

# Interneurons in a two population grid cell network

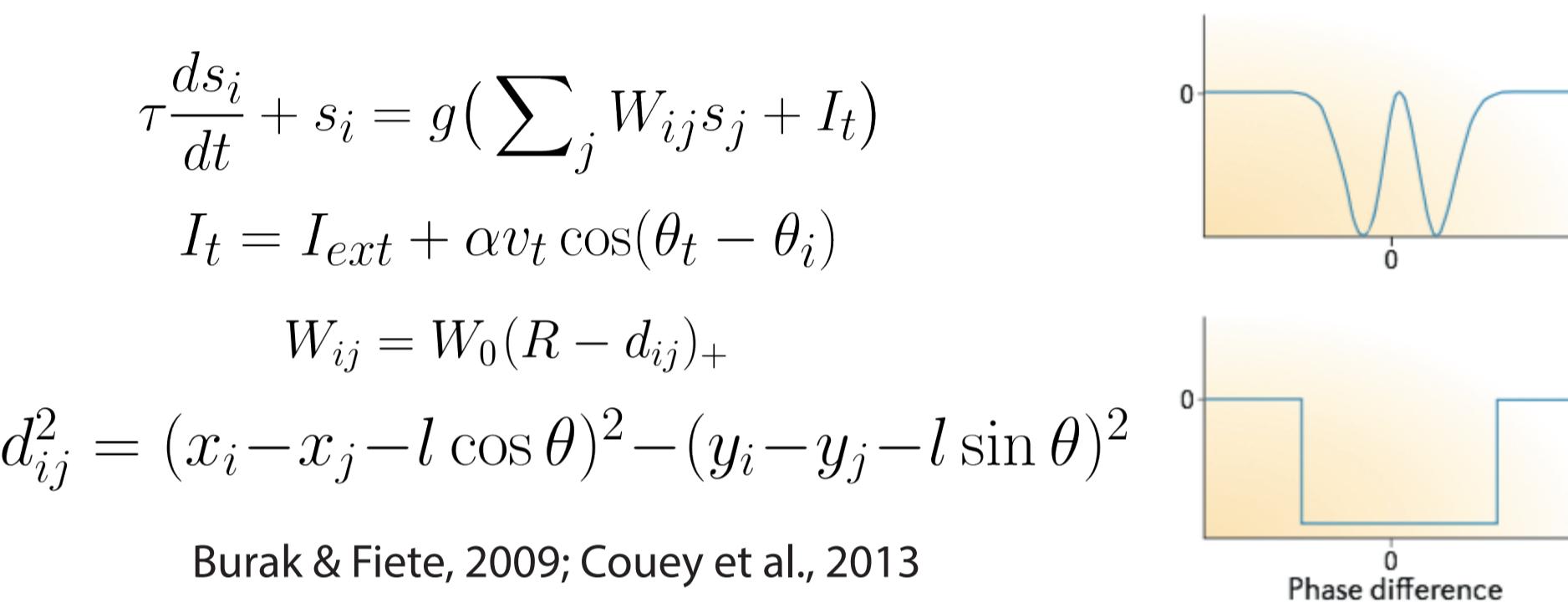
Ziwei Huang, Trygve Solstad, Benjamin Dunn

Kavli Institute for Systems Neuroscience and Centre for Neural Computation, NTNU, Trondheim, Norway

