

1 **Elementary Intracellular Ca Signals approximated as a Transition of Release Channel**
2 **System from a Metastable State**

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Abstract

Cardiac muscle contraction is initiated by an elementary Ca signal (called Ca spark) which is achieved by collective action of Ca release channels in a cluster. The mechanism of this synchronization remains uncertain. We approached Ca spark activation as an emergent phenomenon of an interactive system of release channels. We constructed a weakly lumped Markov chain that applies an Ising model formalism to such release channel clusters and probable open channel configurations and demonstrated that spark activation is described as a system transition from a metastable to an absorbing state, analogous to the pressure required to overcome surface tension in bubble formation. This yielded quantitative estimates of the spark generation probability as a function of various system parameters. We performed numerical simulations to find spark probabilities as a function of sarcoplasmic reticulum Ca concentration obtaining similar values for spark activation threshold as our analytic model, as well as those reported in experimental studies. Our parametric sensitivity analyses also showed that the spark activation threshold decreased as Ca sensitivity of RyR activation and RyR cluster size increased.

38 1. Introduction

39 Robust intracellular signals are achieved by synchronous operation of groups of
40 molecules, each operating stochastically. In cardiac muscle, Ca release channels, ryanodine
41 receptors (RyR), form clusters of 20 to 200 channels (Ca release units, CRU) embedded in
42 the sarcoplasmic reticulum (SR). Within CRUs, individual channels are very close to each
43 other (~30 nm) and arranged in an almost perfect rectangular grid. The channels interact via
44 Ca-induced-Ca-release (CICR)¹ thereby facilitating RyR openings throughout the cluster. The
45 all-or-none event when almost all of the channels in a CRU have been opened is referred to
46 as a Ca spark². Ca sparks can be triggered by a Ca influx via L-type Ca channel (“induced
47 sparks”), or arise spontaneously (“spontaneous sparks”). Induced sparks are signals of
48 excitation-contraction coupling in cardiac muscle and spontaneous sparks contribute to
49 normal cardiac impulse initiation in sinoatrial node cells³. Ca sparks are also elementary
50 signaling events in skeletal muscle⁴ and smooth muscle cells^{5,6}. Networks of beta cell
51 populations generate local Ca signals critical for their function⁷. In neurons high-amplitude
52 local Ca signals, known as puffs, are generated by clusters of IP3 receptors and represent
53 collective events, in which clustered channels are mutually activated also by CICR⁸.

54 Understanding how stochastic transitions of individual molecules are synchronized to
55 generate sparks, puffs and other local signals is an open problem of biological physics and
56 has been the subject of extensive experimental and theoretical research, including multiscale
57 modeling, i.e. bridging scales from individual molecule state transitions to global behavior^{9,}
58 ¹⁰. Stochastic simulations of the Ca signals have been performed in cardiac cells¹¹⁻¹⁸ and
59 neurons,^{8,19,20}. In addition to stochastic modeling, another promising approach to the
60 problem is via network science (see recent reviews^{10,21}). Thus, in more general context,
61 clusters of specialized molecules in different cells and tissues synchronize their states to
62 generate the robust elementary intracellular signals over the thermal noise, thus representing
63 the emergence of the first basic level of dynamic signaling essential for life.

64 Understanding and modeling of local Ca signaling initiation is important for the next
65 scale of events, such as Ca waves. In ventricular myocytes abnormal spontaneous sparks can
66 initiate Ca waves²² and life-threatening arrhythmia²³. In sinoatrial cells local Ca releases
67 occurring under normal physiological conditions in the form of relatively small, locally
68 propagating Ca waves contribute to diastolic depolarization, underlying heart automaticity.
69 These local Ca releases have been extensively investigated in individual cells and tissues,
70 including stochastic simulations and multiscale statistical physics approaches^{11,24,25}. The
71 multiscale modeling, bridging intercellular Ca signaling and Ca waves is an important new
72 approach to assess the origin and velocity of Ca waves in three-dimensions of different
73 biological tissues, e.g. complex dynamic Ca patterns in pancreas tissue slices^{26,27}. In all these
74 circumstances understanding initiation of Ca signals is essential for both basic biophysical
75 research and biomedical applications²⁸.

76 Here we study under what conditions RyRs open simultaneously to create a full Ca
77 spark instead of firing individually or with only partial synchronization, all of which have
78 been observed experimentally under various conditions²⁹. Zima et al.³⁰ found that full sparks
79 start forming as the SR Ca load surpasses 300 μM . Despite its fundamental importance, spark
80 activation has not been systematically studied theoretically or numerically as an emergent
81 phenomenon of an interactive system of release channels. Numerical models of the CRU
82 including interacting, stochastically gated RyR channels were reported by Laver et al.¹³ and
83 Stern et al.¹⁶, focusing on Ca spark termination. This approach was extended towards

84 understanding the effect of different CRU geometries³¹. Other models approximate CRU
85 phenomenologically by a single gating mechanism or as a Markov chain representing a result
86 of interactions of all RyRs within the CRU (the “sticky cluster” model³²). In 2011, Sato and
87 Bers approximated probabilities of different number of RyRs open in the CRU at a given
88 junctional SR Ca level by using the binomial distribution³³. This model was further extended
89 to evaluate spark activation probabilities for RyR clusters of different sizes³⁴. However, due
90 to the assumption of independence for RyRs inherent in the binomial distribution, this
91 approach lacks the effect of RyR interactions crucial for spark initiation via CICR.

92 A new approach to describe CRU operation has recently been introduced by the
93 authors in¹⁷, where the Stern model of the CRU¹⁶ was mapped isomorphically to the Ising
94 model. Further analysis identified the critical parameter (referred to as β , similar to inverse
95 temperature) that determines conditions for Ca leak³⁵. Both these studies focused again
96 mainly on spark termination. The present study is the first application of the Ising formalism
97 to spark activation.

98 2. Material and Methods

99 Here we introduce a new Markov chain describing the numbers of adjacent open
100 channels to explicitly estimate the probability that an open RyR will develop into a spark at
101 each level of SR Ca, thus establishing the threshold SR Ca load at which a spark can occur
102 and offering a mechanistic explanation. Our new approach is that we calculate transition
103 probabilities analytically. However, to compare, we also performed numerical model
104 simulations of spark generation using Stern et al. model¹⁶ in a more recent modification¹⁷.
105 An important feature of our model is an exponential dependence of open probability on local
106 Ca concentration based on experimental data in Laver et al.¹³. However, this dependence
107 remains controversial due to large variability in channel open times measurements³⁶⁻⁴¹.

108 The Stern numerical model of the CRU has been shown to be isomorphic to an Ising
109 model¹⁷, a classical model of statistical physics used to explain spontaneous magnetization.
110 This isomorphism provides a starting point for the present work. The RyRs are assumed to be
111 in a CRU given by a rectangular grid Λ (with their coordinates given as $x = (x_1, x_2)$ and with
112 $(0, 0)$ as the center of a grid with an odd number of elements) with each RyR assuming one of
113 two states: open (+1) or closed (-1). An assignment σ of an open or closed state to each RyR
114 is called a configuration, and the Ising model is a continuous time Markov chain with RyR
115 configurations as states. We notice that σ can be thought of as a matrix, while $\sigma(x)$ is the +1
116 or -1 state of the CRU placed at position x (see⁴² for further explanation of this notation.)
117 The instantaneous transition rates are only non-zero between configurations differing at only
118 one RyR, say at position x , and, upon discretizing time, are given by Eq.6 in¹⁷, which we
119 give here for convenience:

$$120 \quad P(\sigma, \sigma^x) = \begin{cases} \Delta t C e^{2\beta(\sum_{y \in \Lambda_b} \phi(|x-y|)\sigma(y)+h)} & \text{for } \sigma(x) = -1 \\ \Delta t C & \text{for } \sigma(x) = 1 \end{cases} \quad (1)$$

121 Here σ^x is the configuration that coincides with configuration σ except at x where the state is
122 reversed and, for any real number r , $\phi(r)$ is the interaction profile (defined below). Here we
123 embed the grid Λ in a larger grid Λ_b (here the b stands for boundary) where the configuration
124 of boundary RyRs is taken to be always closed (see Supplementary text or¹⁷ for further
125 details). This is to include Ca diffusion out of the CRU in the model.

126 The closing rate C is taken to be constant, and the opening rate is taken to be an
127 exponential of the cleft Ca concentration given by $\lambda^* \exp(\gamma[\text{Ca}])$ fitted to experimental data of
128 Laver et al.¹³ in our previous study¹⁷. The analogues of magnetic field h and inverse
129 temperature β are given by $\beta = \frac{\gamma\psi(U)}{4}$ and

$$131 \quad h = \frac{1}{2\beta} \ln \frac{\lambda}{C} + \sum_{\substack{x \neq 0 \\ x \in CRU}} \phi(|x|) \quad (2)$$

130

132 where U is the distance between RyRs, ψ is the Ca level in the cleft resulting from the
133 opening of an RyR as a function of distance from the open RyR (i.e. an interaction profile,
134 Fig. 1), and, for any real number r (unitless), $\phi(r) = \psi(rU)/(\psi(U))$ is a natural choice of
135 scaling for the interaction profile function ϕ . Upon construction of the isomorphic mapping
136 between the CRU and an Ising model, we see that h and β as given above for the CRU play
137 the identical role in the equations as they do in the Ising model. Thus, various properties that
138 are known for the Ising model will carry over to the CRU, in particular the order-disorder
139 phase transition in β and the influence of magnetic field h . This has been studied in depth in
140 ³⁵.

141

142 3. Results

143 3.1. The new Markov chain.

