the background in its immediate vicinity, formed from the observations that precede and follow it along the scan path. The quantity tested is the difference between the two, and the lag distance k sets how far from the measurement those neighboring observations are drawn. The methods developed in this section differ only in how many neighboring observations contribute to that local estimate and how they are weighted. The approach follows the methodology developed in PNNL (2023).

While classical detection approaches assume a mostly stationary, homogeneous background radiation field, real-world scanning surveys often encounter spatial variability in background levels. Changes in characteristics due to variability in surface geology or anthropogenic fallout depositional patterns for land surveys, and variability in building materials for indoor surveys, can lead to wide variability in recorded measurements. Without appropriate correction, such variability can mask localized contamination or produce false detections. As a statistical method, **lag- k differencing** provides one way to address these challenges. In the lag- k approach, the survey data are treated as a linear time series, and one evaluates differences between observations separated by k positions in the sequence—typically comparing the k observations preceding and following a given measurement—to account for a potentially changing background signal. This approach allows hypothesis testing while accommodating gradual spatial or temporal trends in the data (PNNL, 2023).

Lag- k differencing techniques can be broadly categorized into one-sided and centered approaches. In one-sided differencing, each observation is compared to a value either k steps ahead of the point of interest (forward lag- k) or behind the point of interest (backward lag- k).¹ In

¹ For CCD, it is assumed that measurements are recorded at a set frequency (e.g., every 1 or 2 seconds) and that scan speed remains constant (e.g., as measured in meters per second for NaI detector scanning, or by detector width for beta scanning). Therefore, the lag- k distance can be assumed to be represented by a certain fixed number of recorded measurements, which always reflects the same distance between measurements.

contrast, in centered differencing, each observation is compared to the midpoint of points symmetrically spaced k steps around the current position. Both of these techniques enhance detection by suppressing low-frequency background variations and amplifying localized anomalies. However, they exhibit distinct tradeoffs: one-sided methods are easy to implement and useful for directional scans but introduce asymmetry, potentially biasing detection depending on scan direction. Centered differencing is spatially balanced, offering improved accuracy near central regions of anomalies, but suffers from data loss at the boundaries and increased variance.

To address these limitations, several types of lag- k smoothing are evaluated in the sections below.

3.1 Values for k

The selection of the lag distance k is a critical step in applying lag- k differencing methods. The lag parameter directly affects the sensitivity and specificity of detection; a smaller k may preserve excessive background variation, while an excessively large k may smooth over localized contamination. An appropriate lag parameter is essential for capturing the structure of serial dependence within the data. Thus, a principled statistical approach is needed for selecting an optimal k under real survey conditions.

One common technique used in time-series analysis, particularly within the Autoregressive Integrated Moving Average (ARIMA) modeling framework, is to use autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to guide the selection of k . The bibliography in Section 13 provides references containing more detailed information on these techniques.

The ACF measures the linear relationship between observations of a time series at different lags. Specifically, it quantifies the correlation between x_t and x_{t-k} , where k is the lag. The ACF helps identify the presence of temporal dependence in a series and is especially useful in diagnosing patterns such as seasonality and the presence of autoregressive (AR) or moving average (MA) components.

The PACF measures the degree of association between a time series and its lagged values, after controlling for the values at all shorter lags. While the ACF captures both direct and indirect effects, the PACF isolates the direct effect of x_t on x_{t-k} .

The PACF is particularly useful for identifying the order p of an AR(p) model. In such cases, the PACF typically shows a sharp cutoff after lag- p , indicating that the necessary structure has been accounted for by including terms to lag- p .

To determine an appropriate k , the ACF and PACF are first calculated for a given sequence of background radiation measurements. The ACF quantifies the correlation between a time series and its lagged versions, offering insight into how strongly current values are related to past values at varying distances. In contrast, the PACF isolates the direct correlation between the series and a specific lag, removing the influence of all intermediate lags. Both functions are computed across a range of lag distances ($k = 1, 2, \dots, K$), with the choice of K informed by the maximum spatial extent over which nearby observations are expected to be correlated. This enables characterization of the underlying spatial structure in the background radiation, providing a foundation for selecting model parameters or smoothing scales.

The resulting ACF and PACF plots are then analyzed to determine the optimal lag distance k . This is identified as the point where the autocorrelation structure becomes negligible—specifically, where the ACF or PACF crosses zero or falls within statistical insignificance for all higher lags. That point indicates the lag distance beyond which serial dependence is no longer meaningful; it can thus be used as a cutoff for modeling or differencing. Selecting this optimal k ensures that any subsequent spatial filtering or anomaly detection method will be calibrated to reflect the actual extent of background correlation, reducing the risk of under- or over-smoothing the data. In other words, with this choice of k , the differencing process effectively removes correlated background noise while preserving signal anomalies due to contamination.

While traditionally used in time-series forecasting, these diagnostic tools translate well to spatially ordered data sequences, such as those collected in scanning surveys, where measurements exhibit serial correlation based on traversal paths or environmental gradients.

In field applications, the choice of k may also be informed by domain-specific knowledge (e.g., detector integration time, scan speed, or expected contamination plume size) and can be refined iteratively using model validation techniques or simulated performance assessments.

Dependence Cutoff Optimization Procedure

The qualitative criterion described above—selecting the first lag at which the ACF or PACF becomes negligible—can be made reproducible, tunable, and defensible by formalizing it as a practical optimization procedure. This step is especially important for CCD, where the very large sample sizes produced by continuous acquisition render conventional significance bounds uninformative: because those bounds narrow as the number of observations grows, nearly every lag registers as statistically significant, leaving the analyst without an objective stopping point. The procedure below instead defines negligibility in practical terms and confirms it through a collection of stability rules, yielding a transparent justification for the selected k . As with the ACF and PACF inspection it formalizes, it is applied to a representative background-only sequence.

A practical correlation threshold, denoted by b , is first specified by the analyst (for example, $b = 0.05$). Any lag whose autocorrelation satisfies $|\rho| \leq b$ is treated as practically negligible. Unlike a significance limit, this threshold is chosen from the requirements of the application rather than from the sample size, and it can be tied directly to the detection-limit derivation that follows. The variance expressions in Equations 7 and 8 assume independence between x_i and its neighboring observations; the practical threshold b therefore represents the level of residual autocorrelation whose contribution to σ_D —and hence to L_C and L_D —is judged negligible. Selecting k so that all higher lags fall within b is what makes that independence assumption, and the resulting detection limits, defensible.

Each lag is then treated as a candidate cutoff. For a candidate lag- k , every subsequent correlation is classified as either inside the practical bound ($|\rho| \leq b$) or outside it. A defensible cutoff is one beyond which the correlation structure remains reliably inside the bound, not merely one at which it happens to touch zero.

To assess this reliably, a family of moving-window stability rules is applied. For each window size $w = 3, 4, 5, \dots$, up to a user-specified maximum, a minimum number of the w correlations must lie inside the practical bound. That minimum is set by a required fraction f (for example, $f = 0.80$), so that a window of 10 requires 8 values inside the bound, a window of 15 requires 12, and so on. Evaluating many window sizes simultaneously guards against isolated dips that would prematurely satisfy a single-point rule.

For each candidate lag and each rule, a rule score is computed as follows:

$$\text{Rule Score} = (\text{Inside Count} - \text{Required Count}) / \text{Window Size}$$

where Inside Count is the number of correlations within the bound and Required Count is the minimum needed to satisfy the rule. Negative values indicate the rule fails, zero indicates it is met exactly, and positive values indicate the requirement is exceeded; the score thus measures the margin by which practical stability is achieved or missed.

For each candidate lag, the individual rule scores are combined into a weighted support score—an average of the rule scores in which larger windows receive greater weight, because they assess stability over longer stretches of the correlation structure. Weighted support is the primary optimization metric: values at or above zero indicate that the stability rules are, on balance, satisfied.

The selected cutoff is the earliest candidate lag at which the weighted support score reaches or exceeds a specified threshold (typically zero) and remains at or above that threshold for a user-specified number of consecutive lags. The consecutive-lag requirement prevents a single fluctuation from triggering the cutoff and, for the spatially ordered sequences produced by scanning surveys, corresponds to requiring that dependence has decayed over a contiguous span rather than at one isolated distance.

The procedure is carried out independently on the ACF and the PACF, and the two support profiles are compared. The function that provides the strongest and most stable evidence for a cutoff is selected, and the result is reported as the chosen function (ACF or PACF), the selected lag- k , the weighted support score, and the practical threshold b . This supplies the explicit basis for choosing between the two diagnostics that visual inspection of the plots alone does not.

Three diagnostic displays accompany the selection and support its documentation in a survey report: a correlation plot showing the ACF or PACF by lag, with the selected cutoff highlighted; a support plot of weighted support against candidate lag, which shows the threshold crossing; and a rule heatmap showing the outcome of every rule across candidate lags, which makes transparent why a particular k was chosen.

Finally, because the practical threshold b , the required fraction f , and the maximum window size are analyst-defined, a sensitivity analysis is performed by repeating the entire procedure across a grid of these parameters and recording the cutoff selected in each case. From the minimum, maximum, median, and most frequently selected lag, the robustness of the final choice of k can be evaluated: a narrow spread means the cutoff is insensitive to reasonable changes in assumptions, whereas a wide spread signals that k should be reported with its uncertainty and reconciled against domain knowledge, accounting for factors such as detector integration time, scan speed, and expected plume size. Documented in this way, the selection of k becomes an auditable step rather than a matter of visual judgment.

3.2 Generalized Midpoint Lag- k Differencing (Arbitrary k)

Let x_i be the i^{th} observation along the transect. Generalized midpoint (MP) differencing extends the technique of lag- k differencing by allowing flexible lag distances:

$$D_{i,MP} = x_i - \frac{(x_{i+k} + x_{i-k})}{2} \quad (\text{Eq. 4})$$

Statistical Properties

Assuming that the background data are random variables from a Poisson distribution where the criteria are met to approximate them as $x_i \sim N(\mu_B, \sigma_B^2)$, the statistical properties of the differenced signal $D_{i,MP}$ can be analyzed as follows.

Expected Value

Each individual component of the expected value has an expected value of μ_B . Therefore—

$$E(D_{i,MP}) = E(x_i) - E\left(\frac{x_{i+k} + x_{i-k}}{2}\right) = \mu_B - \frac{\mu_B + \mu_B}{2} = 0 \quad (\text{Eq. 5})$$

Variance

The MA is defined as follows:

$$\bar{x}_{MP} = \frac{(x_{i+k} + x_{i-k})}{2} \quad (\text{Eq. 6})$$

This average is based on two independent observations, each with variance σ_B^2 . Thus, the variance of the average is as follows:

$$\text{Var}(\bar{x}_{MP}) = \text{Var}\left(\frac{(x_{i+k} + x_{i-k})}{2}\right) = \frac{(\sigma_B^2 + \sigma_B^2)}{4} = \frac{2\sigma_B^2}{4} = \frac{\sigma_B^2}{2} \quad (\text{Eq. 7})$$

Assuming independence between x_i and its surrounding values (a reasonable assumption for sufficiently large k or weak autocorrelation), the variance of the differenced signal is as follows:

$$\text{Var}(D_{i,MP}) = \text{Var}(x_i) + \text{Var}(\bar{x}_{MP}) = \sigma_B^2 + \frac{\sigma_B^2}{2} = 1.5 \times \sigma_B^2 \quad (\text{Eq. 8})$$

This leads to the assumption that $D_{i,MP} \sim N(0, 1.5\sigma_B^2)$.

Now, let T^* be the multiplying factor on the background standard deviation to yield the standard deviation of the differences. For example, in this case, $T^* = \sqrt{1.5}$. The critical limit becomes the following:

$$L_{C,MP} = z_\alpha \times T^* \times \sigma_B = z_\alpha \times \sqrt{1.5} \times \sigma_B \quad (\text{Eq. 9})$$

Therefore, as derived in PNNL (2023), the detection limit becomes the following:

$$L_{D,MP} = z_{\alpha} \sigma_B T^* + \frac{z_{\beta}^2}{2} \left(1 + \sqrt{\left(1 + \frac{2\sigma_B T^*}{z_{\beta}} \right)^2 + \frac{4\sigma_B T^*}{z_{\beta}} \left(\frac{z_{\alpha}}{z_{\beta}} - 1 \right)} \right) \quad (\text{Eq. 10})$$

This can be simplified by setting alpha (α) and beta (β) equal to each other, which yields the following:

$$L_{D,MP} = 2z_{\alpha} \sigma_B \times T^* + z_{\alpha}^2 = 2z_{\alpha} \sigma_B \times \sqrt{1.5} + z_{\alpha}^2 \quad (\text{Eq. 11})$$

Strengths and Limitations

A notable strength of this approach is its flexibility to adjust spatial sensitivity through the tuning of the parameter k , allowing users to tailor the analysis based on the expected size of the contamination footprint. This flexibility makes the method suitable for a wide range of scenarios, from detecting localized hotspots to identifying broader spatial trends. However, this same flexibility introduces a challenge: the choice of k requires either a priori knowledge of the spatial structure of the contamination or an optimization process that aligns with the specific objectives of the survey. Without careful selection, the method may under- or over-smooth the data, potentially obscuring key spatial features.

To further refine detection in environments with spatially varying background radiation, the investigation is expanded beyond fixed-lag differencing to consider more flexible summarization techniques that evaluate each measurement x_i in the context of its local neighborhood. Specifically, two smoothing strategies are examined: centered MA and centered exponentially weighted moving average (EWMA). These strategies allow for dynamic, data-adaptive background estimation, which can improve the robustness of detection under the nonstationary background conditions typically encountered in CCD-based scanning surveys. The next two sections describe the mathematical properties of each technique—including its bias, variance, and impact on detection sensitivity—which shed light on the tradeoff, in each case, between responsiveness to localized anomalies and suppression of background trends. This comparison offers valuable insight into which summarization strategies provide optimal performance for real-world CCD applications.

3.3 Differencing with a Centered Moving Average

An alternative to using the midpoint in the smoother is to evaluate each observation relative to the average of surrounding points, thereby forming a smoothed local background estimate. This approach, referred to as differencing with a centered MA, is defined as follows:

$$D_{i,MA} = x_i - \frac{1}{2k} \sum_{j=1}^k (x_{i-j} + x_{i+j}) \quad (\text{Eq. 12})$$

This formula subtracts the mean of the $2k$ neighboring observations (i.e., k observations before and after x_i) from the central value. It is symmetrical, centered, and particularly effective at emphasizing deviations from a local background trend.

Statistical Properties Under Background-Only Conditions

Assuming that the background data are random variables from a Poisson distribution where the criteria are met to approximate them as $x_i \sim N(\mu_B, \sigma_B^2)$, the statistical properties of the differenced signal $D_{i,MA}$ can be analyzed as follows.

Expected Value

Each individual component of the expected value has expected value μ_B . Therefore—

$$E(D_{i,MA}) = E(x_i) - E\left(\frac{1}{2k} \sum_{j=1}^k (x_{i-j} + x_{i+j})\right) = \mu_B - \mu_B = 0 \quad (\text{Eq. 13})$$

Variance

The MA is defined as follows:

$$\bar{x}_{MA} = \frac{1}{2k} \sum_{j=1}^k (x_{i-j} + x_{i+j}) \quad (\text{Eq. 14})$$

This average is based on $2k$ independent observations, each with variance σ_B^2 . Thus, the variance of the average is as follows:

$$\text{Var}(\bar{x}_{MA}) = \frac{1}{(2k)^2} \times 2k \times \sigma_B^2 = \frac{\sigma_B^2}{2k} \quad (\text{Eq. 15})$$

Assuming independence between x_i and its surrounding values (a reasonable assumption for sufficiently large k or weak autocorrelation), the variance of the differenced signal is as follows:

$$\text{Var}(D_{i,MA}) = \text{Var}(x_i) + \text{Var}(\bar{x}_{MA}) = \sigma_B^2 + \frac{\sigma_B^2}{2k} = \sigma_B^2 \left(1 + \frac{1}{2k}\right) \quad (\text{Eq. 16})$$

Therefore, the inflation factor for the variance due to this differencing is equivalent to that of the variance for generalized MP lag- k differencing when $k=1$, and it becomes smaller as k increases.

Implications for Detection Limit Calculation

Given the assumptions above and that the distribution of the difference is of the form

$D_{i,MA} \sim N(0, T^{*2} \sigma_B^2)$, the same ideas can be used to derive the critical value and detection limit

as were used for generalized MP lag- k differencing. In this case, $T^* = \sqrt{\left(1 + \frac{1}{2k}\right)}$.

Now the critical limit (L_C) becomes the following:

$$L_{C,MA} = z_{\alpha} \times T^* \times \sigma_B = z_{\alpha} \times \sigma_B \times \sqrt{\left(1 + \frac{1}{2k}\right)} \quad (\text{Eq. 17})$$

The detection limit (L_D), assuming $\alpha = \beta$, is as follows:

$$L_{D,MA} = 2z_{\alpha} \sigma_B \times T^* + z_{\alpha}^2 = 2z_{\alpha} \sigma_B \times \sqrt{\left(1 + \frac{1}{2k}\right)} + z_{\alpha}^2 \quad (\text{Eq. 18})$$

This formulation allows adaptive smoothing: by increasing k , one can reduce the variance of the background estimate at the cost of reduced localization sensitivity.

Strengths and Limitations

One advantage of the proposed method is its ability to suppress local fluctuations caused by stochastic noise, which enhances the stability and interpretability of spatial patterns. By smoothing these short-term or highly localized variations, the method allows underlying structures to emerge more clearly. Additionally, it is designed to adapt to gradual spatial trends, making it well suited for capturing broad-scale gradients without overfitting to transient or erratic variations in the data. Finally, symmetric differencing removes directional bias along the traversal order: because the observations preceding and following each measurement are weighted identically, the differenced value is unchanged if the transect is traversed in the opposite direction. This is a property of the one-dimensional ordering and should not be read as isotropy. The methods operate on the sequence in which the measurements were recorded and therefore treat only the along-transect direction; estimating the local background from a two-dimensional neighborhood would require a spatial covariance model in place of a lag distance and is beyond the scope of the methods developed here.

Despite its strengths, the method has several limitations. First, it assumes independence between each observation and its neighboring values, an assumption that may not strictly hold in practice, especially in datasets with strong local spatial autocorrelation. This can lead to biased estimates if nearby values are, in fact, correlated. Additionally, larger values of the smoothing parameter k tend to dampen fine-scale variability, which, while helpful for noise reduction, may reduce the method's sensitivity to subtle or small-scale contamination events that are important in certain applications. Finally, the approach requires complete and evenly spaced data, limiting its applicability in settings with missing observations or irregular spatial sampling, where interpolation or imputation may be needed before analysis.

3.4 Differencing with Centered Exponentially Weighted Moving Average Smoothing

To improve spatial balance while retaining the adaptive smoothing benefits of exponential weighting, a centered EWMA approach can be considered. Unlike the recursive, backward-looking EWMA used in control charts, centered EWMA smoothing applies symmetric exponential weights around each observation x_i . This makes it more suitable for retrospective analysis of CCD survey data, where a full sequence of measurements is available *post hoc*.

The centered EWMA-smoothed background around x_i is defined as follows:

$$s_i = \frac{\sum_{j=1}^k w_j (x_{i-j} + x_{i+j})}{\sum_{j=1}^k 2w_j} \quad (\text{Eq. 19})$$

where the weights are given by $w_j = (1 - \lambda)^j$. The differenced signal is then as follows:

$$D_{i,EWMA} = (x_i - s_i) \quad (\text{Eq. 20})$$

Here, λ is a smoothing constant that controls the decay of the weights. Smaller values of λ result in broader smoothing (i.e., more influence from distant neighbors), while larger values create an emphasis on local information.

Value for λ

To facilitate side-by-side comparisons of EWMA and lag- k differencing techniques, the smoothing parameter λ can be interpreted as a function of the effective window size k . A correspondence commonly used in practice is as follows:

$$\lambda = \frac{2}{(2k + 1)} \quad (\text{Eq. 21})$$

This choice of λ approximates the smoothing behavior of a centered MA with window width $(2k + 1)$. This formulation provides a practical guideline for choosing λ based on the desired level of background suppression: smaller values of λ (associated with larger k) yield greater smoothing and slower responsiveness, while larger λ values emphasize more recent data and enable quicker detection of transients.

Statistical Properties Under Background-Only Conditions

Assuming that the background data are random variables from a Poisson distribution where the criteria are met to approximate them as $x_i \sim N(\mu_B, \sigma_B^2)$, the statistical properties of the differenced signal $D_{i,EWMA}$ can be analyzed as follows.

Expected Value

Under the conditions above, all components in the smoothing window have the same expected value, μ_B , so the expected value of the differenced signal is again 0:

$$E(s_i) = \mu_B \Rightarrow E(D_{i,EWMA}) = \mu_B - \mu_B = 0 \quad (\text{Eq. 22})$$

Variance of the Centered EWMA-Differenced Signal

Let $W = \sum_{j=1}^k w_j$, and assume independence between the measurements in the smoothing window. The variance of the weighted average becomes the following:

$$\text{Var}(s_i) = \frac{\sum_{j=1}^k 2w_j^2 \sigma_B^2}{(2W)^2} = \frac{\sigma_B^2 \sum_{j=1}^k w_j^2}{2W^2} \quad (\text{Eq. 23})$$

Assuming x_i is independent of the surrounding values, the variance of $D_{i,EWMA}$ is the following:

$$\text{Var}(D_{i,EWMA}) = \text{Var}(x_i) + \text{Var}(s_i) = \sigma_B^2 + \frac{\sigma_B^2 \sum_{j=1}^k w_j^2}{2W^2} = \sigma_B^2 \left(1 + \frac{\sum_{j=1}^k w_j^2}{2W^2} \right) \quad (\text{Eq. 24})$$

This expression reflects the variance inflation introduced by centered EWMA smoothing. As $\lambda \rightarrow 1$, the weights concentrate at the nearest neighbors, so that their smoothing behavior approaches that of centered MP lag- k differencing. As $\lambda \rightarrow 0$, the smoothing window broadens and the variance inflation approaches that of a uniform MA.

Detection Limit for Centered EWMA Differencing

Again, given the assumptions above and assuming the distribution of the difference is of the form $D_{i,MA} \sim N(0, T^{*2} \sigma_B^2)$, the same ideas can be used to derive the critical value and detection

limit as were used for generalized MP lag- k differencing. In this case, $T^* = \sqrt{1 + \frac{\sum_{j=1}^k w_j^2}{2W^2}}$.

Now the critical limit (L_C) becomes the following:

$$L_{C,EWMA} = z_\alpha \times T^* \times \sigma_B = z_\alpha \times \sigma_B \times \sqrt{1 + \frac{\sum_{j=1}^k w_j^2}{2W^2}} \quad (\text{Eq. 25})$$

The detection limit (L_D) is as follows:

$$L_{D,EWMA} = 2z_\alpha \sigma_B \times T^* + z_\alpha^2 = 2z_\alpha \sigma_B \times \sqrt{1 + \frac{\sum_{j=1}^k w_j^2}{2W^2}} + z_\alpha^2 \quad (\text{Eq. 26})$$

This generalizes the classical detection limit framework to accommodate exponentially weighted background estimation.

Strengths and Limitations

One advantage of the centered EWMA approach is its ability to adapt smoothly to spatial gradients in background radiation levels, making it effective for environments where background conditions change gradually across space. The method also retains spatial symmetry, with differencing is balanced across all directions, which reduces potential bias introduced by

directional filtering. Additionally, the method supports fine-tuning of parameters, such as the weighting scheme or window width, to align with specific characteristics of the measurement noise or the anticipated size of anomalies. This flexibility makes the centered EWMA approach broadly applicable to a range of survey conditions and anomaly detection goals.

However, the approach is not without limitations. First, it requires access to surrounding data points during postprocessing, which may pose challenges in real-time or edge-computing applications where only local information is available. Moreover, interpretation of the filter's weights and window width depends on the context, requiring a clear understanding of the spatial structure of both background noise and target anomalies. Finally, the method assumes independence in the calculation of variance—an assumption that may not hold in the presence of spatially autocorrelated backgrounds, potentially leading to underestimation or mischaracterization of uncertainty in such cases.

3.5 Summary of Differencing Methods and Comparison to Currie's Approach

Table 1 summarizes the key properties of each lag- k differencing method relative to Currie's classical approach (Currie 1968).

Table 1 Key Properties of Various Lag- k Methods and the Currie Approach

Method	Difference Definition	Variance	T^*
MARSSIM — Non- CCD*	None	$\sigma_B^2 = \mu_B$	Not applicable
MARSSIM- CCD**	None	σ_B^2	Not applicable
Generalized MP Lag- k	$x_i - \frac{(x_{i+k} + x_{i-k})}{2}$	$1.5 \times \sigma_B^2$	$\sqrt{1.5}$
MA	$x_i - \frac{1}{2k} \sum_{j=1}^k (x_{i-j} + x_{i+j})$	$\sigma_B^2 \left(1 + \frac{1}{2k}\right)$	$\sqrt{\left(1 + \frac{1}{2k}\right)}$
Centered EWMA	$(x_i - s_i)$, where s_i is the exponentially weighted average of the neighbors	$\sigma_B^2 \left(1 + \frac{\sum_{j=1}^k w_j^2}{2W^2}\right)$	$\sqrt{\left(1 + \frac{\sum_{j=1}^k w_j^2}{2W^2}\right)}$

* "MARSSIM—Non-CCD" uses the Currie classical approach with the MARSSIM two-stage scanning equation, which assumes the background variance equals the mean count and divides by $\sqrt{0.5}$ for surveyor efficiency. Shown for comparison only.

** "MARSSIM-CCD" uses the same global background estimate, but uses the variance instead of the mean and no surveyor efficiency factor.

Each localized method estimates the local background from neighboring observations, and that estimate carries sampling variability of its own. Differencing adds it to the variability of the measurement, so the standard deviation of the differences always exceeds that of a single background measurement. T^* is the factor by which it does, and because the critical and

detection limits are proportional to the standard deviation of the differences, T^* passes directly into the detection limit.

Its value follows from how many observations enter the background estimate. MP differencing uses two, giving $T^* = \sqrt{1.5} \approx 1.22$; MA uses $2k$, giving $\sqrt{(1 + 1/2k)}$, or about 1.02 at $k = 10$; centered EWMA weights all observations exponentially and falls between the two. The MARSSIM-CCD approach estimates the background globally, so $T^* = 1$. T^* is thus the cost of localization, and it sets the tradeoff examined in Sections 3.9 and 3.10: pooling more observations lowers the cost but leaves the method less able to follow a background that changes from place to place. Under stationary conditions, there is no structure to remove and the low- T^* methods are preferred—the $A = 0$ standard deviations in Table 2 stand at 1.00, 1.02, 1.02, and 1.21 times σ_B , matching the predicted values. Where the background varies, the variability MP incurs is offset by the structure it removes, while the $T^* = 1$ of the global approach is illusory, its σ_B inflated by the trend the method cannot remove.

When these methods are applied in practice, each measure within the variance box is replaced with the actual sample variance of the differences from the observed data. For example, for generalized MP lag- k differencing, $1.5 \times \sigma_B^2$ in the equation is replaced with the estimated variance of the differences, or $\hat{\sigma}_{D,MP}^2$.

3.6 Choosing the Appropriate Detection Method

The choice of differencing method should be informed by the nature of the background radiation, the expected spatial characteristics of anomalies, and the operational priorities of the survey. The method of Currie (1968) is ideal when the background is stable and measurements are globally consistent, but it does not account for local variability. Generalized MP lag- k differencing offers flexibility for targeting small elevated areas of varying sizes and balances spatial sensitivity with reasonable variance inflation. MA smoothing is useful for surveys with moderate local variation, providing a fixed-window background estimate with improved robustness against noise. When background gradients are present or dynamically changing, centered EWMA smoothing provides an adaptive, data-driven solution that symmetrically weights surrounding observations, making it particularly effective for environments with gradual background shifts. Ultimately, method selection should consider not only statistical performance but also the geospatial characteristics of the area surveyed, data availability, and the tradeoff between detection sensitivity and the risk of false positives.

It follows that the a priori and postprocessing stages should not be treated as separate method selection problems. The a priori MDC is a statement about the decision rule to be applied to the survey data, and it describes the survey performed only if the same method and the same lag distance are used in both. Where the two requirements conflict—the reference area analysis indicating one lag distance and the expected extent of an elevated area requiring another—the larger should be adopted and the a priori MDC recomputed at that value.

The comparisons presented in Sections 3.9 and 3.10 are performed on background-only data, and this bears on how they should be read. Where no source is present, the methods differ only in the variability of the differenced signal, represented by T^* , and those pooling the most observations therefore produce the lowest detection limits. A background-only reference area cannot, however, exhibit the behavior of the alternative distribution. When an elevated area is present in survey data, and its extent is comparable to the neighborhood used to estimate the local background, observations affected by the source contribute to that estimate. The estimated

background is drawn upward, the expected difference is attenuated, and the sensitivity actually achieved falls short of the value derived from reference area data. This cost is not represented in the a priori comparison, which therefore favors the smoothed methods; it is most pronounced for centered EWMA, in which the weights assigned to neighboring observations never fully vanish, and least pronounced for generalized MP differencing, in which only two observations enter the background estimate and both may be placed beyond the expected extent of an elevated area by appropriate selection of k .

3.7 Bias and Precision Checks on Detection Limit

In real-world radiological detection scenarios—particularly in field environments—the assumptions underlying the classical calculations of the critical limit (L_C) and detection limit (L_D) are often violated. Traditional methods, which rely on idealized assumptions such as normality or Poisson-distributed counting statistics with constant variance, may yield inaccurate or misleading results when the background data are overdispersed—that is, more variable than the assumed model predicts, so that the variance exceeds the mean—or skewed, autocorrelated, or otherwise nonconforming. Overdispersion commonly arises where the surveyed area contains more than one radiological population or a spatial trend, so that the recorded variability reflects real differences in background in addition to counting statistics. In such cases, alternative statistical approaches are necessary to ensure valid and defensible detection decisions.

