

Research article

Stochastic persistence and global attractivity of a two-predator one-prey system with S-type distributed time delays

Zeyan Yue, Lijuan Dong and Sheng Wang*

School of Mathematics and Information Science, Henan Polytechnic University, Jiaozuo, Henan 454003, China.

* Correspondence: Email: wangsheng2017@hpu.edu.cn.

Abstract: In this paper, well-posedness and asymptotic behaviors of a stochastic two-predator one-prey system with S-type distributed time delays are studied by using stochastic analytical techniques. First, the existence and uniqueness of global positive solution with positive initial condition is proved. Second, sufficient conditions for persistence in mean and extinction of each species are obtained. Then, sufficient conditions for global attractivity are established. Finally, some numerical simulations are provided to support the analytical results.

Keywords: persistence in mean; extinction; predator-prey system; time delay; global attractivity

1. Introduction

In 1977 and 1984, Freedman and Waltman ([1,2]) studied the following two-predator one-prey system:

$$\begin{cases} \frac{dx_1(t)}{dt} = x_1(t) [r_1 - a_{11}x_1(t) - a_{12}x_2(t) - a_{13}x_3(t)], \\ \frac{dx_2(t)}{dt} = x_2(t) [-r_2 + a_{21}x_1(t) - a_{22}x_2(t) - a_{23}x_3(t)], \\ \frac{dx_3(t)}{dt} = x_3(t) [-r_3 + a_{31}x_1(t) - a_{32}x_2(t) - a_{33}x_3(t)], \end{cases} \quad (1.1)$$

where $x_i(t)$ stands for the size of the i th population and all the parameters are positive constants.

However, the deterministic system has its limitation in mathematical modeling of ecosystems since the parameters involved in the system are unable to capture the influence of environmental noises [3–5]. Therefore, it is of enormous importance to study the effects of environmental noises on the dynamics of population systems. Assume that the parameters r_i are affected by white noises, i.e., $r_1 \leftrightarrow r_1 + \sigma_1 B_1(t)$, $-r_2 \leftrightarrow -r_2 + \sigma_2 B_2(t)$, $-r_3 \leftrightarrow -r_3 + \sigma_3 B_3(t)$, where $B_i(t)$ are mutually independent standard Wiener processes defined on a complete probability space (Ω, \mathcal{F}, P) with a

filtration $\{\mathcal{F}_t\}_{t \geq 0}$ satisfying the usual conditions. Then, the stochastic two-predator one-prey system with white noises can be expressed as follows:

$$\begin{cases} dx_1(t) = x_1(t) [r_1 - a_{11}x_1(t) - a_{12}x_2(t) - a_{13}x_3(t)] dt \\ \quad + \sigma_1 x_1(t) dB_1(t), \\ dx_2(t) = x_2(t) [-r_2 + a_{21}x_1(t) - a_{22}x_2(t) - a_{23}x_3(t)] dt \\ \quad + \sigma_2 x_2(t) dB_2(t), \\ dx_3(t) = x_3(t) [-r_3 + a_{31}x_1(t) - a_{32}x_2(t) - a_{33}x_3(t)] dt \\ \quad + \sigma_3 x_3(t) dB_3(t). \end{cases} \quad (1.2)$$

On the other hand, "all species should exhibit time delay" in the real world, and incorporating time delays in biological systems makes the systems much more realistic than those without time delays ([6–10]). Hence, in this paper we concern the dynamics of the following stochastic two-predator one-prey system with S-type distributed time

delays:

$$\begin{cases} dx_1(t) = x_1(t) [r_1 - \mathcal{D}_{11}(x_1)(t) - \mathcal{D}_{12}(x_2)(t) \\ \quad - \mathcal{D}_{13}(x_3)(t)] dt + \sigma_1 x_1(t) dB_1(t), \\ dx_2(t) = x_2(t) [-r_2 + \mathcal{D}_{21}(x_1)(t) - \mathcal{D}_{22}(x_2)(t) \\ \quad - \mathcal{D}_{23}(x_3)(t)] dt + \sigma_2 x_2(t) dB_2(t), \\ dx_3(t) = x_3(t) [-r_3 + \mathcal{D}_{31}(x_1)(t) - \mathcal{D}_{32}(x_2)(t) \\ \quad - \mathcal{D}_{33}(x_3)(t)] dt + \sigma_3 x_3(t) dB_3(t), \end{cases} \quad (1.3)$$

where $\mathcal{D}_{ji}(x_i)(t) = a_{ji}x_i(t) + \int_{-\tau_{ji}}^0 x_i(t+\theta) d\mu_{ji}(\theta)$, $\int_{-\tau_{ji}}^0 x_i(t+\theta) d\mu_{ji}(\theta)$ are Lebesgue-Stieltjes integrals, $\tau_{ji} > 0$ are time delays, $\mu_{ji}(\theta)$ are nondecreasing bounded variation functions defined on $[-\tau, 0]$, $\tau = \max_{i,j=1,2,3} \{\tau_{ji}\}$.

2. Persistence in mean and Extinction

Denote $A_{ij} = a_{ij} + \int_{-\tau_{ij}}^0 d\mu_{ij}(\theta)$, $D_1 = r_1 - \frac{\sigma_1^2}{2}$, $D_i = r_i + \frac{\sigma_i^2}{2}$ ($i = 2, 3$) and

$$\begin{cases} \Theta = \begin{vmatrix} A_{11} & A_{12} & A_{13} \\ -A_{21} & A_{22} & A_{23} \\ -A_{31} & A_{32} & A_{33} \end{vmatrix}, \quad \Theta_1 = \begin{vmatrix} D_1 & A_{12} & A_{13} \\ -D_2 & A_{22} & A_{23} \\ -D_3 & A_{32} & A_{33} \end{vmatrix}, \\ \Theta_2 = \begin{vmatrix} A_{11} & D_1 & A_{13} \\ -A_{21} & -D_2 & A_{23} \\ -A_{31} & -D_3 & A_{33} \end{vmatrix}, \quad \Theta_3 = \begin{vmatrix} A_{11} & A_{12} & D_1 \\ -A_{21} & A_{22} & -D_2 \\ -A_{31} & A_{32} & -D_3 \end{vmatrix}. \end{cases}$$

Assume that $\Theta > 0$. For the matrix corresponding to Θ (respectively, Θ_k), denote by M_{ij}^Θ (respectively, $M_{ij}^{\Theta_k}$) the complement minor of the element at the i -th row and the j -th column ($i, j, k = 1, 2, 3$).

