Time Analyzing Electromagnetic Fields in Paranormal Research: A Binomial Modeling Approach for Field Analysis of Purportedly Anomalous Phenomena

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Abstract

This paper describes several characteristics of field-collected electromagnetic fields (EMF) and the means used to analyze them in context of time and observed phenomena or behavior. With the use of nine sets of time-dependent EMF samples, we demonstrate (a) the general, normal distribution properties of EMF; (b) exceptions to EMF normal distribution modeling; (c) methods for modeling a distribution of EMF into a binomial distribution; (d) conversion of the binomial-modeled data into discrete time-dependent trials. From these points, it is shown that, when converted into a binomial model, the overall EMF data set represents a population-level probability for any given time period sampled. The use of random sampling from these data sets proves that the overall binomial probability of the converted EMF data set represents a random-population probability that researchers can test against. The resulting model allows for time-synced binomial testing of any environmental phenomena with observed behaviors or anomalies to determine above chance association. Finally, we will discuss the implications of this technique with other randomly occurring environmental data.

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As a Social Psychologist who studies religion and ideology, I have always had a passion for paranormal phenomena. It was approximately five years ago when the author launched a series of research projects to scientifically investigate locations reported by ghost-hunting organizations to produce recurrent anomalous phenomena. One of our first and ongoing projects was the study of electromagnetic fields (EMF) and their association with perceived paranormal phenomena. We have been examining both somatic perceptions and vetted audio or video recordings ever since. Surprisingly, little work has been done on the subject. Five years and thirty plus data-logged investigations later, we have experimented with and designed protocols that have resulted in what we believe to be a reliable association between EMF and externally vetted and captured phenomena (Laythe & Owen, 2013). More recently, we have found a relationship between individual somatic perceptions of phenomena in a controlled séance environment and geomagnetic field spikes (GMF: Laythe, Laythe, & Woodward, 2016).

This approach to examining EMF required considerable thought regarding how to both model and test EMF in comparison to other environmental phenomena and somatic reports. We believe that the association of known physics (i.e., EMF) to such controversial phenomenon as haunting and PK represents a step toward a working scientific method for operationalizing such phenomena. However, working with environmental data requires some creativity with time beyond what many social scientists typically use in inferential statistics.

This paper has several goals. First, we will address reliable modeling, as well as the behavior of EMF in context of time and location. Second, and more importantly, we will introduce methods for determining the random probability of EMF readings-spikes as specified by the researcher. Third, we will demonstrate that random sampling with these methods are unnecessary in determining probability when using time-dependent binomial trials. Finally, we will exemplify the use of binomial trials to model EMF so that any series of events in time can be statistically tested against their random probability of obtaining an EMF (or any other environmental phenomena) spike given the particular sample.

EMF Data for the Purpose of Verification

There are three data-sets of EMF from which we verify the claims in the current work and that serve as proof of the methods employed. The current paper is presented as a mathematical proof rather than a research paper meant to clarify statistical and theoretical points. EMF data was collected in two locations: a residential location our organization was asked to investigate (although no evidence of anomalous activity was found), and a (to our knowledge) regular residential location from which two sets of data were collected. Data was collected with the use of 3-axis magnetometers constructed by the author using microprocessors and data logging components of Arduino design. These meters collect EMF data at the 0 to 8 Hz range (GMF) at a rate of two samples per second, on three axis, and were collected as raw volt input on a range of -10000 to 10000. The resulting data provides nine (3 separate sets of data with 3 axis each: x, y, z), to analyze for the purpose of the current work.

EMF, Its Description, and Previous EMF Research

For those unfamiliar with electromagnetic fields, EMF represents the far left end of the known energy spectrum (measured in hertz (Hz)). EMF is usually assigned to the 0-100 Hz range of the EM spectrum. Thus, EMF is part of the spectrum of energy that includes infrared light, visible light, and at high frequencies, x-rays, gamma rays and beyond (OpenStax, 2015; Tipler, 1987). Usually, EMF is measured at what is referred to as "Mains Frequency," which is 50 or 60Hz, depending on the country of origin. It is referred to as Mains Frequency for the reason that the artificially created electrical current of our electrical grid creates an associated magnetic field. Thus, all electrically powered technology gives off EMF at a 50 to 60 Hz range as a condition of an electrical current passing through them (Thide, 2004; Tipler, 1987; World Health Organization, 2016).

The geomagnetic field (GMF) is the natural magnetic field that surrounds the Earth. Due to the rotation of high-temperature metals in the Earth's core, the GM field maintains life on Earth by shielding life forms from harmful solar and space radiation (OpenStax, 2015; Thide, 2004). GMF is typically assigned less than 10 Hz within the EM-spectrum. At the Earth's surface, various topography and geology can produce increases and decreases in the magnitude of GMF, and solar flares create considerable increases in magnitude of GMF for a region (Gearhart & Persinger, 1986; Thide, 2004).

Regardless of its frequency, EMF-GMF is often measured in terms of magnitude, usually in either microtesla or milligauss. Either represent the amount of energy (e.g., B-field; Open Stax, 2015) EMF is producing at the location of a meter. There has been some previous work using EMF measurements in association with anomalous phenomena. For instance, Braithwaite (2004, 2006) has taken measurements of GMF and shown significantly greater amounts of GMF in a specific area of a purportedly haunted location. Joines and Roll (2013) have recently associated EMF readings with recurrent spontaneous psychokinesis (RSPK) events. More generally, researchers have found either increases in magnitude or changes in variability in testing reportedly haunted versus non-haunted locales (Braithwaite, 2004, 2006; Braithwaite, Perez-Aquino, & Townsend, 2004; Braithwaite & Townsend, 2005; Maher, 2000; Nichols & Roll, 1998; Roll & Persinger, 2001; Wiseman, Watt, Greening, Stevens, & O' Keeffe, 2002; Wiseman, Watt, Stevens, Greening, & O'Keeffe, 2003). A common problem with the above studies was the collection of EMF data without respect to EMF variation over time. These studies, per normal inferential tests, simply averaged the readings, regardless of the moment-to-moment variability of EMF magnitude.

