



# Lévy-noise versus Gaussian-noise-induced Transitions in the Ghil-Sellers Energy Balance Model

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**Abstract.** We study the impact of applying stochastic forcing to the Ghil-Sellers energy balance climate model in the form of a fluctuating solar irradiance. Through numerical simulations, we explore the noise-induced transitions between the competing warm and snowball climate states. We consider multiplicative stochastic forcing driven by Gaussian and  $\alpha$ -stable Lévy -  $\alpha \in (0, 2)$  - noise laws, and examine the statistics of transition times and most probable transition paths. While the Gaussian noise case - used here as a reference - has been extensively studied in a plethora of studies on metastable systems, much less is known about the Lévy case, both in terms of mathematical theory and heuristics, especially in the case of high- and infinite-dimensional systems. In the weak noise limit, the expected residence time in each metastable state scales in a fundamentally different way in the Gaussian vs. Lévy noise case with respect to the intensity of the noise. In the former case, the classical Kramers-like exponential law is recovered. In the latter case, power laws are found, with the exponent equal to  $-\alpha$ , in apparent agreement with rigorous results obtained for additive noise in a related - yet different - reaction-diffusion equation as well as in simpler models. The transition paths are studied in a projection of the state space and remarkable differences are observed between the two different types of noise. The snowball-to-warm and the warm-to-snowball most probable transition path cross at the single unstable edge state on the basin boundary. In the case of Lévy noise, the most probable transition paths in the two directions are wholly separated, as transitions apparently take place via the closest basin boundary region to the outgoing attractor.

## 1 Introduction

### 1.1 Multistability of the Earth's Climate

The climate system comprises five interacting subdomains: the atmosphere, the hydrosphere (water in liquid form), the upper layer of the lithosphere, the cryosphere (water in solid form), and the biosphere (ecosystems and living organisms). The climate is driven by the inhomogeneous absorption of incoming solar radiation, which sets up nonequilibrium conditions. The system reaches an approximate steady state where macroscopic fluxes of energy, momentum, and mass are present throughout its domain, and entropy is continuously generated and expelled into the outer space. The climate features variability on a vast range of spatial and temporal scales as a result of the interplay of forcing, dissipation, feedbacks, mixing, transport, chemical



reactions, phase changes, and exchange processes between the subdomains; see Peixoto and Oort (1992) Lucarini et al. (2014a),  
25 Ghil (2015), and Ghil and Lucarini (2020).

In the late 1960s Budyko and Sellers independently proposed that in the current astronomical and astrophysical configuration  
the Earth could support two distinct climate states, the present day Warm (W), and a competing one characterised by global  
glaciation, which is the Snowball (SB) state. Their analysis was performed using one-dimensional energy balance models  
(EBM)s, which, despite their simplicity, were able to capture the essential physical mechanism in action, i.e. the interplay  
30 between two feedbacks associated with the energy exchange among the Earth, the Sun, and the space. The Boltzmann feedback  
is associated with the fact that warmer bodies emit more radiation, and is a negative, stabilizing one. Instead, the instability of  
the system is due to the presence of the so-called ice-albedo feedback: an increase in the ice-covered fraction of the surface leads  
to further temperature reduction of the planet because ice reflects efficiently the incoming solar radiation. These mechanisms are  
active at all spatial scales, including the planetary one; see Budyko (1969) and Sellers (1969). Such pioneering investigations  
35 of the multistability of the Earth's climate were later extended by Ghil (1976) and Ghil and Childress (1987), who provided a  
comprehensive mathematical framework for the problem based on the study of the bifurcations of the system. The main control  
parameter defining the stability properties is the solar irradiance  $S^*$ . Below the critical value  $S_{W \rightarrow SB}$ , only the snowball state is  
permitted, whereas above the critical value  $S_{SB \rightarrow W}$ , only the warm state is permitted. Such critical values, which determine the  
region of bistability, are defined by bifurcations that emerge when, roughly speaking, the strength of the positive, destabilising  
40 feedbacks becomes as strong as the negative, stabilizing feedbacks.

Only later these predictions were confirmed by actual data. Indeed, geological and paleomagnetic evidence suggests that  
during the Neoproterozoic era, between 630 and 715 million years ago, the Earth went at least twice into major long-lasting  
global glaciations that can be associated with the SB state; see Pierrehumbert et al. (2011) and Hoffman et al. (1998). Mul-  
ticellular life emerged in our planet shortly after the final deglaciation from the last SB state (Gould, 1989). The robustness  
45 and importance of the competition between the Boltzmann feedback and the ice-albedo feedback in defining the global stability  
properties of the climate has been confirmed by investigations performed using higher complexity models (Lucarini et al.,  
2010; Pierrehumbert et al., 2011), including fully coupled climate models (Voigt and Marotzke, 2010). While the mechanisms  
described above are pretty robust, the concentration of greenhouse gases as well as the boundary conditions defined by the  
extent and position of the continents have an impact on the values of  $S_{W \rightarrow SB}$  and  $S_{SB \rightarrow W}$  as well as on the the properties of  
50 the competing states. The presence of multistability has a key importance in terms of determining habitability conditions for  
Earth-like exoplanets; see Lucarini et al. (2013) and Linsenmeier et al. (2015).

Additionally, several results indicate that the phase space of the climate system might well be more complex than the scenario  
of bistability described above. Various studies (Lewis et al., 2007; Abbot et al., 2011; Lucarini and Bóday, 2017; Margazoglou  
et al., 2021) performed with highly nontrivial climate models report the possible existence of additional competing states, up  
55 to a total of five (Brunetti et al., 2019; Ragon et al., 2021). In Margazoglou et al. (2021) it is argued that, in fact, one can see  
the climate as a multistable system where multistability is realised at different hierarchical levels. As an example, the tipping  
points (Lenton et al., 2008; Steffen et al., 2018) that characterise the current (W) climate state can be seen as a manifestation  
of a hierarchically lower multistability with respect to the one defining the dichotomy between the W and SB states.



## 1.2 Transitions between Competing Metastable States: Gaussian vs Lévy Noise

60 Clearly, in the case of autonomous systems where the phase space is partitioned in more than one basin of attraction of the corre-  
sponding attractors and the basin boundaries, the asymptotic state of the system is determined by its initial conditions. Things  
change dramatically when one includes time-dependent forcing which allows for transitions between competing metastable  
states (Ashwin et al., 2012). In particular, following the viewpoint originally proposed by Hasselmann (1976), whereby the  
fast variables of the climate system act as stochastic forcings for the slow ones (Imkeller and von Storch, 2001), the relevance  
65 of studying noise-induced transitions between competing states has become apparent (Hänggi, 1986; Freidlin and Wentzell,  
1984).

This viewpoint, where the noise is usually assumed to be Gaussian distributed, has provided very fruitful insight on the mul-  
tiscale nature of climatic time series (Saltzman, 2001), and is related to the discovery of phenomena like stochastic resonance  
(Benzi et al., 1981; Nicolis, 1982). Metastability is ubiquitous in nature and advancing its understanding is a key challenge in  
70 complex system science at large (Feudel et al., 2018).

In general, the transitions between competing metastable states in stochastically perturbed multistable systems take place,  
in the weak noise limit, through special regions of the basin boundaries, named edge states. The edge states are saddles:  
trajectories initialised in the basin boundaries are attracted to them, but there is an extra direction of instability, so that a small  
perturbation sends an orbit towards one of the competing metastable states with probability one (Grebogi et al., 1983; Ott,  
75 2002; Kraut and Feudel, 2002; Skufca et al., 2006; Vollmer et al., 2009). In previous papers, we have shown that it is possible  
to construct edge states in high-dimensional climate models Lucarini and Bódai (2017) and to prove that the population of each  
metastable state and the statistics of the noise-induced transitions can be understood (Lucarini and Bódai, 2019; Lucarini and  
Bódai, 2020; Margazoglou et al., 2021) by considering the nonequilibrium quasi-potential formalism introduced by Graham  
(1987) and Graham et al. (1991). In the case the edge state supports chaotic dynamics, we refer to it as Melancholia (M)  
80 state (Lucarini and Bódai, 2017). The local minima and the saddles of the quasi-potential  $\Phi$ , which generalises the classical  
energy landscape for non-gradient systems, correspond to competing metastable states and to edge states, respectively. The  
system is forced by adding a random - Gaussian distributed - component to the solar irradiance, which impacts, in the form of  
multiplicative noise, only a small subset of the degrees of freedom of the system. We remark that such choice of the stochastic  
forcing does not fully reflect physical realism, as the variability of the solar irradiance has a more complex behaviour (Solanki  
85 et al., 2013). Instead, noise acts as a tool for exploring the global stability properties of the system, and injecting noise as  
fluctuation of the solar irradiance has the merit of impacting the Lorenz energy cycle, thus effecting all degrees of freedom of  
the system (Lucarini and Bódai, 2020).

A major limitation of this mathematical framework is the need to rigidly consider Gaussian noise laws, even if considerable  
freedom is left as to the choice of the spatial correlation properties of the noise. Following Ditlevsen (1999), it has become  
90 apparent that white noise is not the only meaningful option for trying to model noise-induced transitions in the climate system,  
while, instead, more general classes of  $\alpha$ -stable Lévy noise laws might be useful for explaining the observed phenomena.  
Lévy processes (Applebaum, 2009; Duan, 2015), described in detail below in Appendix A, provide a powerful framework



for understanding ultrarapid transitions. Note that the stability parameter  $\alpha \in (0, 2]$ , where the  $\alpha = 2$  case corresponds to the Gaussian case (which is, indeed, a special Lévy process). In what follows, when we discuss Lévy noise laws, we refer to  
95  $\alpha \in (0, 2)$ .

The proposal by Ditlevsen stimulated mathematical investigations into noise-induced escapes from attractors where as stochastic forcing one chooses a Lévy, rather than Gaussian, noise (Imkeller and Pavlyukevich, 2006a, b; Chechkin et al., 2007; Debussche et al., 2013). Such analyses have clarified that a fundamental dichotomy exists with the classical Freidlin and Wentzell scenario mentioned above, even if phenomena like stochastic resonance can be recovered also in this case (Dybiec  
100 and Gudowska-Nowak, 2009; Kuhwald and Pavlyukevich, 2016). Whereas in the Gaussian case transitions between competing attractors occur as a result of the very unlikely combination of many steps all going in the *right* direction, in the Lévy case, transitions result from individual, very large and very rare jumps. Recently, Duan and collaborators have made fundamental progresses in achieving a variational formulation of Lévy noise-perturbed dynamical systems (Hu and Duan, 2020) as well as in developing corresponding methods for data assimilation (Gao et al., 2016) and data analysis (Lu and Duan, 2020). In terms  
105 of applications, Lévy noise is becoming a more and more a popular concept and tool for studying and interpreting complex systems (Grigoriu and Samorodnitsky, 2003; Penland and Sardeshmukh, 2012; Zheng et al., 2016; Wu et al., 2017; Serdukova et al., 2017; Cai et al., 2017; Singla and Parthasarathy, 2020; Gottwald, 2021).

