Fixed recurrence and slip models better predict earthquake behavior than the time- and slip-predictable models: 1. Repeating earthquakes

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Received 27 July 2011; revised 29 November 2011; accepted 15 December 2011; published 18 February 2012.

[1] The behavior of individual events in repeating earthquake sequences in California, Taiwan and Japan is better predicted by a model with fixed inter-event time or fixed slip than it is by the time- and slip-predictable models for earthquake occurrence. Given that repeating earthquakes are highly regular in both inter-event time and seismic moment, the time- and slip-predictable models seem ideally suited to explain their behavior. Taken together with evidence from the companion manuscript that shows similar results for laboratory experiments we conclude that the short-term predictions of the time- and slip-predictable models should be rejected in favor of earthquake models that assume either fixed slip or fixed recurrence interval. This implies that the elastic rebound model underlying the time- and slip-predictable models offers no additional value in describing earthquake behavior in an event-to-event sense, but its value in a long-term sense cannot be determined. These models likely fail because they rely on assumptions that oversimplify the earthquake cycle. We note that the time and slip of these events is predicted quite well by fixed slip and fixed recurrence models, so in some sense they are time- and slip-predictable. While fixed recurrence and slip models better predict repeating earthquake behavior than the time- and slip-predictable models, we observe a correlation between slip and the preceding recurrence time for many repeating earthquake sequences in Parkfield, California. This correlation is not found in other regions, and the sequences with the correlative slip-predictable behavior are not distinguishable from nearby earthquake sequences that do not exhibit this behavior.

Citation: Rubinstein, J. L., W. L. Ellsworth, K. H. Chen, and N. Uchida (2012), Fixed recurrence and slip models better predict earthquake behavior than the time- and slip-predictable models: 1. Repeating earthquakes, *J. Geophys. Res.*, *117*, B02306, doi:10.1029/2011JB008724.

1. Introduction

[2] As deterministic earthquake prediction has fallen out of vogue, probabilistic earthquake forecasting has risen. Initially suggested nearly forty years ago [*Utsu*, 1972a, 1972b; *Rikitake*, 1974; *Hagiwara*, 1974], probabilistic methods consider earthquakes as a renewal process where elastic strain energy accumulates over time and is released in the subsequent earthquake. This idea is based in elastic rebound theory [*Gilbert*, 1884; *Reid*, 1910]. A myriad number of statistical distributions have been suggested to describe earthquake recurrence behavior including the Double Exponential [*Utsu*, 1972b], Gaussian [*Rikitake*, 1974], Weibull [*Hagiwara*, 1974], Lognormal [*Nishenko and Buland*, 1987], Gamma [*Utsu*, 1984], and Brownian Passage Time (Inverse Gaussian) [*Matthews et al.*, 2002]. These models treat earthquake occurrence as a point stochastic process with parameters of mean interval and a measure of dispersion about the mean. When the process depends only on the reset of the system by the last earthquake, it falls into the class of Independent and Identically Distributed (IID) models. For such models, the forecast of the time and/or size of the next event in the sequence does not depend on the specifics of the preceding event, i.e., it is a memoryless system. Properly applied, these models are used to interpret sequences of earthquakes that re-rupture the same fault area, treating them as a point process, but not to earthquake catalogs involving multiple sources. For the most part, the proposed models have employed well-developed statistical distributions with well-studied applications to failure time problems. These models adequately describe the recurrence behavior of many repeating earthquake sequences, but they cannot be discriminated easily from each other [*Ellsworth*, 1995; *Matthews et al.*, 2002]. At present, only an Exponential Distribution (Poisson distribution) can be rejected as a descriptor of most repeating earthquake sequences [*Ellsworth*, 1995].

[3] In contrast to the memoryless assumption of IID models discussed above, some authors have attempted to

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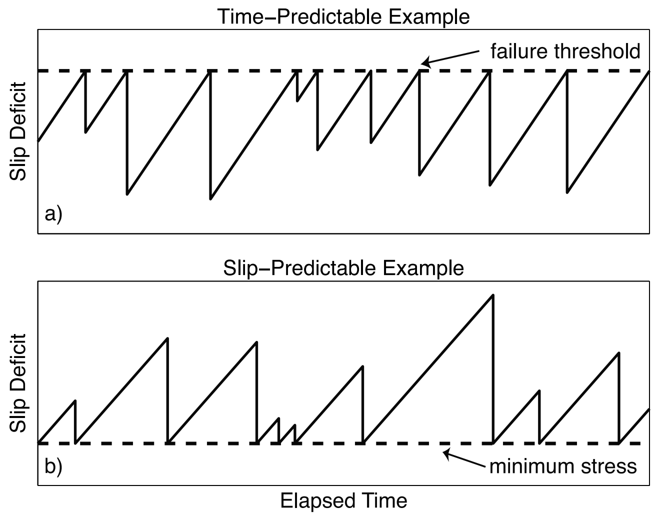

Figure 1. Cartoon showing the idealized behavior of the (a) time-predictable model and (b) the slip-predictable model. Slip deficit is plotted against time, such that a sudden drop in the slip-deficit represents an earthquake. For the time-predictable model (Figure 1a), there is a constant failure threshold that predicts an earthquake once it is reached, although the size of the earthquake is unknown. For the slip-predictable model (Figure 1b), there is a constant minimum stress, such that an earthquake will release all the slip accumulated since the last earthquake. Both of the models have a constant loading rate (slip deficit rate), as indicated by the diagonal lines.

describe recurrence behavior using physical models that depend on the specifics of the sequence to date. Some of the earliest physical models describing earthquake behavior are the time- and slip-predictable models. Initially suggested over thirty years ago [*Bufe et al.*, 1977; *Shimazaki and Nakata*, 1980], these models provide a physics-based method in which earthquake behavior can be predicted. As with the statistical models described previously, these models are based upon the "elastic rebound theory" of *Reid* [1910], which states that stress builds on a fault during the interseismic period, is released in an earthquake and then re-accumulates in the succeeding interseismic period. These models also share the characteristic that they treat earthquakes as a point process. The time-predictable model states that an earthquake will only happen once the stress relieved in the last earthquake has been re-accumulated, thus the interseismic period will increase in length in proportion to the size of the last earthquake (Figure 1a). The slip-predictable model follows a similar idea where all the stress accumulated since the last earthquakes is released in the next earthquake, meaning that as the time since the previous earthquake increases, the next earthquake should increase in size as well (Figure 1b). The simplicity of these models has made them popular tools for describing the behavior of earthquakes. For example, the 2002 earthquake probability model for the San Francisco Bay Area used a variant of the time-predictable model in one branch of its logic tree [*Working Group on California Earthquake Probabilities*, 2003]. In addition to the very simply defined time- and slip-predictable models, variants upon them have been proposed that combine a time- and/or slip-predictable model with a purely statistical Poissonian model [*Cornell and Winterstein*, 1988; *Wu et al.*, 1995]. While these models have been shown to be sufficient for engineering seismic hazard analysis, we choose to focus on the simpler-time and slip-predictable models because they are more widely used.

[4] Initial studies of the time- and slip-predictable models seemed promising, qualitatively showing that the predictions of these models came close to the observations for individual faults [e.g., *Bufe et al.*, 1977; *Shimazaki and Nakata*, 1980]. This led some to further develop these models, adding additional complexity to explain earthquake behavior that they called the time- and magnitude-predictable models [e.g., *Papazachos*, 1989, 1992; *Papazachos et al.*, 1994]. While these authors argued that their models have predictive power [e.g., *Papazachos*, 1989, 1992; *Papazachos et al.*, 1994; *Papazachos and Papadimitriou*, 1997; *Papadimitriou et al.*, 2001], the application was over fault systems, regions, and globally, neglecting the constraint that the time- and slip-predictable models assume that earthquakes are a point process.

[5] While the above studies argue that the time- and slip-predictable models (and variants of them) offer significant predictive power, there are a number of studies that argue against them. For example, *Mulargia and Gasperini* [1995] using a similar region-based method as the studies above rejected the possibility that time and slip-predictable models appropriately explain earthquake behavior. Others have rejected all models that utilize the elapsed time since the previous event to predict future earthquakes and instead argue for clustering [e.g., *Davis et al.*, 1989; *Kagan and Jackson*, 1991]. The time- and slip-predictable models have also been examined and rejected for multiple sections of the San Andreas Fault. Quantitative analysis of paleoseismic recurrence data at Wrightwood on the San Andreas Fault shows that the slip-predictable model does not fit the paleoseismic record and the case for the time-predictable model is weak as well [*Weldon et al.*, 2004]. Statistical analysis and inverted slip distributions for the recurring M6.0 Parkfield earthquakes [*Bakun and McEvilly*, 1984], demonstrates that the Parkfield earthquakes are neither explained by time-predictable model [*Murray and Segall*, 2002] nor the slip-predictable model [*Murray and Langbein*, 2006].

[6] Given the above discussion, the applicability of the time- and slip-predictable models is still clearly under debate. Here we attempt to resolve the debate regarding these models by analyzing repeating earthquakes. The concept of a repeating earthquake source is central to this paper, and for this reason it needs to be carefully defined. These are earthquakes that repeatedly rupture the same fault area in earthquakes of similar magnitude. They are conceptually related to the characteristic earthquake model of *Schwartz and Coppersmith* [1984] that states that faults and fault patches typically rupture in earthquakes of a similar size. To make the correlation to the characteristic earthquake model, we must first demonstrate that these earthquakes meet both of the above criteria by direct measurement. Beginning with the work on earthquake doublets [*Poupinet et al.*, 1984; *Fréchet*, 1985] cross-correlation measurements of differential travel times for pairs of earthquakes have been used to estimate the spatial separation of their moment centroids. When the separation between centroids is less than the rupture dimension of the events, the earthquakes can be considered to rupture the same fault area.

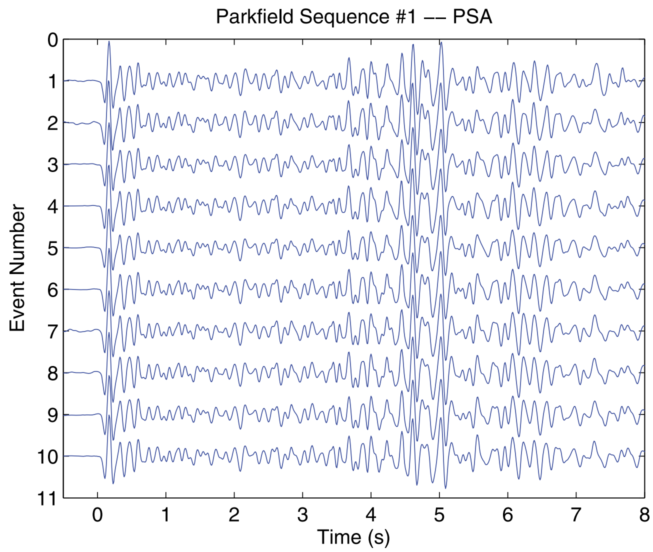

Figure 2. Example of a repeating earthquake sequence as recorded by one station. This is sequence 1 analyzed from Parkfield, as recorded by NCSN station PSA. The events occurred between 1984 and 2001. The seismograms are low-pass filtered with a corner frequency of 10 Hz. The high similarity of the waveforms indicates that they occurred in the same location with the same slip-sense.

Rupture overlap is now commonly confirmed using cross-correlation and double-difference earthquake relocation methods [e.g., *Waldhauser and Ellsworth*, 2000; *Schaff et al.*, 2002; *Uchida et al.*, 2006, 2007; *Waldhauser and Schaff*, 2008]. Repeating earthquakes have also been shown to be of very similar sizes [e.g., *Rubinstein and Ellsworth*, 2010].

[7] We choose to analyze the time- and slip predictable models with repeating earthquakes because they offer many advantages over the data sets previously used to analyze the time- and slip-predictable models. First, the highly similar waveforms of repeating earthquakes (Figure 2) allow for very precise estimation of relative moment, such that the uncertainty in moment is approximately ±6.6%, equivalent to an uncertainty in magnitude of $M_w \pm 0.02$ [*Rubinstein and Ellsworth*, 2010]. This is drastically lower than the uncertainty in magnitude for most earthquakes. High levels of uncertainty plague both supporters and detractors of the time- and slip-predictable models. For example, the NEIC estimates that the 2σ uncertainty in their magnitude estimates is ±0.2 magnitude units (J. Dewey, personal communication, 2011). This gives an uncertainty in moment of ±100% [*Hanks and Kanamori*, 1979]. There are undoubtedly large levels of uncertainty in earthquake size when using paleoseismic data [e.g., *Weldon et al.*, 2004] or geodetic data [e.g., *Murray and Segall*, 2002; *Murray and Langbein*, 2006]. Having much more precise estimates of earthquake size allows for a much stricter test of the efficacy of the models. Another advantage of the small repeating earthquakes employed here is that they occur more frequently than the larger earthquakes that have been used to test the time- and slip-predictable models. The more frequent nature of repeating events provides a larger data set that allows for more robust statistics.

[8] It also seems more likely that repeating earthquakes better fit the fundamental assumptions of the time- and slip-predictable models than many of the larger earthquakes studied above, so it seems sensible that they should be explained by these models. One critical assumption of the time- and slip-predictable models is that the loading rate is constant. We know this assumption is not true when applied to large regions because along strike variability in deformation rates has been observed in multiple locations [e.g., *Murray and Langbein*, 2006; *Konca et al.*, 2008]. Repeating earthquakes also are not subject to the region definition ambiguities that many of the region-based studies mentioned above, as there is a clear way to define repeating earthquakes. Additionally, region-based or even fault-based tests of these models might fail because the stress in a region might not be accommodated by an individual characteristic earthquake. Effectively, fault-based or region-based methods do not represent a point process, while repeating earthquakes rupture approximately the same area every time with very similar slips. We choose repeating earthquakes because they represent the simplest earthquake sources that we know of. Even in the case of the "characteristic" M6 earthquakes in Parkfield, California, it appears that different parts of the fault rupture in successive events [*Murray and Langbein*, 2006], meaning that each patch needs to be evaluated separately instead of jointly. While repeating earthquakes appear to be simpler than most earthquakes we know, there are suggestions that there is some variability in slip distribution from event to event [*Dreger et al.*, 2011].

