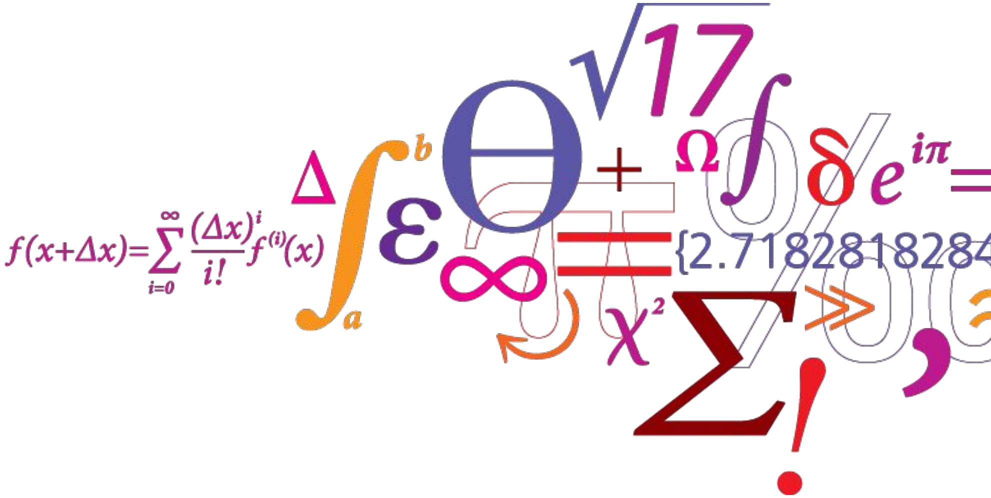
CITIES
Centre for IT Intelligent Energy Systems

DTU

Use of CO2 measurements for indirect classification of presence and occupancy behavior in summerhouses

OB-16 Symposium, Ottawa
3 August 2016



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Henrik Madsen
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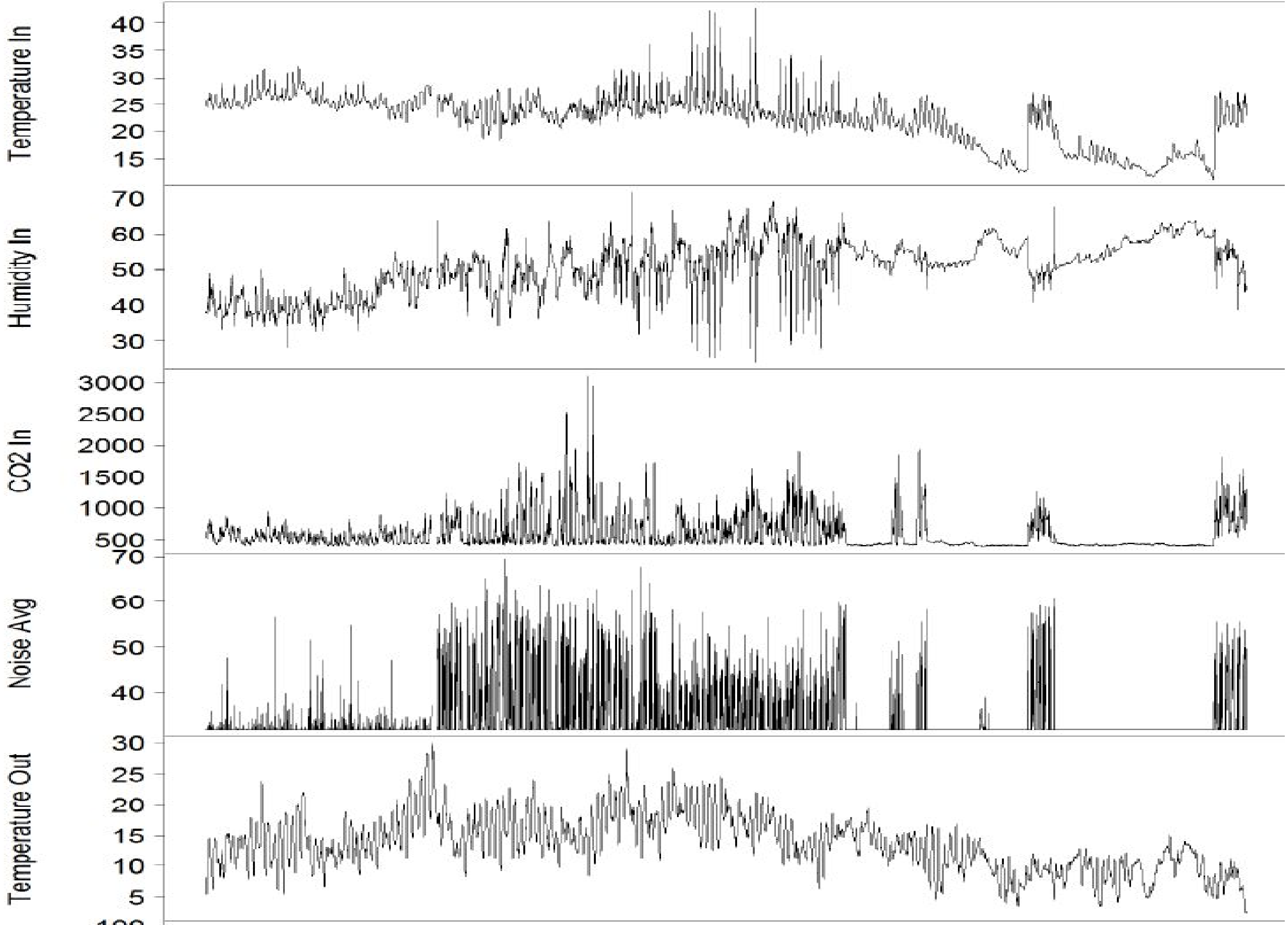
Technical University of Denmark, Copenhagen

Summer houses represent a special challenge

- Large variation in the number of people present in the house
- Power Grids in summer house areas represent a special problem for some DSOs
- Time series of CO_2 measurements are the key to the classification


Temperature In
40
35
30
25
20
15
Humidity In
70
60
50
40
30
CO2 In
3000
2500
2000
1500
1000
500
Noise Avg
70
60
50
40
Temperature Out
30
25
20
15
10
5