Theorem 2.1. For any $(\xi_1, \xi_2, \xi_3)^T \in C([-\tau, 0], \mathbb{R}_+^3)$, system (1.3) has a unique global solution $(x_1(t), x_2(t), x_3(t))^T \in \mathbb{R}_+^3$ on $t \in [0, +\infty)$ a.s. Moreover, for any constant $p > 0$, there are $K_i(p) > 0$ such that

$$\sup_{t \geq 0} \mathbb{E}[x_i^p(t)] \leq K_i(p) \quad (i = 1, 2, 3). \quad (2.1)$$

Proof. The proof is rather standard and here is omitted (see, e.g., [11] and [12]). \square

Lemma 2.1. ([13]) Suppose $Z(t) \in C(\Omega \times [0, +\infty), \mathbb{R}_+)$ and $\lim_{t \rightarrow +\infty} \frac{o(t)}{t} = 0$.

(i) If there exists constant $\delta_0 > 0$ such that for $t \gg 1$,

$$\ln Z(t) \leq \delta t - \delta_0 \int_0^t Z(s) ds + o(t), \quad (2.2)$$

then

$$\begin{cases} \limsup_{t \rightarrow +\infty} t^{-1} \int_0^t Z(s) ds \leq \frac{\delta}{\delta_0} \text{ a.s.} & (\delta \geq 0); \\ \lim_{t \rightarrow +\infty} Z(t) = 0 \text{ a.s.} & (\delta < 0). \end{cases} \quad (2.3)$$

(ii) If there exist constants $\delta > 0$ and $\delta_0 > 0$ such that for $t \gg 1$,

$$\ln Z(t) \geq \delta t - \delta_0 \int_0^t Z(s) ds + o(t), \quad (2.4)$$

then

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t Z(s) ds \geq \frac{\delta}{\delta_0} \text{ a.s.} \quad (2.5)$$

Lemma 2.2. Consider the following auxiliary system:

$$\begin{cases} dX_1(t) = X_1(t) [r_1 - \mathcal{D}_{11}(X_1)(t)] dt + \sigma_1 X_1(t) dB_1(t), \\ dX_i(t) = X_i(t) [-r_i + \mathcal{D}_{ii}(X_i)(t) - \mathcal{D}_{ii}(X_i)(t)] dt \\ \quad + \sigma_i X_i(t) dB_i(t), \quad (i = 2, 3). \end{cases} \quad (2.6)$$

(a) If $D_1 < 0$, then $\lim_{t \rightarrow +\infty} X_i(t) = 0$ a.s. ($i = 1, 2, 3$).

(b) If $D_1 \geq 0$, $-D_i + A_{i1} \frac{D_1}{A_{11}} < 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t X_1(s) ds = \frac{D_1}{A_{11}}, \quad \lim_{t \rightarrow +\infty} X_i(t) = 0 \text{ a.s.} \quad (i = 2, 3).$$

(c) If $D_1 \geq 0$, $-D_i + A_{i1} \frac{D_1}{A_{11}} \geq 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t X_1(s) ds = \frac{D_1}{A_{11}},$$

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t X_i(s) ds = A_{ii}^{-1} \left(-D_i + A_{i1} \frac{D_1}{A_{11}} \right) \text{ a.s.} \quad (i = 2, 3).$$

Proof. By Itô's formula, we have

$$\begin{cases} \ln X_1(t) = D_1 t - A_{11} \int_0^t X_1(s) ds - \mathcal{T}_{11}(X_1)(t) + o(t), \\ \ln X_i(t) = -D_i t + A_{i1} \int_0^t X_1(s) ds - A_{ii} \int_0^t X_i(s) ds \\ \quad + \mathcal{T}_{ii}(X_1)(t) - \mathcal{T}_{ii}(X_i)(t) + o(t), \quad (i = 2, 3), \end{cases} \quad (2.7)$$

where

$$\begin{aligned} & \mathcal{T}_{ji}(X_i)(t) \\ &= \int_{-\tau_{ji}}^0 \int_\theta^0 X_i(s) ds d\mu_{ji}(\theta) - \int_{-\tau_{ji}}^0 \int_{t+\theta}^t X_i(s) ds d\mu_{ji}(\theta). \end{aligned}$$

Case (i) : $D_1 < 0$. Then $\lim_{t \rightarrow +\infty} X_1(t) = 0$ a.s. Hence, for $\forall \epsilon \in (0, \frac{D_1}{2})$ and $t \gg 1$,

$$\ln X_i(t) \leq (-D_i + \epsilon) t - a_{ii} \int_0^t X_i(s) ds, \quad (i = 2, 3). \quad (2.8)$$

So, $\lim_{t \rightarrow +\infty} X_i(t) = 0$ a.s. ($i = 2, 3$).

Case (ii) : $D_1 \geq 0$. Then,

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t X_1(s) ds = \frac{D_1}{A_{11}} \text{ a.s.} \quad (2.9)$$

Consider the following SDDE:

$$\begin{aligned} d\widetilde{X}_i(t) &= \widetilde{X}_i(t) \left(-r_i + \mathcal{D}_{i1}(X_1)(t) - a_{ii}\widetilde{X}_i(t) \right) dt \\ &\quad + \sigma_i \widetilde{X}_i(t) dB_i(t), \quad (i = 2, 3). \end{aligned}$$

Then, $X_i(t) \leq \widetilde{X}_i(t)$ a.s. ($i = 2, 3$). By Itô's formula,

$$\ln \widetilde{X}_i(t) = \left(-D_i + A_{i1} \frac{D_1}{A_{11}} \right) t - a_{ii} \int_0^t \widetilde{X}_i(s) ds + o(t).$$

In view of Lemma 2.1, we obtain:

(1)[†] If $D_1 \geq 0$, $-D_i + A_{i1} \frac{D_1}{A_{11}} < 0$, then $\lim_{t \rightarrow +\infty} \widetilde{X}_i(t) = 0$ a.s. ($i = 2, 3$).

(2)[†] If $D_1 \geq 0$, $-D_i + A_{i1} \frac{D_1}{A_{11}} \geq 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t \widetilde{X}_i(s) ds = a_{ii}^{-1} \left(-D_i + A_{i1} \frac{D_1}{A_{11}} \right) \text{ a.s. } (i = 2, 3).$$

Therefore, for arbitrary constant $\gamma > 0$,

$$\lim_{t \rightarrow +\infty} t^{-1} \int_{t-\gamma}^t X_i(s) ds = 0 \text{ a.s. } (i = 1, 2, 3). \quad (2.10)$$

Based on (2.10) and system (2.7), for $i = 2, 3$,

$$\ln X_i(t) = \left(-D_i + A_{i1} \frac{D_1}{A_{11}} \right) t - A_{ii} \int_0^t X_i(s) ds + o(t).$$

Thanks to Lemma 2.1, we obtain:

(1)[‡] If $D_1 \geq 0$, $-D_i + A_{i1} \frac{D_1}{A_{11}} < 0$, then $\lim_{t \rightarrow +\infty} X_i(t) = 0$ a.s. ($i = 2, 3$).

