

Analysis of time series data measured with wearable devices

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Slides, Python code and demo files at:
<https://shorturl.at/hDps9>

Other useful resources:

pyBOAT - Wavelet analysis
<https://github.com/tensionhead/pyBOAT>

CosinorPy - Rhythmometry analysis
<https://github.com/mmoskon/CosinorPy>



UNIVERSITY OF
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Centre for
Systems
Modelling
& Quantitative
Biomedicine

Menu

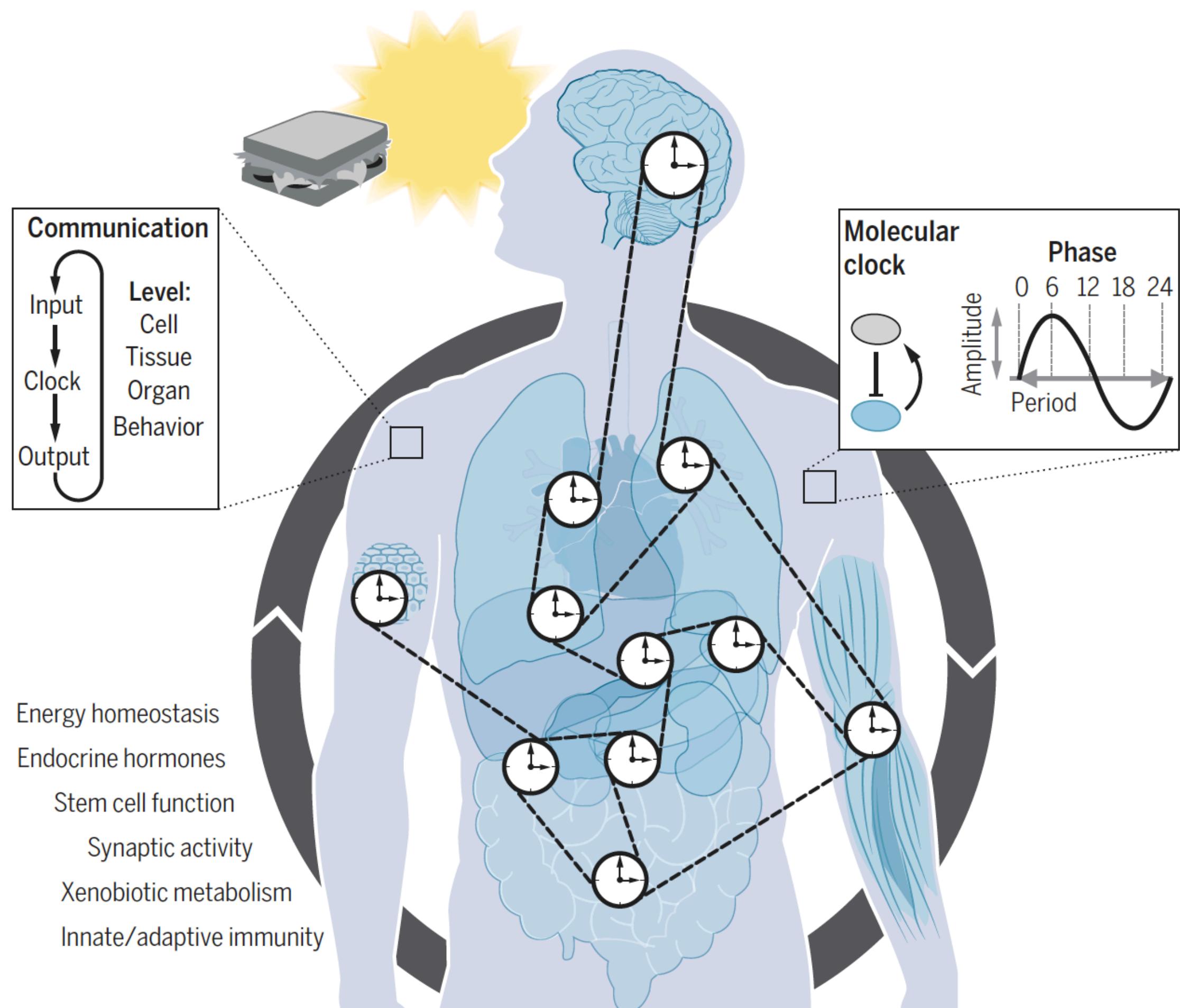
Why do we need to analyse time series data from wearables?

- **Characterise body rhythms.** Quantitatively, at multiple time scales (not just circadian), and at adequate time resolutions.
- **Quantifying variability.** Endogenous, behavioural, environmental. Inter- vs intra-individual.
- **Understanding the effects of chrono-disruptions.** Quantifying fast dynamic responses to perturbations and slow transitions to diseased states.

How do we analyse time series data from wearables?

A dynamical systems view of physiology

Sustaining healthy homeostasis requires
the coordination of body rhythms

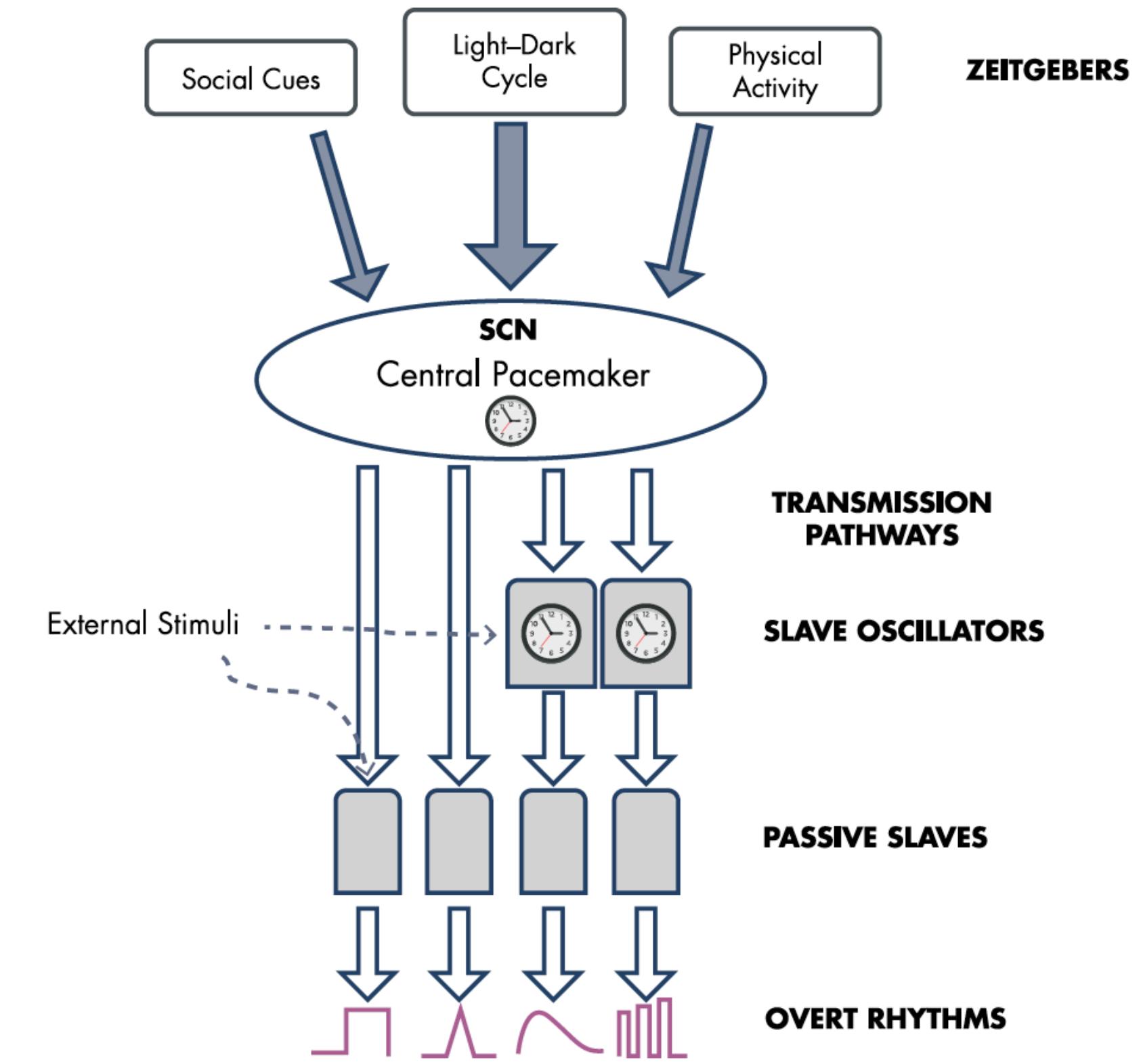


*Chrono*disruption
*Chrono*diagnosis
*Chrono*therapy

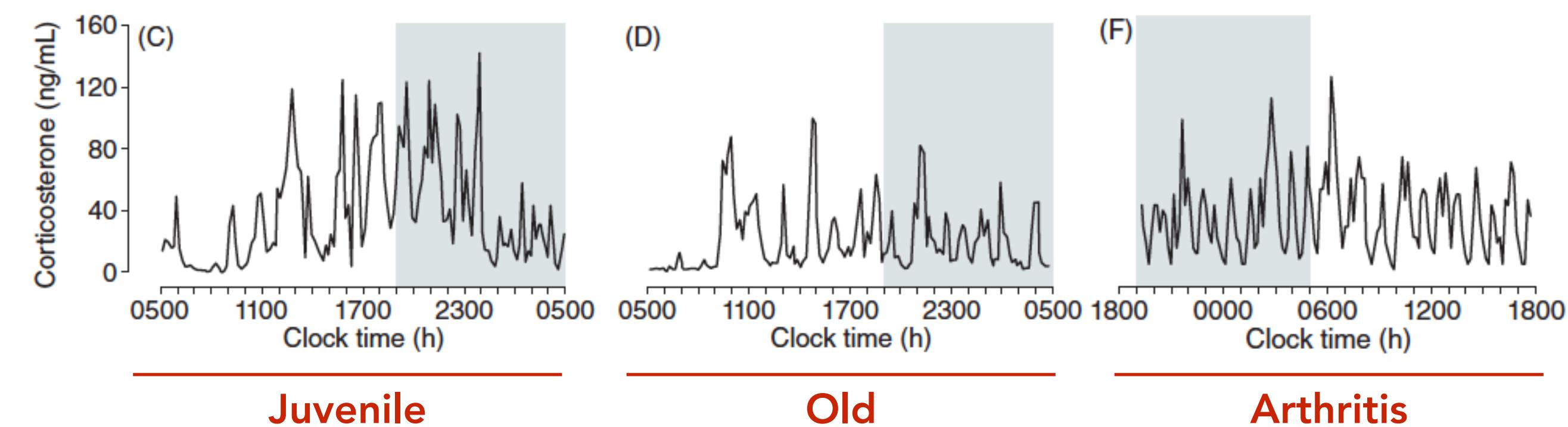
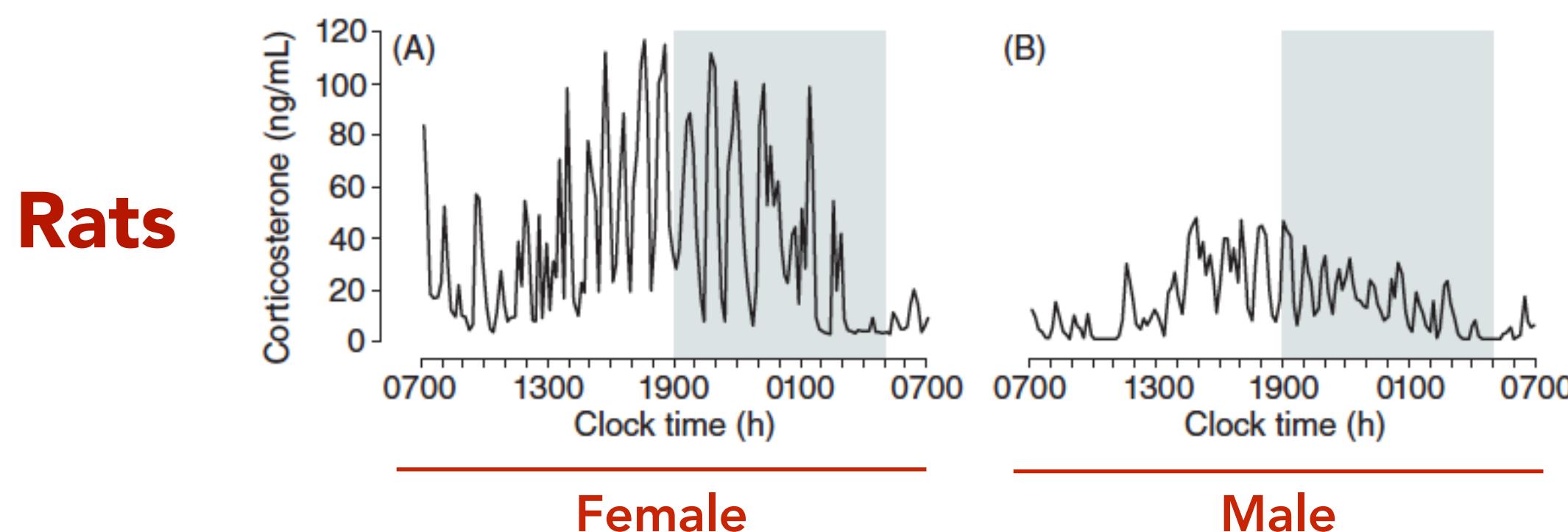
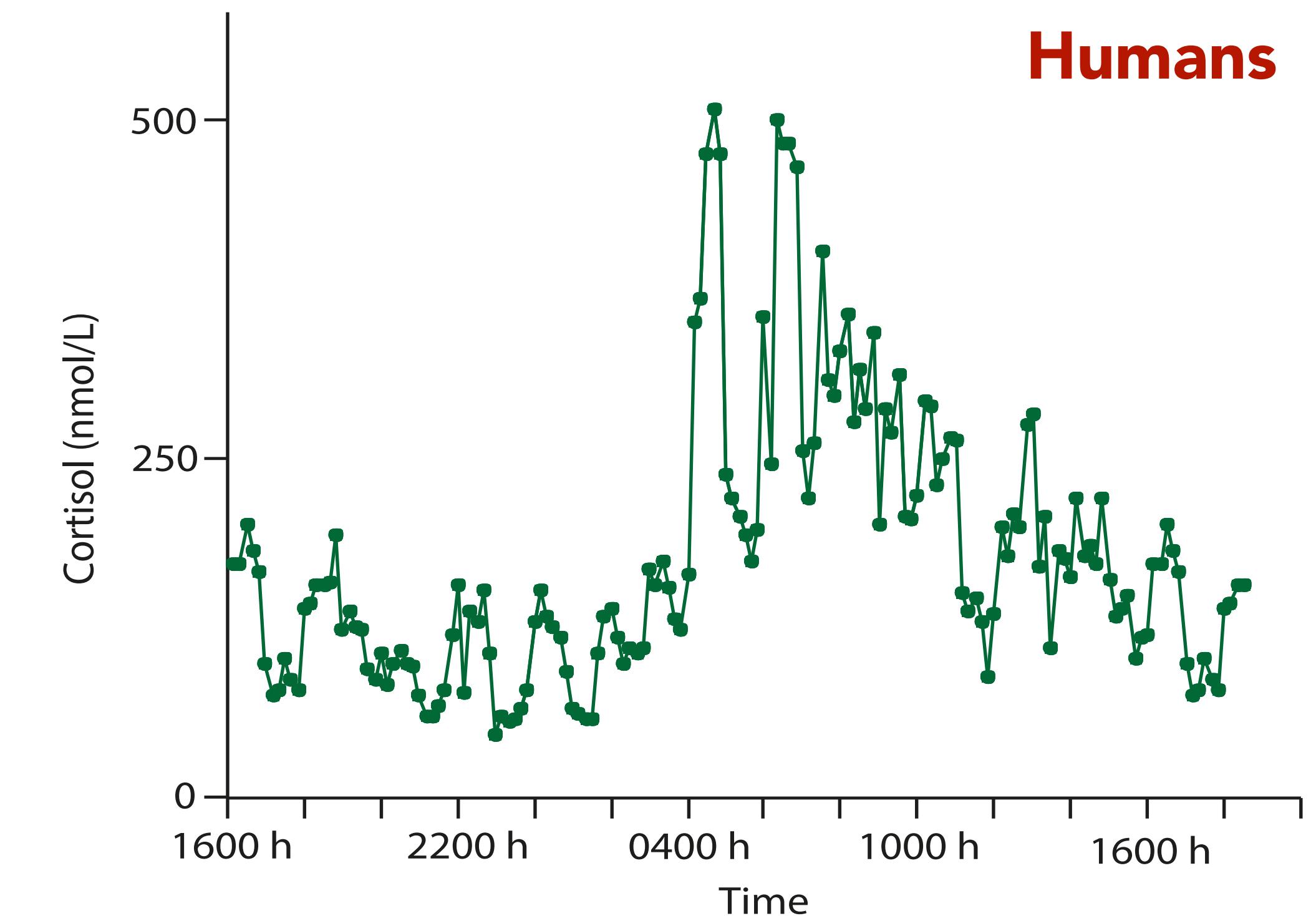
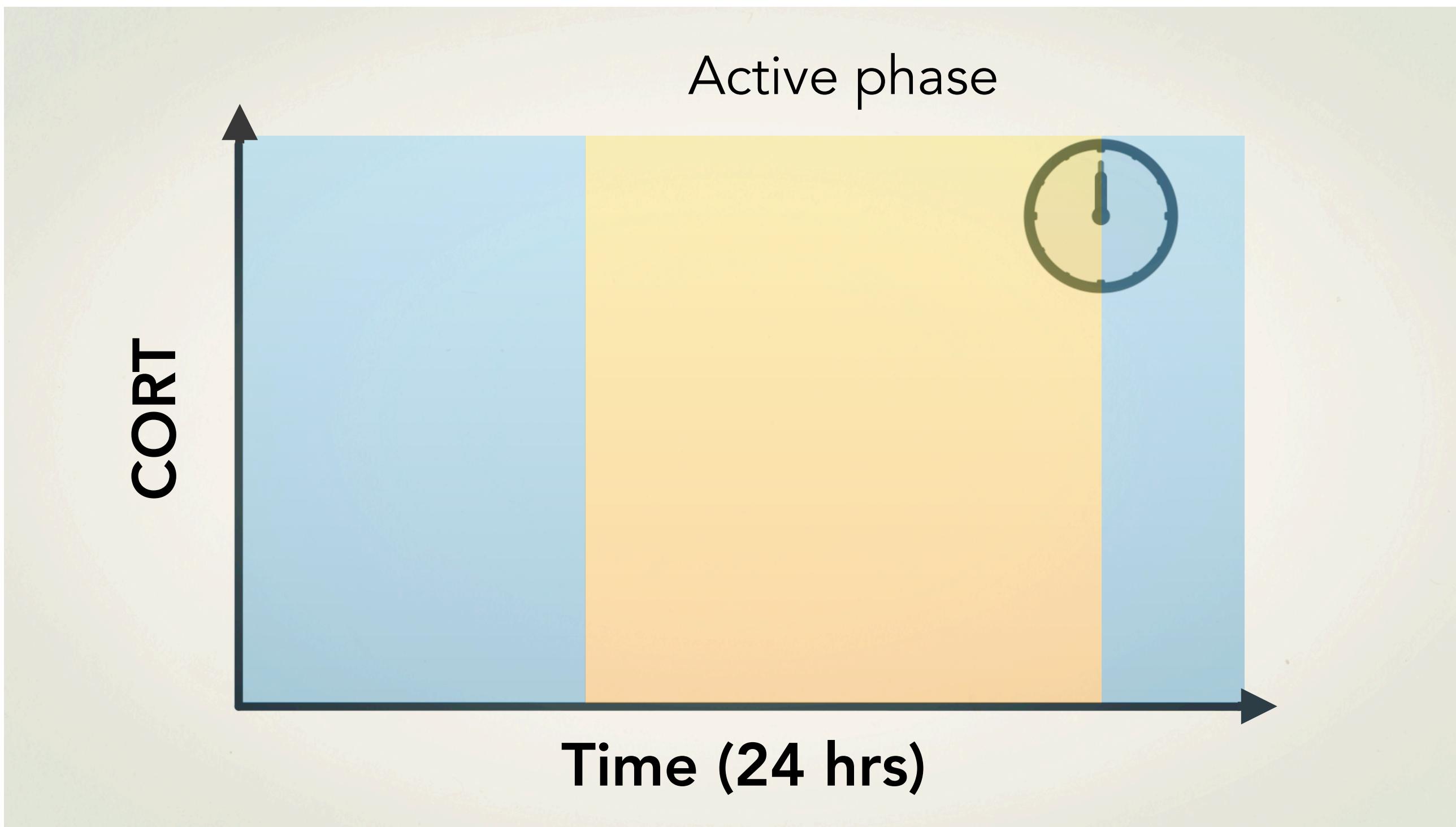
Understanding

Mathematics,
computer science,
& clinical expertise.