The contribution (Gottwald, 2021) is especially worth recapitulating because of its methodological clarity. There, the idea is, following Ditlevsen (1999), to provide a conceptual deterministic climate model able to generate a Lévy-noise-like signal to  
110 describe, at least qualitatively, abrupt climate changes similar to Dansgaard–Oeschger events, which are sequences of periods of abrupt warming followed by slower cooling that occurred during the last glacial period (Barker et al., 2011). A key building block is the idea proposed in Thompson et al. (2017) that a Lévy noise can be produced by integrating the so-called correlated additive and multiplicative (CAM) noise processes, which are defined starting from standard Gaussian processes. The other key ingredient is to consider the atmosphere as the fast component in the multiscale model and deduce, using homogenization  
115 theory (Pavliotis and Stuart, 2008; Gottwald and Melbourne, 2013), that its influence on the slower climate components can be closely represented as a Gaussian forcing. Finally, the temperature signal is cast as the integral of a CAM process.

### 1.3 Outline of the Paper and Main Results

We consider here the Ghil-Sellers Earth's EBM (Budyko, 1969; Sellers, 1969; Ghil, 1976), a diffusive one-dimensional energy balance system, governed by a nonlinear reaction-diffusion parabolic partial differential equation. We stochastically perturb the  
120 system by adding random fluctuations to the solar irradiance, therefore the noise is introduced in multiplicative form. We study the transitions between the two competing metastable climate states and carry out a comparison of the effect of considering Lévy vs Gaussian noise laws of weak intensity  $\varepsilon$ .

The paleoclimatic records indicate that abrupt climate changes like Dansgaard–Oeschger events have a strong non-Gaussian heavy-tailed distribution and discontinuous càdlàg paths, thus motivating scientists to model noise-induced transitions in the  
125 climate system considering  $\alpha$ -stable Lévy process as a source of the stochastic perturbation (Ditlevsen, 1999; Dakos et al., 2008; Corral and González, 2019).



The main challenges of the problem are: a) the fact that we are considering dynamical processes occurring in infinite dimensions (Doering, 1987; Duan and Wang, 2014; Alharbi, 2021); and b) the consideration of multiplicative Lévy noise laws (Løkka et al., 2004; Peszat and Zabczyk, 2007; Debussche et al., 2013). We characterize noise-induced transitions between the competing climate basins and quantify the effect of noise parameters on them by estimating the statistics of escape times and empirically constructing mean transition pathways called instantons.

The results obtained confirm that, in the weak noise limit  $\varepsilon \rightarrow 0$ , the mean residence time in each metastable state driven by Gaussian vs. Lévy noise has a fundamentally different dependence on  $\varepsilon$ . Indeed, as expected, in the Gaussian case the residence time grows exponentially with  $\varepsilon^{-2}$ , thus in basic agreement with the well-known Kramers (1940) law and the previous studies performed on climate models (Lucarini and Bódai, 2019; Lucarini and Bódai, 2020). Instead, in the case of  $\alpha$ -stable noise laws, the residence time increases with  $\varepsilon^{-\alpha}$ . We perform simulations for  $\alpha = \{0.5, 1.0, 1.5\}$ . The obtained scaling is in agreement with what is found for low dimensional dynamics (Imkeller and Pavlyukevich, 2006a, b), as well as with the infinite dimensional stochastic Chafee-Infante reaction-diffusion equation (Debussche et al., 2013) in the case of additive noise. This might indicate that such scaling laws are more general than what typically considered.

Furthermore, we find clear confirmation that, in the case of Gaussian noise in the weak noise limit, the escape from either attractor's basin takes place through the edge state. Indeed, the most probable paths for both thawing and freezing processes meet at the edge state and have distinct instantonic and relaxation sections. In turn, for Lévy noise in the weak-noise limit, the escapes from a given basin of attraction occur through the boundary region closest to the outgoing attractor. Hence, the paths are very different from the Gaussian case (especially so for the freezing transition) and, somewhat surprisingly, are identical regardless the value of  $\alpha$  considered.

The rest of the paper is organized as follows. In Section 2 we present the Ghil-Sellers EBM and summarize its most important dynamical aspects, as well as the steady-state solutions and their stability. The stochastic partial differential equation obtained by randomly perturbing the solar irradiance in the EBM is given in Subsection 3.1, where we also clarify the mathematical meaning of the solution of the stochastic partial differential equation. Subsection 3.2 introduces the mean residence time and most probable transition path between the competing climate states. The numerical methods are also briefly presented. In Section 4 we present and discuss our main results. The comparative analysis of the impact of stochastic forcing due to Gaussian vs Lévy noise is carried out in two directions: taking into account the mean residence time and the mean transition paths between the attractors. Finally, Appendix A presents a succinct description of  $\alpha$ -stable Lévy processes, Appendix B sketches the derivation of the scaling laws for mean residence times presented in Debussche et al. (2013), and Appendix C presents a tabular summary of the statistics of the problem.

## 2 The Ghil-Sellers energy balance climate model

The Ghil-Sellers EBM is described by an one-dimensional nonlinear, parabolic, reaction-diffusion partial differential equation (PDE) (1) involving the surface temperature  $T$  field and the transformed space variable  $x = 2\phi/\pi \in [-1, 1]$ , where



$\phi \in [-\pi/2, \pi/2]$  is the latitude

$$160 \quad C(x)T_t = \frac{4}{\pi^2 \cos(\pi x/2)} [\cos(\pi x/2)K(x, T)T_x]_x + \mu Q(x)[1 - \alpha_a(x, T)] - \sigma T^4 [1 - m \tanh(c_3 T^6)], \quad (1)$$

where  $C$  is the effective heat capacity, and  $T = T(x, t)$  has boundary and initial conditions as follows

$$T_x(-1, t) = T_x(1, t) = 0, \quad T(x, 0) = T_0(x). \quad (2)$$

The equation does not depend explicitly on the time  $t$ . The subscripts  $_t$  and  $_x$  refer to partial differentiation. The first term -  $D_I$  - on the right hand side of (1) describes the meridional heat transport on the Earth's surface, where function  $K(x, T)$  is a  
 165 combined diffusion coefficient, given by

$$K(x, T) = k_1(x) + k_2(x)g(T), \quad \text{with} \quad (3)$$

$$g(T) = \frac{c_4}{T^2} \exp\left(-\frac{c_5}{T}\right). \quad (4)$$

The empirical functions  $k_1(x)$  and  $k_2(x)$  are eddy diffusivities for sensible and latent heat, respectively. The second term -  $D_{II}$  - of (1) describes the heat absorption controlled by the incoming solar radiation  $Q(x)$  as modulated by the surface reflectivity  
 170 (albedo)  $\alpha_a(x, T)$ , given by

$$\alpha_a(x, T) = \{b(x) - c_1(T_m + \min[T - c_2 z(x) - T_m, 0])\}_c, \quad (5)$$

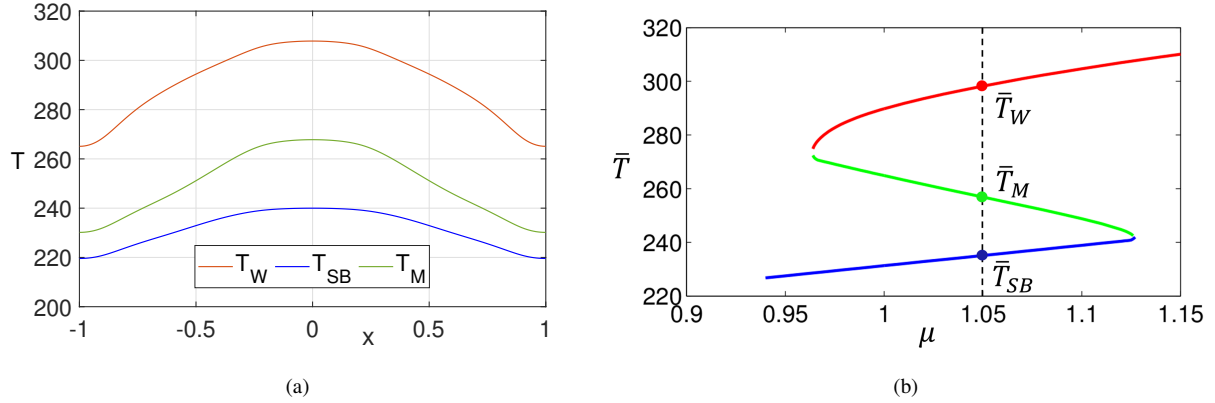
where the subscript  $\{\cdot\}_c$  denotes a cutoff for a generic quantity  $h$  defined as

$$h_c = \begin{cases} h_{min} & h \leq h_{min}, \\ h & h_{min} < h < h_{max}, \\ h_{max} & h_{max} \leq h. \end{cases} \quad (6)$$

The term  $c_2 z(x)$  in (5) indicates the difference between the sea-level and surface-level temperatures, and  $b(x)$  is a tempera-  
 175 ture independent empirical function of the albedo. The parametrization given in Eqs. (5)-(6) encodes the positive ice-albedo feedback. The relative intensity of the solar radiation in the model can be controlled by the parameter  $\mu$ .

The last term -  $D_{III}$  - of (1) describes the energy loss to space by outgoing thermal planetary radiation and is responsible for the negative Boltzmann feedback. It is represented by the product of the Stefan-Boltzmann constant  $\sigma$  and of the emissivity coefficient  $1 - m \tanh(c_3 T^6)$ . Such term describes, in a simple yet effective way, the greenhouse effect by reducing infrared  
 180 radiation losses. The values of the empirical functions  $C(x), Q(x), b(x), z(x), k_1(x), k_2(x)$  at discrete latitudes and empirical constants  $c_1, c_2, c_3, c_4, c_5, \sigma, m, T_m$  are taken from Ghil (1976), as modified in Bódai et al. (2015).

In this study, we consider  $\mu = 1.05$ . For this value of  $\mu$ , two stable asymptotic states - the W and the SB states - co-exist, see Figure 1(b), reproduced from Bódai et al. (2015). Indeed, a codimension one manifold separates the basins of attraction of the W and SB states. We refer to  $D^W$  ( $D^{SB}$ ) as the basin of attraction of the W (SB state). We refer to  $B$  as the basin boundary,  
 185 which includes a single edge state  $M$ . Therefore, the system has three stationary solutions  $T_W(x), T_{SB}(x)$ , and  $T_M(x)$  for the W,



**Figure 1.** (a) Stationary solutions  $T_W(x)$ ,  $T_{SB}(x)$  and  $T_M(x)$  in Kelvin (K) of zonally averaged energy-balance model (1). (b) Bifurcation diagram of the average temperature  $\bar{T}$  as a function of control parameter  $\mu$ , adapted from Bódai et al. (2015).

