# ${\bf Assembly\ of\ Drug\ Epidemiological\ Models-Supplementary\ Materials}$

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## S1. Description of Tang and Ling's Model

Tang and Ling's model [1] is an adaptation of Njagarah and Nyabadza's model [2] by adding 2 relapse processes. The compartments of the model are susceptible (S), light drug user (L), heavy drug user (H), drug user in treatment (T), drug mules/pushers (D), and removed by various causes (R). In the simplified model of Njagarah and Nyabadza [2], relapse from treatment (T) into heavy user (H) is defined as g3(T). Tang and Ling [1] added 2 relapse processes – from treatment (T) to susceptible (S) as g5(T), and from treatment (T) to light drug user (L) as g4(T).

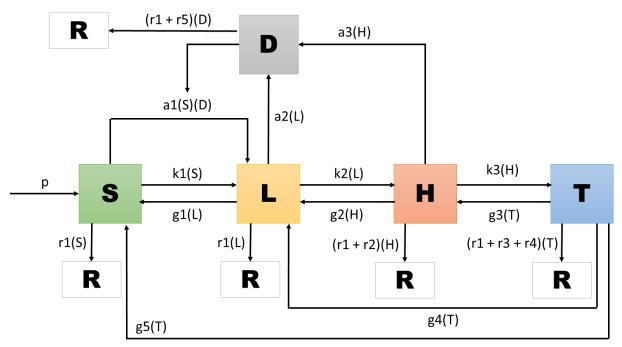


Figure S1. Tang and Ling's model [1].

The parameters are as follow:

	Nominal	
Parameter	Value	Description
		Recruitment rate from general population into susceptible
p	0.02	population (S).
		Rate at which susceptible population (S) become light drug users
k1	0.28	(L) without the effects of drug barons (D).
k2	0.56	Rate at which light users (L) escalates to heavy drug use (H).
k3	0.223	Rate at which heavy users (H) enters rehabilitation (T).
		Rate at which light users (L) quit and become susceptible (S)
g1	0.2	again.
		Rate at which heavy users (H) become light users (L), which
g2	0.4	includes amelioration.
		Rate at which rehabilitated users (T) reverted to heavy drug use
g3	0.25	(H).
g4	0.325	Rate at which rehabilitated users (T) reverted to light drug use (L).
g5	0.283	Rate at which rehabilitated users (T) reverted to susceptible (S).
		Effective contact rate between drug barons (D) and susceptible
a1	0.4	population (S).
		Rate at which light users (L) convert from consumer to seller /
a2	0.04	promoter (D).
		Rate at which heavy users (H) convert from consumer to seller /
a3	0.08	promoter (D).
r1	0.02	Per capita mortality rate of population.
		Removal rate of heavy users (H) due to events related to drug
r2	0.0014	usage.
		Removal rate of rehabilitated users (T) due to events related to
r3	0.003	drug usage.
r4	0.2	Rate at which rehabilitated users (T) permanently quit.
		Removal rate of drug barons (D), which constitutes mainly to law
r5	0.028	enforcement.

### S2. Description of Knolle's Model

Knolle's model [3] estimates the prevalence of drug use before being caught (X) based on the number of charged users (Y), given that a proportion of drug users that may never be caught  $(\sigma X)$  or stopped illicit drug use after being caught  $(\tau Y)$ . The model acknowledges that the proportion of caught users is a product of police search intensity  $(\pi)$  and the exposed population of pre-caught users (f) or caught and charged users (g).

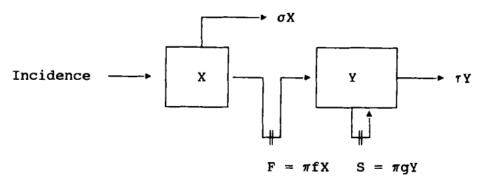


Figure S2. Knolle's model [3].