Beyond addressing violations of model assumptions, these alternative techniques also have an important role in assessing the *precision* and *bias* of L_D estimates derived from standard methods. Techniques such as robust estimation, nonparametric inference, and resampling procedures—including the bootstrap—offer valuable tools for quantifying uncertainty and generating alternative L_D estimates. These techniques can yield not only more resilient thresholds under nonideal conditions, but also independent verification of results obtained under classical assumptions.

The next section focuses on the bootstrap technique, which provides a flexible and powerful approach for estimating L_D in the presence of complex data behavior, as well as a means of evaluating the variability and potential bias of conventional estimates.

3.8 Bootstrap Technique

The bootstrap technique is a nonparametric resampling method used to estimate the sampling distribution of a statistic by drawing repeated samples from the observed data. Bootstrapping provides a robust, nonparametric means of quantifying uncertainty, particularly in complex settings where analytical solutions may be difficult to derive. In the context of the radiological detection problem considered above, the bootstrap technique begins with a set of background measurements assumed to represent the underlying population variability. A large number of bootstrap samples (typically 1,000 or more) are generated by randomly sampling with replacement from the original dataset, each sample being the same size as the original. For each bootstrap replicate, a statistic of interest (e.g., the standard deviation of the background) is computed and used to calculate derived quantities, such as the L_C or L_D , using standard parametric formulas. This process produces a distribution of values that reflects the empirical variability in the background data, enabling the analyst to derive robust point estimates and precision intervals.

Assessing Bias in the Estimated Detection Limit

One potential limitation in conventional L_D estimation is bias, especially when background variation is estimated from small or noisy samples. Using the bootstrap, the empirical bias of the L_D estimator can be assessed directly:

- (1) Compute the L_D from the original dataset:

$$\hat{L}_{D,i,orig} = 2z_\alpha \hat{\sigma}_B \times T_i + z_\alpha^2 \quad (\text{Eq. 27})$$

- (2) Using the set of N differences calculated from the original dataset using each method (e.g., MP, MA, and EWMA), take N samples with replacement and calculate the $\hat{\sigma}_B^*$ and $\hat{L}_D^*$ corresponding to each:

$$\hat{L}_D^{*(m)} = 2z_\alpha \hat{\sigma}_B^{*(m)} \times T_i + z_\alpha^2, \quad m = 1, \dots, M \quad (\text{Eq. 28})$$

where M is the number of bootstrap samples.

- (3) Repeat step (2) B times.
- (4) Compute the average bootstrap estimate:

$$\bar{L}_D^* = \frac{1}{M} \sum_{m=1}^M \hat{L}_D^{*(m)} \quad (\text{Eq. 29})$$

- (5) Estimate the bias:

$$\text{Bias}(\hat{L}_D^*) = \bar{L}_D^* - \hat{L}_{D,orig} \quad (\text{Eq. 30})$$

If bias is substantial, then corrections or alternative estimation strategies may be warranted.

Bootstrap Precision Intervals for the Detection Limit

The bootstrap technique provides a powerful, assumption-light method for constructing a precision interval around the L_D :

$$PI_{Boot}^{(1-\gamma)} = \left[\hat{L}_D^{*(\gamma/2)}, \hat{L}_D^{*(1-\gamma/2)} \right] \quad (\text{Eq. 31})$$

where the endpoints are the empirical $\gamma/2$ and $(1 - \gamma/2)$ quantiles of the $\hat{L}_D^*$ distribution.

This precision interval provides a quantitative measure of the precision associated with the estimated detection limit. It is especially relevant when doing the following:

- reporting L_D estimates in regulatory submissions or technical reports

- comparing L_D values across different survey methods (e.g., lag- k versus classical)
- conducting sensitivity analyses or validation studies
- communicating uncertainty in support of risk-informed decision-making

Importantly, this precision interval is not used to adjust or redefine the detection threshold; the quantity L_D remains a fixed threshold for deciding whether a given signal warrants further investigation. Instead, the precision interval conveys how precisely that threshold is estimated based on available data, which can be particularly useful in quality assurance, method comparison, and transparent reporting contexts.

3.9 Simulation Example

This example is inspired by the methodology presented in Section 4.3.1 of PNNL (2023), which evaluates the performance of various statistical tests for detecting localized contamination in radiological surveys. That study compared traditional, nonlocalized detection approaches with localized hypothesis testing methods—specifically the MP test—under both constant and spatially varying background radiation conditions. The example below extends that framework by incorporating additional smoothing-based methods, including centered MA and EWMA, to assess their ability to identify a point-source contamination event. Detection probabilities are simulated across a range of mean source intensities, and detection limits are compared to evaluate the sensitivity of each method.

The simulation features a synthetic radiological survey consisting of $n = 1,000$ equally spaced spatial locations along a transect. At each location, background radiation levels are modeled as Poisson-distributed counts, with the mean background defined by a sinusoidal function:

$$\mu(x) = 1000 + A \times \sin\left(\frac{2\pi x}{n}\right) \quad (\text{Eq. 32})$$

where A controls the amplitude of background variation. When $A = 0$, the background is constant; when $A > 0$, the background exhibits spatial fluctuation. A point-source contamination is simulated by injecting an additional Poisson-distributed signal at a single location—specifically, where the background is at its minimum—to represent a localized increase in radiation. The source strength is varied from 0 to 250 cpm in increments of 10 cpm, giving 26 source levels, and 1,000 realizations are generated at each level. The detection limit obtained from the simulation is the lowest source level at which the empirical detection probability reaches 0.95, and it is therefore resolved only to within the increment used. The resulting dataset mimics realistic field measurements, including spatial trends and stochastic measurement noise.

Before detection performance is evaluated, the dependence cutoff optimization procedure described earlier in this section is applied to the simulated reference background to establish the lag distance k . The procedure is applied to the background-only realization, before injection of the point source, consistent with field practice in which the correlation structure of the background is characterized before survey data are evaluated. (Deriving k from data containing the injected source would be circular, because the location of contamination is not known in advance of a survey.) Applying the procedure with a practical correlation threshold of $b = 0.075$, a required fraction of 0.80, window sizes up to 15, a consecutive-lag requirement of 6, and a maximum lag of 200 yields a selected lag of $k = 1$.

The choice of practical threshold warrants explanation, because the autocorrelation function is itself estimated and carries sampling error of approximately $1/\sqrt{n}$, or 0.032 for $n = 1,000$. A

practical threshold set below this noise floor will be breached by sampling variability alone: at $b = 0.05$, approximately 11 percent of lags fall outside the bound even when no true correlation is present, which causes the stability rules to fail on randomness and drives the selected lag artificially large. Setting $b = 0.075$, roughly 2.4 times the standard error, ensures that the bound reflects practical negligibility rather than estimation noise. As a general rule, the practical threshold should be no smaller than two to three times $1/\sqrt{n}$.

The selected lag of $k = 1$ indicates that no practical serial dependence is present at any lag. This is the expected result, as the simulated counts are independent Poisson variates about a constant mean, and it confirms that the procedure does not manufacture structure where none exists. The result should be interpreted as an indication that the correlation structure provides no basis for selecting a smoothing scale, rather than as a recommendation to smooth over a single lag. Under stationary conditions, the most efficient local estimate of background is the one formed from the largest available neighborhood, which is the global mean; consistent with this, the detection limits for the MA and EWMA methods decrease monotonically as the window widens and converge from above to the MARSSIM value. A selected lag of 1 therefore constitutes a method-selection result: it indicates that a localized method is not required, and that the global approach is appropriate.

This finding explains the pattern of results reported below. The MARSSIM-CCD method achieves the lowest detection limit because a global background estimate is optimal when no spatial structure is present, while the MP method is penalized because differencing statistically independent observations inflates variance without removing any background structure. The absence of practical dependence in the reference background is the direct cause of both outcomes. For purposes of comparison, and to keep in line with the simulation done by PNNL, the localized methods are nevertheless evaluated at $k = 10$. Under these conditions the detection limit is insensitive to the lag distance across a broad range, varying by less than approximately 2 percent for values of k between 10 and 60, so the comparison presented in Table 2 does not depend materially on this selection. It should also be noted that a lag of 1 is degenerate for the EWMA method, because the smoothing constant $\lambda = 2/(k + 1)$ equals 1 at $k = 1$, meaning that zero weight is assigned to every neighboring observation; a minimum lag of 2 is therefore enforced whenever the localized methods are applied.

For each method, the simulation is repeated 1,000 times per source level. To align with the simulation done by PNNL, a value of 10 is used for k . The detection probability is computed as the proportion of simulations where the observed centered count or difference at the contamination event exceeds a calculated critical limit (L_C). The detection limit (L_D) is determined as the source strength at which the method achieves a 95 percent detection probability. This setup provides a fair and controlled comparison of each method's sensitivity under idealized background conditions.

The divergence is also positional. Repeating the $A = 50$ scenario with the source placed at the maximum of the background rather than at its minimum leaves the localized results unchanged at 130, 110, and 110 cpm, but it moves the achieved MARSSIM detection limit from 180 cpm to 80 cpm, against the same calculated value of 155 cpm. A global background estimate therefore does not describe the detectability actually obtained at any particular location once the background varies.

The detection limits computed from the reference background can be compared directly against the source strength at which each method achieves 95 percent detection in the simulation. For the localized methods, the two agree to within one source-level increment in every scenario, so

the calculated limit predicts the performance actually obtained. For the global method, they diverge as background structure increases: at $A = 50$ the calculated limit of 155 cpm is set against an achieved 180 cpm, and at $A = 100$ the method does not reach 95 percent detection anywhere in the simulated range.

Constant-Background Scenario ($A = 0$)

In this initial scenario, the background radiation level is assumed to be spatially uniform, simulating an idealized survey environment devoid of background drift or natural spatial variability. Each location along the transect is modeled as an independent realization from a Poisson distribution with a constant mean of 1,000 cpm. This controlled setup provides a baseline for evaluating the performance of each detection method under stationary conditions, where global estimates are expected to perform well and localized methods can be assessed for potential variance inflation. Before detection results are explored, the simulated background data are visualized (Figure 1) to establish a reference for subsequent comparisons.

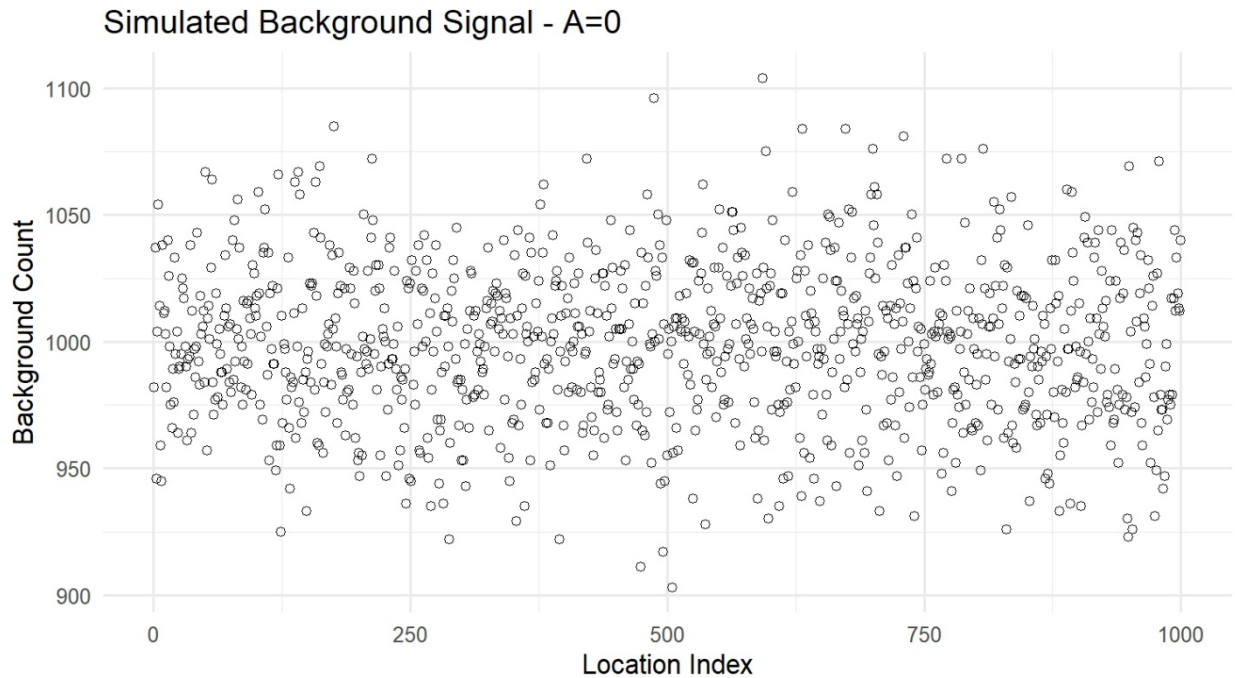


Figure 1 Time-Series Plot of Simulated Background Count Data for $A = 0$

Figure 1 offers a baseline view of a statistically stationary background, representing a scenario with no inherent spatial variability. Such a configuration isolates the performance of a detection method under idealized conditions, where any observed anomalies can be attributed solely to statistical fluctuations or deliberately injected signals, rather than to environmental or structural changes in background. This controlled setting allows for a clear evaluation of each method's sensitivity and precision in the absence of confounding background trends.

Table 2 gives the detection limit statistics for each method under these stationary conditions.

Table 2 Comparison of Standard Deviations, Critical Limits, and Detection Limits for Simulated Background Data with $A = 0$

Technique	Standard Deviation	Critical Limit (L_C)	Detection Limit (L_D)
MARSSIM-CCD	30.77	50.61	103.93
MP	37.34	61.42	125.55
MA	31.36	51.58	105.86
EWMA	31.42	51.68	106.07

Under constant background conditions, the MARSSIM-CCD method demonstrated the lowest observed variability, resulting in the smallest estimated critical and detection limits. This outcome aligns with expectations, as the method leverages a global background estimate that is optimal in stationary environments with no spatial structure. The MA and EWMA methods both performed comparably well, offering a favorable tradeoff between noise reduction and sensitivity. In contrast, the MP method exhibited lower effectiveness in this scenario, as indicated by its higher variability and correspondingly larger detection limit. These findings highlight the importance of aligning the choice of detection method with the background characteristics of the survey environment.

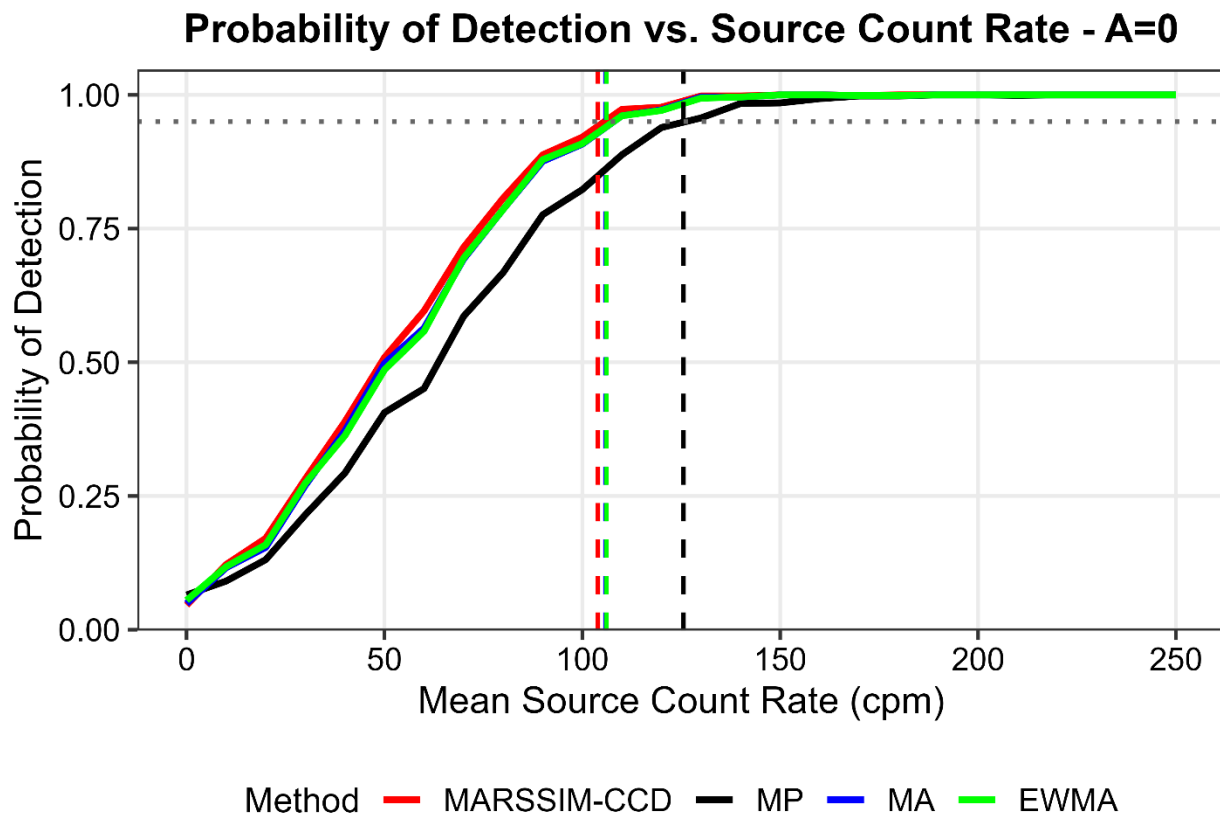


Figure 2 Probability of Detection as a Function of Source Count Rate for Each Method, Using Simulated Background Data with $A = 0$ (note: values for MA and EWMA are approximately the same)

Figure 2 presents the simulation results for the constant-background scenario, in the form of a summary plot giving the probability of detection as a function of the mean source count rate (in cpm), which represents the strength of the injected point-source signal. The x-axis corresponds to the mean signal intensity, while the y-axis shows the empirical probability of detection, calculated as the proportion of simulations in which the method successfully identified the source as exceeding background levels. A horizontal dotted line is drawn at 0.95 to indicate the target detection probability threshold (95 percent), reflecting the commonly used criterion for acceptable sensitivity. Vertical dashed lines mark the estimated detection limits (L_D) for each method, defined as the lowest source strength at which the 95 percent detection probability is achieved. The methods are color-coded for clarity, with red, black, blue, and green respectively corresponding to the MARSSIM-CCD, MP, MA, and EWMA methods.

As Figure 2 shows, the MARSSIM-CCD method (red curve), which relies on a global estimate of the background, demonstrates the highest sensitivity, achieving a 95 percent detection probability at the lowest mean source strength. This can be seen from the fact that the red vertical dashed line (corresponding to the detection limit (L_D) for MARSSIM-CCD) is the leftmost. Such performance is consistent with expectations, as global background estimation is optimal when the background is homogeneous.

The MA and EWMA methods perform similarly well. Their detection probability curves nearly coincide with that of MARSSIM-CCD across the entire source-strength range, and their L_D values are only slightly to the right of the MARSSIM-CCD value. This suggests that although localized averaging introduces a modest increase in variance, it does not substantially degrade sensitivity under constant background conditions. The results thus support their utility, particularly if some background variability may be present.

In contrast, the MP method exhibits lower sensitivity under these conditions: it has the rightmost vertical dashed line, meaning it requires a noticeably higher source strength to reach a 95 percent detection probability. This weakness in performance is expected, as the local differencing of the MP method introduces additional variability when applied to a flat background, thereby inflating the detection threshold.

Figure 2 reinforces the conclusion that, under uniform background conditions, global or smoothed local methods (specifically, MARSSIM-CCD, MA, and EWMA) demonstrate greater sensitivity than the MP method. All three of the former techniques achieve the target 95 percent detection probability at comparatively low source strengths; in other words, they are effective at identifying low-level signals within stable and well-controlled environments. By comparison, the MP method exhibits poorer performance, requiring substantially higher source strengths to reach the same detection threshold.

Nonconstant-Background Scenario ($A = 50$)

In this simulation scenario, the background radiation level varies spatially, representing a more realistic survey environment in which ambient radiation naturally fluctuates across different locations. To emulate such variation, the background mean at each point along the transect is modulated using a sine wave with an amplitude of 50, which introduces a smooth periodic rise and fall in the expected count rates. This structured variability captures the type of background drift that might be encountered in practical field settings, such as surveys conducted over heterogeneous terrain or in environments with subtle environmental gradients. As with the previous scenario, the background data are examined and the underlying spatial variations characterized before the performance of each detection method is assessed.

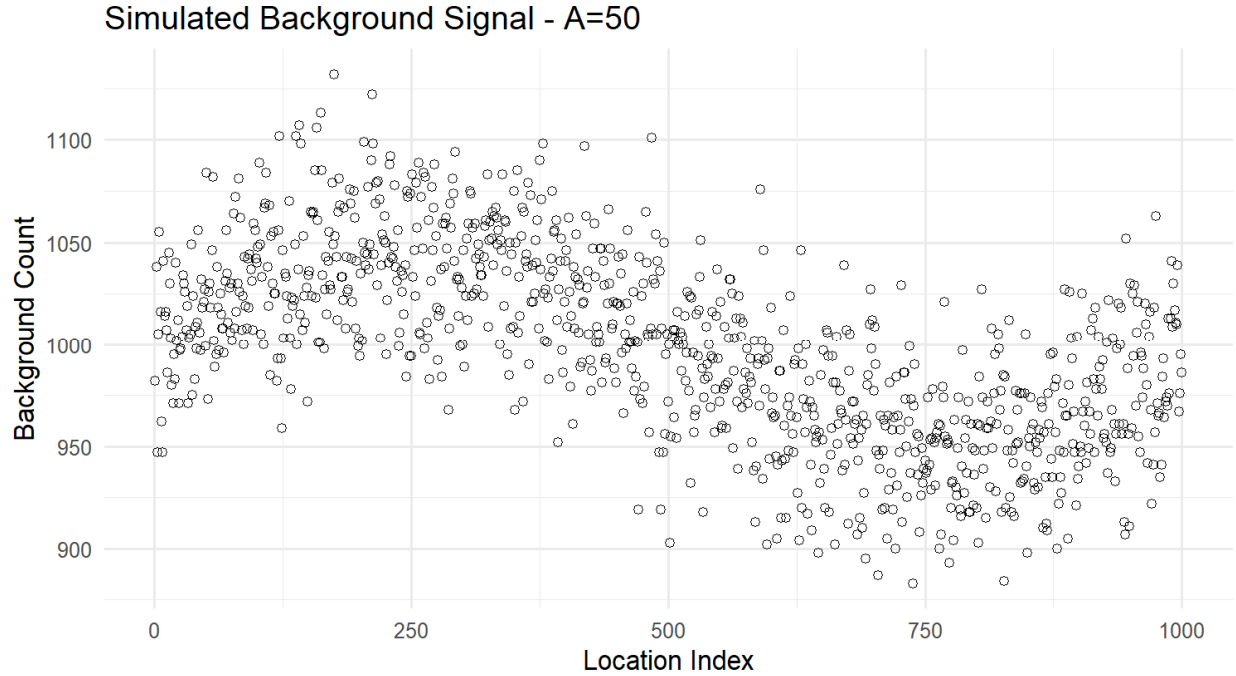


Figure 3 Time-Series Plot of Simulated Background Count Data for $A = 50$

Figure 3 depicts a background radiation field characterized by mean values that vary spatially as described above, resulting in a nonstationary signal with smooth, wavelike fluctuations. Such fluctuations in background counts represent natural environmental variation, which can either obscure true anomalies or mimic contamination, thereby complicating detection. To be effective in such a context, a detection method must account appropriately for background drift to minimize the risk of false negatives or overly conservative detection thresholds. This scenario serves as a critical test of each method's capacity to adapt to local trends in the background signal and accurately isolate genuine point-source anomalies in the presence of structured noise.

The dependence cutoff optimization procedure is performed for this scenario using the same parameter settings as in the constant-background case—a practical correlation threshold of $b = 0.075$, a required fraction of 0.80, window sizes up to 15, a consecutive-lag requirement of 6, and a maximum lag of 200. Holding these settings fixed across scenarios is essential: tuning them separately for each dataset would defeat the purpose of an objective selection procedure. Applied to the background-only realization before injection of the point source, the procedure selects the PACF and a lag distance of $k = 18$.

The ACF provides no usable cutoff for these data. Because the sinusoidal component is a deterministic feature of the mean rather than a stochastic dependence, it induces correlation between observations at every separation along the transect. The ACF consequently remains near 0.5 at all lags examined and never approaches the practical bound within the range over which it can be reliably estimated, which extends to roughly $n/4$. The optimization procedure correctly reports that no cutoff exists on the ACF.

The PACF resolves this ambiguity. By controlling for the values at all shorter lags, it removes the indirect correlation transmitted through the background trend and isolates the direct

dependence between observations. The partial autocorrelations decline from approximately 0.5 at lag 1 to within the practical bound by lag 18, and the procedure therefore selects the PACF as the series providing the stronger and more stable evidence for a cutoff. This behavior parallels that of the field survey data examined later in this section, where the ACF likewise persists across many lags while the PACF exhibits an interpretable decay; the simulation with structured spatial variation is thus a useful analogue for real survey conditions.

It is instructive that the same parameter settings return $k = 1$ for the constant-background scenario and $k = 18$ here. This is because the practical threshold is calibrated against the stationary case, in which the correct answer is known to be the absence of dependence, and is then carried unchanged into the structured-variation case. The procedure distinguishes between the two conditions without any scenario-specific adjustment.

The selected lag is nevertheless sensitive to the analyst-defined parameters. Across reasonable combinations of practical threshold, required fraction, and maximum window size, the selection ranges from approximately 10 to 42, and repeated realizations of the same generating process yield values between 11 and 29. This variation is expected, because the partial autocorrelations in the region of the cutoff are of the same order as their sampling error of $1/\sqrt{n}$. The variation is, however, of limited practical consequence: across lag distances from 10 to 42 the detection limit changes by less than 0.5 percent for the MP method and by less than 2.5 percent for the MA and EWMA methods. The selection is therefore robust in the sense that matters for survey design—the detection limit is insensitive to the precise lag chosen—and the results reported below are not materially dependent on the selected value.

With this complexity in mind, $k = 18$ is chosen for the analysis below. Table 3 presents the detection limit statistics for each method.

Table 3 Comparison of Standard Deviations, Critical Limits, and Detection Limits for Simulated Background Data with $A = 50$

Technique	Standard Deviation	Critical Limit (L_c)	Detection Limit (L_D)
MARSSIM-CCD	46.29	76.14	154.98
MP	37.09	61.01	124.73
MA	31.31	51.50	105.71
EWMA	31.43	51.70	106.10

The results in Table 3 underscore the importance of employing local smoothing or local comparison techniques in nonstationary environments. These techniques (i.e., MA, EWMA, and MP) are better equipped to adapt to spatial fluctuations in background radiation, as evidenced by their lower standard deviation values and stronger detection performance. In contrast, global approaches such as MARSSIM, while effective under uniform backgrounds, become increasingly unreliable as structured variation in the background intensifies. The inability of global methods to account for localized trends can lead to inflated detection limits or missed anomalies. Figure 4 further illustrates these performance differences with a plot of the probability of detection as a function of the source count rate for each method.

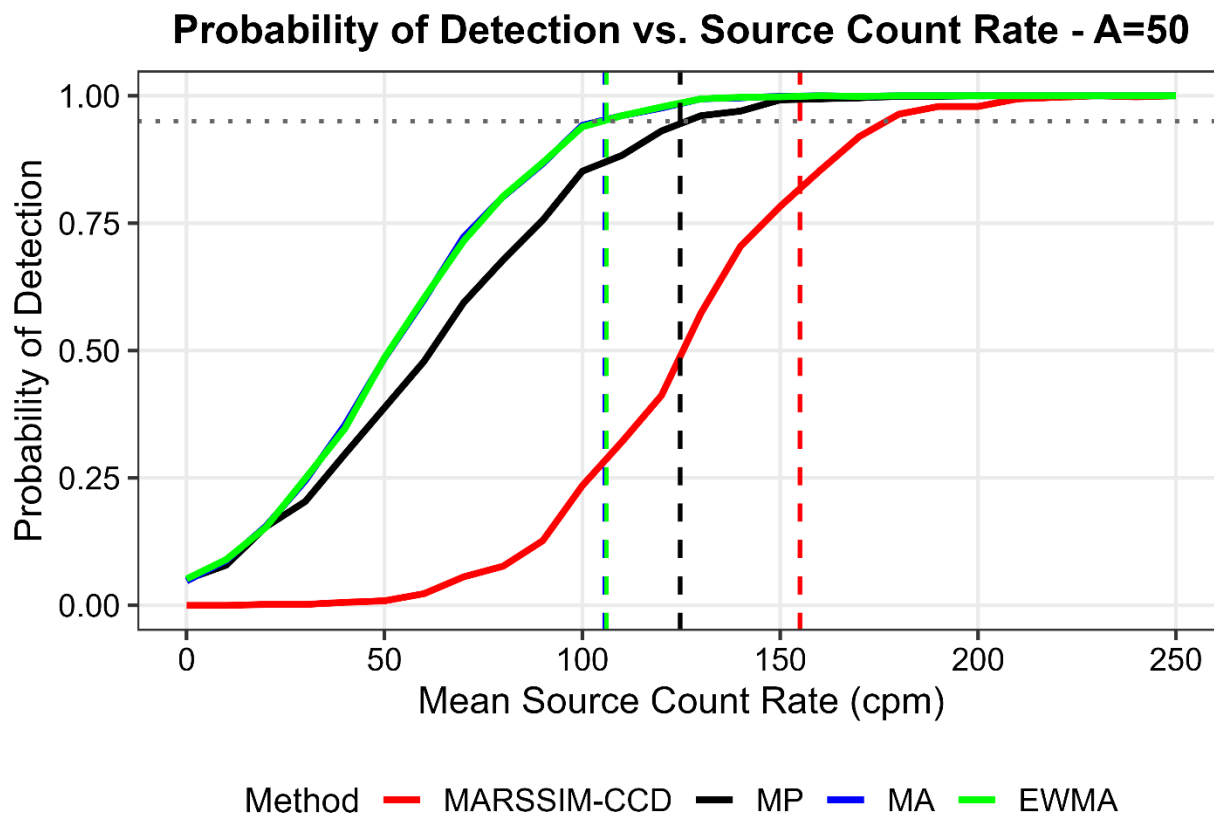


Figure 4 Probability of Detection as a Function of Source Count Rate for Each Method, Using Simulated Background Data with $A = 50$ (note: values for MA and EWMA are approximately the same)

As shown in Figure 4, the four methods vary drastically in performance in this scenario. EWMA has the strongest performance, achieving a 95 percent detection probability at the lowest source strength (indicated by the green vertical dashed line). By assigning greater weight to nearby observations while still smoothing the background, EWMA effectively adapts to local structure, making it well suited for environments with gradual background variation.