SB, and M state, respectively, shown in Figure 1(a). In Ghil (1976) the three stationary solutions were obtained by equating  $T_t$  to 0, and it was shown, through linear stability analysis, that the stationary solutions  $T_W$  and  $T_{SB}$  are stable, while  $T_M$  is unstable. In Bódai et al. (2015) the unstable solution  $T_M$  was constructed using a modified version of the edge tracking algorithm Skufca et al. (2006).

190 Following previous studies (Bódai et al., 2015; Lucarini and Bódai, 2019; Lucarini and Bódai, 2020; Margazoglou et al., 2021), when visualising our results, we apply a coarse-graining to the phase space of the model. In what follows, we perform a projection on the plane spanned by the spatially averaged temperature  $\bar{T}$  and the averaged Equator minus Poles temperature difference  $\Delta T$ , defined as

$$\bar{T} = [T(x, t)]_0^1, \quad (7)$$

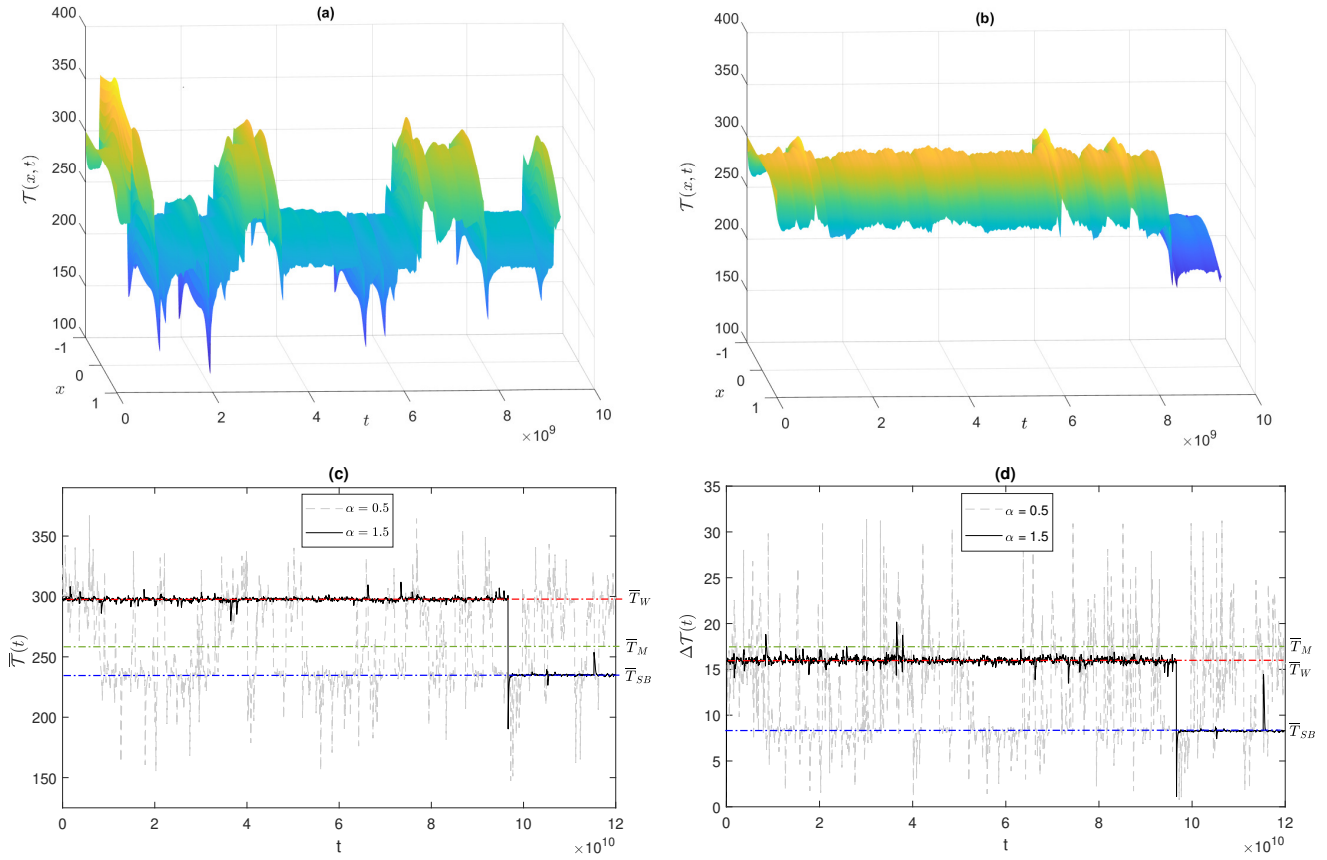
195  $\Delta T = [T(x, t)]_0^{1/3} - [T(x, t)]_{1/3}^1$ , where (8)

$$[T(x, t)]_{x_l}^{x_h} = \frac{\int_{x_l}^{x_h} \cos(\pi x/2) T(x, t) dx}{\int_{x_l}^{x_h} \cos(\pi x/2) dx}. \quad (9)$$

Such a representation allows for a minimal yet still physically relevant description of the system. Indeed, changes in the energy budget of the system (warming versus cooling) are, to a first approximation, related to variations in  $\bar{T}$ , while the large-scale energy transport performed by the geophysical fluids is controlled by  $\Delta T$ . The boundary between high and low latitude in (8) is established at  $x = \pm 1/3$ , i.e. at  $30^\circ N/S$ . Additionally, in some visualizations, we consider as a third coordinate the fraction of the surface with a below-freezing temperature (therefore we expect 1 for global glaciation and 0 for no ice). We refer to this variable as  $I$ , and it is an attempt to extract an observable that resembles the sea-ice percentage of the Earth's surface. Thus, the stationary solutions  $T_W(x)$ ,  $T_{SB}(x)$ , and  $T_M(x)$ , in terms of  $\Delta T$  and  $\bar{T}$ , correspond to  $\Delta T_W = 16$  K,  $\Delta T_{SB} = 8.3$  K,  $\Delta T_M = 17.5$  K;  $\bar{T}_W = 297.7$  K,  $\bar{T}_{SB} = 235.1$  K,  $\bar{T}_M = 258$  K; and  $I_W = 0.2$ ,  $I_{SB} = 1$ , and  $I_M = 1$ .

200





**Figure 2.** The metastable behavior of solution path of stochastic energy-balance model (10) for  $\varepsilon = 0.04$ ,  $T_0 = 300$  K,  $t \in (0, 300)$  years (a)  $\alpha = 0.5$ , (b)  $\alpha = 1.5$  and of (c) temperature average  $\bar{T}$  and (d) temperature contrast at low and high latitudes  $\Delta T$  for  $\varepsilon = 0.01$ ,  $\alpha = 0.5$ ,  $\alpha = 1.5$ . Red/green/blue dashed-dotted lines portray stationary climate states  $\bar{T}_W/\bar{T}_M/\bar{T}_{SB}$ , respectively.

## 205 3 Background and Methodology

### 3.1 Stochastic Energy Balance Model.

In order to analyze the influence of random perturbations on the deterministic dynamics of the climate model described in Section 2, we perturb the relative intensity  $\mu$  of solar radiation by a symmetric  $\alpha$ -stable Lévy process and rewrite Eq. (1) in the form of the following stochastic partial differential equation (SPDE)

$$210 \quad C(x)\mathcal{I}_t = D_I(x, \mathcal{T}, \mathcal{I}_x, \mathcal{I}_{xx}) - D_{III}(\mathcal{T}) + \mathcal{Q}(x)[1 - \alpha_a(x, \mathcal{T})][\mu + \varepsilon \dot{L}^\alpha(t)], \quad (10)$$

with boundary and initial conditions defined by Eq. (2) where  $\mathcal{T}$  is the evolving stochastic temperature field.





Here the parameter  $\varepsilon > 0$  controls the noise intensity and  $(L^\alpha(t)_{t \geq 0})$  is a symmetric  $\alpha$ -stable process defined in Appendix A. As mentioned before, we refer to the Lévy case if the stability parameter  $\alpha \in (0, 2)$ , so that we consider a jump process. We recall that the jumps become more frequent and less intense as  $\alpha$  increases.

215 We define  $\dot{\mathcal{L}}(t) = \mathcal{Q}(x)[1 - \alpha_a(x, T)]\dot{L}^\alpha(t)$ , as the generalised derivative of a stochastic process in a suitably defined functional space. Equation (10) features multiplicative noise. The research interest on this type of SPDEs (Løkka et al., 2004; Doering, 1987; Peszat and Zabczyk, 2007; Duan and Wang, 2014; Alharbi, 2021) is mainly focused on defining weak, strong, mild, and martingale solutions, and in specifying under which conditions these solutions exist and are unique, and in constructing numerical approximation schemes for the solutions (Davie and Gaines, 2000; Cialenco et al., 2012; Burrage and Lythe, 220 2014; Jentzen and Kloeden, 2009; Kloeden and Shott, 2001), among other aspects.

First let us define the concept of mild solution in this context. Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a given complete probability space and  $H(\|\cdot\|, \langle \cdot, \cdot \rangle)$  a separable Hilbert space with norm  $\|\cdot\|$  and inner product  $\langle \cdot, \cdot \rangle$ . Equation (10) can be rewritten in the more general form as follows

$$\begin{aligned} \mathcal{T}_t &= A(x) [E(x, T) \mathcal{T}_x]_x + F(x, T) + \varepsilon G(x, T) \dot{\mathcal{L}}^\alpha(t), \\ 225 \quad \mathcal{T}_x(-1, t) &= \mathcal{T}_x(1, t) = 0, \\ \mathcal{T}(x, 0) &= T_0(x), \end{aligned} \tag{11}$$

where  $A, E, F, G$  are Lipschitz functions defined on  $[-1, 1] \times H$  and  $G(x, T) \dot{\mathcal{L}}^\alpha(t) = \dot{\mathcal{L}}(t)$ . Under certain assumptions (Yagi, 2009), the problem (11) is formulated as a Cauchy problem whose local mild solution, a progressively measurable process  $\mathcal{T}(t)$ , for all  $t \in [0, t_F]$  and  $T_0 \in H$  has the following integral representation

$$230 \quad \mathcal{T}(t) = \Psi(t)T_0 + \int_0^t \Psi(t-s) \Upsilon(\mathcal{T}(s)) ds + \varepsilon \int_0^t \Psi(t-s) G(\mathcal{T}(s)) d\beta + \varepsilon \int_0^t \Psi(t-s) G(\mathcal{T}(s)) d\gamma, \tag{12}$$

where the dependence on  $x$  is kept implicit and  $\beta$  ( $\gamma$ ) is the Poisson random measure (compensated Poisson random measure) defined through Lévy-Itô decomposition.  $\Psi(t)$ ,  $t \geq 0$  is the evolution operator with the generalized semigroup property for the family of sector operators with the bounded inverses, and  $\Upsilon(\mathcal{T}) = \mathcal{T} + F(x, \mathcal{T})$ ,  $\mathcal{T} \in H$  is a nonlinear operator, which we assume Lipschitz to be continuous. Following the abstract theory presented in Yagi (2009), under certain structural assumptions 235 for the operators  $\Psi$  and  $\Upsilon$  and for the functional space, one can prove that the solution (12) is the unique local mild solution of Eq. (11). For illustrative reasons, some sample solutions for different values of  $\alpha$ , simulated by the spatial discretization method (Skeel and Berzins, 1990) adapted to SPDEs, are shown in Figure 2 (a)-(b).