(2)[‡] If $D_1 \geq 0$, $-D_i + A_{i1} \frac{D_1}{A_{11}} \geq 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t X_i(s) ds = A_{ii}^{-1} \left(-D_i + A_{i1} \frac{D_1}{A_{11}} \right) \text{ a.s. } (i = 2, 3).$$

Therefore, the desired assertion (b) follows from combining (2.9) with (1)[‡], and (c) follows from combining (2.9) with (2)[‡]. \square

Lemma 2.3. For system (1.3), $\limsup_{t \rightarrow +\infty} t^{-1} \ln x_i(t) \leq 0$ a.s. ($i = 1, 2, 3$).

Proof. Thanks to Lemma 2.2 and (2.7), system (2.6) satisfies $\lim_{t \rightarrow +\infty} t^{-1} \ln X_i(t) = 0$ a.s. ($i = 1, 2, 3$). From the stochastic comparison theorem, we obtain the desired assertion. \square

Theorem 2.2. For system (1.3):

(i) If $D_1 < 0$, then $\lim_{t \rightarrow +\infty} x_i(t) = 0$ a.s. ($i = 1, 2, 3$).

(ii) If $D_1 \geq 0$, $M_{33}^{\Theta_2} < 0$, $M_{22}^{\Theta_3} < 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s) ds = \frac{D_1}{A_{11}}, \quad \lim_{t \rightarrow +\infty} x_i(t) = 0 \text{ a.s. } (i = 2, 3).$$

(iii) If $D_1 \geq 0$, $M_{13}^{\Theta} \leq 0$, $\Theta_3 < 0$, $M_{33}^{\Theta_2} > 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_i(s) ds = \frac{M_{33}^{\Theta_i}}{M_{33}^{\Theta}}, \quad \lim_{t \rightarrow +\infty} x_3(t) = 0 \text{ a.s. } (i = 1, 2).$$

(iv) If $\Theta_1 > 0$, $\Theta_2 > 0$, $\Theta_3 > 0$, $M_{11}^{\Theta} > 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_i(s) ds = \frac{\Theta_i}{\Theta} \text{ a.s. } (i = 1, 2, 3).$$

(v) If $D_1 \geq 0$, $M_{12}^{\Theta} \geq 0$, $\Theta_2 < 0$, $M_{22}^{\Theta_3} < 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s) ds = \frac{D_1}{A_{11}}, \quad \lim_{t \rightarrow +\infty} x_i(t) = 0 \text{ a.s. } (i = 2, 3).$$

(vi) If $D_1 \geq 0$, $M_{12}^{\Theta} \geq 0$, $\Theta_2 < 0$, $M_{22}^{\Theta_3} \geq 0$, then

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_i(s) ds = \frac{M_{22}^{\Theta_i}}{M_{22}^{\Theta}}, \quad \lim_{t \rightarrow +\infty} x_2(t) = 0 \text{ a.s. } (i = 1, 3).$$

Proof. According to (2.10), for arbitrary constant $\gamma > 0$,

$$\lim_{t \rightarrow +\infty} t^{-1} \int_{t-\gamma}^t x_i(s) ds = 0 \text{ a.s. } (i = 1, 2, 3). \quad (2.11)$$

By Itô's formula and (2.11), we derive

$$\left\{ \begin{array}{l} \ln x_1(t) = D_1 t - A_{11} \int_0^t x_1(s) ds - A_{12} \int_0^t x_2(s) ds \\ \quad - A_{13} \int_0^t x_3(s) ds + o(t), \\ \ln x_2(t) = -D_2 t + A_{21} \int_0^t x_1(s) ds - A_{22} \int_0^t x_2(s) ds \\ \quad - A_{23} \int_0^t x_3(s) ds + o(t), \\ \ln x_3(t) = -D_3 t + A_{31} \int_0^t x_1(s) ds - A_{32} \int_0^t x_2(s) ds \\ \quad - A_{33} \int_0^t x_3(s) ds + o(t). \end{array} \right. \quad (2.12)$$

Case (i) : $D_1 < 0$. From Lemma 2.2 (a), $\lim_{t \rightarrow +\infty} x_i(t) = 0$ a.s. ($i = 1, 2, 3$).

Case (ii) : $D_1 \geq 0$, $M_{33}^{\Theta_2} < 0$, $M_{22}^{\Theta_3} < 0$. Based on system (2.12), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_1(t) \leq (D_1 + \epsilon)t - A_{11} \int_0^t x_1(s)ds. \quad (2.13)$$

By Lemma 2.1 and the arbitrariness of ϵ , we obtain

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds \leq \frac{D_1}{A_{11}} \text{ a.s.} \quad (2.14)$$

Hence, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{cases} \ln x_2(t) \leq \left(\frac{M_{33}^{\Theta_2}}{A_{11}} + \epsilon \right) t - A_{22} \int_0^t x_2(s)ds, \\ \ln x_3(t) \leq \left(\frac{M_{22}^{\Theta_3}}{A_{11}} + \epsilon \right) t - A_{33} \int_0^t x_3(s)ds. \end{cases} \quad (2.15)$$

According to Lemma 2.1 and the arbitrariness of ϵ , we have

$$\lim_{t \rightarrow +\infty} x_i(t) = 0 \text{ a.s. } (i = 2, 3). \quad (2.16)$$

Based on (2.16) and system (2.12), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{cases} \ln x_1(t) \leq (D_1 + \epsilon)t - A_{11} \int_0^t x_1(s)ds, \\ \ln x_1(t) \geq (D_1 - \epsilon)t - A_{11} \int_0^t x_1(s)ds. \end{cases} \quad (2.17)$$

In view of Lemma 2.1 and the arbitrariness of ϵ , we obtain

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds = \frac{D_1}{A_{11}} \text{ a.s.} \quad (2.18)$$

Case (iii) : $D_1 \geq 0$, $M_{13}^{\Theta} \leq 0$, $\Theta_3 < 0$, $M_{33}^{\Theta_2} > 0$. Compute

$$\begin{aligned} & M_{13}^{\Theta} \ln x_1(t) - M_{23}^{\Theta} \ln x_2(t) + M_{33}^{\Theta_2} \ln x_3(t) \\ &= \Theta_3 t - \Theta \int_0^t x_3(s)ds + o(t). \end{aligned}$$

By Lemma 2.3, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$M_{33}^{\Theta} \ln x_3(t) \leq (\Theta_3 + \epsilon)t - \Theta \int_0^t x_3(s)ds. \quad (2.19)$$