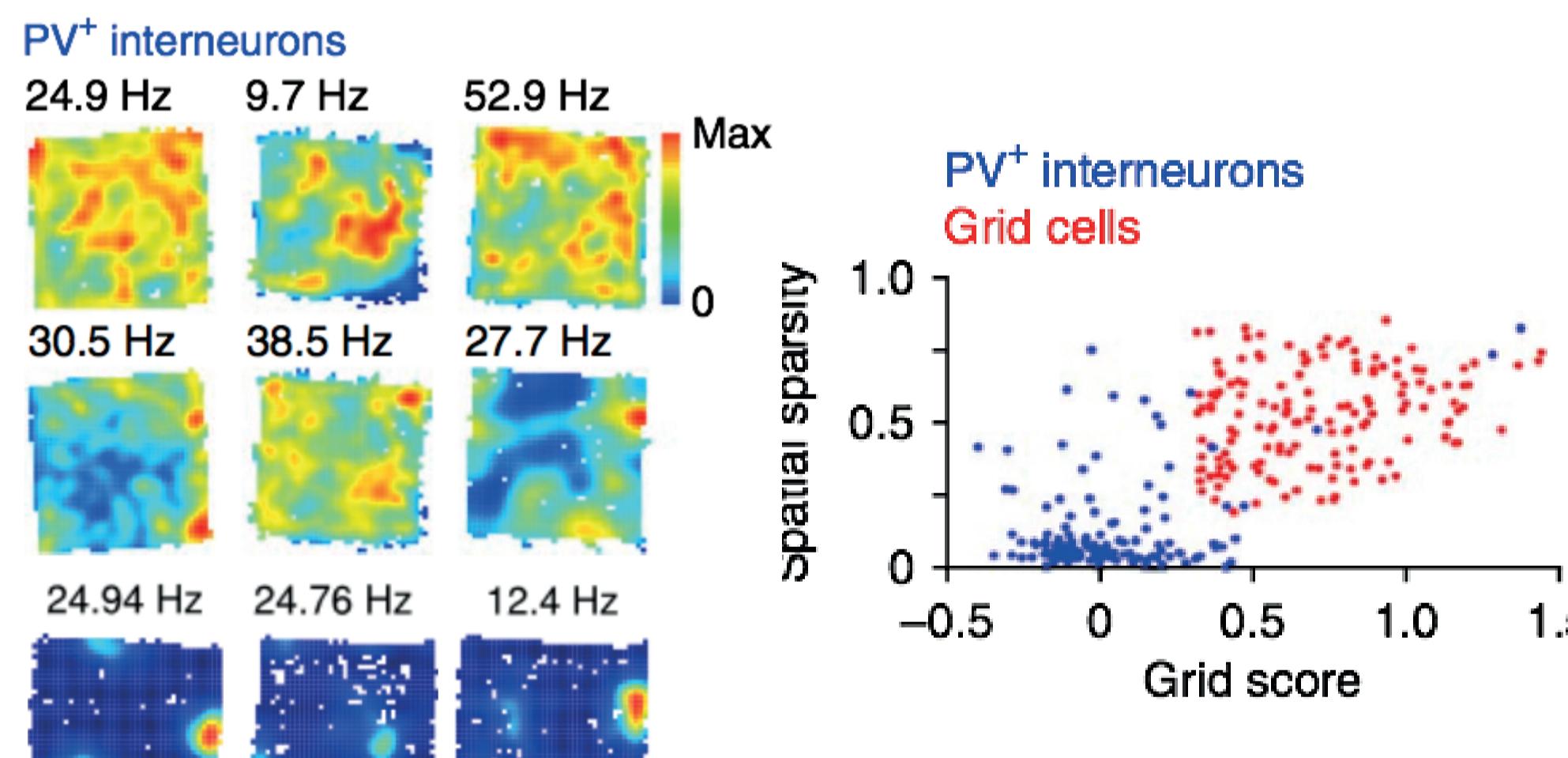
## 1. Introduction

The hexagonal firing pattern of entorhinal grid cells could arise from a competitive mechanism mediated by interneurons (Burak & Fiete, 2009; Couey et al., 2013; Pastoll et al., 2013).