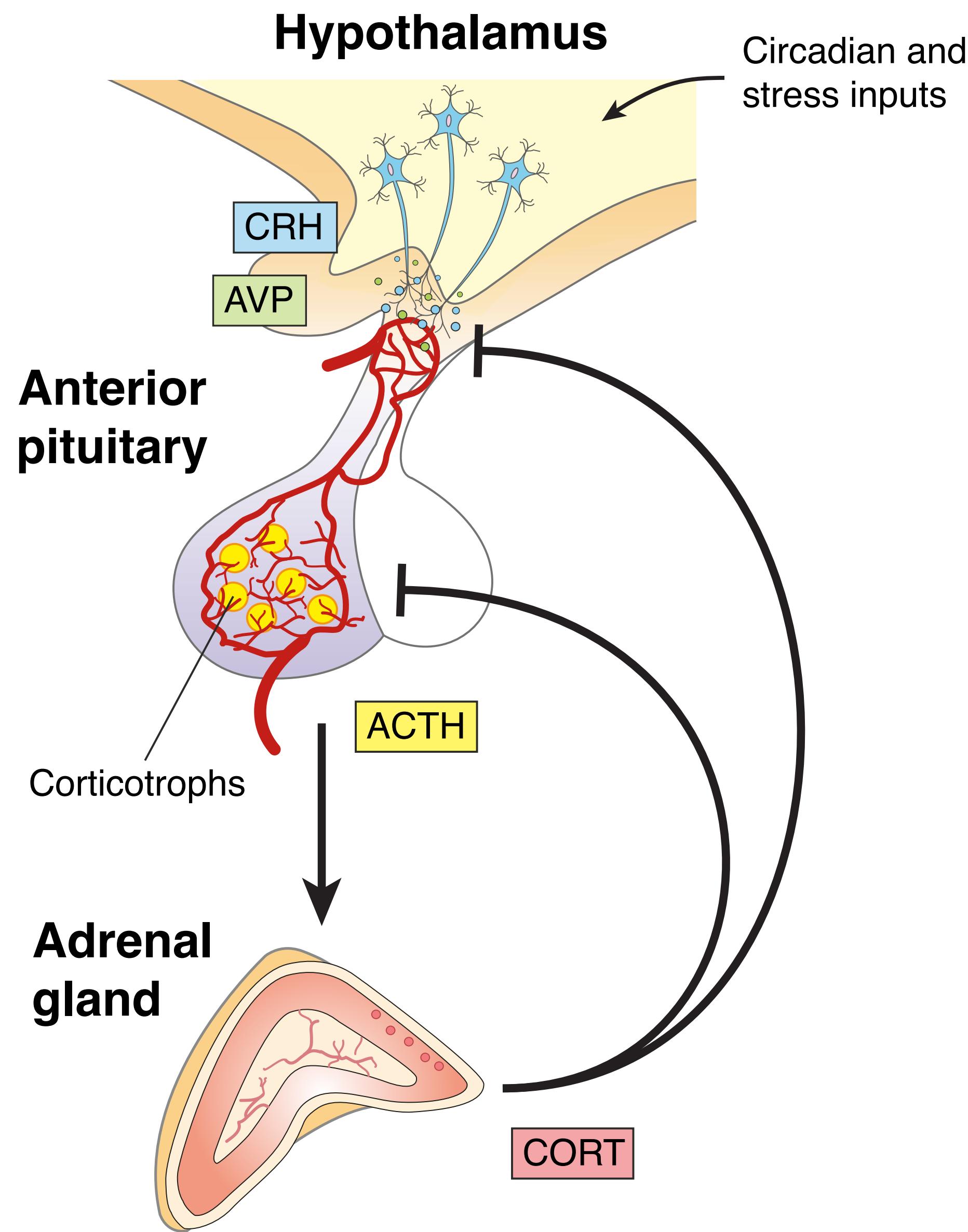
A systems-level view
of body rhythms



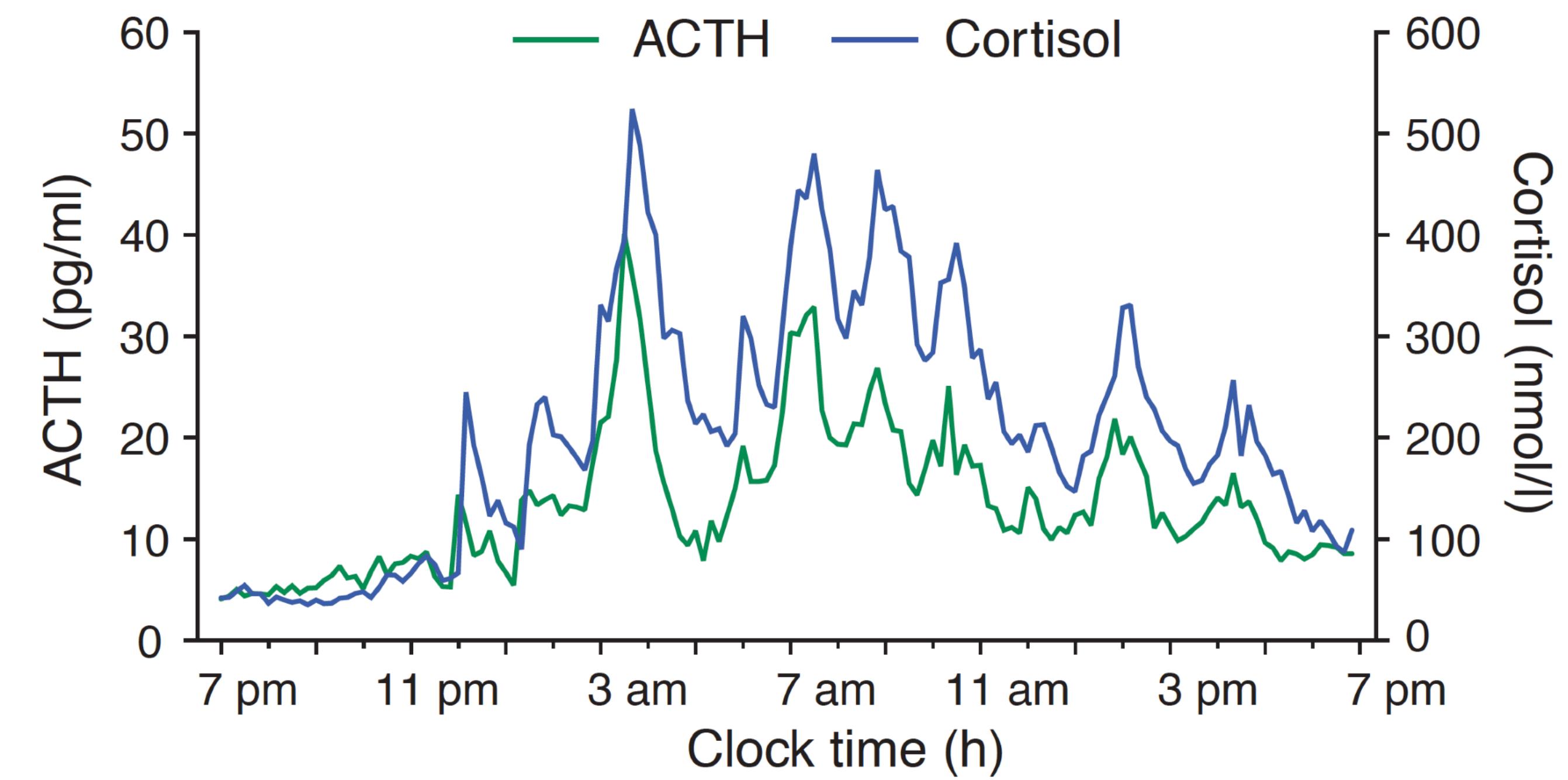
Plasma cortisol levels are dynamic



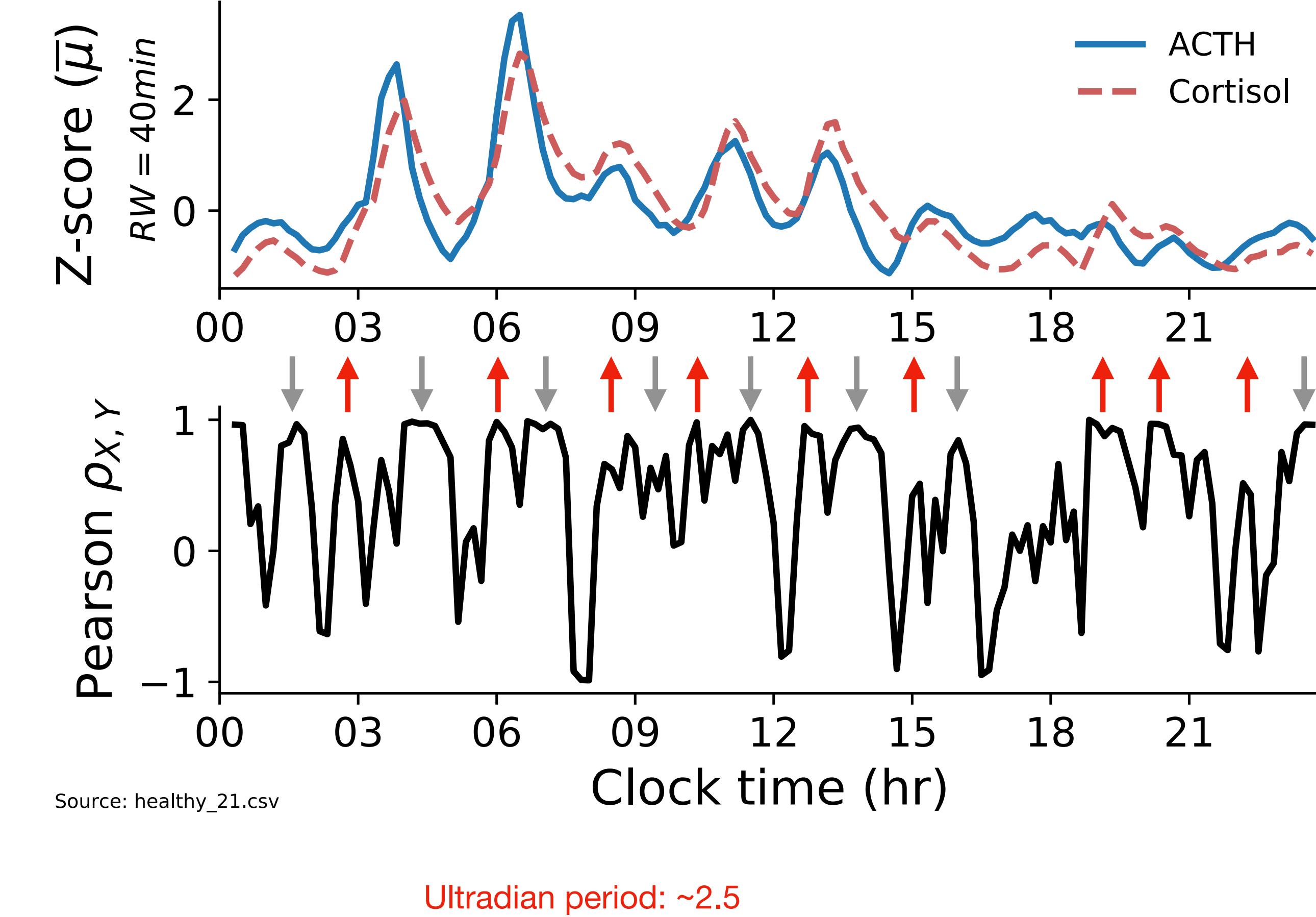
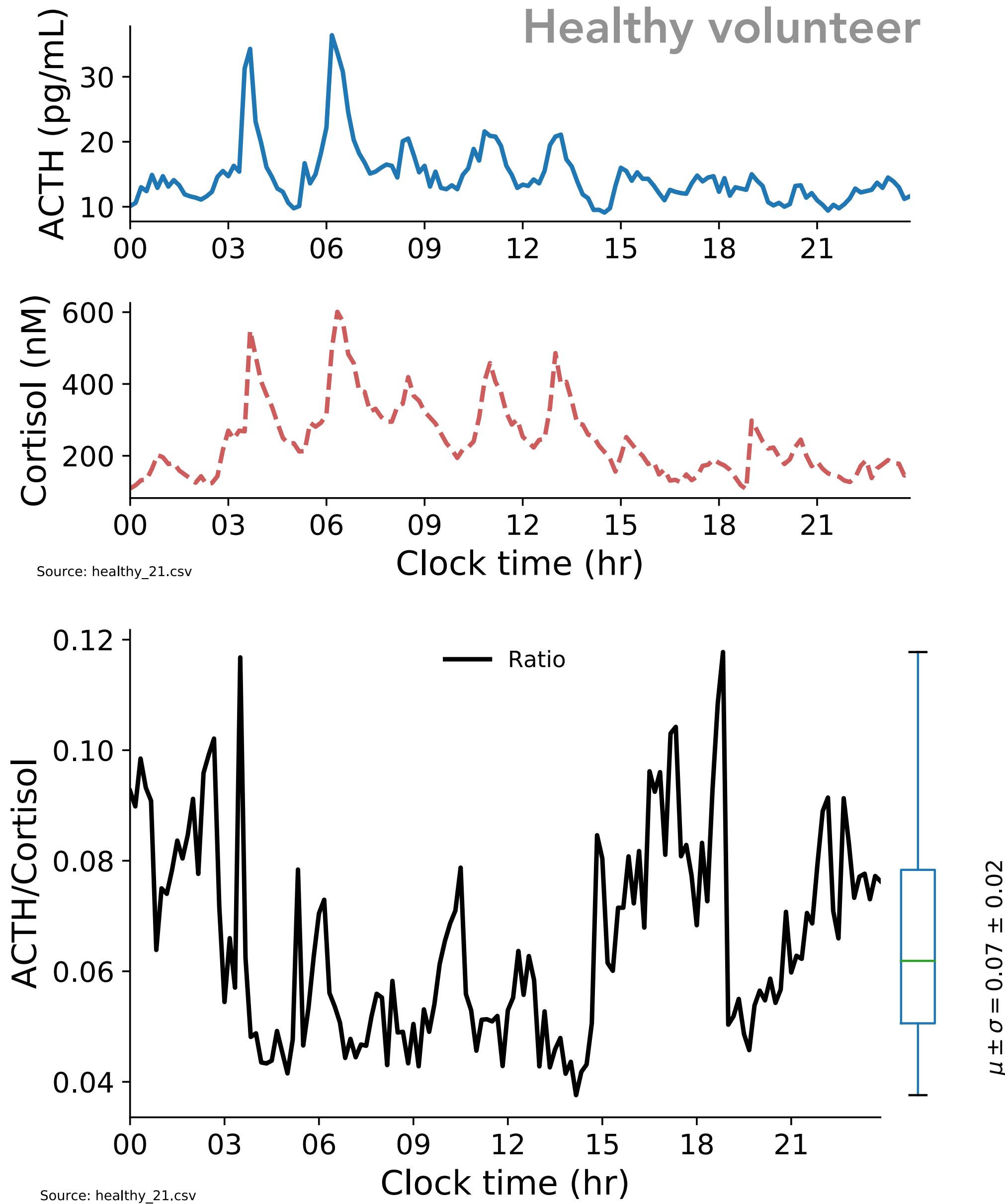
The HPA axis governs dynamic cortisol secretion



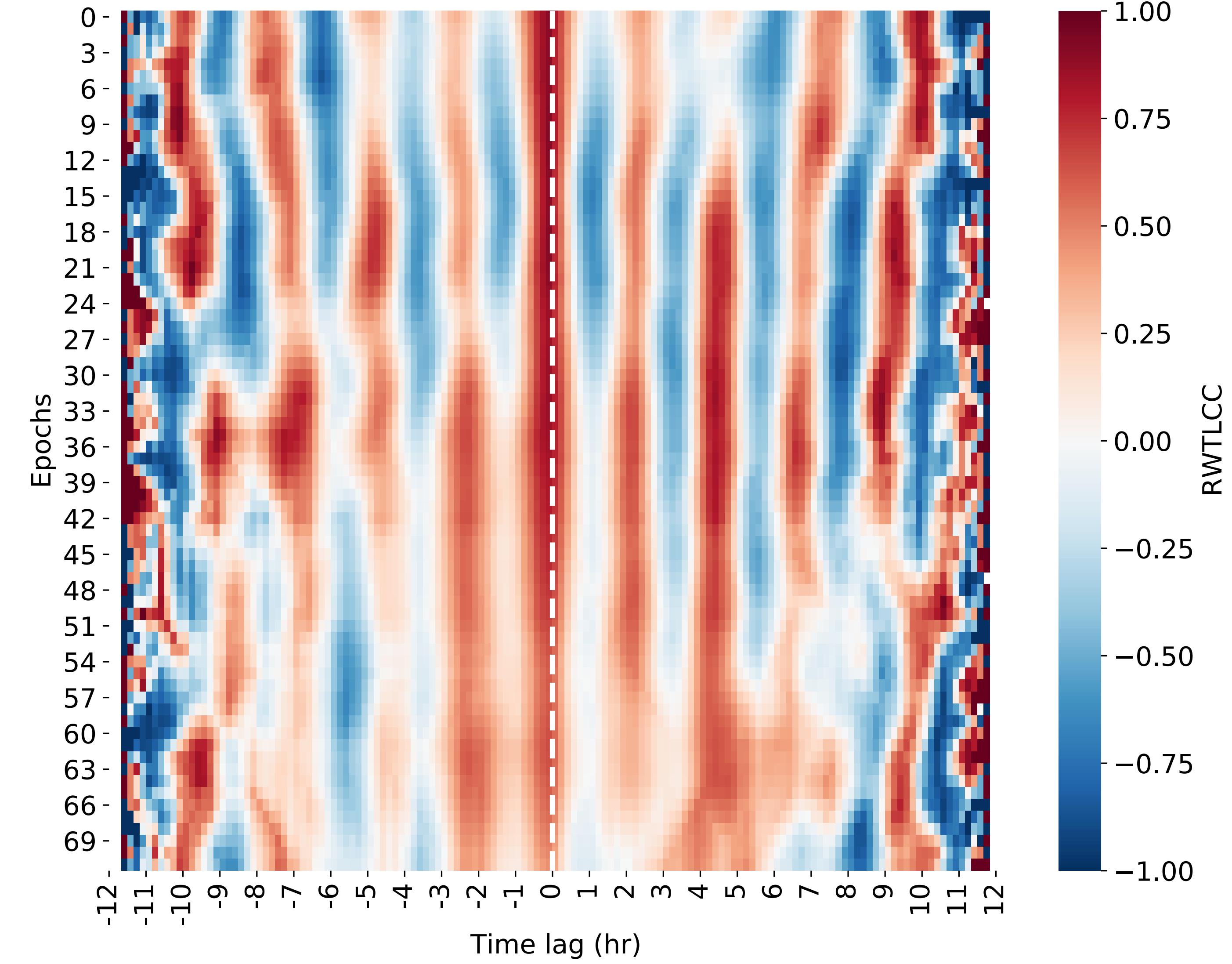
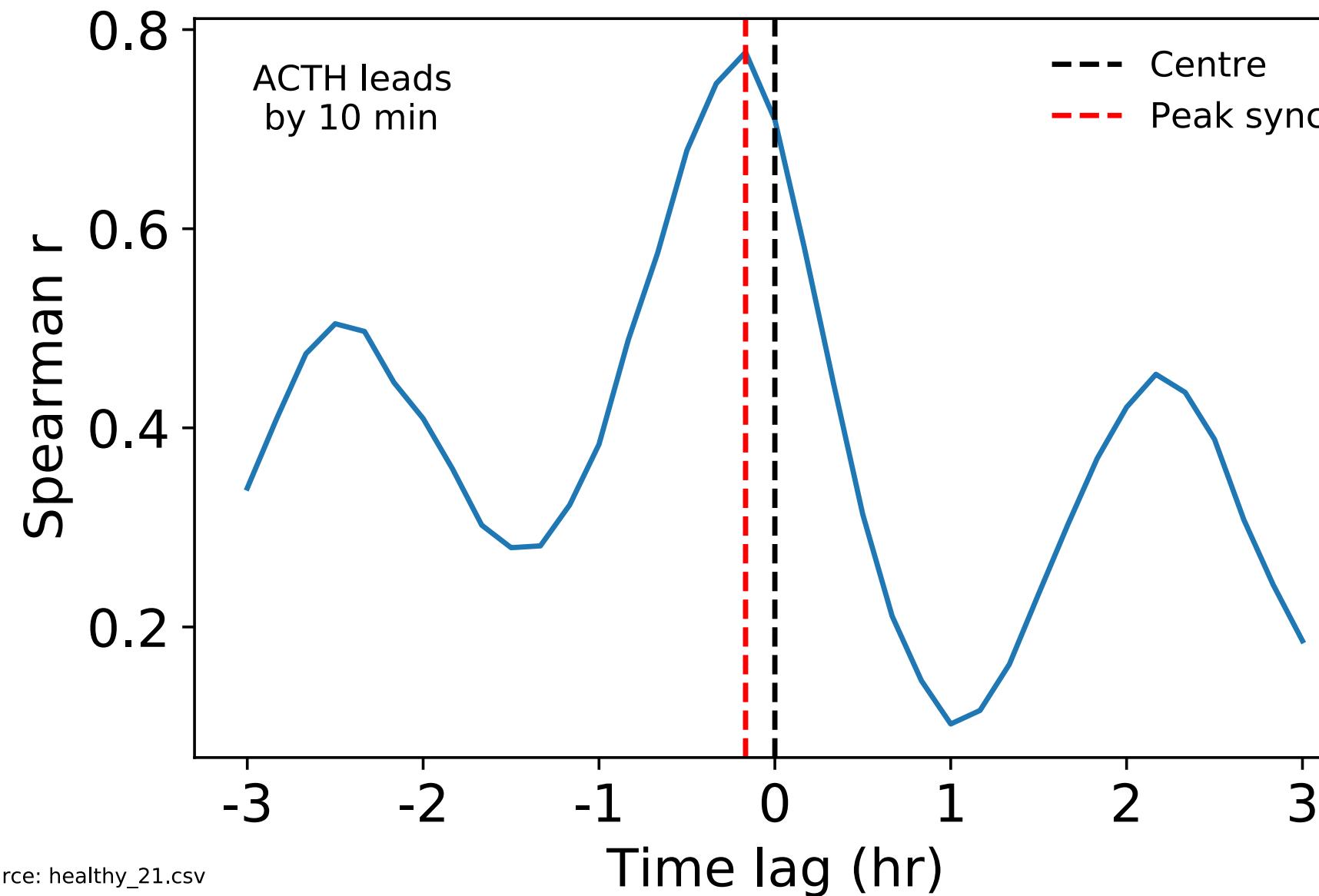
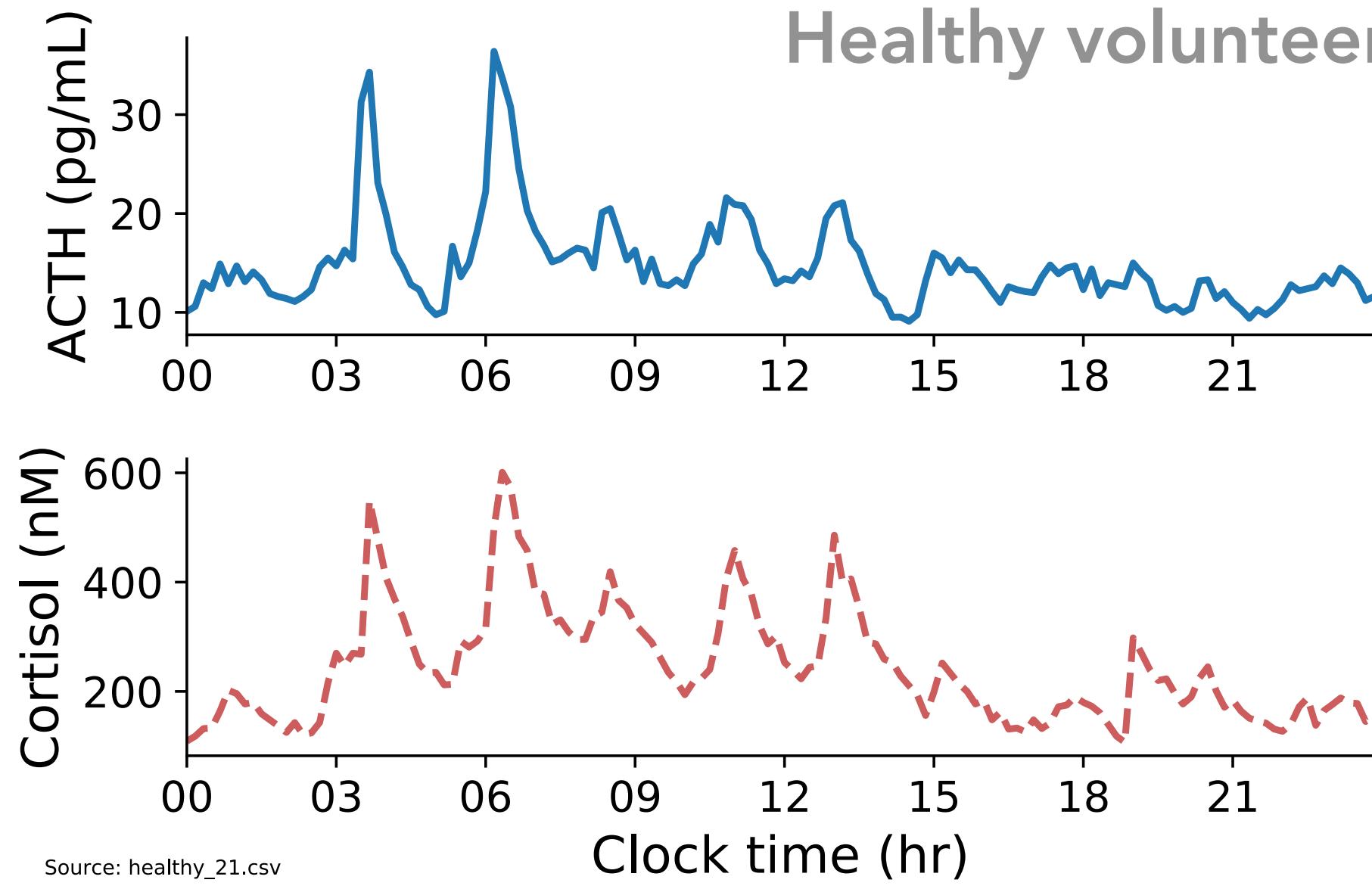
HPA axis rhythms in human blood
(in non-stressed conditions)



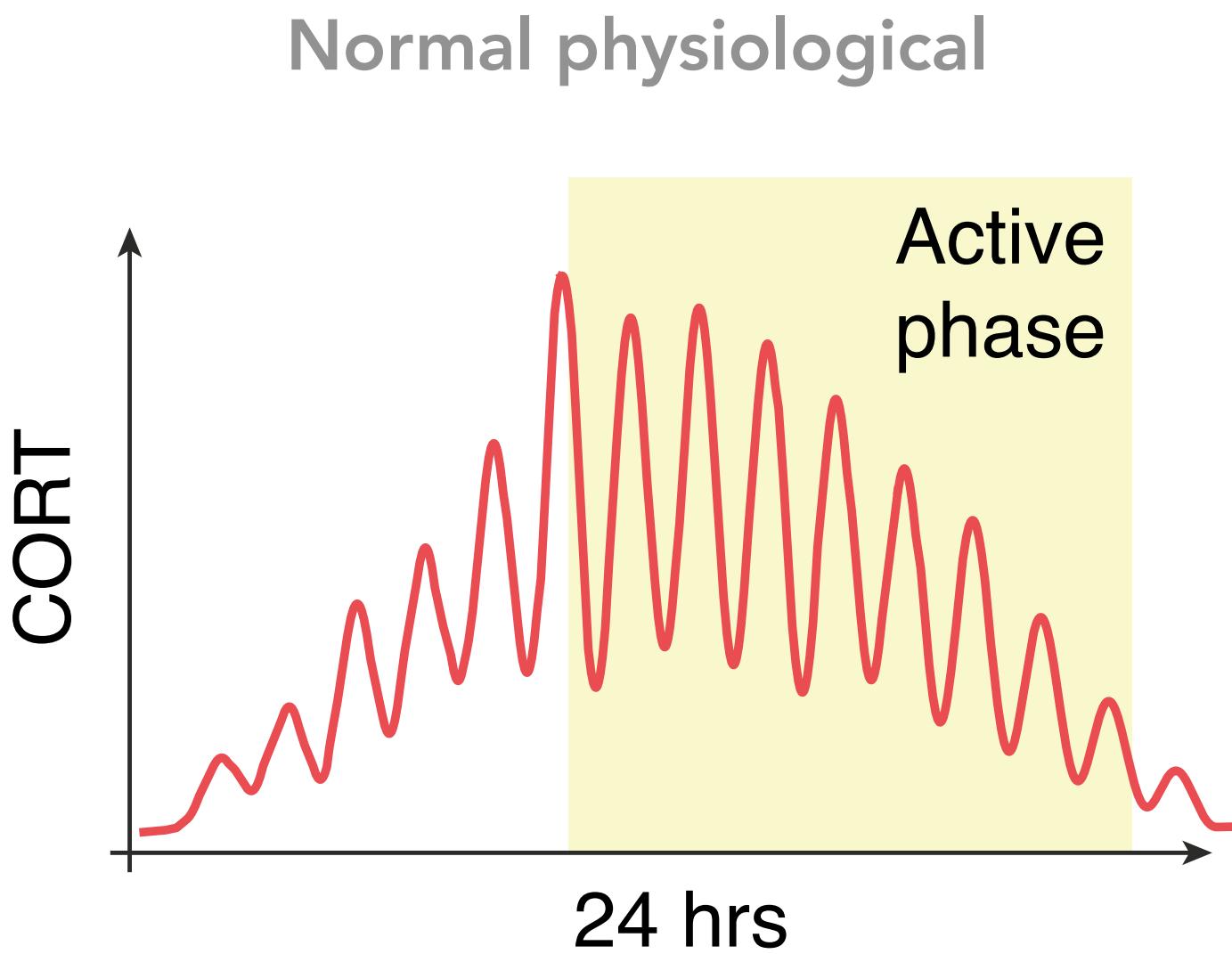
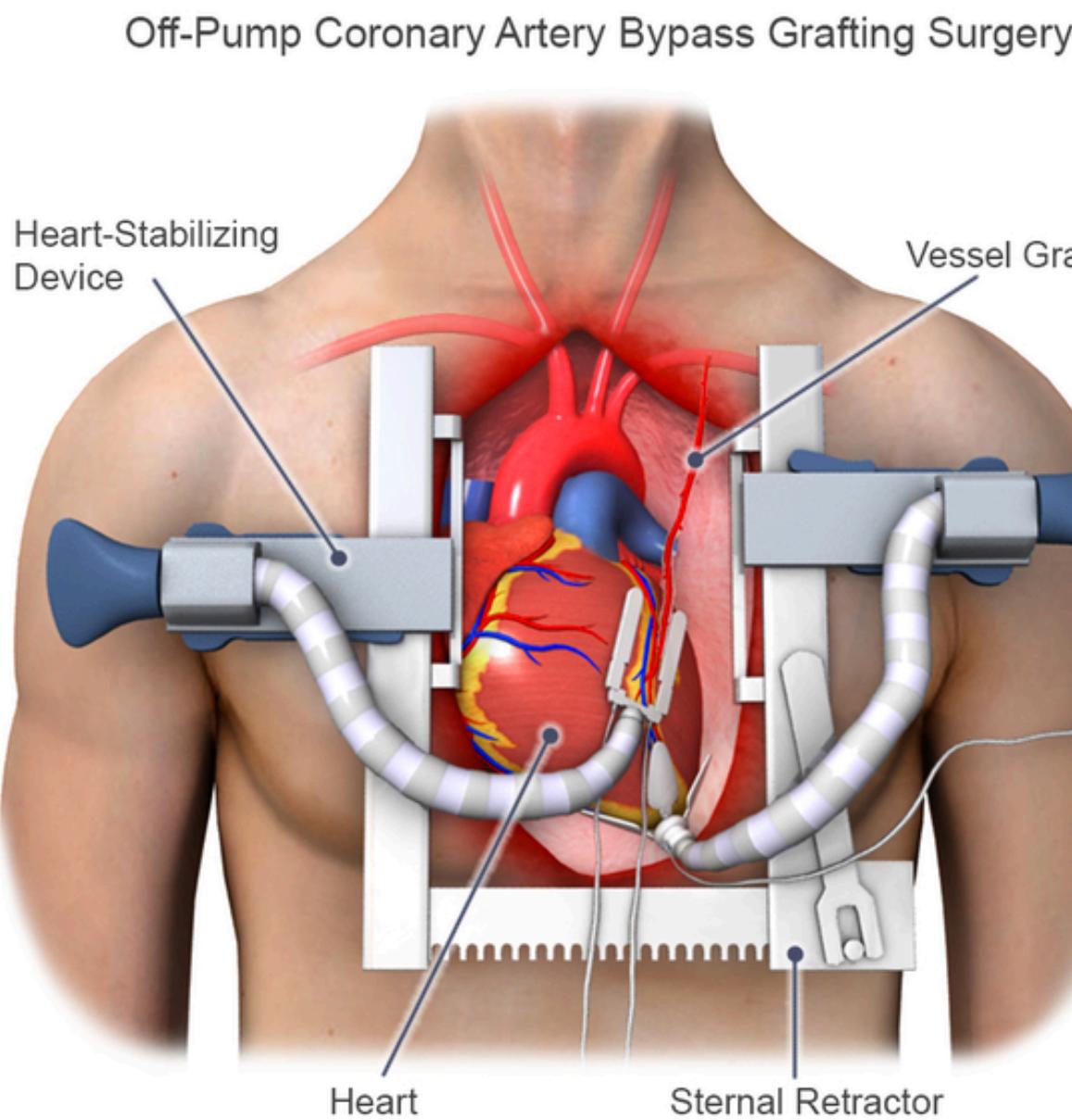
Dynamic relationship between ACTH & cortisol