The parameters are as follow:

	Nominal	
Parameter	Value	Description
σ	0.25	Proportion of drug users that may never be caught.
τ	0.1	Proportion of drug users quit drug use after being caught.
f	0.02	Proportion of pre-caught drug users (X) exposed to police search.
g	0.04	Proportion of post-caught drug users (Y) exposed to police search.
π	5	Intensity of policing / police search.

# S3. Stage 1: Assemble Knolle's Model and Tang and Ling's Model into Model-1

Tang and Ling's model [1] did not cater to policing, which is present in Knolle's model [3]. Pre-caught drug users in Knolle's model [3] can be seen as summation of light (L) and heavy (H) drug users and post-caught drug users can be equivalent to rehabilitated users (T). However, the rate at which heavy users (H) enters rehabilitation (T), original k3 (which equals to 0.223), can be seen as the exposure of heavy drug users (H) to police search. Hence, k3 is redesignated as a product of k3 [proportion of heavy drug users (H) exposed to policing / police search] and k5 (intensity of policing). By extension, light drug users (L) can also be caught by policing activities to rehabilitated users (T), which can be modelled as the product of k4 [proportion of light drug users (L) exposed to policing / police search] and k5 (intensity of policing).

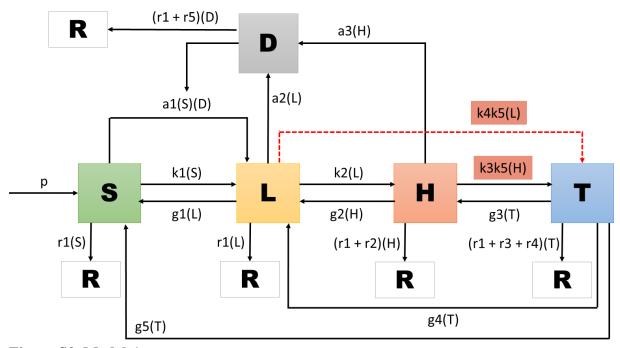


Figure S3. Model-1.

The revised parameters for Model-1 are as follow:

Parameter	Nominal Value	Description
р	0.02	Recruitment rate from general population into susceptible population (S).

Rate at which susceptible population (S) become light of (L) without the effects of drug barons (D).  k2 0.56 Rate at which light users (L) escalates to heavy drug users (3) exposed to police see the control of light drug users (L) exposed to polic	e (H). earch. rch.
k2 0.56 Rate at which light users (L) escalates to heavy drug use 3 0.446 Proportion of heavy drug users (H) exposed to police see 4 0.223 Proportion of light drug users (L) exposed to police search 5 0.5 Intensity of policing / police search.	earch. rch.
k3 0.446 Proportion of heavy drug users (H) exposed to police see k4 0.223 Proportion of light drug users (L) exposed to police sear k5 0.5 Intensity of policing / police search.	earch. rch.
k4 0.223 Proportion of light drug users (L) exposed to police search.  k5 0.5 Intensity of policing / police search.	rch.
k5 0.5 Intensity of policing / police search.	
k5 0.5 Intensity of policing / police search.	
D ( 1 1 1 1 1 ( (T) 1 1 1 1 1	ptible (S)
Rate at which light users (L) quit and become susce	
g1 0.2 again.	
Rate at which heavy users (H) become light users (I	L), which
g2 0.4 includes amelioration.	
Rate at which rehabilitated users (T) reverted to heavy	drug use
g3 0.25 (H).	
g4 0.325 Rate at which rehabilitated users (T) reverted to light dru	ıg use (L).
g5 0.283 Rate at which rehabilitated users (T) reverted to suscept	
Effective contact rate between drug barons (D) and su	usceptible
a1 0.4 population (S).	
Rate at which light users (L) convert from consumer	to seller /
a2 0.04 promoter (D).	
Rate at which heavy users (H) convert from consumer	to seller /
a3 0.08 promoter (D).	
r1 0.02 Per capita mortality rate of population.	
Removal rate of heavy users (H) due to events relate	ed to drug
r2 0.0014 usage.	
Removal rate of rehabilitated users (T) due to events	related to
r3 0.003 drug usage.	
r4 0.2 Rate at which rehabilitated users (T) permanently quit.	
Removal rate of drug barons (D), which constitutes main	nly to law
r5 0.028 enforcement.	