MA performs nearly as well as EWMA, with a detection limit only slightly higher. Its uniform local averaging effectively suppresses background trends while limiting sensitivity to random fluctuations.

MP outperforms MARSSIM-CCD and maintains reasonable sensitivity, although it remains slightly less effective than MA or EWMA. Its symmetric differencing reduces the influence of slow background drift by offsetting gradual changes on either side of the central observation. However, it should be noted that this cancellation arises largely from the structure of the simulated background in this particular scenario, which gradually increases and then decreases around the central point. Symmetric differencing offsets the opposing trends in this structure and reduces the magnitude of the resulting differences. If the central point instead represented a true localized elevation rather than a feature created by the artificial background pattern, the resulting differences could be larger. Consequently, the success of MP in this simulation may overstate its effectiveness for detecting elevated areas in actual survey data. In practice,

measurements surrounding a true source may also be influenced by the source itself, reducing differences between neighboring points and potentially leading to overly optimistic expectations for achievable scan MDC values.

The MARSSIM-CCD method exhibits the weakest performance in this scenario, with the highest detection limit among all methods. This weakness is expected, as MARSSIM-CCD's global estimation of background variance does not account for spatial trends. Consequently, the structured variability of the background in this simulation inflates the method's variance estimate, raising the detection threshold.

These results collectively emphasize the advantage of localized techniques in handling complex, spatially varying backgrounds.

Nonconstant-Background Scenario ($A = 100$)

Next, to explore the performance of each method under more pronounced background variation, an additional scenario is considered in which the amplitude of the background modulation is increased to $A = 100$. This introduces a stronger and more clearly defined periodic structure in the background signal. Figure 5 illustrates the background data in this scenario.

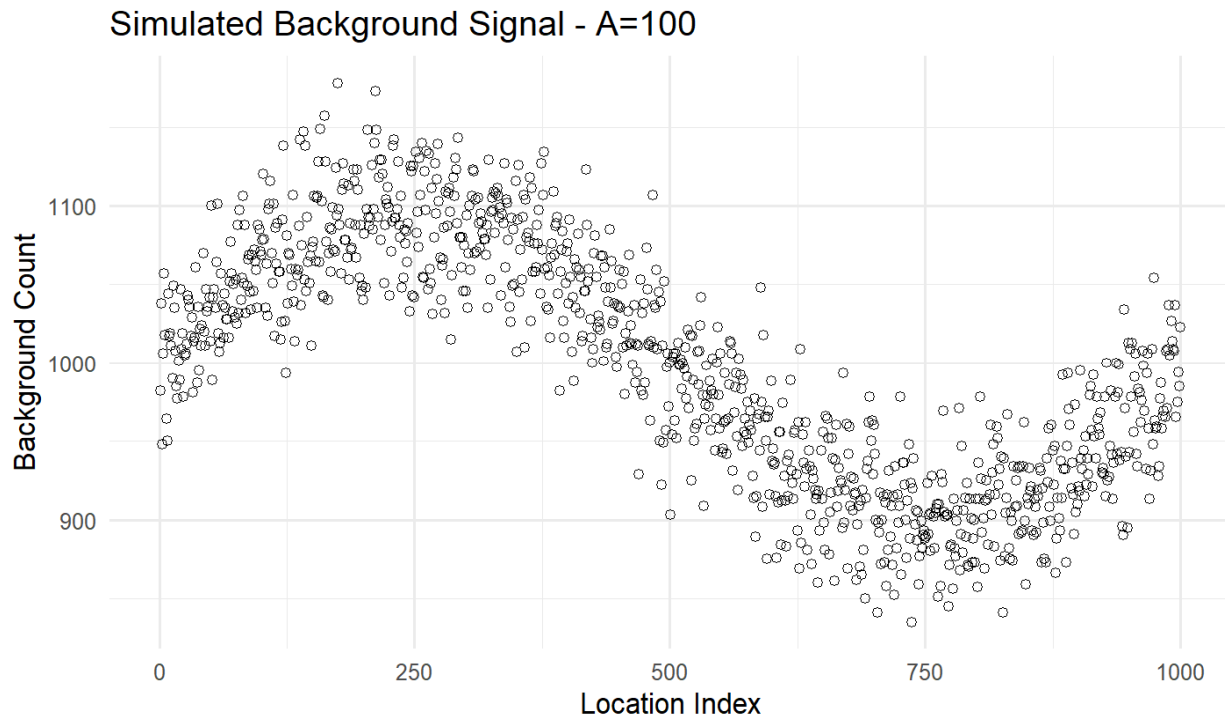


Figure 5 Time-Series Plot of Simulated Background Count Data for $A = 100$

As shown in Figure 5, the residuals of the underlying curve here exhibit even less variability than in the scenario with $A = 50$.

The dependence cutoff optimization procedure applied to this scenario, with the same parameter settings as before, selects the PACF and a lag distance of $k = 17$. This result is nearly identical to the lag of 18 selected for the $A = 50$ scenario, despite the doubling of the

background amplitude. In both scenarios the sinusoidal mean completes a single cycle over the length of the transect, so the spatial scale of the background structure is identical; only its magnitude differs. This suggests that the selected lag is insensitive to the amplitude of the background variation; therefore, a common lag distance may reasonably be applied across survey areas where the background variations differ in magnitude but have comparable spatial structures. The selected lag also falls within the interval over which the detection limit is near its minimum for each of the localized methods. It should not, however, be interpreted as an optimal value: as shown below, the detection limits vary only slightly across a broad range of lag distances, and the optimization procedure should be understood as identifying a defensible value within that range rather than a unique best value.

The sensitivity analysis for this scenario yields selected lags ranging from approximately 6 to 23 across reasonable combinations of the practical threshold, required fraction, and maximum window size—a narrower range than that obtained for $A = 50$. Across this range, the detection limit varies by less than 0.5 percent for the MP method and by less than 4 percent for the MA and EWMA methods. Even the extremes of the parameter space therefore produce detection limits that are practically indistinguishable. It should be noted that automated robustness classifications based solely on the spread of the selected lag may characterize such a result as weakly robust; classifications of that kind describe the stability of the parameter rather than the stability of the decision, and they should always be reported alongside the corresponding variation in the detection limit, which is the quantity of regulatory consequence.

The amplified periodic structure introduced by $A = 100$ results in smoother and more predictable background trends, which may facilitate detection for methods that effectively model or adjust for such a structure. In particular, this setup provides a clearer signal-to-noise environment, allowing for a more distinct evaluation of each method's capacity to identify point-source anomalies. Figure 6 presents the detection results.

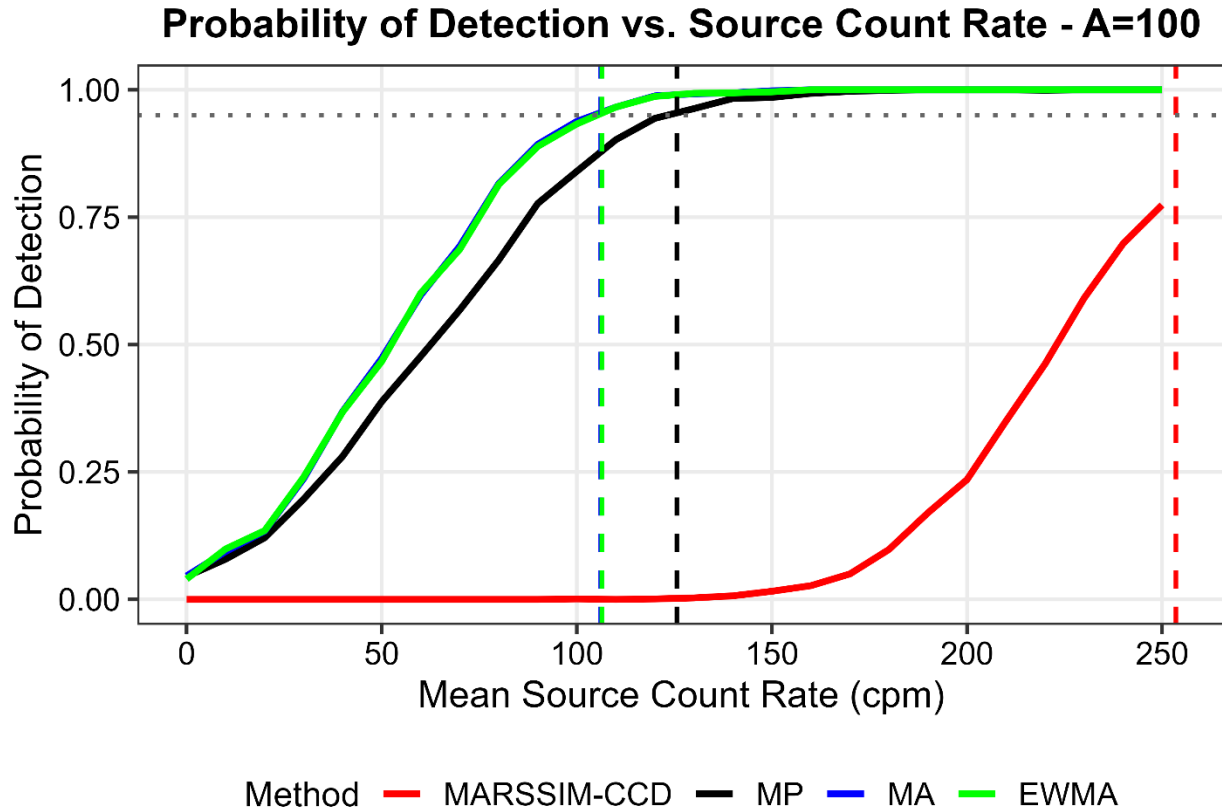


Figure 6 Probability of Detection as a Function of Source Count Rate for Each Method, Using Simulated Background Data with $A = 100$ (note: values for MA and EWMA are approximately the same)

Figure 6 shows that the performance patterns observed in the $A = 50$ scenario persist here: the MP, MA, and EWMA methods continue to exhibit relatively strong detection capabilities, while MARSSIM again performs poorly. In fact, the MARSSIM-CCD detection probability curve fails to reach the 95 percent threshold at all; it barely achieves 75 percent coverage across the range of simulated source strengths. Thus, the predefined upper bound of 250 cpm for the mean source strength—selected based on earlier simulations—is inadequate for MARSSIM-CCD in this scenario. This suggests that under conditions with strong background structure, global methods may require substantially higher signal intensities to achieve reliable detection.

The results of the $A = 50$ and $A = 100$ simulations underscore the importance of accounting for spatial variation in the background when selecting detection methods. When structured variation is present, localized smoothing methods—specifically EWMA and MA—perform considerably better than global methods such as MARSSIM-CCD. These localized methods adapt effectively to structured background variation and are therefore more sensitive to weak point-source signals. The MP method offers an intermediate solution, leveraging local differencing to account for background trends while maintaining computational simplicity. Among all of the approaches considered, EWMA consistently emerges as the most sensitive in the presence of spatially structured noise. Collectively, these findings highlight the need to incorporate background

nonstationarity into detection strategies to ensure robust and reliable identification of low-level sources in complex survey environments.

3.10 Field Survey Example

Section 3.9 provides a simple baseline comparison of the performance of the MARSSIM-CCD, MP, MA, and EWMA methods under well-defined conditions. It is not expected that actual field measurements will conform to these conditions.² Therefore, in this section, the four methods are evaluated using real-world CCD from a scan survey performed in an open land area. The area was approximately 350 meters by 350 meters, for a total of approximately 30 acres. More than 10,000 survey scan measurements with a 2 inch by 2 inch (2"x2") NaI detector, coupled with a rate meter and global positioning system (GPS), were recorded at a nominal frequency of once every 2 seconds.

Figure 7 displays the raw count data in the order in which they were recorded, as the surveyor progressed along the transect. The horizontal axis is the observation index rather than a position coordinate, so the figure shows how the count rate evolves along the scan path rather than its distribution in space. Geographic coordinates were recorded with each measurement, and Section 4 presents the corresponding mapped view for an example dataset. The plot reveals fluctuations that indicate a varying background area. The apparent segments showing higher and lower counts reflect the passage of the transect into and out of the elevated area. A heatmap of the data could be used for further evaluation with advanced geostatistical methods (as discussed in Section 6.3 of NUREG-1507). Examining the raw data in this form is essential for identifying regions of interest, assessing data quality, and selecting appropriate detection and smoothing techniques for subsequent analysis.

² Uniform surfaces, such as flooring and walls composed of a single, common material, may yield data trends similar to those of the simulations. However, gamma measurements in the outdoor environment can be expected to have higher levels (e.g., 6,000 to 12,000 cpm) and variability.

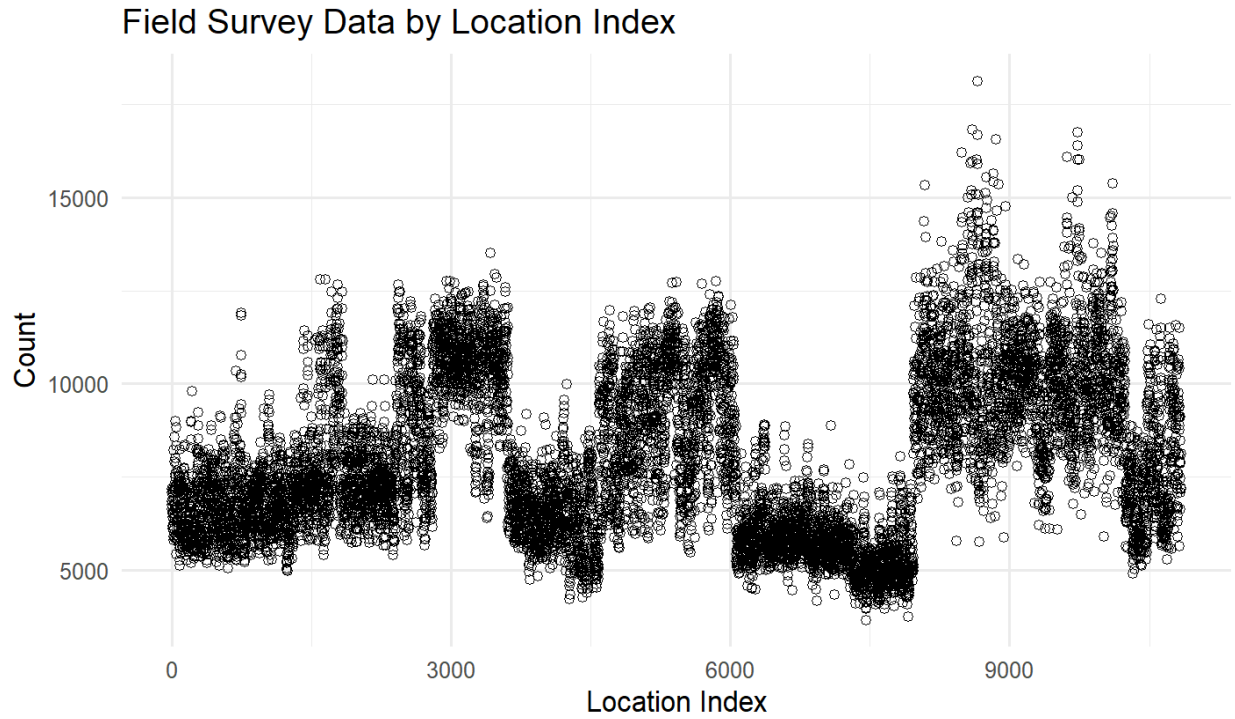


Figure 7 Time-Series Plot of Simulated Field Survey Count Data against Location Index

Given the observed patterns and irregular fluctuations in the raw data, localized smoothing methods such as MA or EWMA are anticipated to provide the most effective signal detection for this dataset. To assess the underlying structure in the data, the ACF and PACF plots for the data, shown in Figure 8, are examined. These plots provide insights into the presence and persistence of potential lag-based relationships, which are critical for selecting and tuning appropriate modeling strategies.

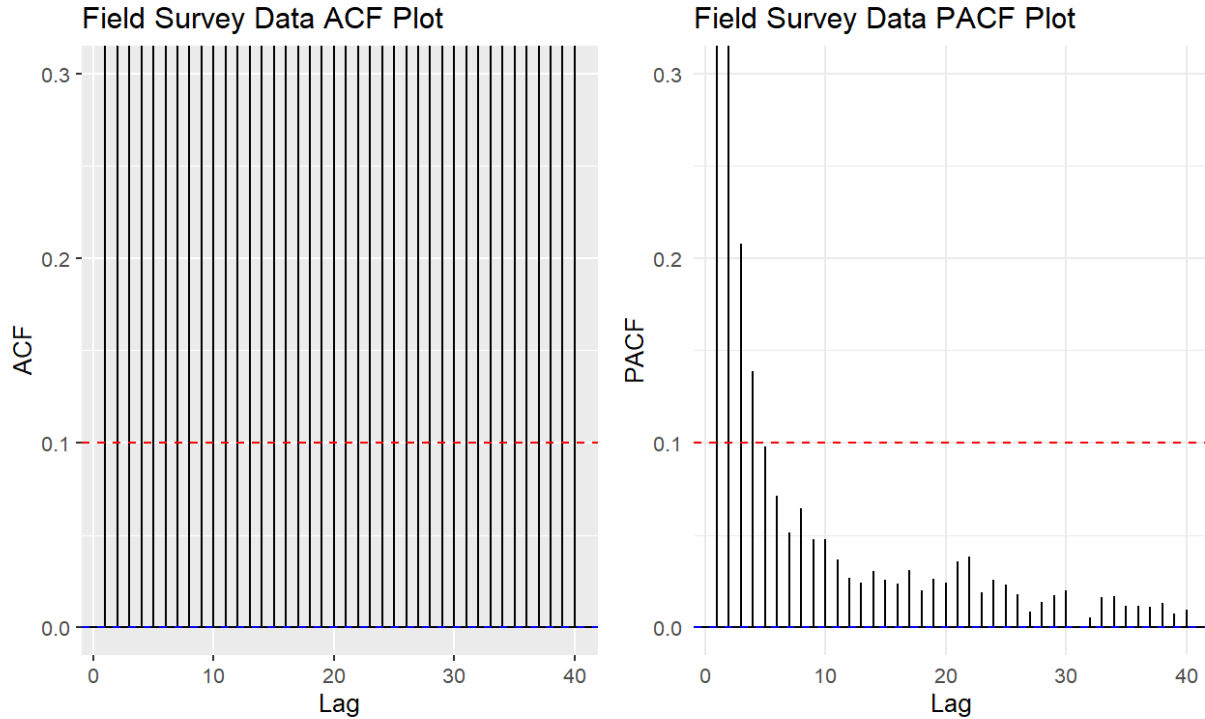


Figure 8 ACF and PACF Plots for Field Survey Data

The ACF and PACF plots provide an initial reading of the dependence structure, and the optimization procedure and its sensitivity analysis then confirm and quantify it. The ACF plot shows correlation persisting across many lags without settling, which indicates strong underlying structure but offers no point at which dependence can be said to have decayed. The PACF is therefore the more informative display; it shows the partial autocorrelations tapering markedly after the first few lags, suggesting that the process can be represented with a short finite memory and that a cutoff lag of roughly 4 to 6 is plausible. The optimization procedure described earlier in this section was applied to establish that value formally, using the same parameter settings adopted throughout the simulation examples: a practical correlation threshold of 0.075, a required fraction of 0.80, window sizes up to 15, a consecutive-lag requirement of 6, and a maximum lag of 200. The threshold of 0.075 is itself supported by these data, in that the selected lag is invariant for thresholds between 0.055 and 0.090. The 0.075 value lies approximately at the center of that interval and comfortably above the sampling-error band of $2/\sqrt{n} = 0.041$, below which the optimization procedure begins to track estimation noise. With these parameters, the procedure selects the PACF and a lag distance of $k = 5$.

The sensitivity analysis was run across reasonable combinations of practical threshold (0.04–0.09), required fraction (0.8–0.9), and maximum window size examined (15, 20). The sensitivity analysis established that the optimal lag distance does not depend on the particular parameter settings chosen, nor on which of several apparent breaks in the correlogram an analyst might have identified by eye: across all combinations of parameters considered, the median selected lag was 5, with an interquartile range of 3 to 5 and a modal value of 5 in 21 percent of cases. Lags outside the interval (3, 7) arose only in corners of the parameter grid.

Table 4 presents the standard deviations of the differenced values for each detection method, alongside the corresponding detection limits (L_D). These metrics quantify the variability reduction and sensitivity of each method. Although the spatial complexity observed in the data suggests that the localized methods will provide superior performance, the results from the MARSSIM—Non-CCD approach are included as a baseline for comparison.

Table 4 Comparison of Standard Deviations and Detection Limits for Field Survey Data

Technique	Standard Deviation (counts/interval)	Detection Limit (L_D) (counts/interval)	Detection Limit (L_D) (cpm)
MARSSIM—Non-CCD	NA	74	2,220
MARSSIM-CCD	48.69	163	4887
MP	32.31	109	3,270
MA	25.92	88	2,639
EWMA	25.38	86	2,587

The standard MARSSIM—Non-CCD method is presented here solely for comparison purposes. Although it yields the smallest L_D , the method is not valid for CCD; and its low value reflects an inappropriate application of using the mean rather than variance for calculating an L_D using the Currie method.

As expected, the standard deviation of the raw data is considerably higher than that of the differenced dataset produced by each localized method, demonstrating the effectiveness of these methods in reducing variability. The EWMA-differenced data exhibit the lowest variability. A similar pattern is observed in the L_D estimates; as in the simulation scenarios with nonconstant background structure, the EWMA method yields the lowest L_D , indicating the highest sensitivity to weak signals. This is followed closely by the MA and MP methods, with the MARSSIM-CCD method producing the highest L_D . These findings reinforce the observation that localized methods perform better than global methods in environments with spatial heterogeneity. In such environments, global methods tend to suffer from inflated variance and diminished detection power.

Given that this analysis was based on real-world data, the bootstrap procedures outlined in Section 3.8 were applied to assess the bias and the precision of the L_D estimates. Through repeated resampling of the differences, distributions of the L_D estimates were obtained from which bias values and precision intervals were derived. Table 5 summarizes the results, including point estimates of bias, lower precision limits (LPLs), upper precision limits (UPLs), and the sizes of the 95 percent bootstrap precision intervals. These metrics offer insight into the reliability and stability of each method when applied to data with real-world variability.

Treating the differences as exchangeable assumes that residual dependence between them is negligible, which is the same condition the lag distance is selected to satisfy (Section 3.1). Where appreciable dependence remains, the resulting intervals will be too narrow and a block resampling scheme would be required. The estimated bias is expected to be small for datasets of this size; it is reported as a check that the distributional assumptions hold rather than as a correction to be applied.

The resampling is applied to the differences rather than to the recorded measurements. Each difference has already been formed using the ordering of the data, so that information has been used before resampling begins and is not discarded by it. The set of N differences produced by a given method is resampled with replacement to the same size, the standard deviation and detection limit are recomputed on each replicate, and the procedure is repeated 1,000 times; because each method produces a different set of differences, each has its own bootstrap distribution. Resampling the recorded measurements themselves would destroy the ordering on which the methods depend and is not performed.

Table 5 Bias and 95 Percent Bootstrap Confidence Intervals for Each Method for Field Survey Data

Type	Bias	LPL (cpm)	UPL (cpm)	UPL–LPL (cpm)
MARSSIM-CCD	–0.531	4,844.65	4,926.72	82.07
MP	0.155	3,238.6	3,302.13	63.53
MA	0.124	2,616.02	2667.53	51.51
EWMA	–0.026	2,562.03	2,613.83	51.8

As shown in the table, EWMA exhibits the smallest bias (in absolute value) and MARSSIM-CCD the largest. However, the magnitude of bias in all cases remains below 1, which is negligible in the context of measurement values on the order of thousands. Thus, in practice, the differences in bias across methods are unlikely to influence decision-making. In terms of precision, the MA method yields the narrowest confidence interval, indicating the greatest stability in the L_D estimates. The EWMA method performs comparably to MA. These results confirm that localized smoothing approaches achieve both low bias and high precision in L_D estimation.

In view of its superior sensitivity and high precision, EWMA emerges as the most effective method for estimating the L_D for this dataset.

Overall, the analysis in Sections 3.9 and 3.10 served to assess the performance of the proposed detection methods across a spectrum of data complexities, comprising data from three simulations and one real-world field survey. The progression of datasets was intentionally designed to incorporate increasing structural and statistical complexity. The first dataset, simulated with constant background radiation, provided a baseline for performance under ideal, stationary conditions. The subsequent simulations introduced structured background variation—first with moderate noise ($A = 50$) and then with more pronounced periodic structure and reduced noise ($A = 100$). Finally, the field survey dataset represented a real-world scenario featuring overlapping spatial patterns, nonstationarity, and elevated variability.³

Across all scenarios in this staged framework, the EWMA method consistently matched or outperformed the alternatives, demonstrating superior adaptability, sensitivity, and precision.

³ The MDCR values of the simulated datasets and the field survey dataset cannot be directly compared, as each has a different basis. The simulated datasets start with a nominal 1,000 cpm mean, whereas the field survey dataset has a mean value around 9,000 cpm.

These results strongly support the use of EWMA as a reliable and effective approach for detection in both controlled and real-world survey settings.

4 Impacts of Varying Radiological Background Within an Area

The example in this section differs from that of Section 3.10 in that the proposed reference area was found to contain two areas of differing radiological background, which are identified, separated, and evaluated individually below.

As described in Section 1, in determining the a priori MDC, a reference area should be selected that is representative (e.g., geologically and radiologically) of the areas to be surveyed. It is possible that from the CCD for the reference area, the distribution of the count rate will appear bimodal, suggesting more than one radiological background within the area. Example gamma walkover data were obtained to illustrate this possibility for a potential reference area. The data were collected using a towed array of six 2"x2" NaI detectors mounted to a vehicle, along with a GPS unit to log geographic coordinates together with the gamma count rate data. The example data were collected from areas referred to as SU1B and SU1C.

Figure 9 displays the time-series plot of the example dataset. This plot shows a distinct segmentation between two subareas of the data. A histogram of the gamma count rate data, given in Figure 10, likewise shows a bimodal distribution. To determine whether the radiological characteristics of the area do indeed vary spatially, the data were plotted using the GPS coordinates collected during the survey (Figure 11). Figure 11 shows a clear spatial difference within the overall area, as the northern section appears to have lower count rates than the southern section. The difference between the two subareas creates increased variability within the combined dataset.

