These estimators are implemented in the Python `astropy` module (Astropy Collaboration 2013, 2018). We have designed our own skewness W-estimator:

$$\hat{\gamma}(X) = \frac{\sum_{|u_i|<1} u_i^3 (1-u_i^2)^2}{\sum_{|u_i|<1} (1-u_i^2)^2}. \quad \text{(F.23)}$$

We have also slightly improved `astropy`'s implementation by iterating on Eqs. (F.20)–(F.23), replacing l_x, l_y, s_x, and s_y with $\hat{\mu}(X)$, $\hat{\mu}(Y)$, $\sqrt{\hat{V}(X)}$, and $\sqrt{\hat{V}(Y)}$, respectively, until a 10^{-5} relative accuracy is reached. The tuning parameter is usually taken as $c = 6$ for the mean and $c = 9$ for the variance, covariance, and skewness.

Appendix G: Dust evolution results assuming a Chabrier IMF

We have performed the modeling of Sect. 5.2.2, assuming a Chabrier (2003) IMF. The data have been corrected accordingly: $M_\star$ has been multiplied by 0.61 and SFR by 0.63 (Madau & Dickinson 2014), as these two quantities were derived assuming a Salpeter (1955) IMF. Figure G.1 shows the fit of the scaling relations; it is the equivalent of Fig. 14. Figures G.2 and G.3 display the PDF of the dust evolution and SFH-related parameters, respectively; they are the equivalent of Figs. 16 and 17. The inferred timescales are displayed in Fig. G.4; it is the equivalent of Fig. 18.

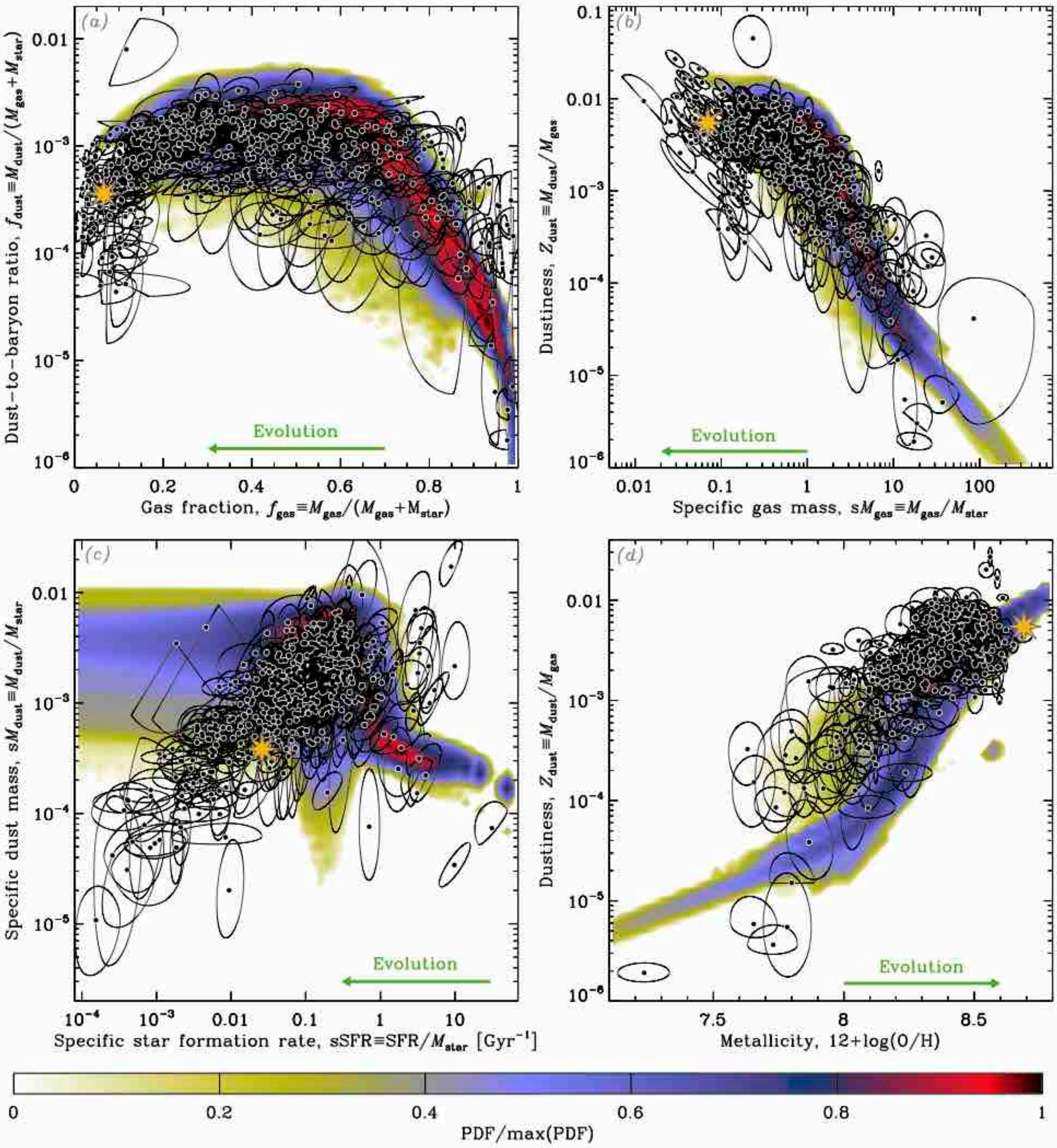

Fig. G.1. Fitted dust evolution tracks, assuming a Chabrier (2003) IMF. This is the equivalent of Fig. 14.