#### S4. Description of Caulkin et al.'s 2009 Model

Caulkin et al.'s 2009 model [4] examines susceptibility into users. It also assumes that once a user, always a user; hence, there is no rehabilitation.

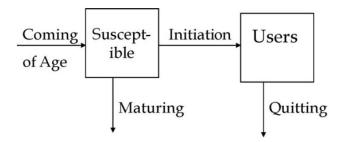


Figure S4. Caulkin et al.'s 2009 model [4].

# S5. Stage 2: Assemble Caulkin et al.'s 2009 Model and Model-1 into Model-2

In Caulkin et al.'s 2009 model [4], maturing from susceptible and quitting from user are not of the same meaning as removal in Model-1. Assuming that quitting in Caulkin et al.'s 2009

model [4] is only possible for light users, then maturing from susceptible and quitting from users in Caulkin et al.'s 2009 model [4] have a different meaning to per capita mortality rate of population. In other words, Model-1 does not allow for maturing or quitting. Hence, two new compartments are added – M for maturing from susceptible, and Q for quitting from light users.

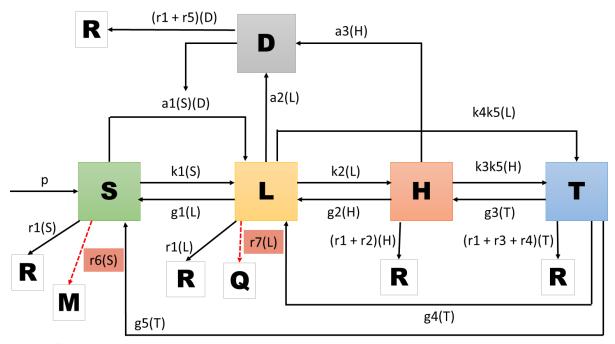


Figure S5. Model-2.

The revised parameters for Model-2 are as follow:

•	Nominal	
Parameter	Value	Description
		Recruitment rate from general population into susceptible
p	0.02	population (S).
		Rate at which susceptible population (S) become light drug users
k1	0.28	(L) without the effects of drug barons (D).
k2	0.56	Rate at which light users (L) escalates to heavy drug use (H).
k3	0.446	Proportion of heavy drug users (H) exposed to police search.
k4	0.223	Proportion of light drug users (L) exposed to police search.
k5	0.5	Intensity of policing / police search.
		Rate at which light users (L) quit and become susceptible (S)
g1	0.2	again.
		Rate at which heavy users (H) become light users (L), which
g2	0.4	includes amelioration.
		Rate at which rehabilitated users (T) reverted to heavy drug use
g3	0.25	(H).
g4	0.325	Rate at which rehabilitated users (T) reverted to light drug use (L).
g5	0.283	Rate at which rehabilitated users (T) reverted to susceptible (S).
		Effective contact rate between drug barons (D) and susceptible
a1	0.4	population (S).
		Rate at which light users (L) convert from consumer to seller /
a2	0.04	promoter (D).

		Rate at which heavy users (H) convert from consumer to seller /
a3	0.08	promoter (D).
r1	0.02	Per capita mortality rate of population.
		Removal rate of heavy users (H) due to events related to drug
r2	0.0014	usage.
		Removal rate of rehabilitated users (T) due to events related to
r3	0.003	drug usage.
r4	0.2	Rate at which rehabilitated users (T) permanently quit.
		Removal rate of drug barons (D), which constitutes mainly to law
r5	0.028	enforcement.
r6	0.01	Rate of susceptible (S) maturing into non-susceptible (M)
r7	0.01	Rate of light users (L) quitting drug use permanently (Q)

#### S6. Stage 3: Description of Caulkin et al.'s 2010 Model

Caulkin et al.'s 2010 model [5] examines the social cost of drug use using the compartments described in Caulkin et al.'s 2009 model [4]. Hence, Caulkin et al.'s 2010 model [5] is out of the scope of this study.