From Lemma 2.1 and the arbitrariness of ϵ , we deduce

$$\lim_{t \rightarrow +\infty} x_3(t) = 0 \text{ a.s.} \quad (2.20)$$

By (2.20) and system (2.12), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{cases} \ln x_1(t) \leq (D_1 + \epsilon)t - A_{11} \int_0^t x_1(s)ds - A_{12} \int_0^t x_2(s)ds, \\ \ln x_1(t) \geq (D_1 - \epsilon)t - A_{11} \int_0^t x_1(s)ds - A_{12} \int_0^t x_2(s)ds, \\ \ln x_2(t) \leq (-D_2 + \epsilon)t + A_{21} \int_0^t x_1(s)ds - A_{22} \int_0^t x_2(s)ds, \\ \ln x_2(t) \geq (-D_2 - \epsilon)t + A_{21} \int_0^t x_1(s)ds - A_{22} \int_0^t x_2(s)ds. \end{cases} \quad (2.21)$$

According to (2.21), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{aligned} & A_{21} \ln x_1(t) + A_{11} \ln x_2(t) \\ & \geq [M_{33}^{\Theta_2} - (A_{11} + A_{21})\epsilon]t - M_{33}^{\Theta} \int_0^t x_2(s)ds, \\ & A_{22} \ln x_1(t) - A_{12} \ln x_2(t) \\ & \leq [M_{33}^{\Theta_1} + (A_{12} + A_{22})\epsilon]t - M_{33}^{\Theta} \int_0^t x_1(s)ds. \end{aligned}$$

Thanks to Lemma 2.3, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$A_{11} \ln x_2(t) \geq [M_{33}^{\Theta_2} - (A_{11} + 2A_{21})\epsilon]t - M_{33}^{\Theta} \int_0^t x_2(s)ds,$$

$$A_{22} \ln x_1(t) \leq [M_{33}^{\Theta_1} + (2A_{12} + A_{22})\epsilon]t - M_{33}^{\Theta} \int_0^t x_1(s)ds.$$

In view of Lemma 2.1 and the arbitrariness of ϵ , we obtain

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_2(s)ds \geq \frac{M_{33}^{\Theta_2}}{M_{33}^{\Theta}} \text{ a.s.} \quad (2.22-1)$$

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds \leq \frac{M_{33}^{\Theta_1}}{M_{33}^{\Theta}} \text{ a.s.} \quad (2.22-2)$$

Thanks to (2.21) and (2.22-2), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_2(t) \leq \left(A_{22} \frac{M_{33}^{\Theta_2}}{M_{33}^{\Theta}} + 2\epsilon \right) t - A_{22} \int_0^t x_2(s)ds. \quad (2.23)$$

Based on Lemma 2.1 and the arbitrariness of ϵ , we obtain

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_2(s)ds \leq \frac{M_{33}^{\Theta_2}}{M_{33}^{\Theta}} \text{ a.s.} \quad (2.24)$$

Combining (2.22-1) with (2.24) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_2(s)ds = \frac{M_{33}^{\Theta_2}}{M_{33}^{\Theta}} \text{ a.s.} \quad (2.25)$$

From (2.21) and (2.25), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_1(t) \geq \left(A_{11} \frac{M_{33}^{\Theta_1}}{M_{33}^{\Theta}} - 2\epsilon \right) t - A_{11} \int_0^t x_1(s)ds. \quad (2.26)$$

Thanks to Lemma 2.1 and the arbitrariness of ϵ , we have

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds \geq \frac{M_{33}^{\Theta_1}}{M_{33}^{\Theta}} \text{ a.s.} \quad (2.27)$$

Combining (2.22-2) with (2.27) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds = \frac{M_{33}^{\Theta_1}}{M_{33}^{\Theta}} \text{ a.s.} \quad (2.28)$$

Case (iv) : $\Theta_1 > 0, \Theta_2 > 0, \Theta_3 > 0, M_{11}^\Theta > 0$. According to Lemma 2.1, (2.19) and the arbitrariness of ϵ , we obtain

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_3(s)ds \leq \frac{\Theta_3}{\Theta} \text{ a.s.} \quad (2.29)$$

In view of system (2.12), we compute

$$\begin{aligned} & M_{11}^\Theta \ln x_1(t) - M_{21}^\Theta \ln x_2(t) + M_{31}^\Theta \ln x_3(t) \\ &= \Theta_1 t - \Theta \int_0^t x_1(s)ds + o(t). \\ & - M_{12}^\Theta \ln x_1(t) + M_{22}^\Theta \ln x_2(t) - M_{32}^\Theta \ln x_3(t) \\ &= \Theta_2 t - \Theta \int_0^t x_2(s)ds + o(t). \end{aligned}$$

Then, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{aligned} M_{11}^\Theta \ln x_1(t) &\leq (\Theta_1 + \epsilon) t - \Theta \int_0^t x_1(s)ds, \\ M_{22}^\Theta \ln x_2(t) &\leq (\Theta_2 + \epsilon) t - \Theta \int_0^t x_2(s)ds. \end{aligned}$$

According to Lemma 2.1 and the arbitrariness of ϵ , we deduce

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds \leq \frac{\Theta_1}{\Theta} \text{ a.s.} \quad (2.30-1)$$

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_2(s)ds \leq \frac{\Theta_2}{\Theta} \text{ a.s.} \quad (2.30-2)$$

Therefore, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$t^{-1} \int_0^t x_i(s)ds \leq \frac{\Theta_i}{\Theta} + \epsilon \text{ a.s. } (i = 1, 2, 3). \quad (2.31)$$

Based on (2.31) and system (2.12), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_1(t) \geq \left(A_{11} \frac{\Theta_1}{\Theta} - \sum_{i=1}^3 A_{1i} \epsilon \right) t - A_{11} \int_0^t x_1(s)ds. \quad (2.32)$$

Thanks to Lemma 2.1 and the arbitrariness of ϵ , we obtain

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds \geq \frac{\Theta_1}{\Theta} \text{ a.s.} \quad (2.33)$$

Combining (2.30-1) with (2.33) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s)ds = \frac{\Theta_1}{\Theta} \text{ a.s.} \quad (2.34)$$

According to (2.31), (2.33) and system (2.12), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_2(t) \geq \left(A_{22} \frac{\Theta_2}{\Theta} - \sum_{i=1}^3 A_{2i} \epsilon \right) t - A_{22} \int_0^t x_2(s)ds. \quad (2.35)$$

From Lemma 2.1 and the arbitrariness of ϵ , we have

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_2(s)ds \geq \frac{\Theta_2}{\Theta} \text{ a.s.} \quad (2.36)$$

