

Background EEG connectivity captures the time-course of epileptogenesis in a mouse model of epilepsy

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- 1 **1. Title**
2 Background EEG connectivity captures the time-course of epileptogenesis in a mouse model of epilepsy
3
- 4 **2. Abbreviated Title**
5 Epileptogenesis in a mouse model of epilepsy
6
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23 PS analysed data, PS and MG writing – original draft, PS, LS, CMM, MPR, CQ, JRT and MG writing –
24 review and editing. JRT and MG contributed equally to this work and are last authors on this work
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107**Abstract**

Large-scale brain networks are increasingly recognized as important for the generation of seizures in epilepsy. However, how a network evolves from a healthy state through the process of epileptogenesis remains unclear. To address this question, here, we study longitudinal epicranial background EEG recordings (30 electrodes, EEG free from epileptiform activity) of a mouse model of mesial temporal lobe epilepsy. We analyse functional connectivity networks and observe that over the time-course of epileptogenesis the networks become increasingly asymmetric. Furthermore, computational modelling reveals that a set of nodes, located outside of the region of initial insult, emerges as particularly important for the network dynamics. These findings are consistent with experimental observations, thus demonstrating that ictogenic mechanisms can be revealed on the EEG, that computational models can be used to monitor unfolding epileptogenesis and that both the primary focus and epileptic network play a role in epileptogenesis.

Significance Statement

We provide the first description of how functional connectivity and network dynamics inferred from background EEG evolve during epileptogenesis. We focus on background EEG because it allows for direct comparison of functional networks before and after experimental intervention. We show that network dynamics inferred by means of computational modelling are different at early and later stages of epileptogenesis. Our findings provide further support for clinical potential of background EEG.

Introduction

Epilepsy is the most common chronic brain disorder affecting around 1 in 100 people worldwide and accounting for 0.6% of the global burden of disease (World Health Organization, 2019). Epilepsy is characterised by recurrent seizures. Seizure recurrence is a particularly important feature, because up to 10% of people worldwide, who do not have epilepsy, have a single seizure during their lifetime (World Health Organization, 2019). In other words, although every brain is able to generate seizures, not every brain is ictogenic, i.e., prone to generating recurring seizures.

Occurrences of epileptiform activity are irregular and unpredictable, but in contrast background brain activity (i.e. periods of activity that are free from obvious epileptiform abnormalities or discharges) is readily observable. There is therefore a significant research effort focused on exploiting the background activity in research and clinical practice. Recent developments in this area, based on the modern, network perspective of epilepsy, have focused on functional network analyses of background EEG and MEG. These studies have revealed altered networks in the background EEG of people with epilepsy when compared to healthy controls (Chowdhury et al., 2014; Schmidt et al., 2014; Coito et al., 2015; Niso et al., 2015; Woldman and Terry, 2015; Schmidt et al., 2016; Soriano et al., 2017) and have uncovered specific features that can help point to the location of an “epileptogenic zone” within networks (van Dellen et al., 2014; Englot et al., 2015; Nissen et al., 2017). The studies above are predominantly concerned with uncovering differences between the EEG of people with epilepsy and healthy controls, and address the question of how ictogenic mechanisms manifest in the EEG. The latter are mechanisms that lead the brain of someone with epilepsy to sporadically transition into seizures from the non-seizure state.

108 However, a key questions in epilepsy research that remains is how does the brain
109 becomes capable of generating recurrent seizures in the first place? This is a question of
110 epileptogenic mechanisms, i.e. what changes does the brain undergo over longer periods
111 of time in order to become ictogenic (Dichter, 2009; Lopes Da Silva et al., 2012;
112 Goldberg and Coulter, 2013; Löscher et al., 2015). Various animal models can be used to
113 explore these mechanisms. Gill et al. 2017, for example, studied a rat model of
114 intraperitoneally administered kainic acid and catalogued the development of alterations
115 to networks derived from fMRI (Gill et al., 2017). However, our understanding of the
116 ways that large-scale brain dynamics evolve following local insult remains poor.
117

118 To address this, we study background functional EEG networks in a well-established
119 mouse model of temporal lobe epilepsy (Bouilleret et al., 1999; Riban et al., 2002;
120 Arabadzisz et al., 2005; Gröticke et al., 2008; Häussler et al., 2012; Lévesque and Avoli,
121 2013). In this model, unilateral injection of kainic acid in the dorsal hippocampus induces
122 a status epilepticus followed by gradual neurodegeneration at the injected hippocampus
123 (Riban et al., 2002; Arabadzisz et al., 2005). Concomitantly, spontaneous epileptiform
124 events can be measured on the EEG at both hippocampi and, after 2-8 weeks,
125 spontaneous and recurrent paroxysmal discharges that are reminiscent of focal and
126 secondarily generalized seizures occur (Riban et al., 2002; Arabadzisz et al., 2005;
127 Chauvière et al., 2012; Huneau et al., 2013; Salami et al., 2014; Sheybani et al., 2018).
128

129 In the current study, we characterise functional connectivity networks before and during
130 epileptogenesis by analysing EEG recorded before kainic acid injection as well as at 7
131 and 28 days after the injection. Our analysis reveals that the progression of
132 epileptogenesis is reflected in changes to background functional connectivity networks,
133 with the focal injection leading to a disruption of network symmetry. We use a
134 mathematical model to understand how these observed changes affect the ways that
135 different nodes contribute to generation of epileptiform activity. Using only the
136 background activity as input to the model, it reveals that nodes outside of the injected
137 hippocampus become more important throughout epileptogenesis. This is in line with
138 previous experiments that demonstrated the emergence of epileptiform activity self-
139 sustained by brain structures outside of the epileptic focus (the injected hippocampus)
140 (Sheybani et al., 2018). These findings present a step towards a network level
141 understanding of epileptogenesis that could be developed to aid diagnosis and treatment
142 of epilepsy.
143

144 **Materials and Methods**

146 **Animals and recordings**

147 We used longitudinal recordings from the experiments described in (Sheybani et al.,
148 2018). We analysed longitudinal recordings from 12 animals (adult male C57BL/6j mice,
149 Charles River) for which data was recorded before unilateral kainic acid injection into the
150 left hippocampus (Day 0) as well as at 7 and 28 days after injection. Of the 12
151 longitudinal datasets 1 was excluded from all analysis due to poor quality of the data. Out
152 of the 11 remaining datasets 4 were excluded from analysis at day 7 due to high number
153 of artefacts and noise in the background EEG. Therefore, we used a total of 11 datasets
154 with recordings at day 0 and day 28, with 7 of the 11 datasets also including recordings at
155 day 7. Additionally, we analysed data recorded from 4 sham control animals (adult male
156 C57BL/6j mice, Charles River) that were unilaterally saline injected into the left
157 hippocampus and had epicranial EEG recorded 28 days after the injection.

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The epicranial EEG was recorded at 4kHz sampling frequency using Digital Lynx SX (Neuralynx, USA). All recordings were re-referenced to the electrode average. We removed power line interference using a 50Hz (and 100Hz and 150Hz harmonics) notch filter and further band-pass filtered the data between 1 and 150 Hz using a zero-phase forward and reverse Butterworth filter of order 2.

From each EEG recording, which lasted around 30 minutes, multiple 1 second background data segments were selected from periods without epileptiform activity (median number of segments 55, min 17, max 83); for data collected on days 7 and 28 the segments were at least 1 second removed from the onset of a generalised spike (GS - interictal epileptic discharges, see (Sheybani et al., 2018)).