Other researchers have focused on the relationship between GMF fields and hallucinations, particularly in the laboratory (Booth, Koren, & Persinger, 2005; Gearhart & Persinger, 1986; Persinger, 2003; St. Pierre & Persinger, 2006; Roll, Persinger, Webster, Tiller, & Cook, 2002; Tsang, Koren, & Persinger, 2004). This process, with the assumption that GMF is producing hallucinations on the site (Persinger & Gearheart, 1986), has traditionally been used to explain haunted location phenomena. However, it is important to note that Persinger and Gearheart (1986) have never actually tested this hypothesis, and as such, it remains a theory. Thus, for the interested researcher, there has been enough EMF/GMF related research conducted to warrant further exploration of EMF-GMF with both subjective and objective anomalous events.

The Accurate Behavior of EMF in the Field from a Distributional Perspective

For several reasons, the practical meaning of EMF magnitude readings and statistical tests of such are very limited and highly prone to erroneous statistical significance (Type I error) in the field. The current research holds that it is important to clear up several misunderstandings in the field about EMF and provide practical guidelines and natural limitations inherent in EMF measurement. First, EMF meters are receptive meters. They register a particular EMF reading at the exact location the meter is placed as a function of the EMF received at that location. Second, EM fields decay at an exponential rate. Essentially, this translates to a 1000 mg field registering 100 at one foot distance, 10 at two feet, and 1 at three feet (Thide, 2004; Tipler, 1987). This is an important aspect of EM fields that is often misunderstood. A power line carrying 10^{15} kilowatts of power, when converted to gauss, will typically register less than one gauss within 30 feet or so of distance, and one milligauss with three additional feet. Third, most meters, even when very sensitive, have a detection diameter of about 8-10 feet (i.e., 5 ft. in any direction from the meter). Fourth, interference in EMF readings from EM-waves (projected as transmissions or energy, as opposed to a field), have their magnetic component greatly reduced. The electrical force compared to the magnetic force of a carrier wave is a ratio upward of over 200 to 1 (Thide, 2004). As such, transmission waves (aside from the fact that commercial EM-spectrum transmissions are at a much higher frequency in the EM spectrum) create little to no magnetic interference for the average receptive EMF meter (Thide, 2004; Tipler, 1987; World Health Organization, 2016). Most carrier wave interference is so magnetically weak it simply forms the EM background noise within a measured area.

Fifth and finally, some metallic surfaces will reflect an EM field. However, these represent poor explanations for variation in an EMF distribution and ineffectual explanations for brief magnitude spikes, if the reflective surfaces are non-mobile (Laythe & Owen, 2013). Metal within houses, and in terms of common sense, chunks of metal in general, are often fixed within their location. Variation in magnitude for a receptive EMF meter would require that either a). The field strength changes, b). The location of the meter has changed, or c). The metal reflecting a field has moved. Common practice for use of EMF meters is to keep them stationary (movement will produce false readings). Metals in buildings do not move or shift on a moment-to-moment basis, Thus, our first listed cause is the only viable source of the change in readings. This is an important point, as we have been able to demonstrate that correlations among five sets of meters collected on an hour-to-hour basis show strong changes in association. These readings were collected in a house without electricity and vetted anomalous phenomena. The practical interpretation of the above is that multiple fields of EMF/GMF were somehow generated in the home, changing the degree of association between meters 20 to 40 feet apart (Laythe & Owen, 2013).

Given all the above, we have argued in Laythe and Owen (2013) that an averaged magnitude reading of EMF, which may be deemed significantly different from some type of control readings, may be invalid. Simply moving the meter 12 inches, due to both the limited detection area of a meter and the exponential decay rate of EM fields, may radically change the mean of EMF in a brief period of time. As such, a magnitude reading from an EMF meter, or small sustained increase in EMF magnitude from a meter over time, is not necessarily a reliable measurement in itself. As the meter cannot provide information of the source of the EM field, the reading is only accurate in the sense of the specific time and precise location of the meter. A change in either the former or the latter may radically change the findings.

It is also relevant to note that all current EMF meter technology converts raw voltage input into an approximate averaged estimate of microtesla or milligauss. This conversion, as a function of sensors using the Hall Effect (OpenStax, 2015) depending on the resolution and accuracy of the meter, can add upward of 10% error of any series of readings. Also, negative readings are not in fact negative. Negative magnitude readings are the same as positive magnitude readings, but represent the magnetic field moving contrary to the Hall Effect sensor (OpenStax, 2015). Thus, conversion into standard scientific notation, or failure to interpret negative readings correctly on an alternate axis, can add error and misleading data, and approximates a series of readings that are still subject to all of the limitations described above.

The essential point is when meter location, exponential decay rates, unknown EM field sources, unit conversion, and receptive meters are all taken into account, any statistical means test of magnitude between two series of readings provides little reliable information. In a very general sense, we may discover a consistently higher amount of EMF at "haunted locations" compared to other locations, but only if multiple meters are deployed and a sufficiently large/varied sample is obtained. In contrast, a single series of EMF readings from a meter in a smaller location (e.g., a room), is very limited in generalizing the reading to the area, or even the room itself unless compared against multiple meters that are appropriately synced in time.

The Distribution of EMF over Time as Approximately Normal and Practical Interpretation

Considering the issues above, the question remains: "What is the point of measuring EMF at all?" The answer lies in collecting EMF data over a period of time, its behavior at points in time, and the examination of its distribution. In contrast to controlled environments of engineering or physics, a precise value of EMF is relatively meaningless in field environments. In our current state of affairs, social scientists examining anomalous phenomena are not attempting to solve a single equation or determine a specific vector of EMF inside a laboratory. However, interesting findings emerge by looking at EMF from a descriptive statistics position and the associated probabilities that occur from it.