#### S7. Description of White and Comiskey's Model

In White and Comiskey's model [6], susceptible (S) represents the coming of age and  $U_1$  represents the population of drug users, while  $U_2$  represents the population of drug users in treatment. The likelihood of susceptible (S) entering drug use  $(U_1)$  is a probability of these two populations meeting. The rate of drug users  $(U_1)$  entering treatment  $(U_2)$  is presented by p. The relapse from treatment  $(U_2)$  to drug use  $(U_1)$  is represented by  $\beta_3$ .

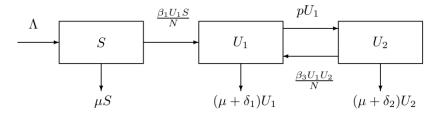


Figure S6. White and Comiskey's Model [6].

# S8. Stage 4: Model-2 Incorporates White and Comiskey's Model Light (L) and heavy (H) drug users in Model-2 are represented as drug users (U<sub>1</sub>), and users under treatment (T) in Model-2 are represented as U2 in White and Comiskey's model [6]. Therefore, Model-2 incorporates White and Comiskey's model [6].

S9. Stage 5: Model-2 Incorporates Mulone and Straughan's Model Mulone and Straughan [7] use the model of White and Comiskey's model [6] without amendments. Hence, Model-2 also incorporates Mulone and Straughan's model [7].

### S10. Description of Nyabadza and Hove-Musekwa's Model

Nyabadza and Hove-Musekwa [8] adapt White and Comiskey's model [6] for methamphetamines. However, drug users  $(U_1)$  in White and Comiskey's model [6] are split into light  $(I_1)$  and heavy  $(I_2)$  drug users in Nyabadza and Hove-Musekwa's model [8]. Users in treatment (T) in Nyabadza and Hove-Musekwa's model [8] are equivalent to  $U_2$  in White and

Comiskey's model [6]. Moreover, Nyabadza and Hove-Musekwa [8] added a compartment, recovered users (R), who are both light drug users (I<sub>1</sub>) and treated drug users (T) in remission.

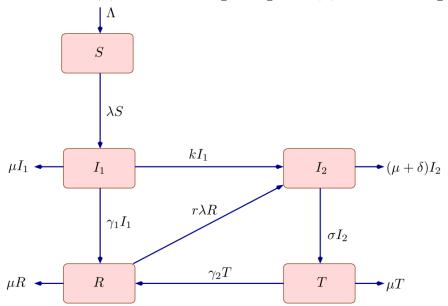


Figure S7. Nyabadza and Hove-Musekwa [8].

# S11. Stage 6: Assemble Nyabadza and Hove-Musekwa's Model and Model-2 into Model-3

Differing from Tang and Ling's model [1], release from treatment (T) no longer reverts to susceptible (S) but redesignated as in remission (Re); hence, g5 is redesignated as the proportion of rehabilitated users (T) entering remission (Re). Incorporating from Nyabadza and Hove-Musekwa's model [8], light users (L) can enter remission (Re) on their own accord through a period of non-usage. However, users in remission (Re) may revert to heavy use (H). In addition to Nyabadza and Hove-Musekwa's model [8], users in remission (Re) may also revert to light drug use (L).

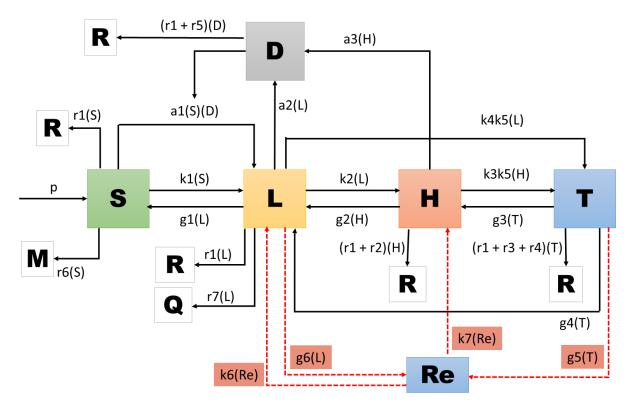


Figure S8. Model-3.