All experiments described in (Sheybani et al., 2018) were conducted in accordance with Swiss Laws on animal experimentation.

Network reconstruction

As in (Rummel et al., 2015; Goodfellow et al., 2016; Schmidt et al., 2016) we treated each EEG channel as recording from a single node of a network. To estimate weights of directed connections between the nodes we combined methods presented in (Rummel et al., 2015; Schmidt et al., 2016). Namely, to measure statistical interdependency between the EEG channels we employed the cross-correlation function:

$$r(x_i, x_j)(t) = \begin{cases} \sum_{t=1}^{T-t} x_i(t+t)x_j(t), & t \geq 0, \\ \sum_{t=1}^{T-|t|} x_i(t)x_j(t+|t|), & t < 0, \end{cases} \quad (2)$$

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$$r_{coeff}(x_i, x_j)(t) = \frac{r(x_i, x_j)(t)}{\sqrt{r(x_i, x_i)(0)r(x_j, x_j)(0)}}.$$

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In practice, we used the Matlab function: `xcorr` with option `coeff`, which normalizes the cross-correlation function in such a way that the auto-correlations at zero lag are equal to 1.

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To estimate the strength of the relationship between channels we used three different approaches based on the extremum of the cross-correlogram $r_{coeff}(x_i, x_j)(\tau)$. In the first method, we follow (Schmidt et al., 2016), and we use the maximum absolute value of the cross-correlogram, $\max_{\tau} |r_{coeff}(x_i, x_j)(\tau)|$. In the second method, we followed suggestion from (Sinha et al., 2017) and use only the values of $\max_{\tau} |r_{coeff}(x_i, x_j)(\tau)|$ for which $r_{coeff}(x_i, x_j)(\tau) > 0$. We refer to the matrices derived with these two methods as C^{ABS} and C^{MAX} , respectively. Finally, to understand the difference between the C^{ABS} and C^{MAX} we also analysed networks estimated using the values of $\max_{\tau} |r_{coeff}(x_i, x_j)(\tau)|$ where $r_{coeff}(x_i, x_j)(\tau) < 0$. We refer to the matrices from the third method as C^{MIN} .

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The cross-correlogram $r_{coeff}(x_i, x_j)(\tau)$ provides a natural way to infer directionality of the estimated connections. The direction of the connections is given by the sign of the lag between the two channels; with $\tau < 0$ meaning that a channel i is leading (transmitting to)

200 channel j . In the paper we adopted notation in which a connection from channel i to j is
 201 noted as element c_{ij} of the connectivity matrix. In this convention, extrema of the cross-
 202 correlation function at $\tau < 0$ make up the elements of the matrix that are above the
 203 diagonal $j > i$ and ones at $\tau > 0$ are below the diagonal $i > j$. The diagonal is equal to 0
 204 (no self-loops).

205
 206 We disregarded any lags longer than 250ms (1000 points) and lags shorter than 2ms (8
 207 time samples). We removed the shortest lags to address the problem of volume
 208 conduction, i.e. spurious correlations between the time series due to common sources of
 209 activity. Such activity is typically detected at very small values of lag between the time
 210 series. We chose 8 samples because they correspond to a single sample at sampling
 211 frequency 512Hz, which is a typical sampling frequency used in clinical acquisition of
 212 intracranial EEG.

213
 214 To increase the accuracy of estimation of the connections, we divided each 1-second data
 215 segment into 21 windows (500ms) with 25ms overlap, and we computed connectivity
 216 matrices for each window.

217
 218 We further checked that values of the coefficients were not solely due to the presence of
 219 dominant intrinsic channel frequencies. For each 1 second data segment we generated
 220 100 sets of univariate Iterative Amplitude Adjusted Fourier Transform (IAAFT)
 221 surrogates (Schreiber and Schmitz, 1996), each containing 30 channels, generated using
 222 10 iterations. A Wilcoxon rank sum test (with Bonferroni correction for 870 comparison)
 223 was used to test, element-wise, whether coefficients in the 21 windows had a different
 224 median than the 2100 surrogate windows. For each 1 second data segment the computed
 225 values of cross-correlation coefficients were averaged and normalized in the same way as
 226 in (Rummel et al., 2015),
 227

$$228 \quad c_{ij} = \frac{\langle c_{ij,data} \rangle - \langle c_{ij,surr} \rangle}{1 - \langle c_{ij,surr} \rangle} s_{ij}. \quad (3)$$

229
 230 Here, $\langle c_{ij,data} \rangle$ is the median value of the coefficients from the data, $\langle c_{ij,surr} \rangle$ is the median
 231 value of the coefficients from the surrogate data, $s_{ij} = 1$ if the family wise error rate,
 232 FWER < 0.05 and 0 otherwise. Finally, we averaged the network topologies over all data
 233 segments in a recording and normalised the coefficients with the sum of all of the
 234 elements of the connectivity matrix. By averaging over multiple segments we aimed to
 235 estimate functional connectivity that accounts for complex bi-directional interactions
 236 between the brain regions generating the recorded activity.

237
 238 To ensure that the variability in the number of data segments did not affect the presented
 239 results, we excluded from analysis 5 data sets that either had a very low number of data
 240 segments or resulted in a low number of connections, see Figure 1.

241 [Figure 1 around here]

242 **Model**

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 244 To model the network dynamics we followed the procedure presented in (Lopes et al.,
 245 2017, 2018), i.e. we analysed to what extent removal of a single node (virtual resection
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247 (Goodfellow et al., 2016; Khambhati et al., 2016)) affects activity of the network that on
 248 average spends half of the time in the active state. The simulations proceeded as follows:

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- 1.) The dynamics of each node was modelled using the theta model (Ermentrout and Kopell, 1986), which has been shown to well approximate the predictions of neural mass models close to a saddle-node on invariant circle bifurcation (Lopes et al., 2017):

$$255 \quad \frac{d\theta}{dt} = 1 - \cos\theta + (1 - \cos\theta)I(t), \quad (4)$$

$$I(t) = I_0 + I_{noise} \mathcal{N}(0,1).$$

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Here, I_0 is the intrinsic model parameter, $I_{noise} = 6$ is noise intensity and $\mathcal{N}(0,1)$ is a random number from a normal distribution with mean 0 and variance 1. We set $I_0 = -1.2$ to ensure that in the absence of noise a stable steady state existed in the system. To couple the nodes, we used the functional connectivity matrix C ; with elements c_{ij} . Coupled equations have the following form (Lopes et al., 2017):

$$263 \quad \frac{d\theta_i}{dt} = 1 - \cos\theta_i + (1 - \cos\theta_i)I_i(t), \quad (5)$$

$$I_i(t) = I_0 + I_{noise} \mathcal{N}_i(0,1) + \omega \sum_{j=1}^N c_{ji} [1 - \cos(\theta_j - \theta_j^*)] / N.$$

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Here, ω is a global scaling factor of the weights c_{ji} of the incoming connections of the node i ; N is the total number of nodes in the network. The θ_j^* is the steady state of node j . Parameters $I_0 = -1.2$ and $I_{noise} = 6$ are the same at each node. For each simulation, we used a time step of 0.01, and the duration of the simulation was 4.0e6 time steps. See (Lopes et al., 2017) for more details.