### 3.2 Noise-induced Transitions: Mean residence Times

By incorporating stochastic forcing into the system, its long-time dynamics change significantly, allowing transitions between 240 the competing basins. This dynamical behaviour is called metastability, and is graphically captured by Figure 2, where in plots (a-b) a typical spatio-temporal evolution of the temperature field is shown, for stability parameters  $\alpha = 0.5$  and  $\alpha = 1.5$ , respectively. Instead, in plots (c-d) the temporal noise-induced evolution of global temperature  $\bar{T}$  and the averaged Equator



and Poles temperature difference  $\Delta T$  (as defined in Eqs. (7)-(8)) is shown for the same  $\alpha$ . In what follows, we investigate the time statistics and the paths of the transitions between such basins.

245 In a complete probability space  $(\Omega, \mathcal{F}, \mathbb{P})$  we define the first exit time  $\tau_x$  of a càdlàg mild solution  $\mathcal{T}(\cdot; x)$  of (10) starting at  $x \in D^{W/SB}$  domain of warm/snowball climate stable state as

$$\tau_x(\omega) = \inf\{t > 0 | \mathcal{T}_t(\omega, x) \notin D^{W/SB}\}, \quad \omega \in \Omega, x \in H. \quad (13)$$

The mean residence time is then expressed by  $\mathbb{E}[\tau_x(\omega)]$ . In the case of the infinite dimensional multistable reaction-diffusion system described by Chafee-Infante equation under the influence of additive infinite-dimensional  $\alpha$ -stable Lévy noise -  $\alpha \in$   
 250  $(0, 2)$  - it was shown (Debussche et al., 2013) that in the weak-noise limit  $\varepsilon \rightarrow 0$  the mean residence time in one of the competing basins of attraction increases as  $\varepsilon^{-\alpha}$ . For this time scale of  $\varepsilon$  the jump diffusion system reduces to a finite state Markov chain with values in the set of stable states. Details of this method are given in Appendix B. Similar results have been obtained for bistable one-dimensional SDEs (Imkeller and Pavlyukevich, 2006a, b).

As mentioned above, things are radically different for the special case  $\alpha = 2$ , which corresponds to Gaussian noise. In  
 255 this case, we revisit Eq. (11) and we define  $\dot{L}^{\alpha=2}(t) = \dot{W}(t)$ , where  $(W(t)_{t \geq 0})$  is a Wiener process. We then define  $\dot{W}(t) = G(x, \mathcal{T})\dot{W}(t)$  as the generalised derivative of a Wiener process in a suitably defined functional space. In the weak noise limit, one can express the statistics of transition times using large deviation laws (Varadhan et al., 1985). While the corresponding finite dimensional problem is thoroughly documented in the literature (Freidlin and Wentzell, 1984), and has been applied in a similar context by some of the authors (Lucarini and Bódai, 2019; Lucarini and Bódai, 2020; Ghil and Lucarini, 2020;  
 260 Margazoglou et al., 2021), the treatment of infinite dimensional SDEs driven by an infinite dimensional Wiener process via the Freidlin-Wentzell theory requires further extension. In the present context, we refer to Budhiraja and Dupuis (2000) and Budhiraja et al. (2008) and references therein where the problem of an infinite dimensional reaction-diffusion equation driven by an infinite dimensional Wiener process has been addressed.

We assume that steady state conditions and ergodicity are met, and we also assume that the analysing system is bistable and  
 265 a unique edge state is present at the basin boundary, as in the case studied here. One has that the mean residence time in either basin of attraction decreases exponentially with increasing noise intensity  $\varepsilon$  and is given by a generalized Kramers' law

$$\mathbb{E}[\tau_{W/SB}(\varepsilon)] \approx \exp\left(\frac{2\Delta\Phi_{W \rightarrow M/SB \rightarrow M}(\mathcal{T})}{\varepsilon^2}\right), \quad (14)$$

where  $\Delta\Phi_{W \rightarrow M} = \Phi_M(\mathcal{T}) - \Phi_W(\mathcal{T})$  is the height of the quasi-potential barrier in the W attractor, and, correspondingly  $\Delta\Phi_{SB \rightarrow M}(\mathcal{T}) = \Phi_M(\mathcal{T}) - \Phi_{SB}(\mathcal{T})$  is the height of the quasi-potential barrier in the SB attractor, and  $\Phi$  is the Graham's quasi-  
 270 potential mentioned above (Graham, 1987; Graham et al., 1991).

### 3.3 Noise-induced Transitions: Most Probable Transition Paths

In the weak noise limit, the most probable path to escape an attractor is defined by a class of trajectories named “instantons” (Grafke et al., 2015; Bouchet et al., 2016; Grafke et al., 2017; Grafke and Vanden-Eijnden, 2019) or maximum likelihood



275 escape paths (Lu and Duan, 2020; Dai et al., 2020; Hu and Duan, 2020; Zheng et al., 2020).. However, considering different  
noise laws result into possibly radically different instantonic trajectories Dai et al. (2020); Zheng et al. (2020).

In our case, the theory indicates that if the stochastic forcing is Gaussian, under rather general hypothesis, the instanton  
will connect the attractor W/SB with the edge state M. Hence, M acts as gateway for noise induced transitions *if the noise is*  
*Gaussian*. Once the quasi-potential barrier is overcome, a free fall “relaxation” trajectory links M with the competing attractor  
SB/W. For equilibrium systems, (e.g. for gradient flows) where detailed balance is achieved, the relaxation and instantonic  
trajectories within the same basin of attraction are identical. On the contrary, for non-equilibrium systems, the relaxation  
and instantonic trajectories will differ, and will only meet at the attractor. See a detailed discussion of this aspect and of the  
dynamical interpretation of the quasi-potential  $\Phi$  in Lucarini and Bódai (2020) and Margazoglou et al. (2021). Instead, if the  
noise is of Lévy type, the theory formulated for simpler equations suggests that the instanton will connect the attractor with  
a region on the basin boundary that is the nearest, in the phase space, to the attractor, as the concept of quasi-potential is  
immaterial (Imkeller and Pavlyukevich, 2006a, b; Imkeller and von Storch, 2001).

285 In general, the maximum likelihood transition trajectory  $x_M(t)$  can be defined (Zheng et al., 2020; Lu and Duan, 2020) as  
a set of system states at each time moment  $t \in [0, t_f]$  that maximizes the conditional probability density function  $p(\cdot | \cdot; \cdot)$  of  
passage from the origin stable state  $\phi^{W/SB}$  to the destination stable state  $\phi^{SB/W}$  and is expressed as

$$x_M(t) = \arg \max_x [p(\mathcal{T}(t) = x | \mathcal{T}(0) = x_0; \mathcal{T}(t_f) = x_f)] = \frac{p(\mathcal{T}(t_f) = x_f | \mathcal{T}(t) = x) \cdot p(\mathcal{T}(t) = x | \mathcal{T}(0) = x_0)}{p(\mathcal{T}(t_f) = x_f | \mathcal{T}(0) = x_0)}, \quad (15)$$

290 where  $x_0$  ( $x_f$ ) belongs to the basin of attraction  $D^{W/SB}$  ( $D^{SB/W}$ ) and  $p(\cdot | \cdot)$  is the probability density function evolving  
according to the Fokker-Planck equation (Risken, 1996). This method is applicable either if efficient numerical algorithms  
are available to solve the Fokker-Planck equation associated to the studied stochastically driven system, or, empirically, when  
considering a large ensemble of simulations. Note that this is not an asymptotic approach, i.e. it does not require a weak noise  
limit  $\varepsilon \rightarrow 0$  for its application and is applicable for systems with either Gaussian or non-Gaussian noise. Yet, in the weak-noise  
limit, the definition (15) leads to constructing the optimal transition paths described above.

In the following section, for practical purposes, we construct such optimal transition path in the coarse grained 2D phase  
space  $(\bar{T}, \Delta T)$  and 3D phase space  $(\bar{T}, \Delta T, \mathcal{I})$  of the variables defined in Sect. 2 by averaging the ensemble of transitions  
connecting the two competing states in the weak noise limit.

### 3.4 Numerical Methods

300 We solve Eq. (10) through the Matlab *pdepe* function, which is well suited for solving 1D parabolic and elliptic PDEs. We  
discretize the 1D space with a regular grid of 201 gridpoints, following Bódai et al. (2015).

The time span of integration  $t \in [0, T_f]$ , varies for different cases, with  $T_f \in (10^5, 15 \cdot 10^5)$  years, with time stepping of one  
year. Each year, we consider a different value for the relative solar irradiance by extracting a random number  $Z_j$ , see Eq. (16).  
To simulate the stochastic noise term  $\varepsilon L^\alpha(t)$ , which is added in the parameter  $\mu$  in Eq. (10), we use the recursive algorithm



305 from Duan (2015). The process values  $L^\alpha(t_1), \dots, L^\alpha(t_N)$  at each moment  $t_j$ ,  $j \in \mathbb{N}$ , are obtained via

$$L^\alpha(t_j) = L^\alpha(t_{j-1}) + (t_j - t_{j-1})^{\frac{1}{\alpha}} Z_j, \quad j = 1, \dots, N, \quad (16)$$

where the second term is an independent increment and  $Z_j$  are the independent standard symmetric  $\alpha$ -stable random numbers generated by an algorithm in Weron and Weron (1995). See also Grafke et al. (2015) for a detailed explanation of the steps above. For the numerical simulations discussed below, we consider  $\alpha = (0.5, 1.0, 1.5, 2)$  and  $\varepsilon \in (0.0001, 0.3)$ . We select  
310  $\varepsilon$  in such a way that the noise intensity is strong enough to induce at least order of 10 transition, given our constraints in the time length of the simulations, and weak enough that we are not far from the weak-noise limit, where the scaling laws discussed above apply and transitions paths are well-organized. Our simulations are performed taking the Itô interpretation for the stochastic equations.