Homogen Hidden Markov Model

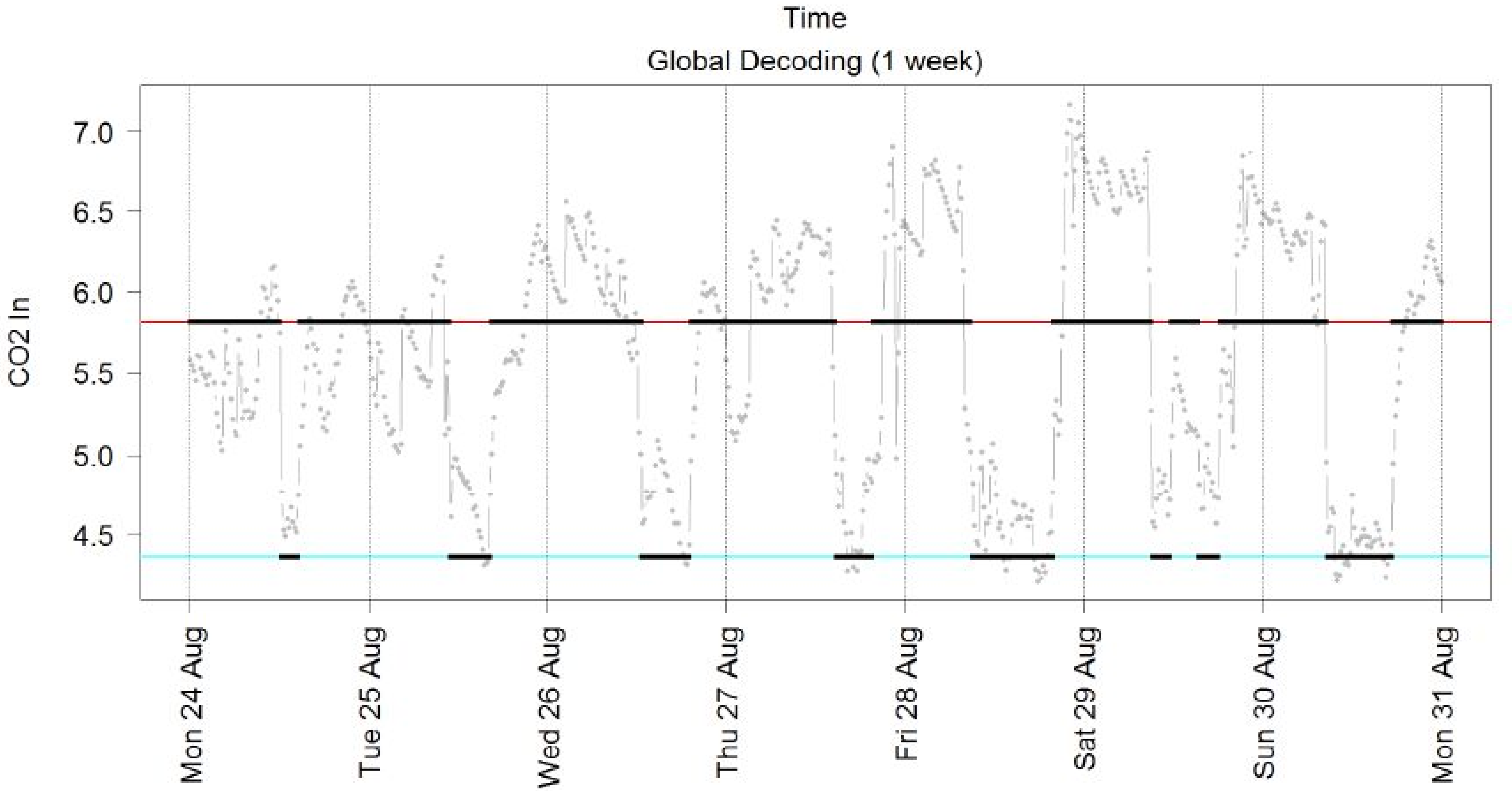
Setting

$$
\begin{aligned}
y_t &= h(CO_{2,t}) \\
p(x_t | x_{t-1}) &\sim \mathbf{\Gamma} \\
p(y_t | x_t) &\sim \mathcal{N}\left(\mu_i, \sigma_i^2\right) \text{ for } i = 1, 2, \cdots, m
\end{aligned}
$$

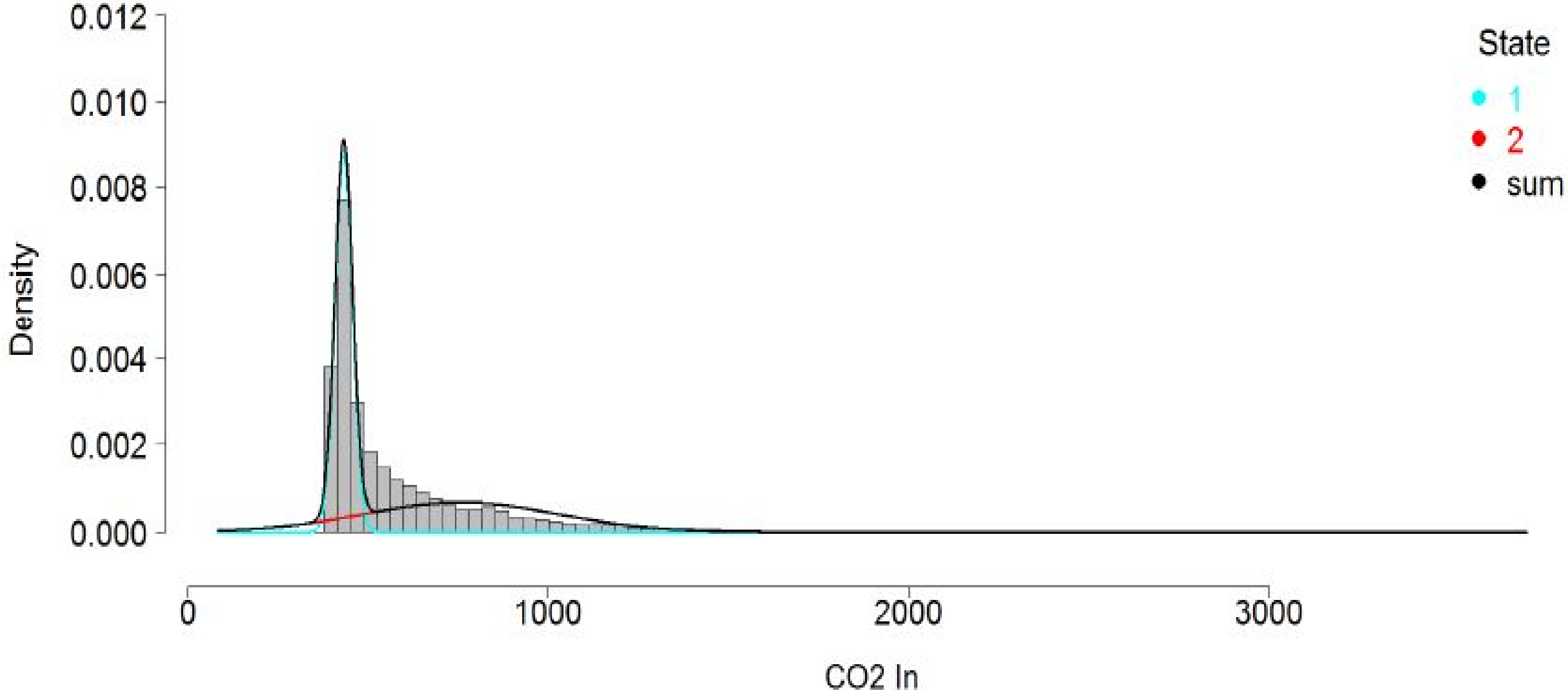
Note that there is no time dependence in the transition probabilities in the homogen case.