The revised parameters for Model-3 are as follow:

	Nominal	
Parameter	Value	Description
		Recruitment rate from general population into susceptible
р	0.02	population (S).
		Rate at which susceptible population (S) become light drug users
k1	0.28	(L) without the effects of drug barons (D).
k2	0.56	Rate at which light users (L) escalates to heavy drug use (H).
k3	0.446	Proportion of heavy drug users (H) exposed to police search.
k4	0.223	Proportion of light drug users (L) exposed to police search.
k5	0.5	Intensity of policing / police search.
k6	0.05	Rate of relapse from remission (Re) to light drug use (L).
k7	0.01	Rate of relapse from remission (Re) to heavy drug use (H).
		Rate at which light users (L) quit and become susceptible (S)
g1	0.2	again.
		Rate at which heavy users (H) become light users (L), which
g2	0.4	includes amelioration.
		Rate at which rehabilitated users (T) reverted to heavy drug use
g3	0.25	(H).
g4	0.325	Rate at which rehabilitated users (T) reverted to light drug use (L).
g5	0.283	Rate at which rehabilitated users (T) enter remission (Re).
		Proportion of light drug users (L) entering remission (Re) on their
g6	0.005	own accord
		Effective contact rate between drug barons (D) and susceptible
a1	0.4	population (S).

		Rate at which light users (L) convert from consumer to seller /
a2	0.04	promoter (D).
		Rate at which heavy users (H) convert from consumer to seller /
a3	0.08	promoter (D).
r1	0.02	Per capita mortality rate of population.
		Removal rate of heavy users (H) due to events related to drug
r2	0.0014	usage.
		Removal rate of rehabilitated users (T) due to events related to
r3	0.003	drug usage.
r4	0.2	Rate at which rehabilitated users (T) permanently quit.
		Removal rate of drug barons (D), which constitutes mainly to law
r5	0.028	enforcement.
r6	0.01	Rate of susceptible (S) maturing into non-susceptible (M)
r7	0.01	Rate of light users (L) quitting drug use permanently (Q)

#### S12. Stage 7: Model-3 Incorporates Wang et al.'s Model

Wang et al. [9] uses Mulone and Straughan [7], which is White and Comiskey's model [6] without amendments. Hence, Model-3 also incorporates Wang et al.'s model [9].

#### S13. Description of Kalula and Nyabadza's Model

Kalula and Nyabadza [10] use a closed model with known input  $(N_P)$  into susceptible population (S), which proceed to light  $(U_L)$  or heavy  $(U_H)$  drug use. Importantly, it is possible for susceptible population (S) to enter heavy drug use  $(U_H)$  without transiting through light drug use  $(U_L)$ . However, light drug users  $(U_L)$  can quit (Q) without treatment  $(U_T)$  but not heavy users  $(U_H)$ .

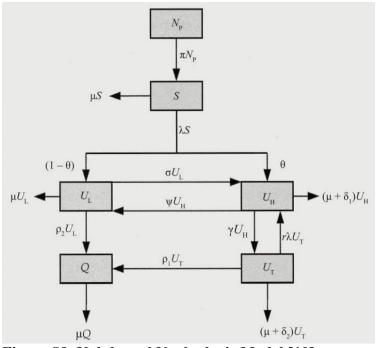


Figure S9. Kalula and Nyabadza's Model [10].

# S14. Stage 8: Assemble Kalula and Nyabadza's Model and Model-3 into Model-4.

Two processes from Kalula and Nyabadza's model [10] were added. Firstly, a very small but important proportion of susceptible (S) may enter into heavy drug use (H) without going through light drug use (L). Secondly, a proportion of rehabilitated users (T) may quit permanently (Q).