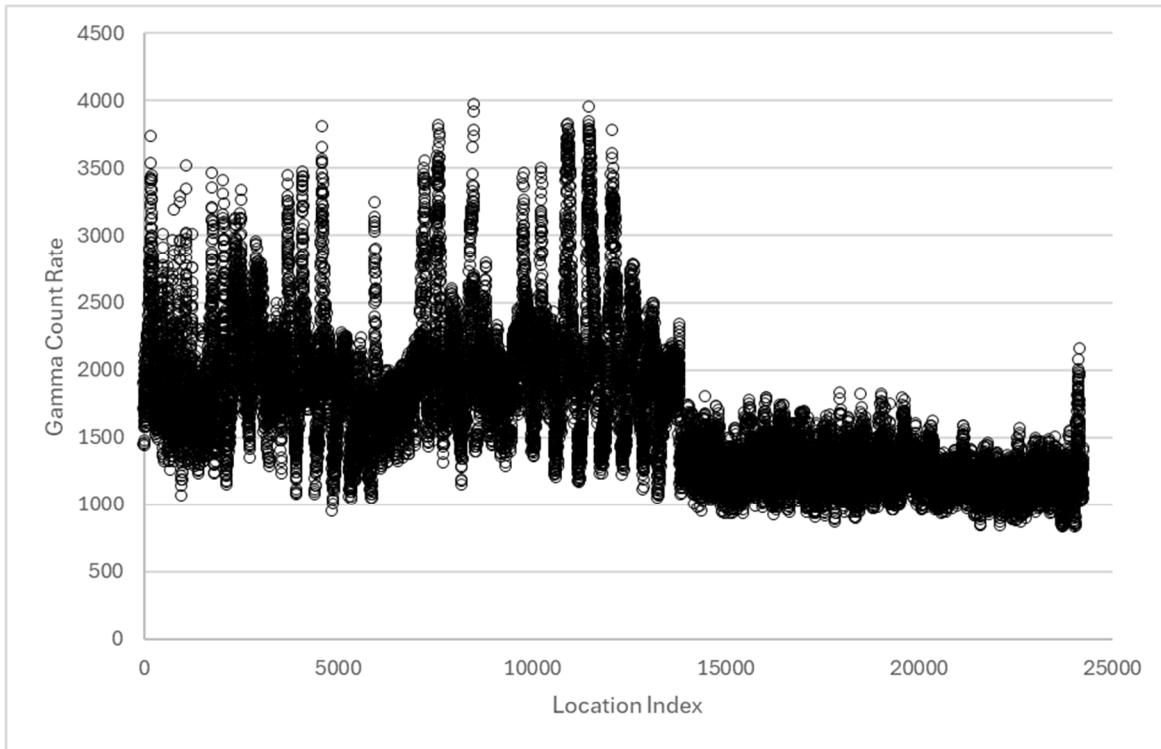


Figure 9 Time-Series Plot of Example Data with Varying Radiological Background

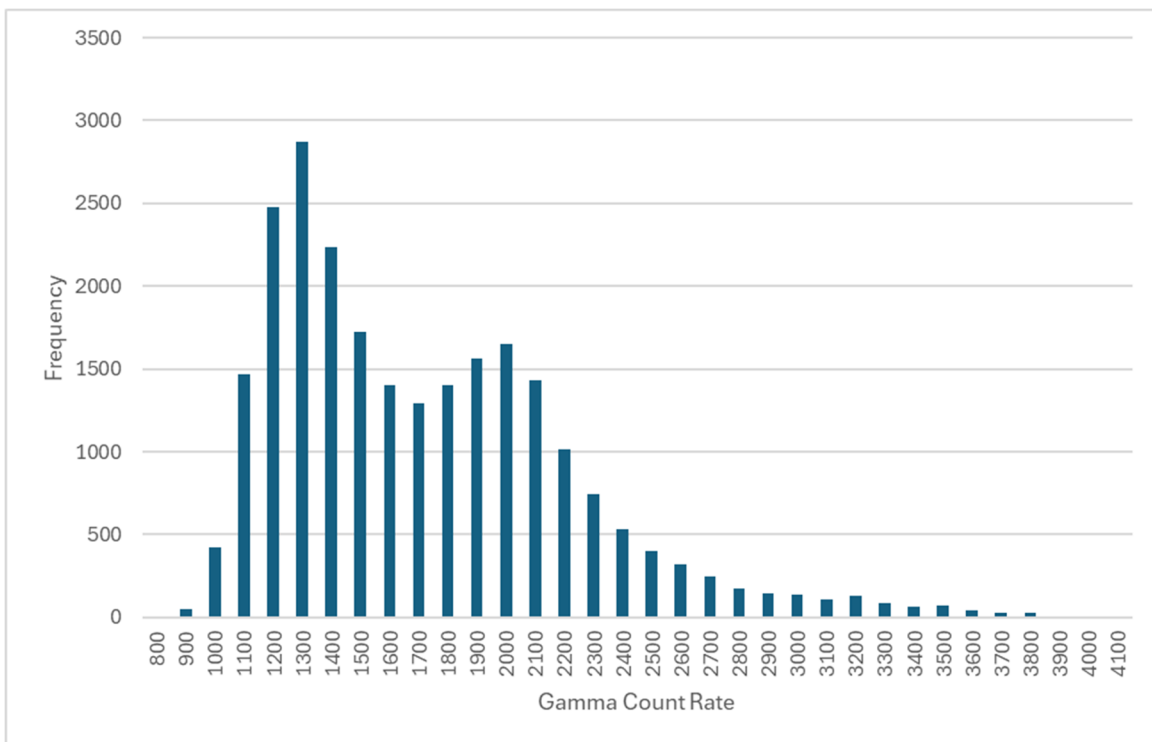


Figure 10 Gamma Count Rate Histogram for SU1B and SU1C Example Data Combined

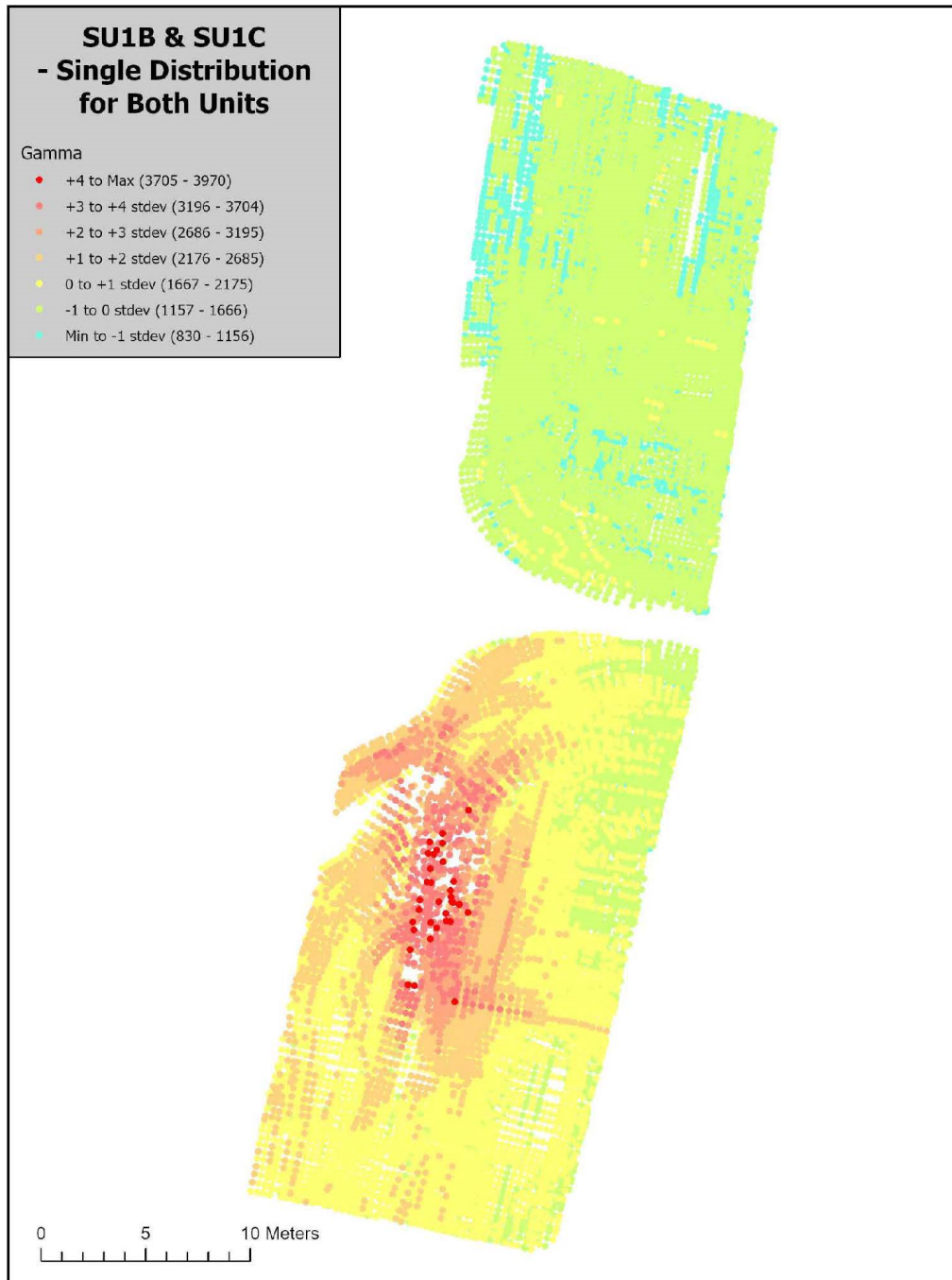


Figure 11 Map of Gamma Count Rate Data for SU1B and SU1C Example Data Combined

Since the proposed reference area can be divided into two subareas with differing radiological characteristics, mapping each subarea separately can allow for a more accurate depiction of the

distribution of activity. Figures 12 and 13 present plots of the data for the southern and northern subareas, respectively.

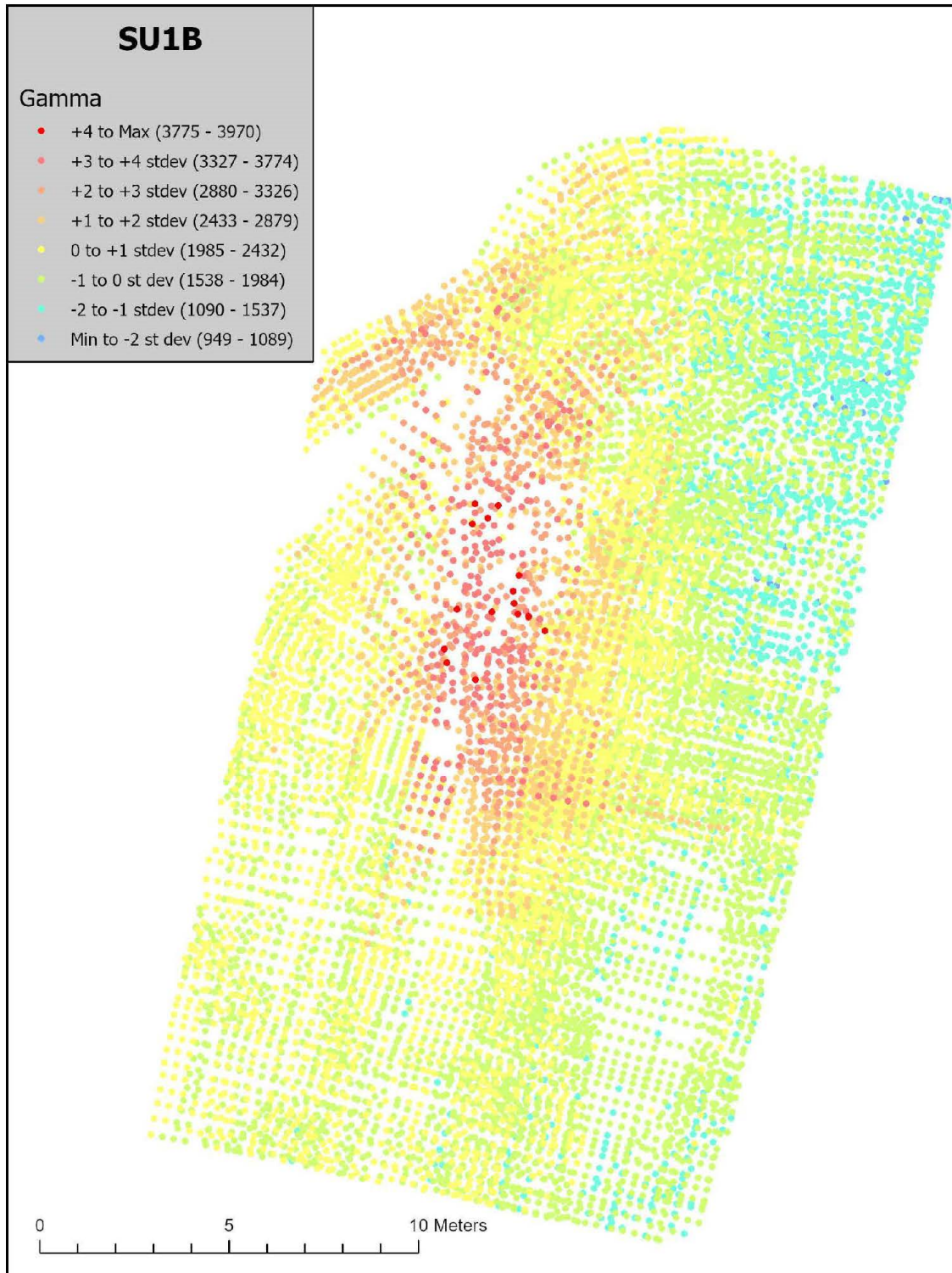


Figure 12 Map of Gamma Count Rate Data for SU1B Example Data

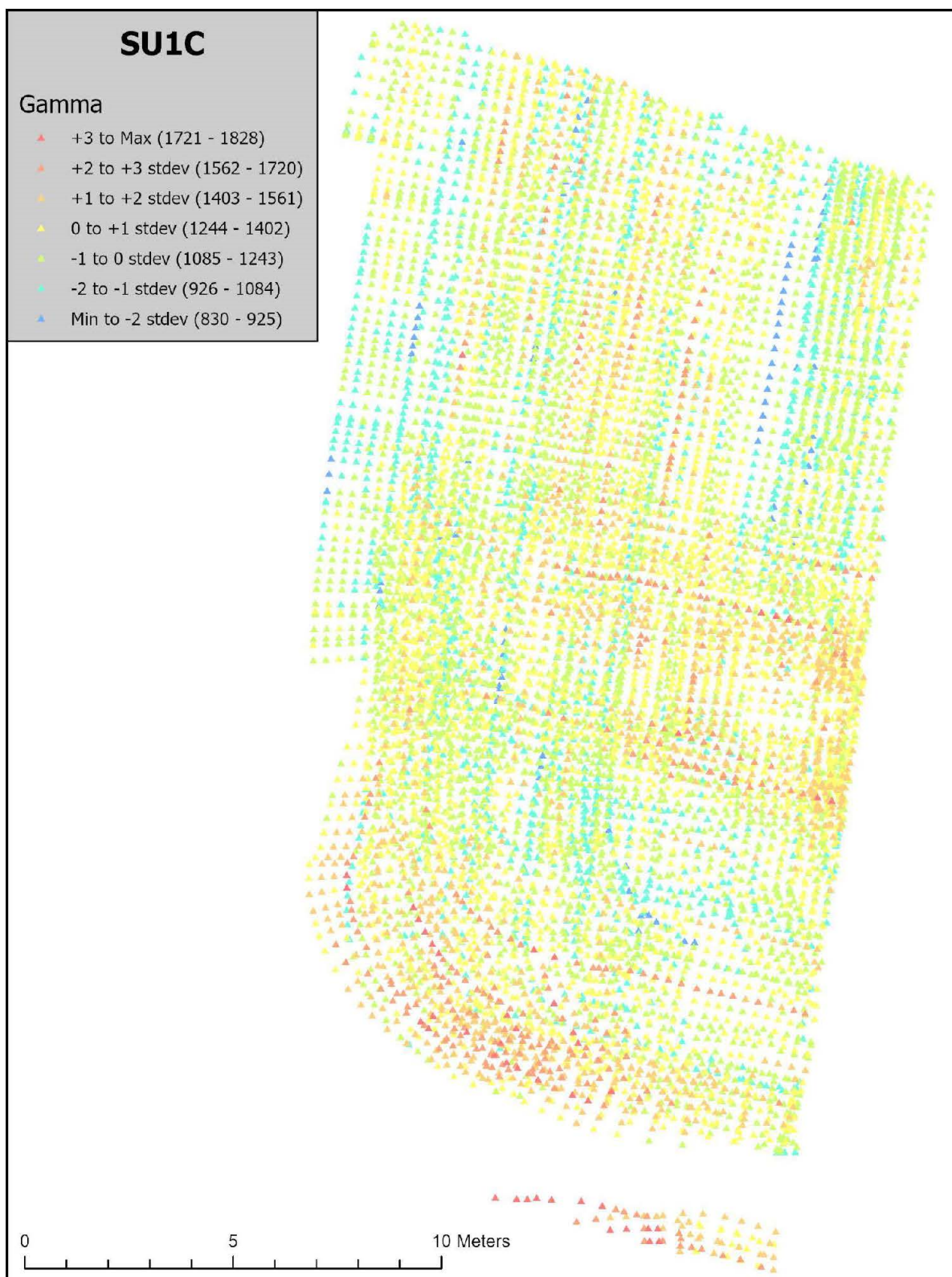


Figure 13 Map of Gamma Count Rate Data for SU1C Example Data

The two distinct subareas having been identified, the corresponding datasets (SU1B and SU1C) were separated to be analyzed independently.

Figure 14 presents the time series of raw counts for SU1B. The average count is approximately 1,984 cpm, with substantial variability and an upward run toward the middle of the sequence.

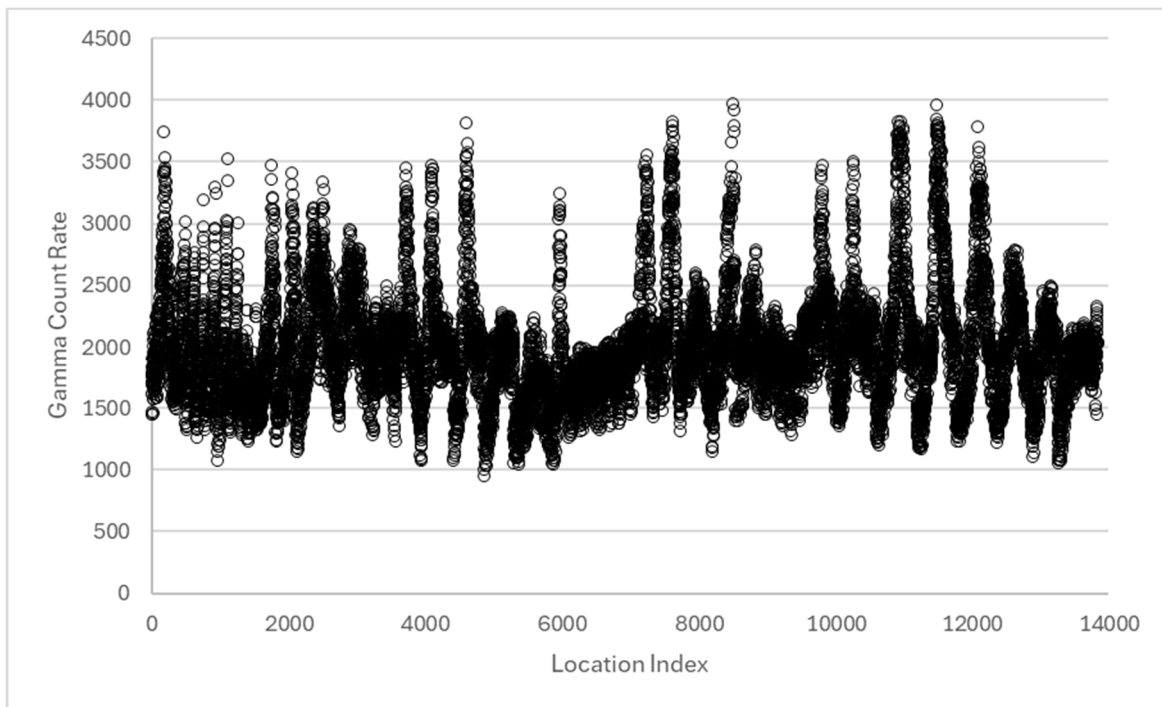


Figure 14 Time-Series Plot of SU1B Example Data

To determine the lag distance to use for the SU1B dataset, the ACF and PACF plots were examined (Figure 15). The ACF plot shows persistent correlation across many lag distances, while the PACF indicates tapering beyond lag 18. This suggests the data may reasonably be modeled using an autoregressive (AR) structure with up to 18 lag terms.

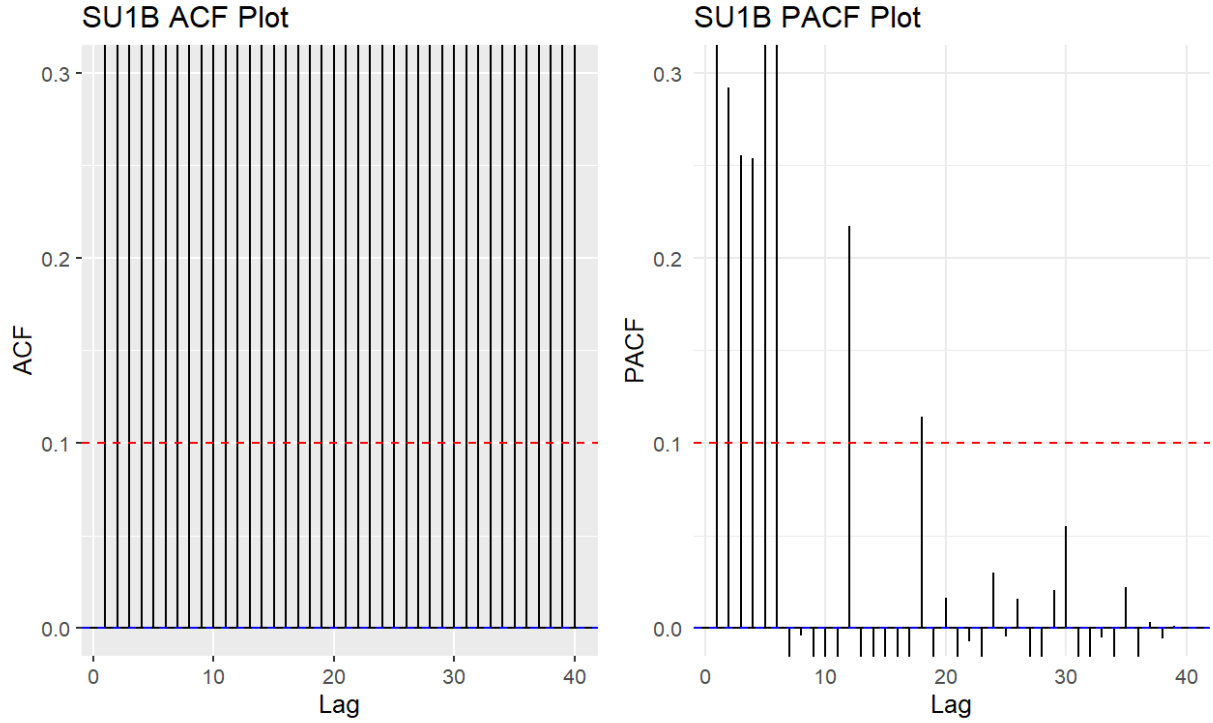


Figure 15 ACF and PACF Plots for SU1B Example Data

The optimization procedure described earlier selects a lag distance of $k = 18$. The selected lag is invariant across practical thresholds between 0.060 and 0.075, and moves in a stepped rather than erratic fashion outside that interval—to 21 at 0.055, to 28 below 0.050, and to 12 at 0.080—indicating that the selection responds to genuine features of the correlation structure rather than to estimation noise; the sampling-error band for this unit is $2/\sqrt{n} = 0.017$, far below the adopted threshold. A sensitivity analysis across 64 combinations of practical threshold, required fraction, and maximum window size gives a median selected lag of 18 with an interquartile range of 12 to 21, a full range of 4 to 30, and 18 as the modal result (occurring in 20 percent of cases).

Table 6 presents the standard deviations of the differenced values for each detection method, along with the corresponding detection limits (L_D). As before, although the spatial complexity of the data suggests that the localized methods will provide superior performance, the results from the MARSSIM-CCD and MARSSIM—Non-CCD approaches are included for comparison.

Table 6 Comparison of Standard Deviations and Detection Limits for the SU1B Example Data

Technique	Standard Deviation (counts/interval)	Detection Limit (L_D) (counts/interval)	Detection Limit (L_D) (cpm)
MARSSIM—Non-CCD	NA	37.73	1,131
MARSSIM-CCD	14.91	51.77	1,553
MP	6.63	24.52	736
MA	7.01	25.77	773
EWMA	7.07	25.97	779

As seen in Table 6, consistent with previous examples, the localized methods produce lower variability and lower values of L_D than the global (MARSSIM) methods. The MP method yields the lowest L_D , followed closely by MA and EWMA, while MARSSIM-CCD performs worst.

The bootstrap procedures outlined in Section 3.8 were applied to assess the bias and precision of the L_D estimates for the SU1B dataset. Table 7 summarizes the results, including point estimates of bias, LPLs, UPLs, and the sizes of the 95 percent bootstrap precision intervals.

Table 7 Bias and 95 Percent Bootstrap Confidence Intervals for Each Method for SU1B Example Data

Type	Bias	LPL (cpm)	UPL (cpm)	UPL-LPL (cpm)
MARSSIM-CCD	0.268	1,529	1,577	47
MP	0.430	719	753	34
MA	0.164	762	785	23
EWMA	0.138	769	791	22

The bootstrap analysis shows that all methods produce negligible bias (<1), with EWMA offering the narrowest precision interval (and hence the greatest stability).

Figure 16 presents the raw count data for SU1C, with an observed mean of approximately 1,243 cpm. Overall, the distribution appears relatively stable, though it exhibits a gradual downward trend across much of the sequence, followed by a distinct upward shift toward the end. This structure suggests serial dependence in the data. For CCD, the observations are ordered in both time and space; the two orderings correspond only to the extent that the scan speed is held constant.

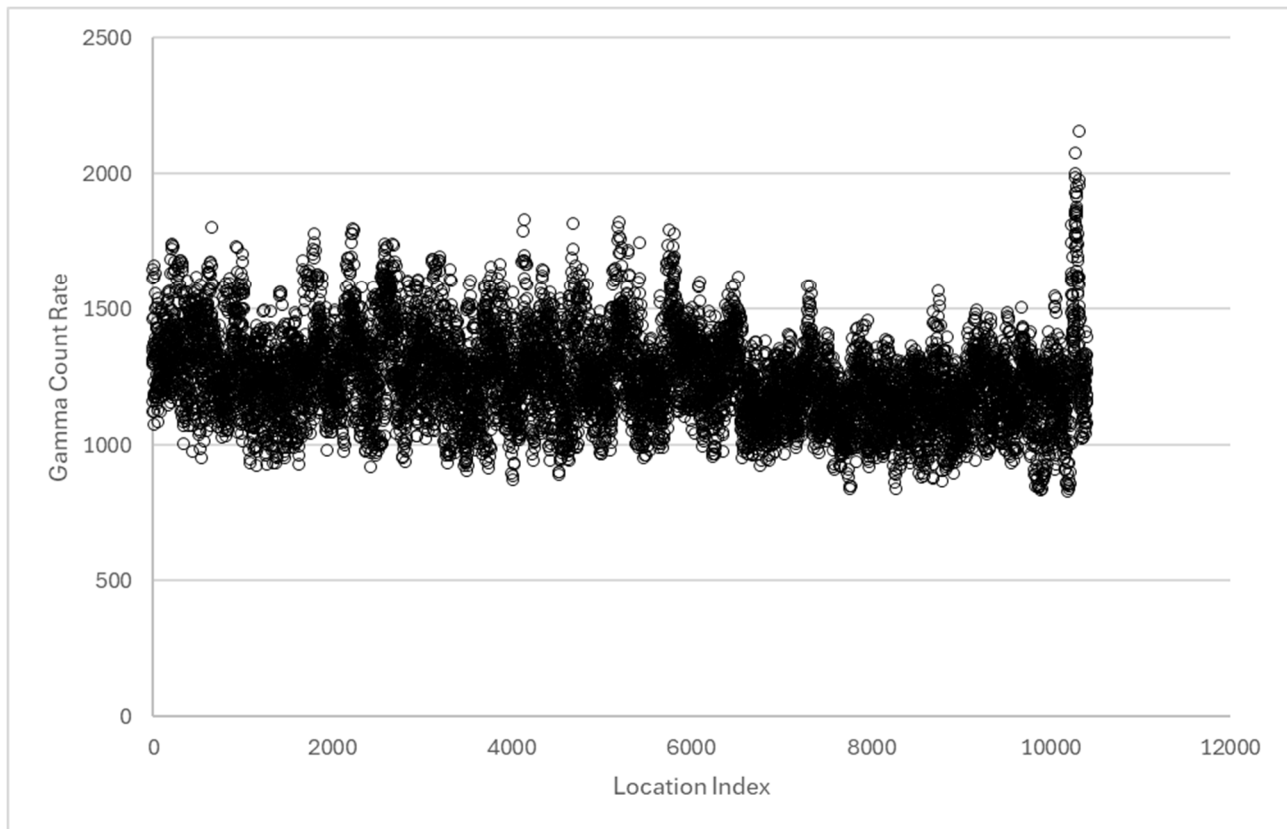


Figure 16 Time-Series Plot of SU1C Example Data

To characterize the autocorrelation and identify an appropriate lag distance for AR modeling, the ACF and PACF plots were examined (Figure 17). The ACF demonstrates a gradual decay, while the PACF exhibits a distinct cutoff after lag 12.

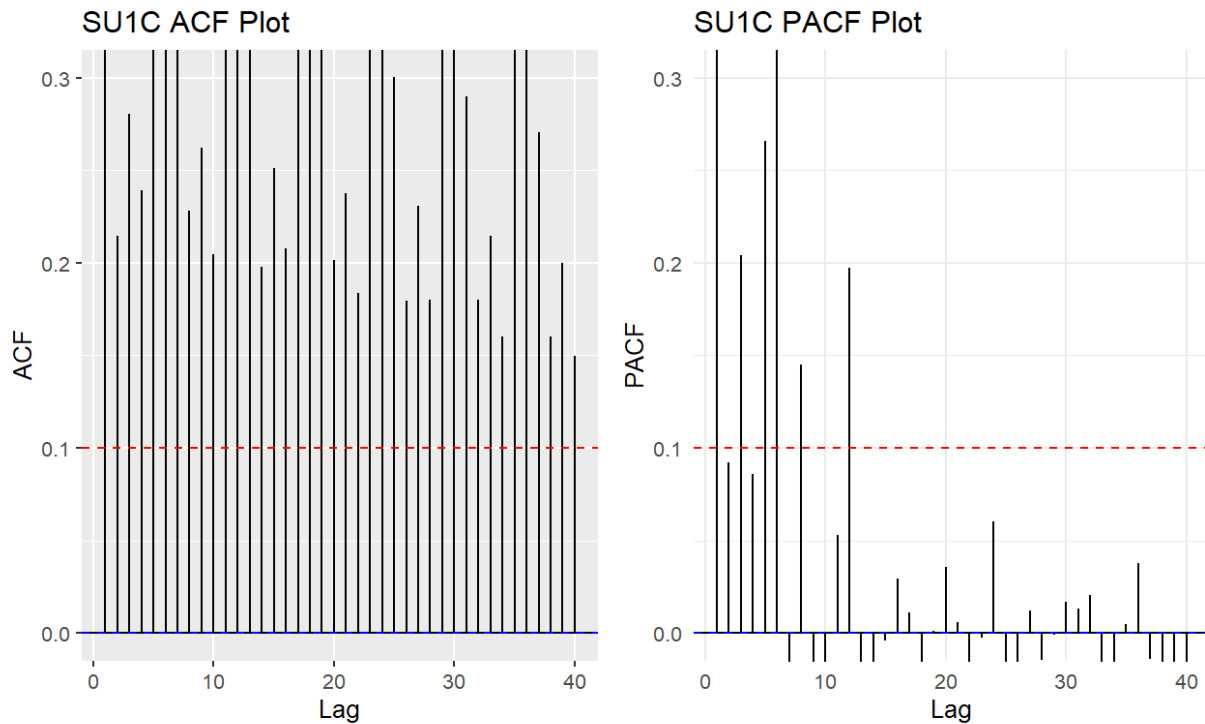


Figure 17 ACF and PACF Plots for SU1C Example Data

The optimization procedure selects a lag distance of $k = 12$. The selected lag is invariant across practical thresholds from 0.040 through 0.090—a considerably broader interval of invariance than obtained for SU1B, with 0.075 well inside it—and moves only to 22 below 0.040 and to 10 above 0.090; the sampling-error band for this unit is $2/\sqrt{n} = 0.020$, far below the adopted threshold. A sensitivity analysis across 64 combinations of practical threshold, required fraction and maximum window size gives a median selected lag of 12 with an interquartile range of 10 to 14, a full range of 3 to 24, and 12 as the modal result (occurring in 41 percent of cases).