We remark that when we consider Lévy noise, it does happen that for some years the solar irradiance has negative values. Of  
315 course these conditions bear no physical relevance. Nonetheless, we have allowed for this to occur in our simulations in order to be able to stick to the desired mathematical framework. We remind that this study does not aim at capturing with any high degree of realism the description of the actual evolution of climate.

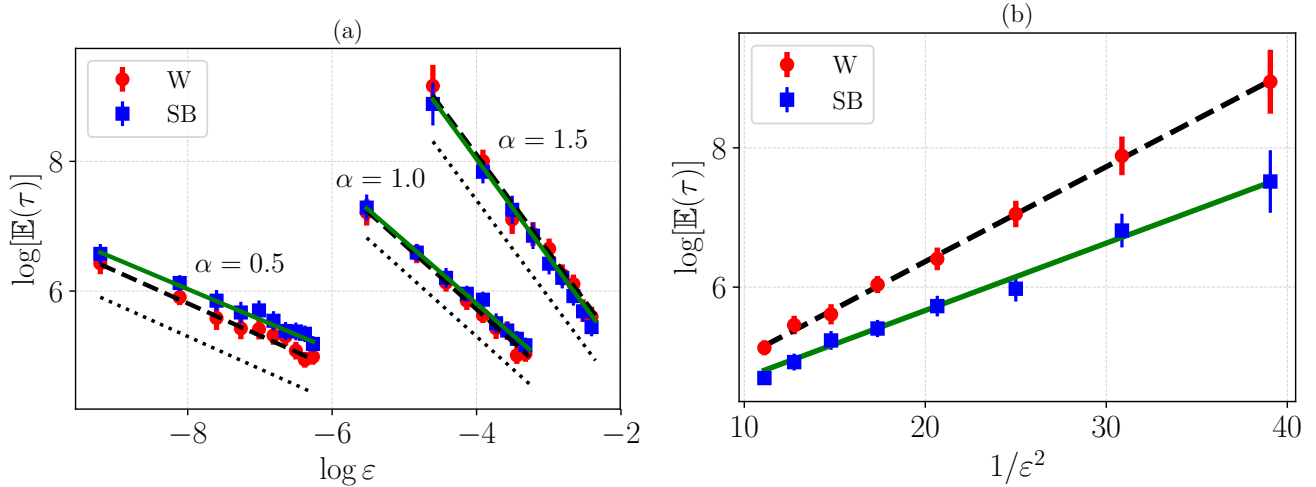
## 4 Results and Discussion

In what follows we aim at addressing three main questions: 1. What is the temporal statistics of the  $SB \rightarrow W$  and  $W \rightarrow SB$   
320 transitions? 2. What are the typical transition pathways? 3. What are the fundamental differences between transitions caused by Gaussian vs. Lévy noise? A summary of the results of the numerical simulations is given in Table A1 in Appendix C, including sample size, i.e. number of transitions, point estimates for mean escape time and its 0.95-confidence intervals for exits from both  $W/SB$  stable basins. See the Data Availability section for information on how to access the supplementary material (Lucarini et al., 2021) containing the raw data produced in this study as well as some illustrative animations portraying noise-induced  
325 transitions between the two competing metastable states.

### 4.1 Mean Residence Time

Our analysis confirms that there is fundamental dichotomy in the statistics of mean residence times between Lévy noise and Gaussian noise-induced transitions.

Fig. 3(a) shows the dependence of the mean residence time in either attractor on  $\varepsilon$  and  $\alpha$  for the Lévy case. The red circles  
330 correspond to permanence in the  $W$  basin, while the blue squares in the  $SB$  basin; see Lucarini et al. (2021) for additional details on the practical steps. The predicted scaling Eq. (B6) is shown by the dotted black line for each  $\alpha$ . We also portray the best power law fit of the mean residence time with respect to  $\varepsilon$  for each value of  $\alpha$ ; the confidence intervals of the exponent is shown in Table 1. Our empirical results seem to indicate, at least in this case, an agreement with the  $\varepsilon^{-\alpha}$  scaling presented in Eq. (B6) and discussed earlier in the paper. This points at the possibility that the  $\varepsilon^{-\alpha}$  scaling might apply in more general  
335 conditions than what has been as of yet rigorously proven, and specifically when multiplicative Lévy noise is considered. The



**Figure 3.** Estimates of the mean residence time  $\mathbb{E}(\tau)$  in years inside the W (blue circles) and SB (red squares) states as a function of the noise intensity  $\varepsilon$ . (a) Lévy noise for  $\alpha = 0.5, 1.0, 1.5$ , with the dotted line being the corresponding prediction from Eq. (B6), while the straight green (SB) and dashed black (W) are the fittings of Eq. (B6) of the relevant dataset. (b) Gaussian noise, with straight green (SB) and dashed black (W) being the fit of Eq. (14).

**Table 1.** Estimates of exponent  $\alpha$  via fitting of Eq. (B6) for the Lévy case (three first columns) and of energy barrier  $\Delta\Phi_{W/SB \rightarrow M}$  via fitting of Eq. (14) for the Gaussian case (last column). In parenthesis is the estimated error of the last digit.

	Lévy			Gaussian
$\alpha$	0.5	1.0	1.5	2
W	0.50(2)	1.00(2)	1.50(1)	$\Delta\Phi_{W \rightarrow M} = 0.068(1)$
SB	0.47(2)	0.97(2)	1.52(4)	$\Delta\Phi_{SB \rightarrow M} = 0.048(3)$

stochastically perturbed trajectories forced by Lévy noise consist of jumps, and the probability of occurrence of a high jump, which can trigger the escape from the reference basin of attraction, is polynomially small in noise intensity  $\varepsilon$ .

The Gaussian case - where no jumps are present - is portrayed in Fig. 3(b). We show in semi-logarithmic scale the mean residence time versus  $1/\varepsilon^2$ . We perform a successful linear fit of the logarithm of the mean residence time in either attractor versus  $1/\varepsilon^2$ , and using Eq. (14), we obtain an estimate of the local quasi-potential barrier  $\Delta\Phi_{W/SB \rightarrow M}$ , which is half of the slope of the corresponding straight lines of the linear fit; see the last column of Table 1. We conclude that for  $\mu = 1.05$  the W basin of attraction has a deeper minimum of  $\Phi$  than the SB one.

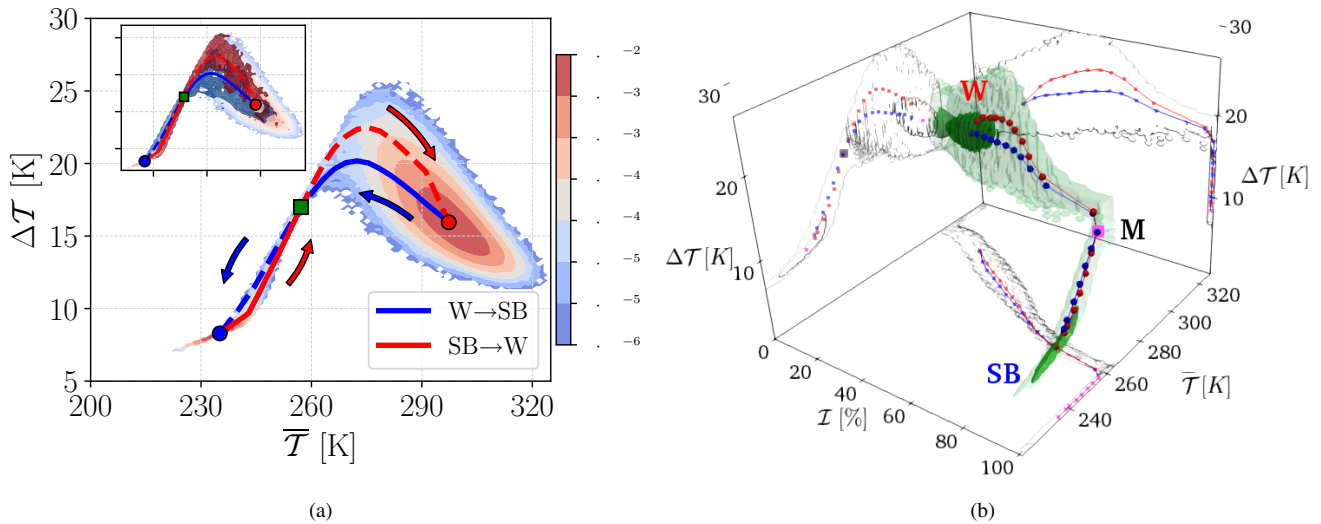


## 4.2 Escape Paths for the Noise-Induced Transitions

We now explore the geometry of the transition paths associated with the metastable behaviour of the system. We first discuss the case of Gaussian noise because it is indeed more familiar and more extensively studied.

### 4.2.1 Gaussian noise

We estimate the transition paths by averaging among the escape plus relaxation trajectories using the run performed with the weakest noise, see Table A1. We first perform our analysis in the 2D-projected state space defined by  $(\bar{T}, \Delta T)$ . We prescribe two small circular-shaped regions enclosing the two deterministic attractors and search the timeseries of the portions of the whole trajectory that leave one of such regions and reach the other one. This creates two subsets of our full dataset, from which we build a 2D histogram for each of the SB  $\rightarrow$  W and W  $\rightarrow$  SB transitions in the projected space. We then estimate the most probable transition paths by finding for each bin value of  $\bar{T}$  the peak of histogram in the  $\Delta T$  direction. The distributions are very peaked, and almost the same result is obtained by computing the average of  $\Delta T$  according to the 2D histogram conditional on the value of  $\bar{T}$ .



**Figure 4.** (a) Invariant measure in the 2D-projected state space defined by  $(\bar{T}, \Delta T)$ . The colored points indicate the deterministic attractors of the SB (blue) M (green) and W (red) states and the blue (red) line is the stochastically averaged transition paths for the  $W \rightarrow SB$  ( $SB \rightarrow W$ ) transitions. Dashed (solid) lines are the relaxation (instantonic) trajectories. The arrows show the direction of transitions. Top left inset: The dark blue (red) contours portray the ensembles of the transition paths between  $W \rightarrow SB$  ( $SB \rightarrow W$ ). Here the system is driven by Gaussian noise with  $\varepsilon = 0.14$ . (b) Invariant measure and most probable transition paths ( $W \rightarrow SB$  in blue and  $SB \rightarrow W$  in red) in the 3D-projected state space defined by  $(\bar{T}, \Delta T, \mathcal{I})$ . The darker green shading indicates higher probability density for the corresponding isosurface. A 2D projection in each plane is shown. The location of the M state is given by a pink square. Here the system is driven by Gaussian noise with  $\varepsilon = 0.16$ .