Table 8.4: Comparison of univariate (log transformed CO_2) homogen HMMs for 2 to 5 states.

	$\mathcal{L}$	p	AIC	BIC
2 states	-9378	6	18768	18814
3 states	-4292	12	8609	8701
4 states	-800	20	1640	1795
5 states	2181	30	-4303	-4071



Time
Global Decoding (1 week)
CO2 ln
7.0
6.5
6.0
5.5
5.0
4.5
Mon 24 Aug
Tue 25 Aug
Wed 26 Aug
Thu 27 Aug
Fri 28 Aug
Sat 29 Aug
Sun 30 Aug
Mon 31 Aug



0.012
0.010
0.008
0.006
0.004
0.002
0.000
Density
0
1000
2000
3000
CO2 In
State
1
2
sum

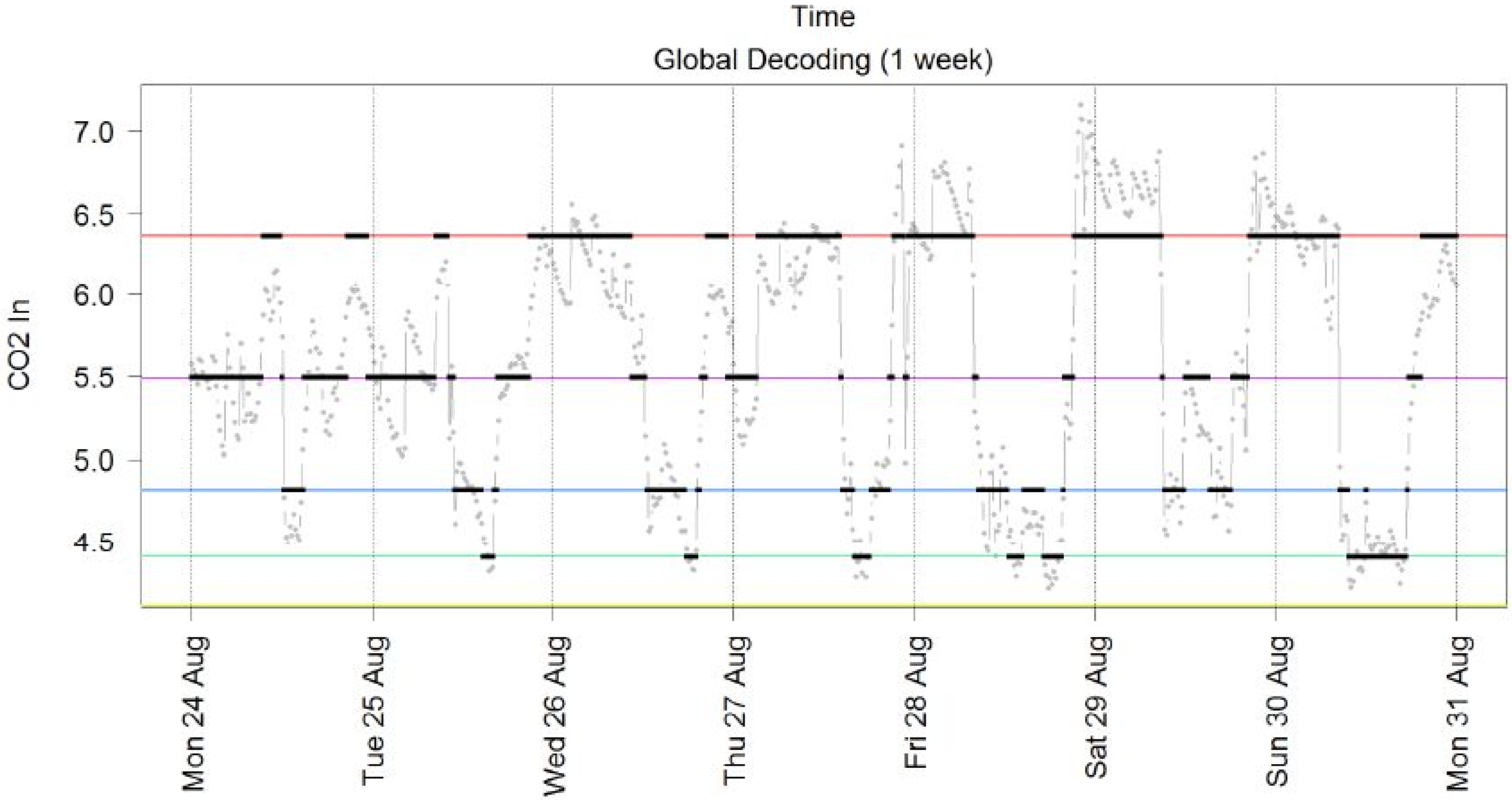
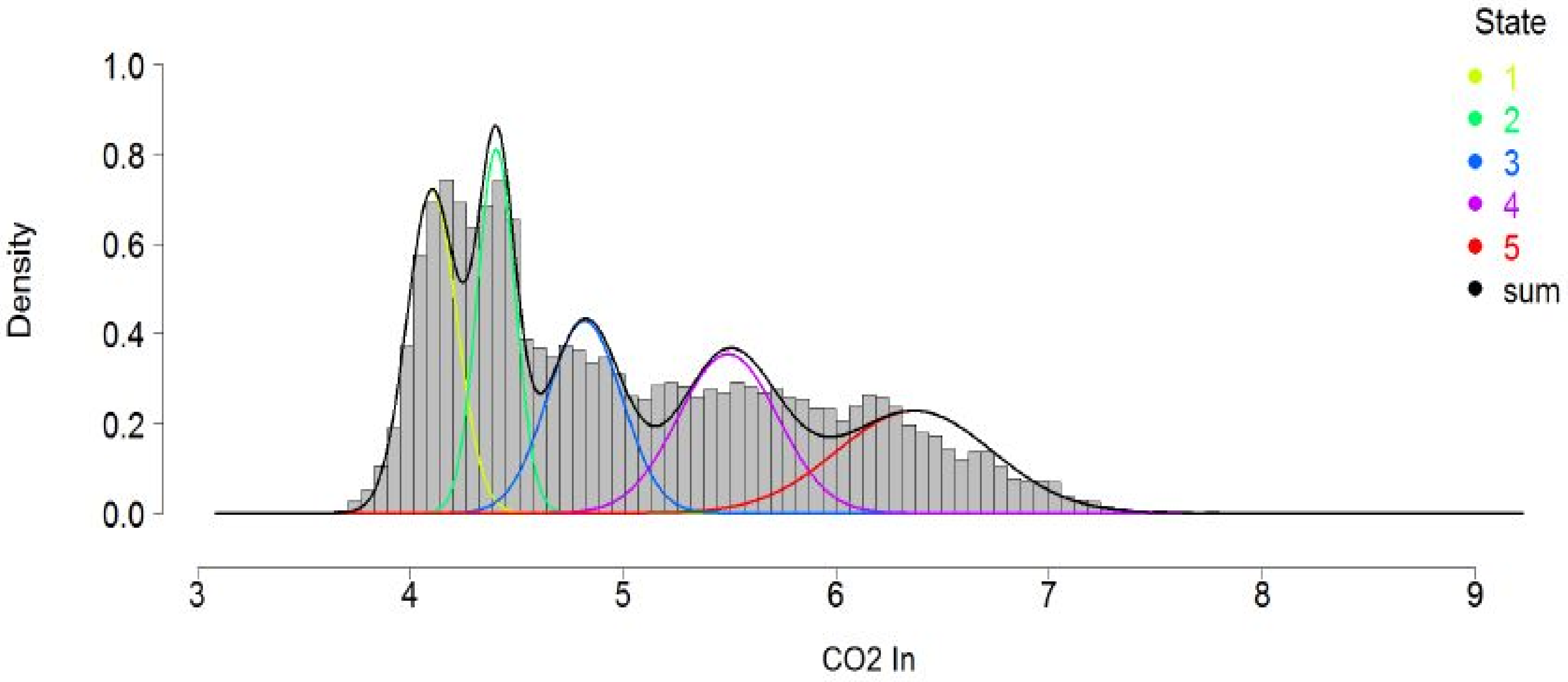
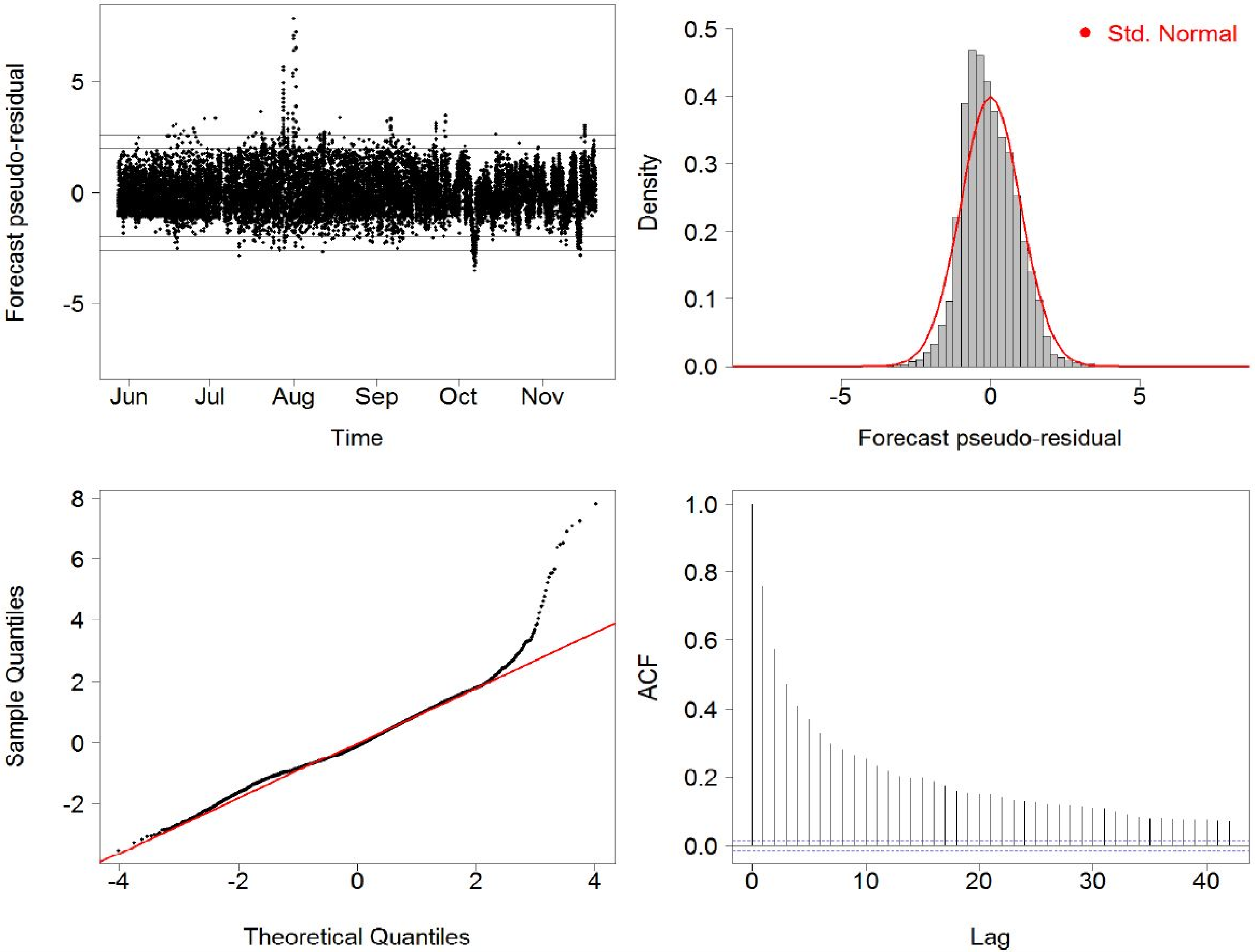


Figure 8.7: Global Decoding of the HMM (log CO_2) with 5 states.