Table 8 presents the standard deviations of the differenced values obtained for SU1C under each detection method, along with the corresponding detection limits (L_D).

Table 8 Comparison of Standard Deviations and Detection Limits for the SU1C Example Data

Technique	Standard Deviation (counts/interval)	Detection Limit (L_D) (counts/interval)	Detection Limit (L_D) (cpm)
MARSSIM—Non-CCD	NA	30	896
MARSSIM-CCD	5.3	20	605
MP	2.34	10	312
MA	4.16	16	492
EWMA	4.4	17	515

MP produces the lowest standard deviation and the lowest detection limit in this survey unit. It also carries the largest bias and the widest precision interval of the three localized methods, because its background estimate rests on only two observations rather than on a full neighborhood. Where maximum sensitivity is the priority, MP is the stronger choice; where the reported detection limit must be reproducible, MA or EWMA is preferable despite the slightly higher value.

As shown in Table 8, the localized smoothing methods once again yield substantial improvements relative to global MARSSIM. The MP method produces the lowest standard deviation and the most favorable detection limit (L_D), outperforming MA, EWMA, and MARSSIM-CCD.

The bootstrap procedures outlined in Section 3.8 were applied to assess the bias and precision of the L_D estimates for the SU1C dataset. Table 9 summarizes the bootstrap results. Across the four detection methods considered, EWMA exhibits the smallest bias and MA the narrowest confidence interval. Across the three localized methods, MP exhibits the largest bias (though this is still negligible) and, by a small margin, the widest confidence interval.

Table 9 Bias and 95 Percent Bootstrap Confidence Intervals for Each Method for SU1C Data

Type	Bias	LPL (cpm)	UPL (cpm)	UPL-LPL (cpm)
MARSSIM-CCD	-0.131	596.67	612.98	16.31
MP	-0.072	306.39	318.99	12.6
MA	-0.024	486.01	498.04	12.03
EWMA	-0.023	508.96	521.39	12.43

Taken together, the analyses of SU1B and SU1C show a consistent ordering. The localized smoothing methods outperform global MARSSIM in every case, and the MP method achieves the lowest standard deviation and detection limit in both survey units. The bootstrap results temper that conclusion rather than overturn it: MP's advantage in the point estimate comes with the largest bias and the widest confidence interval among the localized methods, reflecting the smaller amount of data on which its background estimate rests. MA and EWMA give slightly higher detection limits but estimate them more precisely. Where maximum sensitivity is the priority, MP is the stronger choice; where reproducibility of the reported detection limit matters more, MA and EWMA are preferable.

5 Approach for Selecting Statistical Method

As described in Section 3.1, a structured approach is recommended for determining which method will produce valid and reliable detection limit (L_D) estimates, and therefore a defensible a priori MDCR:

- (1) **Characterize the background structure.** Apply the dependence cutoff optimization procedure of Section 3.1 to a background-only portion of the data. A selected lag of 1 indicates that no practical spatial dependence is present; the background may then be treated as constant and the MARSSIM-CCD method is appropriate. Any larger value indicates spatial structure, and a localized method should be used.

- (2) **Establish the lag distance.** Where a localized method is indicated, the lag selected in step 1 defines the neighborhood over which background is estimated. The lag applied in practice should be the larger of that value and the separation required to place the comparison points outside the expected extent of an elevated area. It should be converted to a physical distance using the scan speed and data acquisition interval before being carried into survey planning.
- (3) **Select from among the localized methods.** Where the selected lag is short, the background is nearly constant across the smoothing window and MA or EWMA estimates it more efficiently. Where the selected lag is long, dependence persists over distances comparable to an elevated area, and the two-point footprint of MP avoids drawing source-affected observations into the background estimate. Step (4) decides between the candidates on bias and precision.
- (4) **Evaluate bias and precision.** Determine the bias and precision intervals of the L_D estimates under the selected method using the bootstrap resampling procedure described in Section 9.3.8. Because the bootstrap makes no distributional assumption, this step also guards against cases in which the differenced values depart from normality. If the bias and precision of the selected method fall within acceptable bounds, the corresponding L_D may be retained.
- (5) **Substitute where indicated.** If the bootstrap analysis reveals significant bias or imprecision in the initially selected method, the L_D estimate corresponding to a method with better performance in the bootstrap procedure should be used instead.

This workflow ensures that the chosen detection limits are statistically sound and matched to the characteristics of the dataset.

6 Scanning with an Energy Window or Spectroscopy for Gamma-Emitting Radionuclides

Section 7 of NUREG-1507 discusses the use of spectrometric techniques to assess radioactivity but is mainly focused on static measurements and not scanning data. However, many of the characteristics and advantages discussed apply to CCD. A significant increase in sensitivity can be achieved using energy-based windows compared with gross instrument counts. Energy window and spectrometric techniques allow a specific radionuclide to be measured by using its characteristic energies to distinguish it from all sources present. As discussed in Section 7, in situ techniques can detect very low concentrations of individual radionuclides. Applying these techniques in a scanning mode also overcomes the field-of-view limitations inherent in static spot measurements, as data obtained from scanning will reflect a larger (scan) area, though with reduced detection levels. Section 7 of NUREG-1507 also discusses the use of window and spectroscopic analytical methods.

As discussed in Section 2 of this document, variability in background count rate can negatively affect the calculated detection limits. This is especially true for measurements reporting gross gamma counts. An increase in gross gamma count rate could be due to a number of factors, including encountering an area with elevated levels of naturally occurring radionuclides, an area contaminated with a radionuclide other than what the surveyor is looking for, or an area contaminated with the radionuclide of interest. Collecting data within a specific energy window (i.e., a specific gamma energy associated with the radionuclide of interest), rather than gross

gamma data, makes it possible to determine when the increased count rate is due to the radionuclide of interest.

Focusing on an energy window, rather than a gross measurement across a broad energy spectrum, may reduce the degree of variability observed in the background data, especially if the radionuclide of interest does not exist in normal background. If the radionuclide of interest does also exist within background, the use of energy window or spectroscopic techniques may be less beneficial, but may still offer some advantages.

Some gamma detection systems allow for CCD to be performed with a complete gamma spectrum, reported as counts within each channel, recorded at regular intervals. An appropriate means of converting between channel number and gamma energy would allow for a single set of CCD to be analyzed for several different energies of interest. This would also allow for the use of other background subtraction techniques (using the Compton continuum) to further reduce the influence of background variability on the overall variance of the dataset, ultimately resulting in a lower MDC.

6.1 Benchtop Testing

A benchtop testing system was constructed to evaluate the effect of background radiation, scan speed, and data collection frequency on CCD. The testing system consisted of a conveyor belt measuring 4 meters by 25 millimeters. A 2"x2" NaI detector was held static at the midpoint of the conveyor belt with a surface-to-detector distance of 10 centimeters. A 1 microcurie (μCi) Cs-137 button source was placed on the conveyor belt. (The small size of a button source makes it more representative of a discrete radioactive particle in a hypothetical survey unit than of a spatially dispersed elevated area. Consequently, while the results of the test described here provide insight into how scan geometry and traverse speed can affect detectability, they have limited application to settings with more dispersed, wide-area elevated residual radioactivity.) Sensors were affixed to the conveyor belt to log the beginning and end of each full-length run. Detector output (measured in counts) was directly recorded every 0.5 second using a standalone microprocessor, which eliminated any signal processing, such as time averaging, that might have been introduced otherwise by a commercially available instrument. The conveyor belt was run at three speeds: 1 meter (m) per second (s), 0.5 m/s, and 0.25 m/s. For each belt speed, gross gamma data were collected for 10 full-length runs of the source on the conveyor belt. Data were also collected, using these parameters, with an energy window centered around the 662 kiloelectron volt (keV) gamma from the Cs-137 short half-life progeny barium (Ba)-137m. Background data were collected using the same parameters, also both as gross gamma data and with an energy window focused on 662 keV.

Figures 18 through 23 display the count rate data as the Cs-137 source was moved along the conveyor belt. The x-axis in each figure ranges from -2 meters to 2 meters, and 0 represents the midpoint, where the detector was located. Each line on the graph represents a separate run of the source along the length of the conveyor belt. As can be seen by comparing the pairs of graphs for each scan speed (Figures 18 and 19, Figures 20 and 21, and Figures 22 and 23), the natural background variation has far less influence when the energy window is used, allowing for easier identification of the Cs-137 source passing underneath the detector.

Figures 24 and 25 respectively show the average gross gamma counts and the average counts within the 662 keV energy window, across the 10 runs, for each scan speed. As can be seen in the two figures, the increase in both gross gamma counts and counts within the energy window as the source passes under the detector is more prominent for lower scan speeds (e.g., 0.25 m/s) than for higher scan speeds (e.g., 1 m/s).

Falkner and Marianno (2019) investigated the effect of increased scan speeds on the geometric efficiency of a typical 2"x2" NaI gamma scintillation detector. In that investigation, MCNP® was used to model the solid angle subtended by a cylindrical detector from a Cs-137 source, as the scan speed increased, to determine the detector efficiency. The study clearly demonstrated that the calculated minimum detectable activity increases as scan speed increases, because of the corresponding decrease in the geometric efficiency of the detector. It also showed that slight variations in scan speed can affect the detector's ability to achieve the desired minimum detectable activity, highlighting the need to ensure a consistent scan speed during surveys.

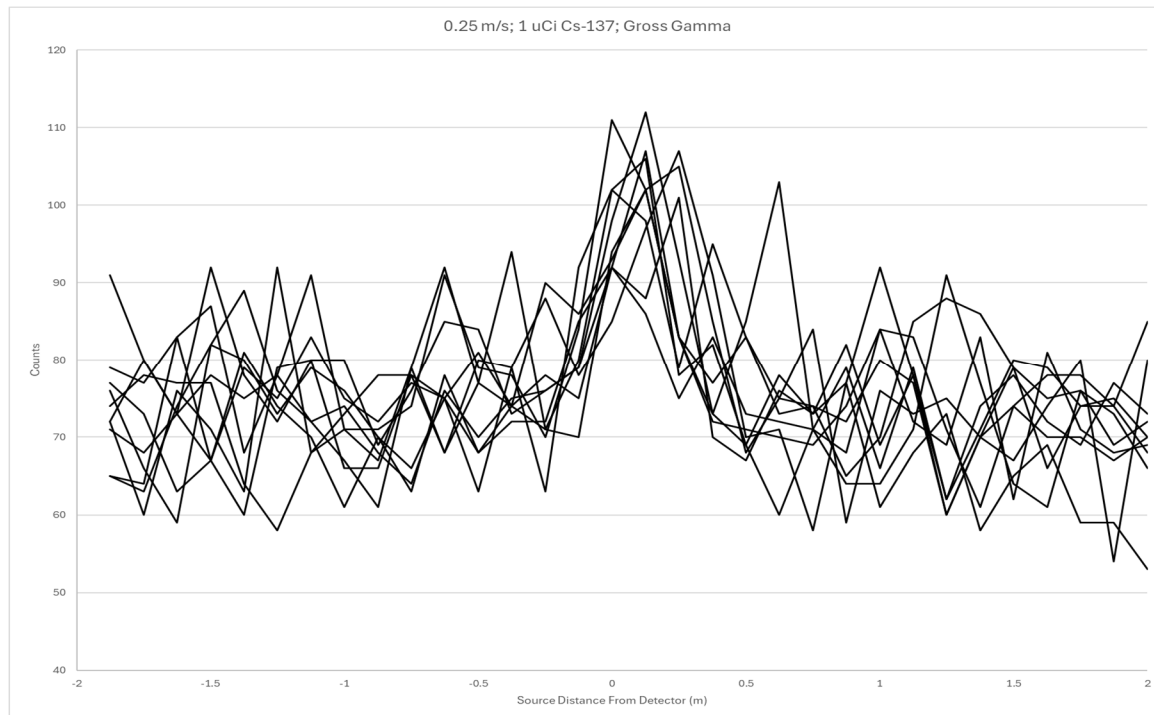


Figure 18 Benchtop Gross Gamma Cs-137 Data for Belt Speed of 0.25 m/s for 10 Runs

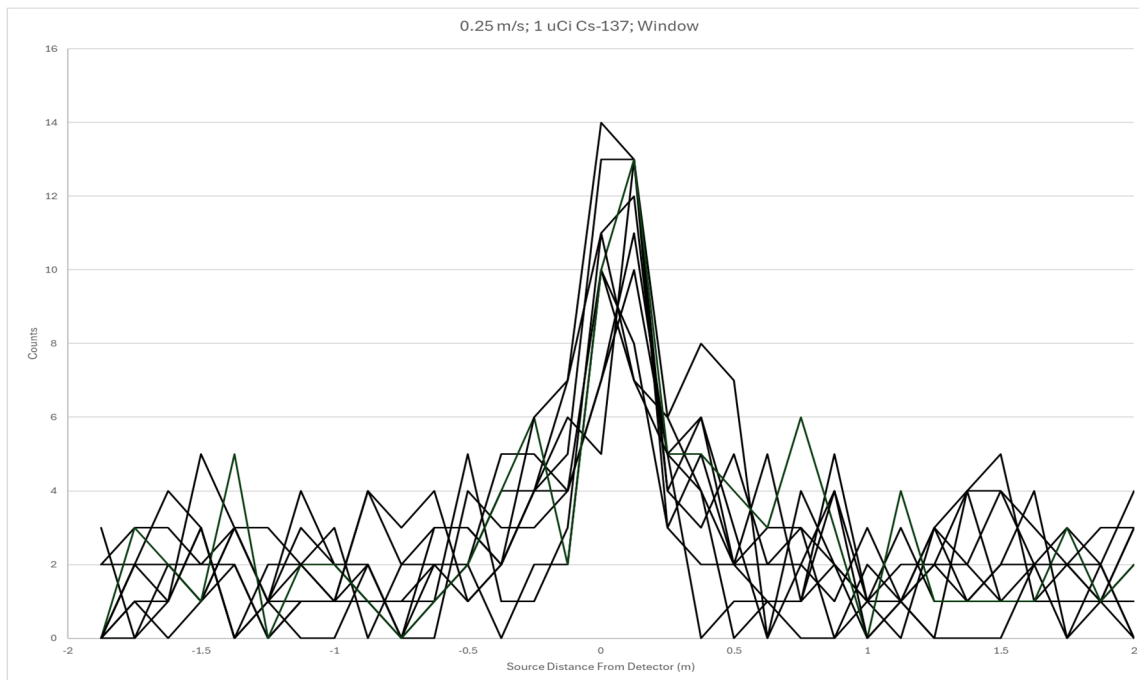


Figure 19 Benchtop 662 keV Window Data for Belt Speed of 0.25 m/s for 10 Runs

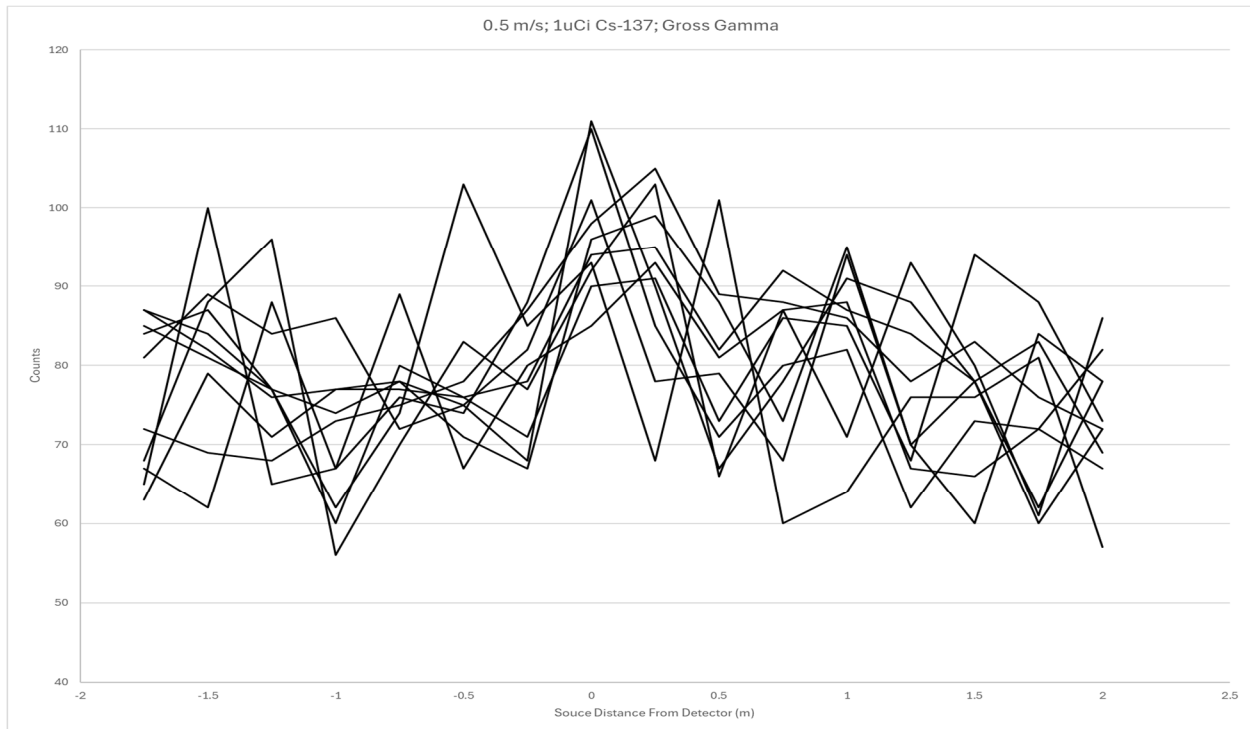


Figure 20 Benchtop Gross Gamma Cs-137 Data for Belt Speed of 0.5 m/s for 10 Runs

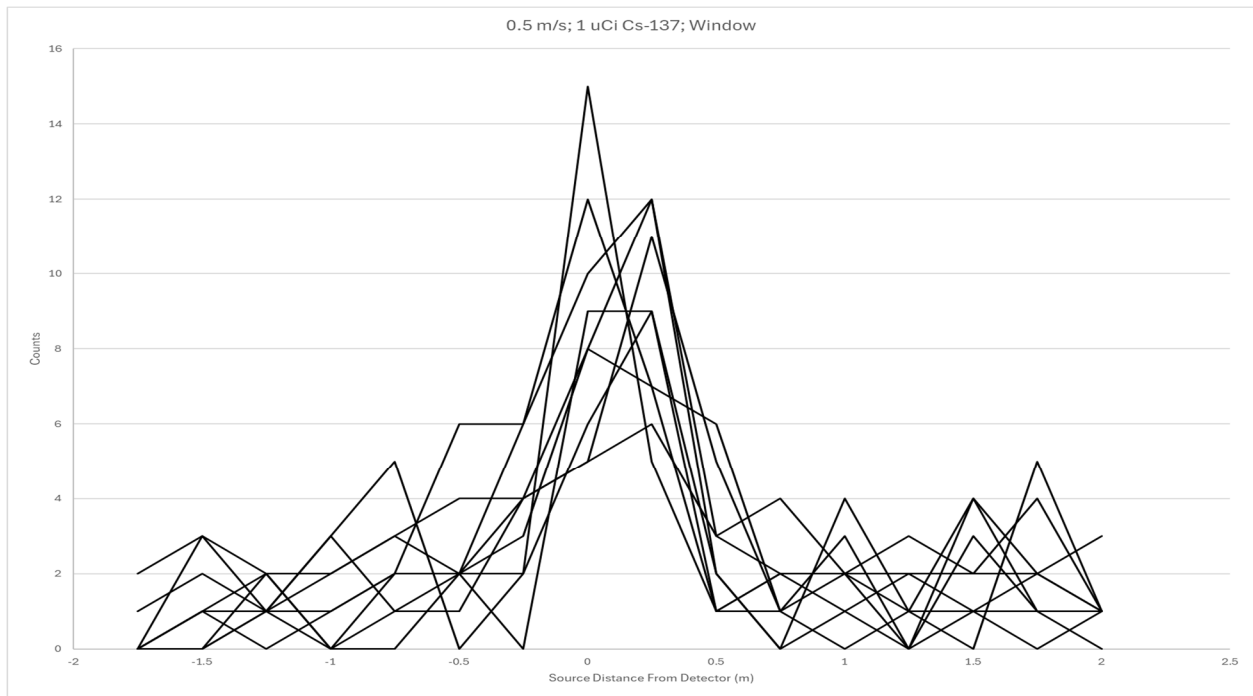


Figure 21 Benchtop 662 keV Window Data for Belt Speed of 0.5 m/s for 10 Runs

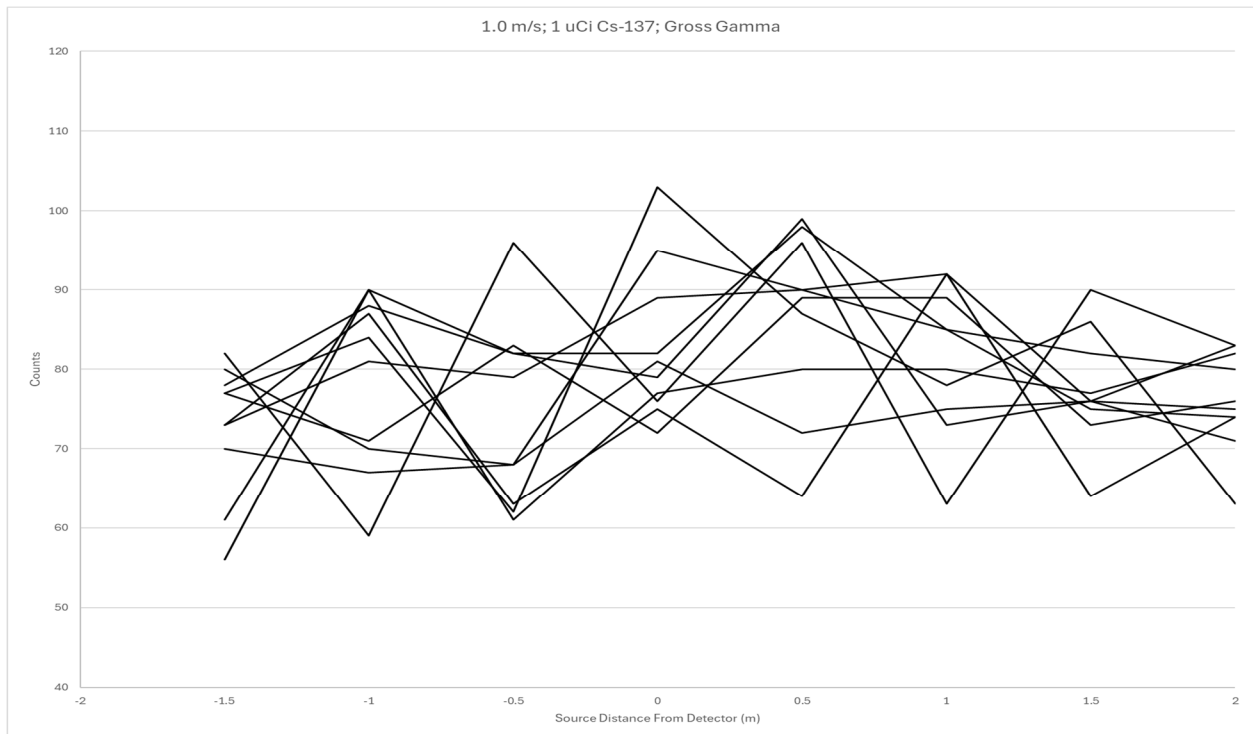


Figure 22 Benchtop Gross Gamma Cs-137 Data for Belt Speed of 1 m/s for 10 Runs

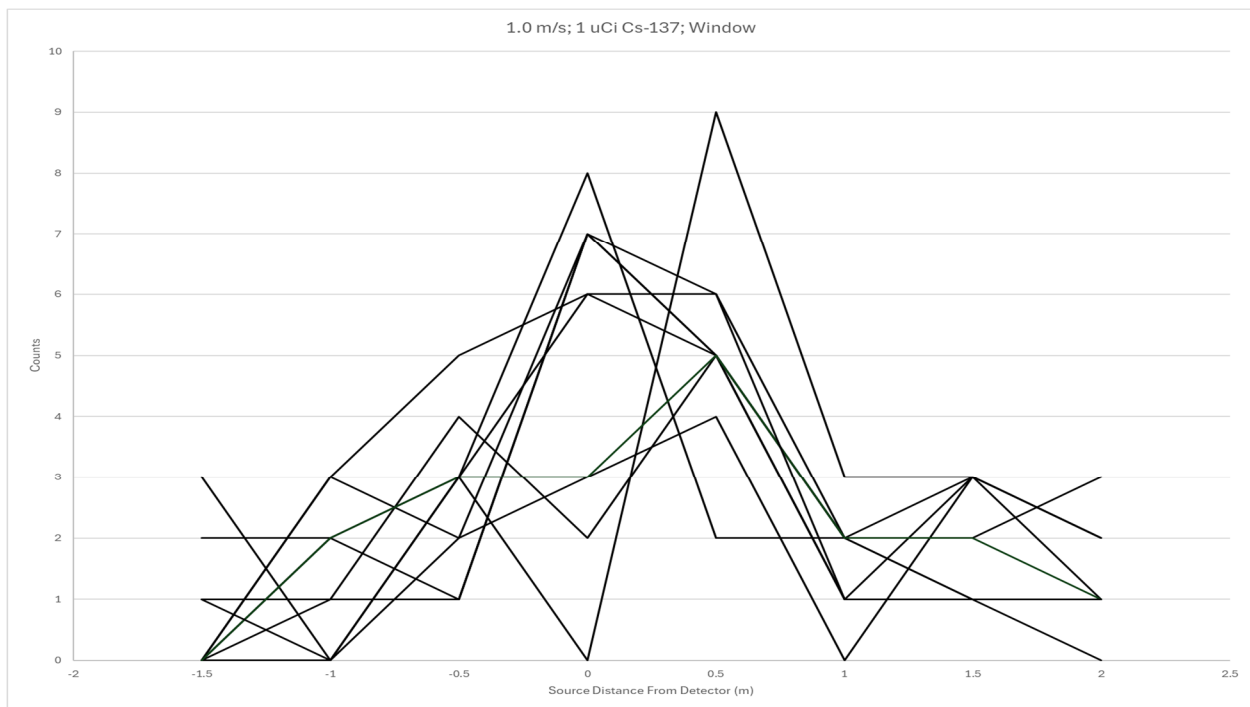


Figure 23 Benchtop 662 keV Window Data for Belt Speed of 1 m/s for 10 Runs



Figure 24 Averaged Benchtop Gross Gamma Background Data and Cs-137 Data for 0.25 m/s, 0.5 m/s and 1 m/s Belt Speeds

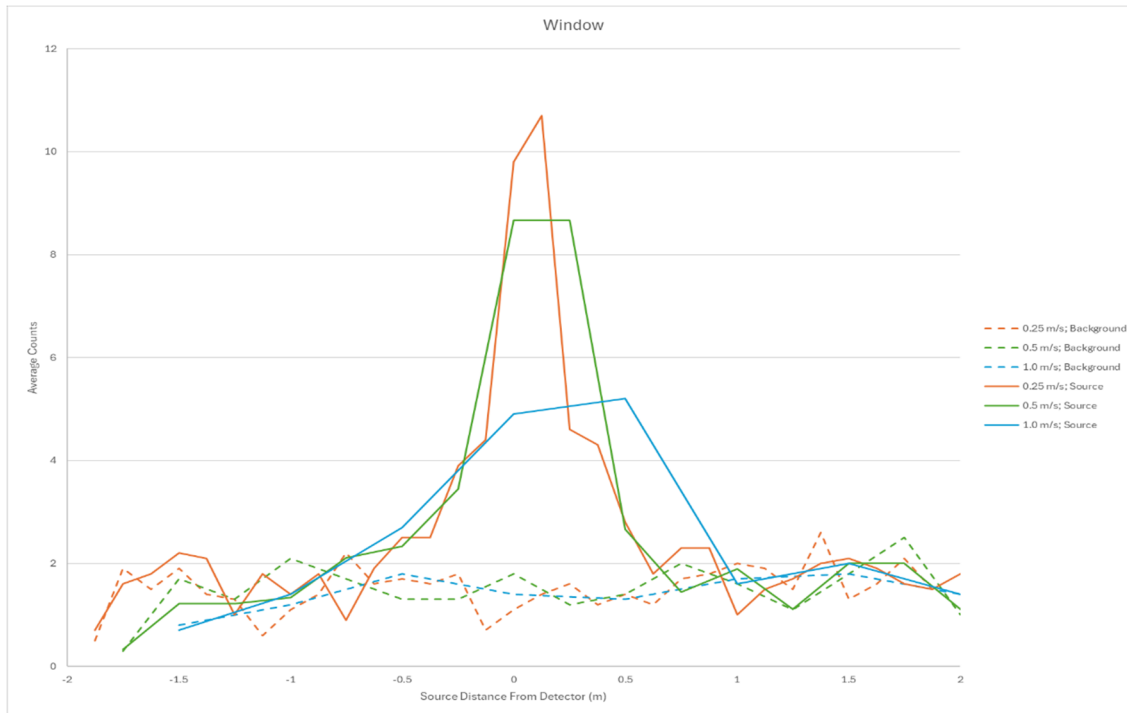


Figure 25 Averaged Benchtop Background Data and Cs-137 Data within 662 keV Window for 0.25 m/s, 0.5 m/s and 1 m/s Belt Speeds

7 Comparing Gross Gamma, Energy Window, and Spectroscopic Continuously Collected Data for a Common Reference Area

This section describes an additional set of experiments performed to evaluate the detection methods studied above, and in particular to examine how the type of data collected could influence the results. The same 2"x2" NaI detector as used in the laboratory experiments was used to collect outdoor gross gamma walkover data in a grassy area with no known radiological contamination. The surveyor moved at approximately 0.5 m/s while holding the detector at a fixed height above the ground. GPS coordinates were collected during the survey and reported along with the gross gamma count rate measurements every second. A second set of data was collected in the same manner, but with the energy window for 662 keV applied. A third set of data was collected in the same area with the same detector, but the detector was set up to collect a 4,096-channel spectrum every second during the survey. For the data analysis, every two 1-second intervals were combined to give a 2-second accumulation time.