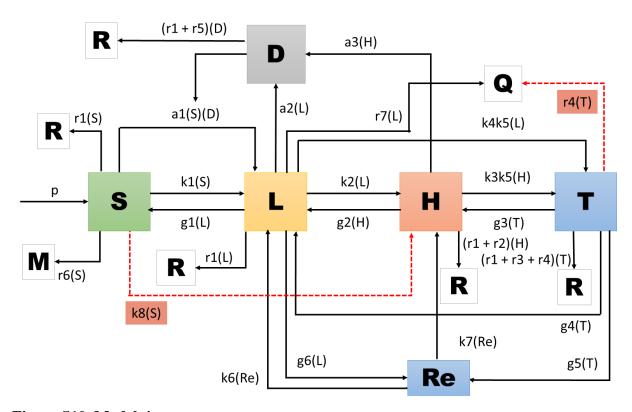


Figure S10. Model-4.

The revised parameters for Model-4 are as follow:

•	Nominal	
Parameter	Value	Description
		Recruitment rate from general population into susceptible
p	0.02	population (S).
		Rate at which susceptible population (S) become light drug users
k1	0.28	(L) without the effects of drug barons (D).
k2	0.56	Rate at which light users (L) escalates to heavy drug use (H).
k3	0.446	Proportion of heavy drug users (H) exposed to police search.
k4	0.223	Proportion of light drug users (L) exposed to police search.
k5	0.5	Intensity of policing / police search.
k6	0.05	Rate of relapse from remission (Re) to light drug use (L).
k7	0.01	Rate of relapse from remission (Re) to heavy drug use (H).
k8	0.001	Rate of susceptible population (S) become heavy drug users (H).
		Rate at which light users (L) quit and become susceptible (S)
g1	0.2	again.
		Rate at which heavy users (H) become light users (L), which
g2	0.4	includes amelioration.

		Rate at which rehabilitated users (T) reverted to heavy drug use
g3	0.25	(H).
g4	0.325	Rate at which rehabilitated users (T) reverted to light drug use (L).
g5	0.283	Rate at which rehabilitated users (T) enter remission (Re).
		Proportion of light drug users (L) entering remission (Re) on their
g6	0.005	own accord.
		Effective contact rate between drug barons (D) and susceptible
a1	0.4	population (S).
		Rate at which light users (L) convert from consumer to seller /
a2	0.04	promoter (D).
		Rate at which heavy users (H) convert from consumer to seller /
a3	0.08	promoter (D).
r1	0.02	Per capita mortality rate of population.
		Removal rate of heavy users (H) due to events related to drug
r2	0.0014	usage.
		Removal rate of rehabilitated users (T) due to events related to
r3	0.003	drug usage.
r4	0.2	Rate at which rehabilitated users (T) permanently quit.
		Removal rate of drug barons (D), which constitutes mainly to law
r5	0.028	enforcement.
r6	0.01	Rate of susceptible (S) maturing into non-susceptible (M)
r7	0.01	Rate of light users (L) quitting drug use permanently (Q)

#### S15. Description of Nyabadza et al's Model

Nyabadza et al. [11] models the availability or density of drugs (D) as a means of susceptible population (S) entering light drug use  $(U_l)$  without coming into contact with light drug users  $(U_l)$ . This can be seen as self-seeking behaviour.

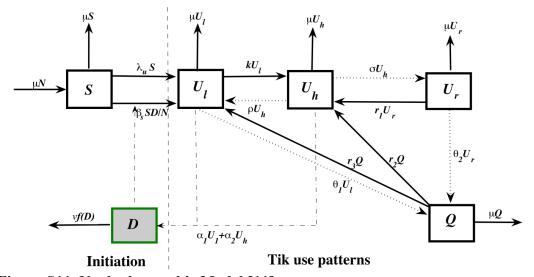


Figure S11. Nyabadza et al.'s Model [11].

S16. Stage 9: Assemble Nyabadza et al's Model and Model-4 into Model-5.

The availability of drugs in the system from Nyabadza et al.'s model [11] is incorporated into Model-4 as parameter k9.