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- 2.) We first estimated the value of $\omega > 0$ for which on average the whole network spends 50% of the time in the active state. ω_{50} was estimated in separate simulations (averaged over 10 runs with independent noise realisation). We used the same definition of the node's active state as in (Lopes et al., 2017). To quantify activity of the whole network we use the brain network ictogenicity (BNI) which is the average time each node spends in the active state (Goodfellow et al., 2016):

$$278 \quad BNI = \frac{1}{N} \sum_{i=1}^N \frac{\text{time node } i \text{ spent in active state}}{\text{duration of simulations}}, \quad (6)$$

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- 3.) We then removed a single node and ran simulations with exactly the same parameters; we normalised the sum in Eq. (5) with N rather than $N-1$ to keep the connection weights exactly the same. We measured the change in the network dynamics by comparing the time spent by the network in the active state before and after removing the node. To this end, we used node ictogenicity NI defined in (Goodfellow et al., 2016):

$$287 \quad NI_i = \frac{0.5 - BNI_{i,post}}{0.5}, \quad (7)$$

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where $BNI_{i,post}$ is the BNI estimated after removing node i from the network. We repeated each simulation 10 times and took the mean value of the NI over the 10 runs with independent noise realisations.

Statistical methods

We used non-parametric, median based statistical methods (Kruskal-Wallis, Mann-Whitney-Wilcoxon or Kolmogorov-Smirnov tests) throughout. To control for multiple comparison during network reconstruction we used the Bonferroni FWER with a significance level of 0.05 (Benjamini and Hochberg, 1995). To control for multiple comparison in the network analysis we used the Benjamini-Hochberg false discovery ratio (FDR) (Benjamini and Hochberg, 1995). Due to small sample sizes we used a significance level of 0.1 for the network analysis. We additionally quantified effect sizes using area under the receiver-operating characteristic (AUROC), which is a non-parametric alternative of the common-language effect size (Hentschke and Stüttgen, 2011). We used this method because it has a simple interpretation:

- AUROC=0.5 means that the scores in the two groups are identical;
- AUROC=0 means that all scores in the tested group are smaller than the scores of the control group;
- AUROC=1 means that all scores in the tested group are larger than the scores of the control group.

All presented significant results have AUROC < 0.2 or > 0.8 meaning that the overlap between the scores in the two groups is less than 20%. In other words, in 80% of the cases a random score from one group exceeds a random score from the other group (Hentschke and Stüttgen, 2011). For the non-parametric 1-way ANOVA analysis (Kruskal-Wallis test) we computed post-hoc AUROC effect sizes of differences between the groups.

To visualize relationships between individual functional connectivity matrices we first quantified pairwise similarity between them by computing the Frobenius distance (Golub and Loan, 1996) for all pairs of matrices,

$$\|A - B\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^m (a_{ij} - b_{ij})^2}, \quad (1)$$

where a_{ij} and b_{ij} are the elements of matrices A and B. Next, we used classical multidimensional scaling to visualize relations captured by the similarity matrix (Borg and Groenen, 2005), using Matlab (Matlab) function `cmdscale`.

Statistical Table

[Table 2 around here]

Code Accessibility

Matlab scripts for the network analysis are available on request from the PS. The model is subject to copyright owned by the University of Exeter (international patent application WO/2017029505).

Results

335 Our goal is to characterise the evolution of large-scale functional brain networks during
336 epileptogenesis. Many measures exist to quantify functional connectivity (Wang et al.,
337 2014), each with different underlying assumptions. We begin with *no a priori* knowledge
338 regarding the way in which the evolving ictogenic mechanisms of the brain may be
339 reflected in functional connectivity. We therefore do not restrict our analysis to a
340 particular frequency band. Considering broadband signals, a natural way to quantify
341 functional connectivity is to study the correlation between signals. To avoid problems
342 associated with volume conduction, we use the cross-correlation function and exclude
343 correlations with maximum at zero lag (Christodoulakis et al., 2015). Focussing on
344 lagged correlations also gives a natural way to build directionality into the networks.
345 Additionally, the resulting correlations can be positive or negative and there are therefore
346 different ways to quantify strength of interactions in the derived functional network.
347 First, one can quantify the strength of the connection using the maximum of the absolute
348 value of the cross-correlogram (Schmidt et al., 2014). We refer to the networks estimated
349 with this method as C^{ABS} . Second, one can neglect negative values (see e.g. reasoning
350 presented in (Sinha et al., 2017)) and use only the values of C^{ABS} at which the cross-
351 correlogram >0 . We refer to networks estimated with this method as C^{MAX} . To analyse
352 the differences between C^{ABS} and C^{MAX} one can also examine the networks derived from
353 the values of C^{ABS} at which the cross-correlogram <0 . We refer to these networks as
354 C^{MIN} . In other words, one can decompose the connectivity matrices C^{ABS} into component
355 matrices C^{MAX} and C^{MIN} . See Materials and Methods for details of the reconstruction of
356 the connectivity matrices. In the following sections, we examine functional connectivity
357 through epileptogenesis using these three methods.

358

359 **Epileptogenesis changes properties of background functional connectivity networks**

360

361 [Figure 2 around here]

362

363 Figure 2 demonstrates the evolution of functional connectivity across the first 4 weeks of
364 epileptogenesis for the three types of networks introduced above. The functional
365 connectivity is described by connectivity matrices: each entry in a connectivity matrix
366 represents a statistical relationship (in this case the extremum of cross-correlogram that
367 occurred for non-zero lag) between EEG signals at two different electrodes. Therefore,
368 the connectivity matrix captures the correlation pattern of a multichannel EEG signal.

369

370 We quantified the differences between the connectivity matrices of individual animals
371 across three different time points (days 0, 7 and 28) by calculating the Frobenius distance
372 between them (see Materials and Methods for detailed description) (Borg and Groenen,
373 2005). Using these distances to visualize the similarity between the matrices reveals that
374 control (Day 0 and Sham) networks are different to post-injection networks (days 7 and
375 28), since they form a distinct cluster compared to matrices derived from recordings at
376 days 7 and 28 for each of the three measures (Fig. 2A, E, I). The clustering of points
377 corresponding to matrices derived from recordings before and after injection visible in
378 Fig. 2 A, E and I demonstrates that the kainic acid injection has a large and consistent
379 effect on the correlation patterns of the epicranial EEG. The clusters, however, do not
380 inform us about which components of the connectivity matrices have changed.

381

382 To study the data on the population level, we compute median correlation matrices for
383 each time point (median over entries c_{ij} of the connectivity matrices). Fig. 2 demonstrates
384 that the median correlation matrices appear to progress from an initially symmetric

385 arrangement at day 0, to asymmetric networks post-injection (days 7 and 28). It also
 386 shows that the C^{ABS} matrices are a composition of the C^{MAX} and C^{MIN} matrices and that
 387 the C^{MAX} and C^{MIN} matrices differ from each other. A characteristic feature of the C^{MAX}
 388 networks is that the connections between contralateral regions appear to be amongst the
 389 strongest connections (the top right and bottom left quadrants of the connectivity
 390 matrices in Fig. 2F-H). To quantify the redistribution of connections post-injection, we
 391 asked whether connections from each electrode to their contralateral equivalent (dark
 392 anti-diagonals of the quadrants) were among the strongest (i.e. in 5% of the strongest
 393 connections). For control networks, 38% of contralateral connections were among the
 394 strongest, whereas this percentage fell to 22% at days 7 and 28. This means that post-
 395 injection, the EEG between hemispheres becomes less synchronized. We note that this
 396 trend was also observed if we considered raw as opposed to normalised connectivity
 397 matrices. Such a decrease in synchronization has previously been shown for the
 398 hippocampi (Arabadzisz et al., 2005), but not for other brain regions. In contrast, for the
 399 C^{MIN} networks the strongest connections are ipsilateral, meaning that they represent
 400 connections within a hemisphere (top left and bottom right quadrants of the connectivity
 401 matrices in Fig. 2J-L).