144 We follow an evolution of a cluster under the conditions of strong interactions (i.e.
145 supercritical β) and favorable magnetic field (i.e. positive and growing) but an initial
146 configuration where all RyRs are closed (maximally unfavorable). For a wide range of
147 positive magnetic field h , this initial condition constitutes a local energy minimum (also
148 known as a metastable state) and the system is highly unlikely to transition to an all-open
149 state. It would require the unlikely event of several RyRs randomly opening next to each
150 other, despite the closed neighbors. Only when h is large enough that one open RyR creates
151 enough Ca flux to strongly influence its neighbors, a spark has a good chance of activating.

152 To quantify these concepts, we introduce a new Markov chain. We define an *open*
153 *cluster* as a collection of channels that are open and adjacent (diagonals don't count). The
154 states of the Markov chain are the size of the open cluster going from 0 to 4 (Fig. 2(a)) and
155 the transition probability for increasing the cluster is computed from Equation (1), but
156 weighted by the relative frequency of configurations both in the initial and the target states.
157 The transition probability of decreasing the cluster is computed from Equation (1) as well,
158 but we assume that when transitioning from 3 to 2 only the outside RyRs can close, resulting
159 in the configuration as in state 2. This assumption is reasonable because the gating of the
160 release channels, including its closing rates of vary strongly under different conditions^{2, 13, 43}.

161

162 3.2. Calculation of transition probabilities.

163 The Markov model we use is the lumped Markov model, see for example Theorem
164 6.4.1 in Section 6.4 of⁴⁴. Lumpability means that it is possible to define the probability of

165 going from one “lump” of states to another independently of how you got to the starting
 166 lump. That ensures that the transition probability between lumps depends only on the lumped
 167 state, i.e. which lump you start from, so that the lumped process is a Markov process. This
 168 construction would be directly applicable to our setup, if the probability of transitioning from
 169 configuration A to a 4-channel configuration (denoted $P(A \rightarrow 4)$) were equal to the probability
 170 of transitioning from configuration B to a 4-channel configuration (denoted $P(B \rightarrow 4)$). Since
 171 these probabilities are not equal, we have performed the computation of spark probability for
 172 two cases: Case 1 setting both probabilities equal to $P(A \rightarrow 4)$ and Case 2 setting both
 173 probabilities equal to $P(B \rightarrow 4)$. The resulting spark probabilities are extremely close as
 174 depicted in Fig. S1 in supplementary material. We expect the true probability to lie between
 175 them. Lastly, we notice that the transition probabilities back from state 3 to 2 are the same for
 176 the two configurations in state 3 which satisfies the condition of strong lumpability.

177

178 Here we show an example of a calculation for the transition matrix of the lumped
 179 Markov process. We compute the probability of going from 1 open channel to 2 open
 180 channels $P(1 \rightarrow 2)$ at an SR level of 300 μM . We find the following:

181 β at 300 μM : 0.6454182 $\Sigma_{y \in \Delta_b} \phi(|x - y|) \sigma(y)$ at 300 μM : -20.79183 h at 300 μM : 18.02184 C (closing channel rate) = 117 s^{-1} 185 $\Delta t = 7 * 10^{-10}$ ms186
$$P(1 \rightarrow 2) = \Delta t C e^{2\beta(\Sigma_{y \in \Delta_b} \phi(|x-y|)\sigma(y)+h)} = (7 * 10^{-10})(117)e^{2(0.645)(-20.79+18.02)}$$
187
$$= 2.297 * 10^{-9}$$

188 Lastly, since there are four different ways for one open channel to turn into two open
 189 (adjacent) channels, we multiply this probability by four to arrive at the final answer of

190
$$P(1 \rightarrow 2) = 9.188 * 10^{-9}$$

191

192 The calculation becomes more involved for $P(2 \rightarrow 3)$. We have a formula for
 193 transition probability from a given configuration to a configuration with one square added.
 194 Looking at Fig. 2(b), to compute $P(2 \rightarrow 3)$, we compute the probability of transitioning from
 195 a configuration with 2 squares to configuration A (in the left branch) and multiply it by 4 and
 196 then add the probability of transitioning from a 2 to configuration B (in the right branch) and
 197 multiply by 2. Lastly, there are two ways obtain $P(3 \rightarrow 4)$: one is a weighted sum of
 198 probabilities of transitioning from configuration A to a configuration of 4 squares and the
 199 second is the appropriately weighted sum of probabilities of transitioning from configuration
 200 B to a configuration of 4 squares. This procedure results in a two possible transition matrices
 201 $M = (P(i \rightarrow j))_{0 \leq i, j \leq 4}$, as mentioned above (see also Fig. S1 in supplementary material).

202

203 If we take ${}^4_0 e_{j \leq 4}$ to be the standard basis vectors numbered from 0 to 4 according the
 204 states, i.e. having 1 in position corresponding to the given state j and 0's everywhere else, the
 205 probability of getting absorbed in state 4 when starting from state 0. Then the probability of
 206 ending up in a particular state after starting in state j is given by the vector $e_j M^k$. To compute
 207 the probability of getting absorbed in state 4, we diagonalize the transition matrix M , i.e. we
 208 find an orthogonal matrix U and a diagonal matrix D such that $M = UDU^T$. Since there are
 209 two states that are absorbing, two eigenvalues will be 1 and others will be smaller than 1. We
 210 order the eigenvalues and the corresponding eigenvectors so that the two eigenvalues that are

211 1 are last. Then as $k \rightarrow \infty$, D^k will tend to a matrix with two 1's at the bottom of the diagonal
 212 and zeros otherwise. We will call this matrix D^∞ . The probability of getting absorbed in state
 213 4 after starting in state 1 therefore will be the fourth entry in the vector $\mathbf{e}_1 U D^\infty U^t$ (for
 214 implementation see our Python code in supplementary material).

215

216 3.3. Model predictions

217 Figure 3(a) shows the results of our analytical model. For various values of SR Ca we
 218 have plotted the conditional probability of transitioning from 2 open channels to 3 open
 219 channels conditioned on not staying in state 2 (solid curve) and the similar conditional
 220 probability of transitioning from 3 open channels to 4 open channels. Since there are two
 221 possible configurations with 3 open channels, we plot both of these in Fig. 3(a): the dotted
 222 line shows the probability from triangle-like configuration A in Fig. 2(b) and the dashed line
 223 shows the probability from straight configuration B. We notice that both curves $P(3 \rightarrow 4)$
 224 are steeper and lie to the left of $P(2 \rightarrow 3)$, so SR Ca at which the transition from 2 open channels
 225 to 3 open channels becomes somewhat likely is the same as SR Ca where the transition from
 226 3 open channels to 4 open channels becomes extremely likely. This indicates the dependence
 227 of growth of the open cluster on its size. On a physics level, this happens because the system
 228 with all channels closed but positive magnetic field and supercritical β is in a local energy
 229 minimum. Each individual channel or small cluster might not open or, if open, close quickly
 230 due to the strong interaction from closed neighbors. But as the open cluster grows, the
 231 "curvature" of its boundary decreases, so the effect from the closed neighbors gets distributed
 232 over more open neighbors and is less likely to close an open channel.

233 The probability of the initial recruitment follows a steep sigmoid curve as a function
 234 of SR Ca load, beginning to rise at around 250 μM . Our analytic results (Fig. 3(b), circles)
 235 match the results of our numerical simulations (Fig. 3(b), triangles) and experimental studies
 236 (Fig. 3(c)). More sensitive spark generation at high SR Ca vs. numerical estimates reflects
 237 analytical model assumption of instantaneous interactions, whereas Ca diffusion causes a
 238 small delay. In numerical model it takes roughly 2.5 ms for the Ca profile to reach its stable
 239 level (Figure 2B of ¹⁷). Approximating the interactions with a step-function which is 0 until
 240 1.25 ms and the full profile after 1.25 ms, and using the closing rate from our numerical
 241 model of $C=0.117 \text{ ms}^{-1}$, we obtain that with probability of approximately 15% the RyR will
 242 close before it has a chance to interact with other channels. On the other hand, with
 243 probability of 85% it will interact and enter into our Markov chain setup. Thus, we scaled the
 244 curve by 0.85 to account for this discrepancy and obtained a closer match at higher SR Ca
 245 (Fig. 3(b), diamonds). Less sensitive spark generation at low SR Ca in analytical model can
 246 be due to other Ising model assumptions, such as its interactions limited to the nearest
 247 neighbors. On the other hand, the threshold of spark activation (300-400 μM) reported in
 248 experimental studies (Fig. 3(c)) is better reproduced by our analytical model than by the
 249 numerical modeling (200-300 μM).

250 While our model was examined for only one specific set of parameters fitted to
 251 experimental data of Laver et al. ¹³, we want to know how the SR Ca threshold for spark
 252 initiation will depend in general on the variety of possible variations of model parameters
 253 determining the RyR opening rate that can be present in variety of experimental,
 254 physiological and pathological conditions in different species. Figure 4 shows the results of a
 255 2-dimensional sensitivity analysis of the SR Ca threshold for spark initiation with respect to
 256 parameters λ and γ in both analytical (a) and numerical (b) models; the opening rate (k) is
 257 taken to be an exponential of the cleft $[\text{Ca}]$ given by $k = \lambda * \exp(\gamma[\text{Ca}])$. The two models

258 predicted the phase transition for spark activation as the function of SR Ca in a wide range of
259 parametric space, but no phase transition with respect to λ and γ (graduate color changes in
260 Fig. 4).

