Formula:

The formula we have used to calculate the bias and variance components are:

$$\text{bias} = E_x(\bar{g}(x) - f(x))^2$$

$$\text{var} = E_x[E_{\mathcal{D}}(g^{(\mathcal{D})}(x) - \bar{g}(x))]^2$$

where $\bar{g}(x) = \frac{1}{N}\sum_{k=1}^{N} g_k(x)$.

Observation:

Hypothesis class	Bias	Variance	Bias+Variance	Expected out of sample error
$\mathcal{H}_0$	1353	473	1827	1830
$\mathcal{H}_1$	1206	2083	3290	3274

NB: Due to randomness of the data and limited number of data points the bias and variance components may change a bit when you recompile the code. I have recorded above the last simulated results.

Explanation:

We see that, for hypothesis class $\mathcal{H}_1$, the sum of bias+var is higher than the hypothesis class $\mathcal{H}_0$. So, the expected out of sample error is also higher for $\mathcal{H}_1$. So, our hypothesis class $\mathcal{H}_1$ will not perform well on the unseen data i.e. the generalization capability of $\mathcal{H}_1$ will be small compared to $\mathcal{H}_0$. So, $\mathcal{H}_0$ will be more appropriate class for prediction.

Since the number of data points in our dataset is very less (in our case it is 3), for a more complicated hypothesis class there will be a lot of possible hypothesis that will try to fit our data. So, may be the bias component will be less but since there are a lot of hypothesis the instability of our learning model will be high.