[9] To first order, these repeating earthquakes should be considered both time- and slip-predictable, in that they are highly regular in both recurrence and slip. Previous studies have, in fact, argued that the recurrence time of repeating earthquakes can be predicted (J. M. Zechar and R. M. Nadeau, Predictability of repeating earthquakes near Parkfield, California, submitted to *Geophysical Research Letters*, 2012) in a short-term sense. While the recurrence of the sequences used by Zechar and Nadeau (submitted manuscript, 2012) can be predicted, we are specifically interested in testing the time- and slip-predictable models and not other models that may predict these quantities. Previous work has considered the fit of the time- and slip-predictable models to repeating earthquakes. *Nadeau and Johnson* [1998] argue that repeating earthquake sequences in Parkfield should be considered to be time- and slip-predictable because the misfit of their predictions typically are on the order of 10–15%. They continue to say that since the fit of the time- and slip-predictable models for these sequences is approximately the same, these events obey elastic rebound theory. We offer the alternative explanation that these sequences have near-constant recurrence and slip such that the time- and slip-predictable models fit the data well, but they are not necessary to explain the data. We also note that the analysis of *Nadeau and Johnson* [1998] is a study of the long-term behavior of these sequences instead of on an event-to-event basis as is conducted in this article.

[10] The long-term slip behavior of repeating earthquakes is such that they appear to release slip in a fashion that is linear with time (Figure 3), i.e., they are slip-predictable. In a long-term sense, repeating earthquakes could also be considered characteristic, in that they have very narrow

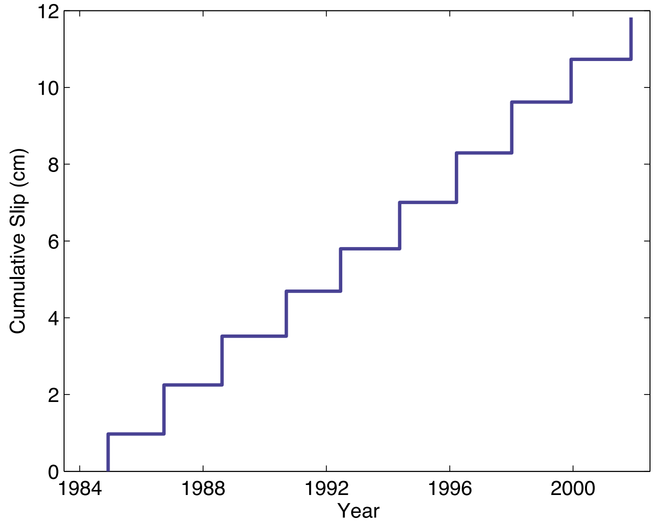

Figure 3. Example of a stair-step diagram for repeating earthquake sequence 1 in Parkfield. Cumulative slip of the sequence is plotted as a function of time. Relative slip is estimated using the SVD method described by *Rubinstein and Ellsworth* [2010], given the assumption of a constant area. Actual slip is then computed using the mean magnitude of the sequence given the following two assumptions: (1) stress drop is 3 MPa; (2) shear modulus is 10 GPa. The extremely regular recurrence and similar slips result in what appears to be a near-linear slip rate.

distributions of moment (median coefficient of variation of 0.10 for the 45 repeating earthquake sequences examined here) (see auxiliary material).[1] Repeating earthquakes appear to be highly regular in recurrence (median coefficient of variation of 0.30 for the 45 repeating earthquake sequences). This is also very clear when examining the data graphically (Figure 4).

[11] While sequences may be regular and predictable in a long-term sense, we are specifically interested in the event-to-event variability, and specifically whether the time- and slip-predictable models provide more information about the next earthquake than other models. Here we choose to test the time- and slip-predictable models against the simplest models possible: a model that has either fixed recurrence interval or fixed slip. A fixed recurrence model could be considered to be a "perfectly-periodic" model and fixed slip model is simplified version of the characteristic earthquake model. The fixed recurrence/slip models are simplified IID models in that they are constant with zero variation around a mean, instead of a typical IID model that has some variation around a mean. We specifically search for occasions where the time or slip-predictable model better predicts the event-to-event behavior of a repeating earthquake sequence than the fixed recurrence or fixed slip models, respectively. Should we find this, it would indicate that the time- and/or slip-predictable models do provide additional value for predicting the behavior of the next earthquake at

[1]Auxiliary materials are available at ftp://ftp.agu.org/apend/jb/2011jb008724.

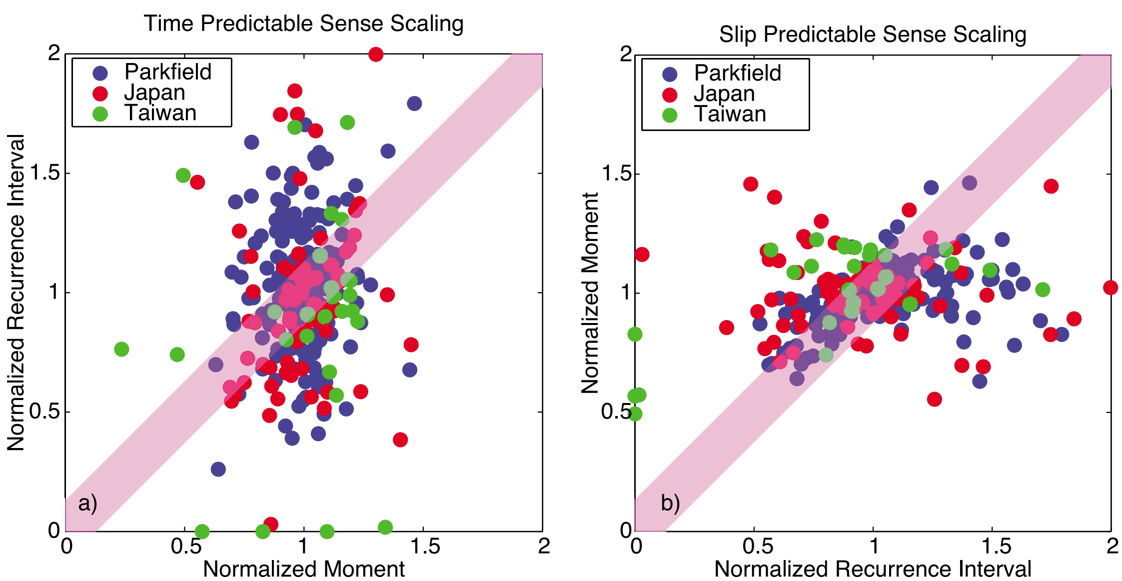

Figure 4. The 334 earthquakes in 45 repeating earthquake sequences in Parkfield (25 sequences, 214 events), Japan (14 sequences, 88 events), and Taiwan (6 sequences, 32 events) plotted in (a) a time-predictable sense, (b) a slip-predictable sense. Moment and recurrence interval are normalized, for each repeating earthquake sequence, such that the mean recurrence interval and mean moment of each event is 1, such that all sequences can be plotted together. Each earthquake within a sequence is plotted as a dot. One can see that there is much more variability in recurrence interval than in moment for the repeating earthquake sequences we examine. The shaded line indicates what the time- and slip-predictable models predict the relationship between moment and recurrence interval given 2σ error bounds based upon the measurements of relative moment [*Rubinstein and Ellsworth*, 2010]. One can clearly see that the majority of the repeating earthquakes do not fall within the shaded region.

the same location, otherwise it will indicate using an IID model that knows nothing about the history of a sequence is more useful in predicting event-to-event behavior.

[12] We examine repeating earthquakes in three regions located in different tectonic settings: Parkfield, California (strike-slip), Taiwan (collisional), and Japan (subduction). For repeating earthquake sequences in the these locations, we find no evidence that they are better described by the time- or slip-predictable models than they would be by similarly simple IID models with invariant recurrence time or constant slip, respectively. The time- and slip-predictable models are one-parameter models that simply invert for a slip-deficit rate (loading rate). We also explore a two-parameter version of these models where we invert for a nonzero intercept. Similar statistical tests show that with the exception of slip-predictability for repeating earthquakes in Parkfield, the two-parameter time- and slip-predictable models do not appear to better describe earthquake behavior than constant recurrence and constant slip models, respectively. While the two-parameter slip-predictable model does have modest predictive power for the Parkfield data, at present we have no way to distinguish these sequences from those that are not well described by the two-parameter slip-predictable model. Thus, while we have demonstrated there is slip-predictable sense scaling, it is of little utility since we have no way of knowing when we can apply this scaling.

[13] To complement this work on natural earthquakes, we also examine the time- and slip-predictable models and their application to laboratory generated earthquakes in a companion paper [*Rubinstein et al.*, 2012]. Like repeating earthquakes, laboratory earthquakes are particularly simple failures that are far more repeatable than most earthquakes. Laboratory earthquakes offer further advantages over regular earthquakes in that some of the key variables (loading rate, exact measurement of slip, completeness of event catalog) that are hidden or ambiguous for repeating earthquakes can be directly measured in the lab. Even with all of the advantages offered by laboratory data, we find that fixed slip and recurrence models better explain the behavior of laboratory earthquakes than the time and slip-predictable models.

2. Models

[14] In this section, we explain the models that we are exploring in this paper. The two key models that we are testing are the time-predictable model and the slip-predictable model. These simple, one-parameter models arise out of elastic rebound theory [*Reid*, 1910] and predict the time and slip of the next earthquake respectively. We test both models against an IID model with either fixed mean recurrence interval or fixed mean earthquake size. We also examine variants of the time- and slip-predictable models that have nonzero intercepts, with the intent of testing whether the size of the preceding earthquake or the time since the previous earthquake hold any predictive power to describe the next earthquake.

2.1. Time-Predictable Model

[15] The time-predictable model is based on the assumption of a constant failure threshold and a constant loading rate (Figure 1a) at an individual location on a fault. It predicts the time of the subsequent earthquake to be the ratio of coseismic slip to the slip deficit rate:

$$t_{i+1} = \frac{s_i}{s'}, \tag{1}$$

where t_{i+1} is the predicted inter-event time, s_i is the slip in the previous earthquake, and s' is the slip deficit rate. Strictly defined, the time-predictable model has a zero-intercept, meaning that if there is an earthquake of zero size, the next earthquake will occur immediately.

[16] In addition to the time-predictable model, we also explore a model where the recurrence time is dependent upon the moment of the previous earthquake, but without the requirement of a zero-intercept. This model allows for a minimum hold time c following an earthquake, such that even if the preceding earthquake was of zero size, the next earthquake could not happen for at least time c:

$$t_{i+1} = \frac{s_i}{s'} + c. \tag{2}$$

We apply this formulation in a way that includes the possibility that this minimum hold time is negative, which would be acausal. The physical interpretation of this model is less clear than the time-predictable model, but we test it nonetheless with the desire to demonstrate whether there is any predictive power in the knowing the size of the preceding earthquake. Others have claimed predictive power when using similar formulations that have a nonzero intercept added to a time-predictable model [e.g., *Papazachos*, 1989].

2.2. Slip-Predictable Model

[17] The slip-predictable model is based upon the assumptions of a constant loading rate and that all the stress accumulated in the interseismic period is released in the following earthquake (Figure 1b). The slip in the upcoming event is calculated as the product of the seismic moment deficit rate and the elapsed time since the most recent event:

$$s_{i+1} = t_{i+1} * s', \tag{3}$$

where, s_{i+1} is the slip-predictable slip in the upcoming earthquake, and t_{i+1} is the elapsed time since the previous event. Strictly defined, the slip-predictable model has a zero-intercept, meaning that if an earthquake immediately follows the previous earthquake, it should be of zero size.

[18] In addition to the slip-predictable model, we also explore a model where the slip is dependent upon the time elapsed since the previous earthquake, but without the requirement of a zero-intercept. This model allows for a minimum earthquake size d, where an earthquake that immediately followed the previous event would be of size d:

$$s_{i+1} = t_{i+1} * s' + d. \tag{4}$$

We include the possibility that this minimum earthquake size d is negative, which would be non-physical. The physical interpretation of this model is less clear than the slip-predictable model, but we test it nonetheless with the desire to demonstrate whether there is any predictive power in the recurrence interval. Others have claimed predictive power when using similar formulations that have a nonzero intercept added to the slip-predictable model [e.g., *Papazachos*, 1992].

2.3. Fixed Slip Model

[19] We validate the slip-predictable model against a simplification of the characteristic earthquake model [*Schwartz and Coppersmith*, 1984]. The characteristic earthquake model states that faults and fault segments tend to generate earthquakes of the same size. We simplify the characteristic earthquake model such that we assume that each earthquake is exactly the same size, fixing the slip to a constant with no variability. We then compare this model to the slip-predictable model and the slip-predictable model with nonzero intercept.

2.4. Fixed Recurrence Model

[20] We validate the time-predictable model against a perfectly periodic earthquake model. This model simply states that there is an equal recurrence time between all earthquakes, with no variability. We determine that the time-predictable model and the time-predictable model with nonzero intercept have predictive power when these models better predict the event-to-event behavior of the repeating earthquakes than the perfectly periodic model.

3. Data

[21] We analyze repeating earthquakes from three different regions worldwide (Figure 5). The intent of analyzing these varied data sets is to validate the claims of the prediction models for earthquakes in varied tectonic environments, such that we can determine whether the time- and slip-predictable models might be generalized and used globally.

[22] For the purposes of this study, we define a repeating earthquake sequence as a sequence of earthquakes that rupture the same physical area of a fault in events of similar size. The repeating earthquake sequences are defined differently in each region. The methods used to identify these sequences are described in sections 3.1–3.3. In addition to the region-specific criteria we apply three criteria to all of the sequences. First, we require a minimum of 5 events in the sequence. This allows for multiple cycles of the repeat to be used to compute a moment deficit rate. Second, we require each sequence to only have events within ± 0.3 magnitude units of each other based on catalog measurements. This ensures that the events are not wildly different from each other. Using precise measurements, we find that these events wind up having a much narrower magnitude distribution that standard catalogs would suggest. Finally, we require that no sequences contain aftershocks of larger earthquakes.