The site data were evaluated using the same framework as applied to the previous examples. Each analysis follows the same structure: visualization of raw data, evaluation of correlation structure, and comparison of localized smoothing methods against CCD and non-CCD MARSSIM approaches where appropriate.

7.1 Gross Gamma Evaluation

Figure 26 presents the time series of raw counts for gross gamma data. The ordered gross-gamma series is nonstationary, with a gradual, near-monotonic decline in central tendency across the traverse. Superimposed on this background trend are meso-scale

fluctuations—spanning from several dozen to a few hundred observation segments—suggesting spatial clustering beyond counting noise. The distribution also includes sporadic high-amplitude excursions (positive outliers) and isolated deficits. Dispersion is not constant: variability increases modestly in the mid-sequence and tightens toward the ends, indicating mild nonconstant variance. Overall, the structure is that of a declining background field with patch-like departures and occasional outliers, rather than a homoscedastic, mean-stationary process. Mild heteroscedasticity of this kind is the condition under which a single global standard deviation misstates the variability—overstating it where the series is quiet and understating it where it is not—which is the argument for the localized methods applied below and for the bootstrap check in step (4) of the Section 5 workflow.

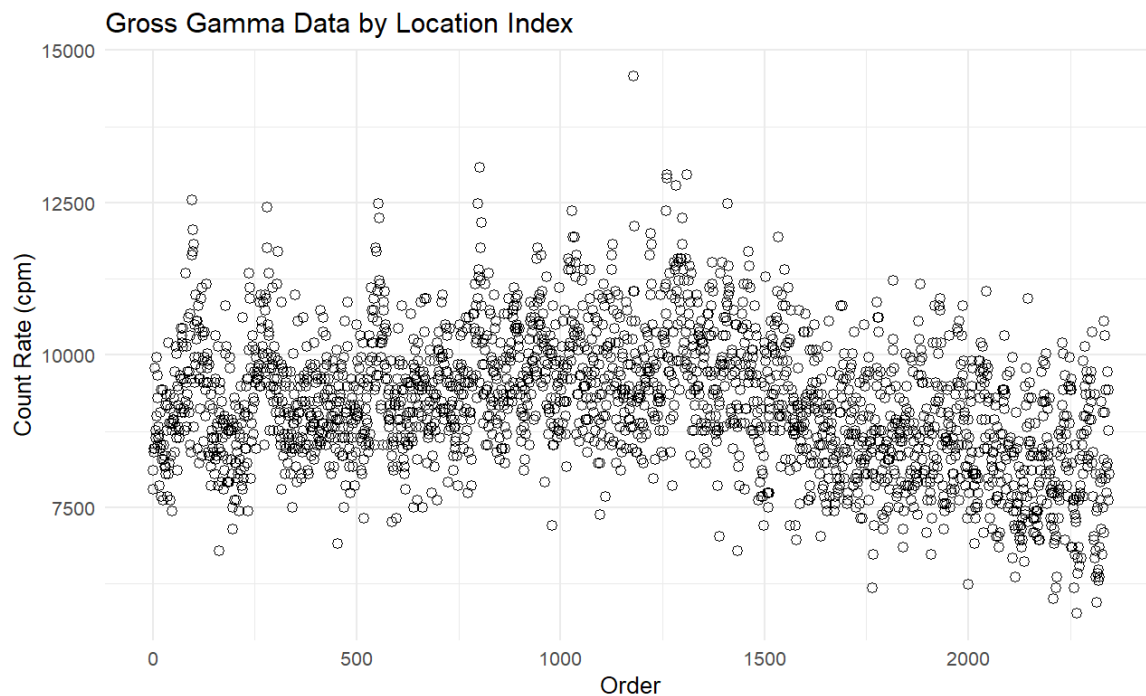


Figure 26 Time-series Plot of Gross Gamma Data

To determine the lag number for this dataset, the ACF and PACF plots were examined (Figure 27).

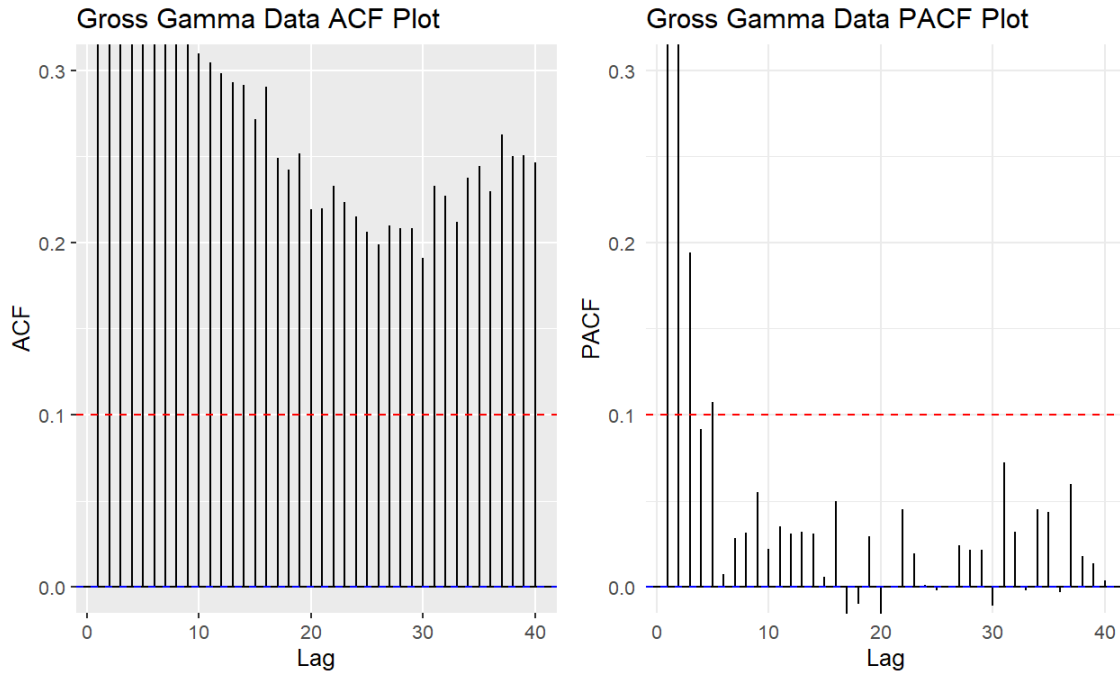


Figure 27 ACF and PACF Plots for Gross Gamma Data

The dependence cutoff optimization procedure yields a lag distance of $k = 5$. Sensitivity to the remaining rule parameters is modest. The median selected lag is 5, the interquartile range is 3 to 5, and 5 is the modal result (occurring in 42 percent of cases); lags outside the interval 3 to 9 arise only in corners of the grid, where the tightest threshold is paired with the most demanding required fraction, or the loosest with the least demanding. The selection is therefore stable throughout the region of the parameter space these data support.

The MARSSIM two-stage row is shown to illustrate the consequence of applying that equation to CCD. It frequently produces the lowest detection limit in these tables, which invites its selection, but the lower value reflects its assumption that the background standard deviation equals the square root of the mean rather than any property of the data. Across the survey units evaluated here, the observed standard deviation ranges from 0.82 to 3.05 times that assumed value, so the equation may understate or overstate the detection limit, and the direction cannot be known without the data it does not use. Choosing it because the number is lower would adopt a bound the data do not support.

Table 10 presents the standard deviations of the differenced values for each detection method, along with the corresponding detection limits (L_D). As before, although the spatial complexity of the data suggests that the localized methods will provide superior performance, the results from the CCD-type and non-CCD-type MARSSIM approaches are included for comparison.

Table 10 Comparison of Standard Deviations and Detection Limits for the Gross Gamma Data

Technique	Standard Deviation (counts/interval)	Detection Limit (L_D) (counts/interval)	Detection Limit (L_D) (cpm)
MARSSIM—Non-CCD	N/A	81.21	2,435
MARSSIM-CCD	36.71	120.4	3,612
MP	32.81	110.65	3,319
MA	27.12	91.93	2,758
EWMA	27.03	91.63	2,748

7.2 Energy Window Gamma Evaluation

Figure 28 presents the raw count data for the energy window survey. Windowed counts look largely stationary across the traverse—there is no clear left-to-right drift. Values cluster in distinct horizontal bands (reflecting discrete counting due to fixed dwell time), with most observations in the low hundreds and occasional spikes reaching several hundred. That pattern suggests a stable background with intermittent elevations rather than a broad gradient. In other words, the level of Cs-137 across the reference area appears relatively uniform, with an expected variability attributable to statistical variation, and no delineated areas of differing activity levels.

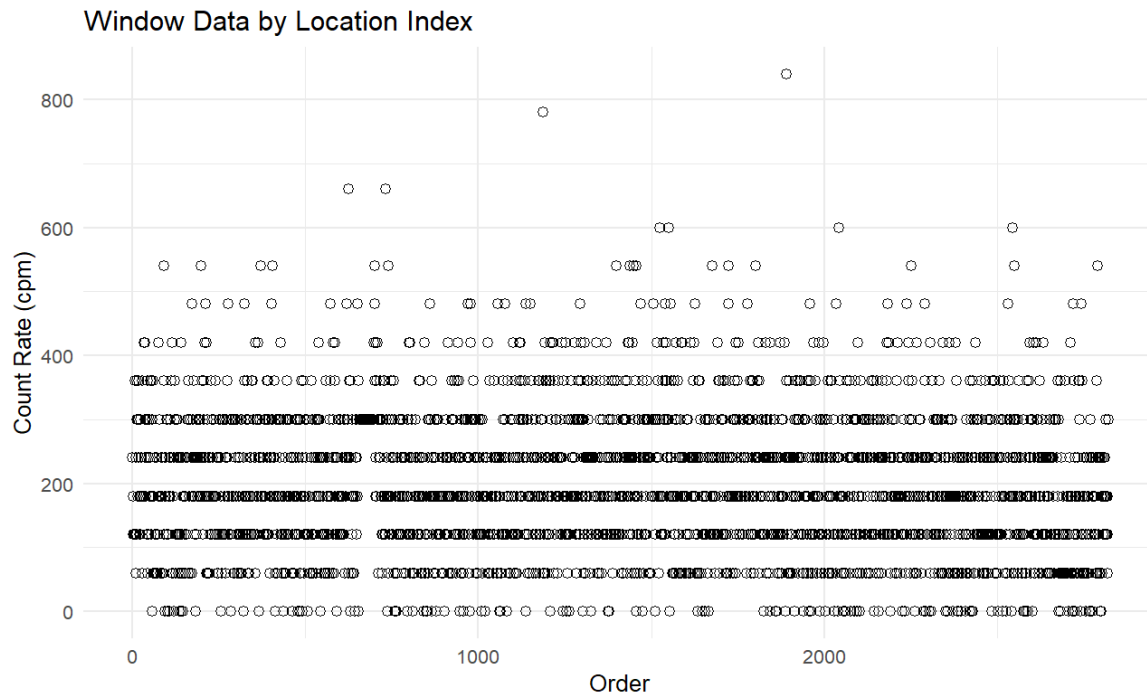


Figure 28 Time-Series CCD Using a 662 keV Energy Window

Next, to determine the lag number for this dataset, the ACF and PACF plots were examined (Figure 29).

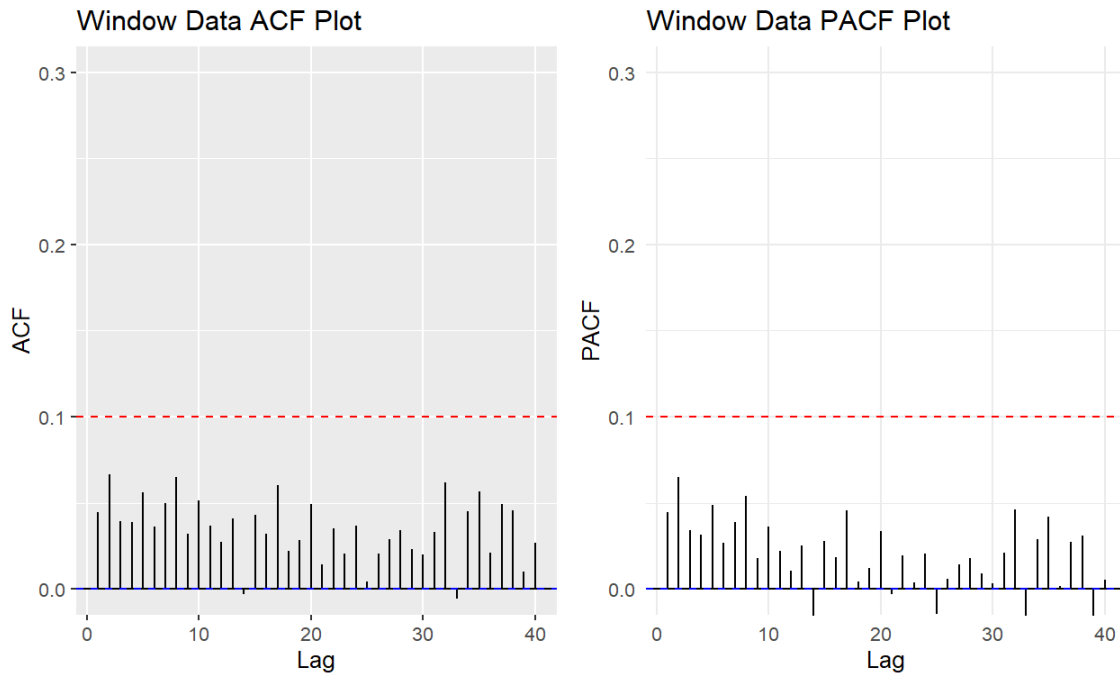


Figure 29 ACF and PACF Plots for the Windowed Data

As seen in Figure 29, all ACF and PACF coefficients for the windowed counts lie within ± 0.10 across lags, indicating negligible serial dependence and behavior consistent with approximate covariance stationarity. Accordingly, localized smoothing is not warranted and should not be applied in estimating the detection limit. The observed variation is instead consistent with an approximately normal distribution, supporting use of the MARSSIM approach to calculate the MDCR.

The mean observed count rate was 197.2 cpm. This leads to an estimated MDCR of 257 cpm. Uncertainty in the MDCR estimate was quantified using a nonparametric bootstrap with resampling at the location level. The resulting 95 percent bootstrap confidence interval was 250 to 266 cpm. The relatively narrow confidence interval indicates that the estimated MDCR of 257 cpm is stable with respect to sampling variability.

7.3 Spectral Gamma Evaluation

The third scan survey involved collecting spectral measurements with a region of interest reflecting the 0.662 MeV primary gamma from the Cs-137/Ba-137m decay. In principle, applying Compton background subtraction to the spectral data would further reduce the ambient background component of the data. However, when Compton background subtraction techniques were applied to these data for the 0.662 MeV peak, the resulting net counts were near zero or even negative. Therefore, the statistics for the methodologies described here would not necessarily apply, and further investigation would be needed.

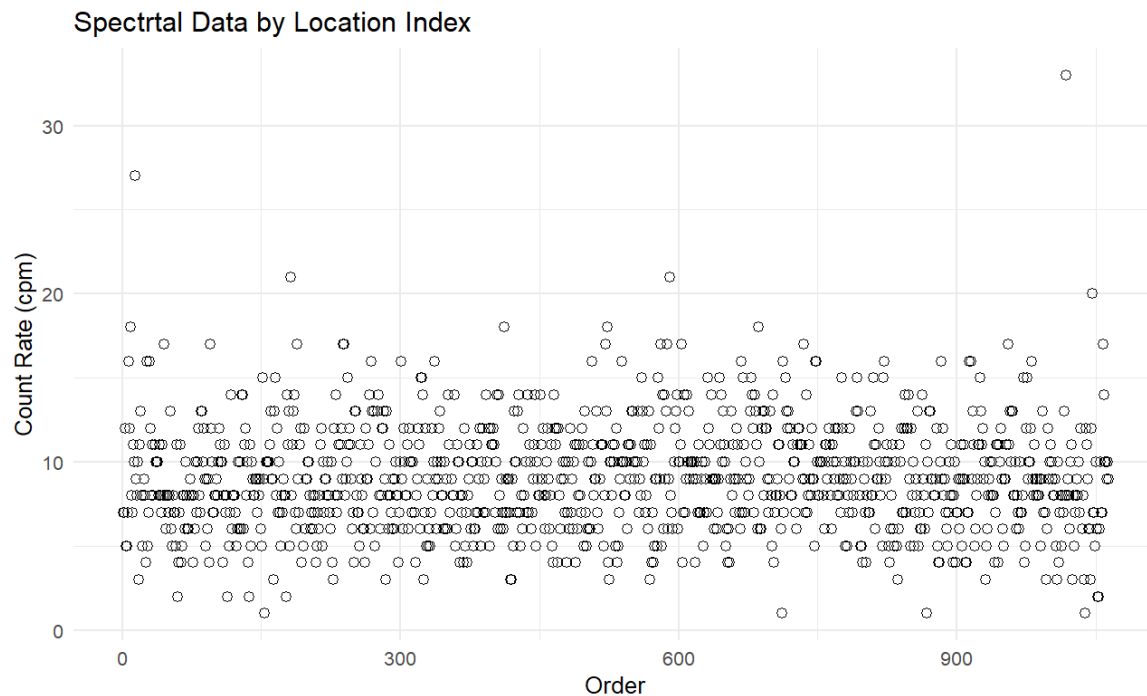


Figure 30 Time-Series Plot of Spectral Data

Figure 30 presents the raw counts for the spectral data. Like the energy window data, these data appear approximately stationary across the traverse: there is no discernible left-to-right drift in central tendency, and variability is broadly consistent. Counts cluster in discrete horizontal bands in the low double digits—as expected from integer counting at fixed dwell—while a small number of isolated positive excursions (reaching about 20–30 counts) occur without persistence. No mesoscale structure (with sustained lifts or dips) is evident, and heteroscedasticity, if present, is minimal. Overall, the pattern is consistent with a stable background field punctuated by occasional spikes, rather than a trend-dominated process.

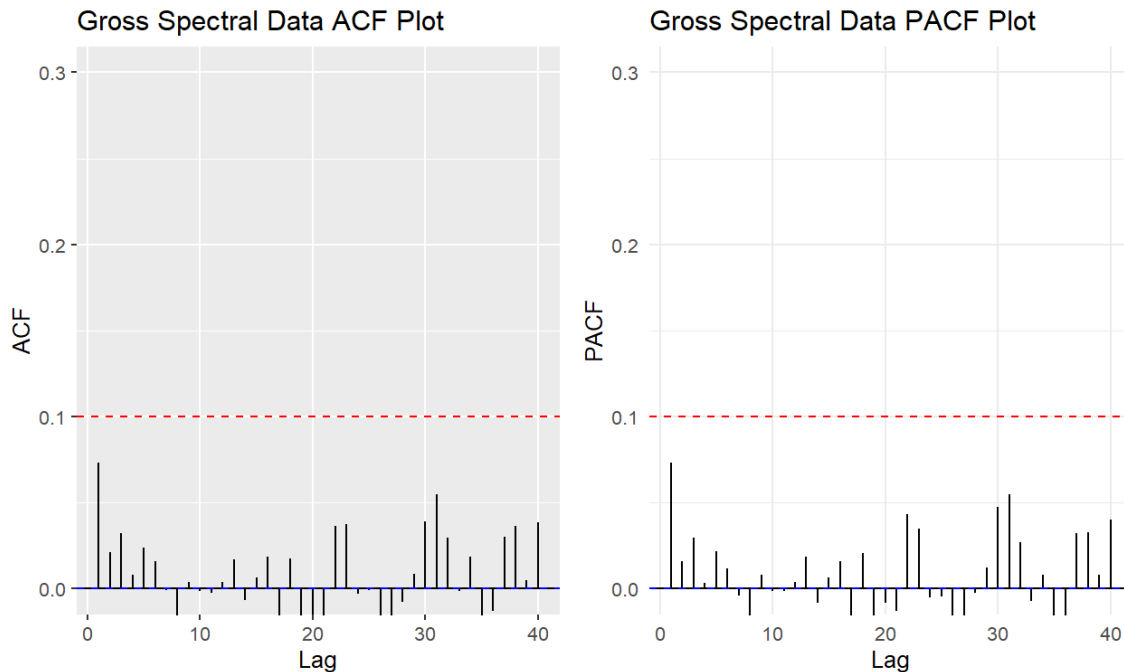


Figure 31 ACF and PACF Plots for Spectral Data

Figure 31 presents the ACF and PACF plots for the gross-spectrum series. All coefficients remain within the approximate sampling bounds, indicating no material serial dependence and, therefore, no need for localized smoothing before estimation. Using a MARSSIM-based procedure, the MDCR was calculated to be 10.8 cpm. Uncertainty was quantified through nonparametric bootstrap resampling, which yielded an estimated bias of -0.002 cpm and a 95 percent bootstrap percentile interval of (10.1, 11.6) cpm. The near-zero bias and narrow interval indicate that the estimate of the detection limit is precise and reliable.

The experiments in this section show how data from various detector set-ups (gross, energy window, and spectral) lend themselves to different methods of analysis, and how energy window and spectral measurements can be used to minimize the impact of background variation and improve detection capability.

8 Determining Minimum Detectable Concentrations from the Minimum Detectable Count Rate

8.1 Background

Sections 6.2 and 6.3 of NUREG-1507 present guidance on radiological surveys conducted with data logging systems that recorded GPS location information along with the radiological survey data. As discussed in Section 1, the a priori scan MDC used for surveys conducted with surveyor vigilance does not apply to the alternative paradigm in which radiological data are collected without the surveyor's listening to an audible count rate or pausing to count longer upon hearing an increase in counts.

This section addresses methods for relating a measurement from an instrument to a corresponding activity or concentration, as discussed in Section 4 of NUREG-1507. It provides a review of certain fundamental concepts in MARSSIM that are discussed in other parts of this document. Oak Ridge Institute for Science and Education (ORISE) has recently published new considerations for surveying discrete radioactive particles that apply to land scanning (ORISE 2023), and these considerations are incorporated in the discussion below. This section also develops initial considerations for computing the a priori lag- k scan MDC in view of the ORISE considerations.

The development of a scan MDC has two stages: (1) development of the MDCR, which is addressed in Section 2, and (2) a correlation of the MDCR to MDC. This second stage is the correlation of the detector response (measured in counts over some time period) to the corresponding concentration, which may be measured, for example, in picocuries per gram (pCi/g) of soil, or in disintegrations per minute (dpm) per 100 square centimeters (cm²) for surface contamination.

As stated in Section 2, once the a priori MDCR has been determined, it can be converted to the MDC as follows:

$$MDC = \frac{MDCR}{\varepsilon_i \times \varepsilon_s} \quad (\text{Eq. 33})$$

where:

MDC = the a priori minimum detectable concentration, in units appropriate for the type of instrument and source media, such as pCi/g for soil and dpm/100 cm² for beta surface measurements

MDCR = the minimum detectable count rate, derived as described in Section 2, typically in cpm or equivalent units representative of the scan time interval (accumulation time)

ε_i = the instrument or detector efficiency

ε_s = the efficiency of the potential contamination source (i.e., source efficiency)

The product of ε_i and ε_s gives the total efficiency, which is the conversion factor relating the MDCR to the MDC. For beta detection, the source efficiency and instrument efficiency are typically determined separately. For gamma detection, they are more typically determined as a combined term. The surveyor efficiency factor (ρ), which is included for the two-stage scanning technique without recorded data, can be excluded. The determination of efficiency for beta and gamma detectors is discussed below.

8.2 Beta Detector Efficiency

Instrument efficiency (ε_i) is defined as the ratio of the net count rate of the instrument to the emission rate of a source for a specified geometry. For beta detection, this typically represents the surface emission rate. Since surface measurements are typically expressed in units of dpm/100 cm², an additional factor may be needed—namely, the area of the detector window (W , cm²)—to convert the detector response to the appropriate units.

Section 4 of NUREG-1507 provides guidance on determining source efficiency for beta measurements and surface-deposited activity, with reference to International Organization for

Standardization (ISO) standards ISO 7503-1:1988, "Evaluation of Surface Contamination—Part 1: Beta Emitters and Alpha Emitters," and ISO 7503-3:2016, "Measurement of Radioactivity—Measurement and Valuation of Surface Contamination—Part 3: Apparatus Calibration."

Sections 5.3 and 5.4 of NUREG-1507 provide an in-depth evaluation of various source configurations and detector responses that can be used to derive the source efficiency. These sections discuss the differences in beta measurements for various surface types (e.g., sealed concrete, scabbled concrete, stainless steel, untreated wood) and how the surface condition affects the total efficiency. These sections also discuss the attenuation effects of overlaying material (e.g., paint, water, dust). Appendix A to NUREG-1507 provides case studies illustrating how instrument efficiency can be derived for various radionuclide mixtures, focusing mostly on beta detection and surface contamination.

8.3 Gamma Detector Efficiency

As described above for beta detectors, the instrument efficiency (ϵ_i) is defined as the ratio of the net count rate of the instrument to the emission rate of a source for a specified geometry. For gamma measurements, instrument efficiency reflects the source geometry, taking into account both the effective scan area and effective depth of contamination.

Instrument efficiency for gamma detectors is simply the ratio of counts recorded to the fluence of the incident gammas. However, determining this ratio can be quite complex, as it depends on characteristics of the incident gamma energy, the chemical composition of the detector (in particular, the attenuation coefficient), and the direction of incidence and path length.

Section 6.2.5 of NUREG-1507 presents one method for modeling the detector's response to its energy response and a corresponding source geometry. This method uses the concepts of count-rate-to-exposure-rate ratio (CPMR) and exposure-rate-to-concentration ratio (ERC). The CPMR may be provided by the detector manufacturer or be available in the literature, but it depends on the gamma energy and may also need to be derived. Table 6-3 of NUREG-1507 lists the CPMR as a function of energy for four types of NaI detectors. The ERC is usually estimated by modeling the exposure rate above a source using MicroShield®. Other methods, such as the use of MCNP® or radiochemical analysis of source samples, may prove equally or more effective.

9 Bench Testing Detector Response Accumulation Time

The likelihood that a source will be seen within CCD depends partly on the scan speed and on the amount of time for which the detector may accumulate counts before registering a measurement. As will be shown below, granularity (i.e., frequent recording of accumulated counts) is advantageous in detecting small elevated areas. Granularity also allows for binning (combining multiple accumulation time periods), which can improve detection of spatially larger elevated areas.

In the evaluation discussed in this section, the background data collected as described in Section 6 were averaged across the 10 runs and then binned appropriately to achieve accumulation times of 0.5 second, 1 second, and 2 seconds. The data were then normalized to counts per second. Figures 32, 33, and 34 illustrate the effect of accumulation time on detector response for gross gamma data at conveyor belt speeds of 0.25 m/s, 0.5 m/s, and 1 m/s, respectively. The time reported for each data point is the end of the (binned) accumulation time interval used. The figures show that increasing the accumulation time reduces variability in the

measured background data by effectively averaging the counts across longer periods, thus masking short, intermittent changes in count rate. The same effect is seen for the background data collected within the 662 keV energy window, as shown in Figures 35, 36, and 37. As discussed in Section 7, energy window data exhibit less variability than gross gamma data. Increasing the accumulation time for the energy window data reduces the variability even further.