To make this case, several facts must be posited. First and foremost, EMF, when collected over time, naturally varies around a central magnitude value. EMF readings are typically averaged by most meters to approximate an accurate reading. Thus. most data sets of EMF will typically form a normal distribution (i.e. Open Stax, 2013). There are, however, some notable caveats to EMF distributions. Although Braithewaite (2004, 2006) demonstrated the EMF-normal distribution claim, we wish to conclusively demonstrate that EMF data collected over time forms an approximate normal distribution. Thus, we provide p-p plots of EMF data collected for the purposes of this paper (See Figures 1 & 2). Means, standard deviations, skew and kurtosis data are provided in Table 1.

Per Table 1 and Figure 1, it can be seen that the vast majority of our EMF distributions show an approximately normal curve. However, per Figure 2, skew (e.g. movement away from central tendency) was significant (> 1.96) in two out of nine data sets (one exceptionally so). Kurtosis (e.g. greater area than expected in the tails per a normal distribution) was significant (> 1.96) in three out of nine data sets (two were extreme readings, $z_1 = 13503$ and $x_3 = 6775$). Examination of Figure 2 shows that the z_1 data set has outlier readings in the right tail, and x_3 has extremely narrow variability. While generally normal, it should also be apparent that the variance of a particular series of collected EMF readings can be radically different from other distributions of EMF. These distributional differences can occur both from the same meter or a different meter in a nearby location (i.e., another room in the same house). Thus, standard deviations of a normally distributed EMF curve can be very small or large as a function of additional EMF interference received by the meter. Similarly, interference can produce outlier readings in one or either tail of the distribution.

The interpretation of EMF variance is that larger variance typically means greater degrees of interference at different points in time from additional EM field(s) that are either a). distant from the location but very strong, or b). very near the location of the meter but comparatively weak, or c). a temporarily generated local field. Determining which is the case is conducted by comparing multiple meters. Very strong mains frequency fields typically come from either large amounts of artificial electricity generation (e.g. unshielded wiring in the home, or close electrical pole wires), or in the case of GMF, solar flares-storms. These would typically be indicated if large variance were seen in the distribution of multiple meters in different locations of the data collection environment. Large variance from EMF on a single meter compared to others is more difficult to explain with regards to its source.

Practically interpreting the above provides important environmental EMF information. With regards to the former, any EMF distribution with greater than 5% scores in either 2*SD* tail (i.e., Kurtosis) implies interference from another similar frequency EM field or fields, the source likely indeterminable. A distribution whose focal point (i.e., mean magnitude) shifts during data collection represents a strong and constant field of EMF that has affected the previous distribution of the meter. A drop represents the absence-removal of a continuous field. From experience in anomalous environments, we can state that, without nearby electronics (i.e. +/- 5 feet from a meter), HVAC equipment, or in the case of GMF, solar flares, these changes quickly become difficult to explain. Conventional physics explanations for these changes often do not provide a viable explanation for EMF in terms of their source or their probability of occurring.

Yet, EMF data is essentially normal, and random by mathematical definition (Solomon, 1987). Thus, per any introductory statistics class, a normal distribution represents both a frequency distribution and a probability distribution of scores. One can deduce an estimate of probability for a range of scores, or the probability of extreme scores (e.g. +/- 2*SD* or 3*SD*) from this distribution. This property should also be obvious because any means test published (e.g., Braithewaite, 2004) regarding EMF requires that this assumption for the test be valid (Myers & Well, 1995). If we accept that data-logged EMF collected over a period of time in the same metric, say in five locations, provides us with contextual environmental data, the variability of those EMF data sets can become very informative. An EMF distribution can change as a function of either overall magnitude or variability of magnitude in its scores. As such, the tails of a distribution of EMF can become inflated with more frequent (e.g. higher and lower magnitude) scores. Thus, the amount of extreme distributional scores in an EMF data set (arbitrarily set as 2*SD* or 3*SD* +/- scores) become relevant, particularly in the context of time, as we will discuss shortly.

Thus, while any researcher knows that their data should be checked for normality, this rule becomes essential for EMF distributions. While generally normal, EMF data should be checked for a). the percentage of scores that occurred in the tails, b). an overall magnitude change that did not occur midway through collecting data, and c). the variance of EMF distributions you wish to test. It should also be stated that, due to large changes in variance from distribution, the assumption of equal variance for inferential tests will sometimes be violated when testing two different EMF distributions.

Normal to Binomial Process

The goal of the remainder of this paper is to demonstrate how researchers can test time-dependent readings of EMF (or any other time-dependent environmental variables e.g., temperature, gravity, infrared light, and so on) with participant behaviors. This method can be applied to any observed event that has been time stamped with a collected EMF distribution. In other words, given 80 observations of phenomena recorded in time, how do we determine the random amount of EMF spikes that would be associated with those 80 observations? Further, in terms of testing, how many EMF-event occurrences have to occur to demonstrate a relationship that is greater than chance?

The procedure described takes the initial probability from the raw distribution of EMF, and subsequently, remodels that distribution into successes and failures. Thus, an initial binomial trial (for clarity, often referred to as Bernoulli trials; Rice, 1995) based on the EMF distribution is created. We then subsequently assign-divide a set amount of EMF readings within a set period of time as a series of time-dependent binomial trials. We then demonstrate how the probability can be used to create an expected value of successes for any given amount of participant observations. We provide a generic example below using the existing data from the x-axis of Meter 1to take the reader systematically through the process.