[23] We filter out aftershocks because the recurrence rate of repeating earthquakes is well known to change subsequent to large earthquakes [*Schaff et al.*, 1998; *Lengliné and Marsan*, 2009; *Okada et al.*, 2007; *Chen et al.*, 2010b]. Along with reduced recurrence intervals, creep and afterslip are frequently observed following large earthquakes [e.g., *Langbein et al.*, 2006], which might imply that the short-term loading rate has changed, violating the assumption of a constant loading rate. Thus, time intervals in which repeating events are activated as aftershocks must be avoided and all aftershocks removed. For this study, we remove aftershocks of $M \geq 6.0$ earthquakes. Aftershocks are typically defined as events following a previous, larger event within certain space-time bounds. We explore three different definitions of the geometric bounds of an aftershock zone [*Kagan*, 2002; *Konstantinou et al.*, 2005; *Wells and Coppersmith*, 1994]. These define the aftershock zone as an exponential function of earthquake magnitude. We choose the *Wells and Coppersmith* [1994] definition of aftershocks, because we find the other two definitions too restrictive, in that they eliminate all of the candidate sequences in Japan and Taiwan. This is a somewhat arbitrary choice, but there is evidence that the *Kagan* [2002] and the *Konstantinou et al.* [2005] definitions of the aftershock zone may be too large. Specifically, both define the aftershock zone of 2003 San Simeon earthquake [*Hardebeck et al.*, 2004] as including the Parkfield area, where no short-term change in seismicity was observed [*Aron and Hardebeck*, 2009], while the *Wells and Coppersmith* [1994] zone does not include Parkfield. More recent work suggests that there was a small change in the seismicity rate [*Meng et al.*, 2010] and larger changes in rates of tectonic tremor well below the seismogenic zone [*Shelly and Johnson*, 2011], but we see no significant changes in recurrence intervals following the San Simeon earthquake for our repeats in Parkfield. Given this, we feel justified in using the *Wells and Coppersmith* [1994] definition. To complete the definition of what an aftershock is, a definition in time is also necessary. For sequences that fall within the geometric bounds of an aftershock zone, we make the arbitrary choice that any repeat that occurs in the three years following a main shock is an aftershock and cannot be used for testing of the time- and slip-predictable models. This rule means that for those sequences that fall within the geometric bounds of an aftershock zone, some sequences end at the time of the main shock, while other sequences start three years following the main shock.

[24] Once we have defined the repeating earthquake sequences, we compute relative moment of the events to very high precision ($\pm 6.6\%$ in moment) and then convert this to relative-slip. We test three different assumptions (relationships) between moment and slip: the constant area assumption, the constant stress drop assumption, and a scaling based upon observations of repeating earthquakes in Parkfield [*Nadeau and Johnson*, 1998]. In the constant area assumption, slip is proportional to moment. For the constant stress drop assumption, slip scales with the cube-root of moment. A recent study in the Parkfield area, suggests that repeating earthquakes are consistent with a constant stress drop scaling [*Imanishi and Ellsworth*, 2006]. The last model we test is a relationship between slip and moment observed for repeating earthquakes in Parkfield, California, which states that slip scales with the sixth-root of moment [*Nadeau and Johnson*, 1998; *Johnson and Nadeau*, 2002]. This model will be referred to as the $M^{1/6}$ assumption.

3.1. Parkfield, California

[25] We examine 25 repeating earthquake sequences near Parkfield, California (Figures 5b and 5c, see auxiliary material). The events lie on the creeping section of the San Andreas Fault, a strike-slip plate boundary between the North American and Pacific Plates. The events are believed

to be loaded by creep in areas immediately adjacent to the repeating events.

[26] The repeating earthquake sequences are a subset of those that were initially defined by *Rubinstein and Ellsworth* [2010] and occurred 1984–2005. The data we analyze comes from the Northern California Seismic Network (NCSN), a network of short-period one-component geophones. Candidate members of earthquake families were defined using

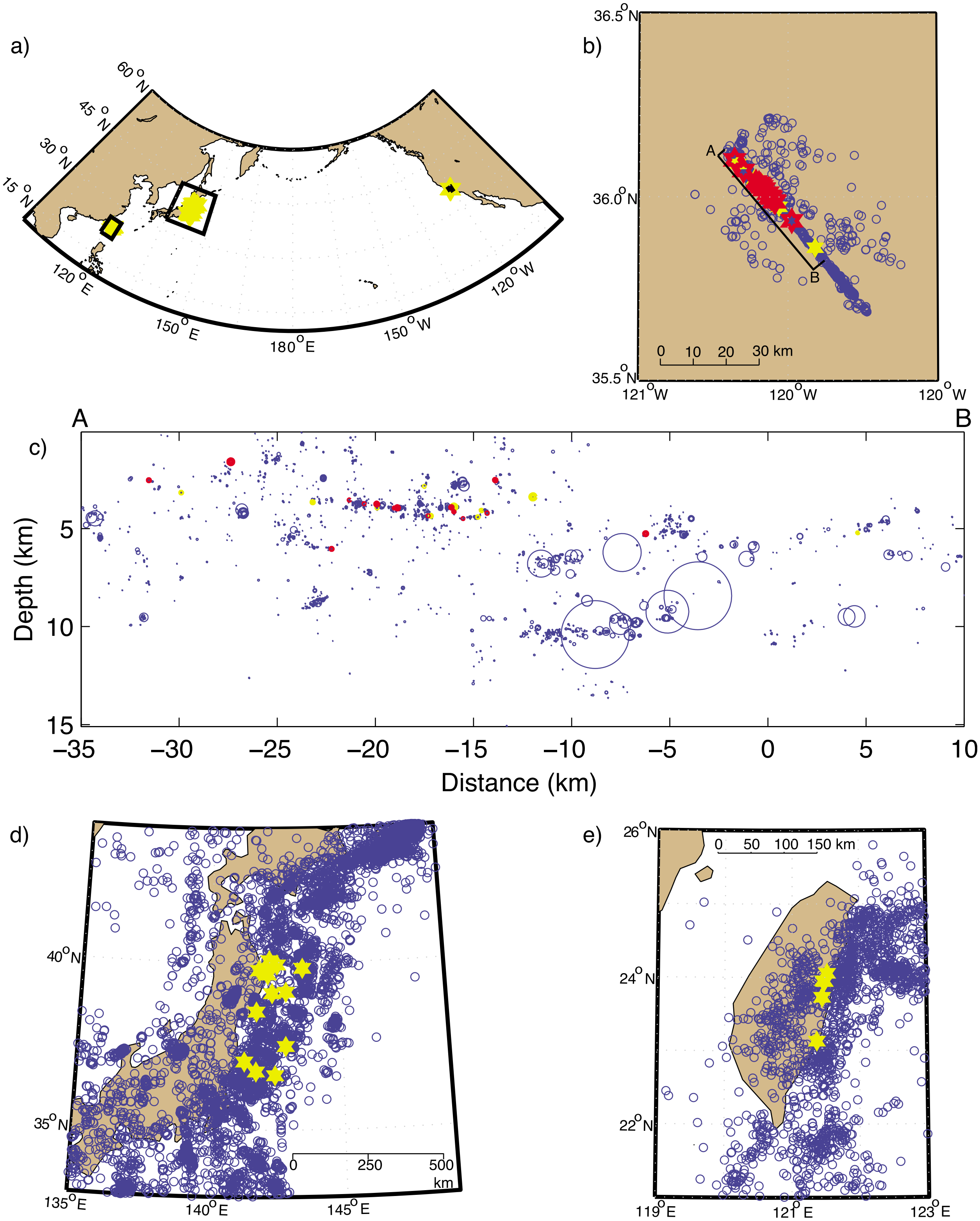

Figure 5

windows of 128 samples in length (1.27 s) that are centered upon the *P* arrival that have either (1) at least 5 stations that recorded the events with correlation coefficient of 0.98 and higher or (2) the correlation coefficient of their waveforms exceeds 0.95 at a minimum of five stations and at those same stations the standard deviation of the double-differenced delay time between those events is less than 0.002 s, implying that the event centroids are very close to each other. We validate the families by relocating the events [*Waldhauser and Ellsworth*, 2000] and requiring that the events overlap at least 50% assuming a 30 bar stress drop, or could overlap at least 50% given 2σ errors from the relocation. We hand-selected the repeating earthquake sequences, selecting those sequences that we could be confident were complete. Specifically, we removed sequences that appeared to have a "hole" (i.e., the recurrence time appeared to double) so that our repeating earthquake sequences were complete. While this selection process means our statistical test is not over all kinds of seismicity, it does ensure that we are not testing models of earthquake behavior on incomplete data sets. Additionally, if we can demonstrate that the time and slip-predictable models apply to this subset of repeating earthquake sequences, it gives hope that they may work for seismicity on the whole, or alternatively if they do not work, it implies that they do not work generally. Following the aftershock definition in section 3, we removed all events that occurred on September 28, 2004 or later (the day of the M6.0 Parkfield earthquake).

3.2. Japan

[27] We analyze 14 repeating earthquake sequences off the east coast of the Tohoku region of Japan (Figure 5d, see auxiliary material). These events are occurring in the Japan Trench, the subduction plate boundary where the Pacific Plate is subducted underneath the Okhotsk plate. The plate boundary is believed to be partially coupled in this region [*Uchida et al.*, 2003, 2009; *Pacheco et al.*, 1993; *Peterson and Seno*, 1984], and the repeating earthquakes in this region are thought to be loaded by the adjacent creep [*Uchida et al.*, 2005]. These sequences were initially defined by *Uchida et al.* [2006, 2009] and occurred between 1995 and 2009. The events that occurred prior to March 2007 were identified by *Uchida et al.* [2009]. Repeating earthquake families were defined using waveform cross-spectrum analysis of 40 s seismograms requiring a coherence exceeding 0.95 at 2 or more stations for the following frequencies: 1, 2, 3, 4, 5, 6, 7, and 8 Hz. As with the Parkfield sequences, we remove aftershocks based on a catalog of Japanese seismicity and sequences that appear to have "holes" in their chronology.

3.3. Taiwan

[28] We analyze 6 repeating earthquake sequences in the Hualien region of Taiwan (Figure 5e, see auxiliary material). The sequences are found in Eastern Taiwan adjacent to the Longitudinal Valley Fault. The Longitudinal Valley fault is an active collisional plate boundary between the Philippine Sea Plate and the Eurasian Plate with a convergence rate of 8 cm/a. Approximately 3 cm/a are accommodated on the Longitudinal Valley Fault [*Huang et al.*, 2010]. Similar to the repeating earthquakes sequences we examine in Japan and Parkfield, active creep is observed and is believed to load the repeating events [*Chen et al.*, 2009]. These sequences are a subset of those defined by *Chen et al.* [2009] and occurred between 1994 and 2004. Repeating earthquake families were defined using 10.5 s seismograms filtered between 2 and 8 Hz and the following two criteria: (1) 75% of the data must have a maximum cross-correlation coefficient greater than 0.75 and a differential *S-P* time of 0.02 s or less or (2) 50% of the data must have a maximum cross-correlation coefficient greater than 0.85 and a differential *S-P* time of 0.01 s or less [*Chen et al.*, 2008]. Like the sequences from the other regions, aftershocks and sequences with "holes" were removed.

4. Testing the Time-Predictable Model

4.1. Qualitative Assessment of Time-Predictability

[29] We first examine the time-predictable model. It predicts that recurrence time scales with the size of the previous event (Figure 1). If we plot recurrence time against slip in the previous earthquake, the time-predictable model predicts positive slopes, with the recurrence time increasing with increasing slip in the preceding earthquake. Examining this relationship for the repeating earthquakes described in section 3, we find that there is little evidence that the time-predictable model adequately predicts the behavior of the repeating earthquakes (Figure 6). Most of the repeating earthquake sequences in all three regions look like scattered data without a clear trend. For those sequences where we can see a trend in the data, there are many sequences where the recurrence time decreases with increasing preceding slip, counter to the predictions of the time-predictable model. Qualitatively, the lack of a consistent relationship between slip (moment) and the subsequent inter-event time indicates

Figure 5. Locations of repeating earthquakes studied. (a) Map showing the locations of all the repeating earthquakes studied. Black boxes indicate the zoomed regions shown in the remaining subplots. Yellow stars indicate repeating earthquakes studied. (b) Map of repeating earthquakes and seismicity in Parkfield. Yellow stars indicate repeating earthquakes where a two-parameter slip-predictable model did not better describe the repeating earthquakes. Red stars indicate repeating earthquakes where a two-parameter slip-predictable model better described the repeating earthquakes. Blue circles represent the relocated seismicity $M \geq 1.0$ in the region 1/1984–6/2005 [*Thurber et al.*, 2006]. Black line indicates extent of cross section shown in Figure 5c. (c) Cross-sectional view of seismicity in Parkfield (1/1984–6/2005). Circles are sized to represent the rupture area assuming a circular elastic crack with 3 MPa stress drop. Blue circles are background seismicity, yellow circles are repeating earthquakes where a two-parameter slip-predictable model did not better describe the repeating earthquakes, and red circles indicate repeating earthquakes where a two-parameter slip-predictable model describes the repeating earthquakes better. (d) Map of repeating earthquakes and seismicity in Japan. Yellow stars indicate repeating earthquakes and blue circles represent the JMA catalog of $M \geq 5.0$ seismicity in the region for 2/1995–9/2009. (e). Map of repeating earthquakes and seismicity in Taiwan. Yellow stars indicate repeating earthquakes and blue circles represent the NEIC-PDE catalog of $M \geq 4.0$ seismicity in Taiwan 8/1991–12/2007.

that the time-predictable model does not explain the behavior of the repeating earthquakes in Parkfield, Japan, and Taiwan. With regards to the qualitative relationships discussed above and shown in Figure 6, we note that it only shows recurrence time versus moment – thus assuming a constant slip area. The other moment-slip relationships described in section 3 are not shown because while the slope of the lines will vary in these slip relationships, the sign of the slope will not change nor will the consistency of the trend.