State
1
2
3
4
5
sum
Density
1.0
0.8
0.6
0.4
0.2
0.0
3
4
5
6
7
8
9
CO2 In

CO_2 In



Forecast pseudo-residual
5
0
-5
Jun
Jul
Aug
Sep
Oct
Nov
Time
Density
0.5
0.4
0.3
0.2
0.1
0.0
Std. Normal
-5
0
5
Forecast pseudo-residual
Sample Quantiles
8
6
4
2
0
-2
-4
-2
0
2
4
Theoretical Quantiles
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
10
20
30
40
Lag

Inhomogen Hidden Markov Model

Setting

$$y_t = h(CO_{2,t})$$
$$p(x_t | x_{t-1}) \sim \mathbf{\Gamma}_t$$
$$p(y_t | x_t) \sim \mathcal{N}\left(\mu_i, \sigma_i^2\right) \text{ for } i = 1, 2, \cdots, m$$

Note that there is time dependence in the transition probabilities in the inhomogen case.

Inhomogen Markov-switching with auto-dependent observations

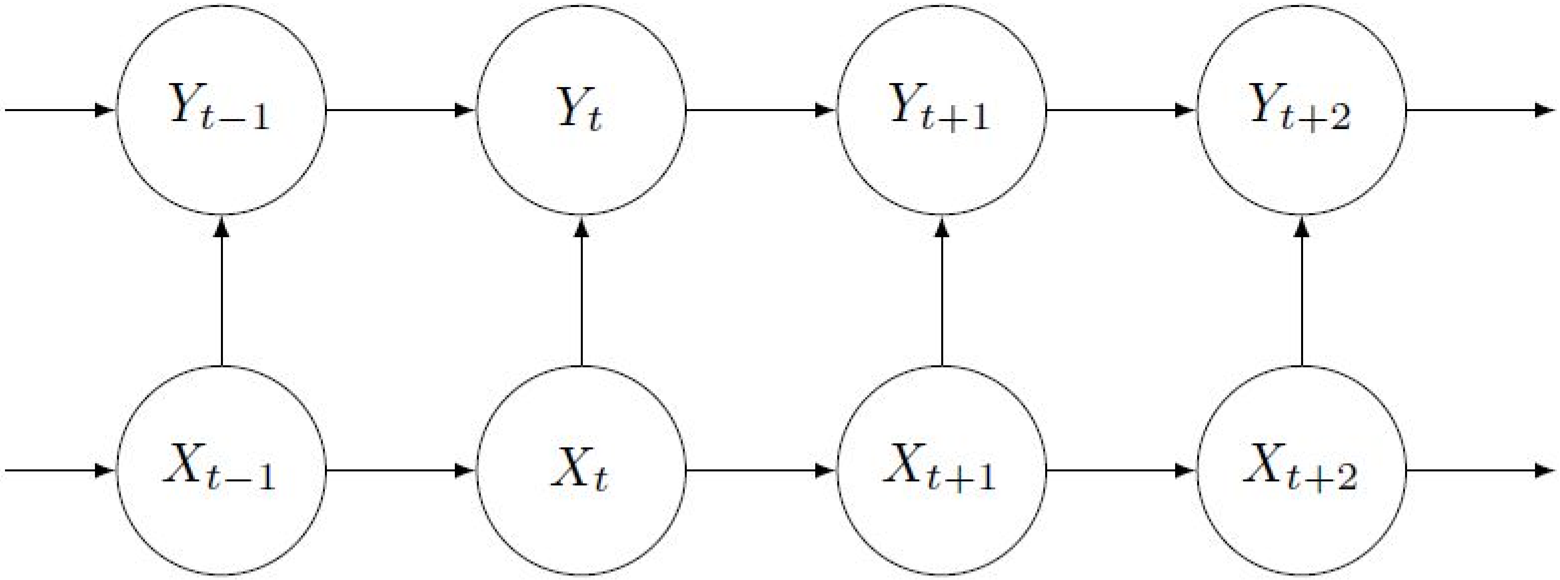


Figure 8.10: Directed graph of Markov switching AR(1).

Inhomogen Markov-switching AR(1)

Setting

$$y_t = h(CO_{2,t})$$
$$p(x_t | x_{t-1}) \sim \mathbf{\Gamma}_t$$
$$p(y_t | x_t, y_{t-1}) \sim \mathcal{N}\left(c_i + \phi_i y_{t-1}\ ,\ \sigma_i^2\right) \text{ for } i = 1, 2, \cdots, m$$

Note that there is time dependence in the transition probabilities in the inhomogen case.

Interpretation of the states

- State 1: Absence or sleeping
- State 2: Long term absence
- State 3: Outdoor interaction
- State 4: Presence (high activity)
- State 5: Presence (long term, low activity)

Table 8.11: Coefficients of final model.

	State 1	State 2	State 3	State 4	State 5
Stationary Mean (μ)	4.208	4.155	5.335	29.499*	8.535*
Standard deviation (σ)	0.038	0.062	0.373	0.131	0.034
AR(1) Intercept (c)	0.125	0.380	1.318	0.029	0.009
AR(1) Coefficient (ϕ)	0.970	0.909	0.753	0.999	0.999
β_0	3.042	7.643	21.982	2.364	8.532
β_1	0.985	0.481	-0.797	-1.274	0.178
β_2	-0.757	-0.661	-1.138	-0.913	1.481
β_3	0.561	0.862	0.695	0.370	-1.546