402
 403 [Figure 3 around here]

404
 405 To quantify the breakdown of synchronization, we calculated the degree imbalance
 406 (outdegree-indegree) of nodes in the functional connectivity networks of individual
 407 animals. Degree imbalance is an aggregated measure that quantifies the strength of
 408 connectivity for each node. Statistically, if $\text{outdegree}_{\text{weighted}} > \text{indegree}_{\text{weighted}}$ the EEG
 409 signal recorded on a node temporally leads some of the other nodes and the node can be
 410 interpreted as a “source” of activity if not, the node lags other nodes on average and it
 411 can be considered a “sink” ($\text{outdegree}_{\text{weighted}} < \text{indegree}_{\text{weighted}}$).

412
 413 Interestingly, although network topologies are different for each of the three methods
 414 considered, the degree imbalance of the C^{ABS} , C^{MAX} and C^{MIN} networks are similar. Figure
 415 3A-C, E-G and I-K show the distribution of median degree imbalance across nodes. At
 416 day 0, the configuration is symmetric, with sinks (blue nodes in Fig. 3A, E and J)
 417 predominantly in anterior and posterior regions. The maximum absolute values of the
 418 degree imbalance at day 0 are approximately two times lower than at days 7 and 28. At
 419 day 7 the degree imbalance increases, with sources located at the left posterior and the
 420 right anterior regions. This pattern persists through to day 28. Interestingly, many of the
 421 nodes that became sources are located above the left hippocampus i.e. the site of initial
 422 intrahippocampal injection (Sheybani et al., 2018).

423
 424 Figure 3A-C, E-G and I-K show the network topology of the top 5% of the strongest
 425 connections of the median connectivity matrices presented in Fig. 2. These network
 426 corroborate our observations based on the connectivity matrices: C^{ABS} matrices are a
 427 composition of the C^{MAX} and C^{MIN} matrices; the strongest connections in the C^{MAX}
 428 matrices are contralateral and the strongest connections in C^{MIN} matrices are ipsilateral.
 429 Taken collectively, Fig. 2 and Fig. 3 describe changes in symmetry of the connectivity
 430 matrix and illustrate the large-scale breakdown of synchronization between right and left
 431 hemispheres that can be revealed from background EEG through epileptogenesis.

432
 433 In addition to analysing the degree imbalance of nodes, we analysed global properties of
 434 the functional connectivity networks; see Table 2 and Fig. 3D, H and L. For all three

435 types of network the same measures (Spectral norm, Variance of neighbour weighted
436 outdegree and Degree of asymmetry) were found to be significantly different on day 0
437 and days 7 and 28 (FDR<0.05, Kruskal-Wallis test with Benjamini-Hochberg FDR
438 correction for 19 tested network measures - chosen to capture in a non-redundant way the
439 most important topological and spectral properties of the networks); see Table 2 for all
440 the analysed measures. Values of these three measures increase over the time-course of
441 epileptogenesis; as an example, Fig. 3D, H and L illustrate increasing median of the
442 degree of asymmetry (Li and Zhang, 2012). These changes in local and global network
443 properties further indicate that the underlying functional connectivity pattern of
444 background activity becomes progressively more irregular and spatially heterogeneous
445 post injection.

446
447 [Table 2 around here]

448 449 **Epileptogenesis changes network dynamics**

450
451 [Figure 4 around here]

452
453 An important question is how these alterations to the pattern of functional connectivity
454 inferred from background EEG influence the ways that nodes contribute to the generation
455 of epileptiform dynamics. To make this mechanistic link, we studied a mathematical
456 model of spiking dynamics placed upon the nodes of networks derived from each animal
457 (see Material and Methods). To measure the contribution that each node in a network has
458 to the generation of epileptiform rhythms we use “Node Ictogenicity” (NI) introduced in
459 (Goodfellow et al., 2016) (see Material and Methods). Figure 4 shows the distribution of
460 NI at days 0, 7 and 28 for the three types of networks. At day zero, which we use as a
461 reference point, we see that the NI is distributed symmetrically through the network, but
462 with slightly elevated values in frontal regions. This means that, if the network was
463 ictogenic, nodes in frontal regions would contribute more to the generation of
464 epileptiform dynamics. At day 7, the C^{ABS} networks, shown in Fig. 4B, displays
465 significantly higher NI for multiple nodes in the left posterior and right anterior regions.
466 This pattern persists at day 28 (see Fig. 4C), though nodes with elevated NI are now
467 constrained to fewer regions. For the C^{MAX} networks, illustrated in Fig. 4E and F
468 significant increases in NI above baseline only occur at day 28. Finally, for the C^{MIN}
469 networks, NI increases significantly at a single node, the location of which changes
470 between days 7 and 28. On both days the node with significantly elevated NI resides
471 within the region shown to be affected by the TTX silencing, as identified from Fig. 12B
472 in (Sheybani et al., 2018). In the experiments described in (Sheybani et al., 2018) the
473 kainate injected hippocampus (left) was silenced using an intrahippocampal TTX
474 injection. After the TTX injection on day 7, interictal generalised spikes (GS) subsided.
475 The same procedure on day 28 did not affect the frequency of occurrence of GS.

476
477 Generalised spikes are interictal epileptic discharges recently reported to be a
478 predominant EEG marker of evolving abnormal dynamics during the latent as well as
479 chronic phase of the disease in the Kainic acid model (Sheybani et al., 2018). GS travel
480 across the whole epileptic network and have also been observed in humans (Aarts et al.,
481 1984; Mohamed et al., 2001; Moseley et al., 2012). In (Sheybani et al., 2018) it was
482 shown that the frequency of occurrence of GS increases during epileptogenesis and that
483 their occurrence is correlated with increased jerky movements. Furthermore, by day 28
484 GS no longer depend on the activity of the injected hippocampus, which was captured in

485 the TTX silencing experiment and evolution of the location of their onsets throughout
486 days 0 to 28, see Fig. 6E in (Sheybani et al., 2018). At day 7, GS originate predominantly
487 from the left and right posterior regions, which are covered by the increase in NI in left
488 posterior regions and also node 9 in the C^{ABS} networks. However, changes in NI are also
489 observed in anterior regions in our model results. At day 28, GS originate predominantly
490 from the right posterior regions, which is best captured by the evolution of NI in C^{MAX}
491 networks.

492 Discussion

493 Network analyses are increasingly being used in order to refine diagnosis, prognosis and
494 treatment for epilepsy (Schmidt et al., 2014; Englot et al., 2015; Niso et al., 2015;
495 Rummel et al., 2015; Tracy and Doucet, 2015; Goodfellow et al., 2016; Schmidt et al.,
496 2016; Smith and Schevon, 2016; Lopes et al., 2017, 2018). In humans, functional
497 connectivity derived from the background EEG are known to be altered in epilepsy. For
498 example (Englot et al., 2015) showed that patients with focal epilepsies (temporal and
499 neocortical) had decreased resting-state functional connectivity in multiple brain regions.
500 In addition, people with idiopathic generalized epilepsies, as well as their first-degree
501 relatives, have been shown to have elevated mean-degree and mean-degree variance of
502 background functional EEG networks (Chowdhury et al., 2014).