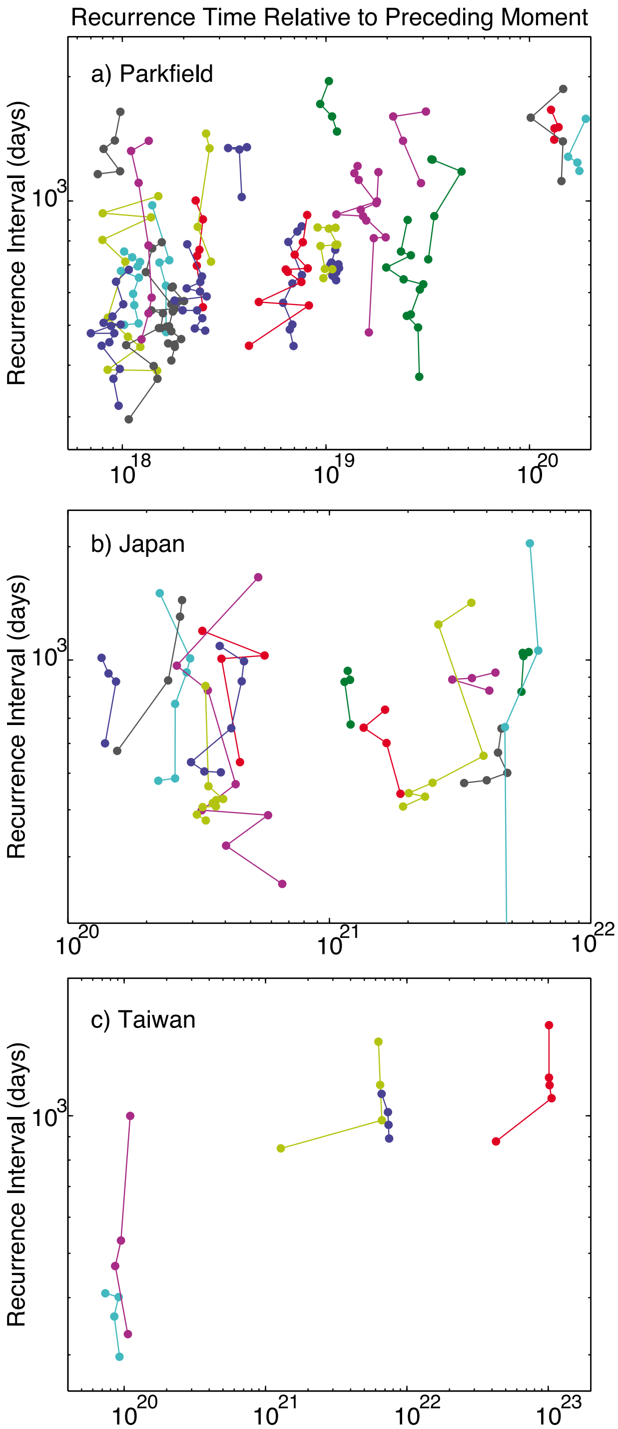

Figure 6. The qualitative fit of the time-predictable model for all the repeating earthquake sequences examined in (a) Parkfield, (b) Japan, and (c) Taiwan. Recurrence time for each event within an individual sequence is plotted against the moment of the preceding event. The sequences are colored differently so that they can be distinguished from each other. Lines connect all the earthquakes within a sequence, but do not imply the chronological ordering of the events. A sequence that is time-predictable is expected to have a positive slope, i.e., the recurrence interval would increase as the size of the last event is increased. Moment of the events is used as a proxy for slip, following the constant area assumption. Using other moment-slip relationships will change the shape of the lines, but not the trend or lack thereof, which is a qualitative measure of whether a sequence is time-predictable. Sequence 1 in Taiwan is removed because some of its repeats are very short and including it in this plot would make it difficult to see the other sequences on the same figure. A consistent trend in a time-predictable sense (positive slope) cannot be found in this data.

4.2. Cross-Validation to Compare the Time-Predictable Model to the Perfectly Periodic Model

[30] Since we are interested in evaluating the predictive power of these models, we evaluate them using leave one out cross-validation, similar to a jack-knife test [*Tukey*, 1958; *Efron*, 1979]. Leave one out cross-validation is a method that evaluates how well a model predicts the behavior of the data that it is being used to describe. In this process, each data point is removed individually, the model is computed from the remaining data and the value of the omitted data is then predicted. The residual between the predicted value and the observed value gives an estimate of the quality of fit of the model for that individual data point. We can assess the overall predictive power for any individual model for a given data set by computing the RMS of the prediction-errors for each data point. Using cross-validation, we are able to evaluate the predictive power of these models without having to wait for later events to happen.

[31] We cross-validate to determine whether the time-predictable model or the perfectly periodic model better describes the repeating earthquake sequences that we are studying. The time-predictable model is deemed superior to the perfectly periodic model when the RMS of its cross-validation prediction-errors is lower. To evaluate the time-predictable model we cross-validate each repeating earthquake sequence six times since we have two models (time-predictable and perfectly periodic) and three slip/moment relationships. The results of this analysis are rather surprising in that many more sequences appear to be fit by the time-predictable model than qualitative analysis would have suggested (Table 1). Most notably, for the constant stress-drop assumption and the $M^{1/6}$ assumption the time-predictable model better predicts the behavior of four of six of the repeating earthquakes in Taiwan than the perfectly periodic model. It is also striking that half or more than half of the repeating earthquakes in Japan are better explained by the time-predictable model given any of the assumptions. Parkfield is also remarkable in that 11 of the 25 sequences are better fit by the time-predictable model given the $M^{1/6}$ assumption.

Table 1. Number of Sequences That Appear to Be Time-Predictable[a]

	Constant Area	Constant Stress Drop	Slip α $M_0^{1/6}$
Parkfield	6/25	9/25	11/25
Japan	7/14	8/14	8/14
Taiwan	2/6	4/6	4/6

[a]This table lists the fraction of the total number of sequences where cross-validation indicates that the time-predictable model better predicts the behavior of the repeating earthquakes than the perfectly periodic model.

4.3. Reshuffling to Determine How Often a Sequence Would Randomly Appear to Be Fit by the Time-Predictable Model

[32] While these results suggest that the time-predictable model might be useful for predicting the timing of repeating earthquakes and earthquakes in general, we must explore whether these observations are significant or simply a result of the data distribution. To this end, we first determine how likely it is that the data in a randomly reordered repeating earthquake sequence given a moment:slip relationship will be better fit by the time-predictable model than the perfectly periodic model. Given this information, we then compute how likely it is that the total number of sequences observed to be better fit by the time-predictable model (given a moment:slip assumption) would occur randomly.

[33] To compute how likely it is that any individual sequence would randomly appear to be better fit by the time-predictable model we shuffle the relationship between the recurrence times and the slips. This maintains the distribution of the recurrence times and slips, but breaks any relationship between recurrence and slip. We then cross-validate to determine whether the time-predictable model better describes the randomly reordered repeating earthquake sequences than a perfectly periodic model. The assumption underlying this process is that an earthquake sequence that was perfectly fit by the time-predictable model would not appear time-predictable when reshuffled.

[34] For sequences that have at least 8 events in them (and thus 7 recurrence times) we compute 1000 unique reshuffles that are different from the original ordering of the data. For all other sequences we compute all of the available reshuffles, which is simply *n!* where *n* is the number of events in the sequence. Using the random reshuffles we compute the likelihood that any sequence given a slip:moment relationship would randomly appear to be better fit by the time-predictable model (Figure 7). Examining the probability that any individual sequence would be better fit by the time-predictable model with randomized data, we find that many sequences could very often appear to be fit by it. For each region, one can see at least one sequence that more than 50% of the time would appear to be better fit by the time-predictable model simply by random chance. Given these results, it now seems somewhat likely that the number of sequences that we observe to be better fit by the time predictable model is simply a result of random chance.

[35] Before we assess the likelihood that the number of sequences we observed to be better fit by the time predictable model could be observed by random chance, we note a relationship between the number of sequences that appear to be better fit by the time-predictable model and the exponent in the slip:moment relationship. Examining the reshuffled data (Figure 7), we see that the probability that a sequence is better fit by the time-predictable model increases as the exponent in the slip:moment relationship decreases, i.e., the number of sequences that appear to be better explained by the time predictable model increases going from the constant area assumption to the constant stress drop assumption to the $M^{1/6}$ assumption. We also see this in the actual data (Table 1). We believe that this is happening because reducing the exponent of the moment reduces the variability in the slip, the independent variable in the case of the time-predictable model. If the independent variable is not actually related to the dependent variable, i.e., it's random, by reducing the independent variable, we reduce the variability in the model predictions of dependent variable. Assuming the independent and dependent variable are not related, this would likely reduce the prediction-error.

[36] As noted above, this process relies upon the assumption that an earthquake sequence that is perfectly explained by the time-predictable model would not appear time-predictable when it is reshuffled. We verify this assumption using synthetic data sets that are perfectly fit by the time-predictable model. These data sets are generated where moment has a coefficient of variation of 0.10 in a lognormal distribution, the same coefficient of variation as the earthquake data we use in this study given a constant area assumption. The coefficient of variation of slip decreases with decreasing exponent in the slip-moment relationship. For short sequences (less than 8 events), which are the majority of the sequences studied, the likelihood that sequences that are perfectly fit by the time-predictable model are better fit by the time-predictable model when reshuffled (i.e., a false positive) is approximately 15–22%, depending on the number of events and the slip-moment relationship. For larger data sets (10–15 events), this likelihood decreases to 4–9%. Given these numbers, we can expect false positive observations where sequences appear to be better explained by the time-predictable model when they are actually not. The low probabilities, though, indicates that there will be few false positives, meaning that our reshuffling test is fair.

4.4. Computing the Probability Distribution of the Number of Sequences That Appear to Be Fit by the Time-Predictable Model

[37] Having computed the likelihood that any repeating earthquake sequence will be better fit by the time-predictable model based on its data distribution alone, we can now compute the likelihood that the number of sequences that we observe to be better fit by the time-predictable model is a result of random chance. We examine this relationship for each region and slip:moment scaling. We separate the regions from each other for two main reasons: (1) the behavior (and predictability of it) of repeating earthquakes may vary from region to region and (2) the repeating earthquakes in each region have been defined differently and thus the characteristics of the repeating earthquakes in each region might be different. To examine how likely it is that the number of sequences observed to be better fit by the time-predictable model is a result of chance, we must explore all the possible combinations. For the Parkfield case, there are 25 repeating earthquake sequences, and thus there are 2^{25} possible combinations. To compute the random probability of 0 repeating

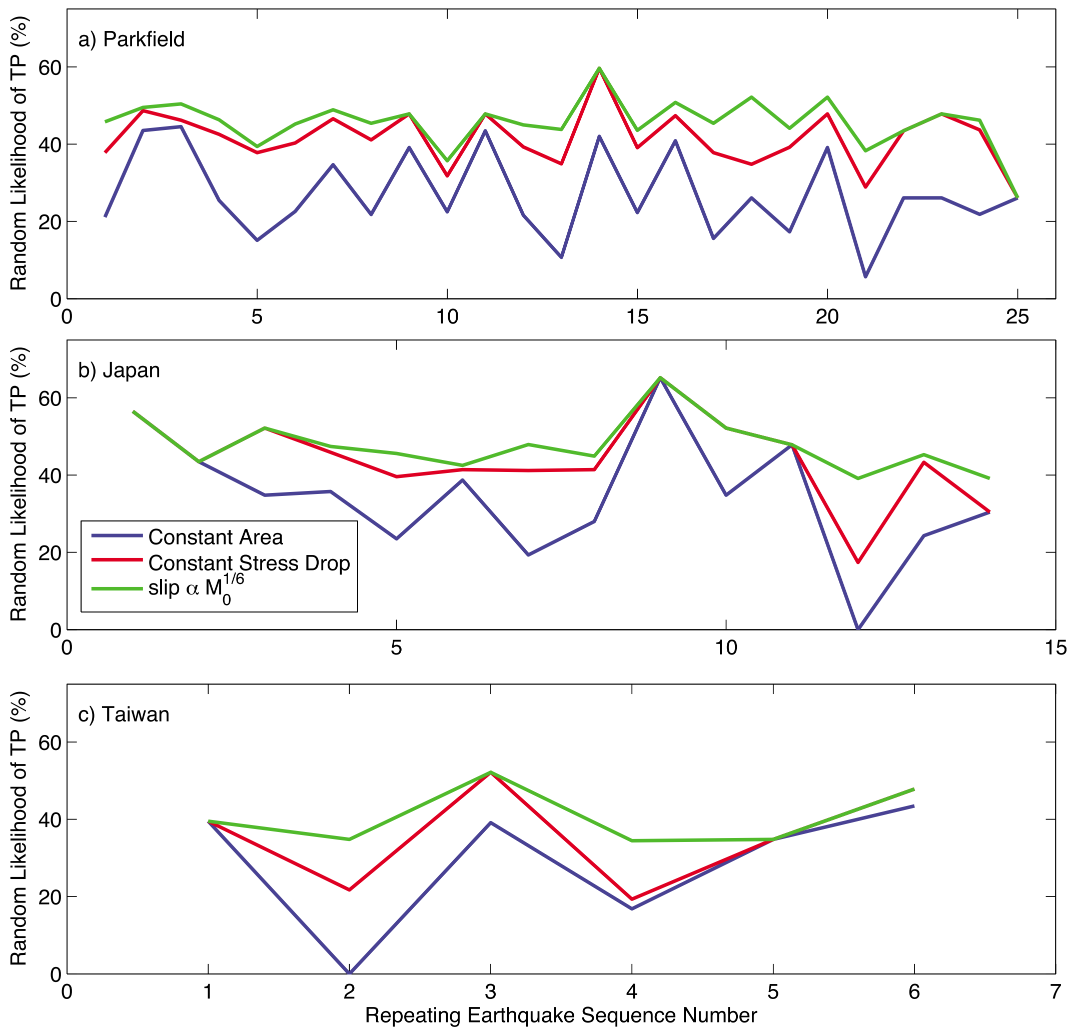

Figure 7. Results of reshuffling experiments showing how likely each repeating earthquake sequence is to appear to be fit by the time-predictable model simply as a result of its data distribution. All the sequences in (a) Parkfield, (b) Japan, and (c) Taiwan are shown separately. The reshuffling experiments using the different slip:moment assumptions are shown with three different colored lines. These results indicate that 20–40% of the data would appear time-predictable even if there was no connection between recurrence interval and slip.

earthquake sequences being better fit by the time predictable model, we simply need to compute the product of the probabilities that each sequence is better explained by perfectly periodic model. Things are more complicated as the number of time-predictable sequences increases since we need to compute the probability of each possible combination of time-predictable/not-time-predictable sequences and sum them over all the possible combinations. Computing these probabilities based on all the combinations gives a probability distribution of how many sequences can be expected to be better explained by the time-predictable model for a given region and slip:moment relationship.