> *EXAMPLE*: A researcher desires to examine whether sufficiently high EMF occur at the specific times a participant reports an experience. An EMF meter is placed in a room with data-logging capacity, sampling EMF at 2 samples per second. Data is then collected for 3.45 hours (n = 24909). A EMF spike is defined as any EMF score above or below two standard deviations. Approximately 1.05 % of scores meet this criteria (n = 262). 80 subjective experiences are reported by the participant, and their time logged in correspondence with the scores of EMF received at the time. The researcher wishes to know: a). what is the random expected amount of associations that would occur with 80 experiences, and b). how does the researcher test for a non-random association (i.e. greater than chance occurrence with EMF-experiences).

Converting Raw EMF Data to Successes and Failures

The very first step in testing time-dependent trials is to obtain a binomial probability from the initial distribution of EMF scores. This is first done by assigning a critical value regarding what score in the distribution will count as an abnormally high reading. We have previously used both +/- 2SD (Laythe, Laythe & Woodward, 2016), and +/- 3SD (Laythe & Owen, 2013) as critical value criteria. Two and three standard deviation values typically will create scores that occur in the tails of the distribution.

Once this cutoff criteria has been established, the data from the EMF distribution is converted into a nominal variable by coding scores above and below the cutoff as 1 (e.g., spike), and scores within the cutoff as 0 (e.g., not spike). An easy parallel to use at this point is to randomly sample from a deck of cards. Like the original EMF distribution, any value from a 2 to an Ace may be obtained for any given series of random card selections. However, we now desire to focus purely on whether an individual draws an Ace. Thus, we know that only four Aces exist in the deck, and only an Ace will constitute a 1 (e.g., a success).

By summing the amount of successes collected and dividing this number by the total n of the EMF data set, a percentage probability of obtaining a success (i.e., a 1) is determined. It is important to include at this point that the shape of the distribution of data is now irrelevant. By nominally coding the data, an exact percentage of random successes or failures is obtained. The assumption of normality is only relevant if a successful score is assumed to be the product of a normal distribution at either 2*SD* (i.e., 5%), or 3SD (i.e., 1%). We address normality assumptions for this process below:

Conversion to Binomial Distribution

The binomial probability distribution provides a means of testing a series of successes or failures where a probability is desired for k successes out of n number of trials (Myers & Well, 1995). The mass probability function of the binomial distribution is provided below:

$$f(k;n,p) = \Pr(X = k) = \binom{n}{k} p^k (1-p)^{n-k} \tag{1.1}$$

k = the probability of obtaining a set amount of successes out of n trials (e.g., 3/10 successes).
n = the number of trials.
p = the established probability of obtaining a single success.
q (1-p) = the probability of obtaining a single failure.

Although not traditionally thought of in this way, by coding our original EMF distribution to isolate cutoff scores (per the example 2SD scores), the approximately normal EMF distribution (using x_1 as an example) can be conceptually remodeled into 24909 binomial trials, where k =1 n = 1 p = .01 and q = .99. As there is only one sample selected at a time, the odds of obtaining a spike from only one selection is exactly .0105. This is essentially no different from our previous card example. Each draw of the card is an individual trial (*n* =1) where the probability of success (e.g., an Ace) is determined by the probability of obtaining an Ace out of 52 cards ($p = 4/52$) versus any other card ($q = 48/52$).

Obtaining a probability for a binomial trial in this manner assumes that the overall data set of EMF, appropriately coded, serves as an approximate population random probability. This overall probability for obtaining a success-failure is then suitable to use as a population probability for any given series of time-dependent trials selected by the researcher. In case the use of the overall data set as a population probability for trials is questioned, we provide 300 random trials (with use of the Excel RAND function) of 3000 and 6000 data points taken from each set of EMF data, where $n = 1$ and $k = 1$. Results can be seen in Table 2. All sets of randomly selected data taken from each EMF data set closely approximates-varies around the original data sets of EMF, and the probability obtained from said data sets. Specifically, the averaged difference from the random sampled probabilities and the original EMF data sets is .2% for the 3000 samples, and .3% for the 6000 samples. This demonstration serves as proof that the initial probabilities for binomial trials should be taken from the data sets themselves. Given enough samples, random sampling to obtain probabilities will eventually mimic the probability of the original EMF dataset.

As the probabilities from the original data sets of EMF are appropriate for use, it should also be evident that assumptions of probability regarding the distribution of the data itself can be used. Thus, if data is normally distributed, and the percentage of random successes is less than 5%, one can forego the exact probability and make a conservative random probability estimate of 5% of successes-hits based on a normal distribution. We emphasize that using this method creates an assumed expected random probability of 5% based on the assumption that EMF should be normal. It also, in our current example, is five times more conservative (i.e., obtaining successes significantly greater than 1% of the sample as opposed to obtaining successes significantly greater than 5% of the sample) in terms of the expected proportion of random successes expected. This was the general method we used in Laythe and Owen (2013) because we desired a conservative (i.e., inflated) estimate of random probability. The probabilities of success at 3*SD* were closer to 1%, as the example above.

The "normal assumption method" is a viable alternative to the precise probability for researchers who wish to maintain a conservative, random, and expected estimate to test against for controversial phenomena. In essence, this process of assuming a higher probability is a manual method of adjusting the expected *p* value for the binomial test itself. Regardless of whether the exact probability or assumed probability is used, all the subsequent steps remain the same. We leave the decision to use the actual probability or an assumed one up to the researcher, so long as the actual probability does not exceed the assumed normal probability.

Expanding the Binomial Model to Create Binomial Trials Dependent on Time

So long as we view each sample in the data set as one binomial trial, where $k = 1$ and $n = 1$, our previous examples and probabilities regarding the binomial model holds true. However, in order to model a series of time-dependent binomial trials, we have to take into account time and readings collected by second. This is done by taking the amount of samples collected per second, and then determining the duration of each EMF trial so that a distinct period of time is associated with the occurrence of events being collected.