503
504 Here we have provided the first characterisation of how functional connectivity inferred
505 from background EEG evolves during epileptogenesis. During epileptogenesis,
506 functional connectivity networks that are initially regular and symmetric become
507 irregular and asymmetric. This corresponds to a loss of functional connectivity between
508 hemispheres, both in the normalised connectivity presented in Fig. 2 and if the raw
509 connectivity is considered. These changes observed using EEG are in line with previous
510 studies of fMRI functional connectivity derived in the tetanus toxin model (Otte et al.,
511 2012), and could be underpinned by changes in white matter tracts (Otte et al., 2012) or
512 changes to dynamics within localized brain regions. However, it differs from the analysis
513 of the fMRI-derived functional connectivity in the systemic kainic acid model of TLE
514 which displayed stronger connections in comparison with control animals (Gill et al.,
515 2017). Potential reasons for these discrepancies include the intraperitoneal administration
516 of kainic acid used in (Gill et al., 2017) causing more widespread changes in the brain
517 tissue than intrahippocampal administration. Furthermore, functional networks reported
518 in (Gill et al., 2017) were estimated using long duration recordings (tens of minutes vs
519 seconds in our study) from anesthetized animals (awake head fixed animals in the current
520 study). Additionally, neither of these previous studies addressed the process of
521 epileptogenesis through repeated observations within the same animal.

522
523 To relate our findings of altered functional connectivity to the generation of epileptiform
524 activity, we used a mathematical model. The model allowed us to define the relative
525 contribution of nodes to the generation of epileptiform dynamics. Our model showed that
526 the set of nodes that are important for epileptiform dynamics evolves over 4 weeks of
527 epileptogenesis. Two of the three different methods we used to compute functional
528 connectivity network revealed nodes outside of the injected hippocampus that were
529 important contributors to epileptiform dynamics. Specifically, significant changes in the
530 NI distribution of the C^{MIN} connectivity networks (at which the cross-correlogram <0)
531 capture the increase of NI over the injected hippocampus, which occurs 7 days after the
532 injection and persist through to day 28. In contrast, the C^{MAX} connectivity networks (at
533

534 which the cross-correlogram >0) reveal changes in the distribution of NI only at day 28,
535 involving multiple nodes that are located outside the injected hippocampus.

536
537 We hypothesise that, C^{MIN} and C^{MAX} networks reflect two mechanisms that generate GS.
538 The first mechanism is local and related to the initial insult (the injected hippocampus),
539 whereas the other mechanism is distributed and is a consequence of network remodeling.
540 Importantly, Fig. 4D-F show that the second mechanism emerges at a time subsequent to
541 the initial insult. This interpretation is consistent with the results of (Sheybani et al.,
542 2018) in which pharmacological silencing of the injected hippocampus at day 7 stopped
543 GS, whereas it had no effect when performed at day 28. This suggests the evolving
544 importance of a distributed network throughout epileptogenesis. In other words, results
545 of the modelling suggest that the injected hippocampus is driving the epileptiform
546 activity at day 7, whereas at day 28 the activity is driven by both the injected
547 hippocampus as well as the wider network.

548
549 Additionally, we note that changes in NI across individual nodes are directly interpretable
550 in terms of generation of the GS and the results of the silencing experiments, while
551 typical graph theory measures (e.g. degree imbalance or degree asymmetry) do not allow
552 such direct interpretation. This observation provides further support for the use of
553 mathematical models to uncover regions of the brain that are important for generating
554 abnormal dynamics and to aid the interpretation of experimental and clinical data
555 (Goodfellow et al., 2016; Schmidt et al., 2016; Bartolomei et al., 2017; Hebbink et al.,
556 2017; Lopes et al., 2017; Melozzi et al., 2017; Proix et al., 2017; Lopes et al., 2018). A
557 natural next step would be to model the process of epileptogenesis itself to better
558 understand why these changes occur, and why they occur in specific brain regions.
559 Insights into spatial and temporal evolution of epileptogenesis could help to develop new
560 treatments (Dichter, 2009; Lowenstein, 2009; Löscher and Brandt, 2010; Lopes Da Silva
561 et al., 2012; Goldberg and Coulter, 2013; Löscher et al., 2015) and uncover reasons for
562 seizure recurrence after epilepsy surgery (Mathon et al., 2017).

563
564 We express caution in relating observations made in this study to human epilepsy, as we
565 expect mouse epicranial EEG contains contributions from brain structures that are
566 subcortical in humans (e.g. hippocampus) and therefore would contribute less to the
567 background human EEG (Gotman, 2008; Lam et al., 2017). The recordings analysed
568 herein are perhaps more analogous to ECoG or depth electrode recordings in humans. In
569 this scenario, the approach of modelling activity recorded from invasive electrodes has
570 shown promise in predicting the outcome of surgery in people with diverse “focal”
571 epilepsies (Goodfellow et al., 2017; Lopes et al., 2017; Sinha et al., 2017; Lopes et al.,
572 2018). Our study advances our understanding of such approaches and demonstrates a
573 framework that allows for their experimental validation.

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735 **Legends**

736

737

738 **Figure 1. Criteria for excluding recordings from analysis.** Number of segments selected in a
 739 recording vs number of non-zero elements in the average adjacency matrix estimated from all the
 740 segments in the recording. Each dot represents a single recording. Recordings represented by the
 741 encircled dots were excluded from the analysis. **A**, matrices estimated using C^{ABS} ; **B**, matrices
 742 estimated using C^{MAX} ; **C**, matrices estimated using C^{MIN} . All the method produced average
 743 adjacency matrices with similar number of non-zero elements.

743

744

745 **Figure 2. Analysis of background functional connectivity reveals changes over the time**
 746 **course of epileptogenesis.** **A, E and I** Individual connectivity matrices represented as dots in the
 747 first two principal dimensions of the multidimensional scaling of Frobenius distances between
 748 the individual connectivity matrices. Each dot represents a single matrix (green – day 0; yellow –
 749 day 7; red – day 28; grey – Sham control; empty symbols: circle, diamond and square represent
 750 the median of the connectivity matrices). The first three principal MDS dimensions represent
 751 around 70% of the relations encoded in the raw Frobenius distances ($R^2_{ABS}=0.66$, $R^2_{MAX}=0.72$,
 752 $R^2_{MIN}=0.7$, R is Pearson's correlation coefficient between the Frobenius distances in the matrix
 753 space and the Euclidian distances in the reconstructed space); for clarity only the first two
 754 coordinates are plotted. **B-D, F-H, J-L**, Median functional connectivity matrices (indicated with
 755 empty symbols in panels **A, E and I**) resulting from the three different measures at different days
 756 with color-coded connection weights (Day 0 over 11 matrices, Day 7 over 6 matrices, Day 28
 757 over 8 matrices; different numbers of matrices for individual days due to quality of recordings,
 758 see Materials and Methods for details).