261 Thus far, we performed our simulations with fixed SR Ca levels and initial RyR
262 opening in the center of the grid. In reality, RyR can open at any location and when the
263 system progresses to spark activation (assumed at 4 open channels), the SR Ca level gets
264 slightly depleted (by $\sim 3.5\%$ in the example of numerical simulations in Fig. 5 and Videos S1
265 and S2 in supplementary material). Thus, a more realistic probability curve for the threshold
266 SR Ca level that takes into account these factors is expected to be shifted to larger values.
267 Furthermore, previous studies also showed that spark behavior depends substantially on RyR
268 cluster size^{34, 46, 47}. Therefore, we performed additional numerical simulations comparing the
269 emergence of sparks with free running SR vs. fixed SR for various sizes of clusters of
270 interacting RyRs with initial opening of RyR in a random location (Fig. 6). Our first finding
271 was that the SR spark activation threshold increases as the size decreases. Furthermore, the
272 difference between simulations with free-running vs. fixed SR was most pronounced for
273 small cluster sizes and less so for larger ones. We found that for an 11x11 cluster, the shift of
274 the spark activation threshold was rather small from about 220 μM to 250 μM . Our respective
275 simulations using our standard CRU model of 9x9 RyR cluster showed a notable shift of the
276 threshold from 250 μM to about 300 μM (black dashed curve vs. solid curve in Fig. 6A). The
277 shift increased for 7x7 cluster (from 300 μM to 400 μM), and further substantially increased
278 (from 400 μM to 650 μM) for the smallest cluster of 5x5 we tested. We summarized our
279 results with various sizes of RyR clusters in Fig. 6B and fitted them with a power function.

280

281 4. Discussion

282 The present study provides a mechanistic view on the spark initiation threshold in a
283 CRU system of interacting RyRs via local CICR. Mathematically speaking, one can view
284 spark activation as equivalent to a system transitioning from a local energy minimum (also
285 known as a metastable state) to a global one. Thus, spark activation is analogous to the
286 pressure required to overcome surface tension in bubble formation. When an open cluster
287 forms in a background of closed channels, the interaction between the closed and the open
288 channels happens only at the boundary of the open cluster. When the open cluster is small,
289 there are more closed channels per open channel at the boundary. As the open cluster gets
290 bigger, this ratio gets more favorable for the open channels. This reflects the “curvature” of
291 the boundary as in bubble formation. This interpretation is reasonable for a large variety of
292 model parameter values, as the SR Ca threshold varies continuously with the model
293 parameters (Fig. 4).

294 In this study, we use numerical and analytical approaches to study Ca spark
295 activation. We examined spark activation at different fixed SR Ca levels and found a sharp
296 transition at about 300 μM level where sparks were robustly generated. Zima et al.³⁰ reported
297 spark and non-spark Ca SR leak types in ventricular myocytes. As SR Ca load grows above
298 $\sim 300 \mu\text{M}$, Ca sparks contribute to the leak in a liner fashion (Fig. 3(c)). We further performed
299 simulations for more realistic scenarios with free-running SR in which Ca gets depleted as
300 RyRs open and also for a wide variety of different RyR cluster sizes (Figs 5 and 6). The spark
301 activation threshold is shifted towards larger values as cluster size decreases mainly due to
302 boundary effects: 1) the interaction profile of an open RyR decreases for smaller CRU sizes
303 in general and especially for the RyRs in the CRU periphery, as released Ca quickly leaks to

304 cytoplasm via the CRU boundary; 2) the relative contribution of RyRs at the CRU boundary
305 increases as CRU size decreases. Thus, in a real cell, for a given SR Ca level, the activated
306 sparks will be coming from all the clusters with sizes whose thresholds are below the given
307 level. For example, at 300 μM sparks from CRUs of sizes more than 81 will be contributing
308 to the total spark mediated leak, at 400 μM the CRUs of sizes more than 49 will contribute,
309 and finally near 650 the 25's will start contributing to the total. Considering also that cluster
310 sizes are heterogeneous⁴⁸, we expect that this will yield the near linear growth of spark-
311 mediated leak flux evident in experimental data (Fig. 3(c)).

312 Our model includes measurable parameters of the system that can be further varied to
313 understand the impact of realistic factors for spark activation. These are present in our model
314 via their impact on the Ca profiles, numerically generated by Stern model¹⁶. Such factors
315 include SERCA pumping rate to increase SR Ca, connectivity of free SR and junctional SR
316⁴⁹, Ca buffering (e.g. via calsequestrin), phosphorylation of key Ca cycling molecules, etc.
317 While spontaneous Ca release during diastole can trigger life-threatening arrhythmia²³, the
318 increased diastolic Ca release contributes to normal generation of spontaneous pacemaker
319 potentials driving the heartbeat³. Thus, our approach could help in directing pharmacological
320 interventions to avoid regimes of spontaneous spark activation in cardiac muscle cells in
321 cardiac disease²³ or to promote such regimes in cardiac pacemaker cells in sick sinus
322 syndrome (insufficient pacemaker function)⁵⁰. Lastly, our new analytical approach provides
323 a substantial computational advantage to evaluate the conditions for spark activation within
324 Ca release channel clusters. Calculating the dynamics for all states in the full Markovian
325 representation of a CRU using the analytic solution to Markov matrix would involve taking
326 exponentials of enormously large matrices. Thus, the benefits of this novel approach are to
327 get insight into RyR system behavior using minimal computational cost.

328 5. Study limitations

329 We assume that once the open cluster reaches 4 in size, it always initiates a spark and
330 we call the size 4 cluster the initial recruitment. We do not compute the probability of
331 transitioning from 4 to 5, we call it $P(4 \rightarrow 5)$, because the enumeration of all the possible
332 clusters becomes cumbersome. However, it is clear that the curve $P(4 \rightarrow 5)$ as well as further
333 curves such as $P(5 \rightarrow 6)$ would be much steeper and lie to the left of $P(3 \rightarrow 4)$, in a similar
334 way as $P(3 \rightarrow 4)$ is steeper and lies to the left of $P(2 \rightarrow 3)$ as evidenced in Fig. 3(a). Thus, it
335 is reasonable to let 0 and 4 be absorbent states. We also assume that from a state of 3 open
336 channels only two of the channels (the ones closest to the outside) can close. This will have
337 skewed our results slightly toward activation, but the effect will be small and within the range
338 of uncertainty caused by variability in RyR closing rates.

339

340 Supplementary Material

341 1. Supplementary text: Mathematical formulations mapping a CRU to Ising model

342 2. Supplementary figure S1

343 3. Supplementary computer code: Python code that computes the probability that a spark
344 initiates from a given open RyR at various SR Ca

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345 4. Supplementary data: the table of interaction profiles at various SR Ca (ψ values) needed to
346 run the Python code

347 5. Supplementary videos:

348 Video S1

349 Top panel: an example of Ca spark generated by our numerical model, including activation
350 and termination. The spark is generated by a 9x9 square grid of RyR channels. Initial SR Ca
351 = 1 mM. [Ca] is coded by red shades: 0 is pure black, 30 μ M is pure red. The spark evolves
352 from one open channel. Closed channels are shown by green arrows and open channels are
353 shown by white arrows. Low panel: simultaneous time course of number of open RyRs.

354 Video S2

355 The same spark as in Video 1 but shown at a finer time scale to clearly display activation
356 phase and evolution of open RyR configurations (described in Fig. 2). [Ca] is coded by red
357 shades: 0 is pure black, 200 μ M is pure red. Time and # of open RyRs are shown in the top.