For the purposes of the example presented previously, let us set a 5-second window in which an observed event does or does not occur. As 10 readings are taken over a period of 5 seconds, per our example, the binomial coding of EMF data are now nested into binomial trials. Using x_1 as an example, $n = 10$ (10 success-failure opportunities), $k = 1$ (the amount of successes required by the researcher given n trials), *p* converts to .104 (representing the inflated probability accounting for 10 opportunities for a success) and *q* becomes .896. As we have now nested every 10 readings into one binomial trial, the total EMF data set is divided by trial *n* to provide the total number of 5-second trials (i.e., 2490.9 5-second trials where each trial has a random $k = 1$ success probability of .104).

Using our playing card example for clarity, we now allow the participant to make multiple draws of the deck. Continuing to use the criteria of only an Ace as a success-hit, we now allow the participant to draw four cards, one per second. Furthermore, we declare that any of the four draws that contains an Ace constitutes a success for the entire trial. Thus, in binomial terms, $n = 4$ (four draws of the deck), $k = 1$ (one success is all that is required for the four selections to be declared successful, $p = .22$ (4/52 with four opportunities to draw the Ace), and $q = .78$. From our playing card example, it should be clear that every 4 seconds represents one trial, and the odds of success (*p*) every 4 seconds is .22.

Applying Time Binomial Trials to Determine Random Expected Probabilities

From the above, it should be apparent once the probability of our time-dependent binomial trials are determined, that the probability of obtaining a success from one binomial trial determines the probability of obtaining success for n number of binomial trials randomly selected from the data set. We know for this particular trial the odds of success (in the case of x_1 $n = 10$ $k = .104$). This probability can now be used for *any n number of 5-second trials* where we wish to test the random occurrence of EMF in association with time-synced events.

> EXAMPLE: As above, our researcher has found 80 events that have occurred concurrently within five seconds of his or her EMF data set. He or she wishes to know the probability of an EMF spike in any 5-second interval corresponding to the events recorded. An EMF spike is defined as one 2SD reading per 10 readings ($n = 10$, $k = 1$). Using $p = .104$, from our x_1 meter 1 data set, the expected random amount of EMF spike periods should be approximately 8 trials out of 80.

Thus, once the initial distribution is divided into periods of time representing n independent binomial trials, the probability of success from one trial can be multiplied across x trials (representing the amount of time-synced observations you have). Successes within those selected 5-second trials, if random, *should not significantly differ* from the amount of trials times the binomial probability of success of one 5-second trial.

Testing Against Binomial Expected Probabilities to Determine Non-Random Association

The method for determining an expected random probability association of EMF with independent observations has been demonstrated. Now, how can one analyze it if the amount of associations are greater than expected by chance? We discuss our two preferred inferential methods below.

Binomial Test. A binomial test can be performed, which is by far the most precise method of analyzing this type of time-dependent data. The mean of the binomial distribution is expressed as the following:

$$np \tag{1.2}$$

In addition, variance of the binomial distribution is defined as,

$$np(1-p) \tag{1.3}$$

Dividing the original EMF data set into a series of binomial trials creates a higher level data set where the odds of success are derived from a binomial distribution (i.e. from x_1, $n = 2490.9$ trials, with a p of success = .104). Per our example, it can be seen that, for any given n trials, the probability of .104 remains constant in terms of obtaining successes-hits. Only the number of trials changes, as each sample is an independent binomial trial (due to natural variation of EMF over time). Thus, by using the probability of this trial (.104) multiplied by the number of observations you are comparing (from above 80) obtains the mean (8.35) expected chance associations in time. Multiplying the mean times q (.896) provides the variance. The square root of the variance can be used to create the standard deviation (2.72), and thus a 95% confidence interval to test against (i.e. 2.88 to 13.76, or 2 to 14). As such, more than 14 occurrences of EMF with 80 observations has less than 5% occurring by chance. It can be easier by simply conducting the probability directly with a binomial calculation. Say that 19 out of 80 observations contained an EMF success period. The odds of this occurring by chance is .0003, a significant finding.

To demonstrate this application, we remodeled the original random sample data into 5-second and 10-second periods, representing 300 random samples of $n = 10$ and $n = 20$ trials. We then tested the number of successes obtained against the expected amount of successes, which was based on the probabilities obtained from the EMF binomial data. Results can be seen in Table 3.

Using random samples as an approximation of n selected observations of relevant behavior associated with EMF nested as 5 or 10 second trials, it can be seen that, across all but one random sample (x_2 produced significantly lower successes in the $n = 10$, $k = 1$ condition, binomial $p < .01$), the obtained random successes fall within the confidence interval generated by the collected EMF binomial data. In fact, the averaged z-score for the difference between these random trials, compared to the expected EMF successes from the actual data, are very small ($n = 10$, $k = 1$ samples; average z of difference = .29; $n = 20$ $k = 1$ samples; average z of difference = .06). Thus, (as the events were randomly selected) the randomly sampled trial successes closely mimicked the expected random successes determined by the data set binomial probabilities.

Finally, we note that a geometric distribution model of EMF will not fit due to the assumption of infinite trials. Likewise the negative binomial distribution is not appropriate because of the assumption of a limit of successes obtained (Rice, 1995). The hypergeometric distribution, in theory, could be used as a substitute for the binomial, but requires removing the observed samples from the total data, as the hypergeometric distribution assumes success without replacement (i.e., 24909 samples minus 80 observations, a .3% change in population sample size) . Most EMF data sets are very large in terms of *n*; the actual difference in testing via a hypergeometric or binomial is practically extremely small (Rice, 1995). Keeping observed counts in the population will typically inflate the expected random proportion by a small amount. Thus, it creates a slightly more conservative random observed ratio to test against. As such, we recommend use of the simpler and more elegant binomial model.