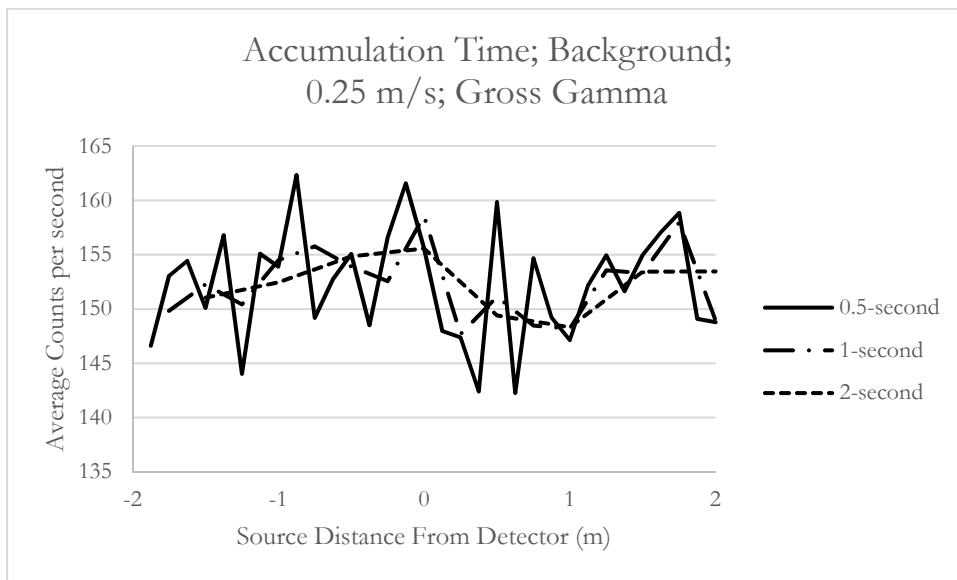


Figure 32 Benchtop Average Gross Gamma Background Count Rate Data with Belt Speed 0.25 m/s, for Varying Accumulation Times

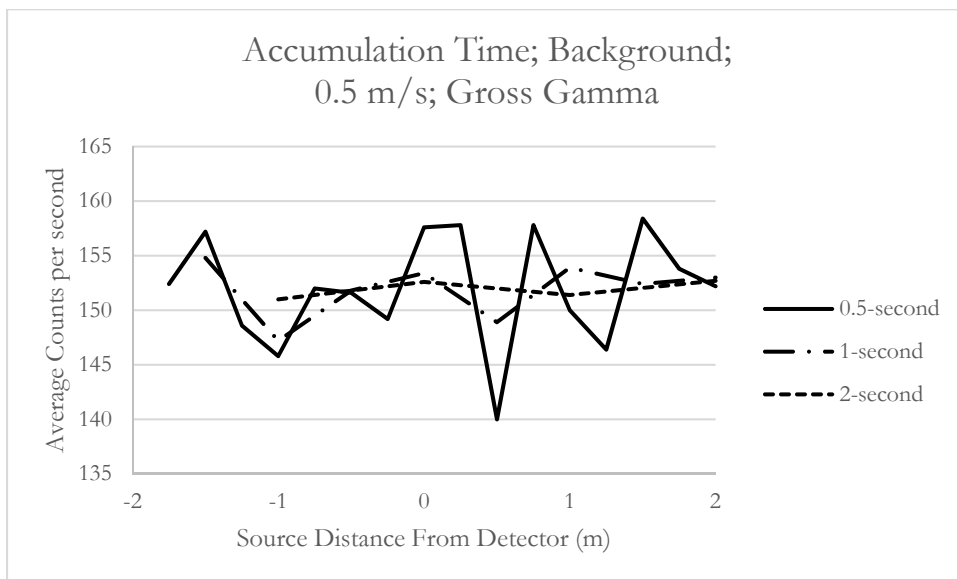


Figure 33 Benchtop Average Gross Gamma Background Count Rate Data with Belt Speed 0.5 m/s, for Varying Accumulation Times

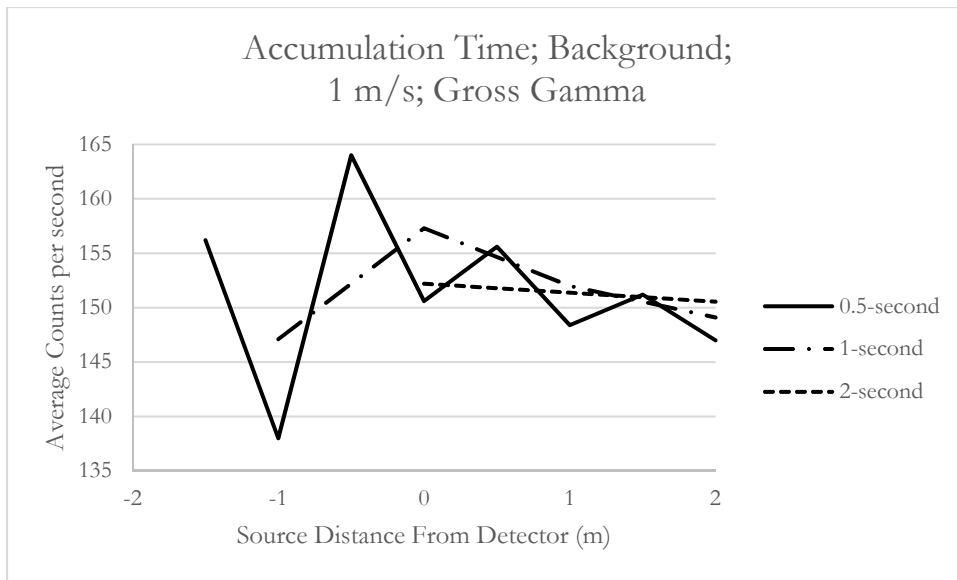


Figure 34 Benchtop Average Gross Gamma Background Count Rate Data with Belt Speed 1 m/s, for Varying Accumulation Times

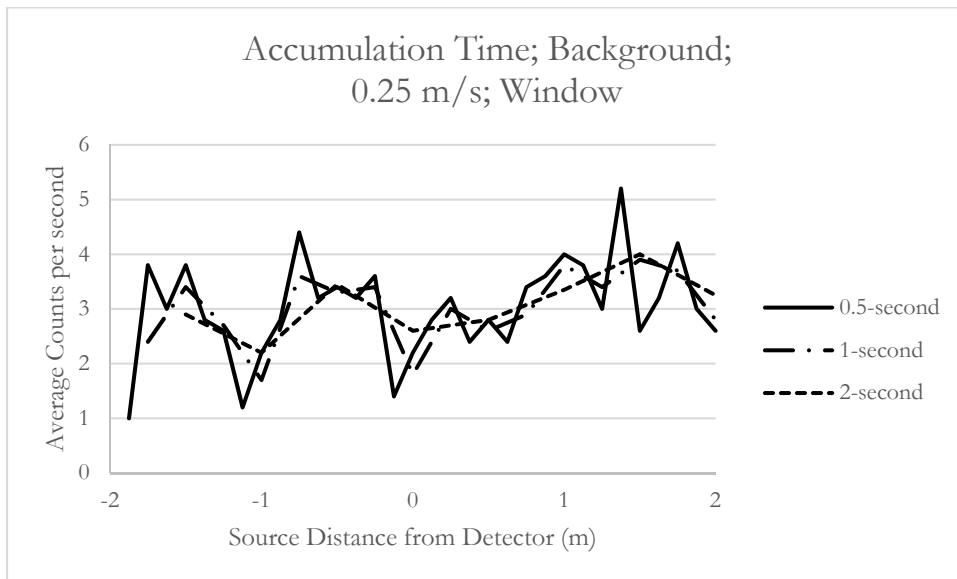


Figure 35 Benchtop Average Background Count Rate Data Within 662 keV Energy Window with Belt Speed 0.25 m/s, for Varying Accumulation Times

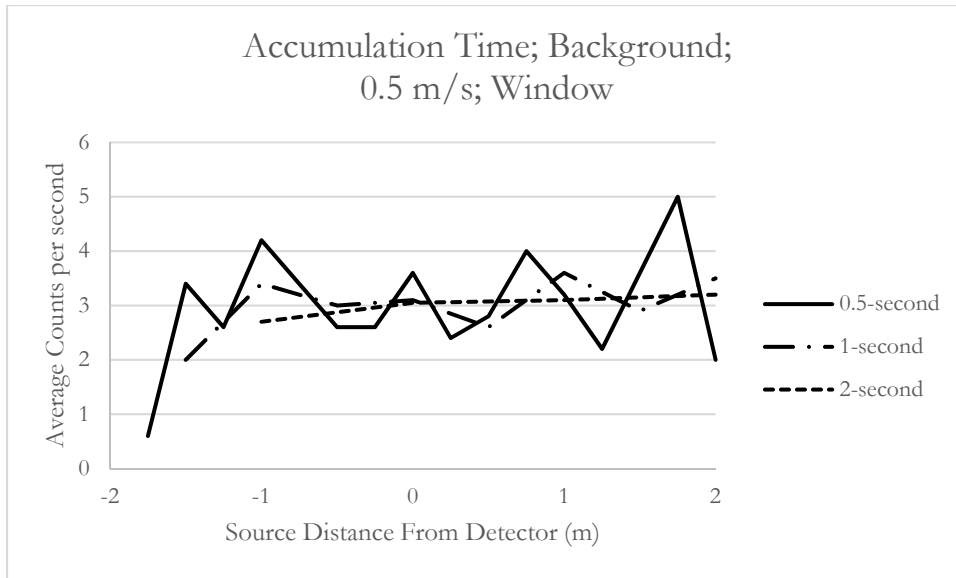


Figure 36 Benchtop Average Background Count Rate Data Within 662 keV Energy Window with Belt Speed 0.5 m/s, for Varying Accumulation Times

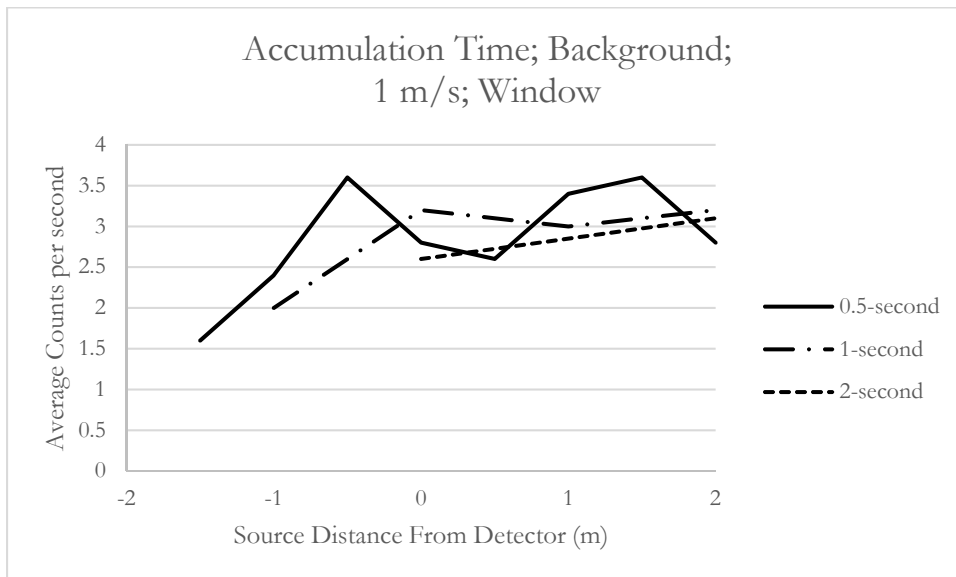


Figure 37 Benchtop Average Background Count Rate Data Within 662 keV Energy Window with belt speed 1 m/s, for Varying Accumulation Times

Similarly, the data collected with the Cs-137 source as described in Section 6 were averaged across 10 runs and then binned to achieve accumulation times of 0.5 second, 1 second, and 2 seconds. The data were then normalized to counts per second. For each measurement, the position of the source was registered in relation to the detector at the end of the accumulation period. Figures 38, 39, and 40 illustrate the effect of accumulation time on detector response for gross gamma data at conveyor belt speeds of 0.25 m/s, 0.5 m/s, and 1 m/s, respectively.

It can be seen from the figures that as the accumulation time increases, the magnitude of the peak in the count rate when the source is nearest to the detector decreases. This is because, with longer accumulation times, the reported measurement at the peak includes counts from areas farther from the source; the average count rate for the time interval is thus lower. The decrease in peak height with increased accumulation time is most clearly seen in Figure 38, where the belt speed is 0.25 m/s. In actual field surveys, this effect could lead to masking of a source; the smaller a source is, the more likely it is to be missed. (If the source is larger than the distance traversed by the detector during the accumulation time, then the accumulation time will have less of an effect on the detectability of the source.) This relationship between accumulation time and the magnitude of the peak count rate from the source is also seen with the 662 keV energy window data in Figures 41, 42, and 43.

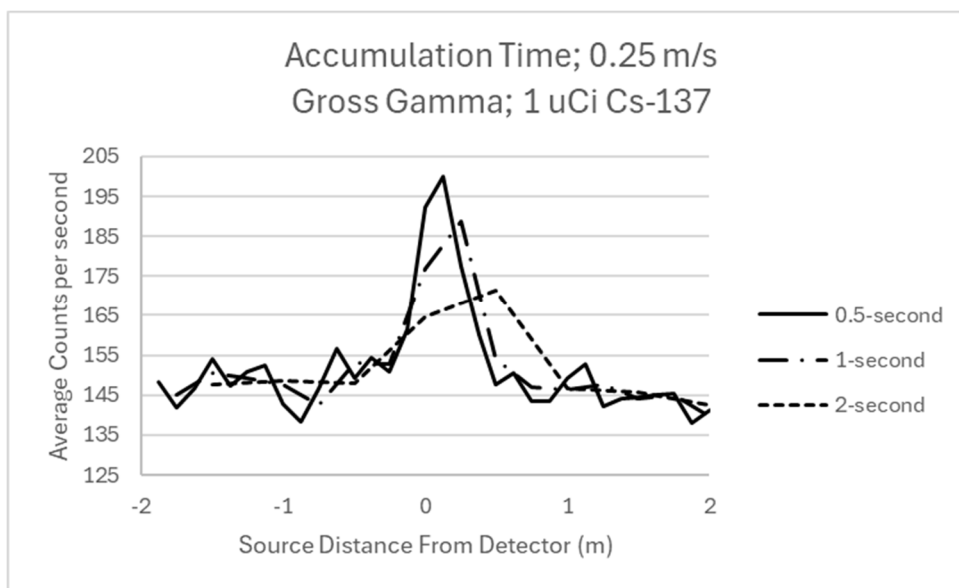


Figure 38 Benchtop Average Gross Gamma Cs-137 Count Rate Data with Belt Speed 0.25 m/s, for Varying Accumulation Times

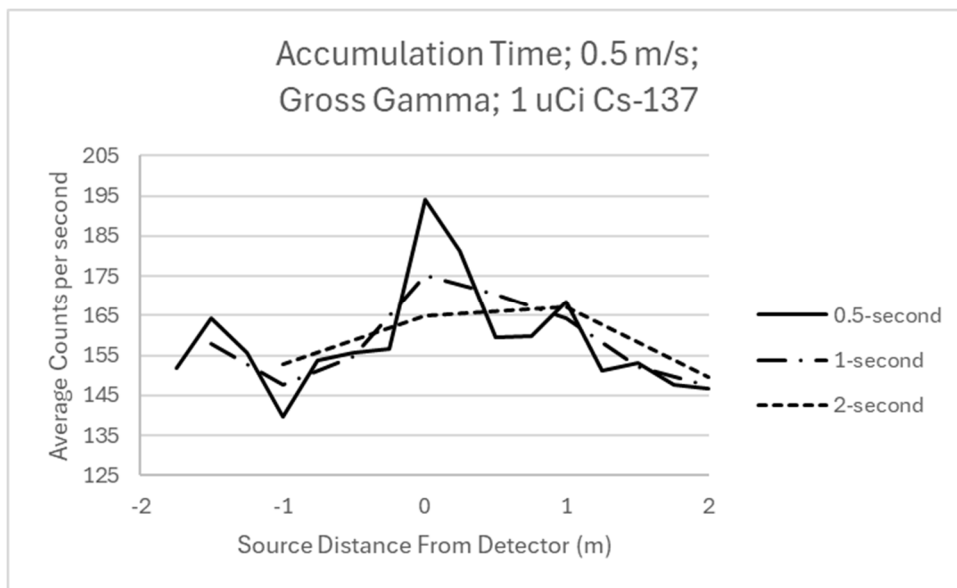


Figure 39 Benchtop Average Gross Gamma Cs-137 Count Rate Data with Belt Speed 0.5 m/s, for Varying Accumulation Times

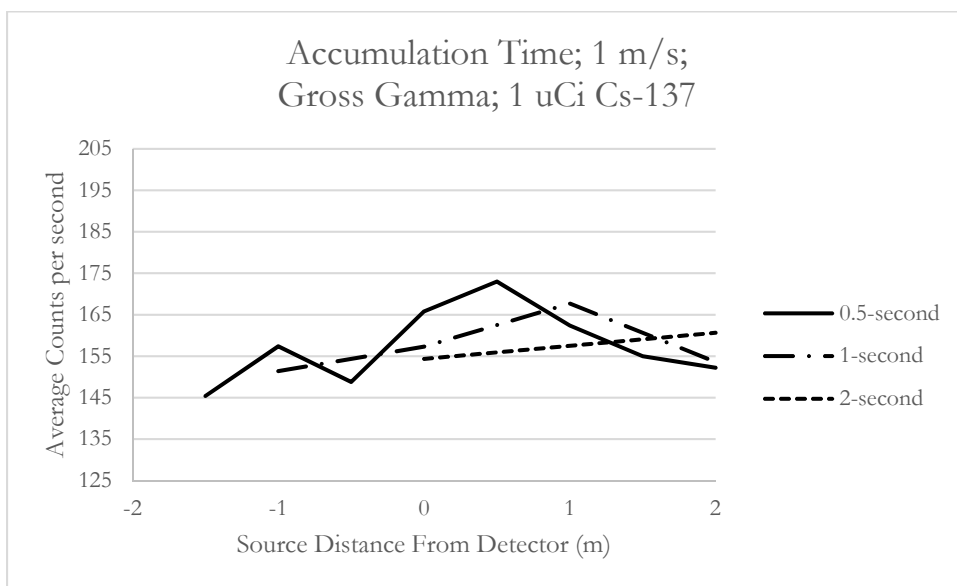


Figure 40 Benchtop Average Gross Gamma Cs-137 Count Rate Data with Belt Speed 1 m/s, for Varying Accumulation Times

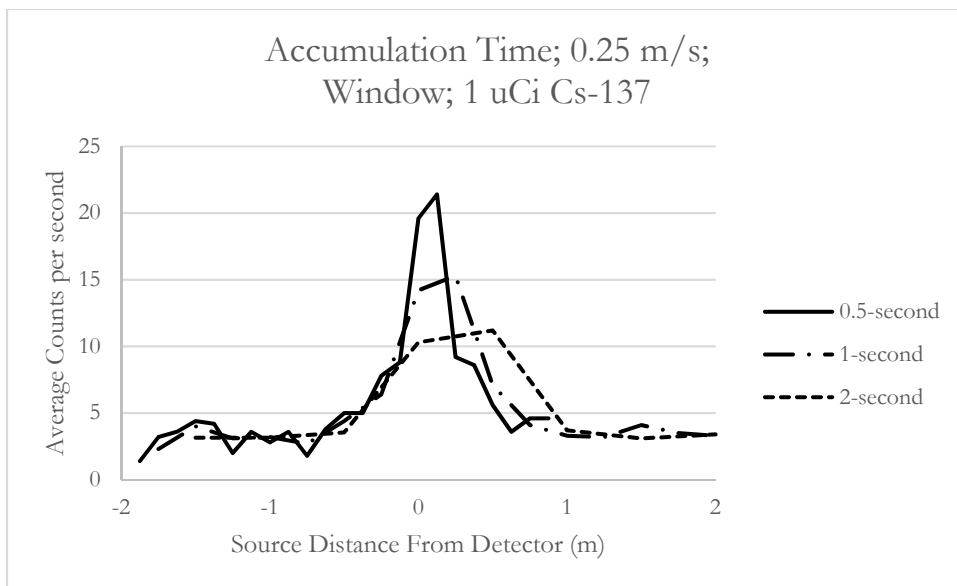


Figure 41 Benchtop Average Cs-137 Count Rate Data Within 662 keV Energy Window with Belt Speed 0.25 m/s, for Varying Accumulation Times

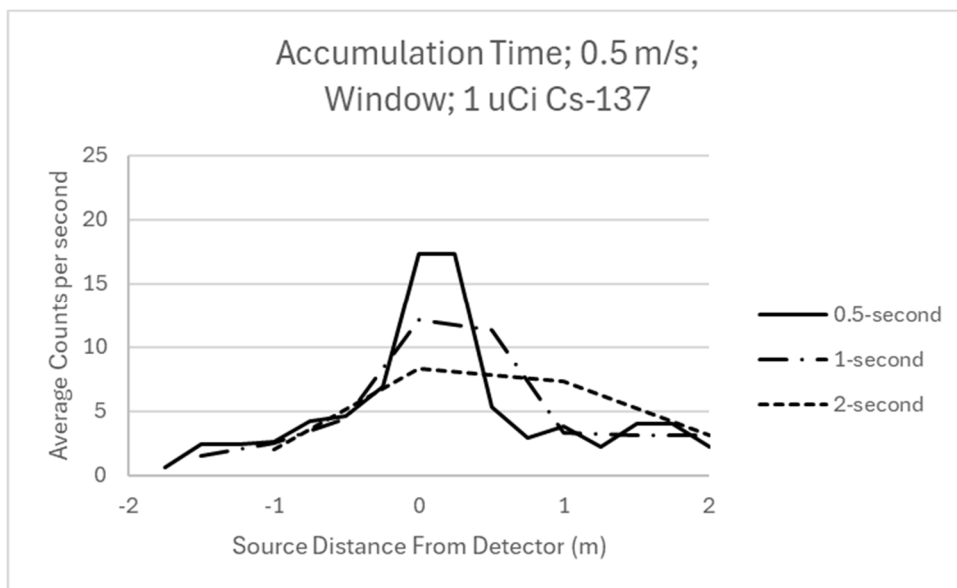


Figure 42 Benchtop Average Cs-137 Count Rate Data Within 662 keV Energy Window with Belt Speed 0.5 m/s, for Varying Accumulation Times

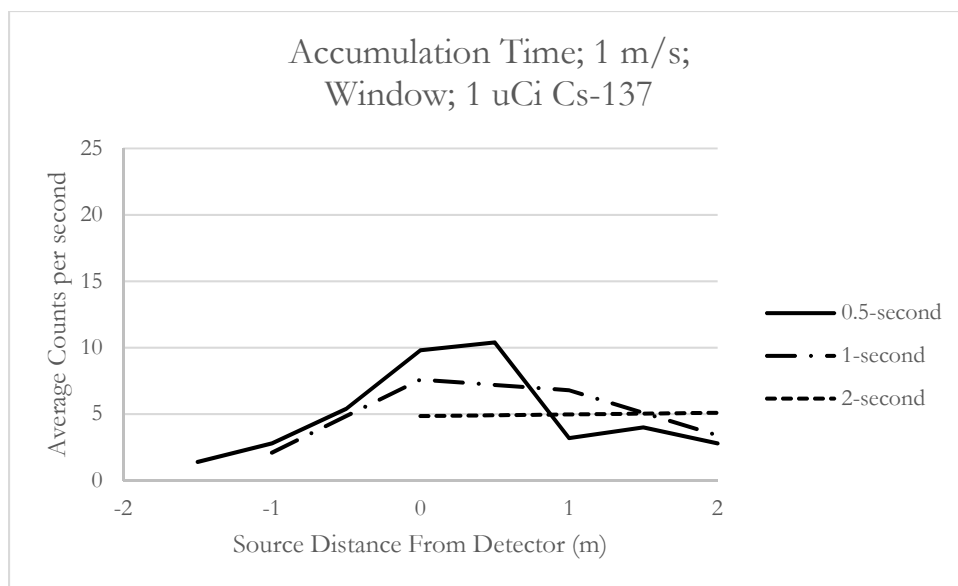


Figure 43 Benchtop Average Cs-137 Count Rate Data Within 662 keV Energy Window with Belt Speed 1 m/s, for Varying Accumulation Times

As observed earlier, at first glance it may seem desirable for surveys to use longer accumulation times, since they lead to less variability in the background data and thus a lower MDCR. However, this benefit must be balanced against the chance of missing a source during the actual survey, because of the averaging effect described in the previous paragraph. For point sources and smaller distributed sources, the increase in count rate as the detector passes over the source may last only a short time, depending on the source strength and scan speed, and thus might easily be masked by a longer accumulation time. For sources distributed over a larger area, the increase in count rate could last longer and so could remain detectable even with a relatively long accumulation time.

The use of a longer accumulation time also leads to the collection of fewer total data points during the survey. For smaller reference background areas and smaller survey units, this could result in too few data points being collected to provide confidence in the data. Hence the choice of accumulation time for a survey should be informed by the characteristics of the sources that may be encountered (in particular, their size and distribution) and by the overall size of the areas to be surveyed. The next section further illustrates these considerations.

10 Scanning Localized Versus Wide Elevated Areas: Techniques, Considerations, and Effect on Minimum Detectable Concentration

MARSSIM does not directly account for how the scanning method affects the detector's ability to detect small areas with elevated levels of contamination. As discussed in Section 9, for small elevated areas, the accumulation time (the time that the elevated area is within the detector's field of view) has a significant effect on detection. Using slower scan speeds increases the accumulation time, while using faster scan speeds decreases it.

The NRC has also recognized the potential for discrete radioactive particles (DRPs). Specific guidance is provided in draft DUWP-ISG-03, "Contamination Control, Radiological Survey, and

Dose Modeling Considerations to Support License Termination at Sites with Environmental Discrete Radioactive Particle Contamination” (NRC 2024).⁴

A study by ORISE (ORISE 2023) describes the effect of survey technique, including soil cover thickness and surveyor scan speed, on DRP detection capability. Applying a modeling and evaluation approach similar to that of ORISE (2023), this section examines how the MDCR for CCD can be impacted by small or isolated areas of elevated activity. The “optimistic” and “pessimistic” scenarios developed by ORISE for DRPs can be applied to a MARSSIM-defined small elevated area, or “hotspot.” There are two scan paths to consider for CCD: (1) the serpentine path that is typically used for scans with vigilance, and (2) a straight path such as that used for detectors in a towed array over a survey area. The serpentine and straight scan paths each have an optimistic and a pessimistic view, due to the location of an assumed volumetric source.

10.1 Serpentine Path

In accordance with the ORISE technique, the physical setting of the surveyor and surrounding environment is modeled in a three-dimensional Cartesian coordinate system (i.e., with x-, y-, and z-axes). The hypothetical surveyor is standing in the +z direction and walking in the +y direction with constant velocity (v) measured in m/s. As the surveyor progresses in the forward (+y) direction, the detector moves side to side along the $\pm x$ direction, maintaining a constant ground-to-detector distance. Detector position through the surveyor’s transect is modeled as a sine curve, which represents the detector’s flat, serpentine motion during a survey transect.

To adequately represent the sine curve (ORISE 2023), coordinates are generated specifying the location of 100 evenly spaced points along the sine curve as the surveyor moves 1 meter in the +y direction. Figures 44 and 45 illustrate the detector position, as viewed in the xy plane (looking in the $-z$ direction), along a portion of the surveyor’s transect. Each detector position (represented by each dot in Figures 44 and 45) occurs at a specific time which depends on the surveyor’s forward velocity; it is assumed that the time from one dot to the next is always the same. For example, if the detector starts at location (0.0 m, 0.0 m), the surveyor’s velocity is 0.5 m/s, and the surveyor will traverse the 1-meter interval displayed in each of Figures 45 and 46 in 1 second, then, with 100 points depicted, the time between each pair of consecutive points is 0.02 second. Certain points in the figures are numbered to show the relative locations of the detector during the scans.

Figure 44 illustrates the optimistic (serpentine) path, in which the detector eventually passes directly over the hotspot. Figure 45 illustrates the pessimistic (offset) path, in which the detector follows a similar trajectory, but the detector-to-hotspot distance is maximized.

For the pessimistic evaluation, the hotspot is centered with half of its area in the survey lane and half in the adjacent lane, and the center of the detector gets close to but never passes immediately over the center of the hotspot.

10.2 Towed Array Example

Similarly, Figures 46 and 47 depict optimistic and pessimistic views of three detectors moving in the same direction over an elevated area of the same size. The optimistic scenario places the elevated area at the center of the 1-meter path, while the pessimistic scenario places half of the

⁴ Comments have been received on DUWP-ISG-03, and a revision to the guidance is planned.

elevated area in the 1-meter path and the other half in the next survey lane. The paths of the three detectors are labeled A, B, and C in both figures. A towed array will have a straight-line path with no vigilance but with more control of speed (and thus of the distance covered during each accumulation time interval).