[38] These probability distributions are shown for all 9 combinations of region and slip scaling relationships in Figure 8. For these probability distributions we identify the largest 5% of the data and smallest 5% of the data, giving us the region where 90% of the random reshuffled combinations lie. If our observations of the number of sequences that appear to be better fit by the time-predictable model fall outside these bounds, we can be 90% certain that we are observing a real phenomenon. For the nine combinations, we see that none of the nine fall outside the 90% bounds. This strongly suggests that the observation that the time-predictable model describes many repeating earthquake sequences well is merely a function of the data distribution. Thus we cannot reject the null hypothesis that there is no predictive value in the time-predictable model.

5. Testing the Slip-Predictable Model

[39] We follow a similar method as described in sections 4.1–4.4 to test whether the slip-predictable model better describes repeating earthquakes than a fixed slip model. In the slip-predictable model, we expect the slip in an earthquake to scale with time since the last event, i.e., releasing all the slip accumulated since the last event. Therefore, if we plot the slip against the time since the last event, we expect to see a positive trend. Examining the

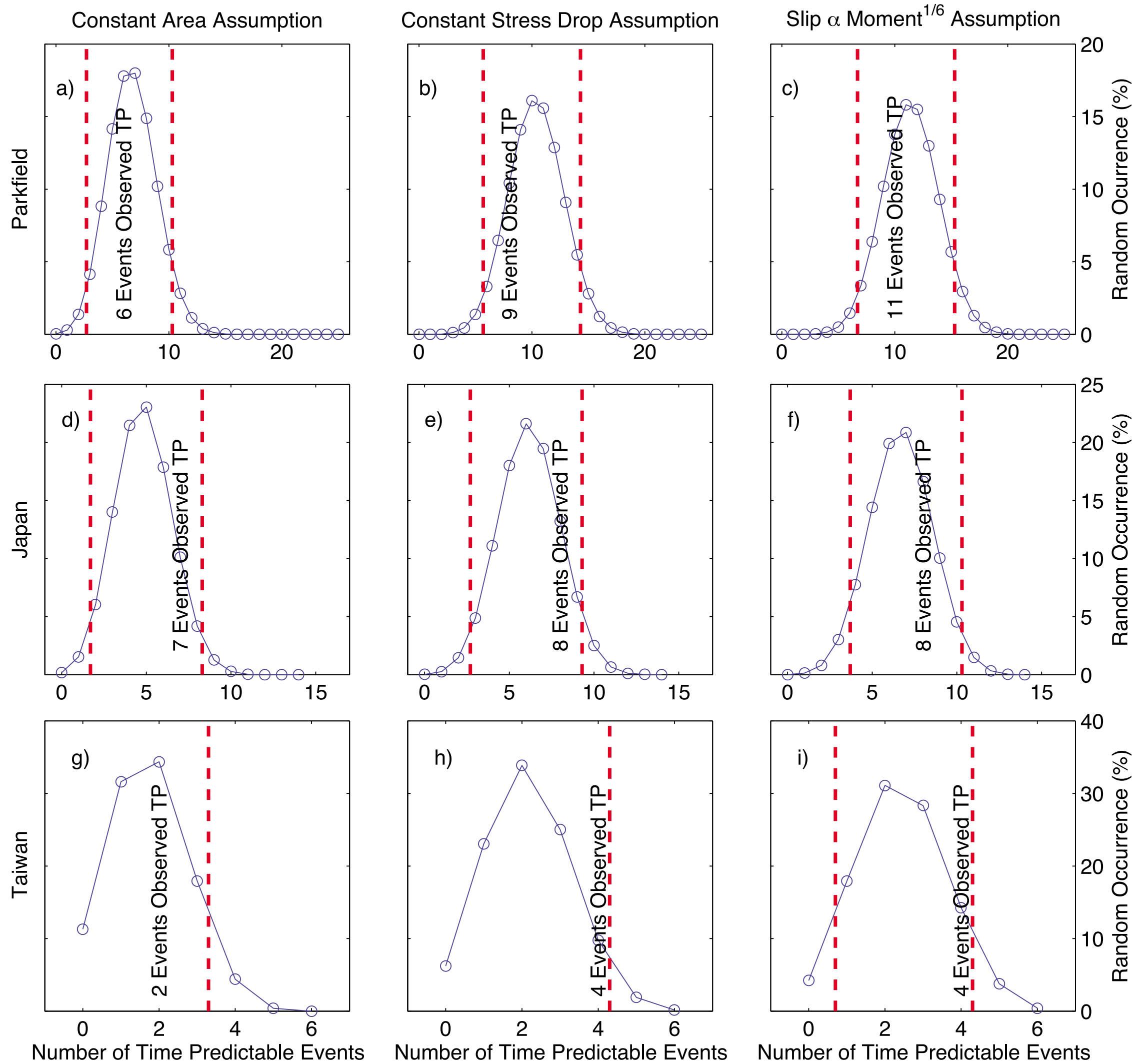

Figure 8. Probability distributions of the number of sequences that would be randomly fit by the time-predictable model for repeating earthquake sequences in (a–c) Parkfield, (d–f) Japan, and (g–i) Taiwan. Each slip-moment distribution is plotted separately for each region. A dashed, vertical line indicates that less than 5% of the data lies above/below the line, effectively forming a 90% confidence bound. For Figure 8g, only an upper bound line is shown because the smallest possible number of sequences to be fit by the time-predictable model is zero, and its probability is more than 10%, so there is no lower bound using the method used for the other plots. In each panel, a vertical line of text indicating the number of sequences observed to be fit by the time-predictable model is plotted such that it lies in the appropriate location on the probability distribution. If this text falls outside either of the two 90% confidence bounds (or above the 95% confidence bound in Figure 8g), we have 90% (or 95% in Figure 8g) confidence that the observation is non-random. All of our observations fall within the 90% confidence bounds, such that we cannot reject the null hypothesis that the fixed recurrence model better predicts the behavior of the repeating events than the time-predictable model.

Parkfield repeating earthquake sequences, qualitatively it appears that these sequences follow the predictions of the slip-predictable model; many of the sequences appear to have a fairly linear, positive trend (Figure 9a). The Japanese and Taiwanese sequences, though, do not appear to be fit by the slip-predictable model in a qualitative sense (Figures 9b and 9c).

[40] Using cross-validation, we compare the predictions of the slip-predictable model to those of the fixed slip model described in section 2.3. We find that very few of the sequences appear to be better described by the slip-predictable model than the fixed slip model (Table 2). The results for Japan and Taiwan are as we expect, they do not appear to have a strong trend and thus are not well described by the slip-predictable model. The results in Parkfield, though, are surprising given that there is a clear, positive trend for many of the repeating earthquake sequences (Figure 9a). The ill fit of the slip-predictable model likely arises from the strict definition of the slip-predictable model that we use in this test. Specifically, we

require that the intercept of the line describing the relationship between slip and the recurrence interval equal zero, as in equation (3) instead of equation (4). This gives the slip-predictable model a physical meaning, i.e., when an earthquake happens, it uses up the entire available slip budget, such that if an earthquake occurs immediately after the last one, it will be of zero size. This requirement means that a positive slope, while a necessary condition for the slip-predictable model, is not sufficient to ensure that a repeating earthquake sequence is better described by it than a fixed slip model. An example of how the slip-predictable model fails to describe an individual sequence is shown in Figure 10 for Parkfield repeating earthquake sequence 19. When we normalize all the sequences and examine them together, we can see that the broader population of the sequences do not have a zero-intercept scaling in either a time- or slip-predictable sense (Figure 4). Since it appears that slip does depend on inter-event time in Parkfield but the repeating earthquakes are not explained by the slip-predictable model in a strict sense, later we explore the possibility that there is a relationship between slip and recurrence time while allowing for a nonzero intercept as in equation (4).

[41] We use the same reshuffling method described in section 4.3 to determine how likely it is that any individual sequence would be better fit by the slip-predictable model just based on its data distribution. Very few sequences have high probabilities of being randomly better fit by the slip-predictable model (Figure 11). The maximum probability of any sequence randomly being better fit by the slip-predictable model is approximately 21%, 39%, and 26% in Parkfield, Japan, and Taiwan respectively, with the average being far lower. This is consistent with our observation of very few sequences having lower prediction-errors for the slip-

Table 2. Number of Sequences That Appear to Be Slip-Predictable[a]

	Constant Area	Constant Stress Drop	Slip α $M_0^{1/6}$
Parkfield	3/25	0/25	0/25
Japan	2/14	1/14	0/14
Taiwan	0/6	1/6	0/6

[a]This table lists the fraction of the total number of sequences where cross-validation indicates that the slip-predictable model better predicts the behavior of the repeating earthquakes than the fixed slip model.

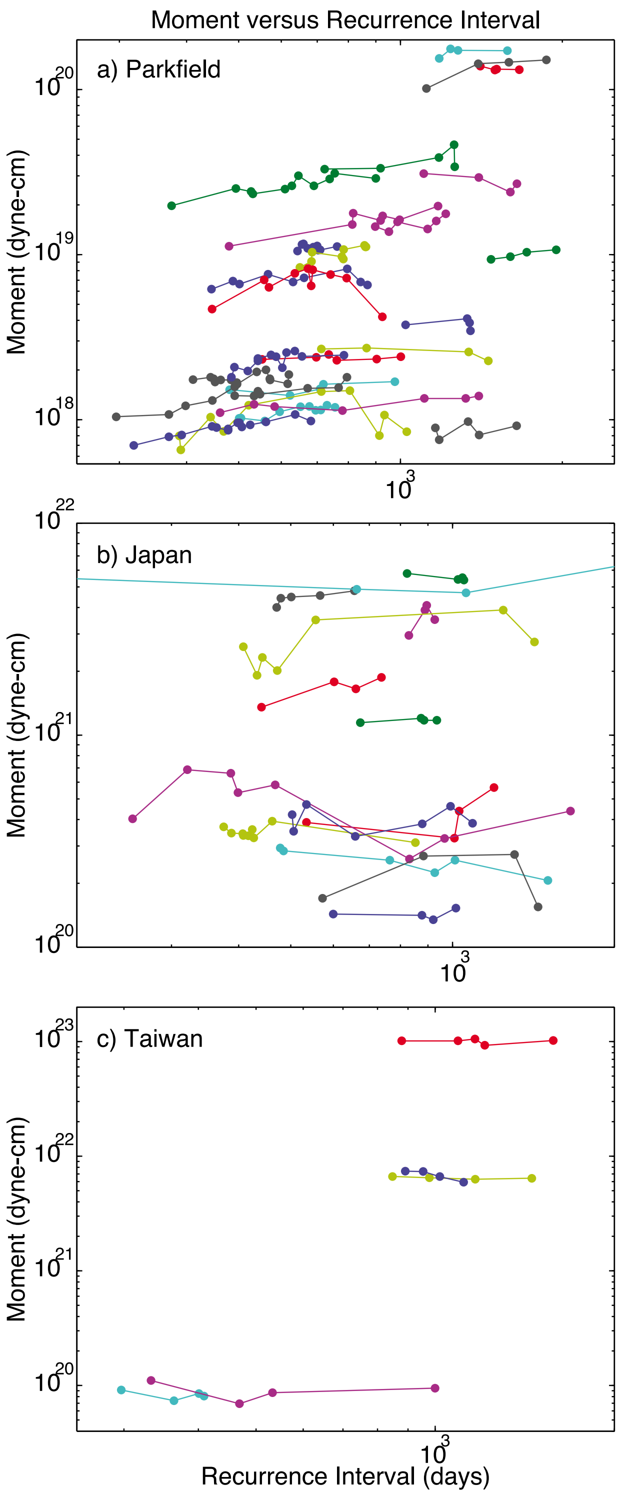

Figure 9. The qualitative fit of the slip-predictable model to all the repeating earthquake sequences examined in (a) Parkfield, (b) Japan, and (c) Taiwan. Moment for each event within an individual sequence is plotted against its recurrence interval. The sequences are colored differently so that they can be distinguished from each other. Lines connect all the earthquakes within a sequence, but do not imply the chronological ordering of the events. A sequence that is fit by the slip-predictable model is expected to have a positive slope, i.e., slip would increase as the time since the last event is increased. Moment of the events is used as a proxy for slip, following the constant area assumption. Using other moment-slip relationships will change the shape of the lines, but not the trend or lack thereof, which is a qualitative measure of whether a sequence is time-predictable. Sequence 1 in Taiwan is removed because some of its repeats are very short and including it in this plot would make it difficult to see the other sequences on the same figure. Many of the sequences in Parkfield have a consistent positive trend, indicating that the slip-predictable model may be useful in describing the behavior of these events. The sequences in Japan and Taiwan do no appear to have a consistent trend, suggesting that the slip-predictable model does not predict the behavior of these events well.