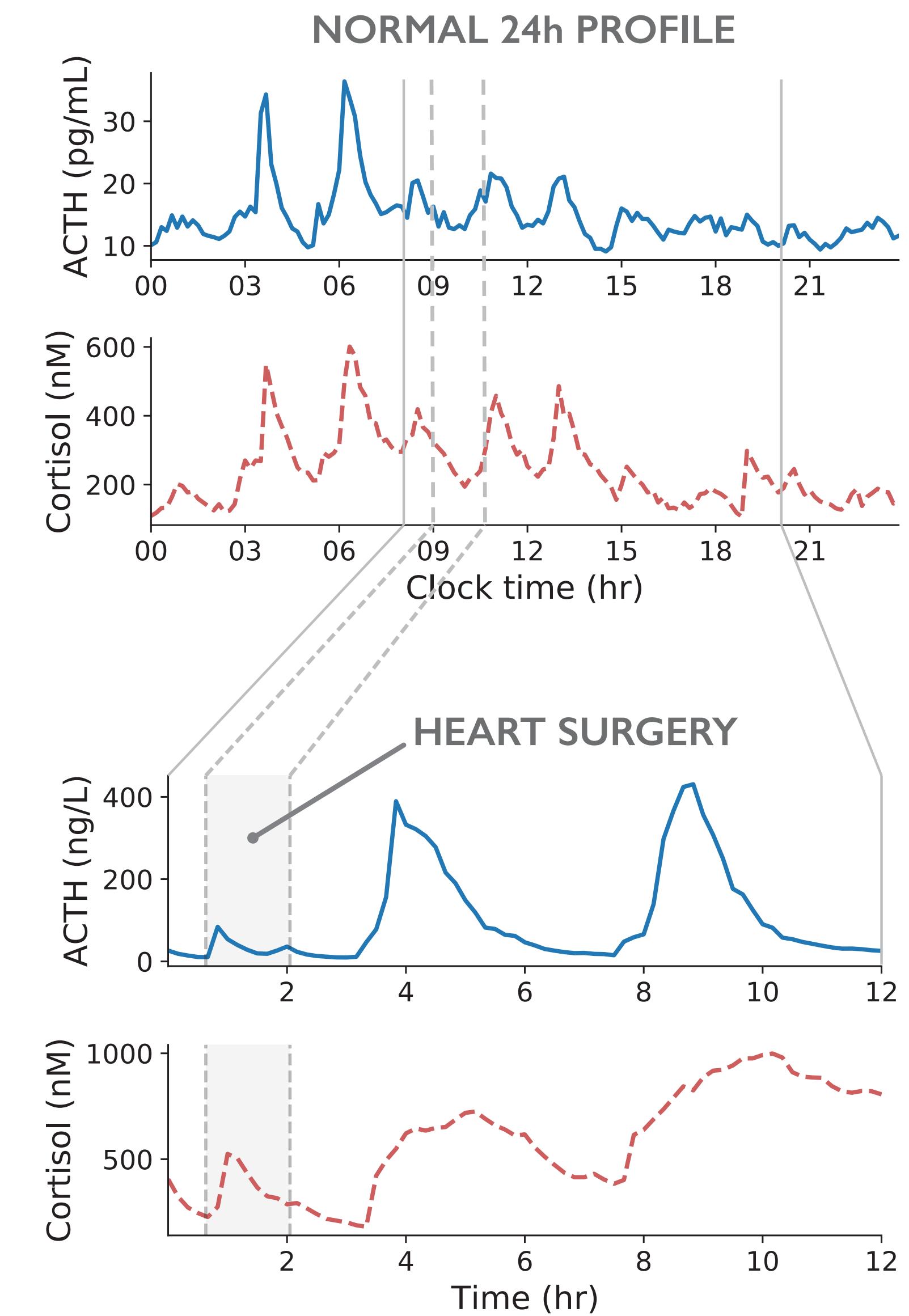
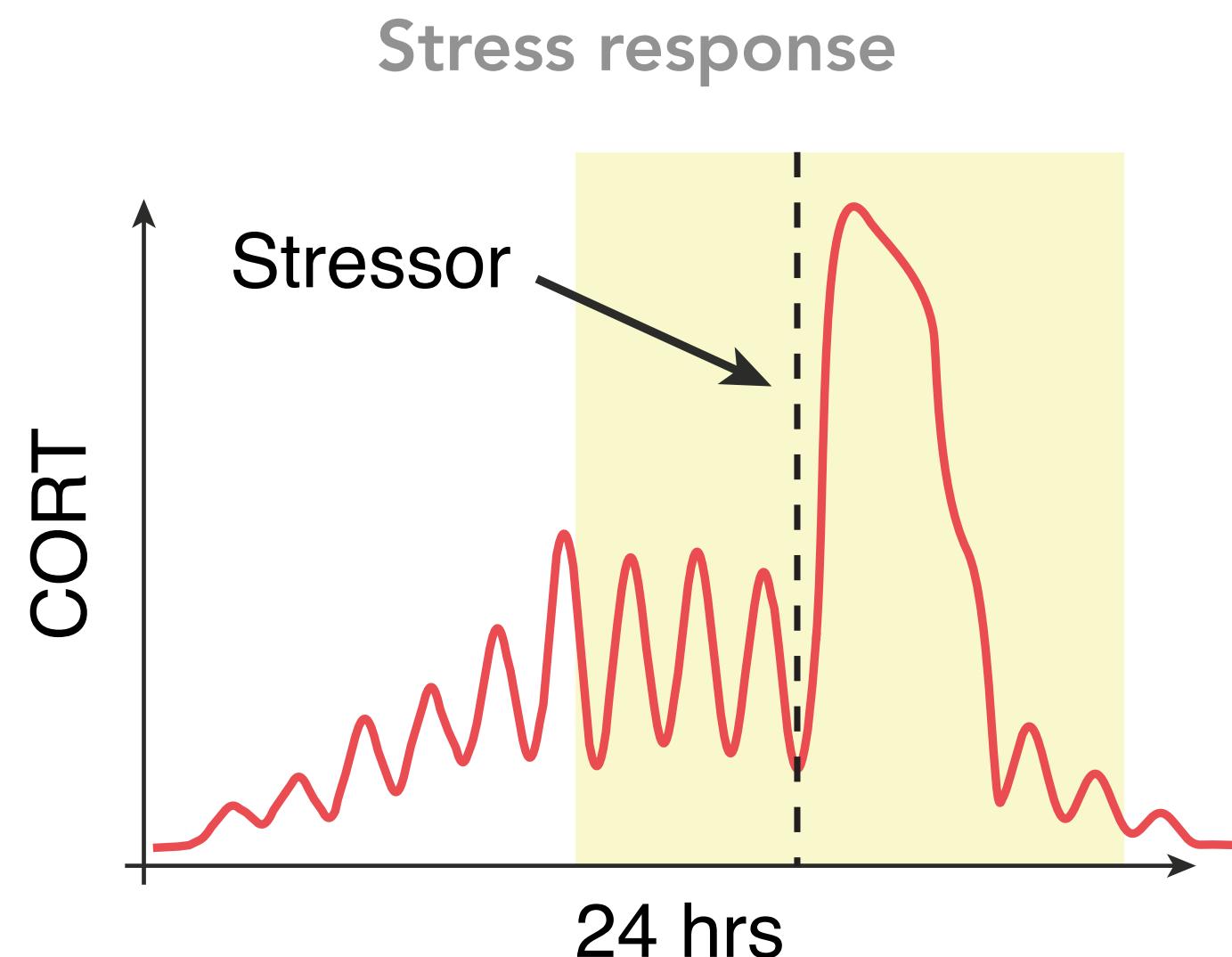
Dynamic relationship between ACTH & cortisol



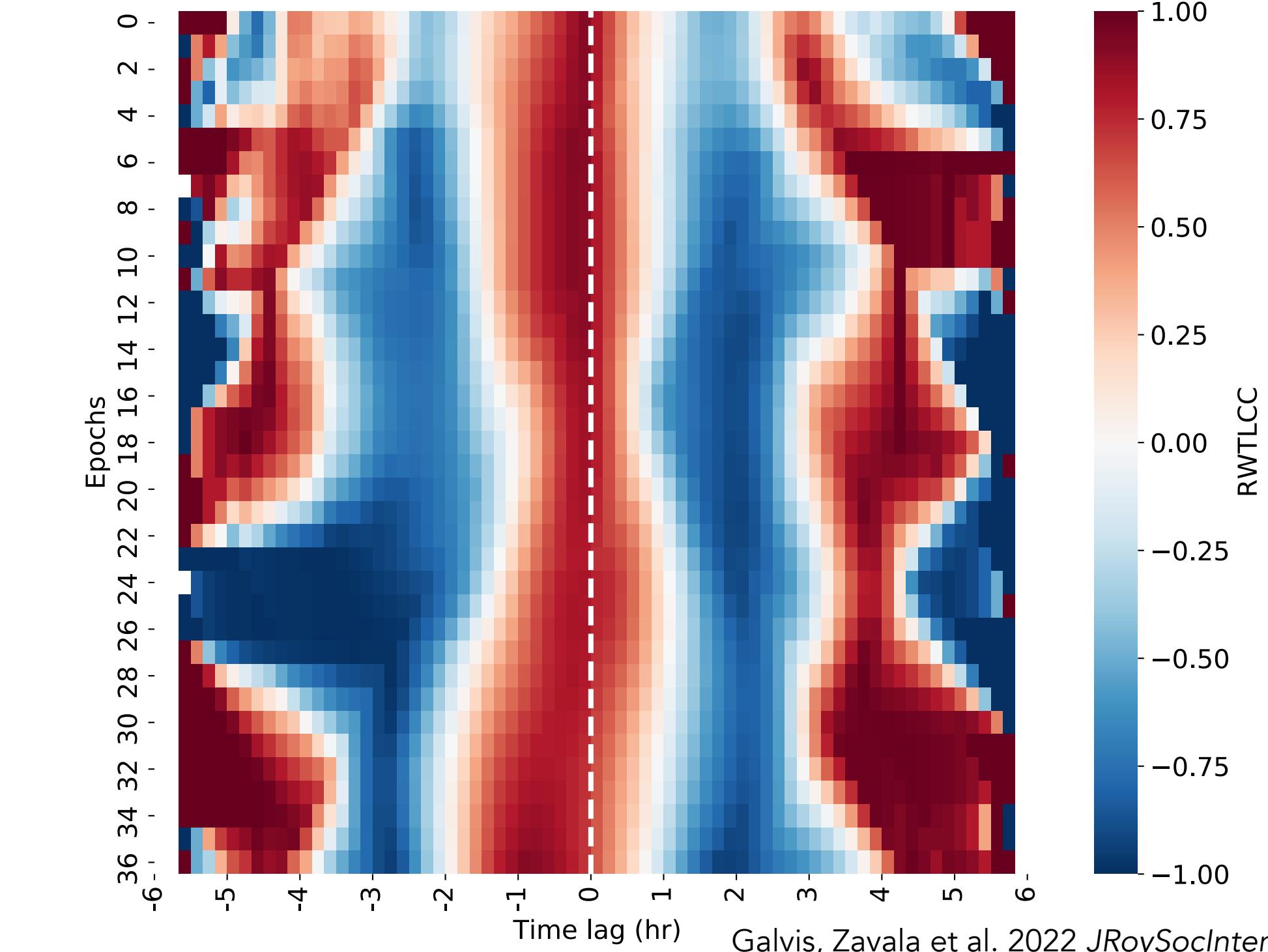
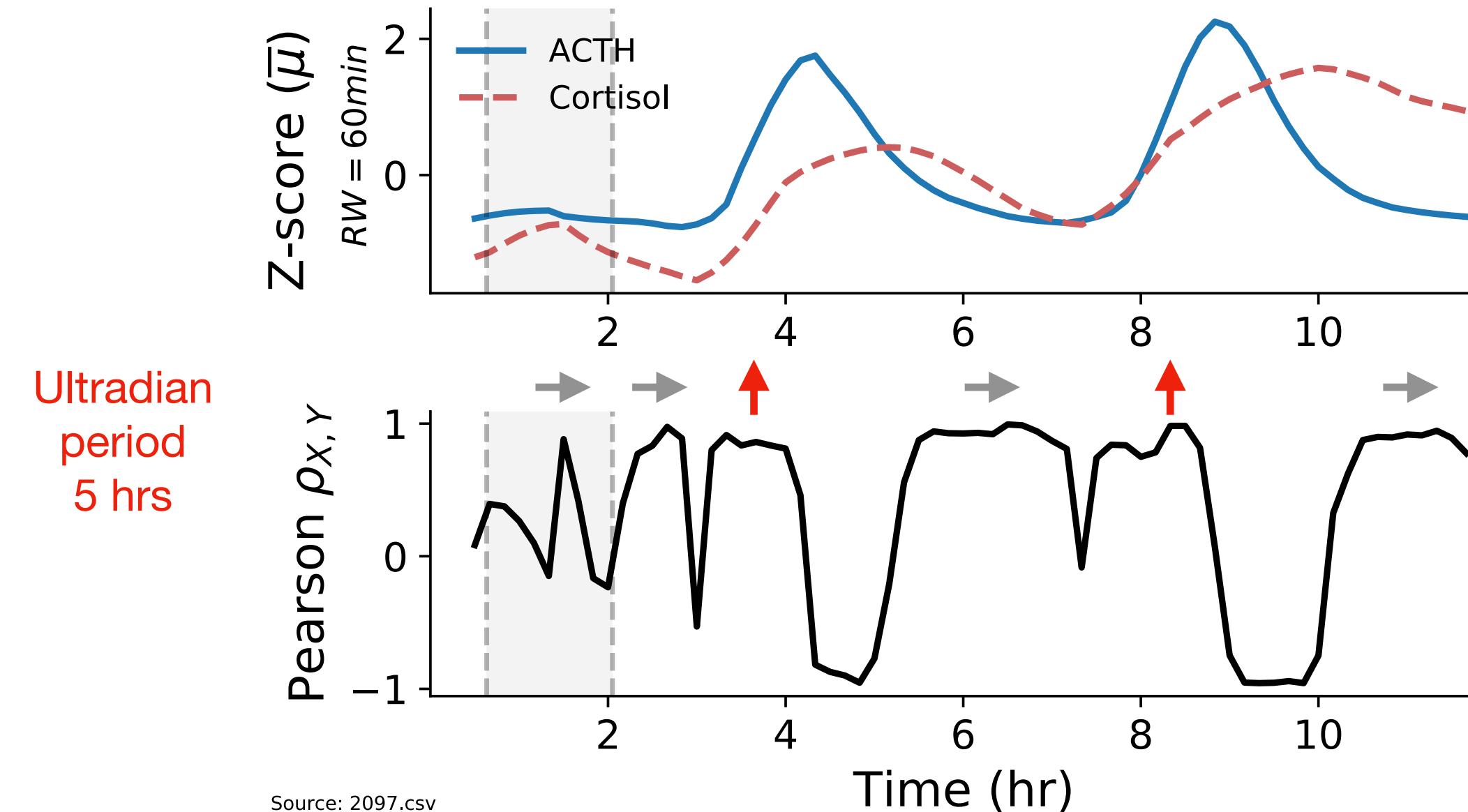
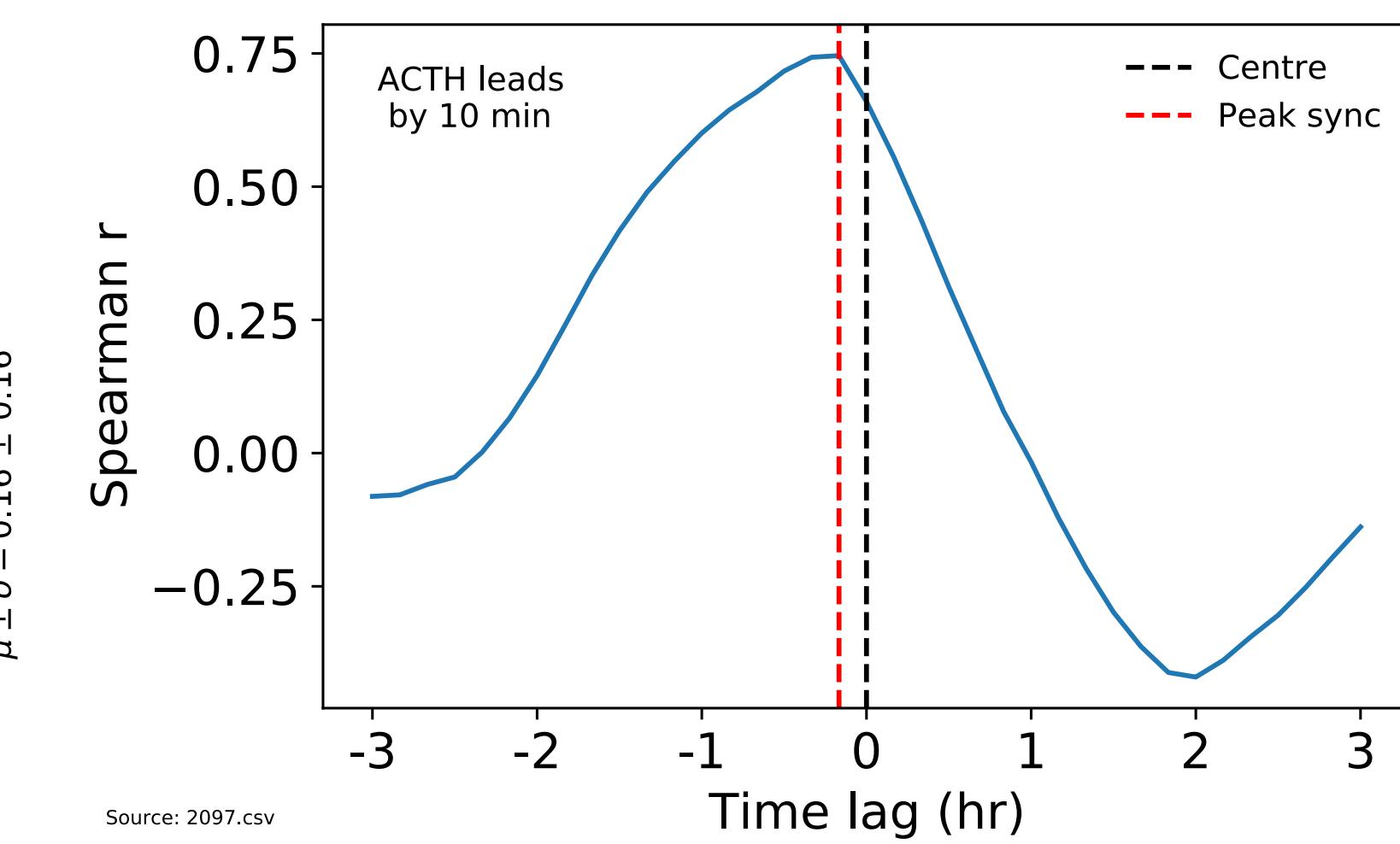
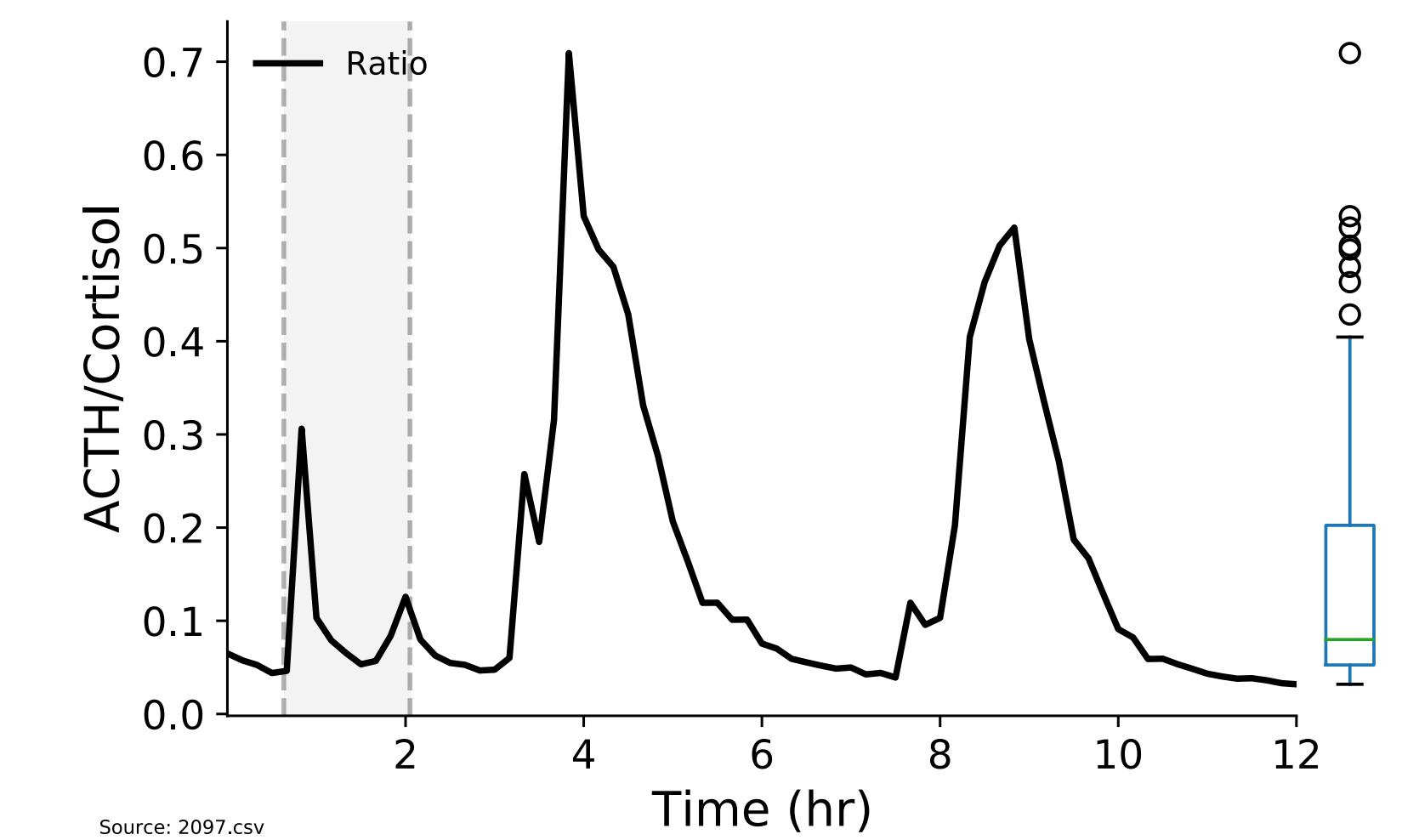
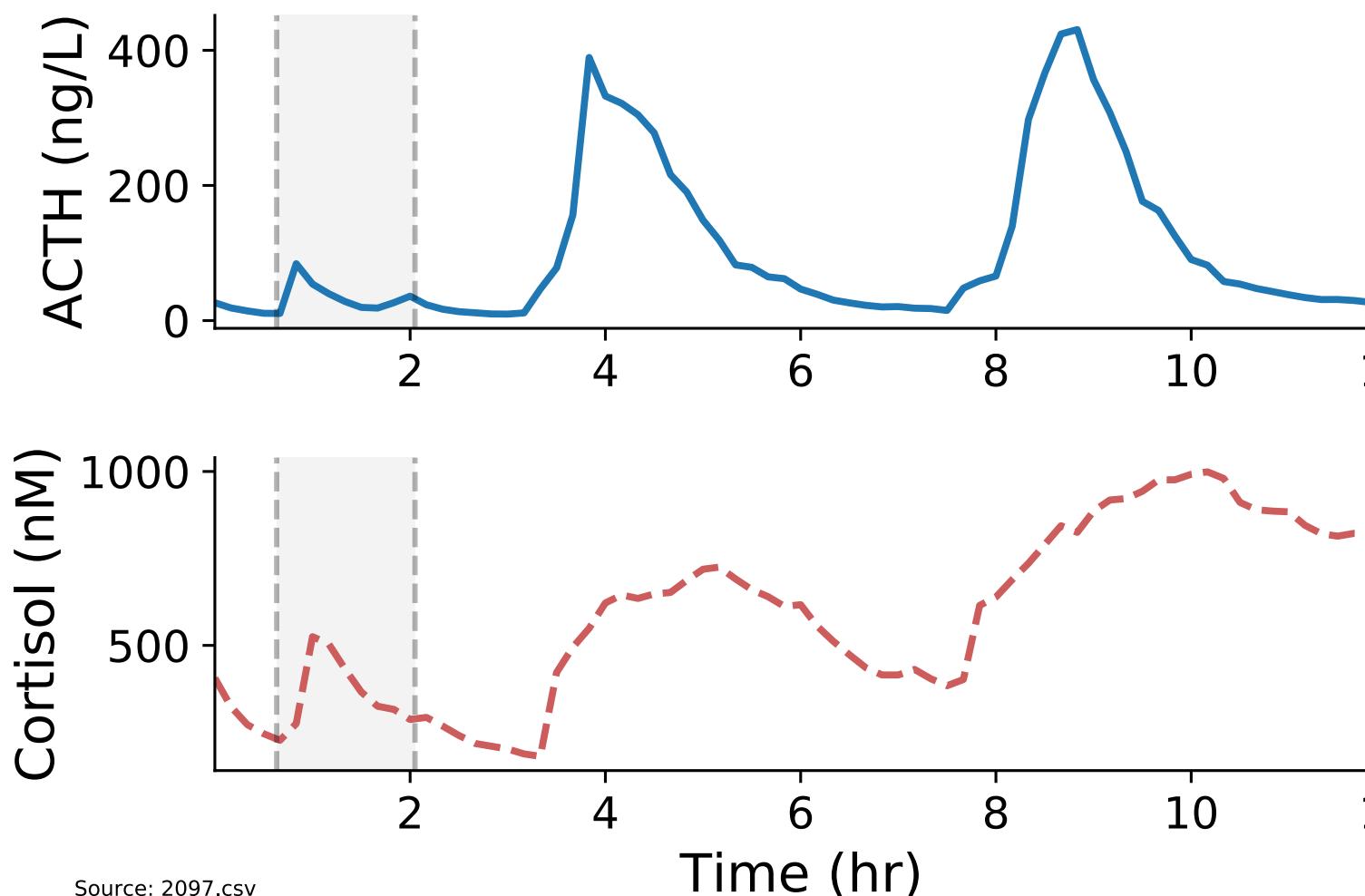
Case study: stress induced by heart surgery



	controls (<i>n</i> = 3)	patients (<i>n</i> = 10)
age	54 ± 13.8 years	65 ± 6.2 years
height	180 ± 6.7 cm	173 ± 6.4 cm
weight	87.5 ± 13.7 kg	83 ± 10.7 kg
BMI	26.9 ± 2.1 kg m ⁻²	27.8 ± 4.1 kg m ⁻²
sampling duration	24 h	12 h
anaesthesia start time	—	8.26 h (± 22 min)
surgery start time	—	9.19 h (± 22 min)
surgery end time	—	12.15 h (± 60 min)
surgery duration	—	176 ± 58.2 min
critical care stay	—	3 (range 2–7) days
hospital stay	—	5 (range 4–8) days



ACTH/CORT dynamic dissociation following CABG

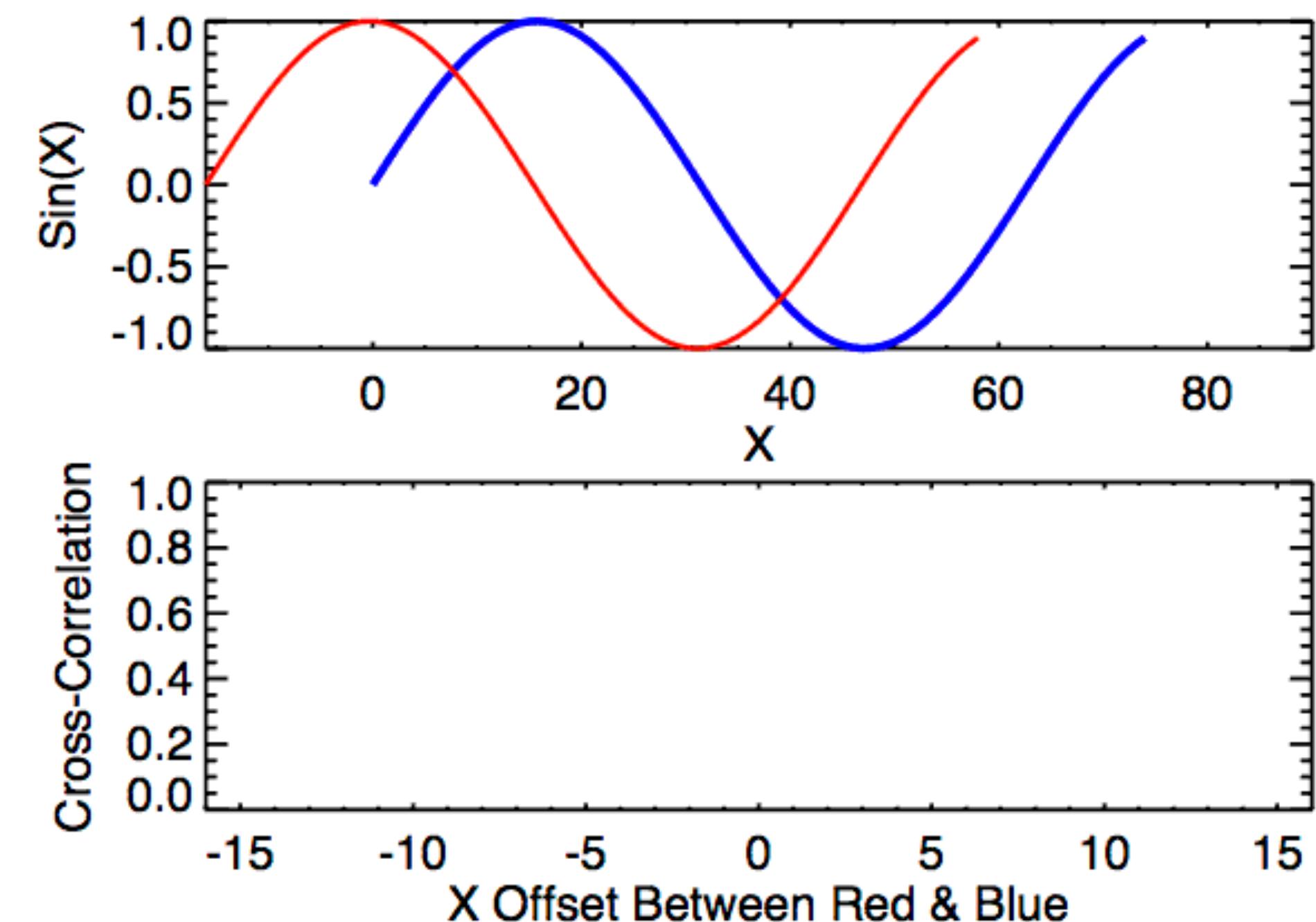


Let's look at some code!