Chi Square Approximation. When *n* and *p* are small, a chi-square used as a test of fit against a ratio of expected random successes can be used to roughly approximate the binomial test (Solomon, 1987). However, we warn the reader that, if n is large ($n > 40$) and *p* is large ($p > .2$), the binomial distribution approaches symmetry. Thus, the non-symmetrical chi-square becomes a poor fit for the data (Jordan & Smith, 1997; Rice, 1995). This is also the case with the poisson distribution, which closely approximates the binomial when *p* is small, but loses its fit once *p* increases, and the binomial distribution becomes symmetrical (Rice, 1995).

In the case of EMF, 2 and 3 *SD* criteria for success typically keeps p sufficiently small to use a chi-square to model the binomial (e.g., Laythe & Owen, 2013). Conducting the test involves using the expected random probability to create a ratio of the same count to test the observed findings against. Chi-squares in this case should be used as a goodness-of-fit test from the expected ratio (i.e., a one sample test). It should not be conducted as a test of independence between two ratios. The nature of this type of data is a comparison of a selected sample against a population of expected values.

Deriving an Expected Probability from Multiple Sets of EMF Data

In some cases, we have examined events associated with EMF that were collected across several meters (Laythe & Owen, 2013). We have also had to account for successes that occurred from more than one EMF meter in a small enclosed area (Laythe, Laythe, & Woodward, 2016). Regarding the former, it is often the case in field settings that observed phenomena or participant behaviors may occur in different metered locations, and thus be dependent on different meters' distributions of EMF data. In these cases, we recommend averaging the binomial success probabilities and treating multiple meters as a sample of the true population probability of a defined EMF spike. However, per our earlier discussion, extremely high or low individual meter success rates may make this averaged ratio too liberal in its estimation, in which case each series of events must be calculated against the meter it belongs to. Multiple meters may also serve as a good scenario to use the normal distribution 5% or 1% rule, provided as before, that none of the data set success probabilities exceed the 5% or 1% margin.

With regards to the latter, the issue of allowing more than one meter in the same space creates a mathematically complex issue. As was the case in Laythe, Laythe, and Woodward (2016), two separate distributions of meters were used against one set of observations. As such, the joint probability of success within a binomial trial of either meter has to be determined (*p* meter 1 + *p* meter 2). This in actuality sounds much simpler than is actually the case, as meters in close proximity tend to significantly correlate with one another, creating potential dependence. Yet, correlation coefficients are an estimate of shared variance and do not necessarily lend themselves to calculating the exact degree of dependence between the meters. It is likewise the case that an approximate model guess of the joint probability does not create a sense of certainty of the resulting binomial tests.

Thus, the solution is to recode success and failures of two data sets into one data set of binomial trials, where a success of Meter 1 or Meter 2 is counted within one data set (provided that *n* for both samples is synced). By combining the 1s for any given binomial trial as a single success, while maintaining failures (all cases where neither meter was a success), researchers can divide the newly operationalized counts of success by the sample *n* to determine the actual random probability of a success for either meter in a given time period (i.e., $n = 1$ $k = 1$ $p =$ success of meter 1 or meter 2 $q =$ failure of both meters).

Once an $n = 1$ $k = 1$ probability for two meters has been determined, you can expand the time period by increasing *n* to include a wider range of time for any trials (i.e. $n = 2$ or 3, $k = 1$) to allow a success, if so desired. For clarity, what has been described above functions no differently from our example presented earlier in the paper, where success and failures are remodeled into 5-second or 10-second trials. The only difference is that the initial $n = 1$ $k = 1$ probability is an amalgam of the successes of two meters, and not just one. We would also note that this process could be used theoretically to obtain the true random probability of more than two meters. While this method is tedious until the combined binomial *n* = 1 *k* = 1 probability is obtained, it is exact, and generates the genuine probability of a success from either meter given *n* trials (See Laythe, Laythe, & Woodward, 2016 for an example of this method).

Conclusion-Future Directions: EMF Phenomena Hypothesis

The goal of this paper was to demonstrate the properties of EMF data collected over time and the use of binomial coding and testing to examine if EMF is significantly associated with observed phenomena. In conclusion are a couple of caveats and expansions regarding this method.

Regarding these methods with EMF-GMF, it should be apparent that the interesting aspect of testing EMF spikes in time with observed behavior or phenomena is that there, by nature, should not be any relationship. There is no known reason to expect EMF to change as a function of vetted anomalous phenomena (Laythe & Owen, 2013) or in relation to subjective perceptions or sensations in a seance environment (Laythe, Laythe, & Woodward, 2016). Yet, some researchers persist in attempting to explain these spikes by citing a hypothetical source of an interfering EM field as some sort of explanation for time-synced associations between EMF and phenomena (Laythe, 2016; Maher, 2016). It is hoped that we have made a clear case through the data, the physical nature of EMF-GMF, and explanations of receptive meters, that the source of the EMF is irrelevant and difficult to propose beyond improbable hypotheses. More importantly, it fails to explain the above chance association (or the lack thereof) of phenomena with EMF (e.g. Laythe & Owen, 2013, Laythe, Laythe, & Woodward, 2016). Regardless of the source of EMF, we believe that this unexplained association between the behavior of EMF-GMF and anomalous phenomena will persist and is worthy of further research. It is hoped that others will use this binomial modeling and testing method to see if EMF-GMF might be associated with other types of anomalous phenomena, such as RSPK or psi.

Finally, we believe this method is applicable to many parapsychological subjects. As controversy over parapsychological phenomena continues, any association of anomalous phenomena with known measurable energy cannot help but strengthen the validity of parapsychological research. Criticism in psychical research has long centered around the inability to measure a mechanism by which ESP or PK occurs (e.g., Hines, 2003). It might be noted that we have had some success with measuring the transmission of anomalous phenomena by showing its association with EMF using the methods described in this paper. Future research should be dedicated to replicating these findings, and perhaps, to looking at other spectrums and types of energy for additional associations.