358

359 **Acknowledgements**

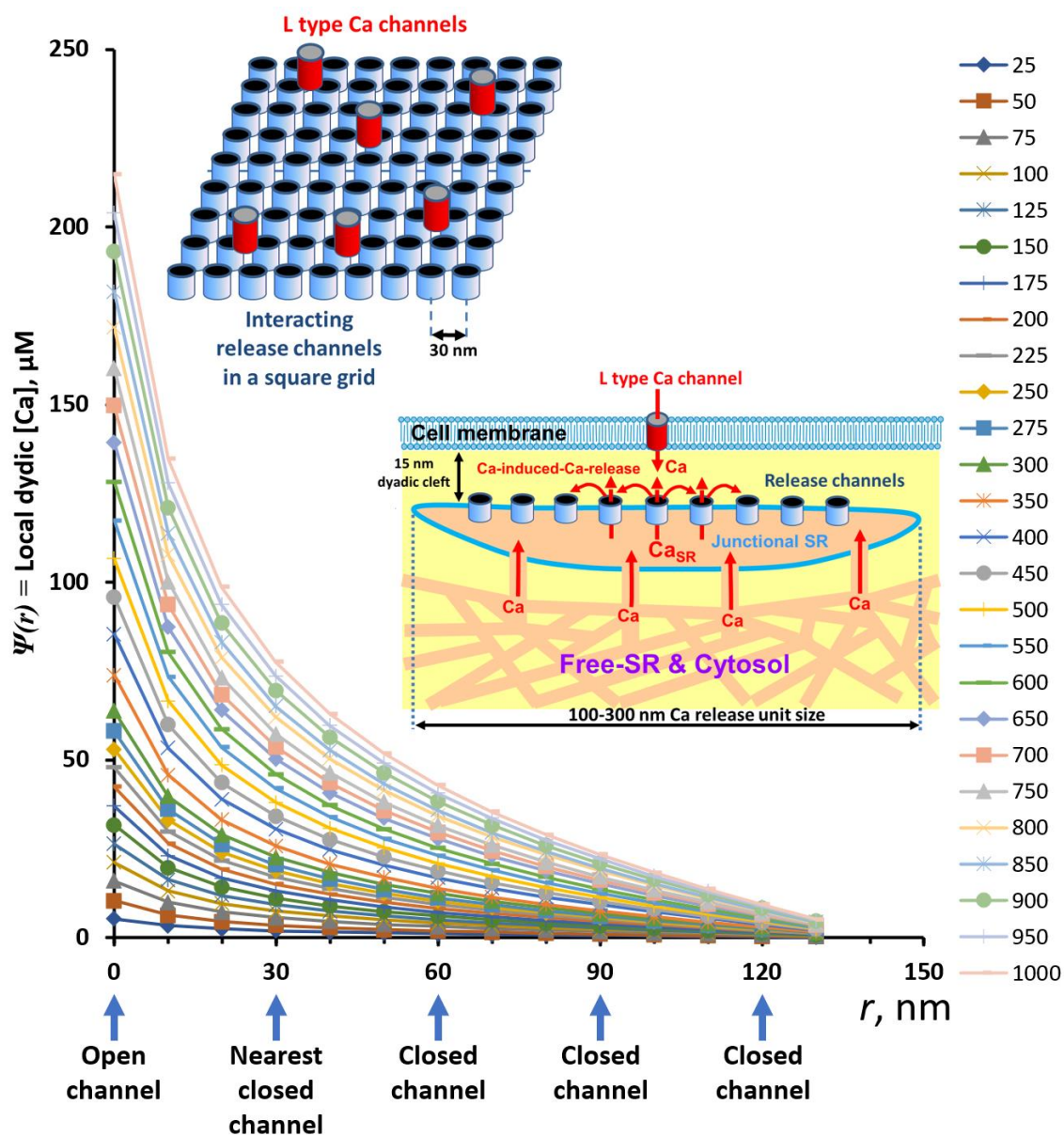
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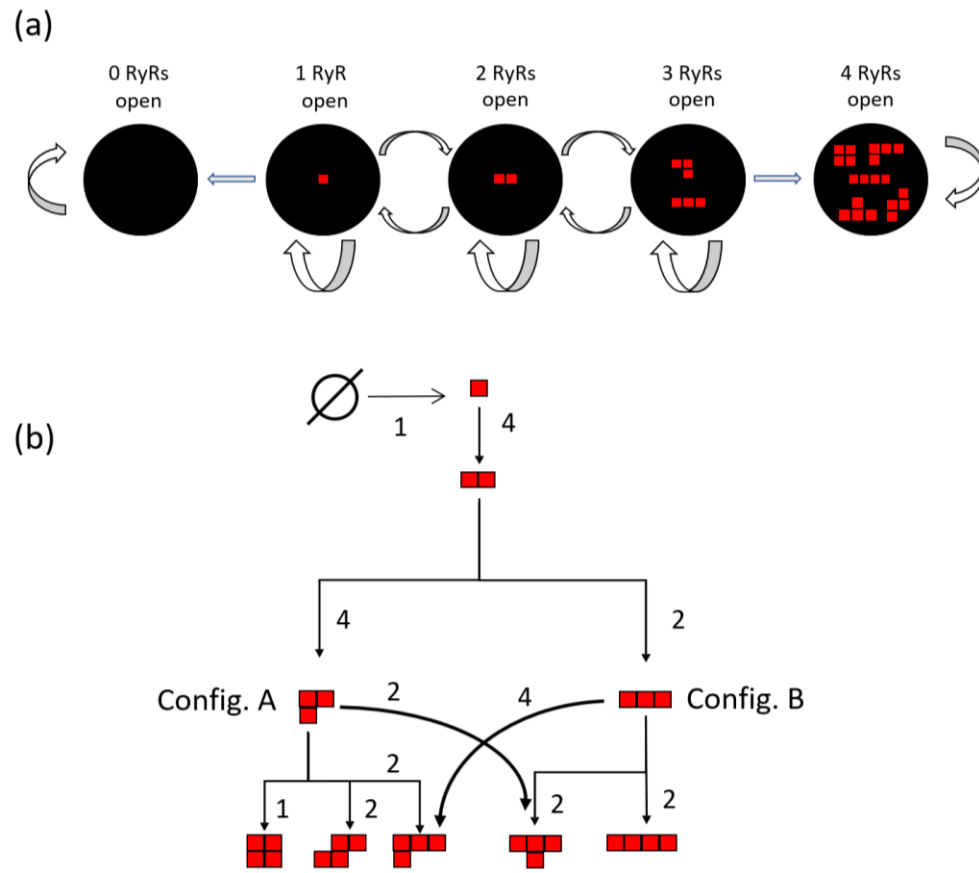
Figures and figure legends



366

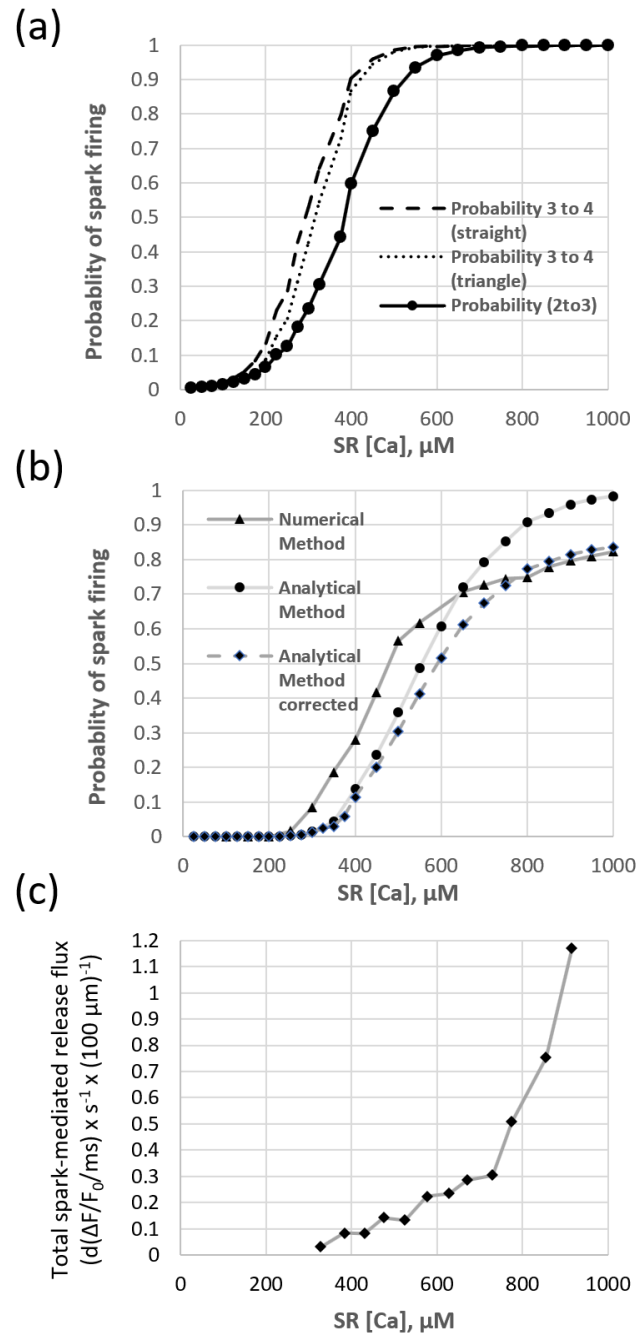
367 **Figure 1. The definition and numerical simulations of RyR interaction profile $\psi(r)$ that**
 368 **determines Ca-induced-Ca release in our model. . $\psi(r)$ is a steady-state [Ca] in the dyadic**
 369 **cleft as a function of distance r when one RyR opens at $r=0$. The plot shows is a family of**
 370 **simulated interaction profiles $\psi(r)$ at various fixed SR Ca loadings from 25 to 1000 μM (right**
 371 **column shows lines and symbols for each curve). Larger [Ca] at the nearest closed channel at**
 372 **higher SR loading indicates stronger channel interactions and stronger Ca-induced-Ca**
 373 **release. The interaction profiles were measured in numerical simulations of sparks as an**
 374 **instantaneous [Ca] in dyadic space 10 ms after the first channel opens for 9x9 RyR grid, the**
 375 **distance between RyRs is 30 nm, and each voxel is 10x10x15 nm in xyz. All other channels**
 376 **were forced to stay closed. See supplemental Excel file for exact values of the profiles that**
 377 **were used in our simulations of analytical model. Insets (modified from ¹⁷) show the RyR**
 378 **grid and its location with respect to SR, cytoplasm, and cell membrane in our CRU model.**
 379 **Please note that L-type channels are not included in our model of spark activation.**

380



381

382 **Figure 2. Our model includes all possible spatial configurations of RyR openings during**
 383 **initial interaction steps of spark activation after one channel is open acting as a**
 384 **nucleation site. (a) Schematic illustration of five-state Markov process simulating the spark**
 385 **evolution in our weakly lumped model. Each arrow represents the event of the Markov**
 386 **process changing from one state to another state with the direction indicated by the arrow.**
 387 **Each black circle shows all possible configurations of open RyRs, independent of how each**
 388 **configuration was reached. (b) Configuration tree. Illustration of all possible configurations**
 389 **and the series of events that could take place to reach each of the configurations. The model**
 390 **has 10 possible configurations, including configuration \emptyset with no open channels. Numbers at**
 391 **each configuration indicate the number of possible ways to reach a given configuration.**