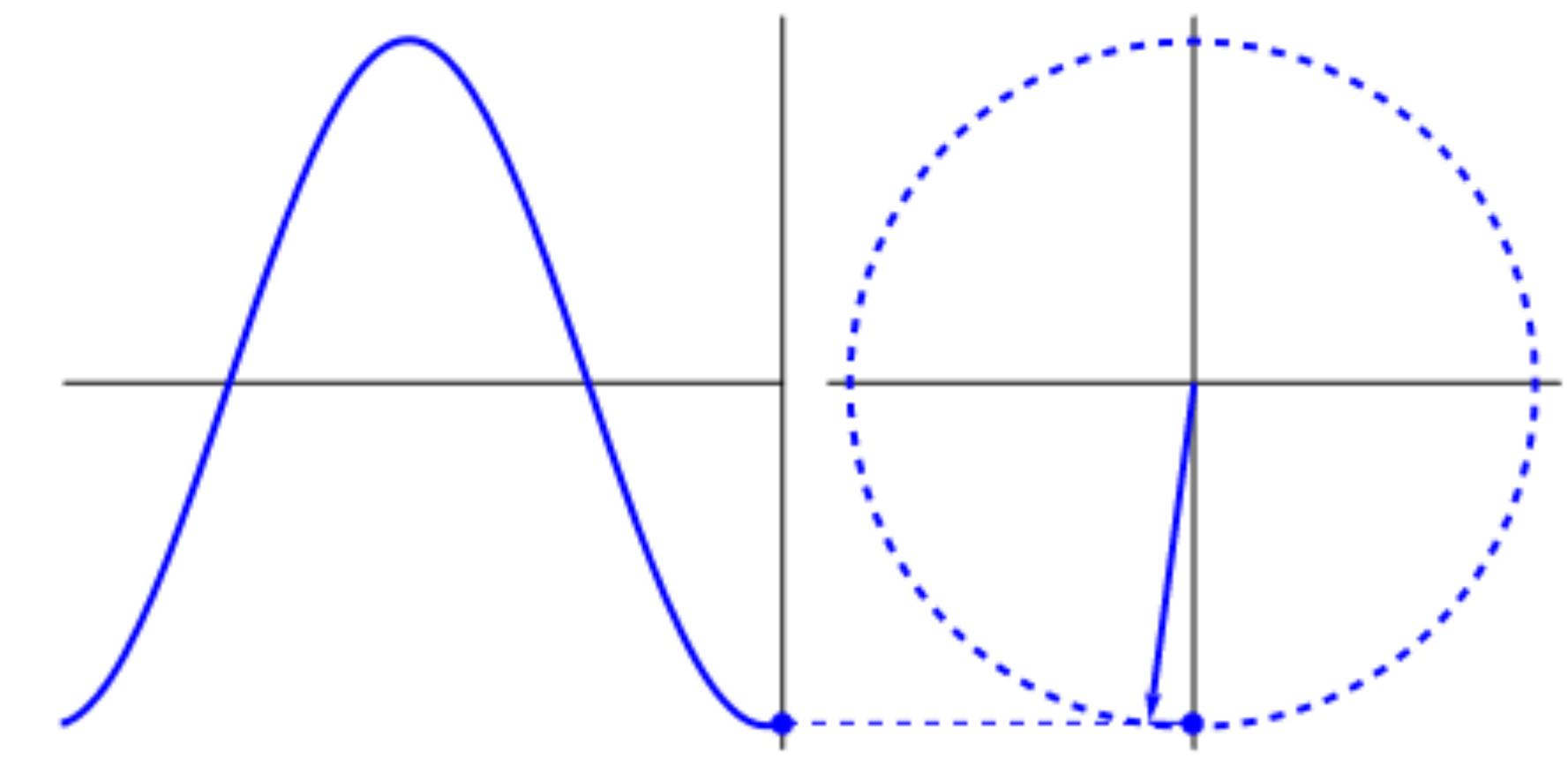
pip install *module_name*

Pearson correlation. The Pearson correlation measures how two continuous signals co-vary over time and indicate the linear relationship as a number between -1 (negatively correlated) to 0 (not correlated) to 1 (perfectly correlated). Two things to be cautious when using Pearson correlation is that 1) outliers can skew the results of the correlation estimation and 2) it assumes the data are homoscedastic such that the variance of your data is homogenous across the data range. Generally, the correlation is a snapshot measure of global synchrony. Therefore it does not provide information about directionality between the two signals such as which signal leads and which follows.

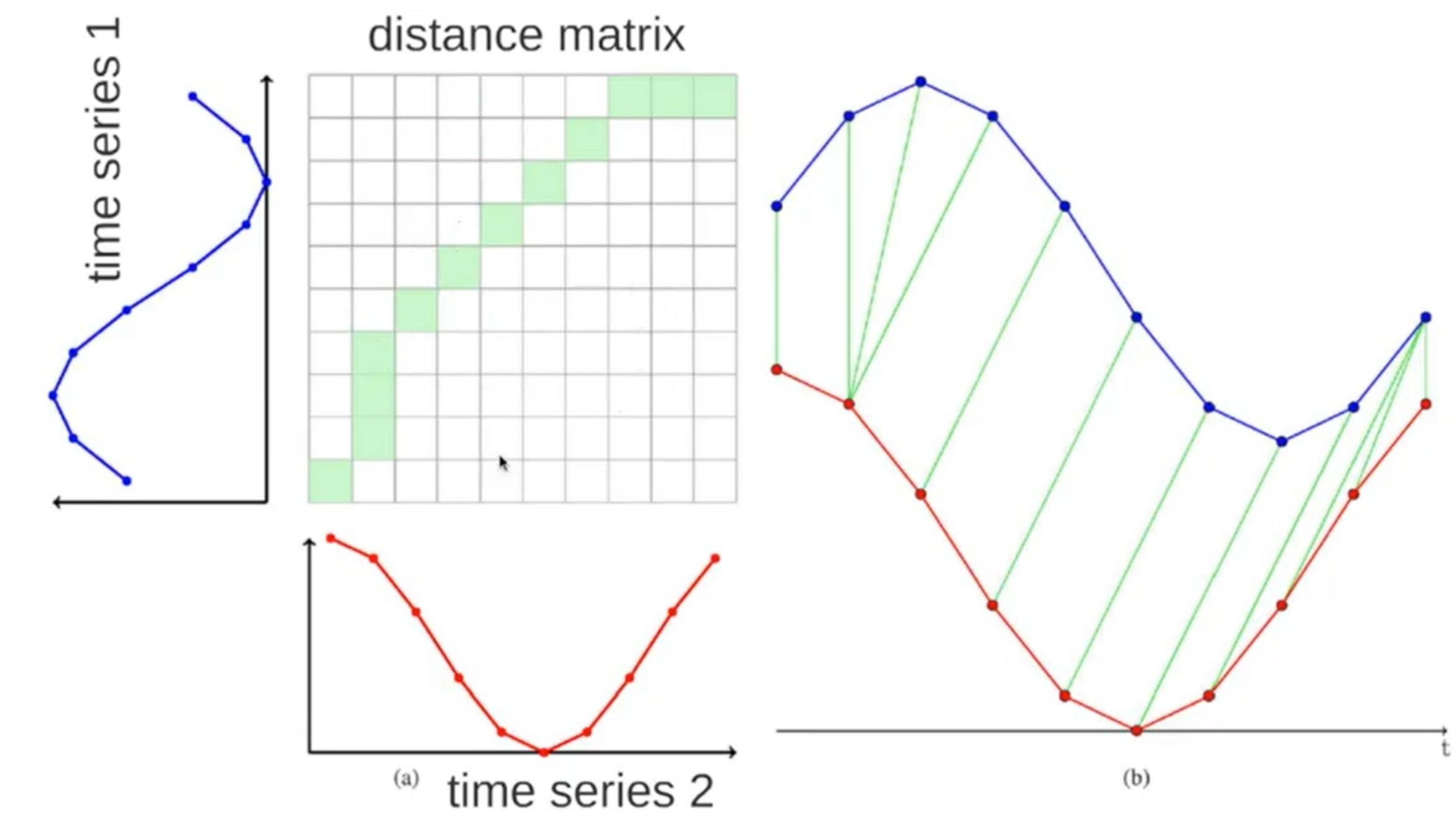
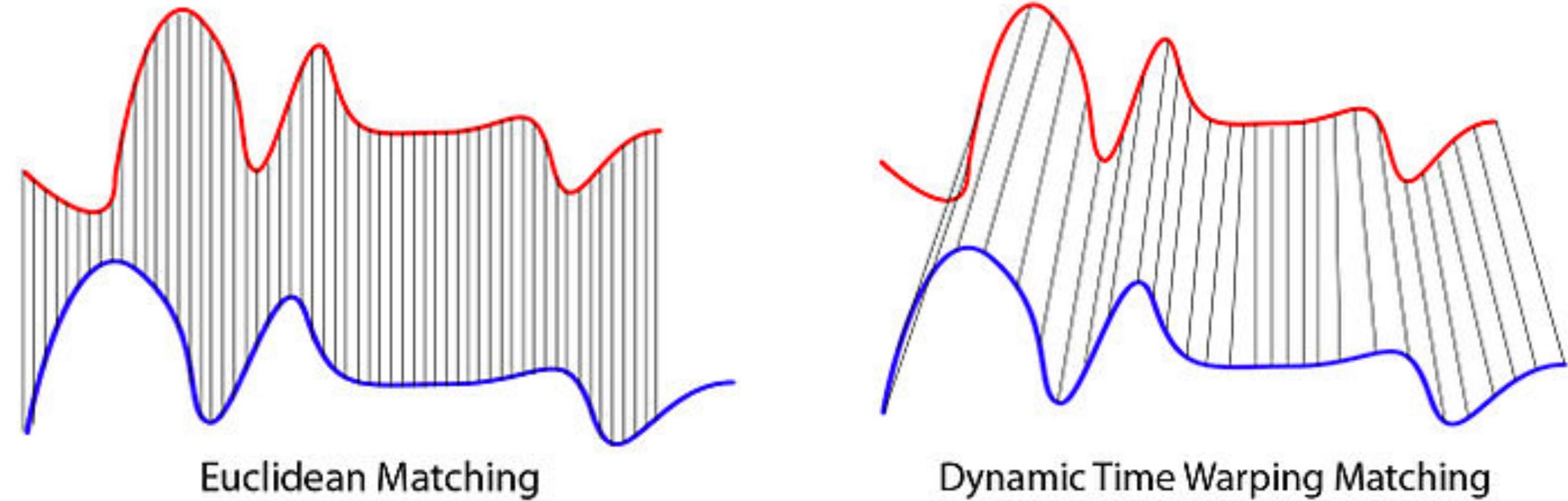
Time Lagged Cross Correlation. The TLCC can identify directionality between two signals such as a leader-follower relationship in which the leader initiates a response which is repeated by the follower.



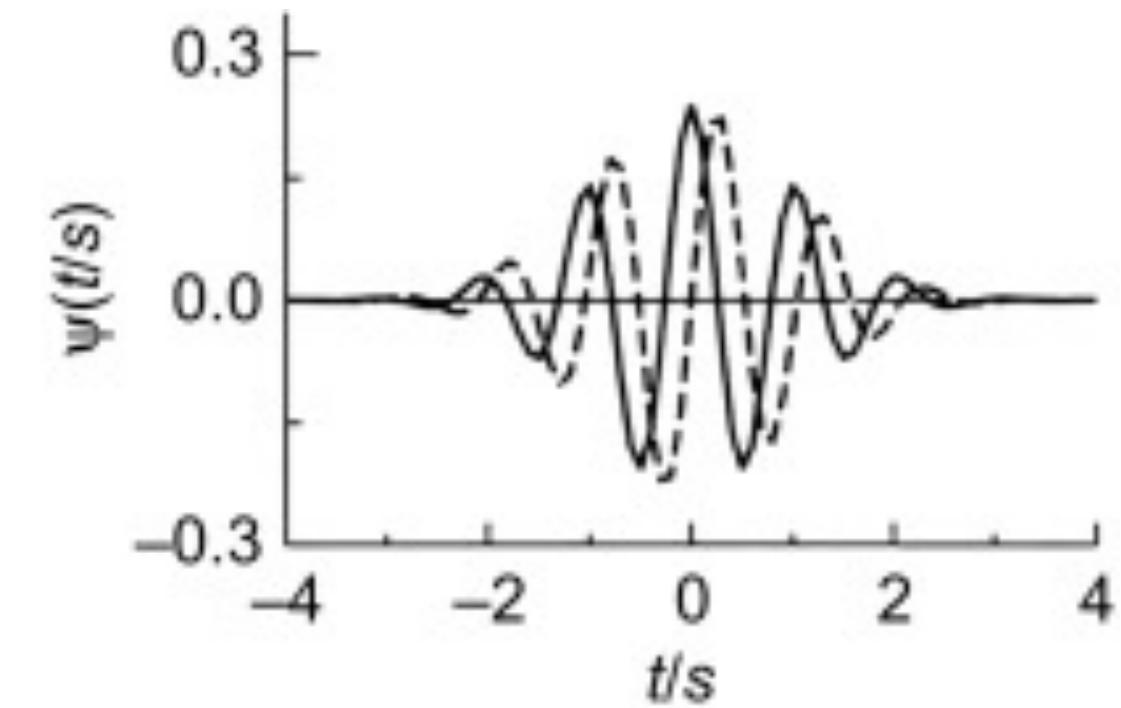
Instantaneous Phase Synchrony. The IPS measures moment-to-moment synchrony between two signals. It can be somewhat subjective because you need to filter the data to the wavelength of interest but you might have theoretical reasons for determining such bands. To calculate phase synchrony, we need to extract the phase of the signal which can be done by using the Hilbert transform which splits the signal into its phase and power. This allows us to assess if two signals are in phase (moving up and down together) or out of phase.



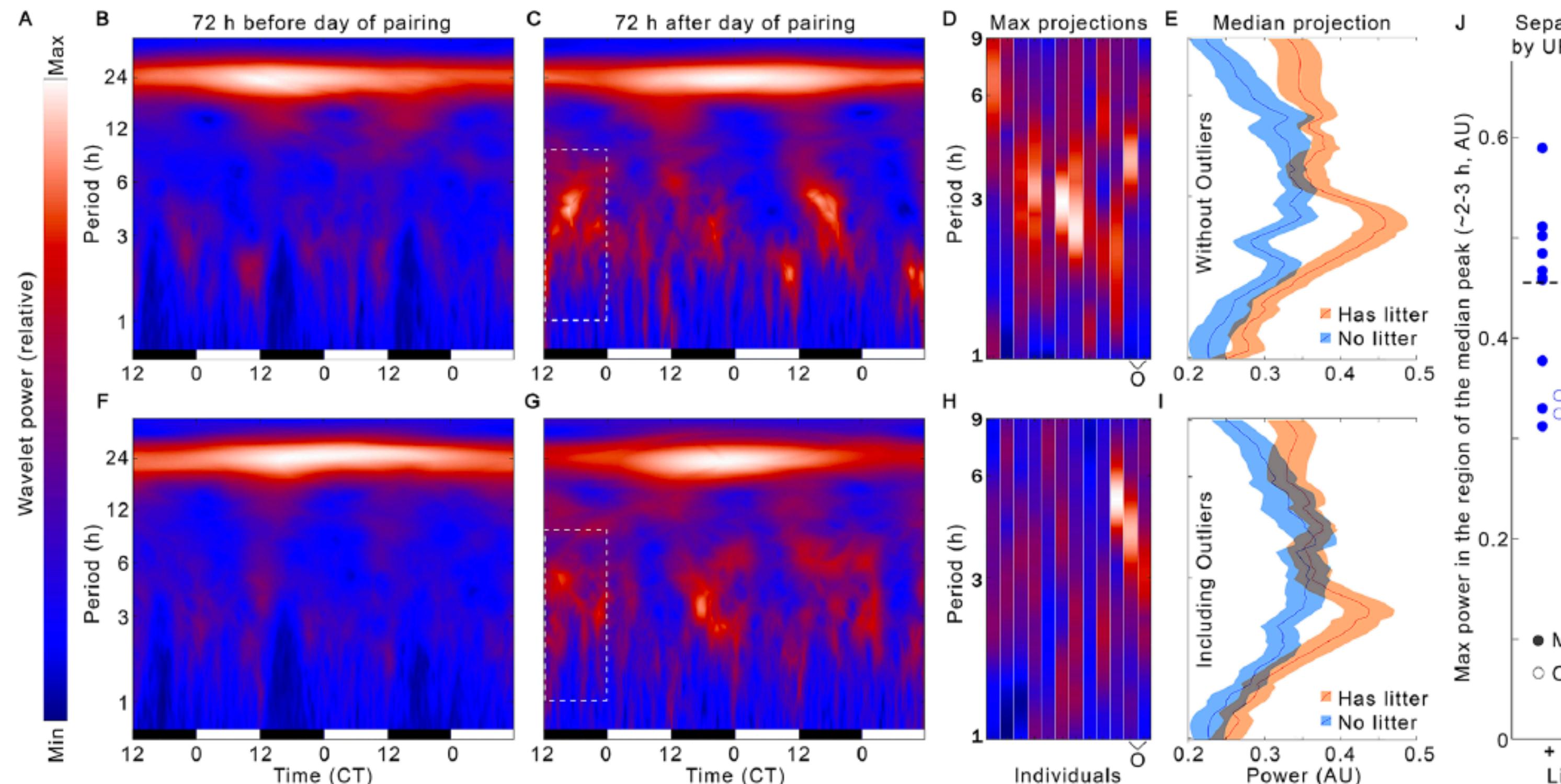
Dynamic Time Warping. DTW is a method that computes the (euclidean) path between two signals that minimize the distance between the two signals. One downside is that it cannot deal with missing values so you would need to interpolate beforehand if you have missing data points.



Wavelet analysis. An alternative to windowed Fourier transforms that also yields a two-dimensional plot showing strengths of variations as a function of both period (or frequency) and time. Unlike Fourier analysis, which characterizes similarities between time series and trigonometric functions of infinite extent, wavelet analysis addresses similarities, over limited portions of the time series, to waves of limited time extent called wavelets.



PLOS ONE



RESEARCH ARTICLE

Detection of Successful and Unsuccessful Pregnancies in Mice within Hours of Pairing through Frequency Analysis of High Temporal Resolution Core Body Temperature Data

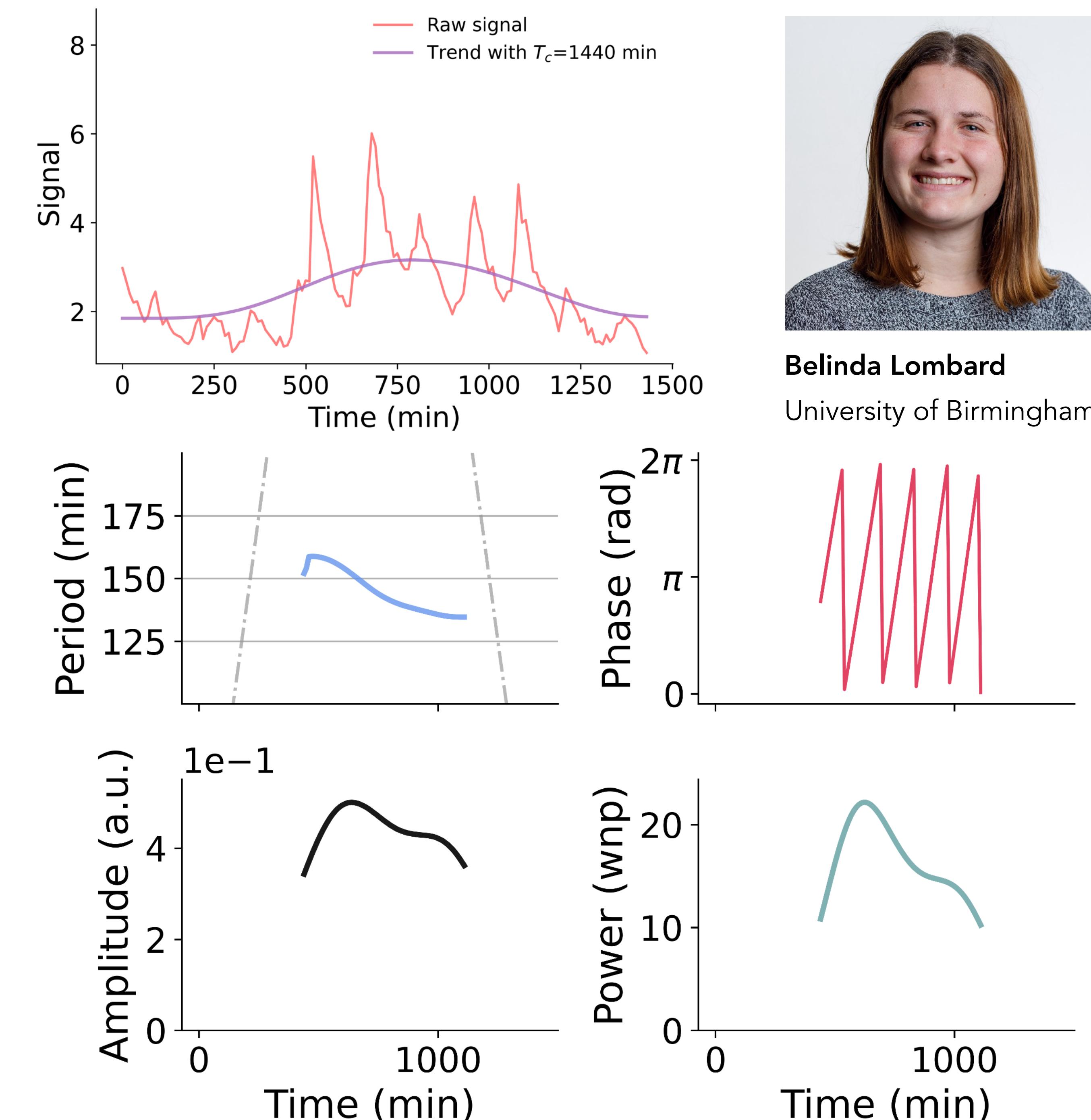
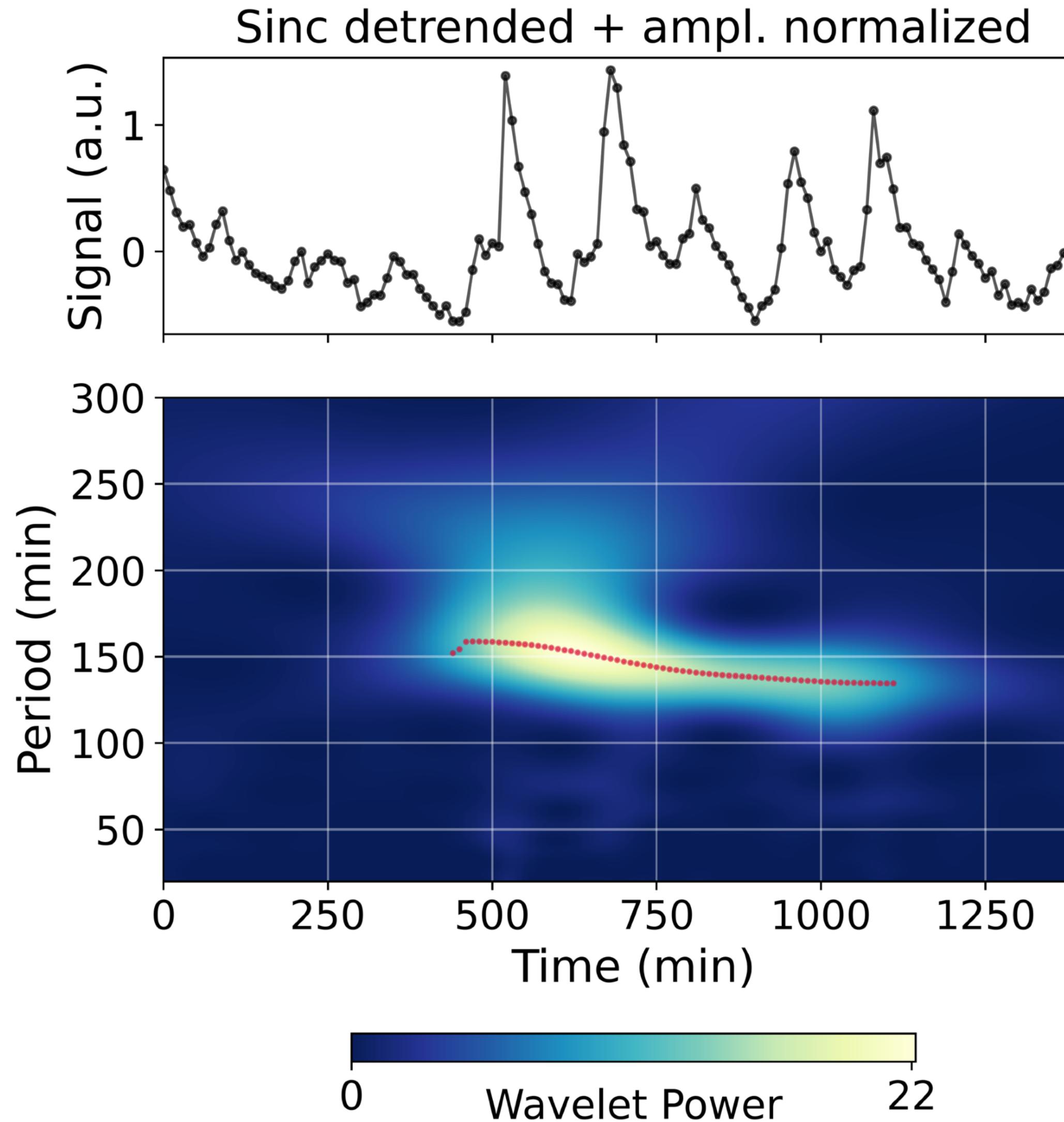
Benjamin L. Smarr¹, Irving Zucker^{1,2}, Lance J. Kriegsfeld^{1,3*}