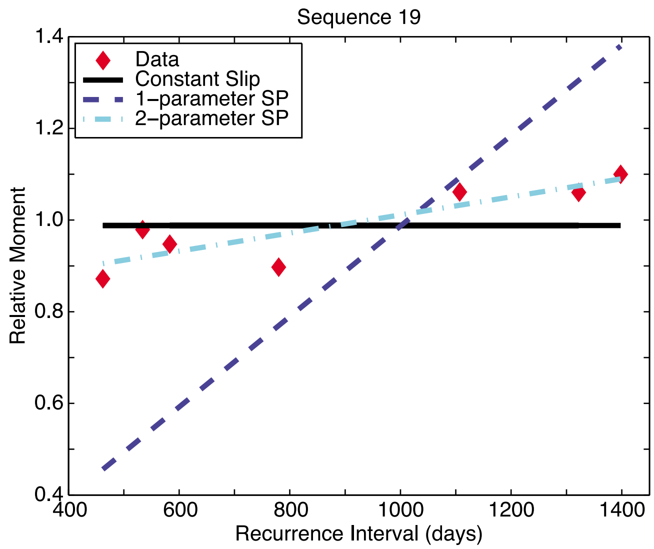

Figure 10. Example of how the slip-predictable model may be failing for the Parkfield repeating earthquake sequences. There appears to be a clear scaling between moment and the recurrence interval, where the events get larger with longer recurrence intervals. A one-parameter slip-predictable model does not fit the data well because it has to go through the origin, while a constant moment explains the small variability much better. Using a two-parameter slip-predictable model fits the data better than either of two other models.

predictable model than for a fixed slip model (Table 2). We also note that as the exponent in the slip:moment relationships decreases, the random likelihood of a sequence being fit by the slip-predictable model also decreases (Figure 11). This is also seen in the observed data (Table 2). This arises because as the exponent decreases, the variability in the slip estimates decreases as well, such that a mean will describe the data increasingly well, while a slip-predictable model will still need to keep a positive slope.

[42] As with the time-predictable model, the reshuffling experiment is based upon the assumption that a data set that is perfectly explained by the slip-predictable model would rarely appear slip-predictable when reshuffled. We perform the same test to verify if this is the case, again using a log-normal distribution, this time for recurrence times with a coefficient of variation of 0.30 (the coefficient of variation of recurrence times in the data). The probability of false positives for reshuffled data that was formerly slip-predictable is low (0–22%), validating the assumption that this experiment rests upon. As with time-predictability, sequences with fewer events are more likely to appear slip-predictable.

[43] We perform the same probability-combination exercise described in section 4.4 to determine the probability that the number of sequences that we observed to be fit by the slip-predictable model arose out of random chance. Exploring the probability distributions, we only find that two of the nine region/slip-moment combinations falls outside of the 90% confidence bounds (Figure 12). This is using the constant area assumption for the repeats in Parkfield and the constant stress drop assumption for Taiwan. This suggests that there may be some real fit of the slip-predictable model, in that we have 2 of the 9 combinations falling outside 90% confidence bounds. Based on random chance and 90% confidence bounds, we would expect one combination to fall outside these bounds. Given that we would expect that 1 of the combinations to fall outside the confidence bounds, having a second should not be particularly surprising as well. Additionally the number of sequences that are well described by these models is very low, 3/25 sequences and 1/6 sequences, so even if there is a real fit, it is of very little utility since it describes only a few sequences well.

6. Testing the Two-Parameter Time- and Slip-Predictable Models

6.1. Two-Parameter Time-Predictable Model

[44] We follow the same methodology as above to test whether using a two-parameter time-predictable model better describes the behavior of the repeating earthquakes in Taiwan, Japan, or Parkfield. We first compare the cross-validation prediction-errors of the perfectly periodic model to those of the two-parameter time-predictable model. Using this test, we find that fewer sequences appear to be fit by the time-predictable model than when using the strictly defined one-parameter model (Table 3). At first glance, this might seem rather peculiar in that a two-parameter model will by definition fit data better than a one-parameter model. While this may be the case, we are examining the predictive power of these models using cross-validation, and not the fit to all of the data. Therefore, it is perfectly possible that the one-parameter time-predictable model would better predict the behavior of a system than the two-parameter version as we see here. Because we are better fitting the initial data and more poorly predicting the omitted data, we can be quite confident that the size of an earthquake tells you nothing about the recurrence interval required until the next event.

[45] As with previous earthquake data, we reshuffle the repeating earthquake data to determine the likelihood that each of these sequences would randomly appear to be fit by the time-predictable model based upon the data distribution. We find significantly lower likelihoods of sequences randomly being better described by a two-parameter time-predictable model (Figure 13). The peak likelihood of any of the sequences being randomly time-predictable in a two-parameter sense is 22–28% for the three regions. Given the small number of sequences observed to be fit by the time-predictable model in a two-parameter sense (Table 3), it seems very likely that what we are observing is very likely just a result of random data.

[46] We next explore if the number of sequences whose behavior is better predicted by the two-parameter model is likely a result of random chance. To this end, we compute the probability distributions for the two-parameter time-predictable model as applied to each region and each slip assumption. For the nine different combinations, each falls within a 90% confidence bound describing random behavior. Based on this, the time-predictability (or lack thereof) we observe for the repeating earthquake sequences using the two-parameter time-predictable model is likely a function of random chance.

6.2. Two-Parameter Slip-Predictable Model

[47] Following the same methodology as used for other models, we compute the number of sequences whose

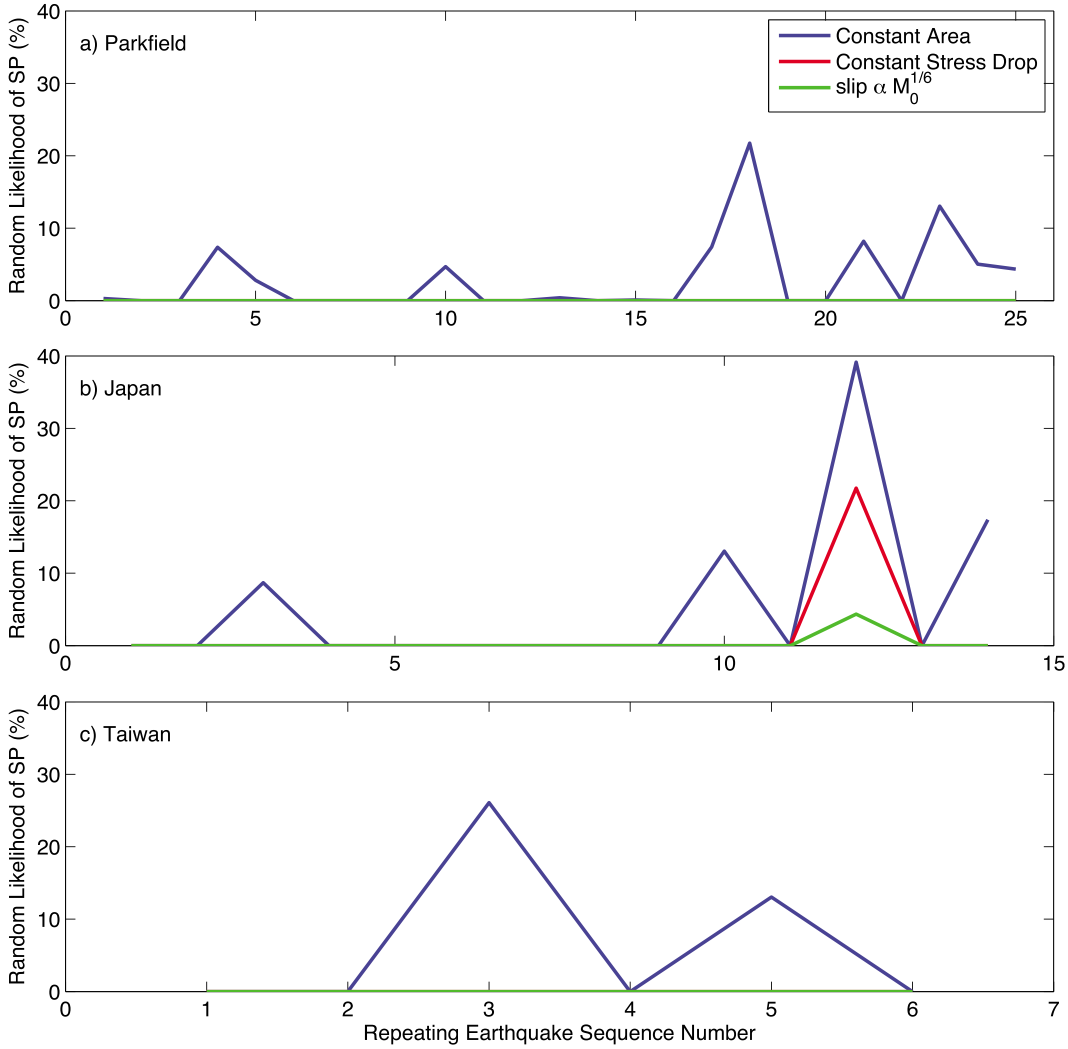

Figure 11. Results of reshuffling experiments showing how likely each repeating earthquake sequence is to appear to be fit by the slip-predictable model simply as a function of its data distribution. All the sequences in (a) Parkfield, (b) Japan, and (c) Taiwan are shown separately. The reshuffling experiments using the different slip:moment assumptions are shown with three different colored lines. This data indicates that it is highly unlikely that these sequences would appear to be slip-predictable simply based upon their data distribution. Any observed fit of the slip-predictable model is likely to be real.

behavior is better predicted by two-parameter slip predictable model than by the fixed slip model. We find that very few sequences are better predicted by the two-parameter slip-predictable model in both Taiwan and Japan, but 14 or 15 of the 25 repeating earthquakes in Parkfield are better described by the two-parameter slip-predictable model depending on the slip-moment assumption (Table 4). This should not be especially surprising given that many of the Parkfield repeating earthquake sequences appear to have a positive correlation between slip and the preceding recurrence interval (Figure 9a).

[48] Performing random reshuffles of the sequences shows that none of the sequences are particularly likely to appear slip-predictable based on their prediction-errors (Figure 14). Most of the sequences are randomly better described by the two-parameter slip-predictable model for 10–30% of the reshuffles. Given these low probabilities, it seems likely that our observations for the sequences in Japan and Taiwan are simply a result of random chance. In contrast, it is unlikely that our observation of 14 or 15 sequences being better described by a two-parameter slip-predictable model in Parkfield is a result of random chance.

[49] Exploring the probability that the number of sequences we observe to be better predicted by the two-parameter slip-predictable model we find that three of the nine slip/region combinations fall outside the 90% confidence bounds (Figure 15). The sequences that fall out of the 90% bounds are all the slip-moment combinations for the Parkfield repeating earthquakes. This implies that our observation of these sequences being fit by the slip-predictable model is very unlikely to be random. If we examine the actual likelihoods of 14 or more sequences being fit by the slip-predictable model, the probability that our observation is non-random ranges between 99.34 and 99.38% depending upon the slip assumption. The probability that all three of these would occur is approximately 2.6×10^{-5}%. We do

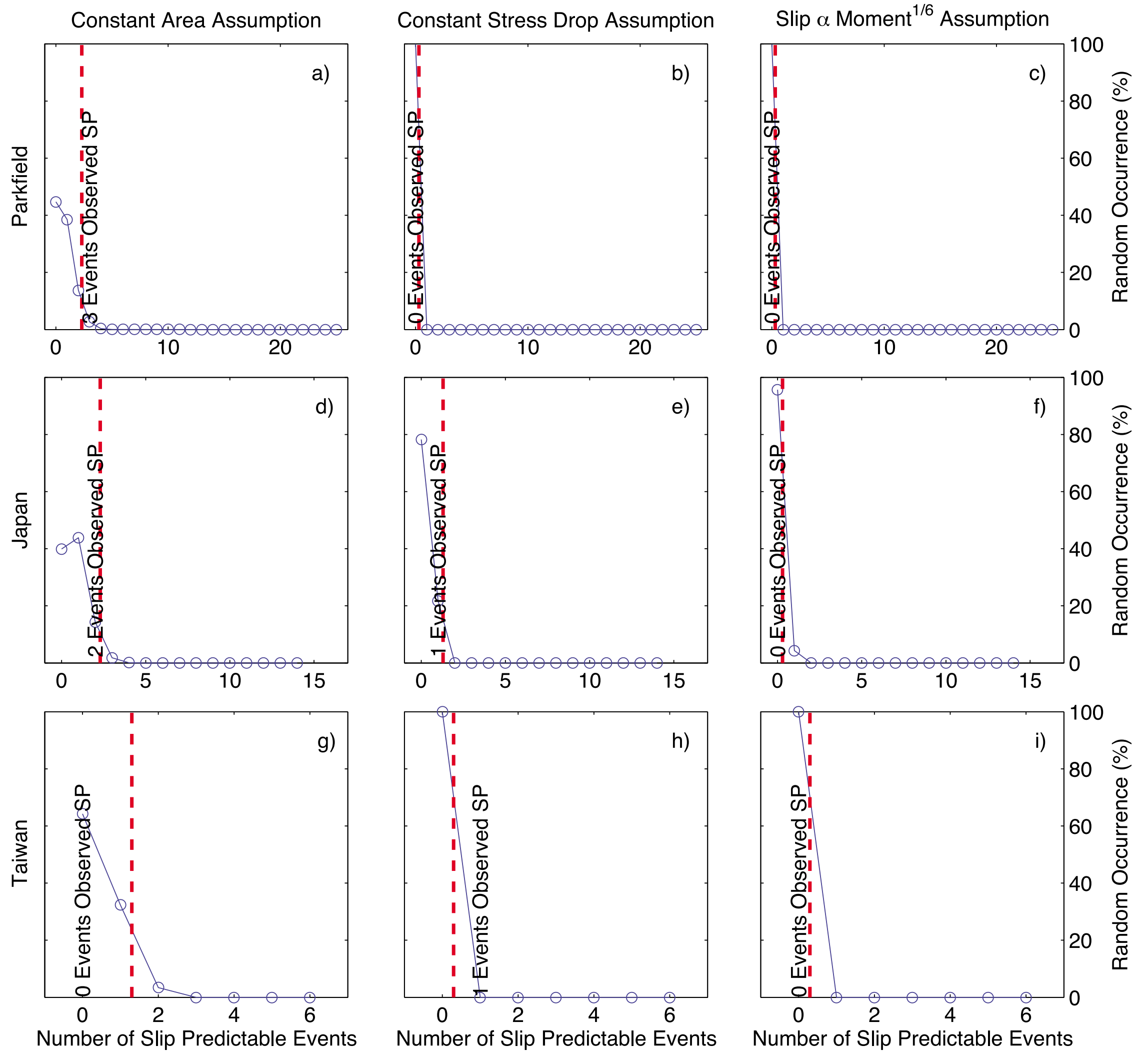

Figure 12. Probability distributions of the number of sequences that would be randomly fit by the slip-predictable model for repeating earthquake sequences in (a–c) Parkfield, (d–f) Japan, and (g–i) Taiwan. Each slip-moment distribution is plotted separately for each region. A dashed, vertical line indicates that less than 5% of the data lies above the line, effectively forming a 95% confidence bound. In each panel, a vertical line of text indicating the number of sequences observed to be fit by the time-predictable model is plotted such that it lies in the appropriate location on the probability distribution. If this text falls above the 95% confidence bound, we have 95% confidence that the observation is non-random. Two of the nine combinations (constant area assumption for Parkfield and the constant stress drop assumption for Taiwan) fall outside the 95% confidence bounds, such that the utility of the slip-predictable model in these cases are likely real at the 95% confidence level. While this may be real, the incredibly low number of sequences observed to be fit by the slip-predictable model indicates that these models are of little use, since they cannot be applied widely.

note that the probabilities of the random occurrence of any individual sequence being better fit by the slip-predictable model is near-constant over all of the slip assumptions in all the regions. This implies that we cannot consider the likelihood of the slip-assumptions independently, although we still can say with 99.34% confidence that the observation of the Parkfield repeating earthquakes being fit by the slip-predictable model is non-random.