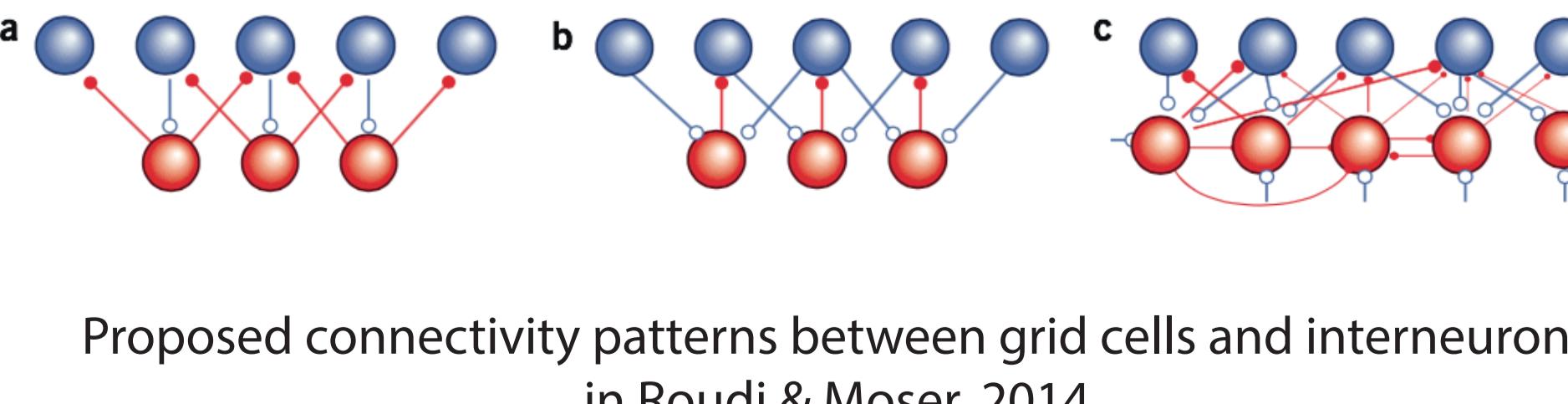
### Effective Inhibition Model



In the simplest realization of a two population model, with one-to-one correspondence between interneurons and grid cells, the interneurons would show grid-like or anti-grid firing patterns. Recent experimental data (Buetfering et al., 2014) showed otherwise: local PV<sup>+</sup> interneurons having aperiodic firing patterns.



Here we asked if two-population continuous attractor model could maintain grid cell firing even if interneurons (a) comprise less than 20% of the neural population and (b) lack spatial periodicity within the same module.



## 2. Model

Two Population Model using Non-negative Matrix Factorization (NMF, Lee & Seung, 2001)