1 Department of Psychology, University of California, Berkeley, United States of America, 2 Department of Integrative Biology, University of California, Berkeley, United States of America, 3 The Helen Wills Neuroscience Institute, University of California, Berkeley, United States of America

* kriegsfeld@berkeley.edu

Wavelet analysis of cortisol rhythms

pyBOAT



Belinda Lombard

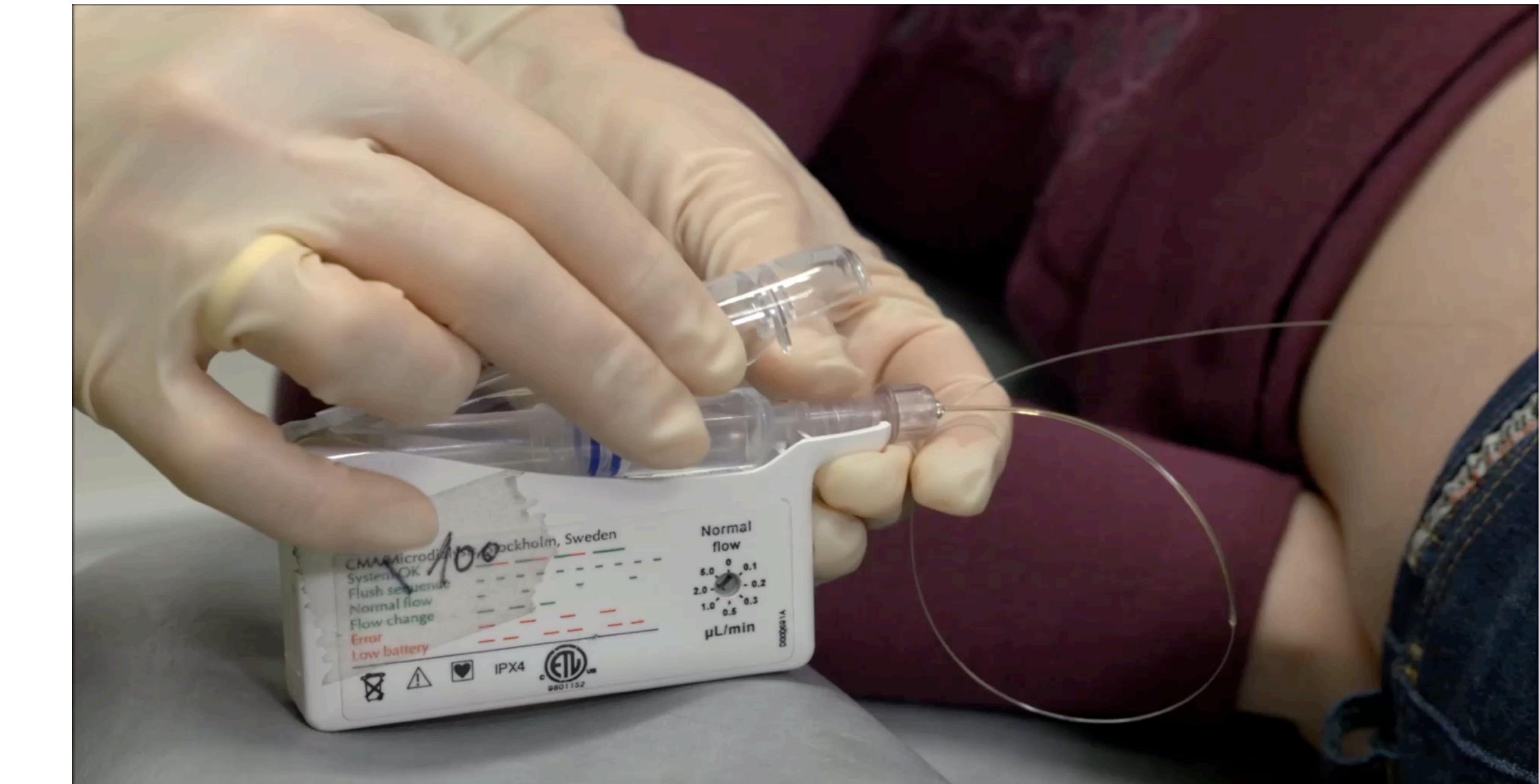
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Measuring cortisol in different compartments

Pros and Cons

Saliva and urine

Easy, cheap, widely available. However, it does not capture rapid cortisol dynamics.

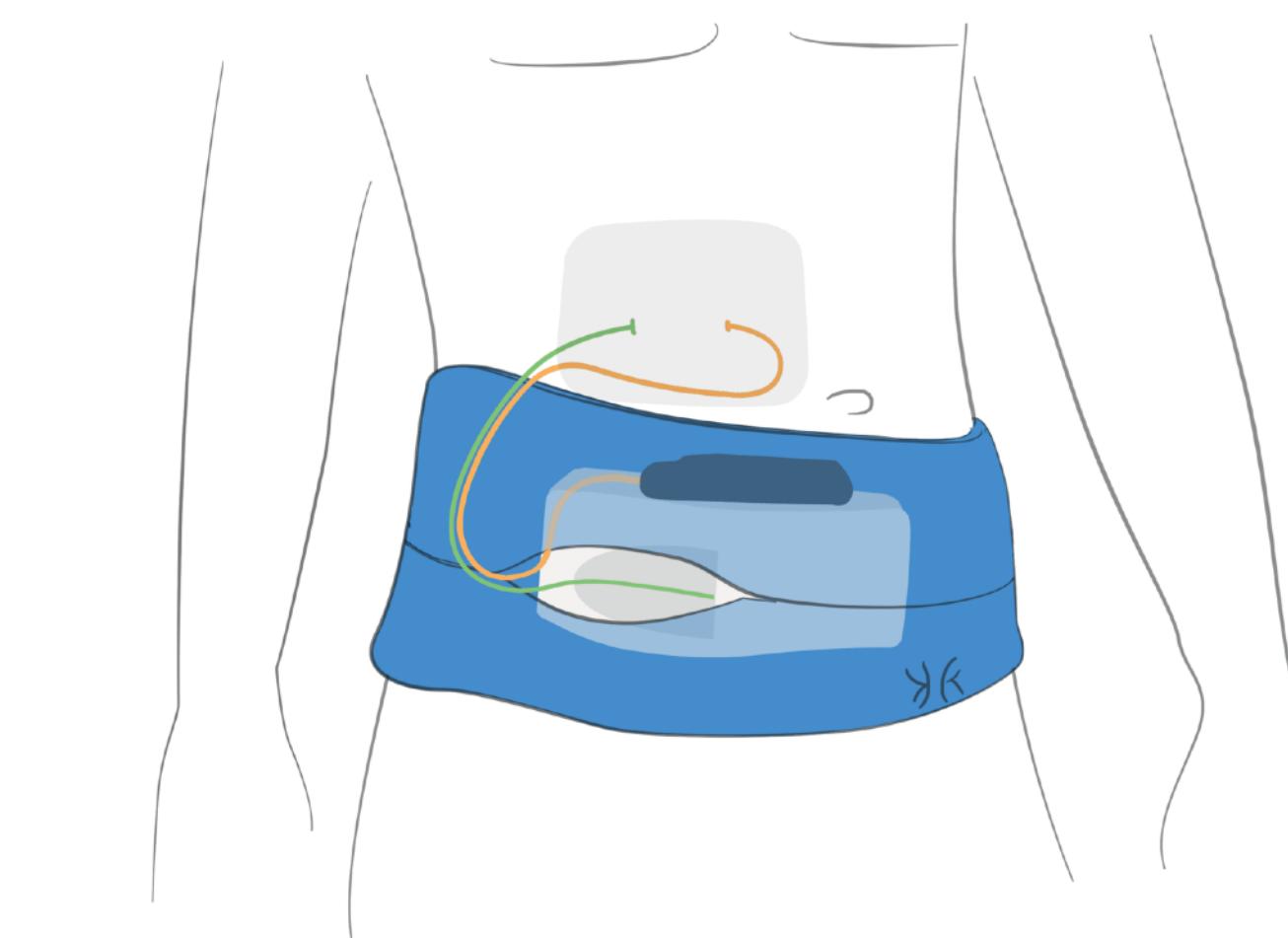


Plasma

The gold standard. Difficult, expensive, limited to some labs.

Interstitial fluid (ISF)

Continuous, high-resolution ambulatory micro-dialysis now possible. Easier, versatile, limited availability. Highly correlated with plasma.



U-RHYTHM ambulatory
micro-dialysis

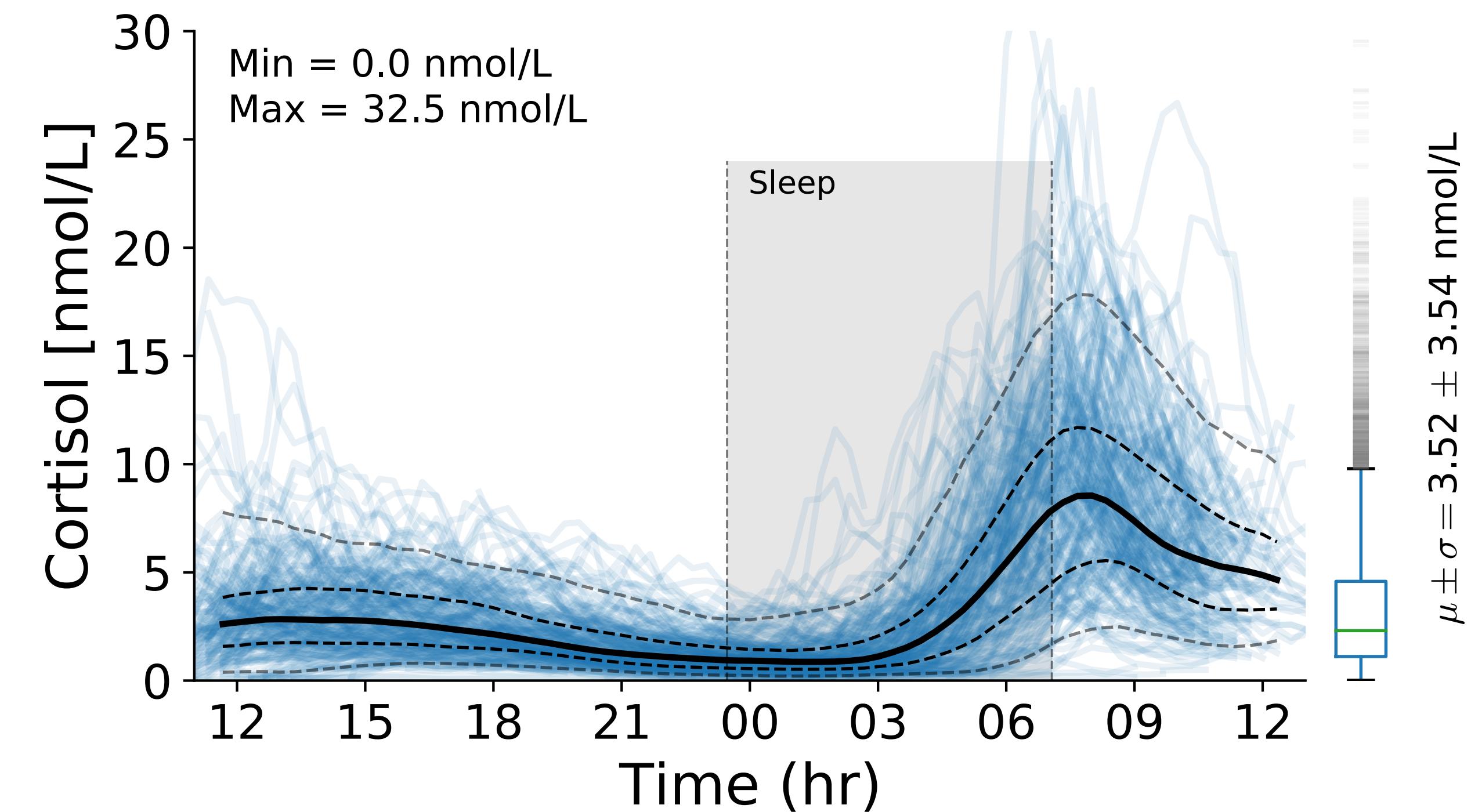
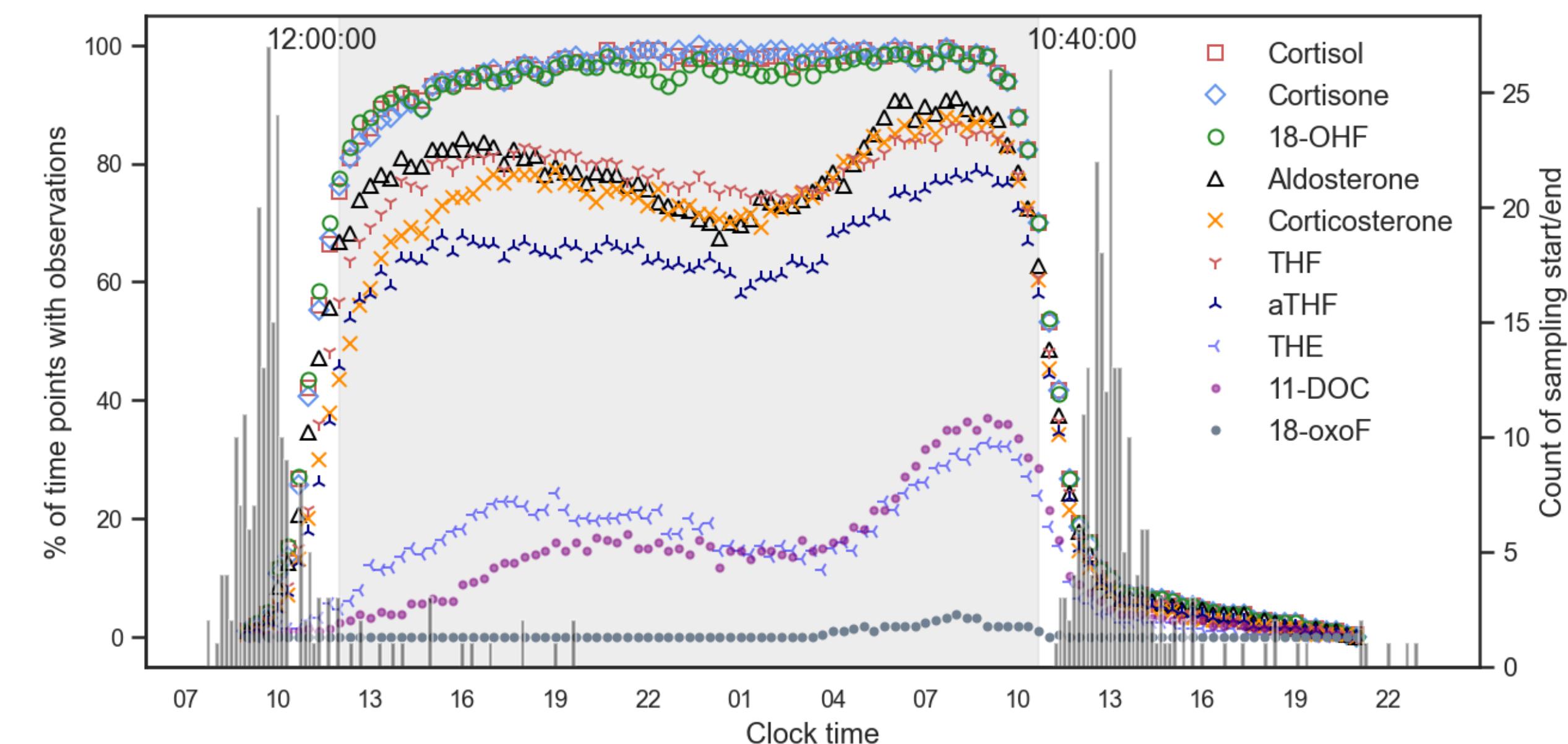
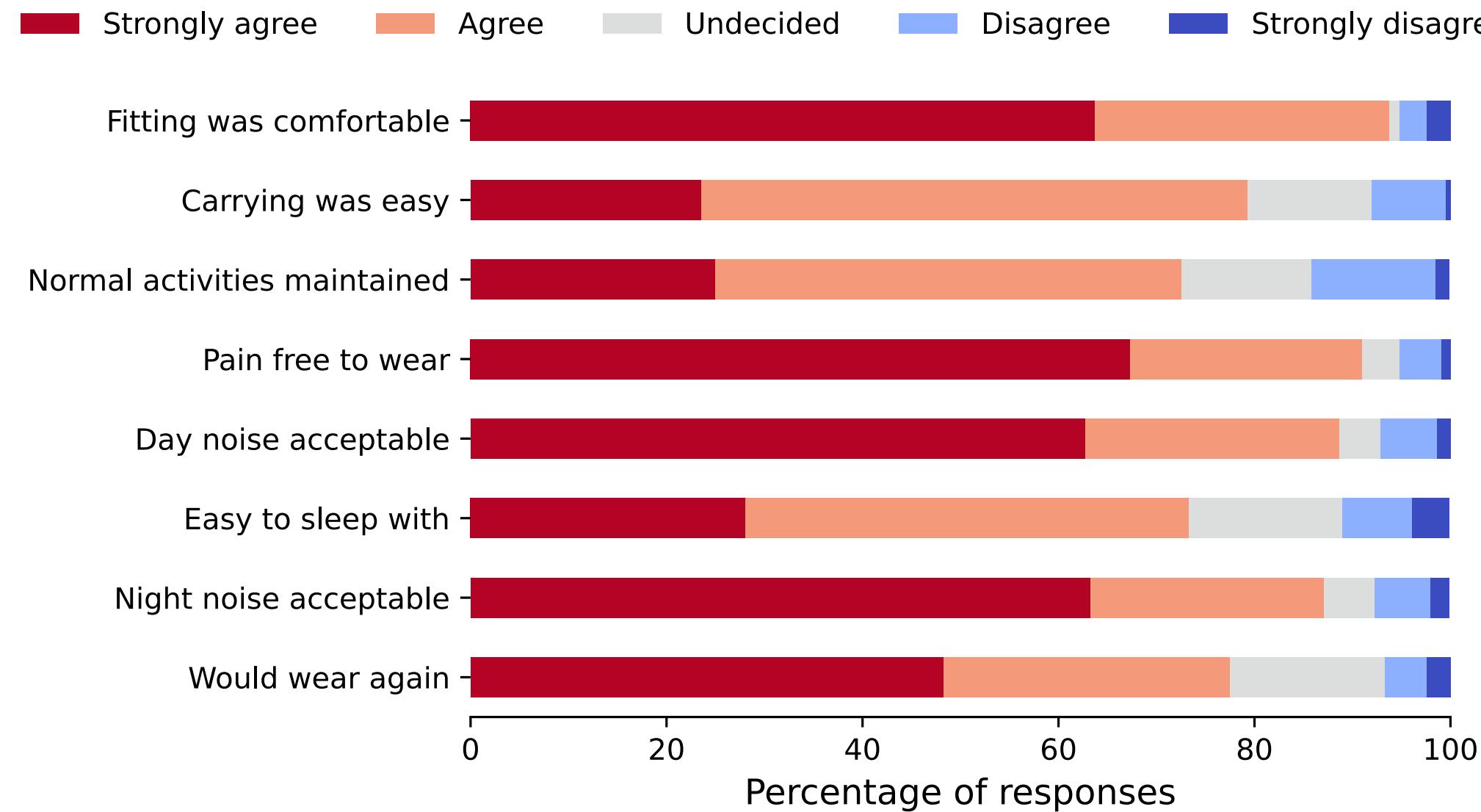



Horizon 2020
Programme

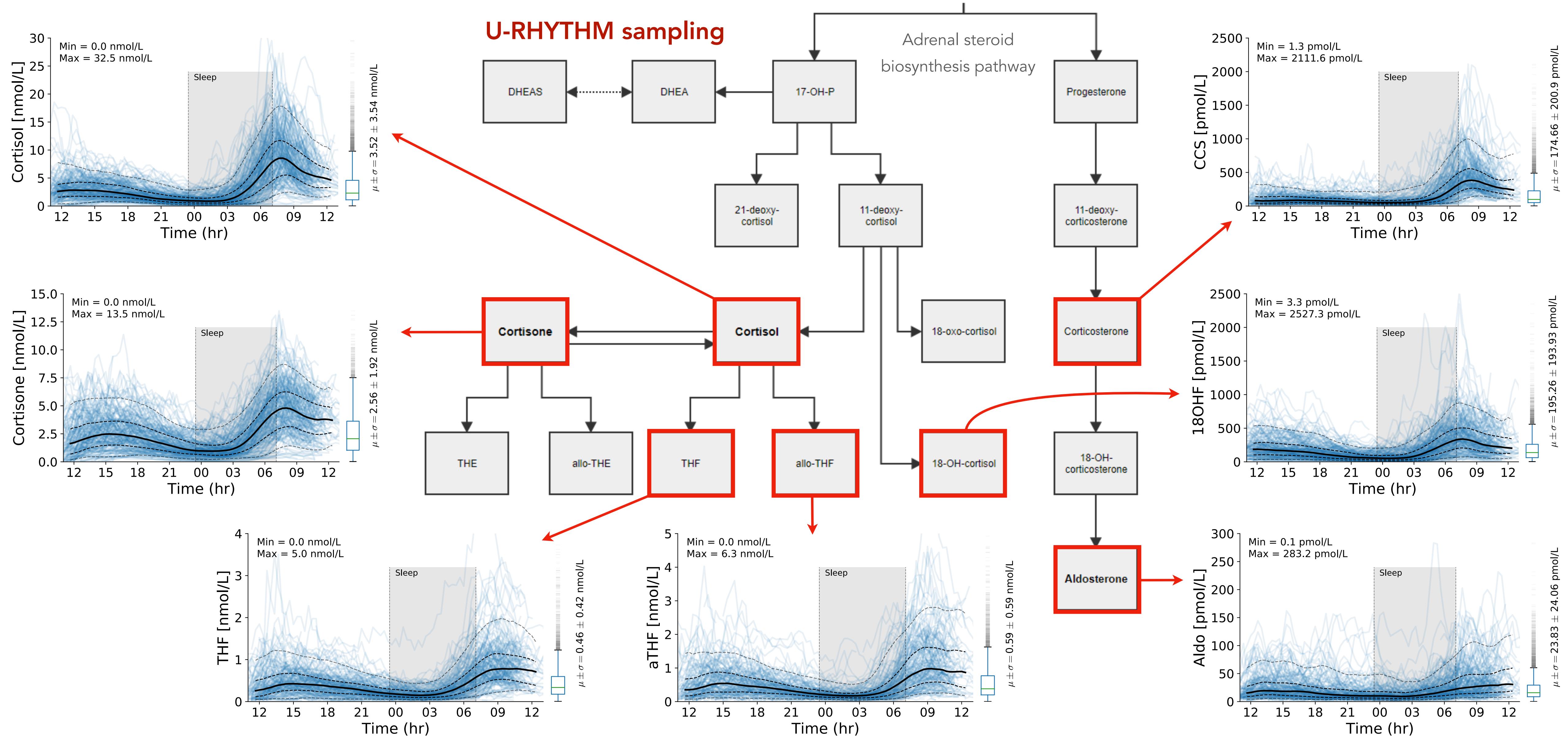

ULTRADIAN

Inter-individual variability in healthy volunteers

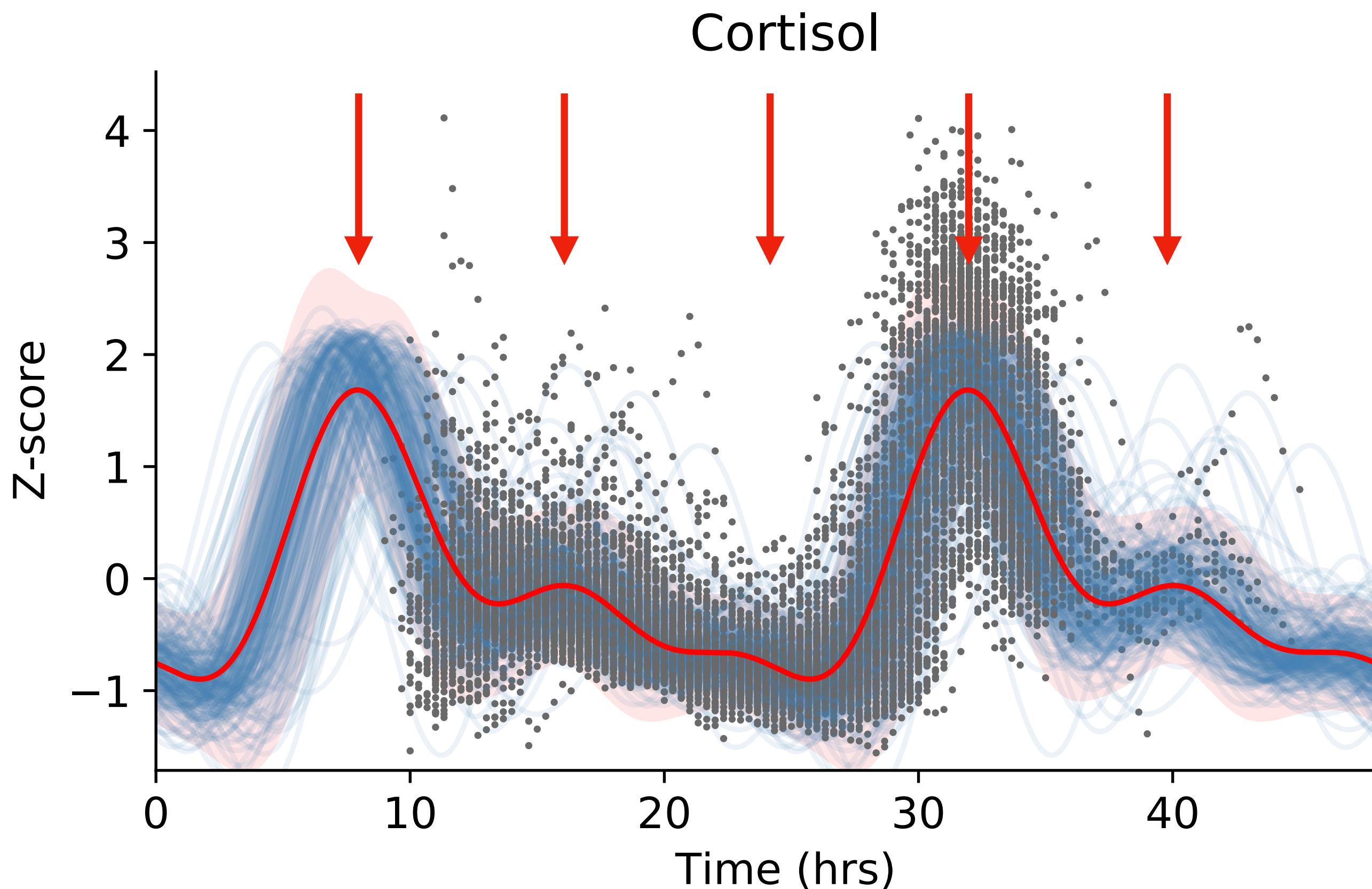
- n = 214 healthy volunteers (98 M, 116 F)
- Age: 20 to 68 years old (42.5 ± 14.1)
- BMI: 16 to 30 kg/m² (23.5 ± 2.7)
- Sleep onset: 23:28 hrs \pm 58 min
- Final wake: 7:04 hrs \pm 76 min
- Samples collected every 20 min (72 samples in 24 hrs)
- Sleep and food diaries