758

759

760 **Figure 3. Illustration of changes of network properties over the time-course of**
 761 **epileptogenesis.** **A-C, E-G, I-K**, Median degree imbalance at individual nodes; blue indicates
 762 indegree>outdegree, red indicates indegree<outdegree. Value of the degree imbalance is colour
 763 and size coded, larger and darker dots indicate higher degree imbalance. Dots filled in black have
 764 a median that is significantly different than the median on day 0 (FDR<0.1, two-sided Wilcoxon-
 765 Mann-Whitney test with Benjamini-Hochberg correction for 30 nodes, effect size AUROC<0.2
 766 for blue nodes or >0.8 for red nodes; exact p-values and effect sizes are presented in Extended
 767 data Figure 3-1). Grey arrows show topology of functional connectivity networks on different
 768 days illustrated using the strongest 5% of connections of the median connectivity matrices shown
 769 in Figure 2. **D, H and L**, boxplots showing the degree imbalance of the individual connectivity
 770 matrices.

770

771

772 **Figure 4. Illustration of changes in spatial distribution of node ictogenicity.** **A-C, D-F, G-I**
 773 Mean values of NI. Grey arrows are the strongest 5% of connections of the median networks.
 774 Value of the NI is colour and size coded, larger and darker dots indicate higher NI. Dots filled in
 775 black have significantly higher median NI than the median on day 0 (FDR<0.1 one-sided
 776 Wilcoxon-Mann-Whitney test with Benjamini-Hochberg FDR correction for 30 nodes, effect
 777 size AUROC>0.8; exact p-values and effect sizes are presented in Extended data Figure 4-1).
 778 Shaded region in panel **H and I** shows nodes affected by the TTX silencing; identified from Fig.
 779 22B (Sheybani et al., 2018).

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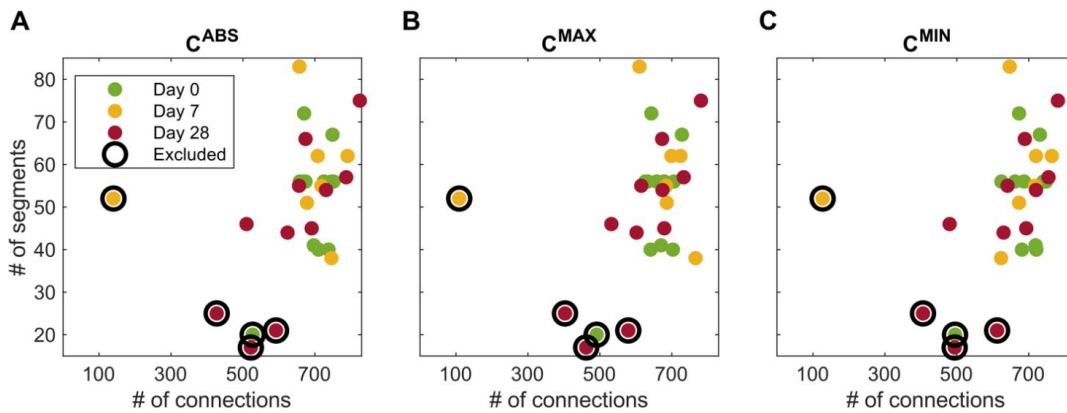
781 **Table 1. Statistical table matrix.** Columns are: part of the results section, the structure of the
 782 data, statistical test, description of the significance levels.

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784 **Table 2. Statistical analysis of network properties for the three kinds of connectivity**
matrices. Table contains values of the Benjamini-Hochberg FDR for the Kruskal-Wallis test for

785 comparison of medians of measures on Day 0, Day 7 and Day 28. In brackets post-hoc effect
786 sizes quantified with AUROC: (Day 0 vs Day 7; Day 0 vs Day 28). In bold values with FDR<0.1
787 and AUROC<0.2 or AUROC>0.8.



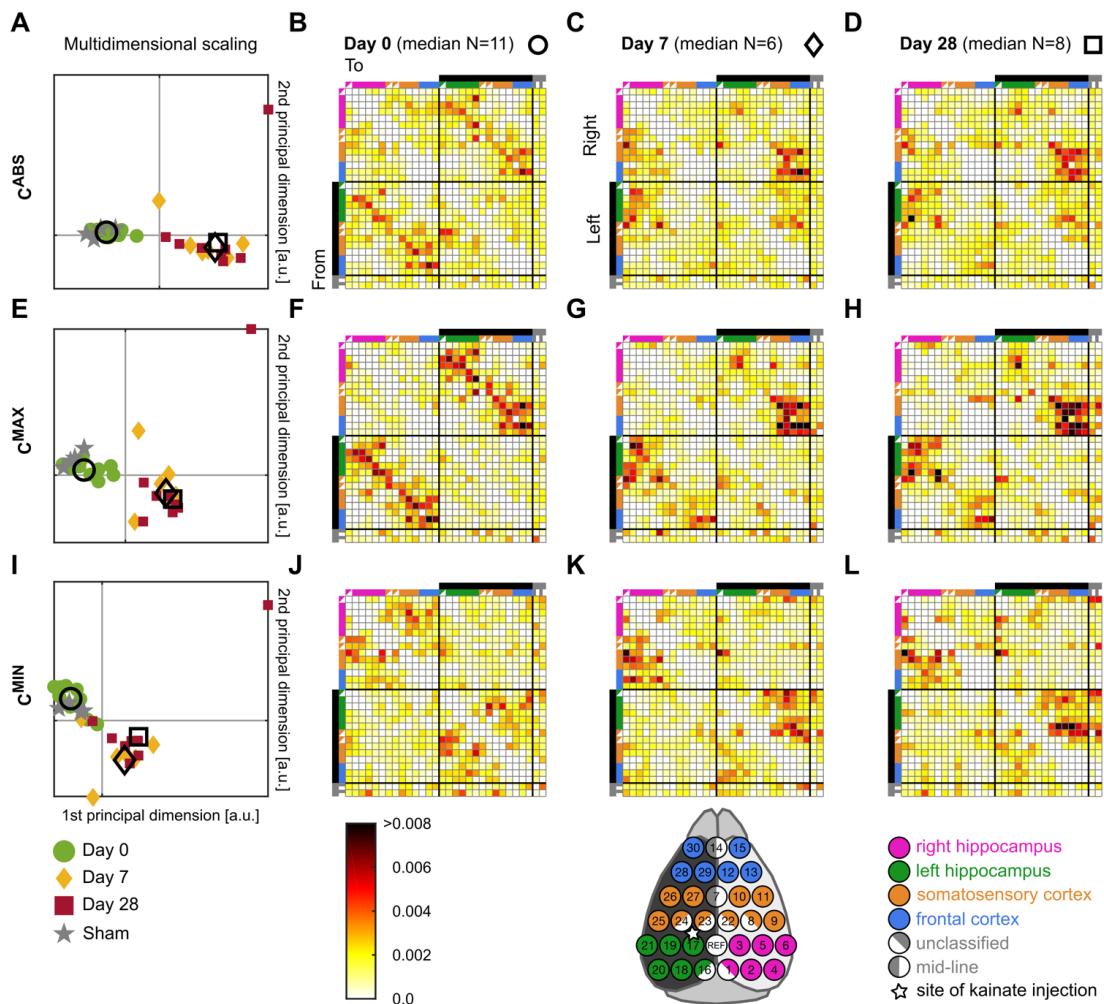
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790 **Figure 1. Criteria for excluding recordings from analysis.** Number of segments selected in a
 791 recording vs number of non-zero elements in the average adjacency matrix estimated from all the
 792 segments in the recording. Each dot represents a single recording. Recordings represented by the
 793 encircled dots were excluded from the analysis. **A**, matrices estimated using C^{ABS} ; **B**, matrices
 794 estimated using C^{MAX} ; **C**, matrices estimated using C^{MIN} . All the method produced average
 795 adjacency matrices with similar number of non-zero elements.