Combining (2.30-2) with (2.36) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_2(s)ds = \frac{\Theta_2}{\Theta} \text{ a.s.} \quad (2.37)$$

Similarly, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_3(t) \geq \left(A_{33} \frac{\Theta_3}{\Theta} - \sum_{i=1}^3 A_{3i} \epsilon \right) t - A_{33} \int_0^t x_3(s)ds. \quad (2.38)$$

Thanks to Lemma 2.1 and the arbitrariness of ϵ , we obtain

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_3(s)ds \geq \frac{\Theta_3}{\Theta} \text{ a.s.} \quad (2.39)$$

Combining (2.29) with (2.39) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_3(s)ds = \frac{\Theta_3}{\Theta} \text{ a.s.} \quad (2.40)$$

Case (v) : $D_1 \geq 0, M_{12}^\Theta \geq 0, \Theta_2 < 0, M_{22}^{\Theta_3} < 0$. By Lemma 2.1, (2.30) and the arbitrariness of ϵ , we have

$$\lim_{t \rightarrow +\infty} x_2(t) = 0 \text{ a.s.} \quad (2.41)$$

Hence, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{cases} \ln x_1(t) \leq (D_1 + \epsilon) t - A_{11} \int_0^t x_1(s)ds - A_{13} \int_0^t x_3(s)ds, \\ \ln x_1(t) \geq (D_1 - \epsilon) t - A_{11} \int_0^t x_1(s)ds - A_{13} \int_0^t x_3(s)ds, \\ \ln x_3(t) \leq (-D_3 + \epsilon) t + A_{31} \int_0^t x_1(s)ds - A_{33} \int_0^t x_3(s)ds, \\ \ln x_3(t) \geq (-D_3 - \epsilon) t + A_{31} \int_0^t x_1(s)ds - A_{33} \int_0^t x_3(s)ds. \end{cases} \quad (2.42)$$

Based on (2.42), we deduce

$$\begin{aligned} & A_{33} \ln x_1(t) - A_{13} \ln x_3(t) \\ & \leq [M_{22}^{\Theta_1} + (A_{13} + A_{33}) \epsilon] t - M_{22}^\Theta \int_0^t x_1(s)ds. \end{aligned} \quad (2.43)$$

Therefore, for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$A_{33} \ln x_1(t) \leq [M_{22}^{\Theta_1} + (2A_{13} + A_{33}) \epsilon] t - M_{22}^\Theta \int_0^t x_1(s)ds. \quad (2.44)$$

In view of Lemma 2.1 and the arbitrariness of ϵ , we deduce

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s) ds \leq \frac{M_{22}^{\Theta_1}}{M_{22}^{\Theta}} \text{ a.s.} \quad (2.45)$$

According to (2.42) and (2.45), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_3(t) \leq \left(A_{33} \frac{M_{22}^{\Theta_3}}{M_{22}^{\Theta}} + 2\epsilon \right) t - A_{33} \int_0^t x_3(s) ds. \quad (2.46)$$

Clearly, (2.20) is true. From (2.20) and (2.42), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\begin{cases} \ln x_1(t) \leq (D_1 + 2\epsilon) t - A_{11} \int_0^t x_1(s) ds, \\ \ln x_1(t) \geq (D_1 - 2\epsilon) t - A_{11} \int_0^t x_1(s) ds. \end{cases} \quad (2.47)$$

In view of Lemma 2.1 and the arbitrariness of ϵ , we obtain (2.18).

Case (vi): $D_1 \geq 0$, $M_{12}^{\Theta} \geq 0$, $\Theta_2 < 0$, $M_{22}^{\Theta_3} \geq 0$. Thanks to Lemma 2.1, (2.46) and the arbitrariness of ϵ ,

$$\limsup_{t \rightarrow +\infty} t^{-1} \int_0^t x_3(s) ds \leq \frac{M_{22}^{\Theta_3}}{M_{22}^{\Theta}} \text{ a.s.} \quad (2.48)$$

According to (2.42) and (2.48), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_1(t) \geq \left(A_{11} \frac{M_{22}^{\Theta_1}}{M_{22}^{\Theta}} - 2\epsilon \right) t - A_{11} \int_0^t x_1(s) ds. \quad (2.49)$$

Based on Lemma 2.1 and the arbitrariness of ϵ , we have

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s) ds \geq \frac{M_{22}^{\Theta_1}}{M_{22}^{\Theta}} \text{ a.s.} \quad (2.50)$$

Combining (2.45) with (2.50) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_1(s) ds = \frac{M_{22}^{\Theta_1}}{M_{22}^{\Theta}} \text{ a.s.} \quad (2.51)$$

By (2.42) and (2.50), for $\forall \epsilon \in (0, 1)$ and $t \gg 1$,

$$\ln x_3(t) \geq \left(A_{33} \frac{M_{22}^{\Theta_3}}{M_{22}^{\Theta}} - 2\epsilon \right) t - A_{33} \int_0^t x_3(s) ds. \quad (2.52)$$

Thanks to Lemma 2.1 and the arbitrariness of ϵ , we deduce

$$\liminf_{t \rightarrow +\infty} t^{-1} \int_0^t x_3(s) ds \geq \frac{M_{22}^{\Theta_3}}{M_{22}^{\Theta}} \text{ a.s.} \quad (2.53)$$

Combining (2.48) with (2.53) yields

$$\lim_{t \rightarrow +\infty} t^{-1} \int_0^t x_3(s) ds = \frac{M_{22}^{\Theta_3}}{M_{22}^{\Theta}} \text{ a.s.} \quad (2.54)$$

The proof is complete. \square

3. Global attractivity

Theorem 3.1. Assume that $2a_{jj} > \sum_{i=1}^3 A_{ij}$ ($j = 1, 2, 3$). Let $X(t; \phi) =: (x_1(t; \phi), x_2(t; \phi), x_3(t; \phi))^T$ be the solution to system (1.3) with initial condition $\phi \in C([-T, 0], \mathbb{R}_+^3)$. Then, for any ϕ and $\phi^* \in C([-T, 0], \mathbb{R}_+^3)$,

$$\lim_{t \rightarrow +\infty} \mathbb{E}[\|X(t; \phi) - X(t; \phi^*)\|] = 0. \quad (3.1)$$

Proof. We only need to show

$$\lim_{t \rightarrow +\infty} \mathbb{E}|x_i(t; \phi) - x_i(t; \phi^*)| = 0 \quad (i = 1, 2, 3). \quad (3.2)$$

Define

$$\begin{aligned} W(t; \phi, \phi^*) &= \sum_{i=1}^3 \left| \ln \left(\frac{x_i(t; \phi^*)}{x_i(t; \phi)} \right) \right| \\ &\quad + \sum_{i,j=1}^3 \int_{-\tau_{ji}}^0 \int_{t+\theta}^t |x_i(s; \phi^*) - x_i(s; \phi)| ds d\mu_{ji}(\theta). \end{aligned}$$