[50] In hopes that this predictability could be used elsewhere we try to distinguish the two-parameter slip-predictable repeating earthquake sequences from those that are not. We try to distinguish them by means of epicentral location,

Table 3. Number of Sequences That Appear to Be Time-Predictable (Two-Parameter)[a]

	Constant Area	Constant Stress Drop	Slip α $M_0^{1/6}$
Parkfield	3/25	3/25	3/25
Japan	1/14	1/14	1/14
Taiwan	0/6	0/6	0/6

[a]This table lists the fraction of the total number of sequences where cross-validation indicates that the two-parameter time-predictable model better predicts the behavior of the repeating earthquakes than the perfectly periodic model.

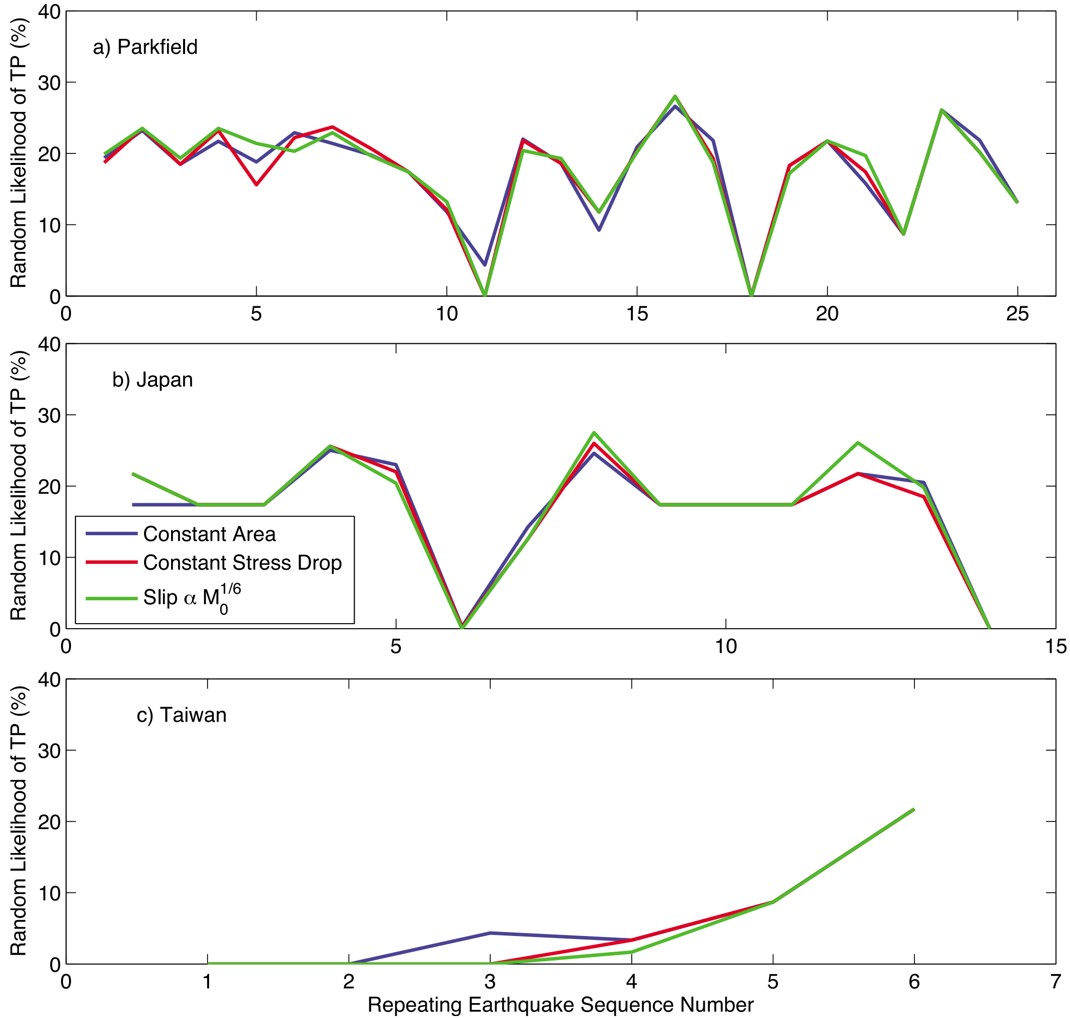

Figure 13. Results of reshuffling experiments showing how likely each repeating earthquake sequence is to appear to be fit by the time-predictable model with a two-parameter model simply as a function of its data distribution. All the sequences in (a) Parkfield, (b) Japan, and (c) Taiwan are shown separately. The reshuffling experiments using the different slip:moment assumptions are shown with three different colored lines. The data from all three regions has low likelihood (<30%) that it will be well predicted by the two-parameter time-predictable model for randomly distributed data.

depth, mean recurrence, number of events, and average moment (Figures 5b and 5c; Data Set S1 in auxiliary material). Unfortunately, none of these criteria can be used to distinguish those sequences that are better described by the two-parameter slip-predictable model from those that are better described by a constant slip model. Given this, it seems unlikely that we will be able to identify sequences that behave in a two-parameter slip-predictable manner.

7. Discussion and Conclusions

7.1. Fixed Recurrence and Slip Models Better Predict Repeating Earthquake Behavior Than the Time- and Slip-Predictable Models

[51] With the aim of elucidating whether the time- and slip-predictable models are appropriate to describe the recurrence and slip-behaviors of earthquakes, we have analyzed natural repeating earthquakes. We examine these earthquakes based on the premise that they more closely fit key assumptions of the time- and slip-predictable models (constant loading rate and highly similar ruptures) than do typical earthquakes. Strictly defined, these models have less predictive power than models that predict the subsequent recurrence interval or slip as the mean of all the other events in the sequence. Examining all the data using both the slip-predictable and time-predictable models we find that the data

Table 4. Number of Sequences That Appear to Be Slip-Predictable (Two-Parameter)[a]

	Constant Area	Constant Stress Drop	Slip α $M_0^{1/6}$
Parkfield	14/25	15/25	14/25
Japan	3/14	3/14	3/14
Taiwan	2/6	2/6	2/6

[a]This table lists the fraction of the total number of sequences where cross-validation indicates that the two-parameter slip-predictable model better predicts the behavior of the repeating earthquakes than the fixed slip model.

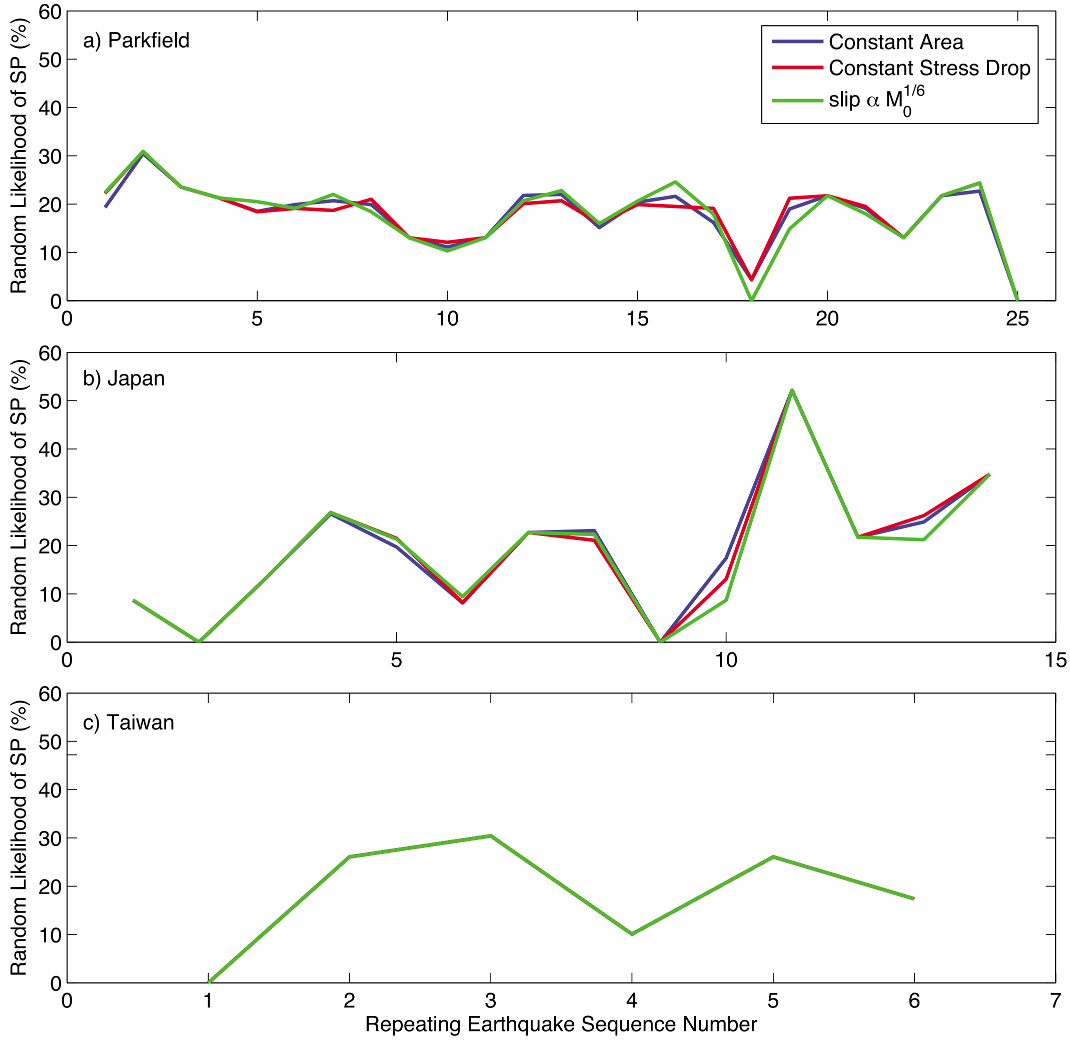

Figure 14. Results of reshuffling experiments showing how likely each repeating earthquake sequence is to appear to be fit by the slip-predictable model with a two-parameter model simply as a function of its data distribution. All the sequences in (a) Parkfield, (b) Japan, and (c) Taiwan are shown separately. The reshuffling experiments using the different slip:moment assumptions are shown with three different colored lines. Most sequences are fairly unlikely to be explained well by the two-parameter slip-predictable model if their recurrence time and slip relationship is shuffled. Thus any slip-predictability observed in the data is likely real.

looks much more like it is scattered around a mean than following along a line with a constant slope and a y-intercept of 0 (Figure 4). More than 50% of the data falls outside 2σ bounds for the slip-predictable model and more than 60% of the data falls outside the 2σ bounds for the time-predictable model. Further tests show that those cases when the time- and slip-predictable models do outperform the fixed recurrence and fixed slip models, respectively, it is likely the result of random chance. In a strict sense, the results of our study indicate that we cannot rule out the null hypothesis that the repeating events are better described by fixed recurrence and slip models than they are the time- and slip-predictable models. While this means that we cannot strictly say that the time and slip-predictable models are inferior, given that we cannot explicitly show that they are superior using a data set of many different repeating earthquake sequences, we can say that if there is any superior value to the time- and slip-predictable models it is very subtle or infrequent so it is of little or no value for predictions.

[52] Repeating earthquake sequences are the earthquake sequences we expect should best fit the assumptions of the time- and slip-predictable models, yet these models poorly explain them. Given this, we conclude that the time- and slip-predictable models, as defined here, have less event-to-event predictive power than simpler fixed recurrence and slip models for any natural earthquakes. Further evidence to this point is provided by the companion manuscript [*Rubinstein et al.*, 2012] which details evidence that laboratory generated earthquakes are better explained by constant recurrence and slip models than the time- and slip-predictable models.