$$\tau \frac{ds_i}{dt} + s_i = g \left( \sum_j J_{ij} u_j + I_t \right)_+$$

$$\tau \frac{du_i}{dt} + u_i = g \left( \sum_j K_{ij} s_j \right)_+$$

$$W \approx JK$$

$$K_{a\mu} \leftarrow K_{a\mu} \frac{(J^T W)_{a\mu}}{(J^T JK)_{a\mu}}$$

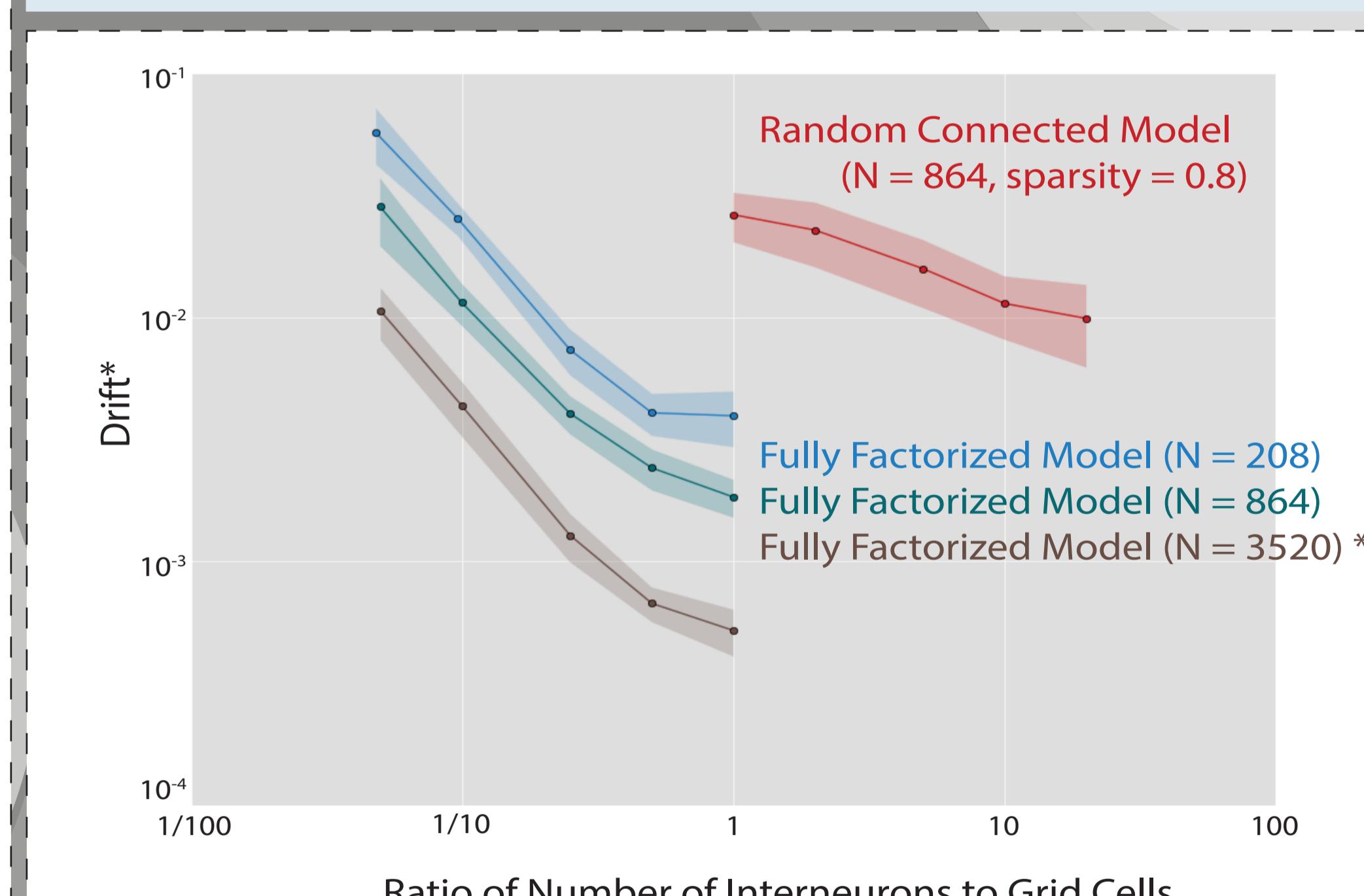
$$J_{ia} \leftarrow J_{ia} \frac{(WK^T)_{ia}}{(JKK^T)_{ia}}$$

We assume two simple cases based on different usages of non-negative matrix factorization:

(1) Random Connected Model: The connections from grid cells to interneurons ( $K$ ) are set to random values with a given sparsity, then the backprojections ( $J$ ) are “learned” by solving NMF for the effective inhibition matrix ( $W$ )

(2) Fully Factorized Model: All connections (both  $J$  and  $K$ ) between grid cells and interneurons are “learned” from random initial conditions by the NMF algorithm.