From Itô's formula, we derive

$$\mathcal{L}[W(t; \phi, \phi^*)] \leq - \sum_{j=1}^3 \left(2a_{jj} - \sum_{i=1}^3 A_{ij} \right) |x_j(t; \phi^*) - x_j(t; \phi)|. \quad (3.3)$$

According to (3.3), we have

$$\begin{aligned} \mathbb{E}[W(t; \phi, \phi^*)] - \mathbb{E}[W(0; \phi, \phi^*)] \\ \leq - \sum_{j=1}^3 \left(2a_{jj} - \sum_{i=1}^3 A_{ij} \right) \int_0^t \mathbb{E}[|x_j(s; \phi^*) - x_j(s; \phi)|] ds, \end{aligned}$$

which implies

$$\int_0^{+\infty} \mathbb{E}[|x_i(t; \phi^*) - x_i(t; \phi)|] dt < +\infty \quad (i = 1, 2, 3). \quad (3.4)$$

Define $G_i(t) = \mathbb{E}[|x_i(t; \phi^*) - x_i(t; \phi)|]$ ($i = 1, 2, 3$). Then,

$$\begin{aligned} |G_i(t_2) - G_i(t_1)| \\ \leq \mathbb{E}[|x_i(t_2; \phi^*) - x_i(t_1; \phi^*)|] + \mathbb{E}[|x_i(t_2; \phi) - x_i(t_1; \phi)|]. \end{aligned} \quad (3.5)$$

Based on Hölder's inequality, for $t_2 > t_1$ and $p > 1$,

$$\begin{aligned} (\mathbb{E}[|x_j(t_2) - x_j(t_1)|])^p &\leq \mathbb{E}[|x_j(t_2) - x_j(t_1)|^p] \\ &\leq 2^{p-1} \mathbb{E}\left[\left(\int_{t_1}^{t_2} x_j(s) \left(r_j + \sum_{i=1}^3 a_{ji} x_i(s) \right. \right. \right. \\ &\quad \left. \left. \left. + \sum_{i=1}^3 \int_{-\tau_{ji}}^0 x_i(s+\theta) d\mu_{ji}(\theta) \right) ds \right)^p \right] \\ &\quad + 2^{p-1} \mathbb{E}\left[\left(\int_{t_1}^{t_2} \sigma_j x_j(s) dB_j(s) \right)^p \right] \\ &\triangleq 2^{p-1} \Upsilon_1 + 2^{p-1} \Upsilon_2 \quad (j = 1, 2, 3). \end{aligned} \quad (3.6)$$

In view of Theorem 7.1 in [14], for $p \geq 2$, we obtain

$$\Upsilon_2 \leq |\sigma_j|^p \left(\frac{p(p-1)}{2} \right)^{\frac{p}{2}} (t_2 - t_1)^{\frac{p-2}{2}} \int_{t_1}^{t_2} \mathbb{E}[x_j^p(s)] ds. \quad (3.7)$$

From Hölder's inequality, we derive

$$\begin{aligned} \Upsilon_1 &\leq 7^{p-1} r_j^p (t_2 - t_1)^{p-1} \int_{t_1}^{t_2} \mathbb{E}[x_j^p(s)] ds \\ &+ \sum_{i=1}^3 7^{p-1} a_{ji}^p (t_2 - t_1)^{p-1} \int_{t_1}^{t_2} \mathbb{E}[x_i^p(s)x_j^p(s)] ds \\ &+ \sum_{i=1}^3 7^{p-1} (t_2 - t_1)^{p-1} \mathbb{E} \left[\int_{t_1}^{t_2} \left(\int_{-\tau_{ji}}^0 x_i(s+\theta) x_j(s) d\mu_{ji}(\theta) \right)^p ds \right]. \end{aligned} \quad (3.8)$$

According to Hölder's inequality, we get

$$\begin{aligned} &\mathbb{E} \left[\int_{t_1}^{t_2} \left(\int_{-\tau_{ji}}^0 x_j(s)x_i(s+\theta) d\mu_{ji}(\theta) \right)^p ds \right] \\ &\leq \frac{1}{2} \left(\int_{-\tau_{ji}}^0 d\mu_{ji}(\theta) \right)^p \int_{t_1}^{t_2} \mathbb{E}[x_j^{2p}(s)] ds \\ &+ \frac{1}{2} \left(\int_{-\tau_{ji}}^0 d\mu_{ji}(\theta) \right)^{p-1} \int_{t_1}^{t_2} \int_{-\tau_{ji}}^0 \mathbb{E}[x_i^{2p}(s+\theta)] d\mu_{ji}(\theta) ds. \end{aligned} \quad (3.9)$$

Based on (3.6)-(3.9), for $p \geq 2$ and $|t_2 - t_1| \leq \delta$,

$$(\mathbb{E}[|x_j(t_2) - x_j(t_1)|])^p \leq M_j |t_2 - t_1|^{\frac{p}{2}}, \quad (3.10)$$

where

$$\begin{aligned} M_j &= 14^{p-1} \left\{ r_j^p K_j(p) + \sum_{i=1}^3 \left[\frac{a_{ji}^p}{2} + \frac{1}{2} \left(\int_{-\tau_{ji}}^0 d\mu_{ji}(\theta) \right)^p \right] \right. \\ &\quad \left. [K_i(2p) + K_j(2p)] \right\} \delta^{\frac{p}{2}} + 2^{p-1} |\sigma_j|^p \left(\frac{p(p-1)}{2} \right)^{\frac{p}{2}} K_j(p). \end{aligned}$$

Combining (3.5) with (3.10) yields

$$|G_j(t_2) - G_j(t_1)| \leq 2 \sqrt[p]{M_j} \sqrt{|t_2 - t_1|}. \quad (3.11)$$

Therefore, (3.2) follows from (3.4), (3.11) and Barbalat's conclusion in [15]. \square

4. Numerical simulations

In this section we provide some numerical simulations to show the effectiveness of our main theoretical results by using the Milstein approach mentioned in [16]. Let $\tau_{ji} = \ln 2$, $\mu_{ji}(\theta) = \mu_{ji}e^\theta$. Denote

$$\text{Param}(i) = \begin{pmatrix} r_1 & a_{11} & a_{12} & a_{13} & \mu_{11} & \mu_{12} & \mu_{13} \\ r_2 & a_{21} & a_{22} & a_{23} & \mu_{21} & \mu_{22} & \mu_{23} \\ r_3 & a_{31} & a_{32} & a_{33} & \mu_{31} & \mu_{32} & \mu_{33} \end{pmatrix}.$$

4.1. Example 1

Let

$$\text{Param}(1) = \begin{pmatrix} 0.9 & 0.2 & 0.4 & 0.2 & 0.4 & 0.8 & 0.2 \\ 0.2 & 0.6 & 0.3 & 0.1 & 0.6 & 0.6 & 0.2 \\ 0.1 & 0.4 & 0.3 & 0.2 & 0.8 & 0.4 & 0.4 \end{pmatrix},$$

subject to $x_1(\theta) = 0.7e^\theta$, $x_2(\theta) = 0.6e^\theta$, $x_3(\theta) = 0.5e^\theta$, $\theta \in [-\ln 2, 0]$.