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	Axis	*n*	Average	Low	High	*SD*	2SD High	2SD Low	Kurtosis	Skew
Meter 1										
	x	24909	223.31	217	230	1.60	226.50	220.12	-0.03	-0.05
	y	24909	-277.17	-283	-271	1.57	-274.04	-280.30	-0.04	-0.02
	z	24909	-478.79	-487	-467	1.82	-475.16	-482.42	13503.16	99.71
Meter 2										
	x	21136	19.73	13	26	1.56	22.85	16.60	0.01	-0.03
	y	21136	-120.00	-127	-111	1.65	-116.69	-123.30	0.27	0.17
	z	21136	-554.81	-562	-542	1.74	-551.32	-558.29	3.02	0.85
Meter 3										
	x	26593	5.24	-253	12.00	2.23	9.69	0.78	6775.38	-58.48
	y	26593	-205.47	-212	-199.00	1.63	-202.21	-208.72	0.00	-0.03
	z	26593	-546.88	-557	-535.00	1.71	-543.45	-550.30	1.04	0.16

Table 1

Descriptive Statistics for Three Sets of EMF Data

	Binomial Random Samples of 300 From Original Data (*n* denotes trials)											
	Samples *n* = 10, *k* =1 (5 Seconds)						**Samples *n* = 20, *k* = 1 (10 Seconds)**					
	Trial *p* *	Obtained Successes	Expected Success 300 Trials*	SD Expected Successes*	95% CI Success* Min	Max	Trial *p* *	Obtained Sucesses	Expected Success 300 Trials*	SD Expected Successes*	95% CI Successes* Min	Max
Meter 1												
x	0.104	30	31.20	5.29	20.63	41.77	0.198	57	59.4	5.29	48.83	69.97
y	0.215	63	64.50	7.12	50.27	78.73	0.384	110	115.2	8.42	98.35	132.05
z	0.255	74	76.47	7.55	61.37	91.57	0.444	139	133.2	8.61	115.99	150.41
Meter 2												
x	0.228	53**	68.40	7.27	53.87	82.93	0.405	128	121.38	8.50	104.38	138.38
y	0.275	83	82.38	7.73	66.92	97.84	0.474	142	142.14	8.65	124.84	159.44
z	0.241	72	72.30	7.41	57.48	87.12	0.424	136	127.17	8.56	110.05	144.29
Meter 3												
x	0.004	2	1.17	1.08	-0.99	3.33	0.008	1	2.37	1.53	-0.70	5.44
y	0.117	32	35.19	5.57	24.04	46.34	0.221	63	66.24	7.18	51.87	80.61
z	0.199	59	59.58	6.91	45.76	73.40	0.358	105	107.34	8.30	90.73	123.95

* Trial p and Expected Successes derived from binomial probability of original EMF dataset.
** Exact binomial $p < .01$

Table 2

Random Samples from EMF Data Demonstrating Probabilities from Original EMF Sample

	Original Data Binomial Conversion n = 1 k = 1			Random Samples Binomial Conversion n = 1 k = 1					
		(2*SD* score)			(2*SD* score)			(2*SD* score)	
	n	Success	Binomial p	Total n	Success	Binomial p	Total n	Success	Binomial p
Meter 1									
x	24909	262	0.0105	3000	30	0.010	6000	57	0.0095
y	24909	591	0.0237	3000	63	0.021	6000	110	0.0183
z	24909	716	0.0287	3000	74	0.025	6000	139	0.0232
Meter 2									
x	21136	542	0.0256	3000	53	0.018	6000	128	0.0213
y	21136	667	0.0316	3000	83	0.028	6000	142	0.0237
z	21136	575	0.0272	3000	72	0.024	6000	136	0.0227
Meter 3									
x	26593	12	0.0005	3000	2	0.001	6000	1	0.0002
y	26593	329	0.0124	3000	32	0.011	6000	63	0.0105
z	26593	582	0.0219	3000	59	0.020	6000	105	0.0175