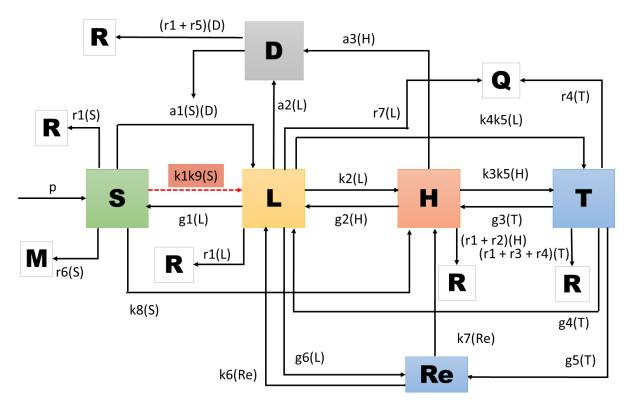


Figure S12. Model-5.

The revised parameters for Model-5 are as follow:

	Nominal	
Parameter	Value	Description
		Recruitment rate from general population into susceptible
р	0.02	population (S).
		Rate at which susceptible population (S) become light drug users
k1	0.28	(L) without the effects of drug barons (D).
k2	0.56	Rate at which light users (L) escalates to heavy drug use (H).
k3	0.446	Proportion of heavy drug users (H) exposed to police search.
k4	0.223	Proportion of light drug users (L) exposed to police search.
k5	0.5	Intensity of policing / police search.
k6	0.05	Rate of relapse from remission (Re) to light drug use (L).
k7	0.01	Rate of relapse from remission (Re) to heavy drug use (H).
k8	0.001	Rate of susceptible population (S) become heavy drug users (H).
k9	1	Availability of drugs in the system.
		Rate at which light users (L) quit and become susceptible (S)
g1	0.2	again.
		Rate at which heavy users (H) become light users (L), which
g2	0.4	includes amelioration.
		Rate at which rehabilitated users (T) reverted to heavy drug use
g3	0.25	(H).
g4	0.325	Rate at which rehabilitated users (T) reverted to light drug use (L).
g5	0.283	Rate at which rehabilitated users (T) enter remission (Re).
		Proportion of light drug users (L) entering remission (Re) on their
g6	0.005	own accord

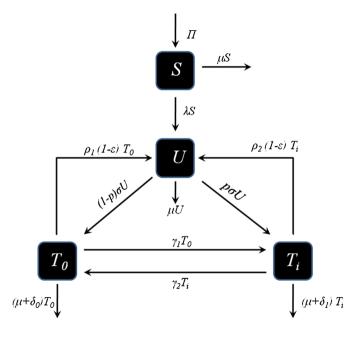
		Effective contact rate between drug barons (D) and susceptible
a1	0.4	population (S).
		Rate at which light users (L) convert from consumer to seller /
a2	0.04	promoter (D).
		Rate at which heavy users (H) convert from consumer to seller /
a3	0.08	promoter (D).
r1	0.02	Per capita mortality rate of population.
		Removal rate of heavy users (H) due to events related to drug
r2	0.0014	usage.
		Removal rate of rehabilitated users (T) due to events related to
r3	0.003	drug usage.
r4	0.2	Rate at which rehabilitated users (T) permanently quit.
		Removal rate of drug barons (D), which constitutes mainly to law
r5	0.028	enforcement.
r6	0.01	Rate of susceptible (S) maturing into non-susceptible (M)
r7	0.01	Rate of light users (L) quitting drug use permanently (Q)

#### S17. Stage 10: Model-5 Incorporates Muroya et al.'s Model

Muroya et al. [12] use White and Comiskey's model [6] without amendments. Hence, Model-5 also incorporates Muroya et al.'s [12].