Case 1. $\sigma_1 = 1.4$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. Then, $D_1 = -0.08$. By Theorem 2.2 (i), all three species are extinctive. See Figure 1(a).

Case 2. $\sigma_1 = 0.1$, $\sigma_2 = 2.0$, $\sigma_3 = 1.9$. Then, $D_1 = 0.895$, $M_{33}^{\Theta_2} = -0.0745$, $M_{22}^{\Theta_3} = -0.046$. From Theorem 2.2 (ii), $x_1(t)$ is persistent in mean, while $x_2(t)$ and $x_3(t)$ are extinctive. See Figure 1(b).

Case 3. $\sigma_1 = 0.1$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. Then, $\Theta = 0.225$, $\Theta_1 = 0.16225$, $\Theta_2 = 0.13375$, $\Theta_3 = 0.09825$, $M_{11}^{\Theta} = 0.14$. In view of Theorem 2.2 (iv), all three species are persistent in mean. See Figure 1(c).

4.2. Example 2

Let

$$\text{Param}(2) = \begin{pmatrix} 0.8 & 0.1 & 0.2 & 0.1 & 0.2 & 0.2 & 0.2 \\ 0.3 & 0.2 & 0.4 & 0.2 & 0.4 & 0.4 & 0.2 \\ 0.2 & 0.2 & 0.2 & 0.1 & 0.2 & 0.4 & 0.2 \end{pmatrix},$$

subject to $x_1(\theta) = 0.7e^\theta$, $x_2(\theta) = 0.6e^\theta$, $x_3(\theta) = 0.5e^\theta$, $\theta \in [-\ln 2, 0]$.

Case 4. $\sigma_1 = 0.1$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. Then, $\Theta = 0.001$, $D_1 = 0.795$, $M_{12}^{\Theta} = 0.01$, $\Theta_2 = -0.00975$, $M_{22}^{\Theta_3} = 0.1975$. According to Theorem 2.2 (vi), both $x_1(t)$ and $x_3(t)$ are persistent in mean, while $x_2(t)$ is extinctive. See Figure 1(d).

Case 5. $\sigma_1 = 0.2$, $\sigma_2 = 1.8$, $\sigma_3 = 1.5$. Then, $\Theta = 0.001$, $D_1 = 0.78$, $M_{12}^{\Theta} = 0.01$, $\Theta_2 = -0.0143$, $M_{22}^{\Theta_3} = -0.031$. Based on Theorem 2.2 (v), $x_1(t)$ is persistent in mean, while both $x_2(t)$ and $x_3(t)$ are extinctive. See Figure 1(e).

4.3. Example 3

Let

$$\text{Param}(3) = \begin{pmatrix} 0.8 & 0.1 & 0.1 & 0.2 & 0.2 & 0.2 & 0.2 \\ 0.2 & 0.2 & 0.1 & 0.2 & 0.2 & 0.2 & 0.4 \\ 0.3 & 0.2 & 0.2 & 0.4 & 0.4 & 0.2 & 0.4 \end{pmatrix},$$