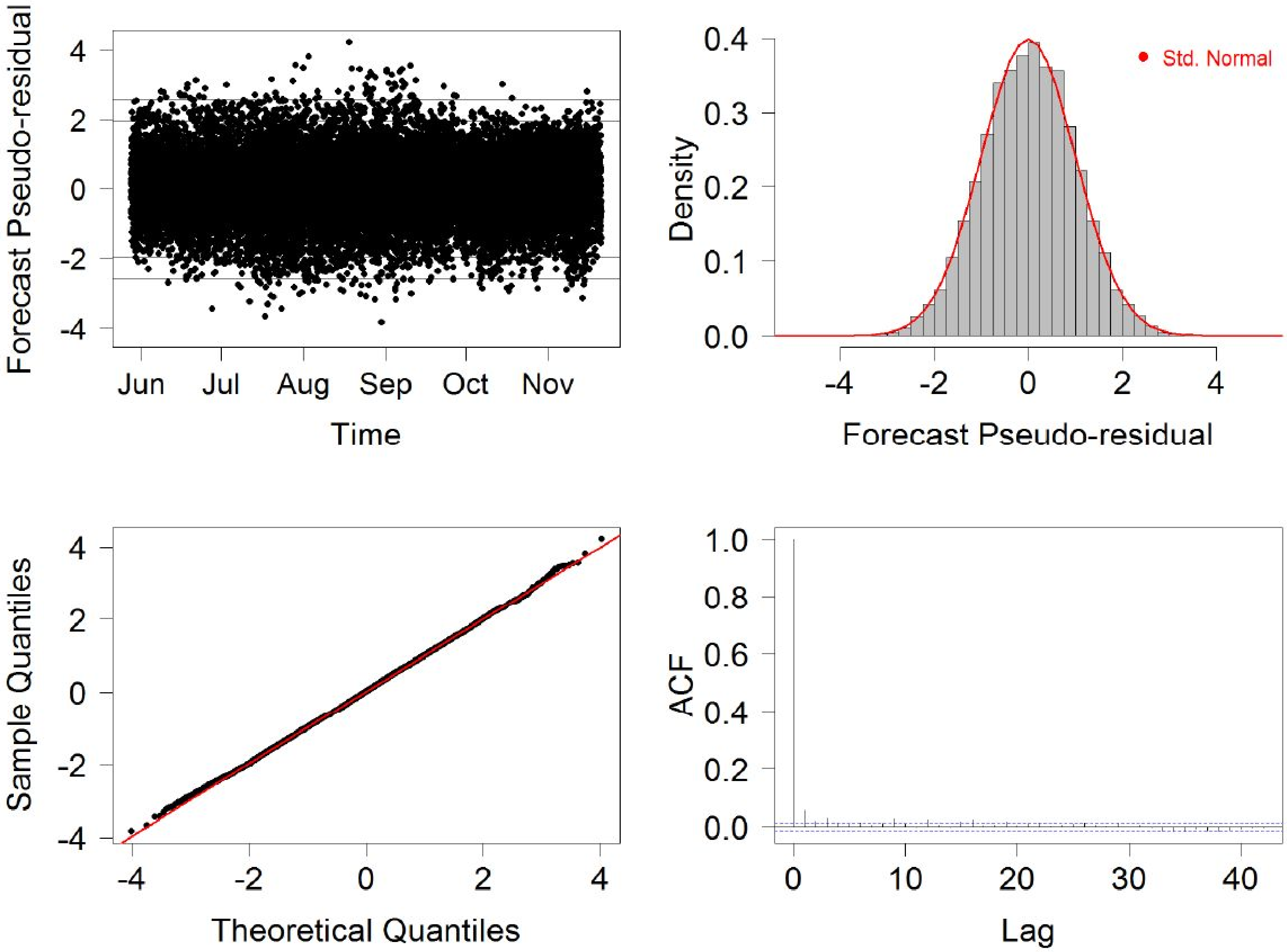
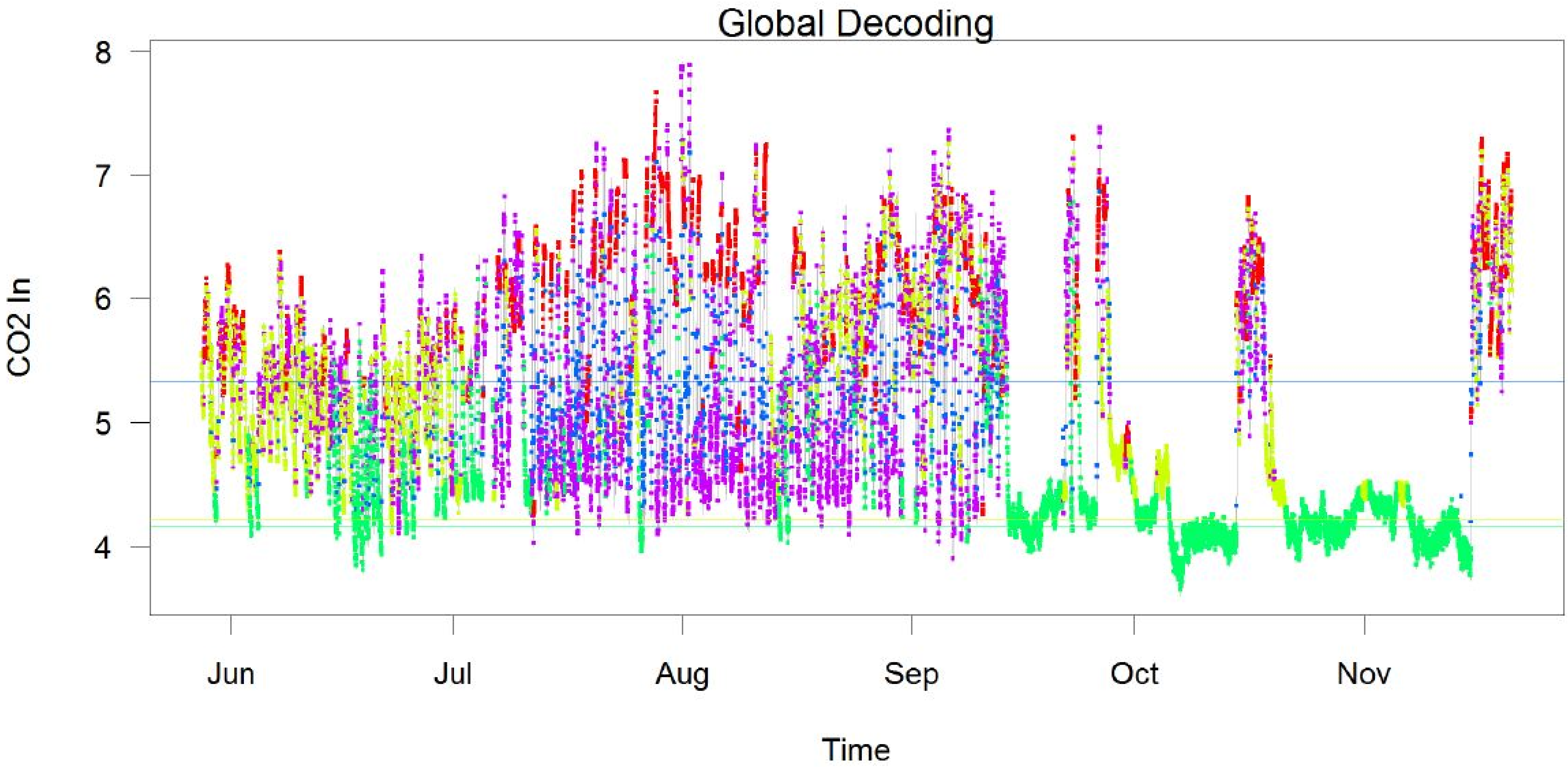