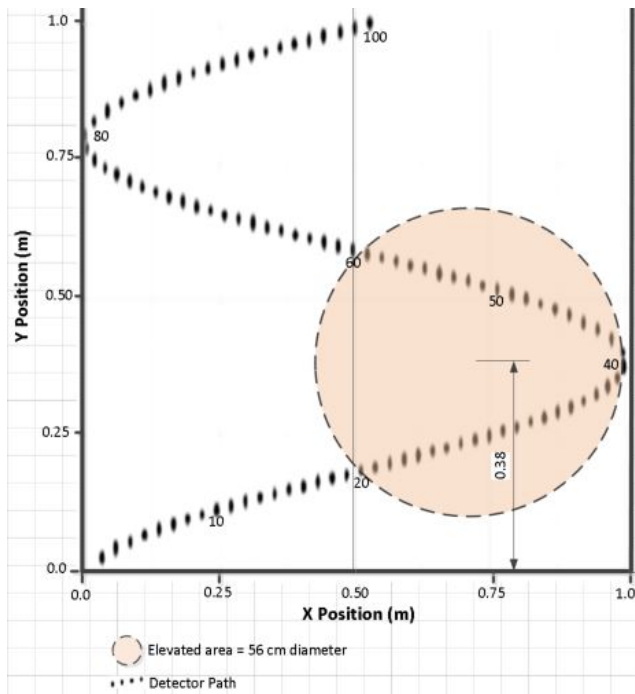


Figure 44 Optimistic Pathway of CCD Walkover Scan with Serpentine Detector Movement for 0.25 m²

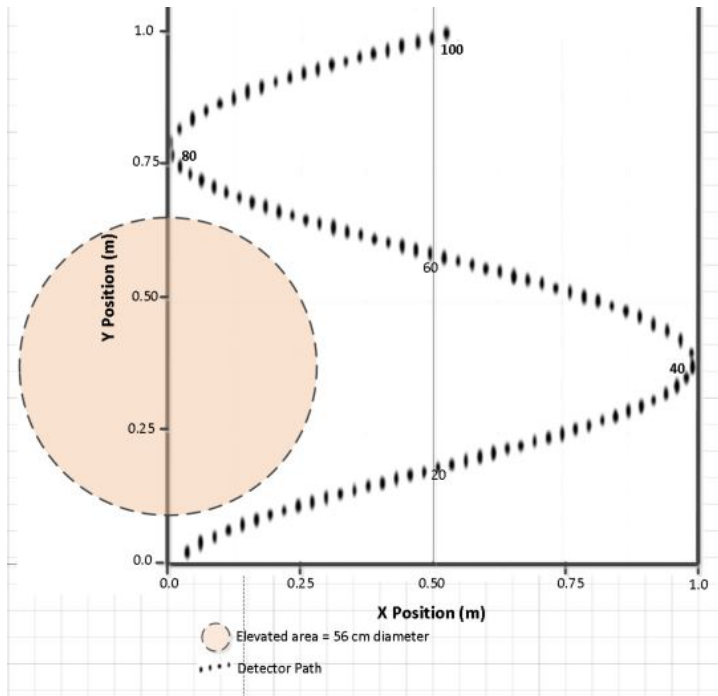


Figure 45 Pessimistic Pathway of CCD Walkover Scan with Serpentine Detector Movement for 0.25 m²

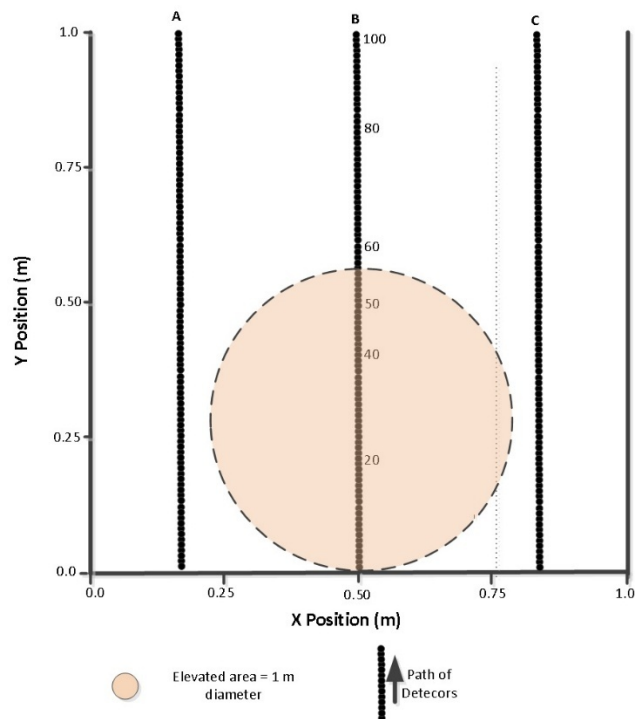


Figure 46 Optimistic Array Configuration for 0.25 m²

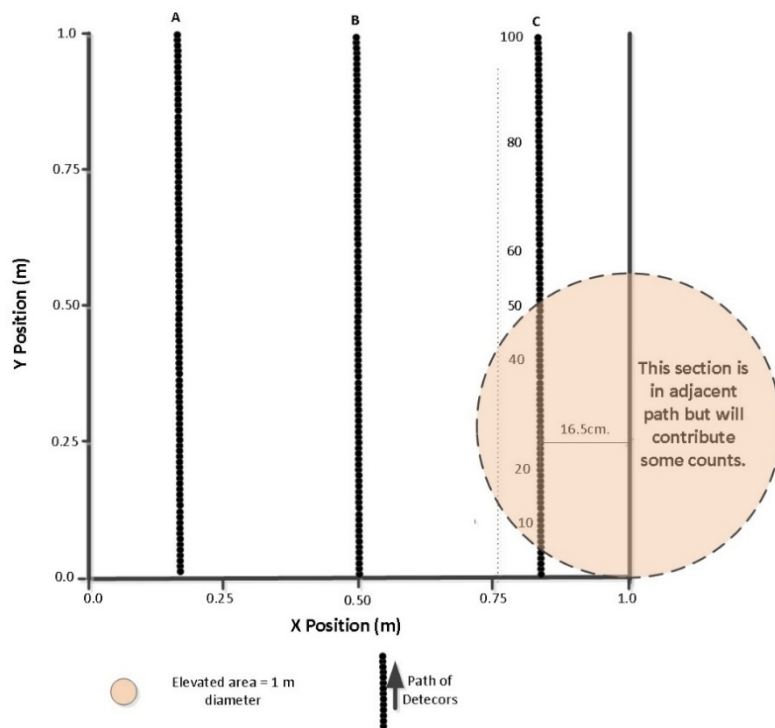


Figure 47 Pessimistic Array Configuration for 0.25 m²

10.3 Modeling of a Small Elevated Area

In evaluating detector response, it is not unusual to assign an efficiency value assuming the detector is positioned over the source center. This assumption is consistent with the MARSSIM two-stage scanning technique, in which an audible increase in count rate is used to identify an elevated area, and then a stationary measurement is taken over the identified area. However, the same assumption may not be a reasonable when using CCD to detect small elevated areas. As shown in Figures 44 through 47, depending on the location of the detector within the scan path, the over-center event may happen only once, or not at all. Therefore, the approach described in this section considers the possibility that the detector will pass to the side of the elevated area (i.e., by some offset).

An area of size 0.25 m² (the standard MARSSIM area) is modeled as follows:

- MicroShield® Version 8.02 is used to model a small area of elevated activity in the soil and determine the net exposure rate produced by a radionuclide concentration at a distance of 10 centimeters above the source. This distance is selected because it is the average height of the 2"×2" NaI scintillation detector above the ground during scanning.
- Modeling analysis of the elevated area is for Cs-137 at a concentration of 1 pCi/g. The same approach can be applied for other gamma-emitting radionuclides, such as cobalt-60. The other factors are held constant, in accordance with the classical model: the source is located at the surface with a thickness or depth of contamination from ground surface of 15 centimeters. The detector observation point is 10 centimeters above the surface and at varying distances from the ground-level center of the elevated area. A soil density of 1.6 grams per cubic centimeter (g/cm³) is assumed.

- The MicroShield® geometry is a cylinder source surrounded by uncontaminated soil as the detector passes to locations outside the perimeter. Figure 48 illustrates this geometry.



Figure 48 MicroShield® Configuration of Shielding and Measurement Locations

For this modeling, the radius of the elevated area is set to 28 centimeters, as shown in Figures 44 and 45. The size of the area provides an observation interval of at least 1 second. An interval assessment frequency of every 0.02 second has been used to provide a sufficiently fine mesh for evaluating the detector position and response as the spatial configuration changes. This configuration places the detector directly over the source during the scan, as in the optimistic view. The exposure rates at each 0.02-meter interval are evaluated, and counts per second and counts per minute are evaluated for 1- and 2-second accumulation times.

The data of counts per interval (0.02 second) for each distance from the elevated area surface center are obtained by applying the nominal 900 cpm per $\mu\text{R/h}$ factor from Section 6.2.5 of NUREG-1507. Table 11 presents the total number of counts over 1- and 2-second intervals, converted to cpm values. Recorded counts over an accumulation time interval must be whole numbers; a fraction of a count cannot exist or be recorded. Therefore, for this example, all fractional counts calculated from the interval modeling are rounded according to conventional rounding methods. Figure 49 presents the exposure rate, as a function of distance from the center of the elevated area, for a MARSSIM standard elevated area (0.25 m^2) with Cs-137 at 1 pCi/g, at a measurement (scan) height of 10 centimeters from the land surface.

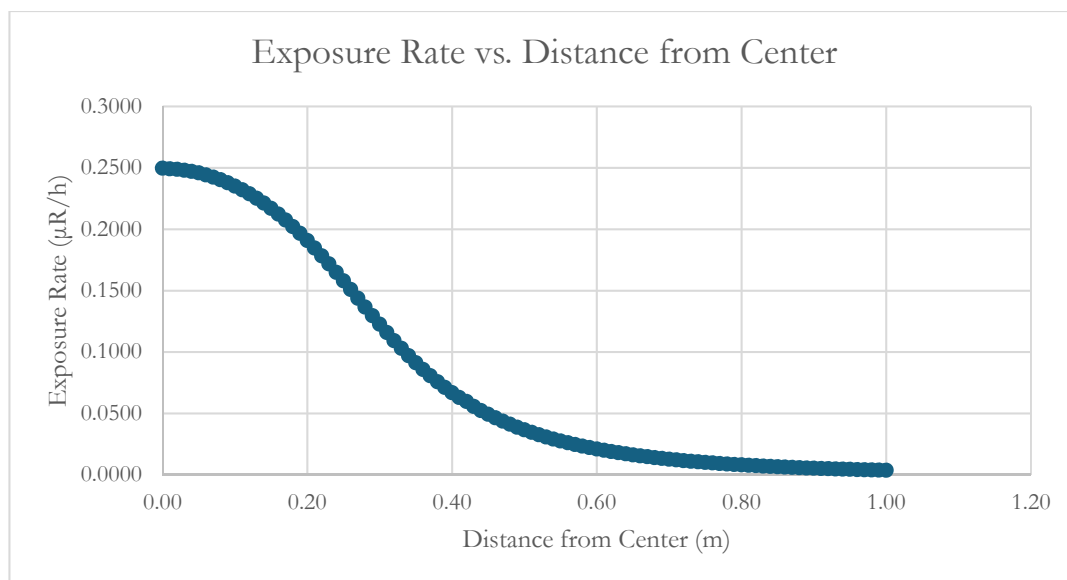


Figure 49 Exposure Rate as a Function of Distance from a 1 pCi/g Cs-137 0.25 m² Elevated Area with Scan Height of 10 cm

As shown in Table 11, the resulting counts (and the corresponding count rates) reflect the increase expected, above what would be the background, from a 0.25 m² elevated area with the specified activity. The expected increase in counts reflects a combination of the orientation of the detector relative to the elevated area and the duration of the scan (i.e., accumulation time). (Refer to Figures 44 and 45.) In the optimistic scenario, for the standard walking survey with a 2-second accumulation time, the detector response to the small elevated area is 7 percent (3/44) of the response to a widespread area of contamination. In the pessimistic scenario, this value is 4.5 percent (2/44).

It is recognized that this model does not take into consideration the inherent randomness (probability) of radioactive decay or of detector interaction that would lead to a signal. The model is intended mainly to illustrate the potential effect on detection levels of elevated areas that are smaller than the detector's field of view over a defined accumulation time.

Table 11 Total Counts over 1- and 2-Second Accumulation Intervals for a 0.25 m² Elevated Area with 1 pCi/g Cs-137, Versus Wide-Area Contamination

Type	Accumulation Interval	Optimistic (counts)	Optimistic Count Rate (cpm)	Pessimistic (counts)	Pessimistic Count Rate (cpm)	Wide Area* (counts)	Wide Area Count Rate (cpm)
Walkover	2 seconds	3	90	2	60	44	1,323
Array	2 seconds	4	120	4	120		

* "Wide area" denotes relatively uniform contamination covering the entire survey area for the accumulation time.

The gross gamma evaluation in Section 7.1 gives an L_D of 92 counts in a 2-second accumulation interval, or 2,748 cpm, for EWMA. That detection limit is derived from the same detector, scan height, and accumulation time as the scenario modeled here, which is what makes the comparison valid. Using the ERC value of 0.247 $\mu\text{R/h}$ per pCi/g and the calibration

factor of 900 cpm per $\mu\text{R/h}$ (both from Section 6.2.5 of NUREG-1507), this MDCR value corresponds to an MDC of approximately 12 pCi/g Cs-137.

The same evaluation can be performed for the energy window data from Section 7, for which the MDCR obtained is 257 cpm (approximately 8 to 9 counts in a 2-second interval). Here, applying the ERC value of 0.247 $\mu\text{R/h}$ per pCi/g and the calibration factor of 900 cpm per $\mu\text{R/h}$ yields an MDC of 1.2 pCi/g.

For the modeled 0.25 m² elevated area, the optimistic scanning scenario with a 2-second time interval gives 3 counts in a 2-second accumulation time (90 cpm) for a 1 pCi/g Cs-137 level. To achieve the calculated 92 counts indicates a Cs-137 MDC value of 31 pCi/g (92 counts, corresponding to the MDCR, divided by 3 counts per pCi/g). For the windowed measurements, the MDCR is 257 cpm, or 8 to 9 counts in the 2-second interval. Dividing 9 counts by 3 counts per pCi/g yields an MDC of 3 pCi/g.

For the pessimistic scanning scenario, the total number of counts in the 2-second interval is 2. For gross scanning, dividing the L_D value of 92 counts by 2 gives an MDC of 46 pCi/g. For the windowed measurements, 9 counts divided by 2 gives an MDC of 4.5 pCi/g.

If the towed array is used for the energy window data, the resulting MDC shows a modest improvement over that for the single-detector scanning. The optimistic count value increases to 4 counts in a 2-second interval, leading to an MDC of 2.25 pCi/g (9 divided by 4) for both the optimistic and pessimistic scenarios.

10.4 Modeling of a Larger Elevated Area

As the elevated area grows, the detector's response will approach its default wide-area response. For the example discussed below, the elevated area is assumed to be approximately 0.8 m², with a radius of 50 centimeters. Figures 50, 51, 52, and 53 illustrate the scanning survey pattern. Each marking interval along the scan path represents a 0.02-second modeling segment. The optimistic path contains about 43 marking intervals over the first second and about 39 more observation points over the next second. The part of the pessimistic path lying over the source contains about 36 markings. The exposure rates at each 0.02-second marking interval are evaluated, and counts per second and counts per minute are calculated for 1- and 2-second accumulation time intervals.

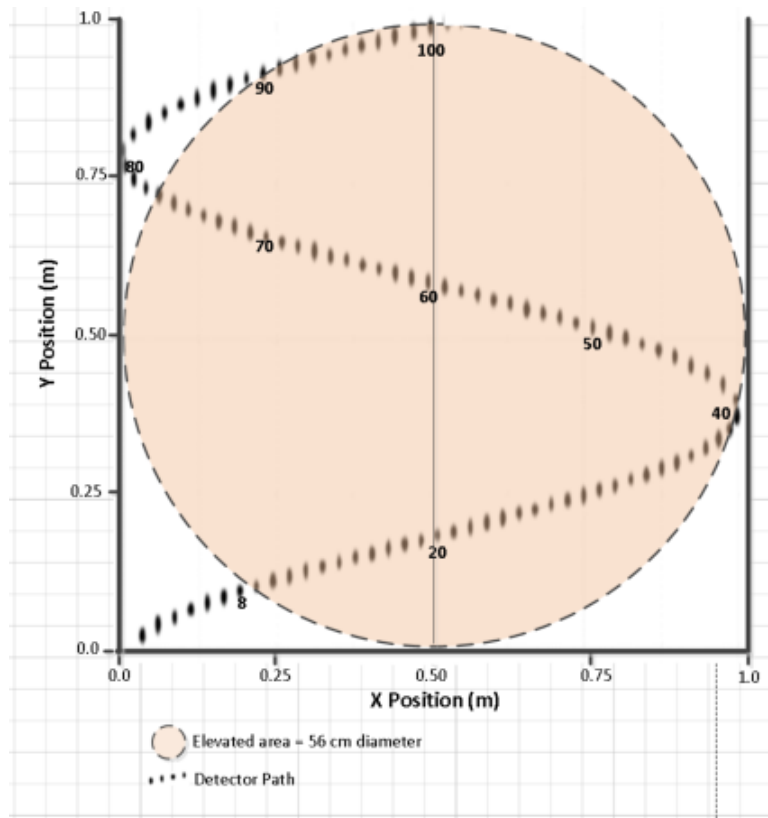


Figure 50 Optimistic Pathway of CCD Walkover Scan with Serpentine Detector Movement for 0.8 m²

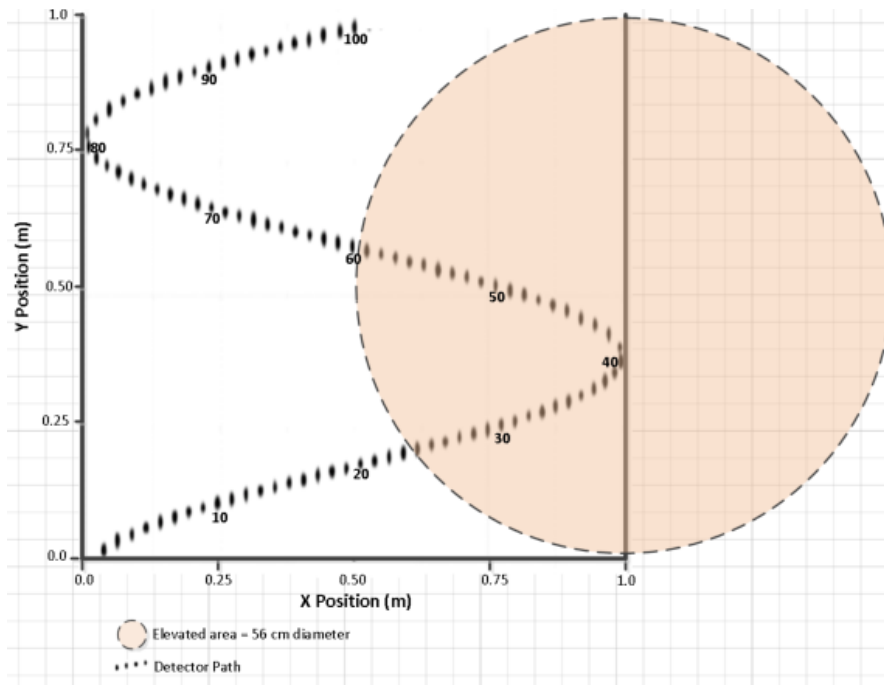


Figure 51 Pessimistic Pathway of CCD Gamma Walkover Scan with Serpentine Detector Movement for 0.8 m²

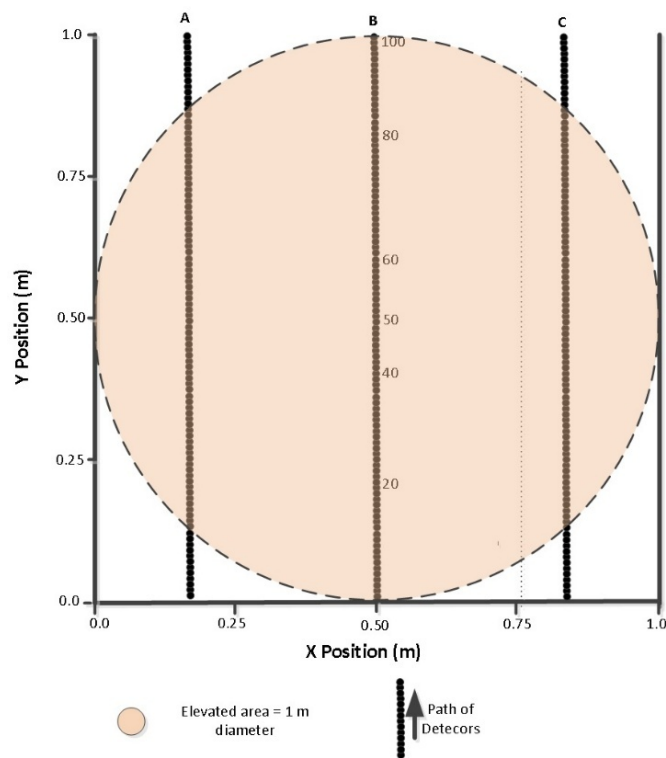


Figure 52 Optimistic Pathway of CCD Towed Scan for 0.8 m²

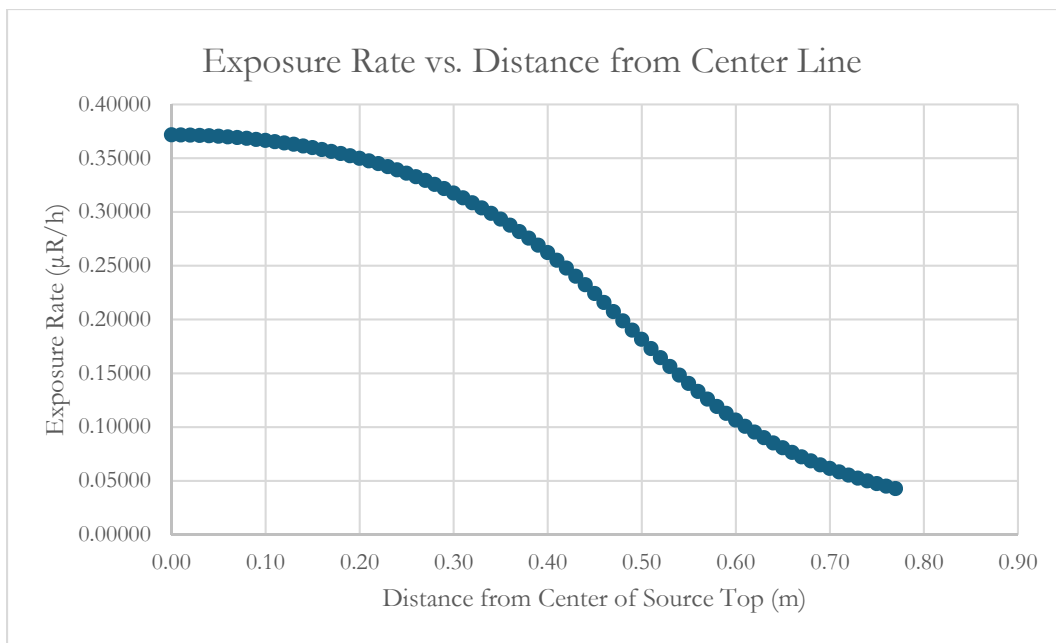


Figure 54 Exposure Rate as a Function of Distance from a 1 pCi/g Cs-137 0.8 m² Elevated Area with Scan Height of 10 cm

Table 12 presents the results of this modeling of source and detector response. As shown in Table 12, the resulting counts (and the corresponding count rates) reflect the increase expected, above what would be the background, from a 0.8 m² elevated area with the specified activity. In the optimistic scenario, the detector response over a 2-second accumulation time is 7 counts, or about 16 percent (7/44) of the response to a widespread area of contamination. For the pessimistic scenario, this value is approximately 11 percent (5/44).

Table 12 Total Counts over 1- and 2-Second Intervals for a 0.8 m² Elevated Area with 1 pCi/g Cs-137, Versus Wide-Area Contamination

Type	Interval	Optimistic (counts)	Optimistic Count Rate (cpm)	Pessimistic (counts)	Pessimistic Count Rate (cpm)	Wide Area (counts)	Wide Area Count Rate (cpm)
Walkover	2 seconds	7	210	5	150	44	1,323
Array	2 seconds	32	960	30	900		

Using the same process as for the 0.25 m² elevated area, the detectability of the 0.8 m² elevated area can be evaluated. Here the optimistic scanning scenario 7 counts in a 2-second accumulation time for a 1 pCi/g Cs-137 level. To achieve the previously calculated 92 counts requires a Cs-137 MDC value of 13 pCi/g (92 counts divided by 7 counts per pCi/g). For the windowed measurements, the MDCR is 257 cpm, or 8 to 9 counts in the 2-second interval; dividing this by 7 counts per pCi/g yields an MDC of ~1.5 pCi/g.

For the pessimistic scanning scenario, the total number of counts in the 2-second interval is 5. For gross scanning, dividing the L_D value of 92 counts by 5 gives an MDC of 18 pCi/g. For the windowed measurements, 9 counts divided by 5 gives an MDC of 1.8 pCi/g.

If the towed array is used for the energy window data, the resulting MDC shows an improvement over that for the single-detector scanning. The optimistic count value increases to 32 counts in a 2-second interval, leading to an MDC of 0.3 pCi/g (9 divided by 32) for both the optimistic and pessimistic scenarios.

As discussed in Section 9, decreasing the scan speed yields better detection capability as more counts are accumulated over the same area; however, increasing the accumulation time alone incurs the risk of masking small elevated areas, as the count data are averaged over longer time periods. This risk is lower for larger elevated areas; for these, increasing the accumulation time alone may be advantageous.

11 Additional Variables Affecting Minimum Detectable Concentrations

11.1 Aspects to Consider

As discussed in Section 4 of NUREG-1507, several aspects of the instrumentation selected for a given survey and how it is to be used to collect data have a direct impact on the measured count rate obtained from the survey. The detector must be properly calibrated for the sources that are expected in the field. This includes calibrating the source-to-detector distance that is planned for a field survey. Selecting the appropriate source-to-detector distance should be part of the DQO process, as this distance affects the detector's field of view and the resulting count rate. Additionally, the detector response for lower-energy beta emitters is more susceptible to changes in the source-to-detector distance, as described in Section 4.2 of NUREG-1507. In some instances, a surveyor may wish to use a collimator to reduce the ambient background radiation. Adding a collimator decreases the field of view of the detector, particularly for lower-energy photons. The decreased field of view should be considered when planning the survey path to ensure adequate coverage of the area.

The characteristics of survey units that could affect survey performance should be identified and factored into the survey planning process. For example, it may not be appropriate to apply an MDC obtained from a reference area survey conducted on a flat area to a survey conducted within a trench, as the detector response within the trench will be influenced by the trench base and sidewalls, particularly for a narrow trench or when the detector field of view would encompass more than just the ground surface. Another characteristic that should be considered in planning is the moisture content of the survey area. Increased moisture can lead to increased attenuation, especially for low-energy gammas, and may need to be corrected for in the source efficiency or in the modeling of source detector response. Ideally, the expected conditions of a survey unit and the intended reference background area should be as similar as possible. The potential effects of humidity and diurnal fluctuations should also be taken into consideration.

As described in Section 5.1 of NUREG-1507, it is generally expected that different types of material, with varying background count rates, will be encountered when surveying a given site or facility. Therefore, initial evaluations of the site should aim to identify the material types present and characterize them appropriately for determining the MDC. Visually similar material types may exhibit noticeably different radiological characteristics. When a survey unknowingly covers an area containing two such materials, it can be a challenge to determine the MDC: a histogram of the survey data may show a bimodal distribution, and a time-series plot may show

temporal differences in the count rates as the detector passes between the two material types. If the MDC were calculated using the entire dataset, then the increased variability resulting from the discrepancy in materials would drive the MDC higher. However, if the areas containing the two materials can be delineated and separated using time-series data, geographic coordinates, or both, then the data can also be separated, and multiple MDCs can be calculated. The latter approach should be considered if, in the planning stages, it is possible to determine what types of background material will be present in the survey area. However, this could be difficult if there are multiple materials with no visible differences.

As explained in Section 1, CCD surveys do not require the surveyor to monitor and react to the detector response during the survey. In most cases, however, CCD are collected by a surveyor who can still see the measured count rate as the survey progresses. It is possible that during a survey, the surveyor could pause in one location, either because it is a potential area of interest or for other reasons, while the detector is still registering and logging the count rate. If the surveyor were to pause on an area with an elevated count rate, this could greatly affect the statistics (i.e., the variance) of the overall dataset, as a larger number of elevated readings would be logged than if the surveyor had not paused. If GPS data are available, then such pauses can be accounted for by plotting the data on a map and identifying clusters due to pauses. It may be necessary to identify and remove the excess data points collected in a single location to obtain a more accurate dataset for the MDC calculations.

11.2 Good Practices for Continuously Collected Data

Additional good practices should be implemented when designing and performing CCD surveys. For example, recording accurate GPS data together with the scanning measurements allows for precise mapping of the measurements. High-quality GPS data (accurate, precise positioning) make it possible to create reliable maps and ensure repeatability of the survey. GPS data with a higher error in positioning accuracy and precision can hinder relocating elevated areas. Furthermore, the position of the GPS antenna in relation to the location of the detector during the survey must be taken into consideration when interpreting the data. Some GPS systems are able to achieve accuracy within a few centimeters; however, if the detector were actually located tens of centimeters or more away from the GPS antenna during the survey, this could lead to misidentification of locations of interest if not taken into account. The specifications for GPS positioning accuracy and precision are important elements to consider in the survey planning (i.e., verifying scan coverage); however, in general, these specifications do not otherwise affect the MDC calculational methods derived herein.

Also, the terrain of a candidate reference area must be considered, especially when the detection system to be used includes instruments mounted onto a push- or power-driven vehicle. Tilting of the vehicle as it passes over rough terrain can decrease the accuracy of the GPS coordinates collected. Rough terrain may also lead to sporadic and unpredictable changes in the detector-to-ground distance, which can reduce the reliability of the data collected at those locations.

Scan speed is also a factor in being able to detect small areas of elevated activity. As discussed in Section 9.1.2, as the scan speed increases, the detectability for smaller areas of elevated activity (i.e., smaller than the scanned areas during the specified accumulation time) decreases. The study by Falkner and Marianno (2019) clearly demonstrated that the calculated minimum detectable activity increases as scan speed increases, because of the corresponding decrease in the geometric efficiency of the detector. It also showed that slight variations in scan speed

can affect the detector's ability to achieve the desired minimum detectable activity, highlighting the need to ensure a consistent scan speed during surveys.

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