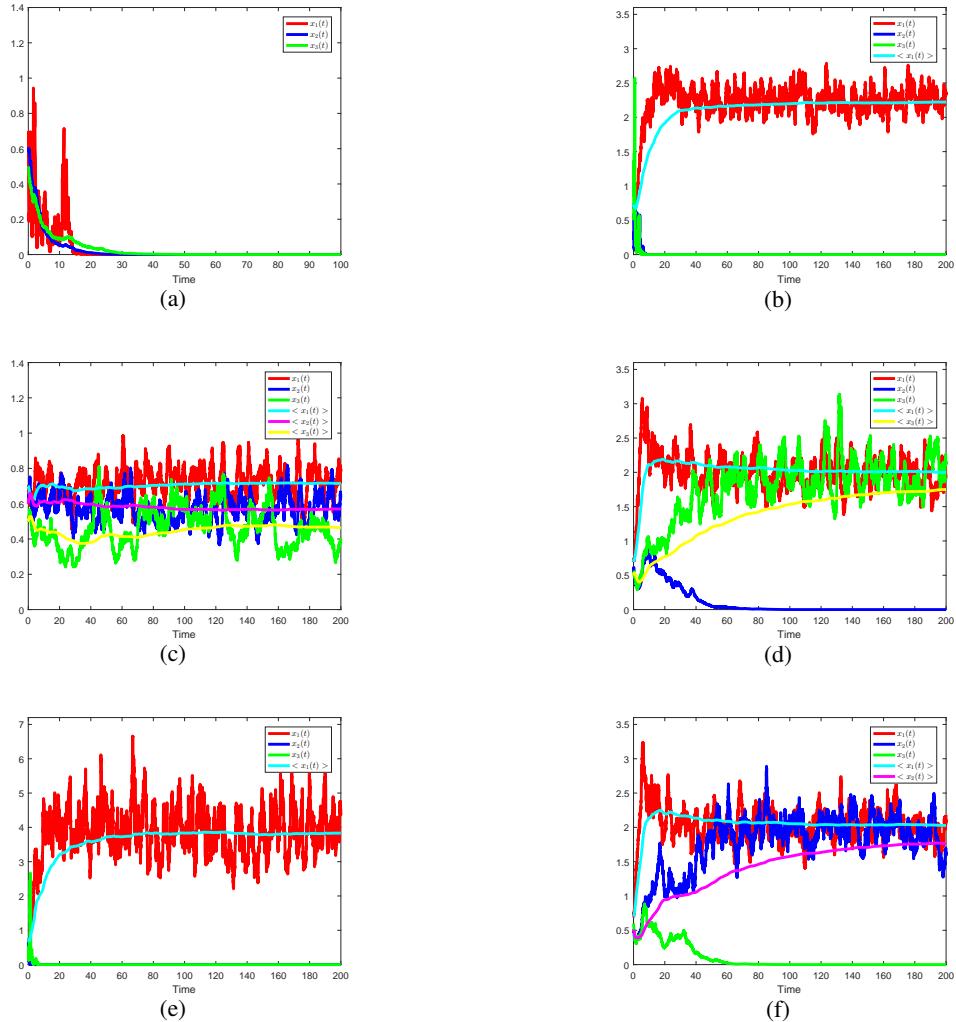


Figure 1. (a) shows the solution to system (1.3) with Param (1) and $\sigma_1 = 1.4$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. This subfigure represents that all species in **Case 1** are extinctive; (b) shows the solution to system (1.3) with Param (1) and $\sigma_1 = 0.1$, $\sigma_2 = 2.0$, $\sigma_3 = 1.9$. This subfigure represents that in **Case 2**, $x_1(t)$ is persistent in mean, while $x_2(t)$ and $x_3(t)$ are extinctive; (c) shows the solution to system (1.3) with Param (1) and $\sigma_1 = 0.1$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. This subfigure represents that all species in **Case 3** are persistent in mean; (d) shows the solution to system (1.3) with Param (2) and $\sigma_1 = 0.1$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. This subfigure represents that in **Case 4**, both $x_1(t)$ and $x_3(t)$ are persistent in mean, while $x_2(t)$ is extinctive; (e) shows the solution to system (1.3) with Param (2) and $\sigma_1 = 0.2$, $\sigma_2 = 1.8$, $\sigma_3 = 1.5$. This subfigure represents that in **Case 5**, $x_1(t)$ is persistent in mean, while both $x_2(t)$ and $x_3(t)$ are extinctive; (f) shows the solution to system (1.3) with Param (3) and $\sigma_1 = 0.1$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. This subfigure represents that in **Case 6**, both $x_1(t)$ and $x_2(t)$ are persistent in mean, while $x_3(t)$ is extinctive.

subject to $x_1(\theta) = 0.7e^\theta$, $x_2(\theta) = 0.5e^\theta$, $x_3(\theta) = 0.6e^\theta$, $\theta \in [-\ln 2, 0]$.

Case 6. $\sigma_1 = 0.1$, $\sigma_2 = 0.1$, $\sigma_3 = 0.1$. Then, $\Theta = 0.001$, $D_1 = 0.795$, $M_{13}^\Theta = -0.01$, $\Theta_3 = -0.00975$, $M_{33}^{\Theta_2} = 0.1975$. Thanks to Theorem 2.2 (iii), both $x_1(t)$ and $x_2(t)$ are persistent in mean, while $x_3(t)$ is extinctive. See Figure 1(f).

All mentioned above can be confirmed by Figure 1.

Acknowledgement

The work is supported by National Natural Science Foundation of China (No.11901166).

Conflict of interest

The authors declare that there are no conflicts of interest.

References

1. H. Freedman, P. Waltman, Mathematical analysis of some three-species food-chain models, *Math. Biosci.*, **33** (1977), 257–276. [http://doi.org/10.1016/0025-5564\(77\)90142-0](http://doi.org/10.1016/0025-5564(77)90142-0)
2. H. Freedman, P. Waltman, Persistence in models of three interacting predator-prey populations, *Math. Biosci.*, **68** (1984), 213–231. [http://doi.org/10.1016/0025-5564\(84\)90032-4](http://doi.org/10.1016/0025-5564(84)90032-4)
3. J. Roy, D. Barman, S. Alam, Role of fear in a predator-prey system with ratio-dependent functional response in deterministic and stochastic environment, *Biosystems*, **197** (2020), 104176. <http://doi.org/10.1016/j.biosystems.2020.104176>
4. Q. Zhang, D. Jiang, Dynamics of stochastic predator-prey systems with continuous time delay, *Chaos Solitons Fractals*, **152** (2021), 111431. <http://doi.org/10.1016/j.chaos.2021.111431>
5. Y. Cai, S. Cai, X. Mao, Analysis of a stochastic predator-prey system with foraging arena scheme, *Stochastics*, **92** (2020), 193–222. <http://doi.org/10.1080/17442508.2019.1612897>
6. F. A. Rihan, H. J. Alsakaji, Stochastic delay differential equations of three-species prey-predator system with cooperation among prey species, *Discret. Contin. Dyn. Syst. Ser.*, **15** (2022), 245. <http://doi.org/10.3934/dcdss.2020468>
7. H. J. Alsakaji, S. Kundu, F. A. Rihan, Delay differential model of one-predator two-prey system with Monod-Haldane and holling type II functional responses, *Appl. Math. Comput.*, **397** (2021), 125919. <http://doi.org/10.1016/j.amc.2020.125919>
8. J. Geng, M. Liu, Y.Q. Zhang, Stability of a stochastic one-predator-two-prey population model with time delays, *Commun. Nonlinear Sci. Numer. Simul.*, **53** (2017), 65–82. <http://doi.org/10.1016/j.cnsns.2017.04.022>
9. K. Gopalsamy, *Stability and Oscillations in Delay Differential Equations of Population Dynamics*, Dordrecht: Kluwer Academic Publishers, 1992. <https://doi.org/10.1007/978-94-015-7920-9>
10. S. Wang, L. Wang, T. Wei, Optimal harvesting for a stochastic logistic model with S-type distributed time delay, *J. Differ. Equ. Appl.*, **23** (2017), 618–632. <http://doi.org/10.1080/10236198.2016.1269761>
11. L. C. Hung, Stochastic delay population systems, *Appl. Anal.*, **88** (2009), 1303–1320. <http://doi.org/10.1080/00036810903277093>
12. S. Wang, L. Wang, T. Wei, Optimal Harvesting for a Stochastic Predator-prey Model with S-type Distributed Time Delays, *Methodol. Comput. Appl. Probab.*, **20** (2018), 37–68. <http://doi.org/10.1007/s11009-016-9519-2>
13. M. Liu, K. Wang, Q. Wu, Survival Analysis of Stochastic Competitive Models in a Polluted Environment and Stochastic Competitive Exclusion Principle, *Bull. Math. Biol.*, **73** (2011), 1969–2012. <http://doi.org/10.1007/s11538-010-9569-5>
14. X. Mao, *Stochastic differential equations and applications*, England: Horwood Publishing Limited, 2007.

-
15. I. Barbalat, Systems dequations differentielles d'osci
d'oscillations, *Rev. Roumaine Math. Pures Appl.*, **4**
(1959), 267–270.
16. D. Higham, An algorithmic introduction to
numerical simulation of stochastic differential
equations, *SIAM Rev.*, **43** (2001), 525–546.
<http://doi.org/10.1137/S0036144500378302>



© 2022 the Author(s), licensee AIMS Press. This
is an open access article distributed under the
terms of the Creative Commons Attribution License
(<http://creativecommons.org/licenses/by/4.0>)