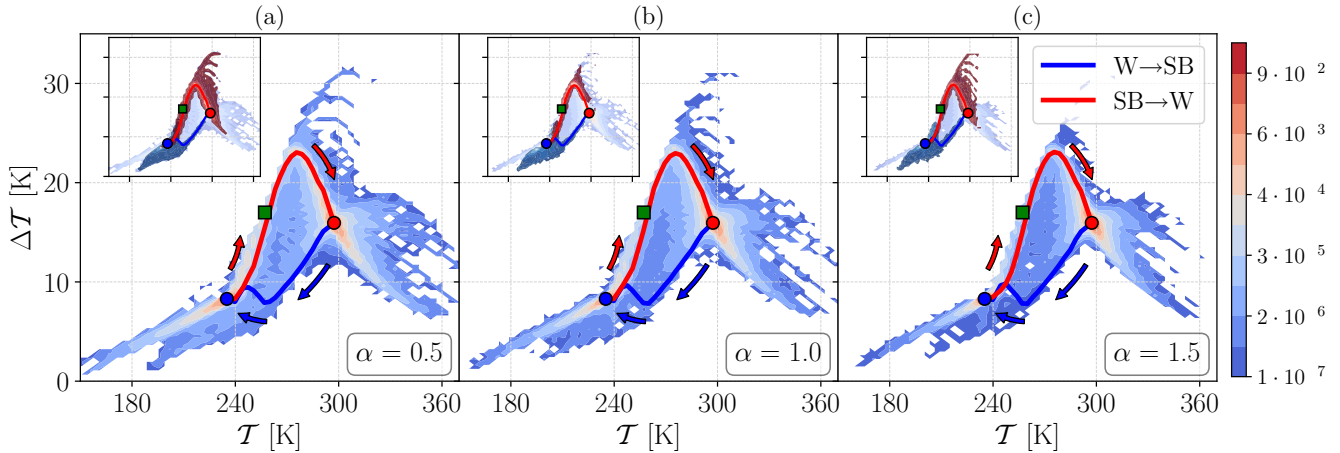


355 In the background of Fig. 4 (a) we show the empirical estimate of the invariant measure in the 2D-projected state space defined by  $(\bar{T}, \Delta T)$ . Additionally, we indicate the position of the deterministic attractors, (SB-blue and W-red circles) and of the M state (green rectangle). In the inset of Fig. 4 (a) we present the ensemble of  $W \rightarrow SB$  ( $SB \rightarrow W$ ) transitions as deep blue (red) contours. The most probable transition paths are shown in blue for the  $W \rightarrow SB$  and in red for the  $SB \rightarrow W$ . The instantonic portion of the blue (red) line is the one connecting the W (SB) attractor to the M state and is portrayed as a solid line, while  
360 the relaxation portion, connecting the M state with the SB (W) attractor, is portrayed as a dashed line. Within each basin of attraction, the instantonic and relaxation trajectories do not coincide, and, instead, only meet at the corresponding attractor and at the M state. This is particularly clear for the W state. The presence of such a loop is a signature of non-equilibrium dynamics, which was also observed in Margazoglou et al. (2021) and has, instead, gone undetected in Lucarini and Bódai (2019); Lucarini and Bódai (2020). See the supplementary material for some illustrative simulations of the transitions.

365 Let's provide some physical interpretation of how the transitions occur. Looking at the  $SB \rightarrow W$  most probable path, the escape includes a simultaneous increase in  $(\bar{T}$  and  $\Delta T)$ . In practice, a  $SB \rightarrow W$  transition takes place when, starting at the SB state, one has a (rare) sequence of positive anomalies in the fluctuating solar irradiance  $\tilde{\mu}$ , i.e.  $\tilde{\mu} > \mu$ . While the planet is warming globally, the Equator is warming faster than the Poles, resulting in a positive rate  $\Delta \dot{T} > 0$ , because it receives, in relative and absolute terms, more incoming solar radiation. Hence, and considering that the Equator also in the SB state  
370 is warmer than the Poles, the melting of the ice occurs first at the Equator, with a subsequent decrease of the albedo in this latitude. Once the system crosses the M state, and supposing that persistent  $\tilde{\mu} < \mu$  do not appear at this stage, the system will relax towards the W state. The relaxation includes a consistent global warming of the planet, but with a change of sign in the rate of  $\Delta \dot{T}$ , and a subsequent decrease of  $\Delta T$  implying that as soon as the temperature at the Equator has risen enough, the Poles will then warm at a faster pace, because the ice-albedo effect kicks in. The global freezing of the planet associated with  
375 the  $W \rightarrow SB$  transition is qualitatively similar but not identical to the reverse  $SB \rightarrow W$  process. Notice a considerable overlap of the transition paths ensembles in both basins of attraction, shown as red and blue contours in the inset of Fig. 4 (a). This implies a weakly non-equilibrium system, contrary to Margazoglou et al. (2021), where the  $W \rightarrow SB$  and  $SB \rightarrow W$  transitions occurred through fundamentally different paths; see discussion therein.

Figure 4 (b) presents the optimal transition paths  $W \rightarrow SB$  and  $SB \rightarrow W$  in a three dimensional projection where we add  
380 as third coordinate the variable  $\mathcal{I}$ , which indicates the fraction of the surface that has subfreezing temperatures ( $T < 273.15$  K). One of the 2D projections included in Fig. 4 (b) corresponds to the projection portrayed in Fig. 4 (a). Here, darker green shadings indicate higher density of points and the red and blue dots sample the highest probability for the  $SB \rightarrow W$  and  $W \rightarrow SB$  transitions paths, respectively. One could argue that the presence of an intersection between the  $SB \rightarrow W$  and  $W \rightarrow SB$  highest probability transition paths in Fig. 4 (a) could have been a simple effect of 2D projection. Instead, we see here that the  $SB \rightarrow W$   
385 and  $W \rightarrow SB$  most probable transition paths also cross in the 3D projection in a well-defined region, which indeed corresponds to the M state (pink square).



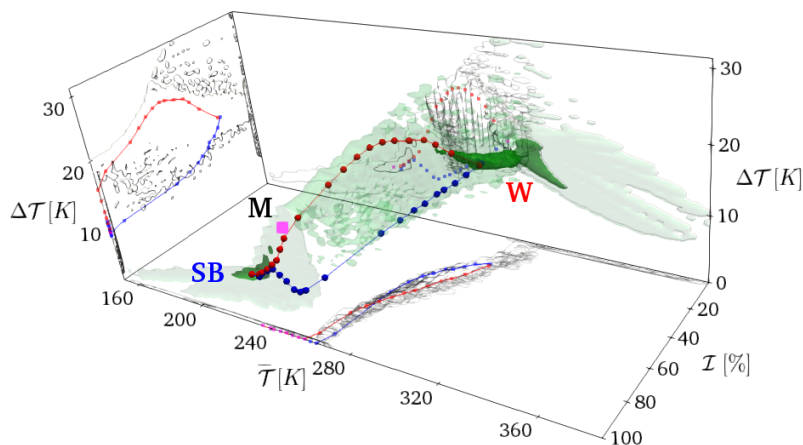


**Figure 5.** Two-dimensional projection of the invariant measure on  $(\bar{T}, \Delta T)$  for different choices of  $\alpha$  for Lévy noise; (a)  $\alpha = 0.5$  and  $\varepsilon = 0.0001$ , (b)  $\alpha = 1$  and  $\varepsilon = 0.004$ , (c)  $\alpha = 1.5$  and  $\varepsilon = 0.01$ . The blue (red) line corresponds to the  $W \rightarrow SB$  ( $SB \rightarrow W$ ) most probable transition path, and the arrows show the direction of transitions. The colored points indicate the deterministic attractors of the SB (blue) M (green) and W (red) states. In the inset left top corner plot of (a-c) the dark blue (red) contours are the ensembles of the transition paths between  $W \rightarrow SB$  ( $SB \rightarrow W$ ).

#### 4.2.2 Lévy noise

There is scarcity of rigorous mathematical results regarding the weak-noise limit of the transition paths between competing states in metastable stochastic systems forced by multiplicative Lévy noise. Indeed, the derivation of analytical results for this type of systems largely remains an open problem. Recently, for stochastic partial differential equations with additive Lévy and Gaussian noise, the Onsager-Machlup action functional has been derived in Hu and Duan (2020), leading to a precise formulation of the most probable transition paths. Hence, we do not have solid mathematical results to interpret what we describe below, where, instead, we need to use heuristic arguments. As far as we know, this is the first attempt to estimate the most probable transition pathway between the metastable states in infinite stochastic systems with multiplicative pure Lévy process.

A striking feature in Figure 5 is that the invariant measure and the structure of the most probable transition paths ( $SB \rightarrow W$  and  $W \rightarrow SB$ ), in the weak-noise limit, are fundamentally different between the Lévy case and the Gaussian one. The invariant measure is highly peaked (dark red in the color scheme) in a small region around the deterministic attractors, as most typically the Lévy noise fluctuations of  $\tilde{\mu}$  are very small. Additionally, the most probable transition paths depend very weakly on the chosen value for the stability parameter  $\alpha$ . This suggests that the geometry of most probable path of transitions does not depend on the frequency and height of the Lévy diffusion jumps, but rather on the qualitative fact that we are considering a discontinuous jump process. Note that each panel of Fig. 5 is computed using data coming from the weakest noise considered for the corresponding value of  $\alpha$ .



**Figure 6.** Same as Fig. 4 (b), but considering a stochastic forcing driven by a Lévy noise with  $\alpha = 1.0$  and  $\varepsilon = 0.004$ .

The  $W \rightarrow SB$  most probable transition path is characterized by the simultaneous decrease of both  $\bar{T}$  and  $\Delta T$ . This implies  
405 that the jump process, causing the transition, leads to a rapid and direct freezing of the whole planet. The path crosses the basin  
boundary very far from the M state. Based on what is discussed in Sec. 3.2, we expect that the transition occurs through the  
nearest region to the outgoing attractor in the basin boundary.

The most probable  $SB \rightarrow W$  transition follows, instead, a path that is somewhat similar to the one found for the Gaussian  
case. We then argue that the closest region in the basin boundary to SB attractor is in the vicinity of the M state. Note, that,  
410 nonetheless, the similarity between the Gaussian and Lévy case is less prominent when we look at 3D paths; compare Figs. 4(b)  
and 6. Indeed, in the Lévy case the  $SB \rightarrow W$  path misses the M state. Further visual confirmation of the difference between the  
Gaussian and Lévy case can be found by looking at the animations included in the supplementary material.