[53] Having demonstrated the time- and slip-predictable models cannot be used to adequately predict the behavior of repeating earthquakes, we also explore whether there is useful predictive information in the relationships between

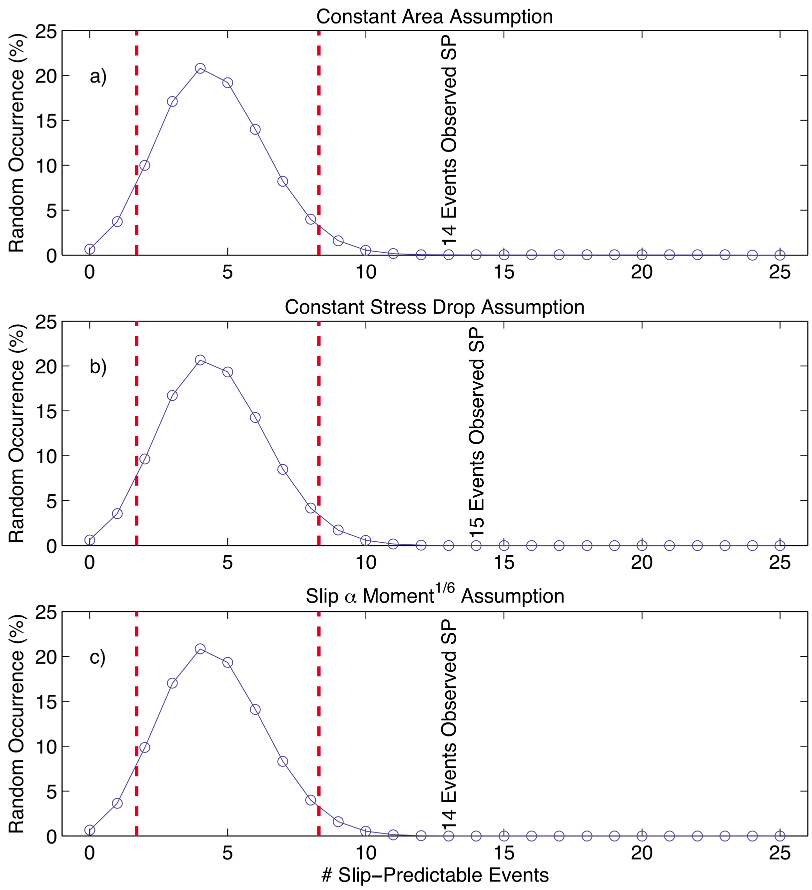

Figure 15. Probability distributions of the number of sequences that would be randomly fit by the two-parameter slip-predictable for the repeating earthquake sequences. Only the three region/slip:moment combinations where the observation falls out of the 90% confidence limits are shown, otherwise figure description is the same as Figure 10. All of these combinations are for Parkfield and two-parameter slip-predictability. This strongly suggests that the slip-predictable scaling observed in Parkfield is real.

recurrence interval and slip by adding an additional parameter to the slip:recurrence-interval relationship. Some have argued that models like this do offer predictive power for earthquakes [e.g., *Papazachos*, 1989, 1992; *Papazachos et al.*, 1994]. This has also been observed for repeating earthquakes during aftershock sequences [e.g., *Chen et al.*, 2010a; *Peng et al.*, 2005; *Marone et al.*, 1995; *Vidale et al.*, 1994]. The applicability of aftershock studies is unclear because loading rates are almost certainly variable during aftershock sequences. Our analysis of the repeating earthquake data indicates that there is a slip-predictable sense scaling for repeating earthquakes in Parkfield and not elsewhere. We find no time-predictable sense scaling. Unfortunately, we have not found a procedure for identifying sequences that are well described by the two-parameter slip-predictable model in Parkfield or in the other regions. This means that while it appears that sometimes there is additional two-parameter slip-predictable information in repeating earthquakes, this model is unusable because we have no way of knowing which earthquakes are well explained by it.

[54] It is unclear as to why the Parkfield sequences are better explained by a two parameter slip-predictable model those elsewhere are not. One possibility is that repeating earthquakes are only slip-predictable in strike-slip regions. This scaling has previously been observed on strike-slip faults in California [*Chen et al.*, 2010a; *Peng et al.*, 2005; *Marone et al.*, 1995; *Vidale et al.*, 1994], but no study prior to this has studied them elsewhere. Another possible explanation as to why we observe slip-predictable type scaling in Parkfield and not elsewhere is that the repeats in each region are slightly different than each other. In this study, the repeating earthquakes sequences are defined differently from region to region, thus there may be some sequences that would be a repeating earthquake sequence in one region but would not be in another. The slip rate may also be more stable in Parkfield than in Taiwan and Japan, thus allowing it to appear slip-predictable in a two-parameter sense while Taiwan and Japan would not appear slip-predictable. Certainly slip-rates and seismicity rates are higher in Taiwan and Japan than in Parkfield, so this may result in larger temporal variations in loading rates and thus a lack of slip-predictability.

7.2. Reasons Why the Fixed Recurrence and Slip Models Better Predict the Behavior of Repeating Earthquakes

[55] In this section we explore why the predictions of the time- and slip-predictable models for the behavior of

repeating earthquakes are worse than those of the fixed recurrence and fixed slip models. We first explore possible non-tectonic reasons and subsequently explore physical reasons why the time- and slip-predictable models do not improve on the predictions of fixed slip and fixed recurrence models.

7.2.1. Non-tectonic Reasons

[56] One possible reason that repeating earthquake behavior is better explained by fixed recurrence and fixed slip models is that our definition of repeating earthquakes is not adequate. To our knowledge there is no agreed upon definition for repeating earthquakes. Even in this study we mix definitions from region to region. The variability of our definitions of repeating earthquakes may certainly explain variable behavior from region to region, but cannot explain the general absence of a fit by the time- and slip-predictable models. It is possible, though, that we are not examining "true" repeating earthquakes where the slip areas overlap, as there is no way to delineate with 100% certainty that all the events in a repeating earthquake sequence are the same event. If we are not examining "true" repeats, this would mean that the time- and slip-predictable models would not hold because we are not examining a point process. While it is a possibility that we are not examining perfect repeats of an earthquake sequence, the rigorous requirements that we apply strongly suggest that we are examining perfect repeats. Furthermore, if we are not examining perfect repeats, it seems highly unlikely that if the time- and slip-predictable models fail for near-perfect repeats they would work for the larger and less similar earthquakes that we are truly interested in describing.

[57] Another possible non-tectonic explanation as to why fixed slip and fixed recurrence models better predict repeating earthquake behavior is that our definition of aftershocks is too permissive in that some of the sequences we are analyzing may contain aftershocks. This would skew our observations due to increased seismicity rates following a large earthquake. As noted in section 3, we have reason to believe that the *Wells and Coppersmith* [1994] definition of aftershocks that we use is reasonable, but it is certainly possible that it could miss some aftershocks. One way we may miss aftershocks is that we only consider main shocks of $M \geq 6.0$. This means that any changes caused by earthquakes $M < 6.0$ are assumed to part of the background rate, which will skew its true value. All earthquakes have aftershocks sequences of varying duration and vigor, meaning that they may cause accelerations or decelerations of repeating earthquakes [*Lengliné and Marsan*, 2009]. Earthquakes as small as magnitude $M \sim = 4.0$ have been shown to change the behavior of repeating earthquakes [*Ellsworth*, 1995; *Chen et al.*, 2010b]. It is unclear how significant this effect is, but defining aftershock zones becomes a larger and larger problem as the cutoff magnitude is reduced, making a low cutoff magnitude an unwieldy problem.

7.2.2. Physical Reasons

[58] While the definition-based reasons above might explain why repeating earthquake behavior is better predicted by fixed recurrence and slip models than the time- and slip-predictable models, it is far more likely that there are physical reasons as to why these models do not work. Fundamentally, we believe these models rely on assumptions that are too simple to describe the complex behavior of the earth.

[59] The key assumption underlying both of the models that we are testing is that there is a long-term constant loading rate. Certainly, this is an unfair assumption, as short-term creep events and slow-earthquakes have been observed globally and nearby to every one of our study regions [e.g., *Liu et al.*, 2009; *Ozawa et al.*, 2003; *Kawasaki et al.*, 2001; *Langbein et al.*, 1999; *Murray and Segall*, 2005]. Since loading rates are variable, the time- and slip-predictable models are bound to fail. As might be expected, variable loading rates have been seen to change seismicity rates [e.g., *Segall et al.*, 2006], including for repeating earthquakes [*Nadeau and McEvily*, 1999; *Ellsworth*, 1995]. Notably, there was an accelerated creep event in the Parkfield area from 1993 to 1998 [*Langbein et al.*, 1999; *Gao et al.*, 2000; *Murray and Segall*, 2005]. *Nadeau and McEvily* [1999] determined that the moment rate of some repeating events accelerated along with this creep event. Clearly loading rate has an effect on repeating earthquakes in one of our study regions so it is important to take into account. We note, though, that for the repeating earthquakes that we study in Parkfield, we do not identify any change in moment rate at the time of this creep event. That repeating events do appear to accelerate with creep rate (and thus a likely loading rate) suggests that earthquakes may be following the elastic rebound model, but a constant loading rate assumption is overly simplistic.

[60] The other key assumptions of the time- and slip-predictable models are likely too simplistic as well. The time-predictable model assumes that there is a constant failure threshold, i.e., once a threshold stress is reached, failure will happen. Laboratory and theoretical work has shown that rocks do not always fail at the same stress [e.g., *Dieterich*, 1979; *Karner and Marone*, 2001], again implying that the time-predictable model is relying on an assumption that is too strict. The slip-predictable model relies on the assumption that the entire slip deficit accumulated since the last earthquake will be released in the subsequent earthquake. Similarly, it seems likely that some slip may not be released in the subsequent event or alternatively released in aseismic processes, making it an unfair assumption as well.

[61] In addition to assuming that there is a constant loading rate for seismic slip, the time- and slip-predictable models are built upon the simplifying assumption that the repeating earthquake studied releases all of the slip in the region. Previous studies of repeating earthquakes have argued this [e.g., *Nadeau and McEvily*, 1999]. For the sequences that we identify as being two-parameter slip-predictable, i.e., the most likely to have a constant loading rate, we test whether they could accommodate all of the slip on the San Andreas. We test whether the repeats could meet the slip rate of the fault using (1) constant stress drops of 3 MPa and 10 MPa, consistent with *Imanishi and Ellsworth* [2006] and (2) stress drops derived from *Nadeau and Johnson* [1998] that vary from event to event and sequence to sequence ranging from 140 MPa to 540 MPa. With this range of parameters, we compute slip rates to vary between 0 mm/yr and 11.7 mm/yr, well below the geologically estimated rate of 20–32 mm/yr [*Toke et al.*, 2011]. Given our results, the repeats that we're observing likely are not accommodating all the slip for a given location on the fault laterally. One way that this can be

accomplished is with multiple, active, parallel strands of the fault that accommodate slip. This has recently been seen in the SAFOD borehole into the Parkfield segment of the San Andreas Fault [*Zoback et al.*, 2010]. It seems probable that the slip partitioning from strand to strand likely varies with time, such that it is likely that the assumption of a constant loading rate does not hold.

[62] One need not accommodate all of the slip in seismic processes for the assumptions of the time- and slip-predictable models to work. They simply assume a constant loading rate, which allows for a constant total loading rate and a constant percentage of the slip that is accumulated in seismic events (as opposed to aseismic events). For repeating earthquakes, in particular, this assumption seems unreasonable. Every laboratory and theoretical study that has attempted to physically model the conditions required to produce repeating earthquakes [*Chen and Lapusta*, 2009; *Beeler et al.*, 2001; *Sammis and Rice*, 2001; *Anooshehpoor and Brune*, 2001; *Johnson and Nadeau*, 2002] has argued that repeating earthquake sequences are taking place near or in regions that primarily accommodate slip aseismically. It seems highly improbable that the seismic:aseismic slip ratio stays constant over many earthquake cycles [*Chen et al.*, 2010a; *Chen and Lapusta*, 2009], making the seismic loading rate variable (as opposed to the total loading rate). Even in the case of a constant total loading rate, a variable seismic loading rate would make the time- and slip-predictable models unusable. A nonlinear evolution of fault strength could also produce a variable slip deficit, forcing the slip-predictable model to fail. The time- and slip-predictable models expect that fault strength evolves linearly as a function of time, which is contrary to laboratory observations that show that it evolves in a logarithmic fashion, increasing rapidly at first [*Dieterich*, 1972]. This would produce larger than predicted slip for events shortly after a previous event. We observe this behavior for the Parkfield sequences. The fact that repeating earthquakes occur in regions where a significant portion of the slip is accommodated aseismically may mean that they are not appropriate to study time- and slip-predictability with these events, as we argued earlier.

7.3. What Are Repeating Earthquakes?

[63] Given that repeating earthquakes do not appear to be predictable from event-to-event by either the time- or slip-predictable models, we are still left to explain the physical processes underlying these events. These sequences are highly regular in both recurrence interval and slip. In essence they are time- and slip-predictable in that we can use their regularity to predict the size and timing of the next event to be the mean of these values of previous events with very low residuals.

[64] To the resolution of modern relocation techniques they are occurring in the same place, and their highly similar waveforms indicate that their slip sense is very consistent. They also appear to be time- and slip-predictable in a long-term sense, in that their cumulative moment as a function of time looks quite linear (this study) [*Nadeau and Johnson*, 1998]. One possible model that would fit these observations is that repeating earthquakes lie in a region of fixed (or near-fixed) size that represents a partially stuck patch within a larger region of predominantly aseismic slip. The partially stuck patch accommodates slip both seismically and aseismically [*Beeler et al.*, 2001; *Chen and Lapusta*, 2009], but the ratio between them is not constant from event to event. Assuming this ratio varies about a mean, the repeating earthquake sequences would appear to have a linear or near-linear accumulation of slip as a function of time (i.e., appear time- and slip-predictable in the long term).

[65] **Acknowledgments.** The authors thank Andy Michael and Jeanne Hardebeck for many insightful discussions from which much of this work spawned. Their gracious assistance while faced with innumerable statistics questions is greatly appreciated. This work benefited from conversations with Nadia Lapusta, Zhigang Peng, Ned Field, Jeremy Zechar, and J. Ole Kaven. Comments from Ross Stein and Jeanne Hardebeck significantly improved an earlier version of this manuscript. Insightful reviews by Roland Burgmann and an anonymous reviewer improved this manuscript.

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