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Detection and characterization of transient forcing episodes affecting earthquake activity in the Aleutian Arc system

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ABSTRACT

Crustal, slow deformation transients can be caused by fluid or magmatic intrusions, and by slow slip on faults. They can affect earthquake dynamics, if they occur close to or within seismically active zones. We here further develop, and test, a statistical method for detecting and characterizing seismicity anomalies that is only based on earthquake occurrence times and locations. We make use of this method to analyze the 2004–2013 seismicity at $m_c = 3.5$ in the Aleutian subduction system, to find six statistically significant anomalies, with typical 1 day duration and 30 to 50 km size, that are likely related to slow deformation transients. They tend to be located in zones characterized by intermediate seismic coupling, and to mark the termination of past large to mega-thrust earthquakes. These anomalies account for a non-negligible (9%) part of the total activity, proving that non-stationary aseismic loading plays an important role in the dynamics of crustal deformation.

1. Introduction

Earthquakes occur as a consequence of accumulating stress in the crust. Estimating the rate at which stress loads a fault is a particularly challenging task, as systematic in situ measurement at seismogenic depth is still out of reach. Monitoring seismicity rates $\lambda(x, y, t)$, i.e., the number of earthquakes per unit time and unit area/volume at location (x, y) and time t, as proxies of stressing rates is a common approach, but it implies modeling how these two quantities relate to one another. Mechanical modeling of earthquake nucleation, e.g., using dislocation and friction models, generally accounts for loading due to long-term tectonic stressing, plus stress changes imparted by seismic sources big enough so that their characteristics are known with good certainty (Stein, 1999). However, it has been evidenced that small, poorly characterized sources also contribute significantly to the dynamics of seismicity (Helmstetter et al., 2005; Marsan, 2005; Meier et al., 2014). Stochastic modeling thus offers an alternative approach, that fully uses the seismicity information at hand, albeit at the cost of simplifying assumptions, in particular that earthquakes of equal magnitude behave the same as triggers. The seismicity rate λ here results from the two distinct contributions of a background aseismic rate μ and a seismic rate ν that can be modeled from the past history of earthquake occurrences: $\lambda(x, y, t) = \mu(x, y, t) + \nu(x, y, t)$.

Recent developments in seismology have emphasized the ubiquity of stress loading contributions from aseismic (i.e., not involving rupturing at seismic velocities), local processes, including silent fault slip within and underneath the seismogenic layer (Schwartz and Rokosky, 2007; Peng and Gomberg, 2010). Episodes of aseismic loading can thus cause changes in seismicity dynamics, if they occur in the proximity of faults close enough to failure. Transient deformation, or therein after 'transients', can therefore be revealed by the occurrence of seismic swarms, which do not obey usual mainshock–aftershock patterns.

Studies aimed at detecting transients with stochastic methods have focused on specific sequences, typically at the scale of tens of kilometers (Hainzl and Ogata, 2005; Llenos et al., 2009; Llenos and McGuire, 2011; Daniel et al., 2011; Peng et al., 2012). They considered that the relative evolution of the loading rate μ is the same at all points of the system, and thus decoupled $\mu(x, y, t) = \mu_x(x, y) \times \mu_t(t)$ to invert for the marginal μ_t. A methodological framework for performing this inversion is described in Marsan et al. (2013a). At the regional scale, from 100 to 1000 km, swarms only cover a small portion of the seismically active surface/volume. It is then inappropriate to consider that μ follows the same evolution everywhere. Transient aseismic loading

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must then be modeled as local, both in space and time, and the decoupling proposed in previous studies must be relaxed.

Preliminary attempts at doing so by Marsan et al. (2013b) were motivated by the question as to whether the swarm activity preceding the 2011 M_w 9.0 Tohoku earthquake was unique or not to this part of the Japanese subduction. The method then developed however provides only a partial account of the significance of the estimated changes in background rate, through the computation of the Akaike Information Criterion (Akaike, 1973). Other approaches have been based on visual inspection of seismicity patterns (Holtkamp and Brudzinski, 2011), or on clustering criteria probing swarm occurrences at specific spatial and temporal scales (Vidale and Shearer, 2006). Zaliapin and Ben-Zion (2013a, 2013b) developed the nearest-neighbor method of Zaliapin et al. (2008) to discriminate swarm activity, using a priori fixed model parameters.

We here extend the approach of Marsan et al. (2013b) by fully measuring the significance level of suspected episodes of aseismic deformation; tests of the method are then run to evaluate its accuracy and resolution power. The analysis of regional seismicity in the Aleutian arc is then performed, to compare the inverted transients with independent accounts of aseismic transients, and to investigate the spatial distribution of these deformation episodes.