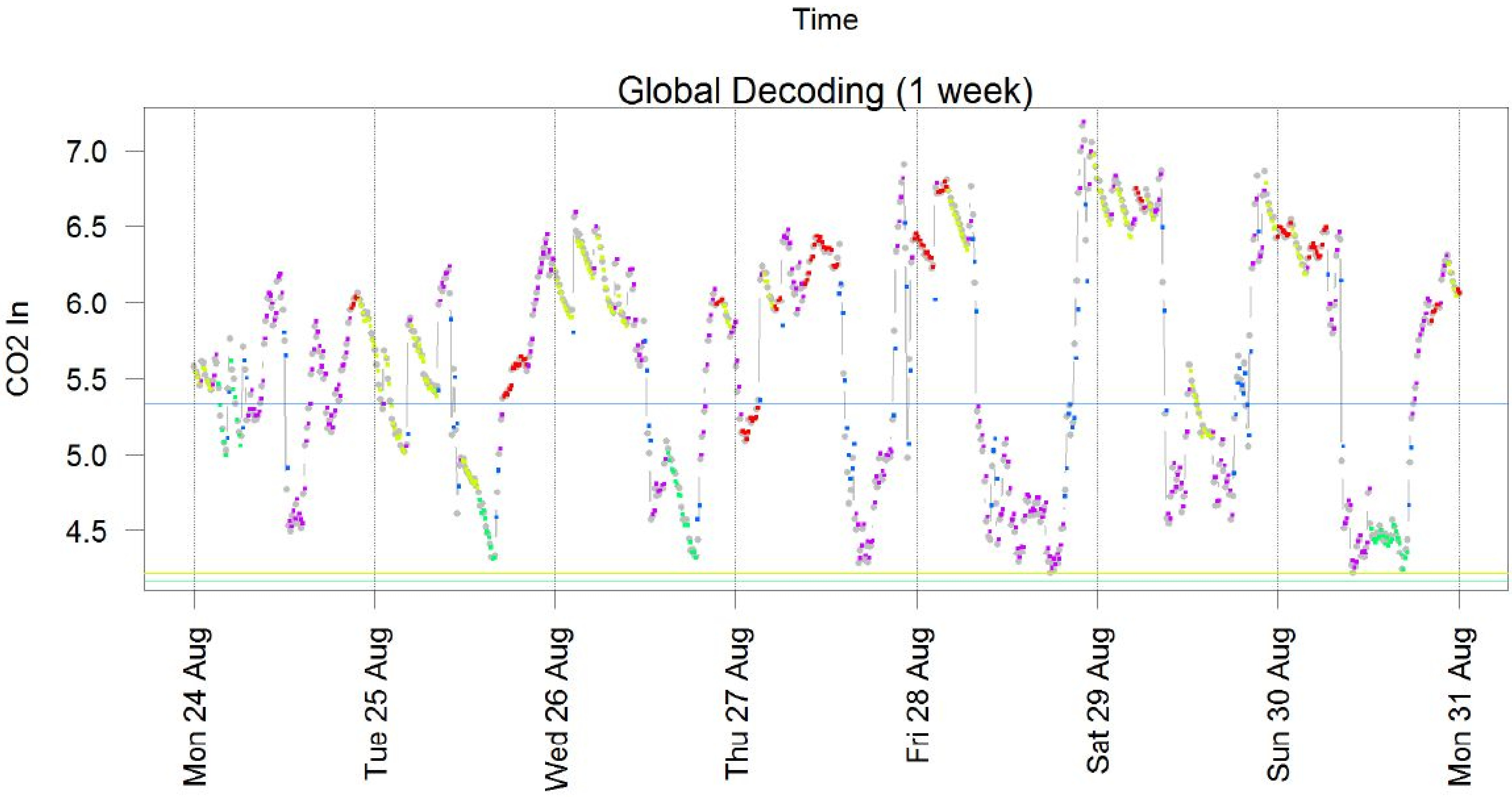