Rhythmic secretion of 7 tissue-free adrenal steroids ($n=214$)



Tissue-free adrenal steroids exhibit circadian and ultradian rhythmicity



Moškon *BMC Bioinformatics* (2020) 21:485
<https://doi.org/10.1186/s12859-020-03830-w>

BMC Bioinformatics

SOFTWARE

Open Access

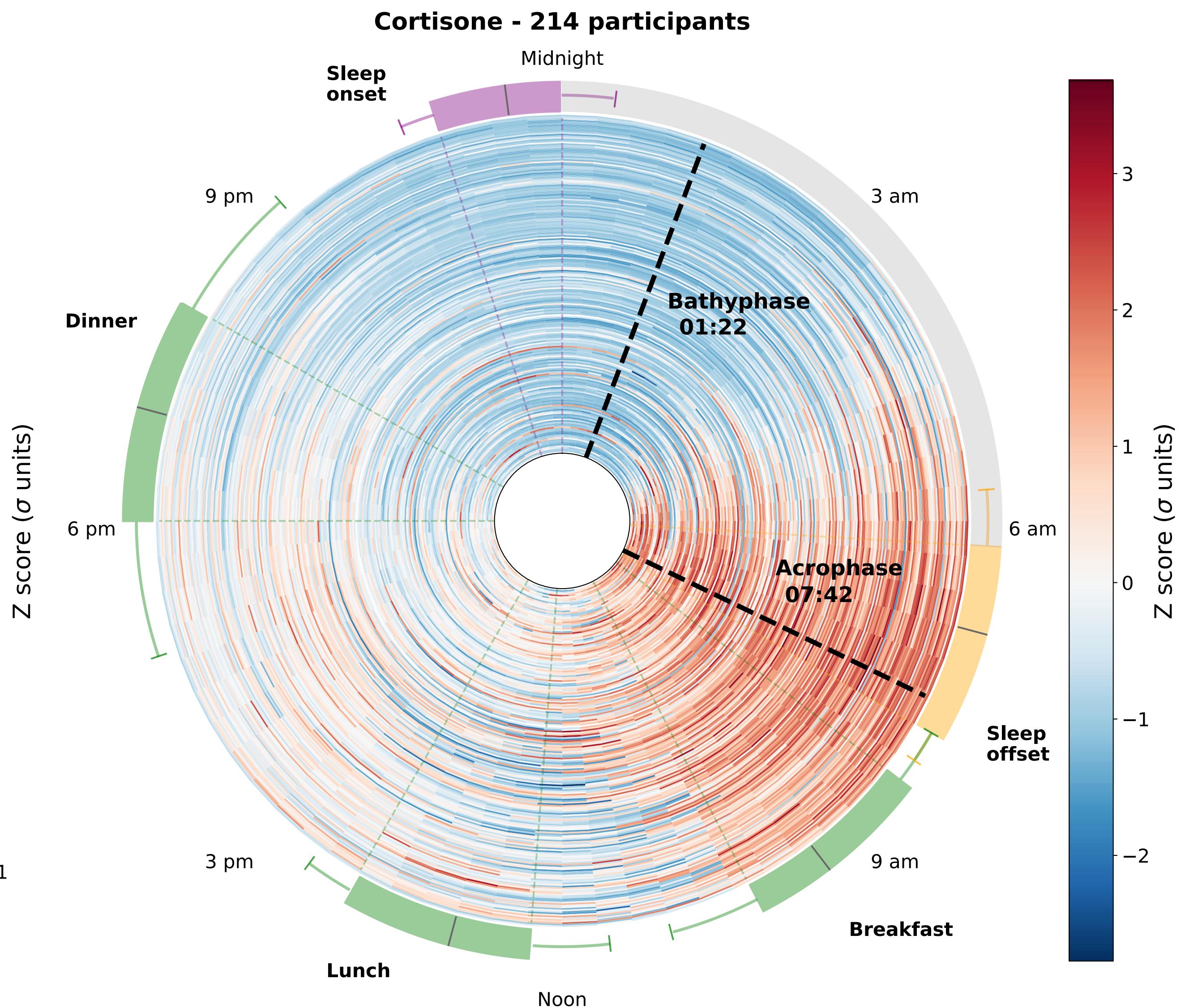
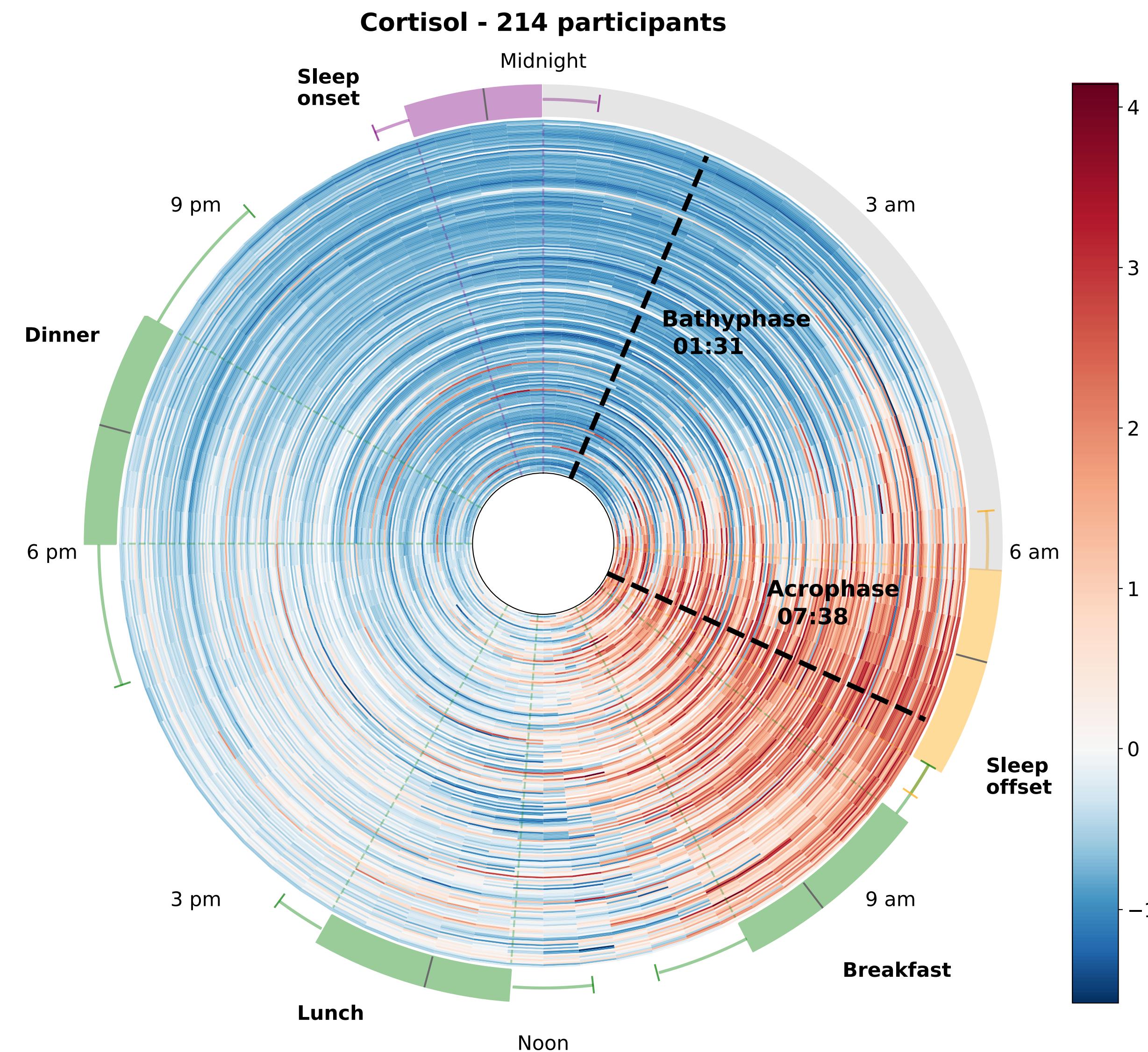
CosinorPy: a python package
for cosinor-based rhythmometry

Miha Moškon^{*}

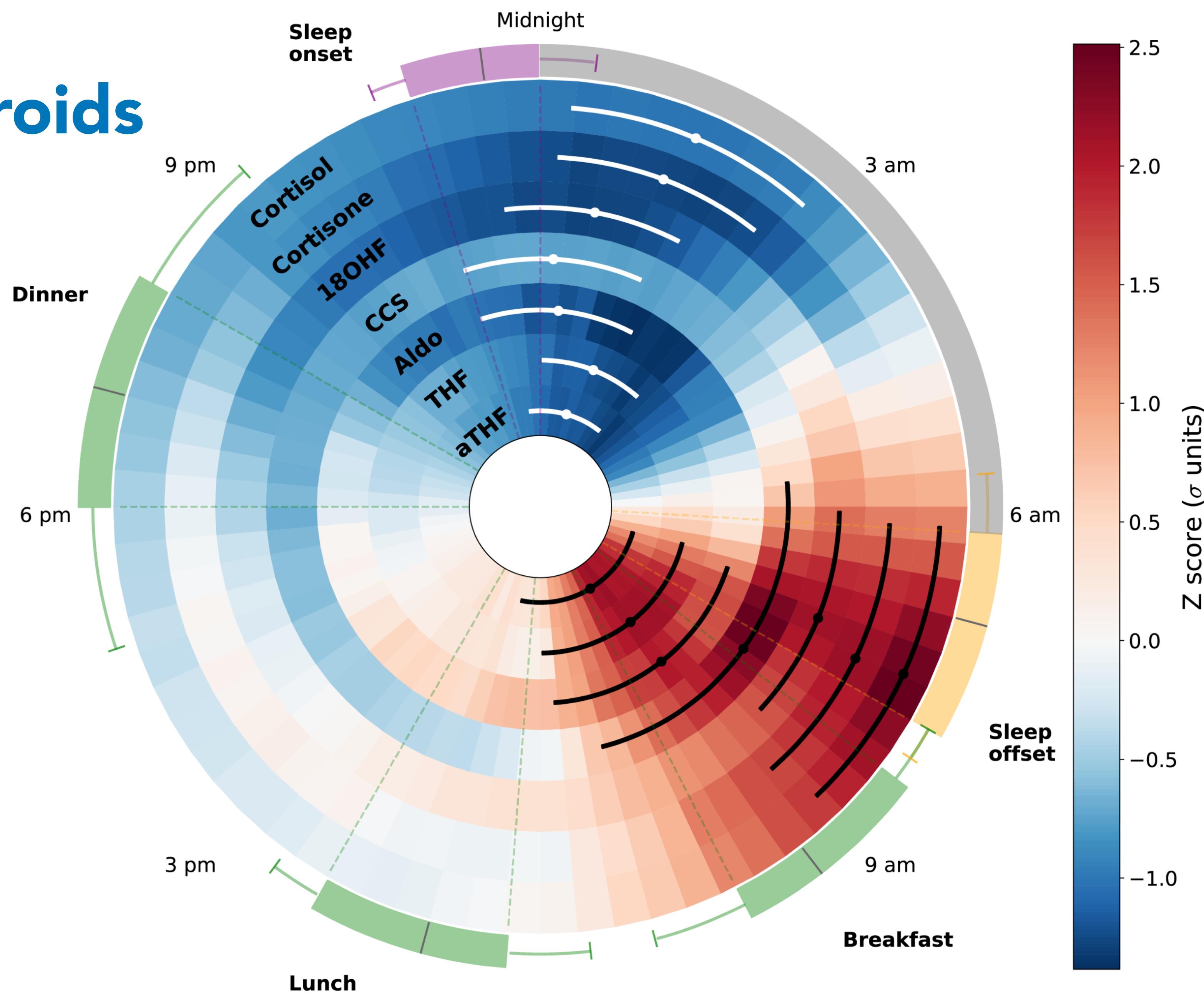
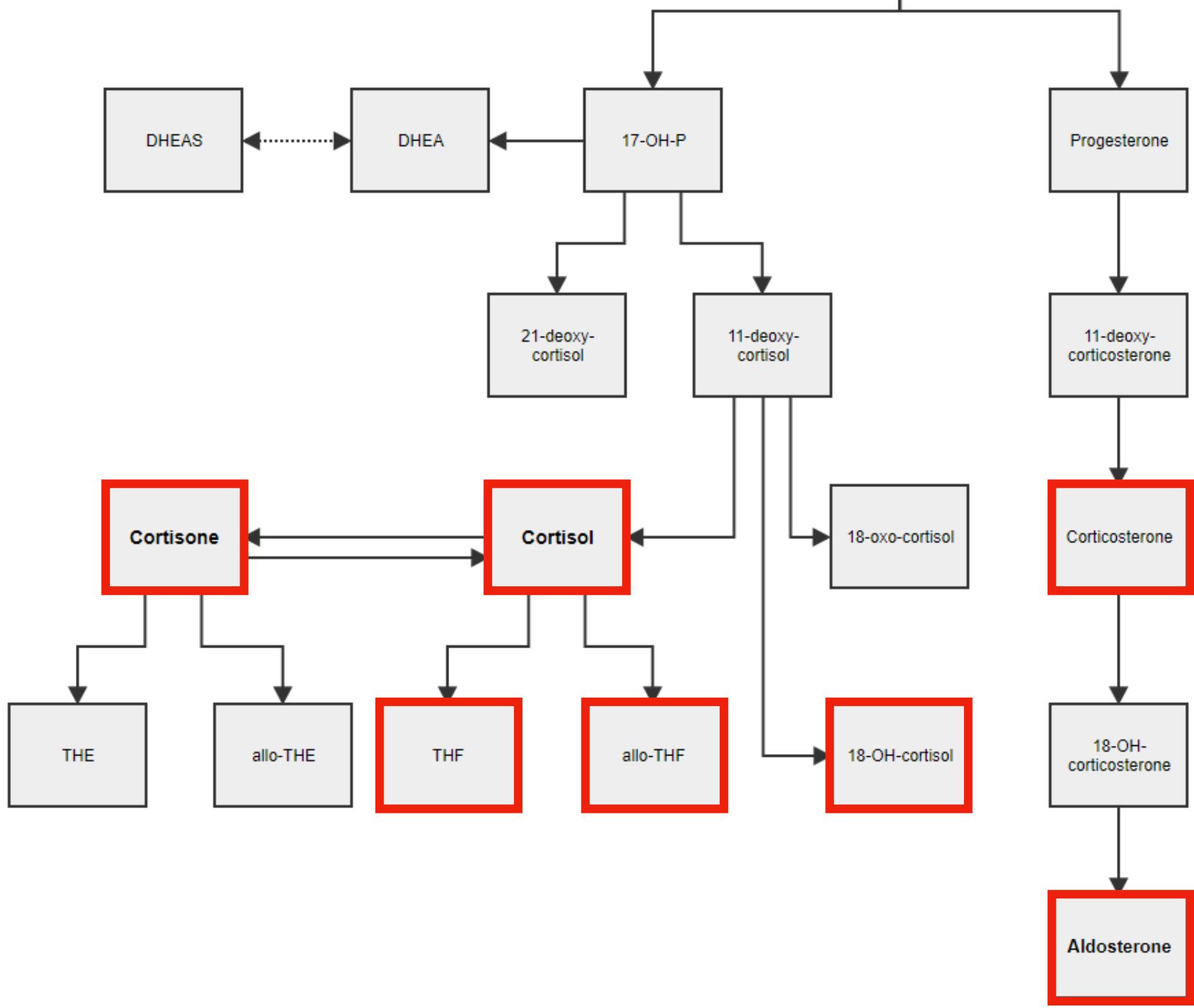
$$y(t) = \sum_{i=1}^N \left(A_{i,1} \cdot \sin \left(\frac{t}{P/i} \cdot 2\pi \right) + A_{i,2} \cdot \cos \left(\frac{t}{P/i} \cdot 2\pi \right) \right) + M + e(t)$$



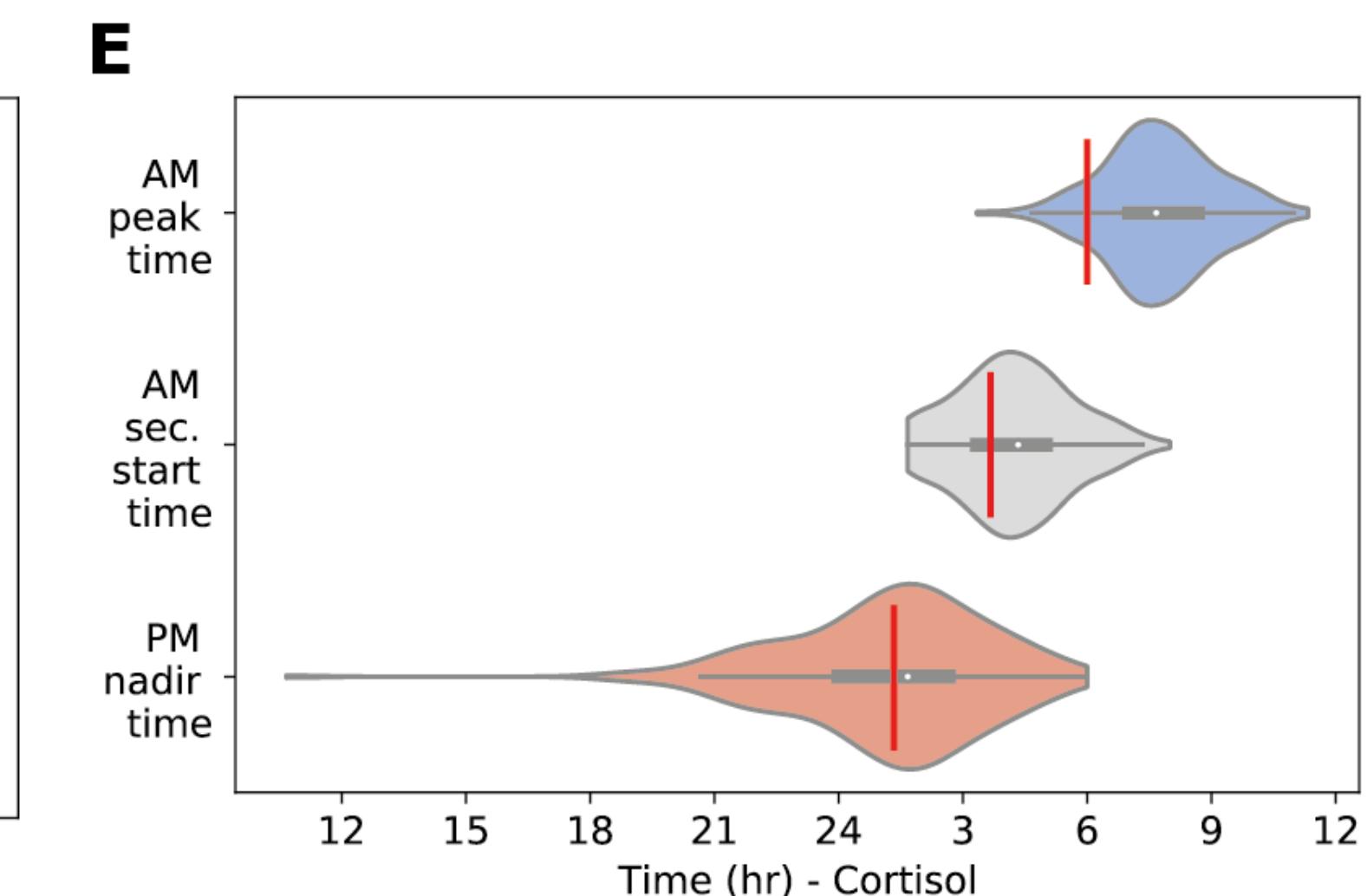
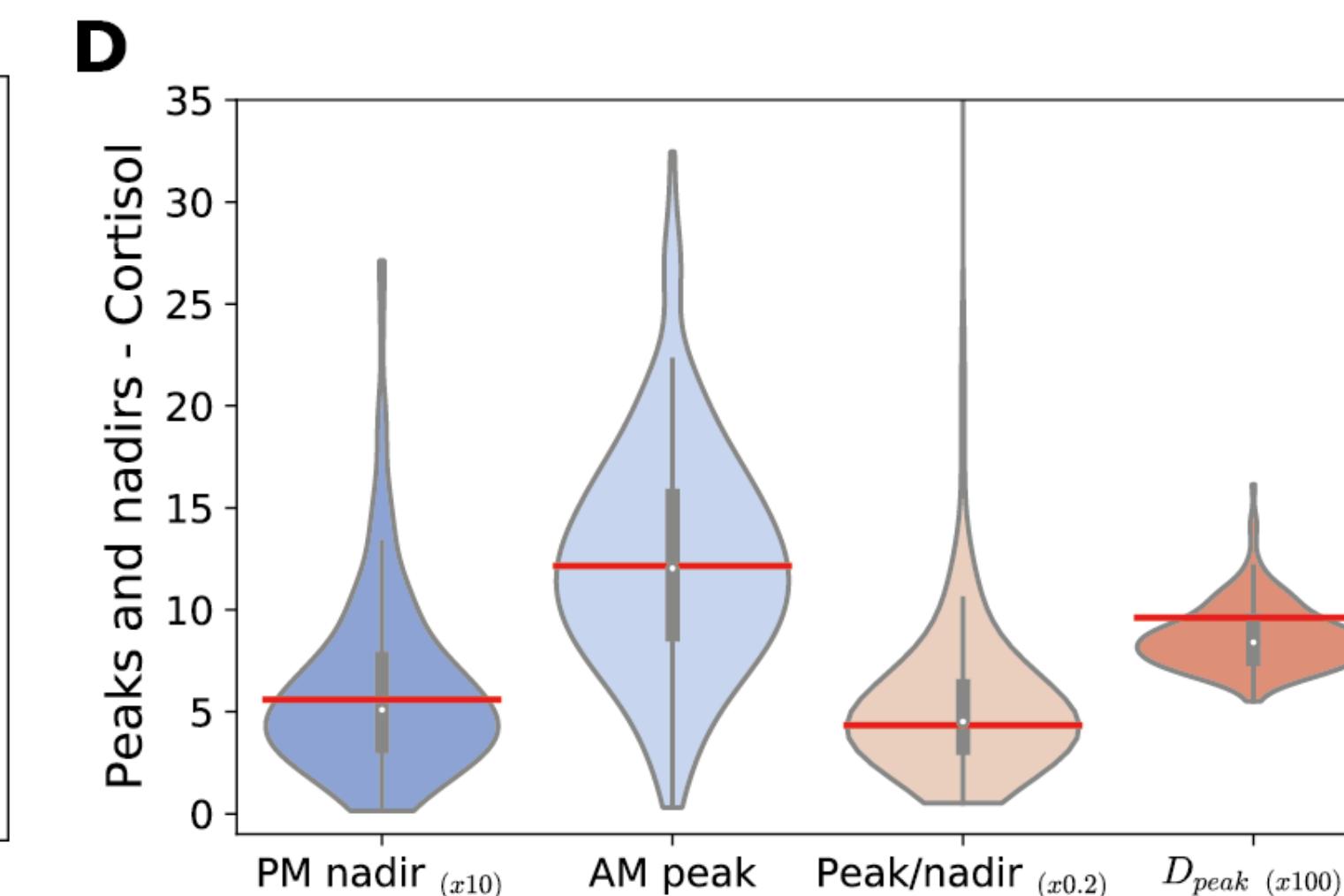
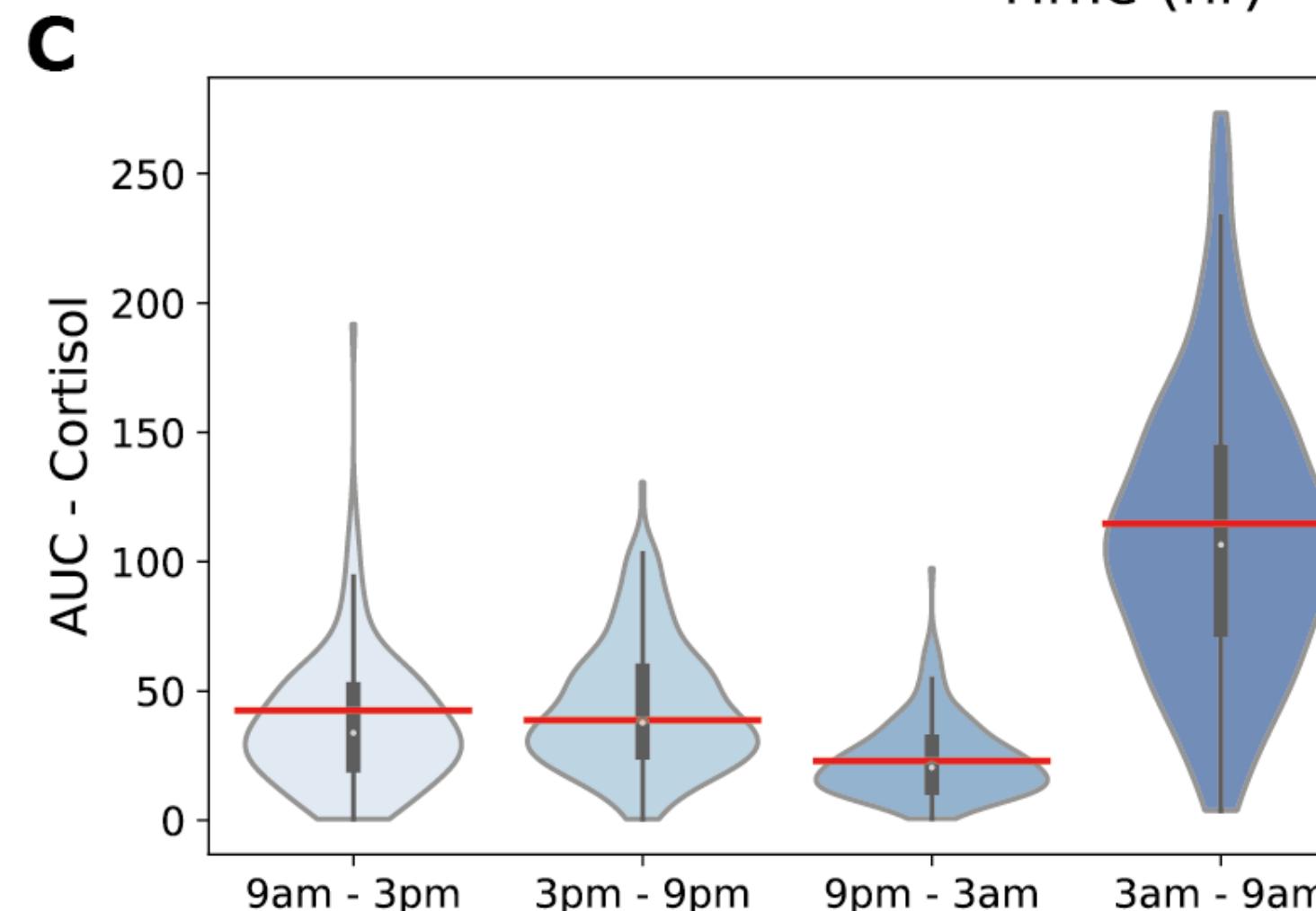
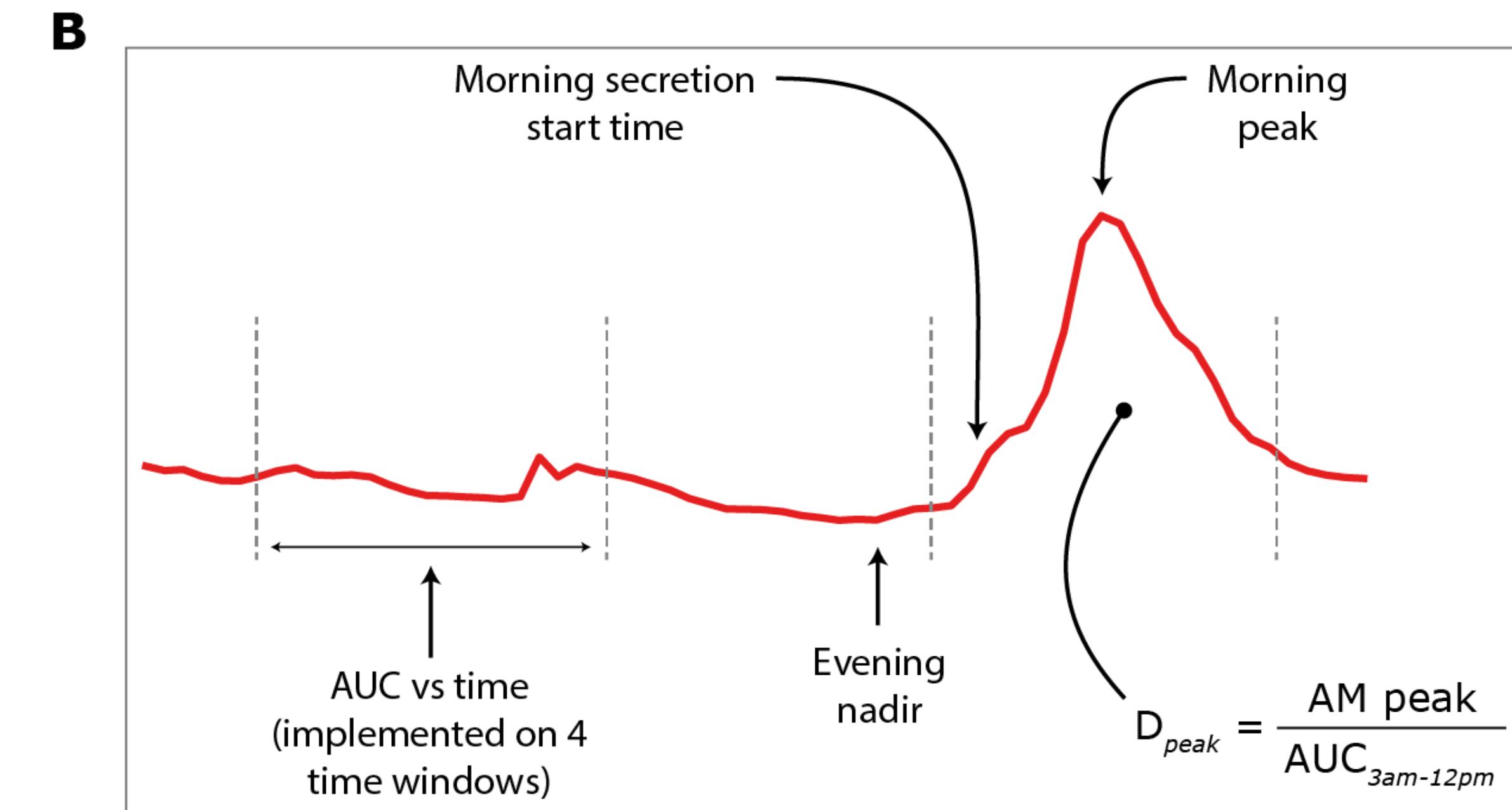
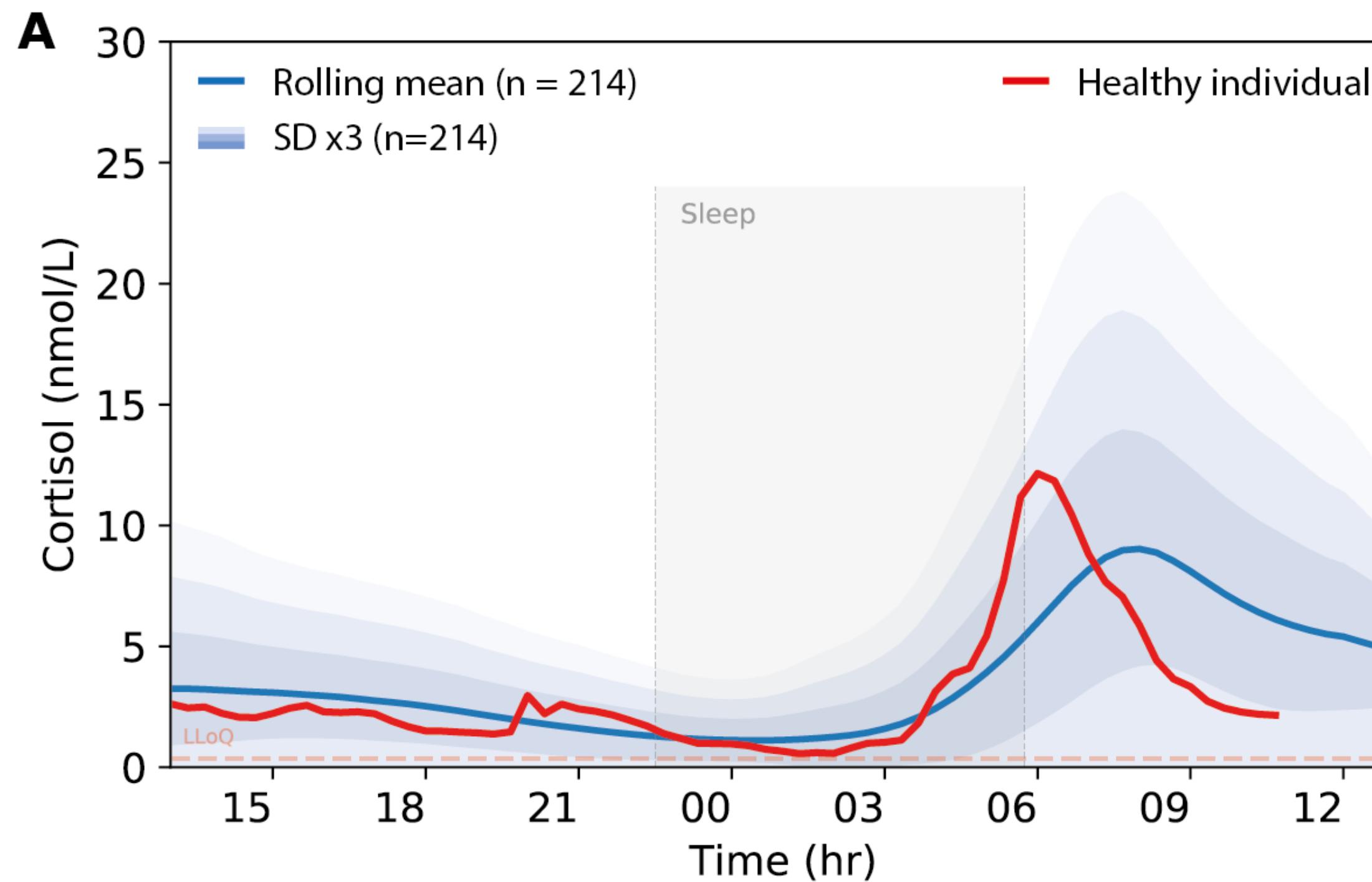
Inter-individual variability in healthy volunteers ($n=214$)