2. Method

We define the seismicity as the combination of two components. The first is the seismicity due to aseismic processes, including tectonic loading. This spontaneous seismicity is not triggered by precursory events and is called the background seismicity. The second term corresponds to aftershocks, i.e, earthquakes triggered by previous shocks. Hereinafter, we assume that this triggering can be modeled by empirical laws (i.e, productivity law, Omori's law (Utsu, 1961; Omori, 1894)). In our approach, the seismicity associated with episodic aseismic phenomena, like deformation transients, can be modeled as an increase in the rate of background activity since it is not triggered by previous earthquakes. The aim is thus to evaluate the spatio-temporal variations of the background seismicity $\mu(x, y, t)$, which embodies both constant tectonic loading and loading through episodic aseismic processes (e.g., fluid intrusions or slow slip events). The latter cause μ to fluctuate in time, unlike the tectonic loading which is assumed to be constant in rate at the time scale of instrumental earthquake catalogs.

The overall approach follows and further develops the method of Marsan et al. (2013b). Two models are optimized against the data, (1) the null-hypothesis model M_0, in which the background activity is only caused by tectonic loading, hence a constant but spatially variable $\mu(x, y)$, and (2) model M_1 in which the background activity also includes time-fluctuating processes, hence allowing $\mu(x, y, t)$ to also vary in time. The two models are then compared using a Monte–Carlo method, to search for significant episodes of changes in background rate, hence of slow, aseismic deformation. Model M_0 is the null hypothesis of no changes in background rate. We now detail the method, which can be divided into 3 steps.

2.1. Null hypothesis: model M_0

We use the space–time ETAS model, which represents earthquakes as points occurring with rate-density $\lambda_\theta(x, y, t)$, defined as the mean number of earthquakes per unit area and unit time. This rate is the sum of two terms:

$$\lambda_\theta(x, y, t) = \mu(x, y) + \nu(x, y, t) \tag{1}$$

with $\mu(x, y)$, the background seismicity, assumed to be constant in time in this first step, and $\nu(x, y, t)$ a term of interactions between earthquakes. The latter term is defined as the product of a temporal and a spatial influence

$$\nu(x, y, t) = \frac{\kappa(m)}{(t + c)^p} \times \frac{(\gamma - 1)L(m)^{\gamma-1}}{2\pi (x^2 + y^2 + L(m)^2)^{(\gamma+1)/2}}$$

where c, γ and p are constants, $L(m)$ and $\kappa(m)$ represent the rupture length and the productivity law, respectively (Ogata, 1988; Zhuang and Chang, 2005). The productivity law $\kappa(m)$ is defined as

$$\kappa(m) = \kappa_0 \times e^{\alpha(m-m_0)}$$

where κ_0 and α are constant and m_0 is the magnitude threshold.

We assume that the rupture length L scales with magnitude according to

$$L(m) = L_0 10^{0.5(m-m_0)} \tag{2}$$

where L_0 is the rupture length for an earthquake of magnitude m_0.

2.1.1. Smoothing

This first model thus requires 6 parameters $\theta = [\alpha, p, c, L_0, \gamma, a\kappa_0]$. The probability ω_i that earthquake i is a background earthquake is

$$\omega_i = \frac{\mu_i}{\mu_i + \nu_i} \tag{3}$$

where μ_i and ν_i are respectively the background seismicity and the interaction term for earthquake i.

We estimate the background intensity $\mu(x, y)$ by smoothing these probabilities (Zhuang et al., 2002) over all earthquakes i:

$$\mu(x, y) = \frac{1}{T} \sum_i \omega_i Z_{\mathcal{L}}(x - x_i, y - y_i) \tag{4}$$

where T is the duration of the catalog and $Z_{\mathcal{L}}(x - x_i, y - y_i)$ is defined as

$$Z_{\mathcal{L}}(x - x_i, y - y_i) = \frac{1}{2\pi \mathcal{L}^2} e^{-\frac{\sqrt{(x-x_i)^2+(y-y_i)^2}}{\mathcal{L}}} \tag{5}$$

with $\mathcal{L}$ a smoothing length.

2.1.2. ETAS parameter estimations and inversions

To optimize the model, we maximize the log-likelihood defined as

$$\ell(\theta) = \sum_i \ln \lambda_\theta(x_i, y_i, t_i) - \int_0^T \iint_S \lambda_\theta(x, y, t)\, dx\, dy\, dt \tag{6}$$

where the integral is performed over the total duration T and surface S of the area containing the target earthquakes.

To optimize model M_0, we follow the method of Zhuang et al. (2002). We start with a uniform background rate $\mu(x, y)$ with an arbitrary positive value. Given this $\mu(x, y)$, the best parameters are searched by maximizing $\ell(\theta)$. The background probabilities ω_i are then computed, and smoothed according to Eq. (5) to yield an updated $\mu(x, y)$. Then the best parameters θ given this new $\mu(x, y)$ are computed, and so on until convergence of the solution, both for θ and μ. This solution does not depend on the initial choice of $\mu(x, y)$, but does depend on the smoothing length $\mathcal{L}$.

To track possible temporal changes in the background rate, we use a discretized version of μ. We define a regular grid in time and space, each cell having a space area $\mathcal{L} \times \mathcal{L}$ and a duration τ. The stationary background rate of cell i with center $\{X_i, Y_i\}$ is therefore