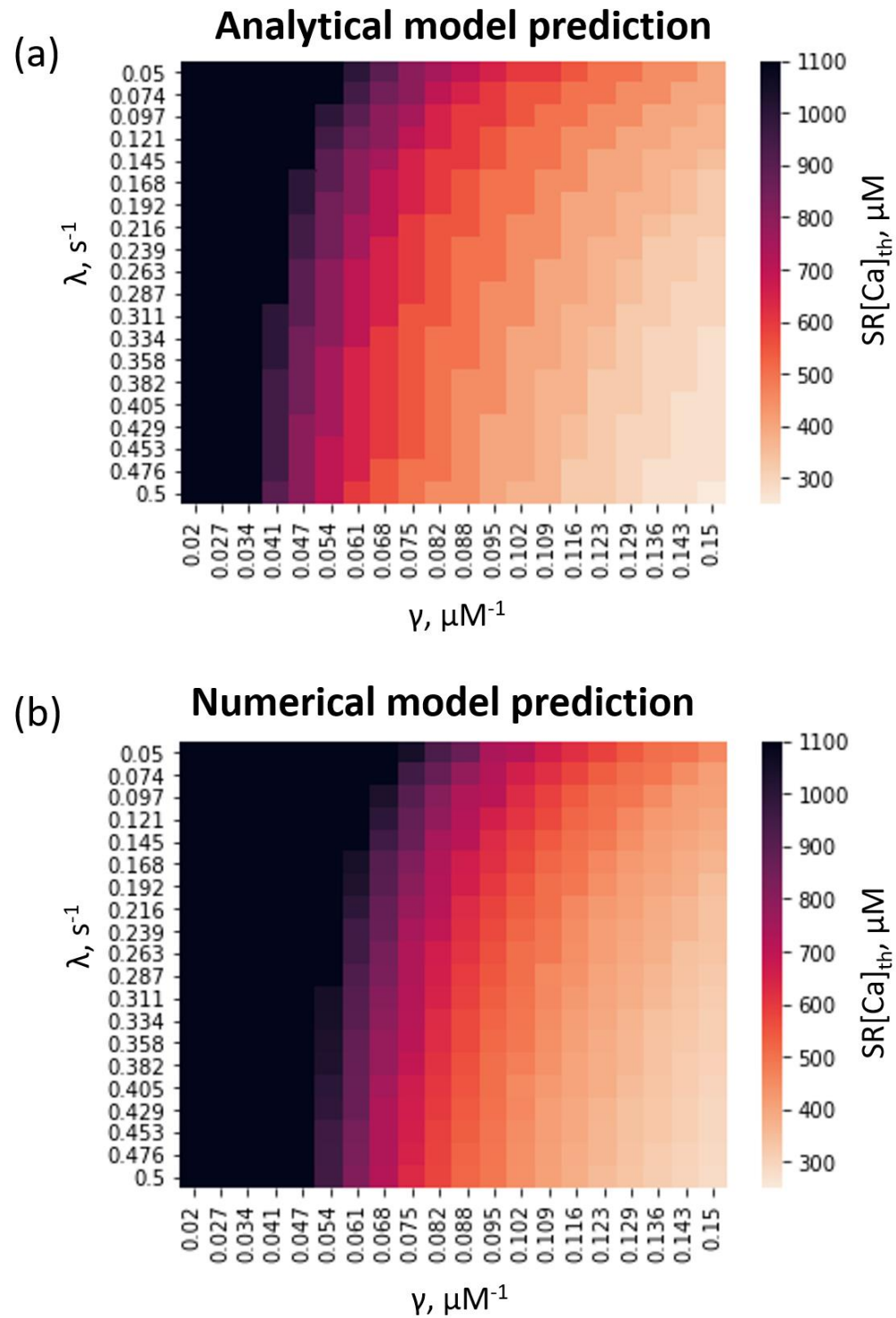


392

393 **Figure 3. Our analytical and numerical models predict the probability of Ca spark**
 394 **activation as a function of SR Ca loading. (a):** The probability of transitioning from 2 open
 395 channels to 3 open channels (circles) and probabilities of transitioning from 3 open channels
 396 to 4 open channels via straight configuration (dash line) or triangle configuration (dotted
 397 line). **(b),** Spark activation predicted numerically and analytically with and analytically
 398 without correction for diffusion delay. In numerical method, probability of spark firing at
 399 each SR Ca was evaluated from 10,000 simulation runs of 200 ms each. In each run at $t=0$
 400 one RyR in the center of 9×9 RyR cluster was set open. Our criterion for spark firing was that
 401 50% of all RyRs open at any moment before all RyRs closed. **(c),** Experimentally defined SR
 402 Ca threshold for Ca spark activation; shown are mean values of total spark-mediated release
 403 flux (measured by confocal microscopy) which were rescanned and replotted from Figure 3B
 404 of³⁰.

405

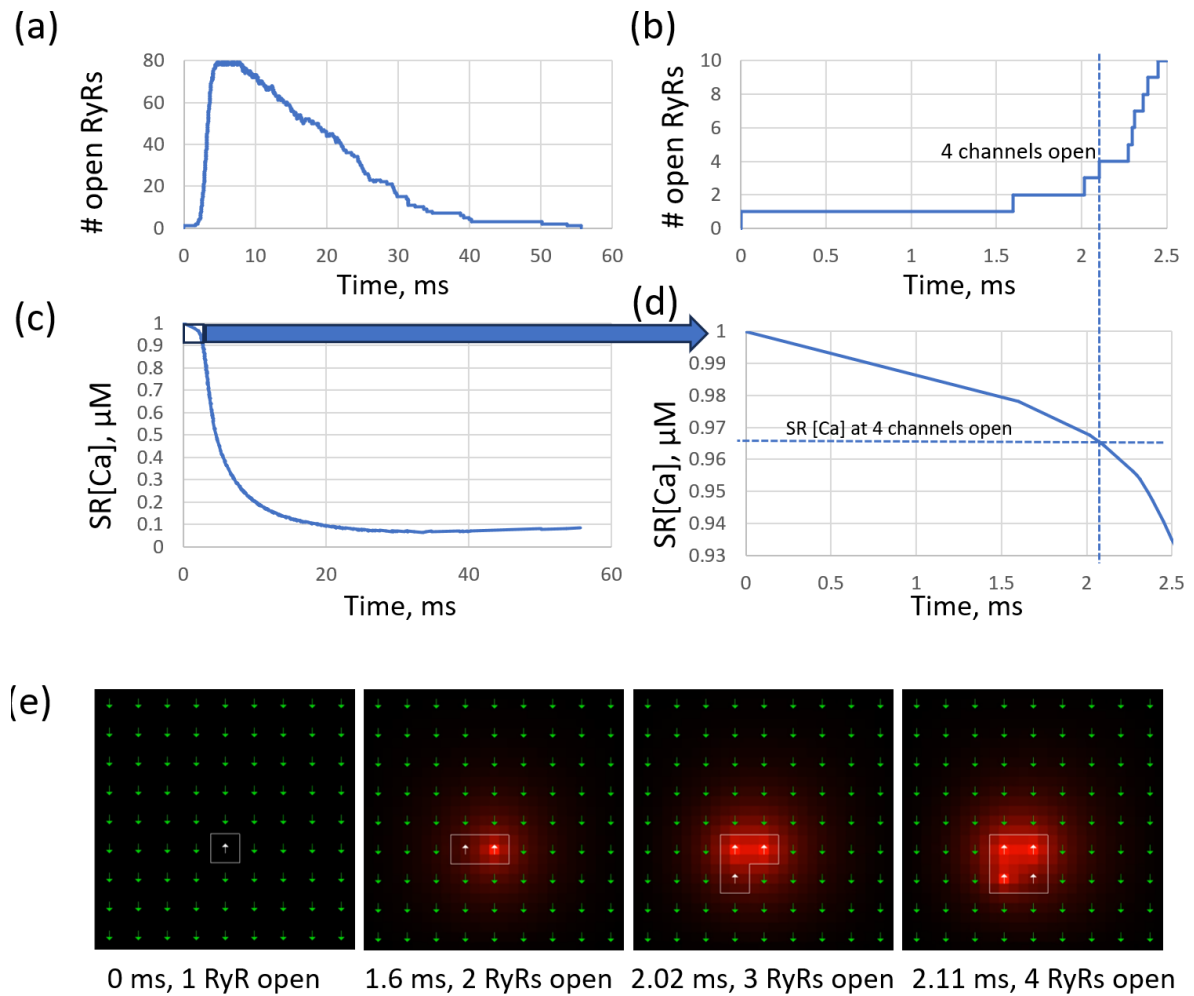
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406

407 **Figure 4. Numerical and analytic models behave essentially the same within a broad**
 408 **range of key model parameters λ and γ . Shown are heatmaps of two-dimensional**
 409 **sensitivity analysis of the SR Ca threshold ($SR[Ca]_{thr}$) for spark initiation with respect to λ**
 410 **and γ in analytical (a) and numerical (b) models; the RyR opening rate is taken to be an**
 411 **exponential of the cleft $[Ca]$ given by $\lambda * \exp(\gamma[Ca])$. For these analyses we set 0.1 probability**
 412 **for spark activation to obtain the associated SR Ca threshold. In turn, in numerical**
 413 **simulations each threshold was defined from a series of spark activation simulation with**
 414 **increasing SR Ca, and probability of spark firing at each SR Ca was evaluated from 10,000**
 415 **simulation runs.**