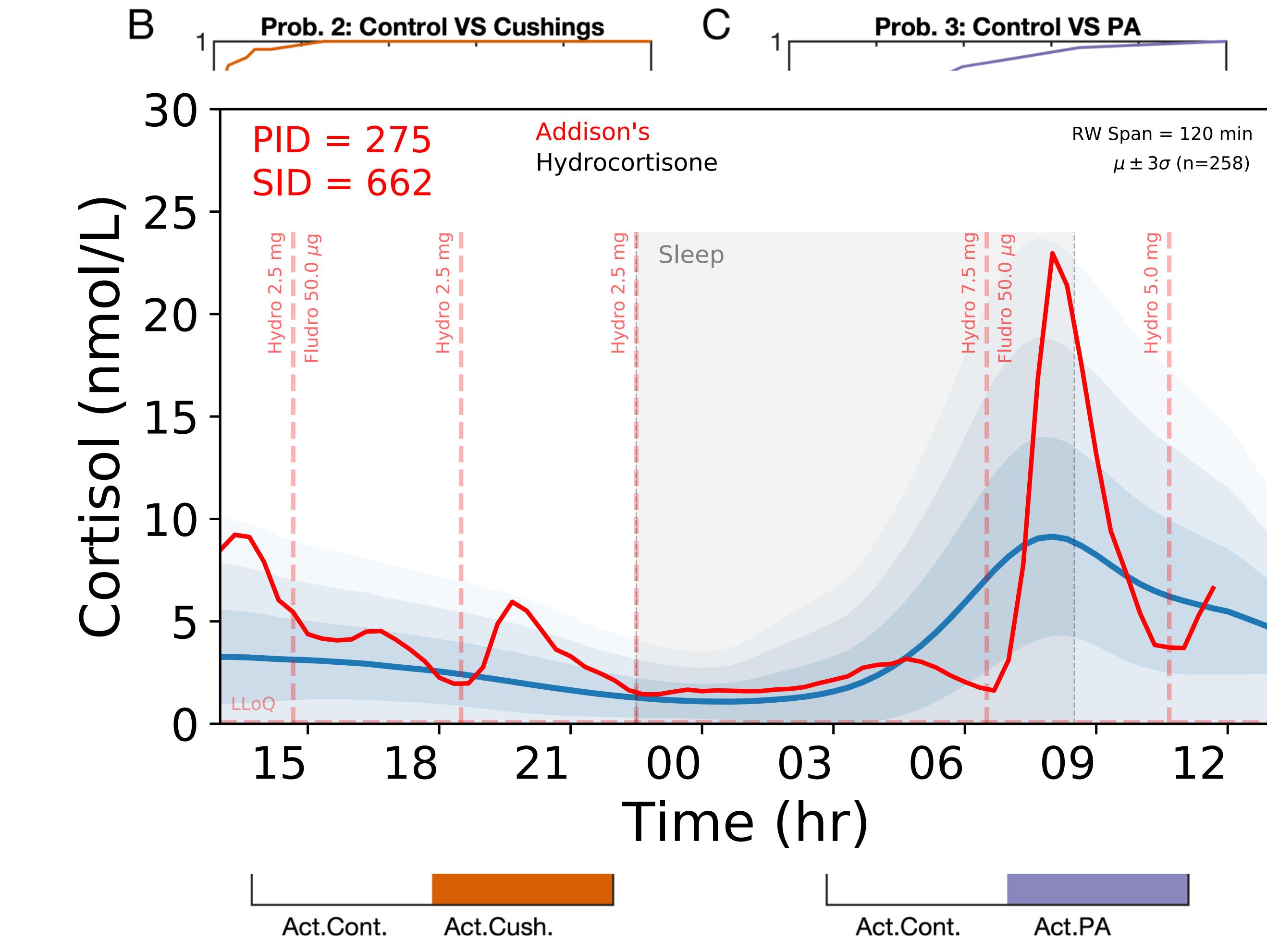
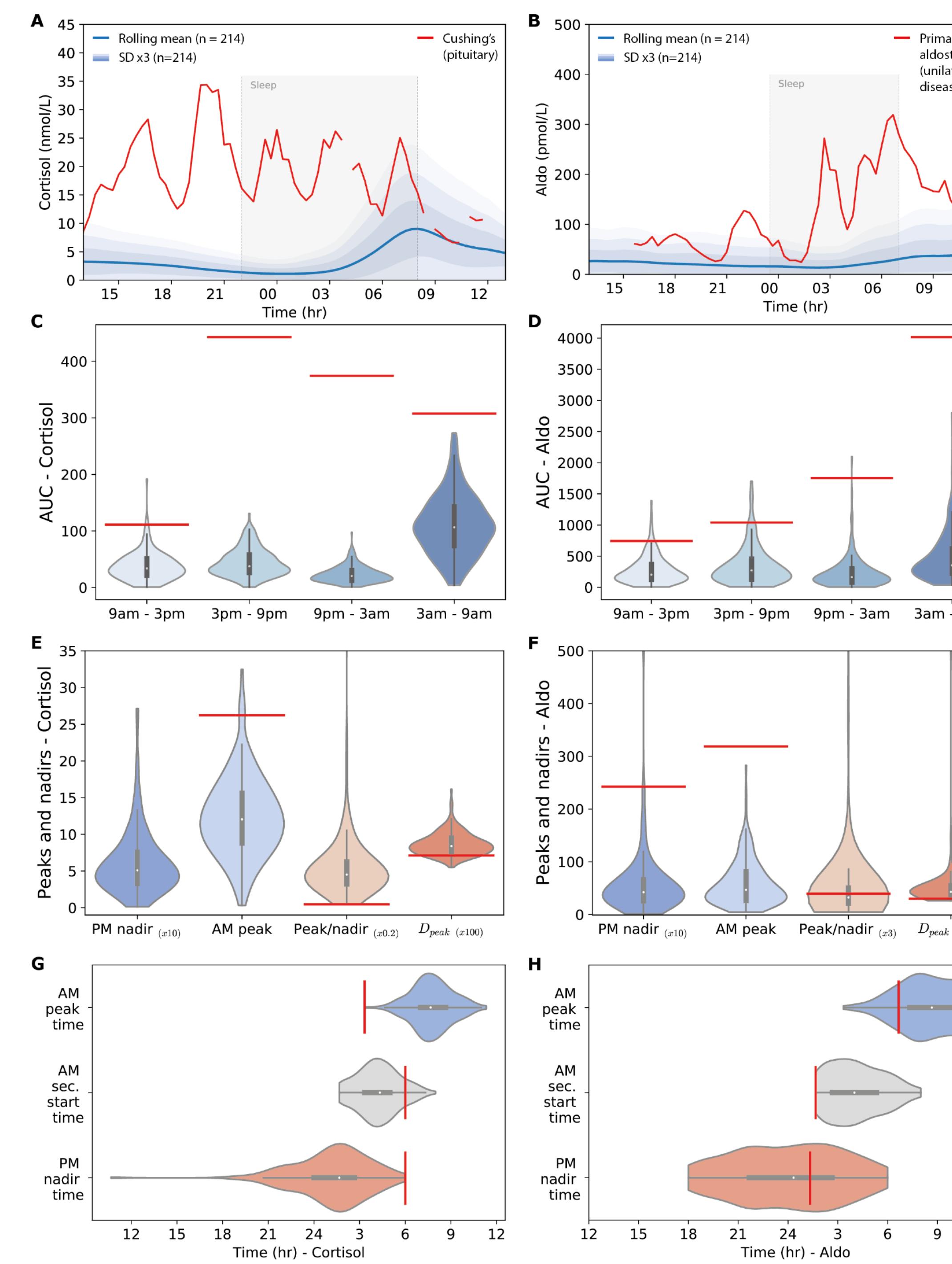
Diurnal dynamics of 7 tissue-free adrenal steroids (averaged over 214 healthy volunteers)



Dynamic biomarkers to quantify variability

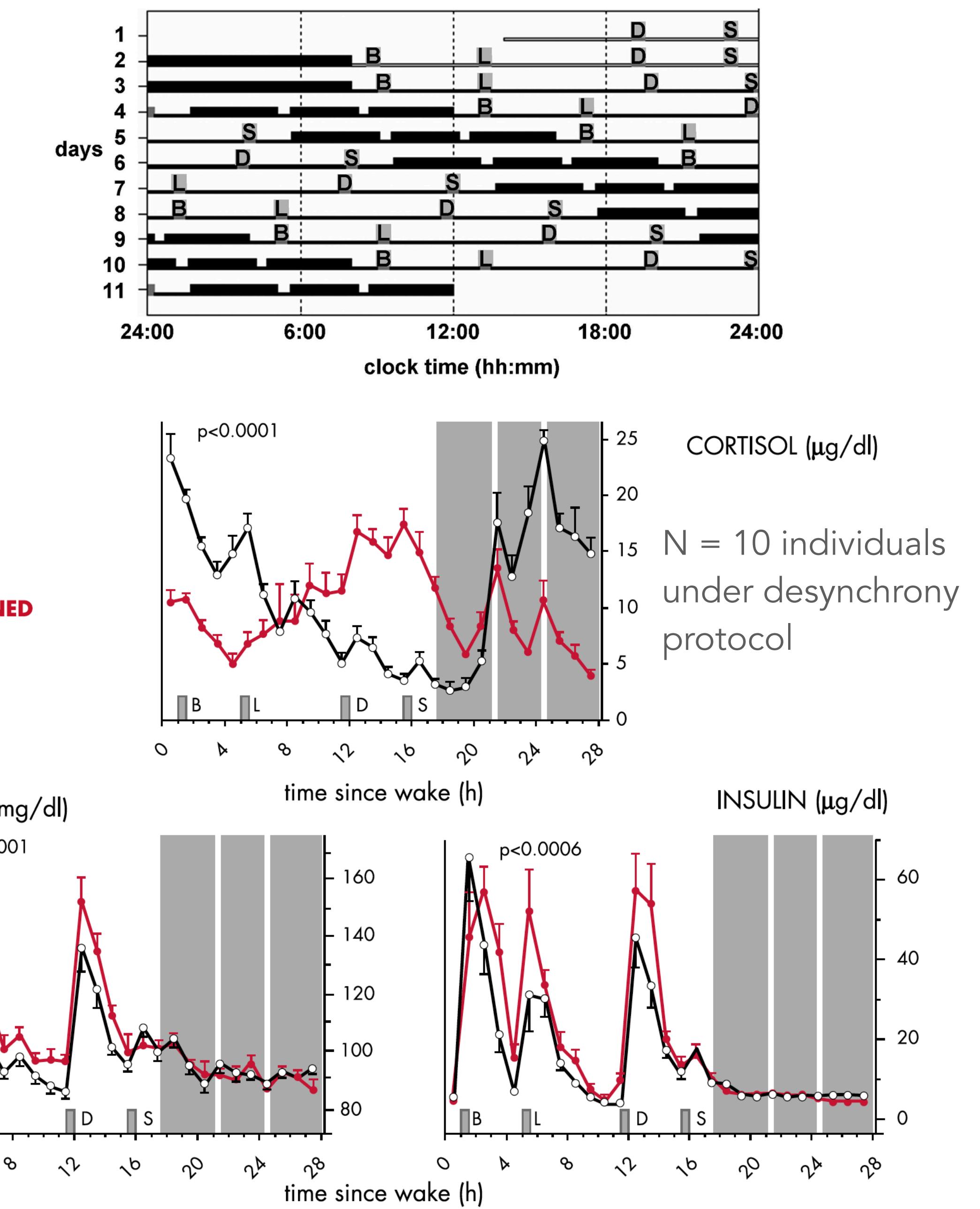
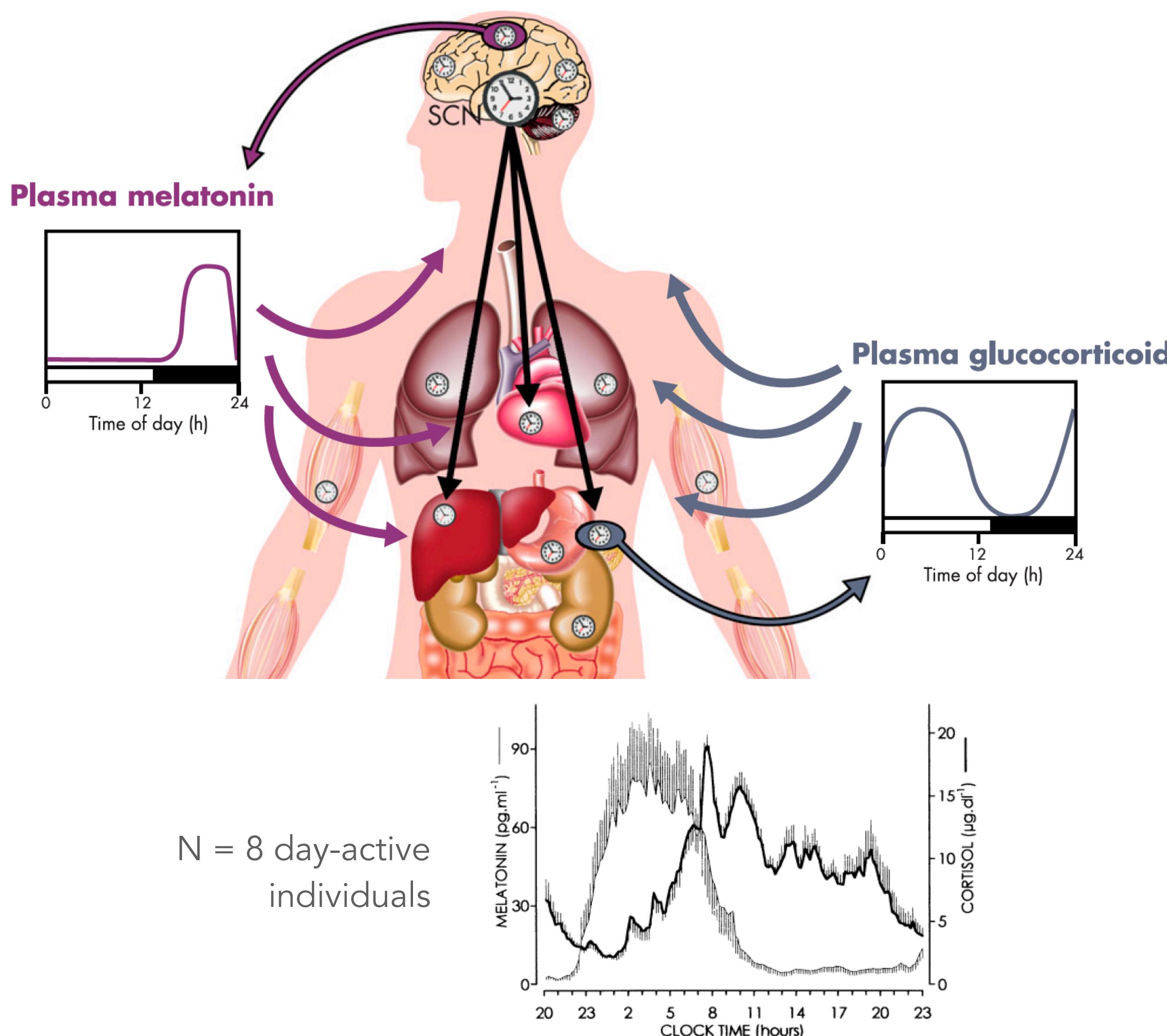


Dynamic biomarkers to support diagnosis and disease mgmt

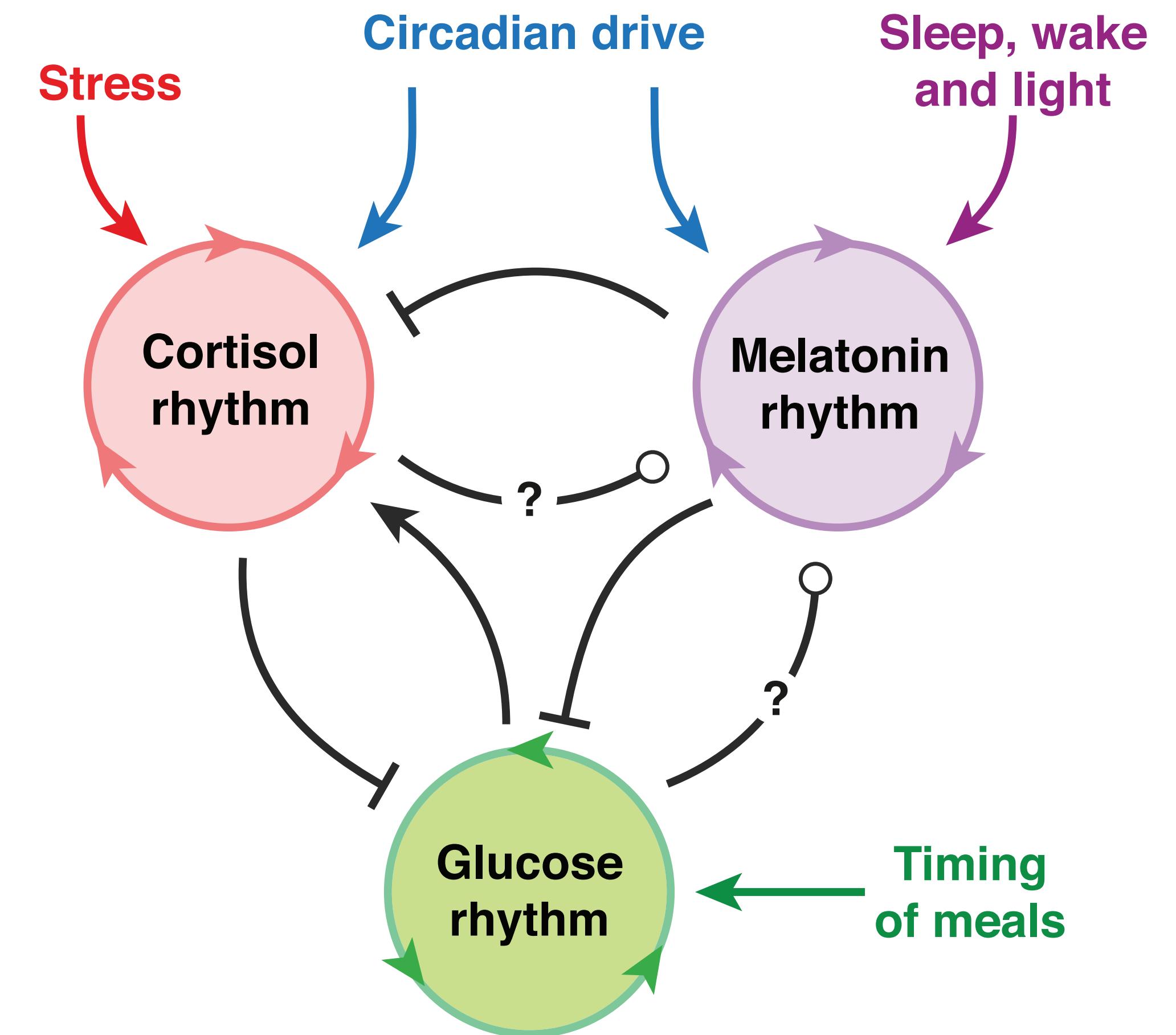
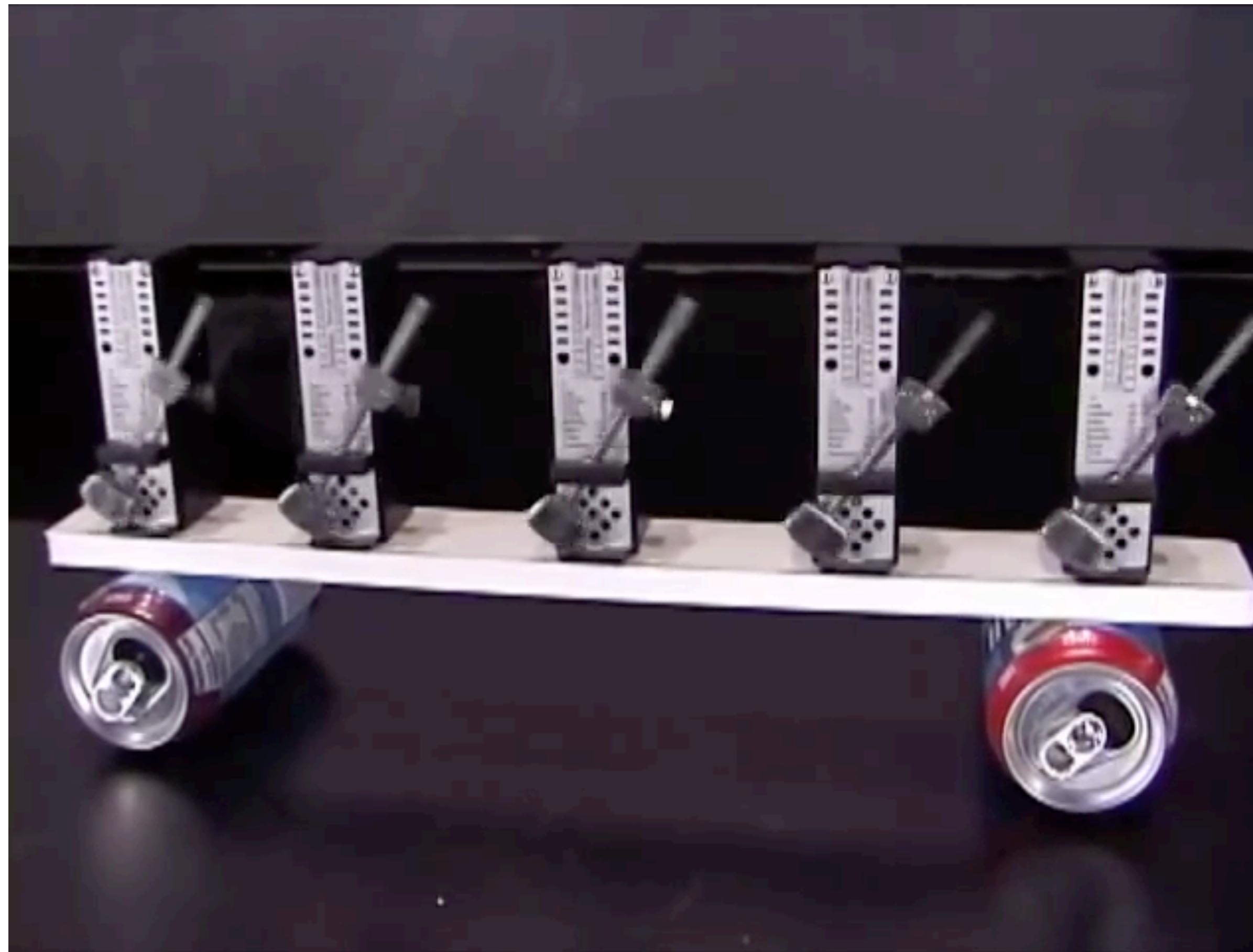