## 3. Drift

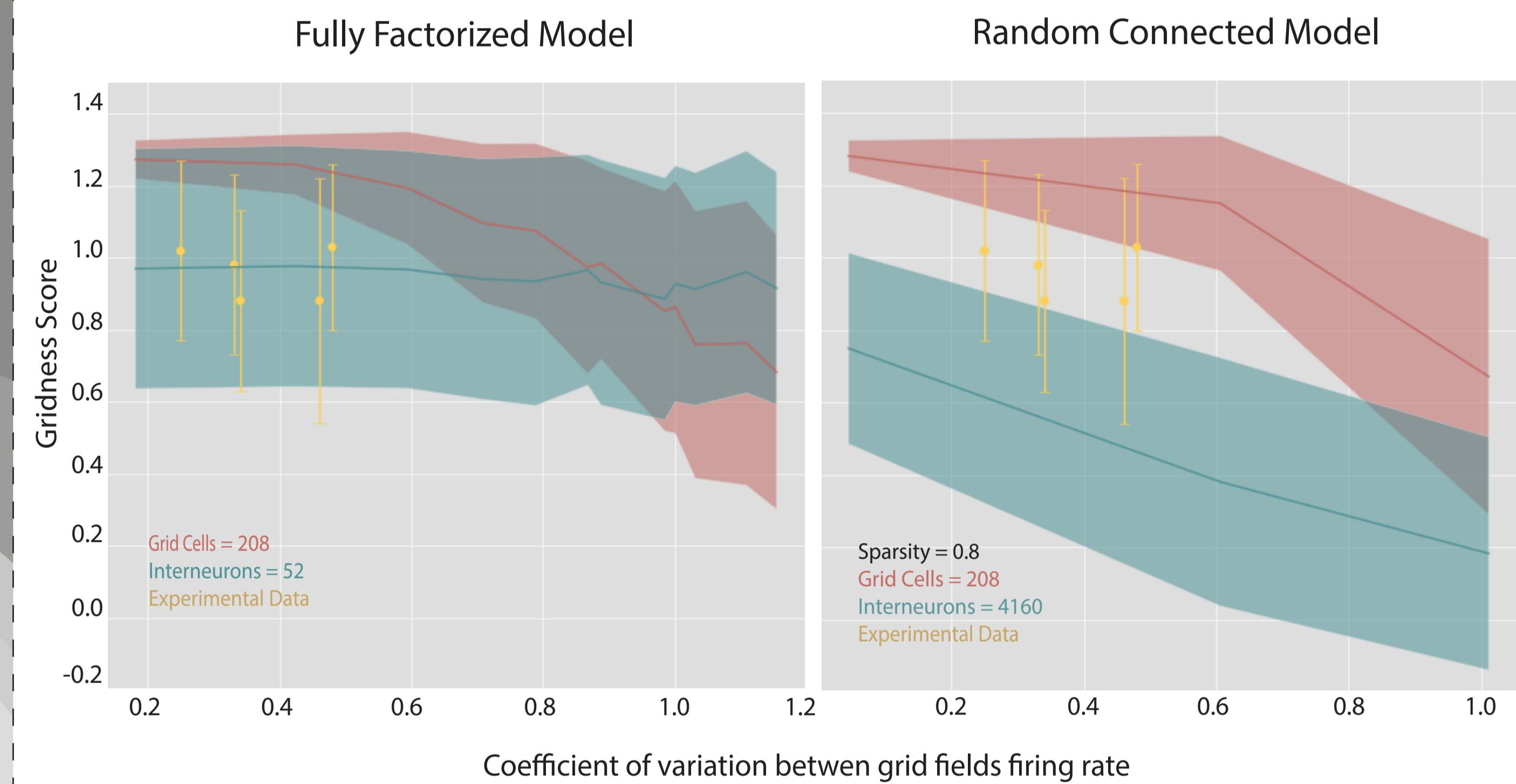


Drift in the models drops exponentially in the fully factorized model as the ratio of number of interneurons to grid cells and the size of networks is increased. In the random connected model, drift decreased linearly but required more interneurons to reach the same level of drift.

\* Drift in the network was measured by the average distance (over 200 repeats) that the activity on the neural sheet shifted during 100 time steps, starting from a random initial position.