Table 3

Binomial Random Time-Dependent Samples with 5-Second and 10-Second Intervals

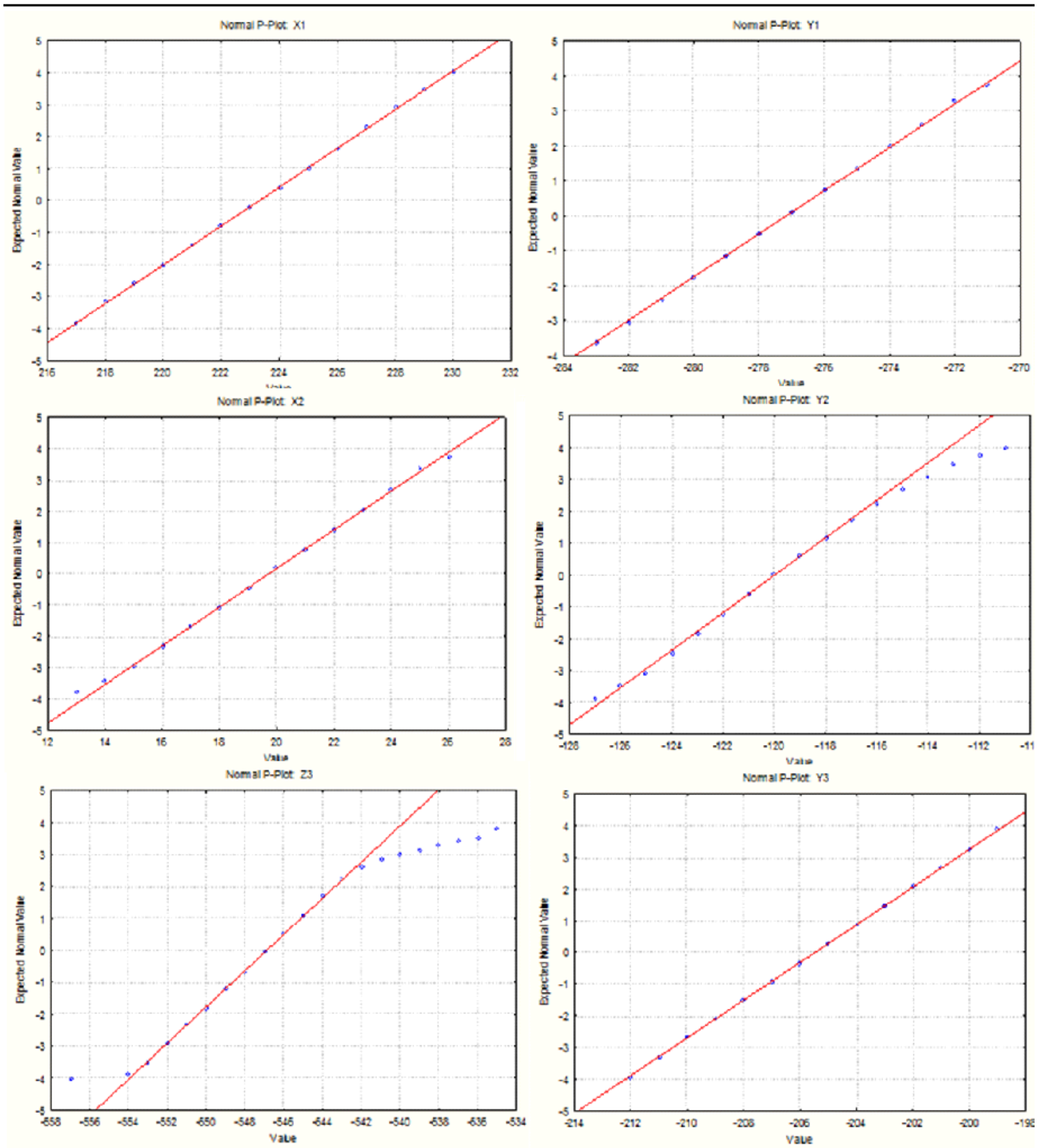

Figure 1

Six Probability Plots of a Normal Distribution of EM Field Data

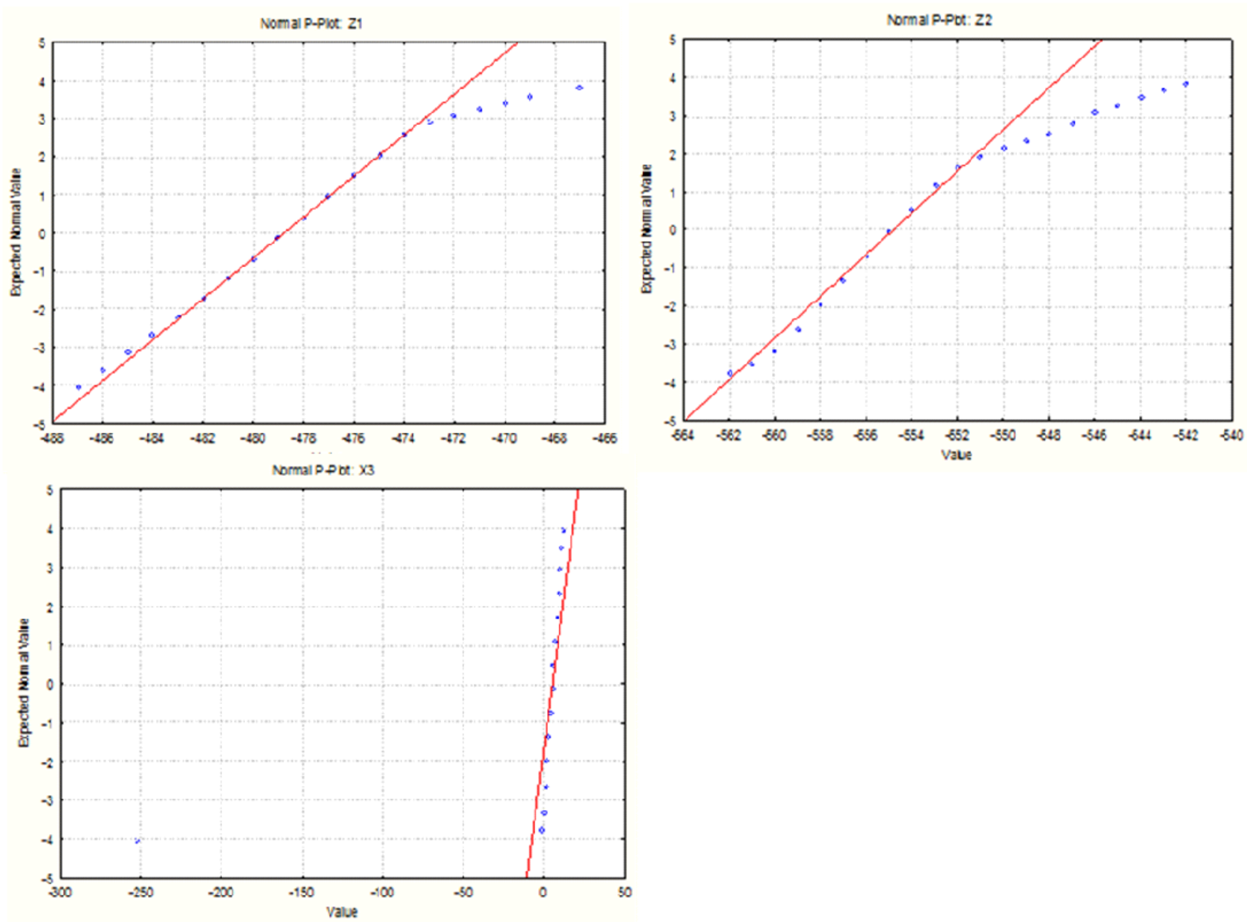

Figure 2

Three Probability Plots Showing High Skew and Kurtosis for EMF Data