Misalignment of endocrine axes

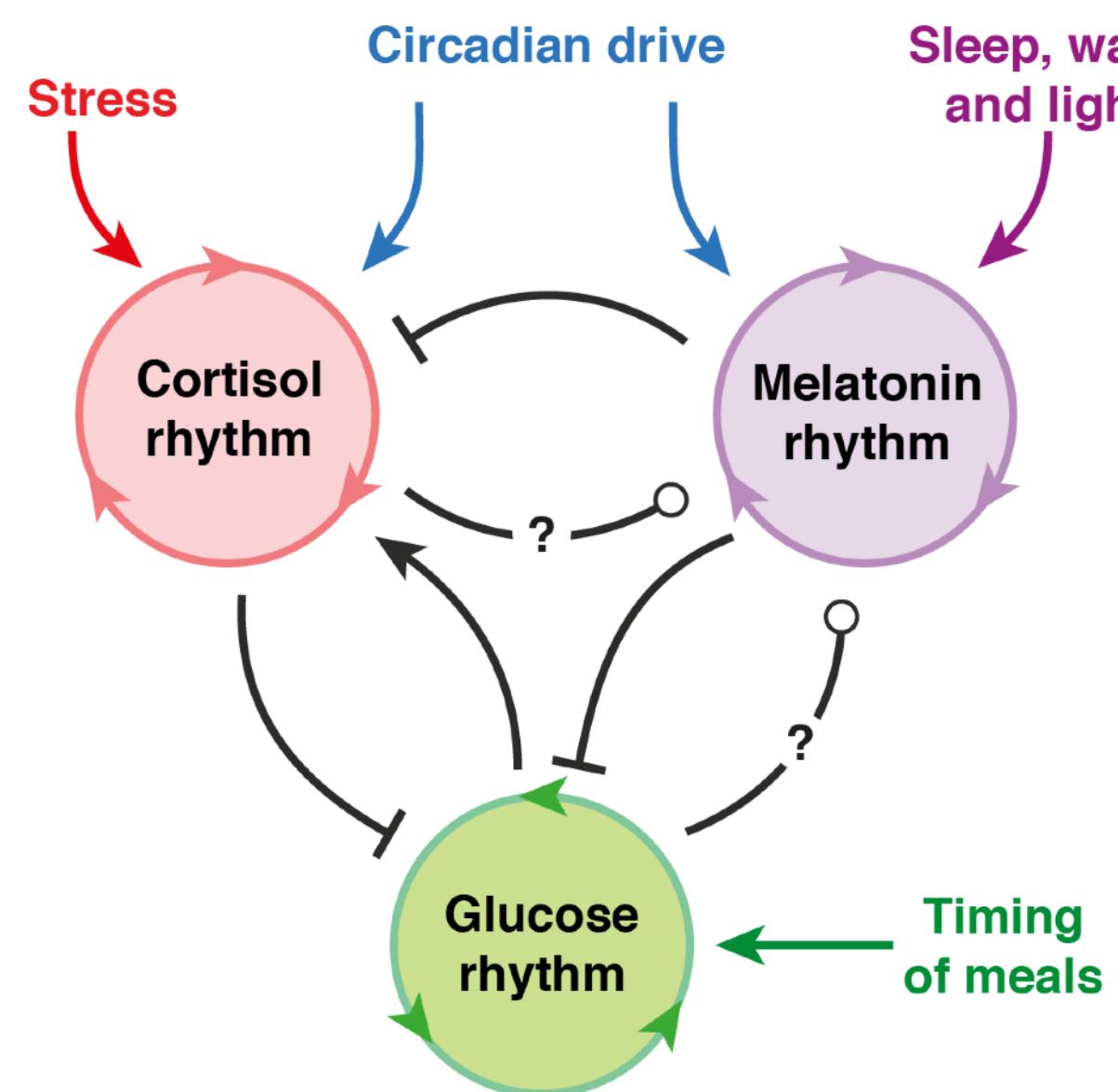
CORT, sleep & metabolism



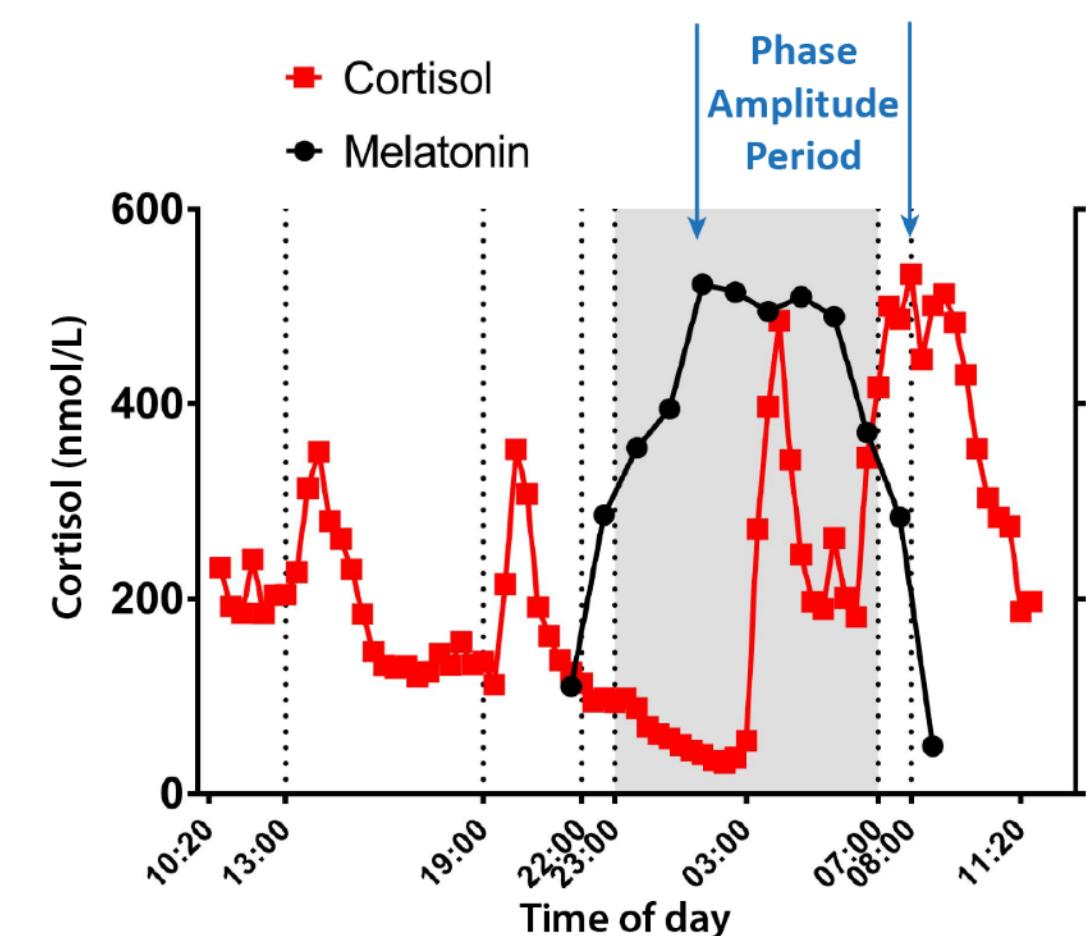
Coupling mechanisms allow the exchange of information



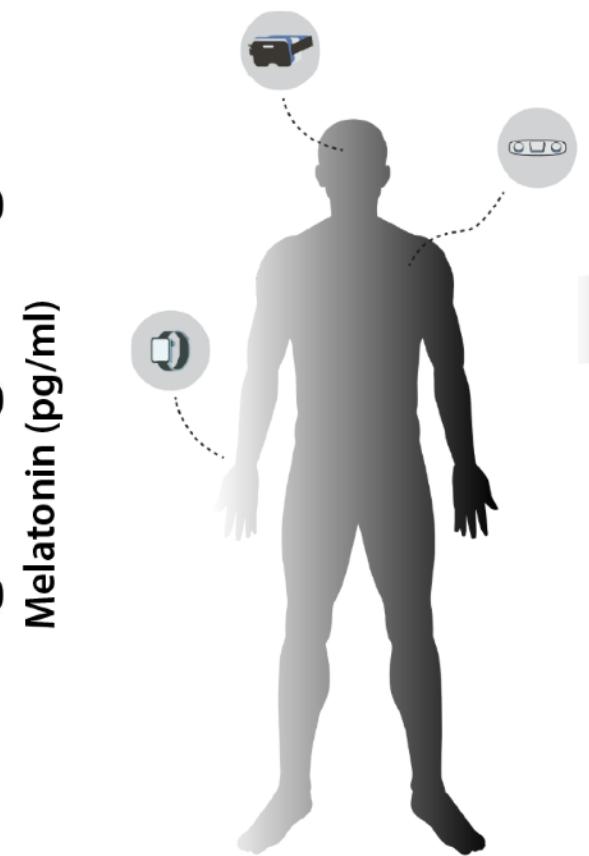
Understanding coupling between endocrine systems



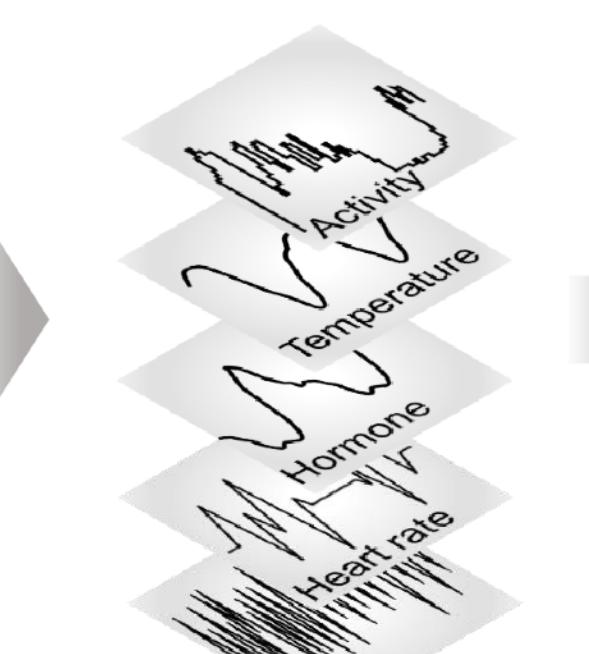
Coupled oscillator modelling
Considers endocrine axes as coupled oscillators subject to perturbations



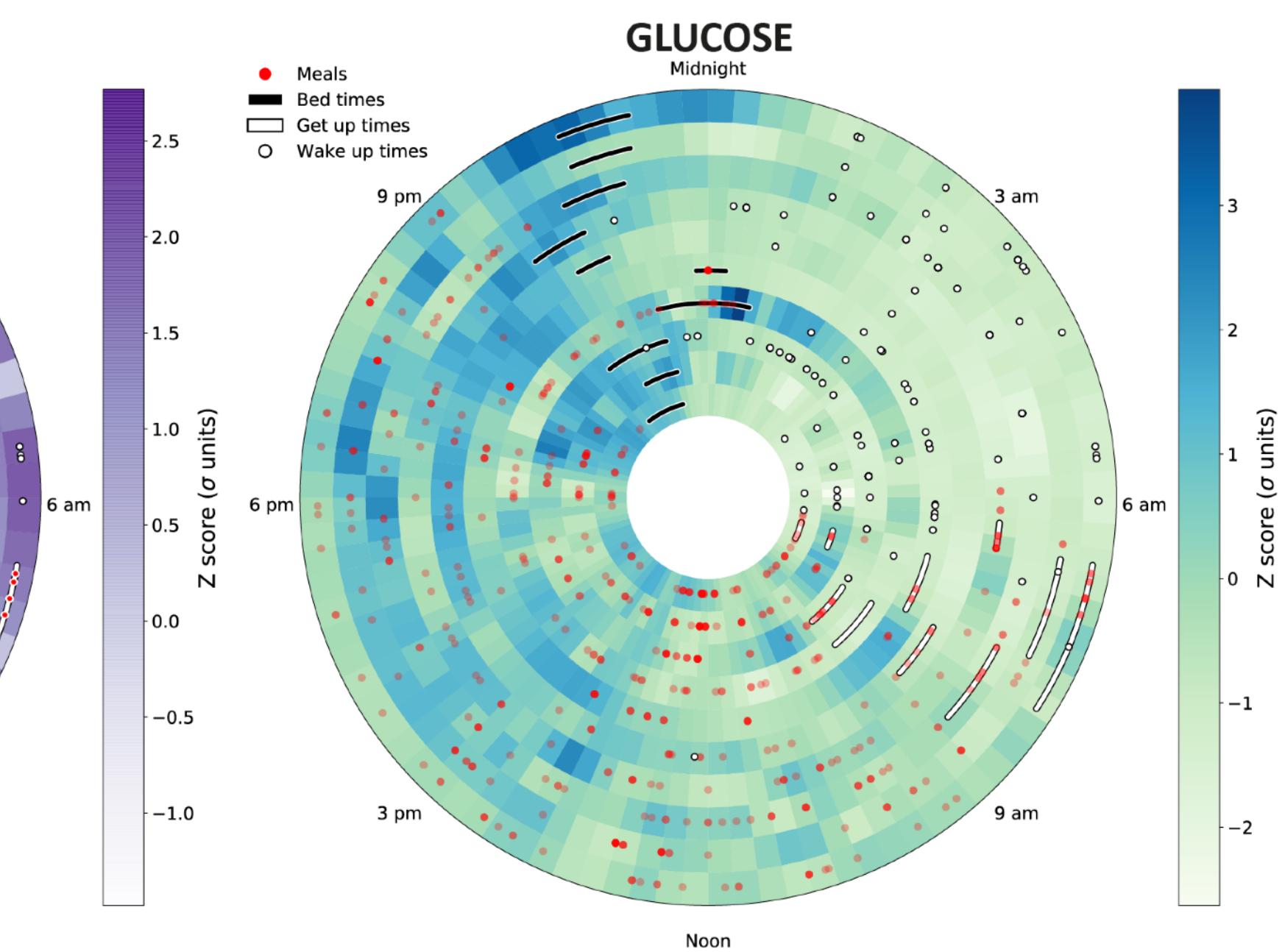
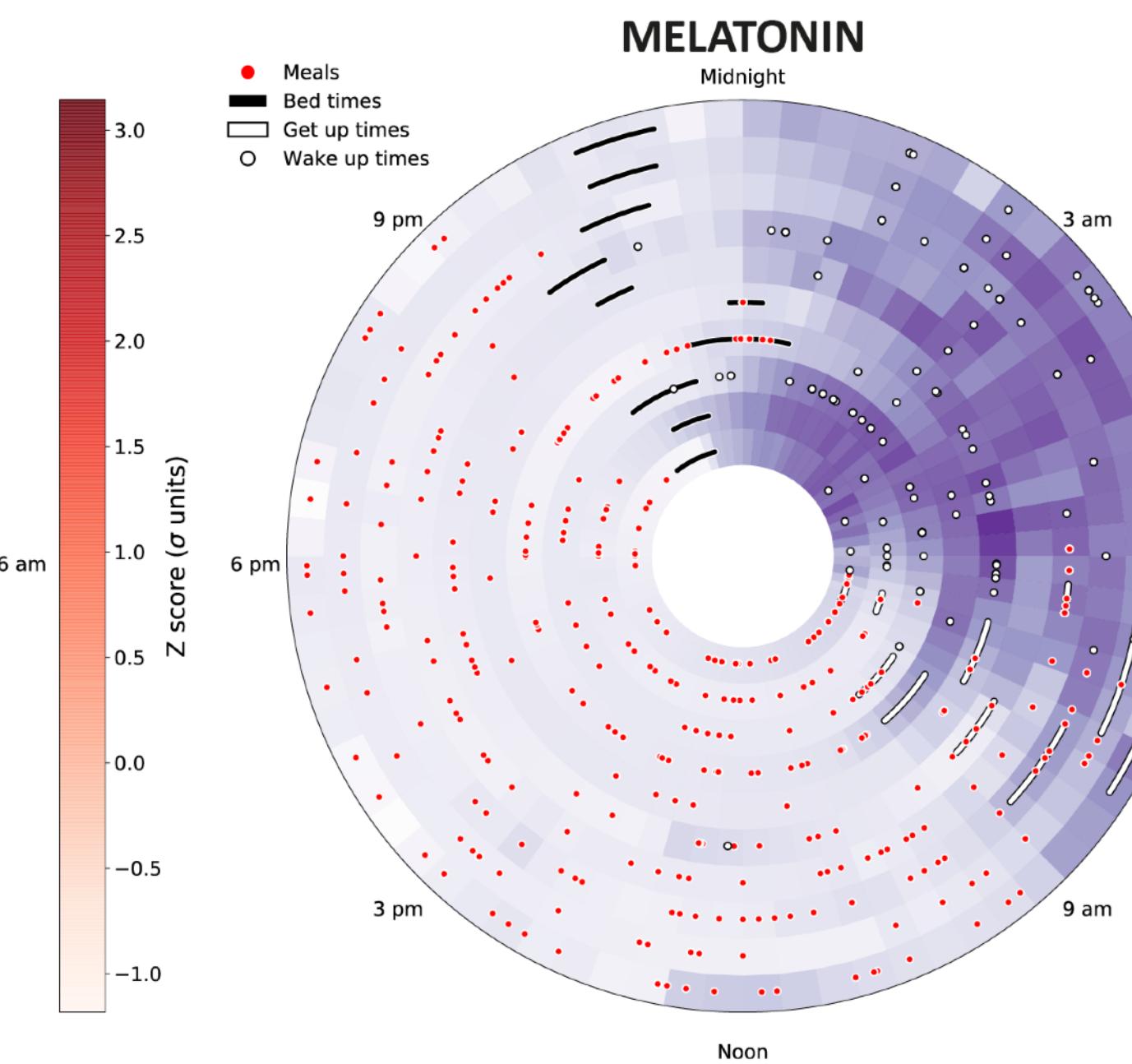
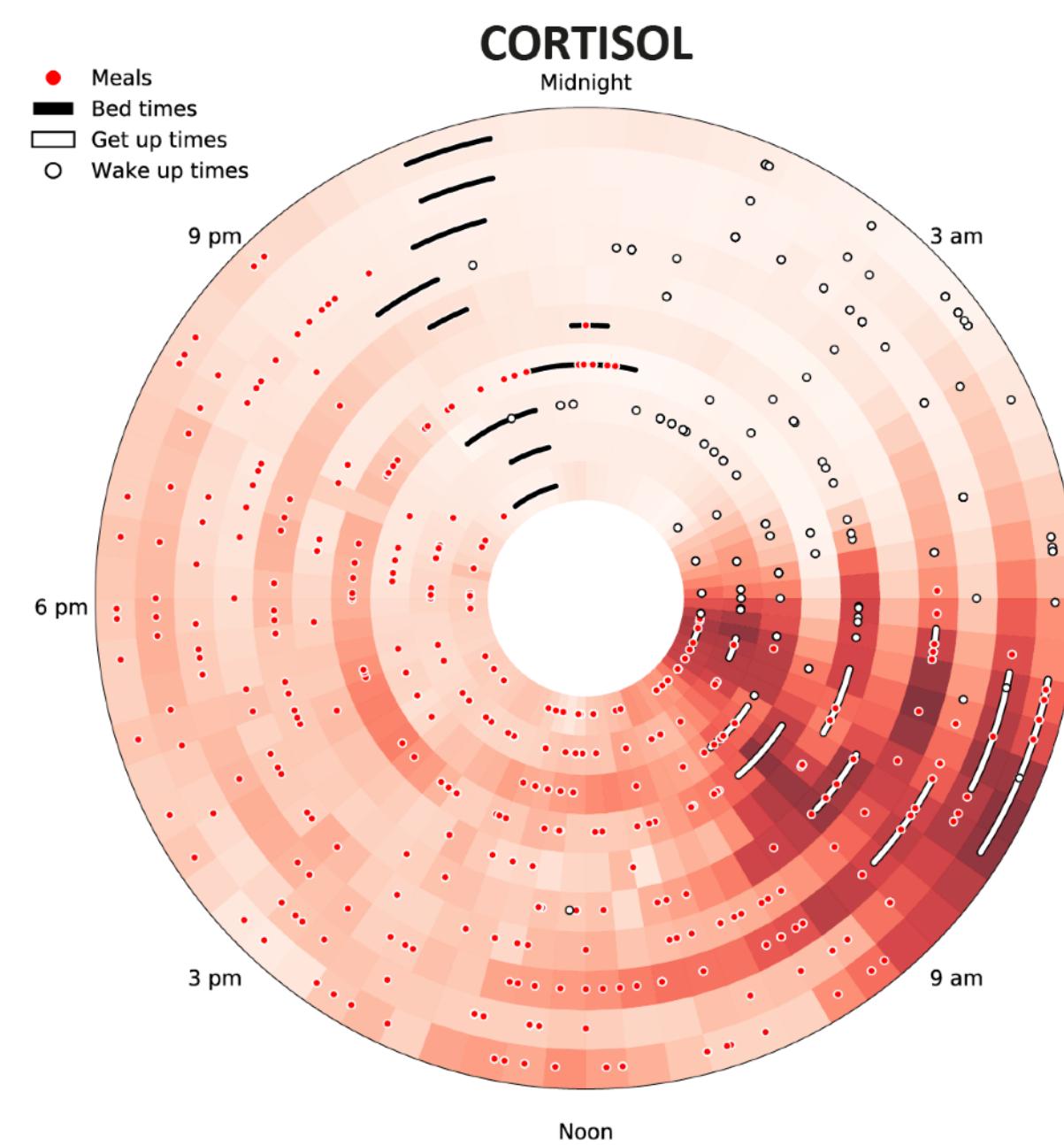
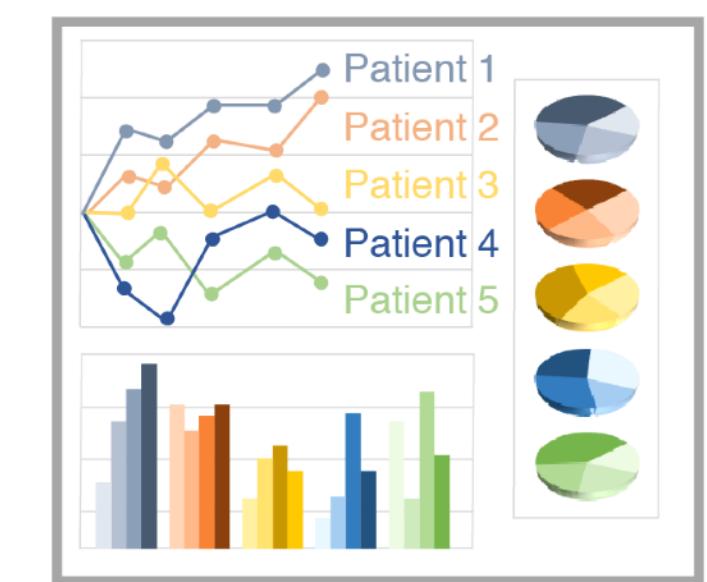
Wearable technology



High-dimensional data



Systems Modeling and Machine Learning



Acknowledgements



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University of Birmingham



Horizon 2020
Programme



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University of Warwick

Prof Michael Chappell

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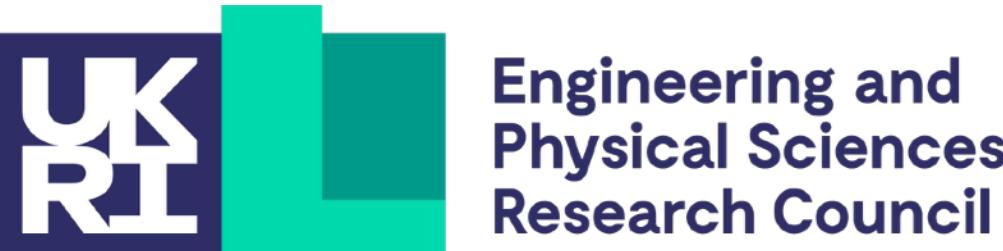
Prof Marco Herrera

CINVESTAV IPN

Prof Moisés Santillán



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