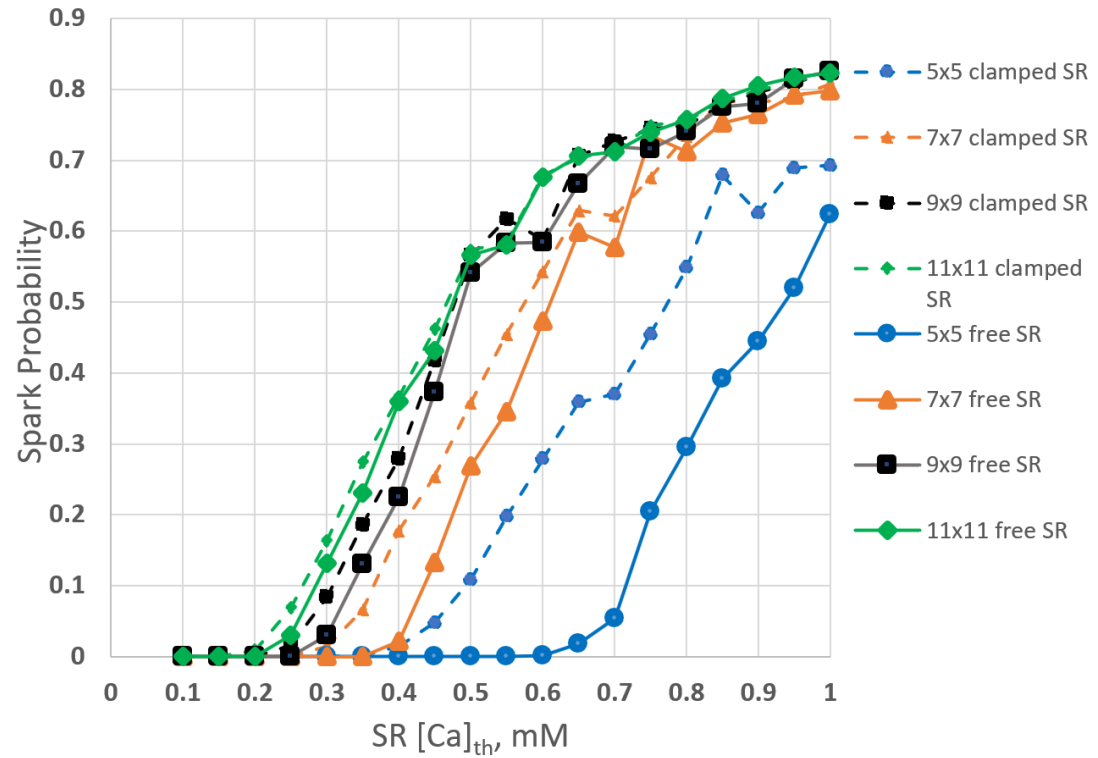
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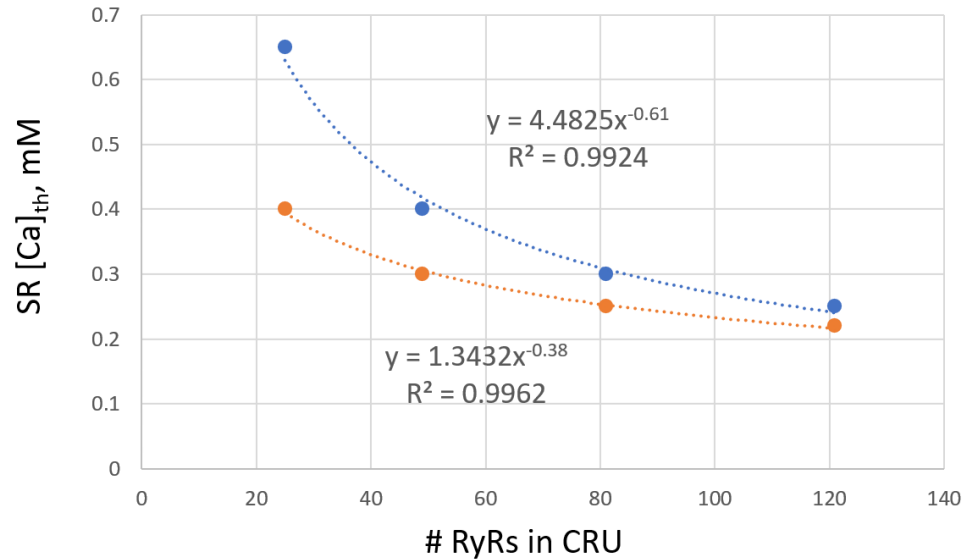
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418 **Figure 5. An example of numerical model simulation of a Ca spark evolution triggered**
 419 **by an opening of one RyR at Time=0 at a random location. (a),** Number of open RyRs as
 420 **a function of time for the entire duration of the spark. (b)** RyR openings for the first 2.5 ms.
 421 **(c),** SR Ca depletion during the entire duration of the spark. **(d),** A minor SR Ca depletion
 422 **at the moment when 4 channels open. (e),** Detailed spatiotemporal CRU system evolution
 423 **from one open channel (white arrow) to 4 open channels in 9x9 RyR grid. The open channel**
 424 **cluster is outlined by white line. In this example, the spark activation evolves via 3**
 425 **transitions, recruiting to fire its neighbors counterclockwise. Channels are shown by green**
 426 **arrows. [Ca] is coded by red shades: 0 μM is pure black and 200 μM is pure red. See more**
 427 **details in Supplementary Videos S1 and S2.**

(a)



(b)



428

429 **Figure 6. Numerical model prediction of probability of Ca spark activation as a**
 430 **function of SR Ca loading for RyR clusters of various sizes. (a),** Spark probabilities with
 431 fixed SR Ca (dashed lines) vs. free-running SR, i.e. SR Ca was not fixed (solid lines). For
 432 each data point, probability of spark firing a was evaluated from 10,000 simulation runs of
 433 200 ms each. In each run at $t=0$ one RyR in a random location in respective RyR cluster was
 434 set open. **(b),** SR Ca threshold as a function of number of RyRs in CRU fitted with a power
 435 function (equations with R^2 values are shown at the plots).

436

437 **References**

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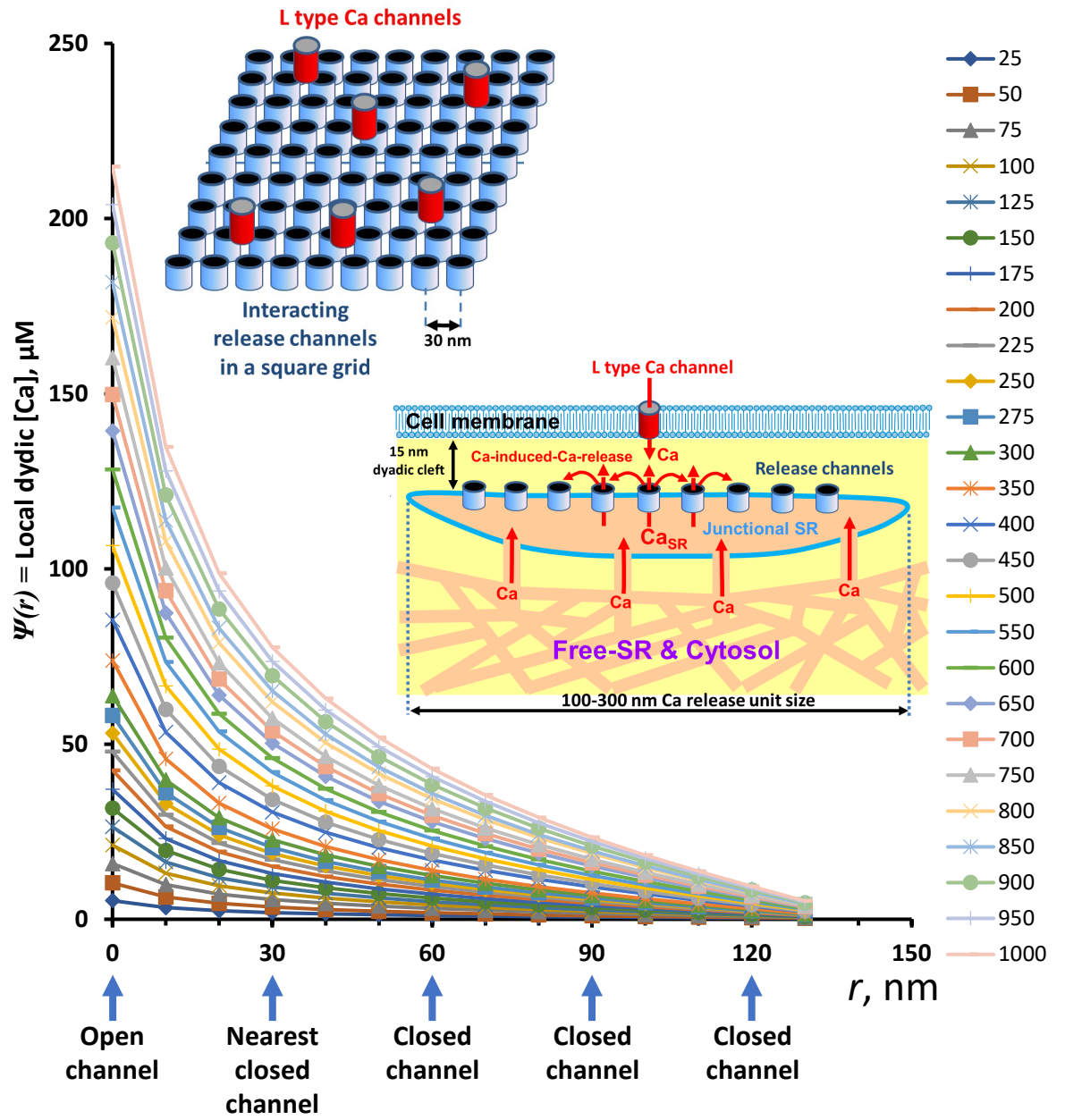


