$\boxed{3(a)}$ Given that $X(t)$ and $Y(t)$ are independent random processes. Their autocovariance $C_{XY}(t_1, t_2)$

$$= R_{XY}(t_1,t_2) - E[X(t_1)]E[Y(t_2)]$$

$= 0$ because they are uncorrelated.

Thus, $E[X(t)Y(t)] = E[X(t)]E[Y(t)]$

$=$ constant.

$$E[Z(t_1)Z(t_2)] = E[X(t_1)Y(t_1)X(t_2)Y(t_2)]$$

$$= E[X(t_1)X(t_2)]E[Y(t_1)Y(t_2)]$$

$$= R_{XX}(t_1-t_2)R_{YY}(t_1-t_2)$$

Therefore, Z is WSS.

$\boxed{3(b)}$ First, we show that $X(t)$ is WSS

$$E[X(t_1)X(t_2)] = E[\cos(\omega_0 t_1+\theta)\cos(\omega_0 t_2+\theta)]$$

$$= E\left[\frac{\cos(\omega_0 t_1-\omega_0 t_2) + \cos(\omega_0 t_1+\omega_0 t_2+2\theta)}{2}\right]$$

$$= \underbrace{\frac{1}{2}\cos(\omega_0 t_1-\omega_0 t_2)} + \frac{1}{2}E[\cos(\omega_0 t_1+\omega_0 t_2+2\theta)]$$

$$= \square + \frac{1}{2}E[\cos(\omega_0 t_1+\omega_0 t_2)\cos 2\theta - \sin(\omega_0 t_1+\omega_0 t_2)\sin(2\theta)]$$

$$= \square + \frac{1}{2}\left(\overbrace{\int_0^{2\pi}\theta\cos 2\theta\, d\theta}^{0} \cdot \cos(\omega_0 t_1+\omega_0 t_2) - \overbrace{\int_0^{2\pi}\theta\sin 2\theta\, d\theta}^{0} \cdot \sin(\omega_0 t_1+\omega_0 t_2)\right)$$

$$= \frac{1}{2}\cos(\omega_0 t_1-\omega_0 t_2)$$

$$E[X(t)] = E[\cos(\omega_0 t+\theta)]$$

$$= E[\cos(\omega_0 t)\cos(\theta) - \sin(\omega_0 t)\sin(\theta)]$$

$=$ constant

Thus, X is WSS.

$$R_Z(t) = R_X(t)R_Y(t)$$

$$= \frac{1}{2}\cos(\omega_0 t)e^{-\alpha|t|}$$

$$= \frac{1}{2}\left(\frac{e^{i\omega_0 t}+e^{-i\omega_0 t}}{2}\right)e^{-\alpha|t|}$$

$$F\{e^{-\alpha|t|}\} = \int_{-\infty}^{\infty} e^{-\alpha|t|}e^{i\omega t}\,dt$$

$$= \int_0^{\infty} e^{-\alpha t}e^{i\omega t}\,dt + \int_{-\infty}^{0} e^{\alpha t}e^{i\omega t}\,dt$$

$$= \frac{1}{\alpha - i\omega} + \frac{1}{\alpha + i\omega} = \frac{2\alpha}{\alpha^2+\omega^2}$$

$$S_Z(t) = F\{R_Z(t)\} = \frac{\alpha}{2(\alpha^2+(\omega-\omega_0)^2)} + \frac{\alpha}{2(\alpha^2+(\omega+\omega_0)^2)}$$

$\boxed{4(a)}$ $E[|Y_m-\mu|^2]$

$$= E[Y_m^2] - 2\mu E[Y_m] + \mu^2$$

$$= \left(\frac{1}{m^2}\left(E[X^2]m + E[X]^2 m(m-1)\right)\right) - \mu^2$$

$$= \frac{(\sigma^2+\mu^2)}{m} + \frac{\mu^2(m-1)}{m} - \mu^2 = \frac{\sigma^2}{m} \to 0$$

when $m \to \infty$

Thus, Y_m converges to μ in MS sense.

$\boxed{4(b)}$ $\sigma_Y^2 = E[Y_m^2] - E[Y_m]^2$

$$= \frac{1}{m^2}\left(E[X^2]m + E[X]^2 m(m-1)\right) - \mu^2$$

$$= \frac{1}{m^2}\left((\sigma^2+\mu^2)m + \mu^2(m(m-1))\right) - \mu^2$$

$$= \frac{\sigma^2}{m} + \mu^2 - \mu^2 = \frac{\sigma^2}{m}$$

From Chebyshev inequality,

$$P\{|X-\mu| \ge \varepsilon\} \le \frac{\sigma_Y^2}{\varepsilon^2} = \frac{\sigma^2}{m\varepsilon^2} \to 0$$

when $m \to \infty$