## 5 Conclusions

It is a well-known that, as a result of the competition between the Boltzmann stabilizing feedback and the ice-albedo desta-  
415 bilizing feedback, under current astronomical and astrophysical conditions the climate system is multistable, as at least two  
competing and distinct climates are present, the W and the SB. More recent investigations indicate that the partition of the  
phase space of the climate system might be more complex, as more than two asymptotic states might be present, some of them,  
possibly, associated with small basins of attraction.

For deterministic multistable systems the asymptotic state of an orbit depends uniquely on the initial condition, and, specif-  
420 ically, on which basin of attraction it belongs to. The presence of stochastic forcing allows for transitions to occur between  
competing basins, thus giving rise to the phenomenon of metastability. Gaussian noise as a source of stochastic perturbations  
has been widely studied by the scientific community in recent years and provided very fruitful insight of the multiscale nature  
of the climatic time series. However it has become apparent that more general classes of  $\alpha$ -stable Lévy noise laws might also



be suitable for modeling the observed climatic phenomena. In this regard, it is important to achieve a deeper understanding of  
425 the possible noise induced transitions between competing stable climate states under  $\alpha$ -stable Lévy perturbations and compare  
them with the Gaussian case.

As a starting point in this direction, we have studied the influence of different noise laws on the metastability properties of  
the randomly forced Ghil-Sellers EBM, which is governed by a nonlinear, parabolic, reaction-diffusion PDE. In the determin-  
istic version of the model, we have three steady-state solutions: two stable, attractive climate states and one unstable saddle,  
430 corresponding to the edge state. The stable states corresponds to the well-known W and SB climates. There is a fundamental di-  
chotomy in the properties of the noise-induced transitions determined by whether we consider a stochastic forcing of intensity  
 $\varepsilon$  with a Gaussian versus an  $\alpha$ -stable Lévy noise law. Note that, instead, the spatial structure of the noise is unchanged. This  
indicates that the phenomenology associated with the metastable behaviour depends critically on the choice of the noise law.  
Not many studies have investigated, numerically or through mathematical theory, the properties of transitions in metastable  
435 systems driven by multiplicative Lévy noise, as done here.

First, in the weak noise limit  $\varepsilon \rightarrow 0$ , the mean residence times inside either competing basin of attraction for diffusions  
driven by Gaussian vs. Lévy noise have a fundamentally different dependence on  $\varepsilon$ . Our results show that the logarithm of the  
mean residence time for Gaussian diffusions scales with  $\varepsilon^{-2}$ , while, instead, a much weaker dependence is found for the Lévy  
case. Indeed, we find that the mean residence time is proportional to  $\varepsilon^{-\alpha}$ , where  $\alpha$  is the stability parameter of the noise law.  
440 This result is in agreement with what has been proven in some special cases for additive Lévy noise, and might indicate that  
these scaling properties are more general than usually assumed.

Secondly, the results obtained for the most probable transition paths confirm that, in the weak-noise limit, escapes from  
basins of attraction driven by Gaussian noise take place through the edge state. Additionally, instantonic and relaxation portions  
within each basin of attraction are clearly distinct, indicating nonequilibrium conditions, yet qualitatively similar. In turn, Lévy  
445 diffusions leave the basin through the boundaries region closest to the outgoing attractor, which seems to be the vicinity  
of the edge state when the thawing transition is considered. The freezing transition, instead, proceeds along a path that is  
fundamentally different. Finally, the most probable transition paths for the Lévy case appear to depend very weakly on the  
value of the stability parameter  $\alpha$ , but seem, instead, determined by the nature of the Lévy noise of being a jump process.

Our findings provide strong evidence that choosing noise laws other than Gaussian leads to fundamental changes in the  
450 metastability properties of a system, both in terms of statistics of the transitions between competing basins of attraction and  
most probable paths for such transitions. Leaving the door open for general noise laws might be relevant both for interpreting  
observational data and for performing modelling exercises for the climate system and complex systems in general.

Let's give an example of the impact of making a wrong assumption on the nature of the acting stochastic forcing. Were we  
to naively interpret one of the panels of Fig. 5 as resulting from the dynamics of a dynamical system perturbed by Gaussian  
455 noise, we would have to conclude that the unperturbed deterministic system possesses at least two edge states on the basin  
boundary separating the competing basins of attraction; see Margazoglou et al. (2021) for a case where this situation applies.  
Hence, we would infer fundamentally wrong properties on the geometry of the phase space.



We might think of Gaussian noise as being associated to the impact of unresolved scales of motion on the resolved ones or actual random fluctuations of some external parameter. Instead, one might interpret  $\alpha$ -stable Lévy noise as describing  
460 succinctly, the impact of what in the insurance sector are called acts of God (e.g. an asteroid hitting the Earth; a massive volcanic eruption; the sudden collapse of the West Antarctic ice sheet). Hence, it might be worth investigating the properties of systems where the stochastic forcing comes as the result of simultaneous Gaussian and  $\alpha$ -stable Lévy noise perturbations.

*Data availability.* All the data used to produce the figures contained in this paper are publicly available as supplementary material in Lucarini et al. (2021) through the data repository <https://doi.org/10.6084/m9.figshare.16802503>.

465 *Video supplement.* Illustrative animations portraying noise-induced transitions can be found in the supplementary material. We further uploaded the relevant material in the YouTube platform with links: [Lévy SB→W](#), [Lévy W→SB](#), [Gaussian SB→W](#), [Gaussian W→SB](#).

*Author contributions.* All authors contributed equally to this work.

*Competing interests.* One the authors is member of the NPG editorial board. No other competing interests are present

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## Appendix A: Stochastic perturbations of Lévy type.

In this section we revise the basic properties of a symmetric  $\alpha$ -stable Lévy process in a Hilbert space in which the solutions  
475 to SPDE (10) are defined. It is pertinent to refer to the distribution law of Lévy increments, its characteristic function, the Lévy-Itô decomposition and the Lévy jump measure for a deeper study of the metastable behavior of the stochastic climate system (10). Let  $(\Omega, \mathcal{F}, \mathbb{P})$  be a given complete probability space and  $H(\|\cdot\|, \langle \cdot, \cdot \rangle)$  a separable Hilbert space with norm  $\|\cdot\|$  and inner product  $\langle \cdot, \cdot \rangle$ . A stochastic process  $(L^\alpha(t)_{t \geq 0})$  is a symmetric  $\alpha$ -stable Lévy process in  $H$  if it satisfies:

1)  $L^\alpha(0) = 0$ , a.s..



480 2) Independent increments: for any  $n \in \mathbb{N}$  and  $0 \leq t_1 < t_2 < \dots < t_{n-1} < t_n$  the vector

$$(L^\alpha(t_1) - L^\alpha(t_0), \dots, L^\alpha(t_n) - L^\alpha(t_{n-1})) \quad (\text{A1})$$

is a family of independent random vectors in  $H$ .

3) Stationary increments: for  $0 \leq l < t$  random vectors  $L^\alpha(t) - L^\alpha(l)$  and  $L^\alpha(t-l)$  have the same law  $\mathfrak{L}(\cdot)$  in  $H$

$$\mathfrak{L}(L^\alpha(t) - L^\alpha(l)) = \mathfrak{L}(L^\alpha(t-l)). \quad (\text{A2})$$

485 4) Sample paths are continuous in probability, i.e. for any  $t \geq 0$  and  $\eta > 0$

$$\lim_{l \rightarrow t} \mathbb{P}(\|L^\alpha(t) - L^\alpha(l)\| > \eta) = 0. \quad (\text{A3})$$

Although neither the incremental nor the marginal distribution of a Lévy process in general are representable by the elementary functions, the Lévy motion is completely determined by the Lévy-Khintchine formula which specifies the characteristic function of the Lévy process.

490 If  $L^\alpha(t)$  is a symmetric  $\alpha$ -stable Lévy process in  $H$ , then:

1) (Lévy-Khintchine formula) Its characteristic function is

$$\Lambda_t(h) = \mathbb{E} \left[ e^{i\langle h, L^\alpha(t) \rangle} \right] = e^{t\psi(h)}, \quad h \in H, \quad t \geq 0,$$

where

$$\psi(h) = \int_H \left( e^{i\langle h, y \rangle} - 1 - i\langle h, y \rangle \mathbf{1}_{\{0 < \|y\| \leq 1\}} \right) \nu(dy), \quad (\text{A4})$$

495 here  $\mathbf{1}_S$  is the indicator function for a set  $S$ , taking 1 on  $S$  and 0 otherwise, and  $\nu$  is a Borel measure (so called the Lévy jump measure) in  $H$  for which  $\int_H (1 \wedge \|y\|^2) \nu(dy) < \infty$  with  $1 \wedge \|y\|^2 = \min\{1, \|y\|^2\}$ . A Borel measure, as well, can be defined as the expected value of the number of jumps of specified size  $Q$  in the unit time interval, i.e.  $\nu(Q) = \mathbb{E}N(1, Q)(\omega)$ ,  $\omega \in \Omega$ .

2) (Lévy-Itô decomposition) For any sequence of positive radii  $r_n \rightarrow 0$  and  $\mathcal{O}_n = \{y \in H \mid r_{n+1} < \|y\| \leq r_n\}$  there exist a sequence of independent compensated compound Poisson processes  $(\bar{L}_n(t))_{t \geq 0}$ ,  $n \geq 0$  in  $H$  with jump measures  $\nu_n(B) =$   
 500  $\nu(B \cap \mathcal{O}_n)$  for  $B \in \mathcal{B}(H)$  the Borel  $\sigma$ -algebra in  $H$  and  $n \geq 1$ , which satisfy  $\mathbb{P}$ -almost surely for all  $t \geq 0$

$$L(t) = \sum_{n=1}^{\infty} \bar{L}_n + L_0(t), \quad (\text{A5})$$

$$\bar{L}_n(t) = L_n(t) - t \int_H y \nu_n(dy), \quad n \geq 1. \quad (\text{A6})$$

3) Its Lévy jump measure  $\nu$  is symmetric in the sense that  $\nu(-Q) = \nu(Q)$  for  $Q \in \mathcal{B}(H)$  and has the specific geometry

$$\nu(Q) = \int_Q \nu(dy) = \int_Q \frac{dr}{r^{1+\alpha}} \sigma(ds), \quad (\text{A7})$$

505 where  $r = \|y\|$  and  $s = y/\|y\|$  and  $\sigma : \mathcal{B}(\partial B_1(0)) \rightarrow [0, \infty)$  is an arbitrary finite Radon measure on the unit sphere of  $H$ .