Fig. 1

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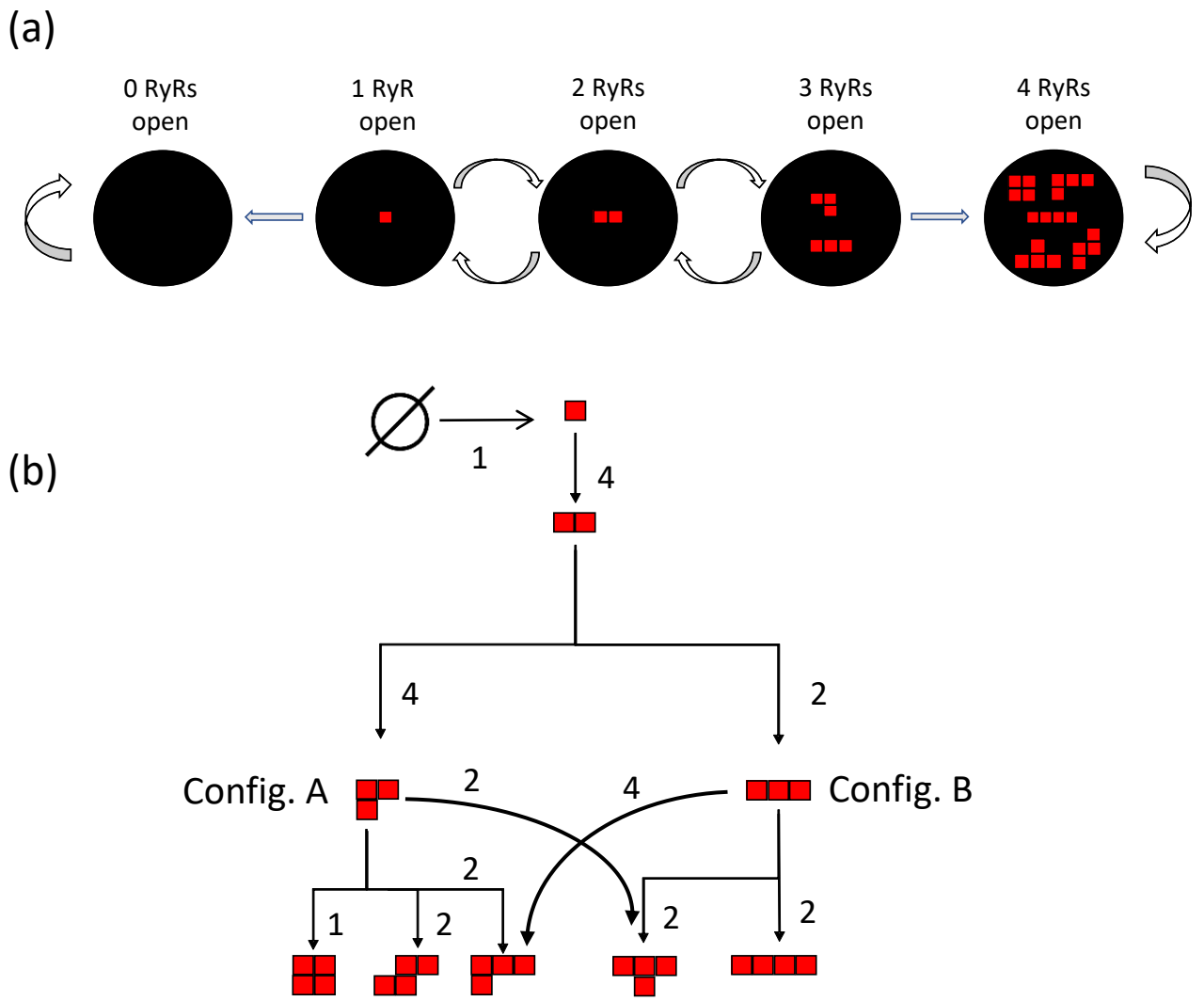


Fig. 2

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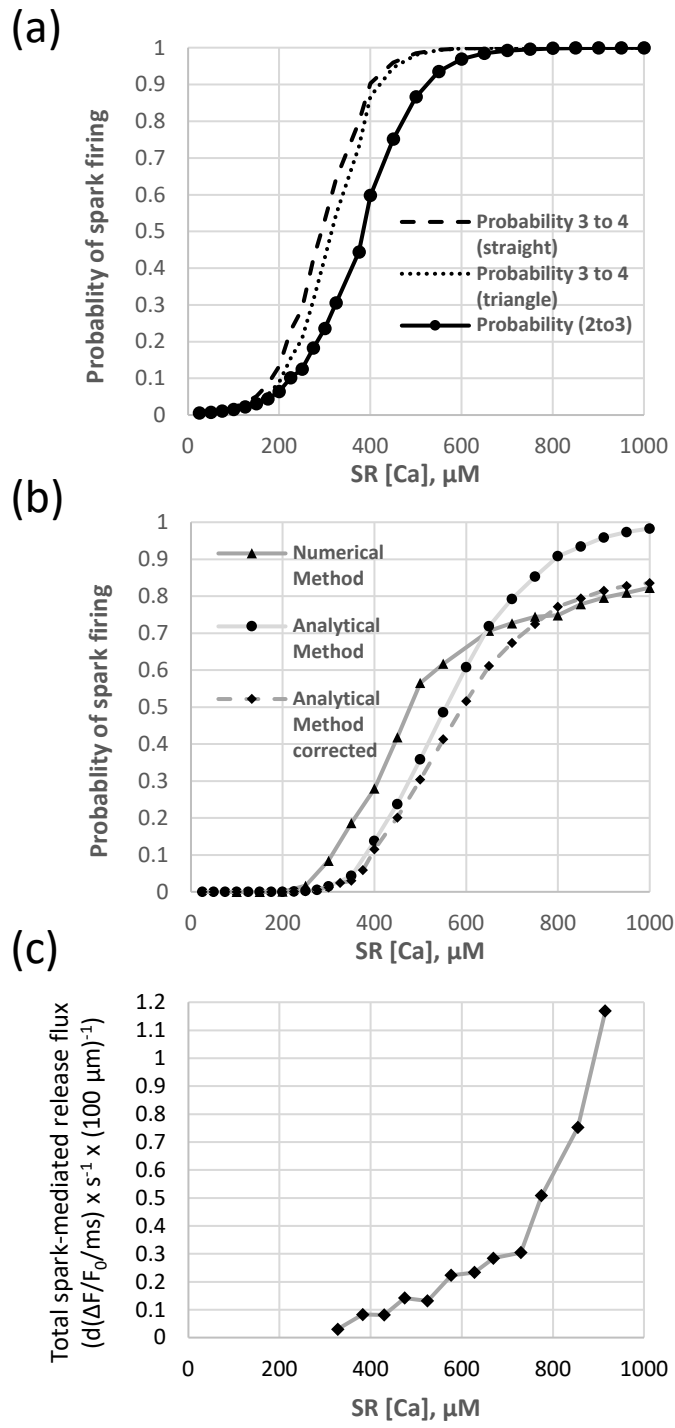


Fig. 3

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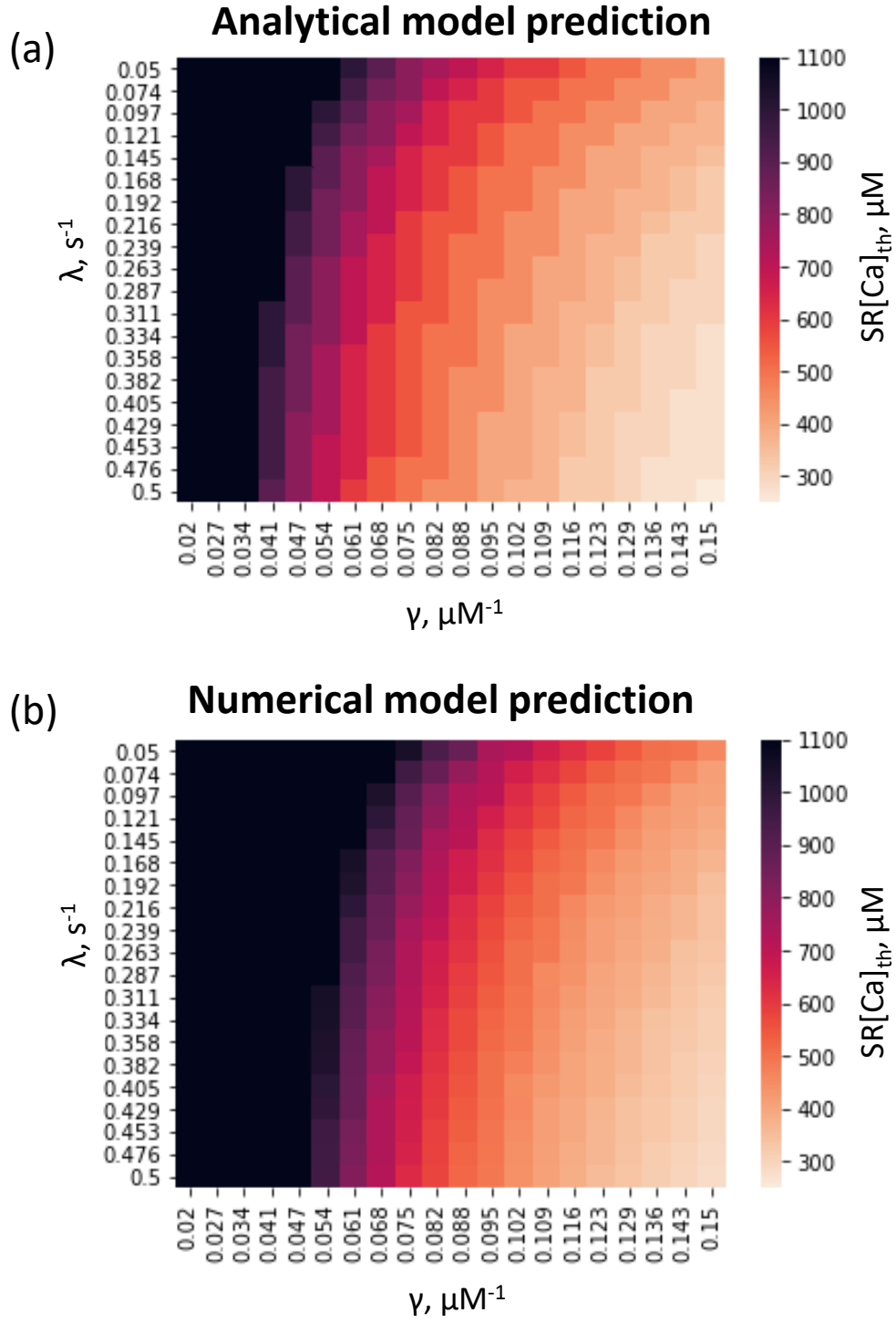