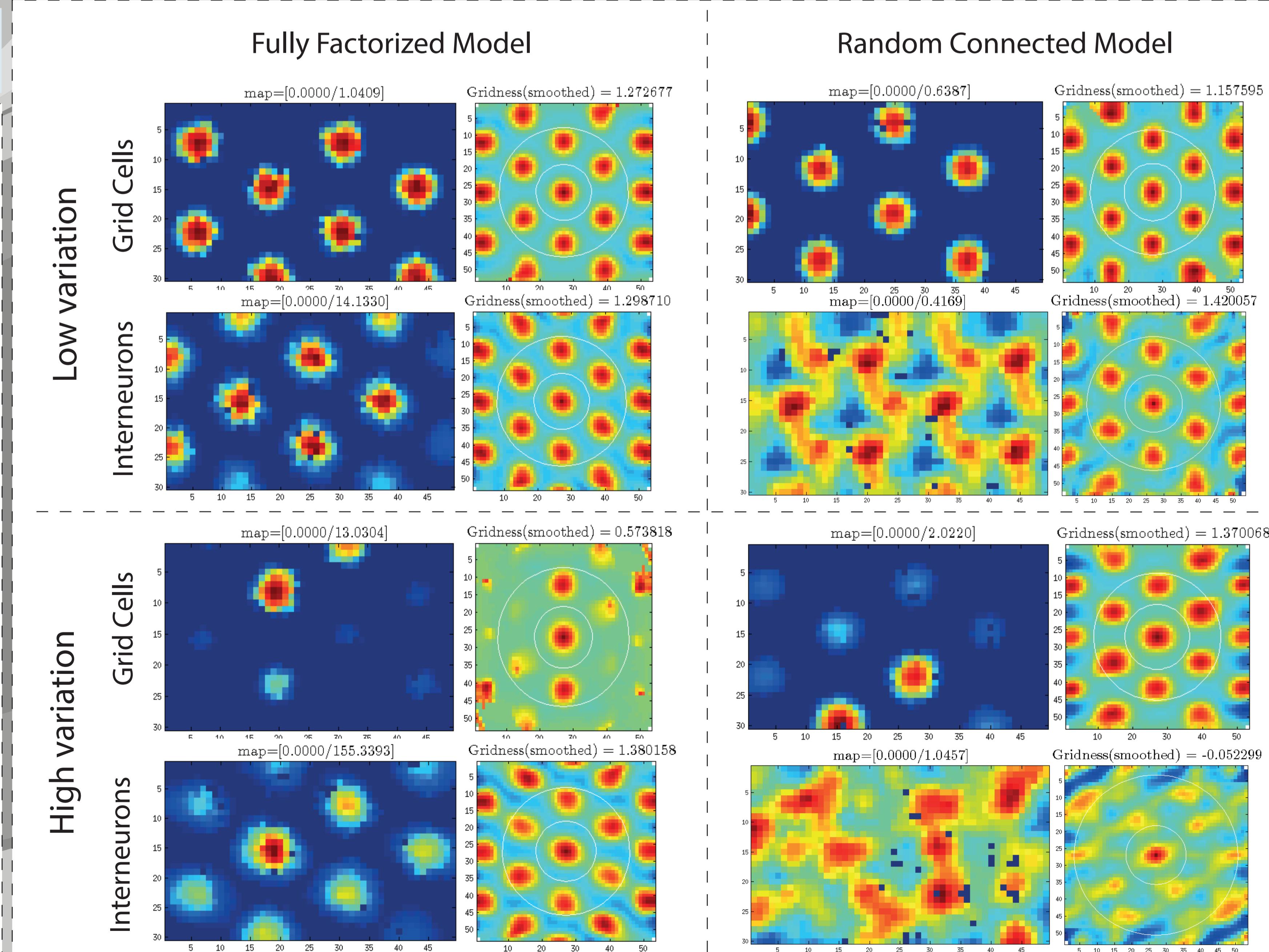
\*\* In a network with 3520 grid cells, 200 interneurons (around 6% of total neuron population) is enough to path integrate accurately.

## 4. Gridness score and grid field variation



Variation between grid fields in this simulation was implemented by varying the external input. Experimental data from grid cells recorded in Stensola et al. 2012.

## 5. Rate maps and autocorrelograms of selective grid cells and interneurons



1. The results suggest that the firing pattern of interneurons within a single module of a continuous attractor grid network can be aperiodic, though it requires a larger proportion of interneurons to grid cells.

2. Well-structured connectivity between grid cells and interneurons from non-negative matrix factorization leads to a grid cell network with a relatively small amount of interneurons. Simulations suggest that interneurons comprising less than 10% of the neuronal population are enough to accurately path integrate. Interneurons in this model have grid or anti-grid firing pattern.