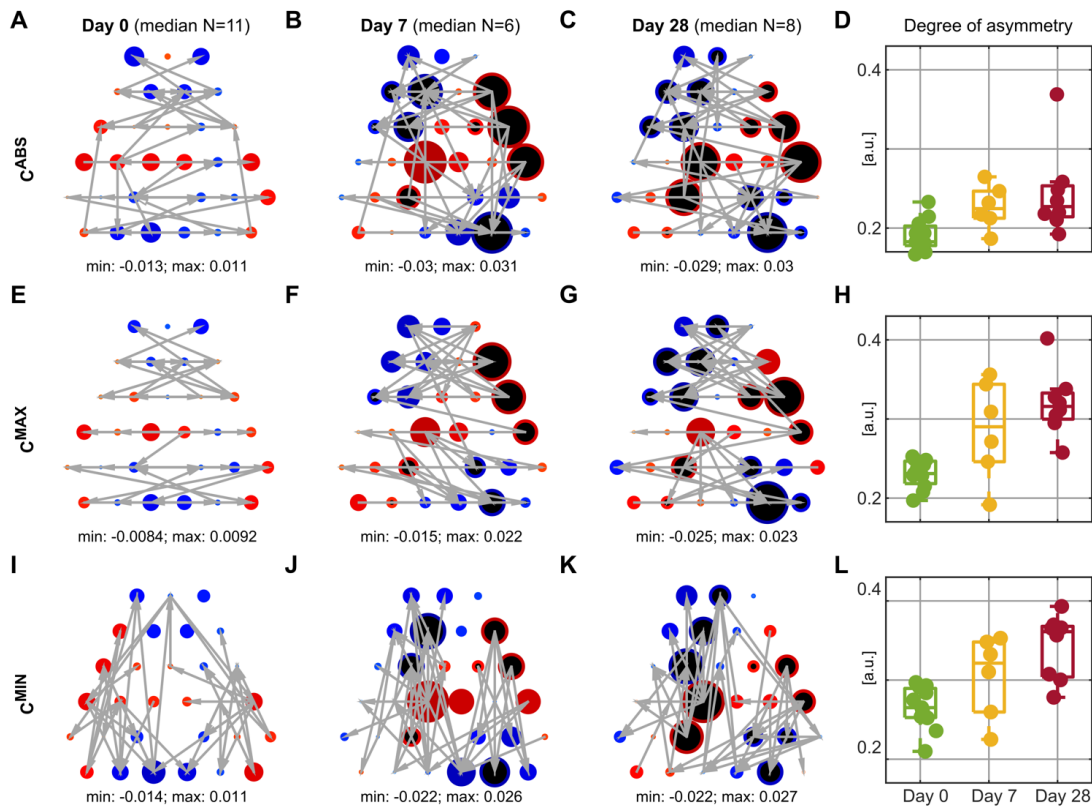
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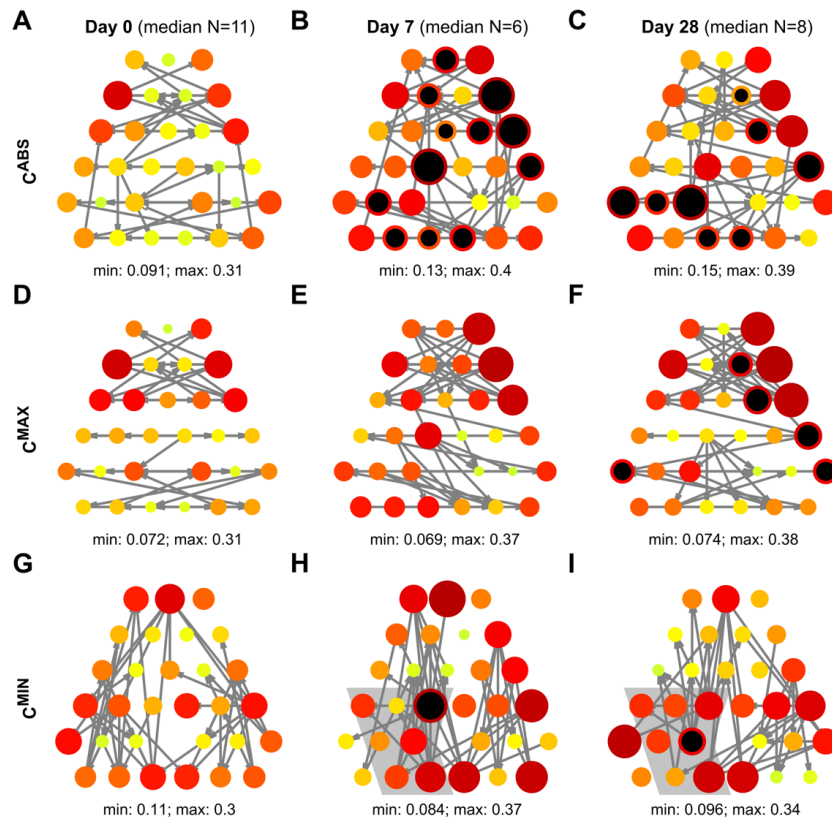
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Figure 2. Analysis of background functional connectivity reveals changes over the time course of epileptogenesis. **A, E and I** Individual connectivity matrices represented as dots in the first two principal dimensions of the multidimensional scaling of Frobenius distances between the individual connectivity matrices. Each dot represents a single matrix (green – day 0; yellow – day 7; red – day 28; grey – Sham control; empty symbols: circle, diamond and square represent the median of the connectivity matrices). The first three principal MDS dimensions represent around 70% of the relations encoded in the raw Frobenius distances ($R^2_{ABS}=0.66$, $R^2_{MAX}=0.72$, $R^2_{MIN}=0.7$, R is Pearson’s correlation coefficient between the Frobenius distances in the matrix space and the Euclidian distances in the reconstructed space); for clarity only the first two coordinates are plotted. **B-D, F-H, J-L**, Median functional connectivity matrices (indicated with empty symbols in panels **A, E and I**) resulting from the three different measures at different days with color-coded connection weights (Day 0 over 11 matrices, Day 7 over 6 matrices, Day 28 over 8 matrices; different numbers of matrices for individual days due to quality of recordings, see Materials and Methods for details).



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Figure 3. Illustration of changes of network properties over the time-course of epileptogenesis. A-C, E-G, I-K, Median degree imbalance at individual nodes; blue indicates $\text{indegree} > \text{outdegree}$, red indicates $\text{indegree} < \text{outdegree}$. Value of the degree imbalance is colour and size coded, larger and darker dots indicate higher degree imbalance. Dots filled in black have a median that is significantly different than the median on day 0 (FDR < 0.1, two-sided Wilcoxon-Mann-Whitney test with Benjamini-Hochberg correction for 30 nodes, effect size AUROC < 0.2 for blue nodes or > 0.8 for red nodes; exact p-values and effect sizes are presented in Extended data Figure 3-1). Grey arrows show topology of functional connectivity networks on different days illustrated using the strongest 5% of connections of the median connectivity matrices shown in Figure 2. D, H and L, boxplots showing the degree imbalance of the individual connectivity matrices.