One can come to more intuitive interpretation of the stability parameter  $\alpha \in (0, 2)$  variation: for smaller values of  $\alpha$ , the process is characterized by higher jumps with a lower frequency. As  $\alpha$  increases, jumps decrease in height and the frequency of their occurrence increases.



## Appendix B: Probabilistic theory for the Lévy noise-induced escape.

510 We briefly recapitulate here the main ideas behind the proof given in Debussche et al. (2013) of how the mean residence time in the competing metastable states of stochastically perturbed Chafee-Infante reaction-diffusion PDE scales with the intensity  $\varepsilon$  of the additive  $L(t)$   $\alpha$ -stable Lévy noise that acts as stochastic forcing.

One proceeds by considering the decomposition of the driving Lévy process with regularly varying jump measure  $\nu$  into small  $\xi^\varepsilon$  and large  $\eta^\varepsilon$  jump components. Let  $\Delta_t L = L(t) - L(t-)$  denote the jump increment of  $L$  at time  $t \geq 0$ , and  $\frac{1}{\varepsilon^\rho}$  for  $\varepsilon, \rho \in (0, 1)$  the jump height threshold of  $L$ . The process  $\eta^\varepsilon$  is a compound Poisson process consisting of all jumps of height  $\|\Delta_t L\| > \varepsilon^{-\rho}$  with intensity

$$\beta_\varepsilon = \nu \left( \frac{1}{\varepsilon^\rho} B_1^c(0) \right) \approx \varepsilon^{\alpha\rho}, \quad (\text{B1})$$

and the jump probability measure outside the ball  $\frac{1}{\varepsilon^\rho} B_1(0)$  by

$$\nu \left( \cdot \cap \frac{1}{\varepsilon^\rho} B_1^c(0) \right) / \beta_\varepsilon, \quad (\text{B2})$$

520 where  $B_1(0)$  is the ball in  $H$  with center in origin and unit radius. The occurrence time of a  $k$ -th large jump is defined recursively by

$$\mathcal{Z}_0 = 0, \quad \mathcal{Z}_k = \inf\{t > \mathcal{Z}_{k-1} \mid \|\Delta_t L\| > \varepsilon^{-\rho}\}, \quad k \geq 1. \quad (\text{B3})$$

The waiting times between successive  $\eta_t^\varepsilon$  jumps have an exponential distribution  $\mathcal{Z}_k - \mathcal{Z}_{k-1} \sim \text{Exp}(\beta_\varepsilon)$ .

Small jump processes  $\xi^\varepsilon = L - \eta^\varepsilon$  due to the symmetry of Lévy measure  $\nu$  is a mean zero martingale in  $H$  with finite exponential moments. Probabilistic events causing small jumps in the stochastic solution of the system are not able to overcome the “force” of its deterministic stable state and therefore, do not contribute to the exit from the basin of attraction. Formally, during the time between two large jumps  $t_k = \mathcal{Z}_k - \mathcal{Z}_{k-1}$ , the solution of (10) following the deterministic path (1) returns to a small vicinity of the stable equilibria  $\phi^{W/SB}$

$$\sup_{x \in D^{W/SB}} \sup_{\mathcal{Z}_{k-1} \leq t \leq \mathcal{Z}_k} \|\mathcal{T}(t) - T(t)\| \rightarrow 0 \quad \text{for} \quad \varepsilon \rightarrow 0. \quad (\text{B4})$$

530 When a first large jump occurs, the solution process moves to the neighboring domain of attraction with probability

$$\begin{aligned} \mathbb{P}(\phi^{W/SB} + \varepsilon \Delta_{t_i} L \notin D^{W/SB}) &= \mathbb{P} \left( \Delta_{t_i} L \in \frac{1}{\varepsilon} [(D^{W/SB})^c - \phi^{W/SB}] \right) \\ &= \frac{\nu \left( \frac{1}{\varepsilon} [(D^{W/SB})^c - \phi^{W/SB}] \cap \frac{1}{\varepsilon^\rho} B_1^c(0) \right)}{\nu \left( \frac{1}{\varepsilon^\rho} B_1^c(0) \right)} \approx \varepsilon^{\alpha(1-\rho)}. \end{aligned} \quad (\text{B5})$$

This is the probability that at time  $t_i$  there will be a jump increment  $\Delta_{t_i} L$  that exceeds the distance between the attractor and its domain of attraction boundary, expressed by the jump probability measure (B2). In the zero-noise limit the mean residence time in a basin of attraction is given by



$$\begin{aligned}
 \mathbb{E}[\tau(\varepsilon)] &\approx \sum_{i=1}^{\infty} \mathbb{E}[Z_i] \mathbb{P}[\inf\{j : \phi^{W/SB} + \varepsilon \Delta_{t_j} L \notin D^{W/SB}\} = i] \\
 &\approx \mathbb{E}[t_1] \mathbb{P}(\phi^{W/SB} + \varepsilon \Delta_{t_1} L \notin D^{W/SB}) \cdot \sum_{i=1}^{\infty} i (1 - \mathbb{P}[\phi^{W/SB} + \varepsilon \Delta_{t_1} L \notin D^{W/SB}])^{i-1} \\
 &\approx \frac{1}{\varepsilon^{\alpha\rho}} \varepsilon^{\alpha(1-\rho)} \left( \frac{1}{\varepsilon^{\alpha(1-\rho)}} \right)^2 = \frac{1}{\varepsilon^{\alpha}},
 \end{aligned} \tag{B6}$$

540 i.e. by the sum of all the mean values of large jump occurrence time times the probability that the minimum of a sample of  
 size  $i$  of jump increments is sufficiently large to get into the neighboring domain of attraction. Thus, at the random time instant  
 of large jumps, the solution process transitions, in an abrupt move, from one attractor to another. Such behavior of the random  
 dynamical system is known as a metastability.

545 In Debussche et al. (2013) it was proved that in the time scale  $\lambda(\varepsilon) = \nu(\frac{1}{\varepsilon} B_1^c(0))$ ,  $\varepsilon > 0$  the metastable shifting of the diffu-  
 sion process between neighborhoods of the two attractors represents a continuous time Markov chain in state space  $\{\phi^{SB}, \phi^W\}$   
 with a transition rate matrix  $\Omega$

$$\Omega = \frac{1}{\mu(B_1^c(0))} \begin{pmatrix} -\mu((D^{SB} - \phi^{SB})^c) & \mu((D^{SB} - \phi^{SB})^c) \\ \mu((D^W - \phi^W)^c) & -\mu((D^W - \phi^W)^c) \end{pmatrix}, \tag{B7}$$

where  $\mu(\cdot)$  is the limit measure of  $\nu$ .

### Appendix C: Estimates for the mean residence time





**(a)**

$\varepsilon$	0.0001	0.0003	0.0005	0.0007	0.0009	0.0011	0.0013	0.0015	0.0017	0.0019
$N^{\circ} SB \rightarrow W$	74	121	162	193	191	218	239	264	286	307
$N^{\circ} W \rightarrow SB$	74	121	162	194	191	218	239	265	287	307
$\mathbb{E} [\tau_{SB}]$	715	457	348	290	299	255	218	216	208	178
$CI_{0.95} [\tau_{SB}]$	[627,803]	[409,504]	[298,397]	[246,333]	[263,335]	[222,288]	[190,245]	[191,241]	[185,232]	[158,198]
$\mathbb{E} [\tau_W]$	618	367	265	226	224	203	200	160	139	146
$CI_{0.95} [\tau_W]$	[540,695]	[329,404]	[221,310]	[189,263]	[191,256]	[177,229]	[172,228]	[141,179]	[124,154]	[130,162]

**(b)**

$\varepsilon$	0.004	0.006	0.01	0.014	0.018	0.022	0.026	0.03	0.034	0.038
$N^{\circ} SB \rightarrow W$	35	50	90	121	152	186	224	255	273	328
$N^{\circ} W \rightarrow SB$	35	51	90	121	152	187	224	256	273	329
$\mathbb{E} [\tau_{SB}]$	1461	1029	568	388	344	265	249	202	189	160
$CI_{0.95} [\tau_{SB}]$	[1235,1687]	[872,1186]	[482,654]	[336,441]	[306,382]	[230,301]	[216,281]	[178,227]	[166,211]	[143,176]
$\mathbb{E} [\tau_W]$	1357	925	531	431	313	270	197	187	177	144
$CI_{0.95} [\tau_W]$	[1124,1589]	[782,1067]	[461,600]	[382,481]	[279,347]	[232,307]	[171,223]	[164,211]	[156,197]	[127,161]

**(c)**

$\varepsilon$	0.01	0.015	0.025	0.035	0.045	0.055	0.065	0.075	0.085	0.095
$N^{\circ} SB \rightarrow W$	5	8	21	37	57	78	118	142	170	231
$N^{\circ} W \rightarrow SB$	5	9	22	37	58	79	118	142	170	231
$\mathbb{E} [\tau_{SB}]$	7226	4410	2025	1383	800	629	418	308	282	191
$CI_{0.95} [\tau_{SB}]$	[5473,8979]	[3458,5362]	[1526,2525]	[1103,1664]	[677,923]	[529,729]	[366,470]	[256,361]	[242,323]	[165,217]
$\mathbb{E} [\tau_W]$	9544	6199	2418	1249	904	637	425	395	304	241
$CI_{0.95} [\tau_W]$	[7402,11686]	[4772,7625]	[1877,2959]	[1033,1464]	[770,1037]	[546,727]	[363,487]	[329,460]	[259,350]	[207,276]

**(d)**

$\varepsilon$	0.14	0.16	0.18	0.20	0.22	0.24	0.26	0.28	0.30
$N^{\circ} SB \rightarrow W$	1	9	27	64	109	155	217	269	360
$N^{\circ} W \rightarrow SB$	1	10	27	64	109	156	217	269	359
$\mathbb{E} [\tau_{SB}]$	5038	1838	908	394	307	222	187	137	109
$CI_{0.95} [\tau_{SB}]$	[2378,7698]	[1138,2538]	[745,1071]	[328,460]	[268,345]	[198,246]	[164,210]	[120,154]	[99, 119]
$\mathbb{E} [\tau_W]$	25870	7700	2656	1153	605	418	273	234	168
$CI_{0.95} [\tau_W]$	[15339,36401]	[4991,10410]	[2121,3191]	[942,1364]	[524,686]	[377,459]	[238,308]	[208,259]	[151,186]

**Table A1.** Estimates and 95%-confidence intervals for the mean residence time  $\tau$  in W and SB basins for Lévy noise with (a)  $\alpha = 0.5$ , (b)  $\alpha = 1.0$ , (c)  $\alpha = 1.5$ , and (d) Gaussian noise. By  $N^{\circ}$  we calculate the average number of transitions per  $10^5$  years of temporal evolution.



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