Figure 8.11: Model diagnostics of the final model.


Global Decoding
CO2 In
8
7
6
5
4
Jun
Jul
Aug
Sep
Oct
Nov
Time


Time
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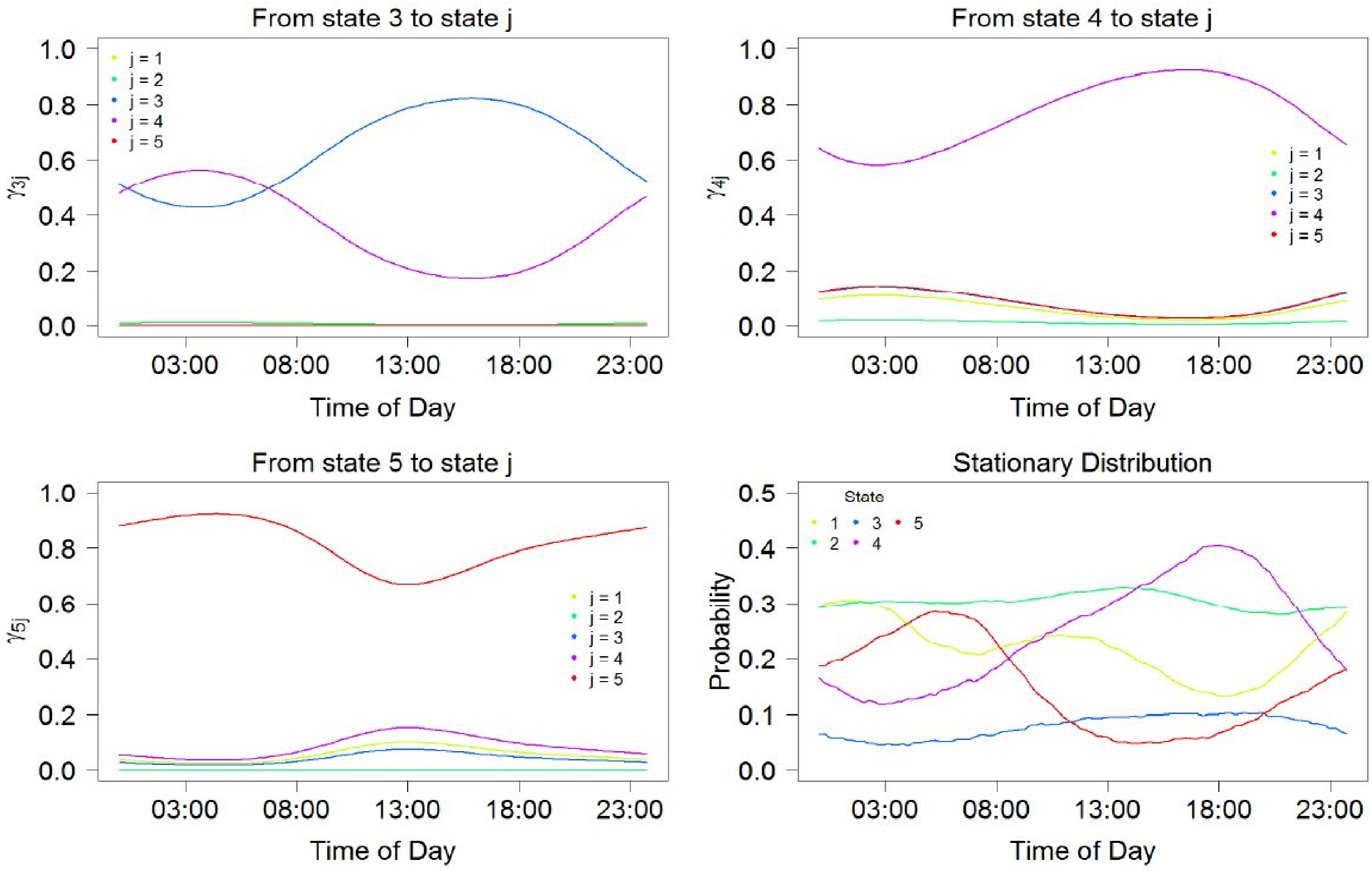

Figure 8.16: Transition probabilities over the day of the final model. The lower right plot is the stationary distribution.

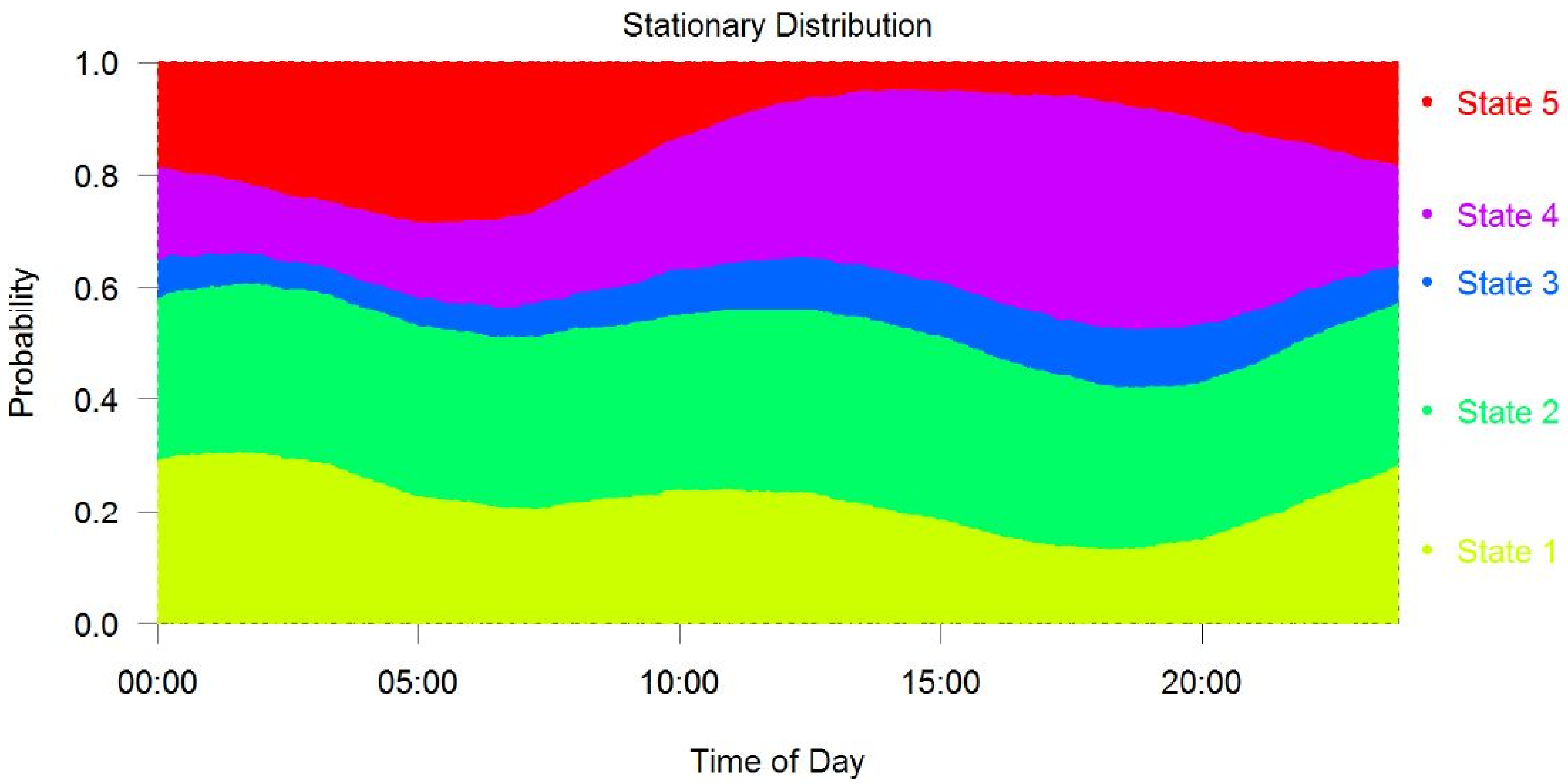

Figure 8.17: Profile of the states over the course of the day. I.e. Stacked stationary probabilities over the course of the day of the final model.