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Figure 4. Illustration of changes in spatial distribution of node ictogenicity. A-C, D-F, G-I
Mean values of NI. Grey arrows are the strongest 5% of connections of the median networks.
Value of the NI is colour and size coded, larger and darker dots indicate higher NI. Dots filled in
black have significantly higher median NI than the median on day 0 (FDR<0.1 one-sided
Wilcoxon-Mann-Whitney test with Benjamini-Hochberg FDR correction for 30 nodes, effect
size AUROC>0.8; exact p-values and effect sizes are presented in Extended data Figure 4-1).
Shaded region in panel **H** and **I** shows nodes affected by the TTX silencing; identified from Fig.
22B (Sheybani et al., 2018).

838 **Table 1. Statistical table matrix.** Columns are: part of the results section, the structure of the
 839 data, statistical test, description of the significance levels.
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RESULTS	DATA STRUCTURE	STATISTICAL TEST	POWER OR CONFIDENCE INTERVALS
Figure 3. A-C, E-G, I-K	No assumptions about the distributions of the degree imbalance on each of the three days.	Two-sided Wilcoxon-Mann-Whitney test with Benjamini-Hochberg multiple comparison/ false discovery ratio (FDR) correction for 30 nodes. Separate comparison for: Day 0 vs. Day 7 and Day 0 and Day 28. We use two-sided test because we expect to see increase and decrease of degree imbalance.	Panel B: FDR ≤ 0.08 , AUROC < 0.2 or AUROC > 0.8 ; Panel C: FDR ≤ 0.08 , AUROC < 0.2 or AUROC > 0.8 ; Panel D: FDR ≤ 0.1 , AUROC < 0.2 or AUROC > 0.8 ; Panel E: FDR ≤ 0.07 , AUROC < 0.2 or AUROC > 0.8 ; Panel G: FDR ≤ 0.07 , AUROC < 0.2 or AUROC > 0.9 ; Panel H: FDR ≤ 0.07 , AUROC < 0.2 or AUROC > 0.9 ; See Extended data Figure 3-1 for values.
Figure 3. D, H and L and Table 2.	No assumptions about the distributions of the network measures.	The Kruskal-Wallis test (non-parametric ANOVA) with Benjamini-Hochberg multiple comparison/ false discovery ratio (FDR) correction for 20 analysed measures.	FDR and AUROC values are reported in the Table 2
Figure 4.	No assumptions about the distributions of the node ictogenicity on each of the three days.	One-sided Wilcoxon-Mann-Whitney test with Benjamini-Hochberg multiple comparison/ false discovery ratio (FDR) correction for 30 nodes. Separate comparison for: Day 0 vs. Day 7 and Day 0 and Day 28. We use one-sided test because only test increase of node ictogenicity.	Panel B: FDR ≤ 0.1 , AUROC > 0.8 ; Panel C: FDR ≤ 0.09 , AUROC > 0.8 ; Panel E: FDR ≤ 0.08 , AUROC > 0.8 ; Panel G: FDR ≤ 0.02 , AUROC = 1; Panel H: FDR ≤ 0.01 , AUROC < 0.9 . See Extended data Figure 4-1 for values.

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Table 2. Statistical analysis of network properties for the three kinds of connectivity matrices. Table contains values of the Benjamini-Hochberg FDR for the Kruskal-Wallis test for comparison of medians of measures on Day 0, Day 7 and Day 28. In brackets post-hoc effect sizes quantified with AUROC: (Day 0 vs Day 7; Day 0 vs Day 28). In bold values with FDR<0.1 and AUROC<0.2 or AUROC>0.8.

NAME OF THE NETWORK PROPERTY	C^{ABS}	C^{MAX}	C^{MIN}
Mean weighted outdegree	0.69	0.83	0.5
Variance of weighted outdegree	0.055 (0.23; 0.13)	0.035 (0.17 ; 0.13)	0.12
Spectral norm	0.0099 (0 ; 0.091)	0.0083 (0.061 ; 0.046)	0.026 (0.11 ; 0.13)
Frobenius norm	0.42	0.47	0.27
Mean neighbour weighted outdegree	0.21	0.24	0.4
Variance of neighbour weighted outdegree	0.0099 (0.03 ; 0.079)	0.0131 (0.076 ; 0.1)	0.0233 (0.71 ; 0.89)
Mean betweenness	0.20	0.75	0.66
Variance of betweenness	0.098 (0.12 ; 0.48)	0.44	0.3
Mean pagerank	0.4	0.96	0.58
Variance of pagerank	0.17	0.47	0.27
Mean length of the shortest path between two nodes	0.29	0.47	0.4
Variance of length of the shortest paths	0.17	0.8	0.4
Mean harmonic closeness centrality	0.29	0.47	0.4
Variance of harmonic closeness centrality	0.068 (0.91 ; 0.62)	0.2	0.5
Assortative mixing (Pearson's total weighted degree correlation)	0.17	0.66	0.058
S-metric - sum of the product of nodal degrees across edges	0.81	0.5	0.78
Degree of asymmetry – largest eigenvalue of the skew-symmetric part of the Laplacian of a directed graph (Li and Zhang, 2012).	0.026 (0.14 ; 0.1)	0.011 (0.21; 0)	0.026 (0.26; 0.045)
Mean spectrum – mean of eigenvalues of symmetric part of the Laplacian matrix of the directed graph (Li and Zhang, 2012).	0.74	0.8	0.14
Variance of spectrum – variance of eigenvalues of symmetric part of the Laplacian matrix of the directed graph (Li and Zhang, 2012).	0.4	0.25	0.88
Maximum of spectrum – largest eigenvalue of symmetric part of the Laplacian matrix of the directed graph (Li and Zhang, 2012).	0.17	0.25	0.76

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857 **Extended data**

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861 **Figure 3-1. Detailed illustration of changes in spatial distribution of degree imbalance (DI).**

862 **A-C** Boxplots of distributions of DI values on each node on Day 0 (green), Day 7 (yellow) and
863 Day 28 (Red). Shaded yellow bar indicates significant difference between Day 0 and Day 7.

864 Shaded red bar indicates significant difference between Day 0 and Day 28. Text labels are: first

865 row FDR, second row (AUROC) for comparison of Day 0 and Day 28; third row FDR and

866 fourth row (AUROC) for comparison of Day 0 and Day 7. Two-sided Wilcoxon-Mann-Whitney

867 test with Benjamini-Hochberg FDR correction for 30 nodes, effect size measured as AUROC.

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871 **Figure 4-1. Detailed illustration of changes in spatial distribution of node ictogenicity (NI).**

872 **A-C** Boxplots of distributions of NI values on each node on Day 0 (green), Day 7 (yellow) and

873 Day 28 (Red). Shaded yellow bar indicates significant difference between Day 0 and Day 7.

874 Shaded red bar indicates significant difference between Day 0 and Day 28. Text labels are: first

875 row FDR, second row (AUROC) for comparison of Day 0 and Day 28; third row FDR and

876 fourth row (AUROC) for comparison of Day 0 and Day 7. One-sided Wilcoxon-Mann-Whitney

877 test with Benjamini-Hochberg FDR correction for 30 nodes, effect size measured as AUROC.

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