Figure 4

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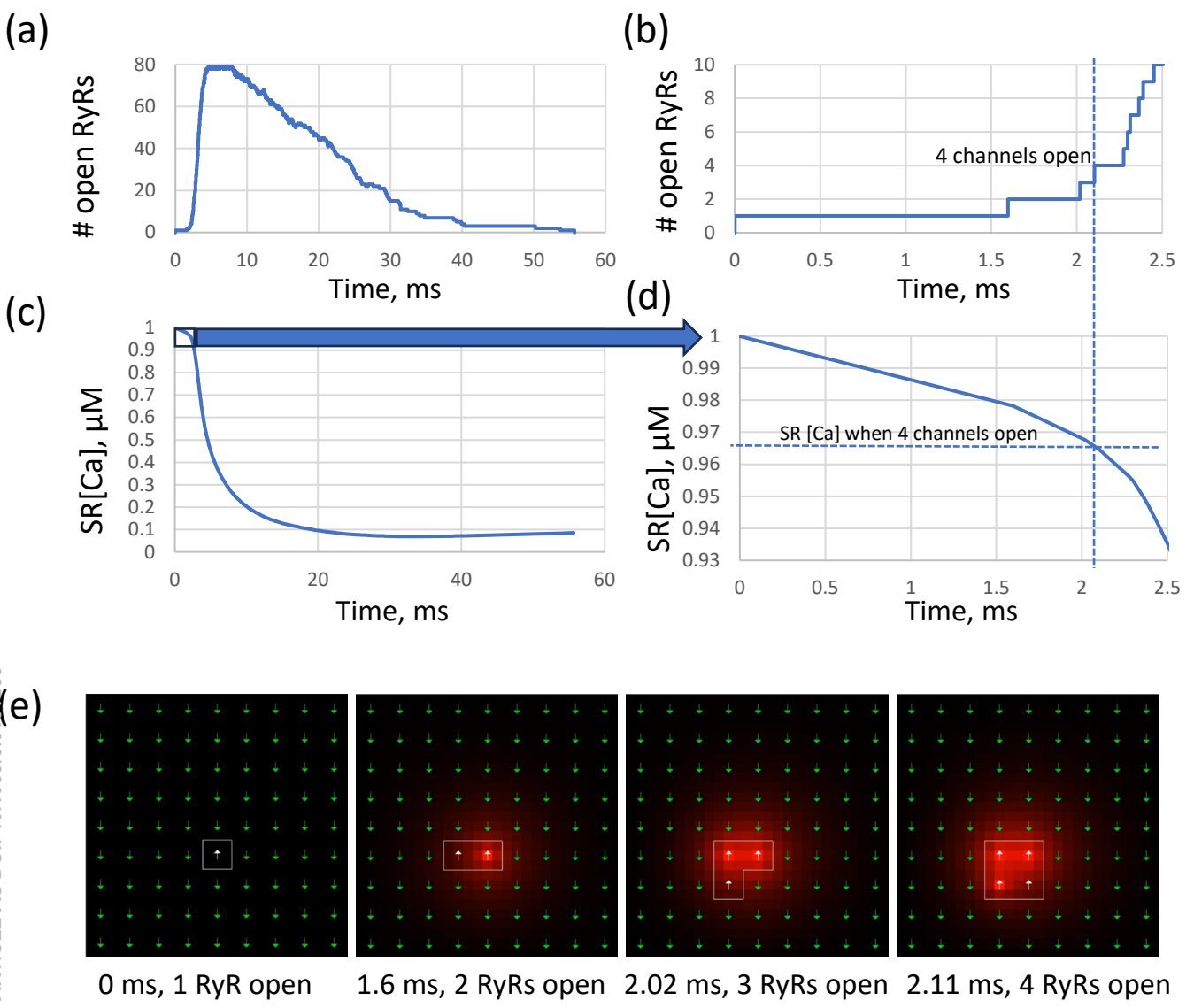
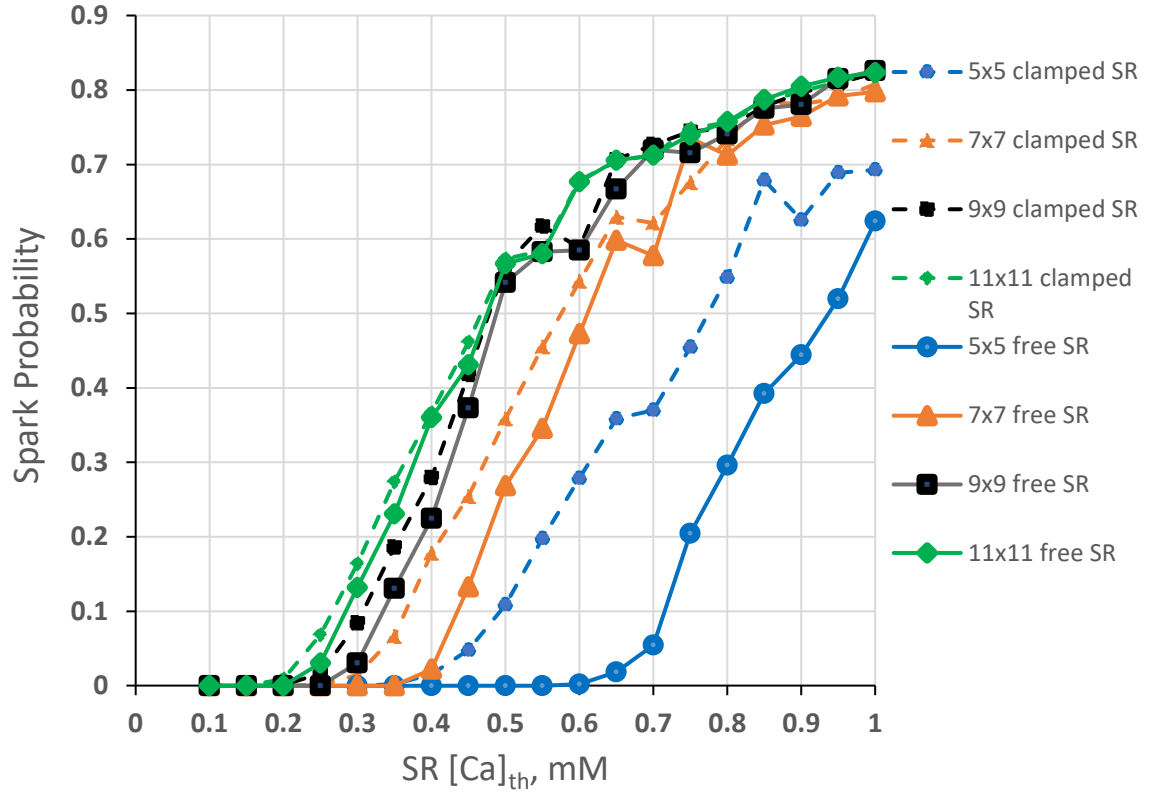


Figure 5

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(a)



(b)

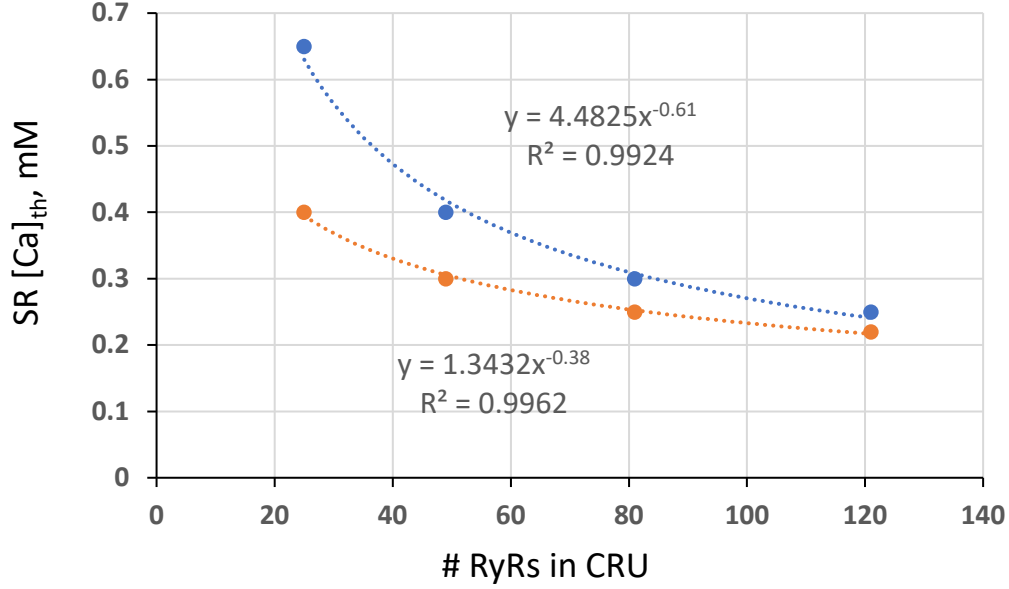


Figure 6