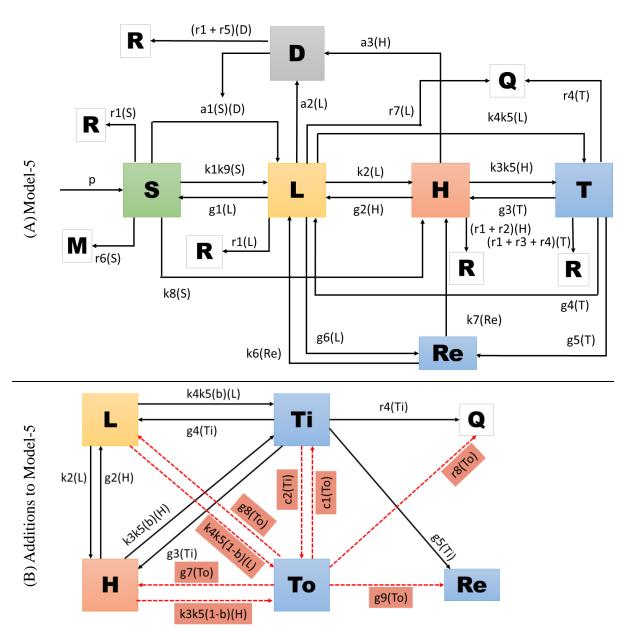
#### S18. Description of Mushanyu et al. 2015's Model

Mushanyu et al. [13] define a 4-compartment model for methamphetamine usage as S being the population at risk of being initiated into methamphetamine abuse, U are those initiated into methamphetamine abuse,  $T_o$  are those in rehabilitation as out-patients, and  $T_i$  are those in rehabilitation as in-patients.



S19. Stage 11: Assemble Model-5 and Mushanyu et al. 2015's Model into Model-6

In Mushanyu et al. [13]; S, being the population at risk of being initiated into methamphetamine abuse, corresponds to susceptible (S) in Model-5. U, those initiated into methamphetamine abuse, corresponds to both light (L) and heavy (H) user in Model-5.  $T_o$  and  $T_i$  corresponds to treatment (T) in Model-5. However, to incorporate Mushanyu et al. [13] into Model-5, treatment (T) is split into in-patient treatment ( $T_i$ ) and out-patient treatment ( $T_o$ ). Hence, the following processes are added into Model-5 to form Model-6:



**Figure S13. Model-6 Assembly.** Panel A shows Model-5. Panel B shows the addition to Model-5 to form Model-6.

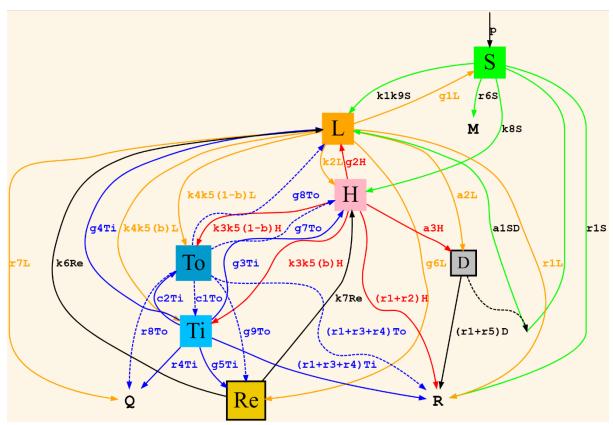


Figure S14. Model-6.

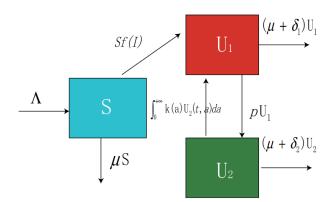
The revised parameters for Model-6 are as follow:

	arameters for Model-6 are as follow:
Parameter	•
p	Recruitment rate from general population into susceptible population (S).
	Rate at which susceptible population (S) become light drug users (L) without
k1	the effects of drug barons (D).
k2	Rate at which light users (L) escalates to heavy drug use (H).
k3	Proportion of heavy drug users (H) exposed to police search.
k4	Proportion of light drug users (L) exposed to police search.
k5	Intensity of policing / police search.
k6	Rate of relapse from remission (Re) to light drug use (L).
k7	Rate of relapse from remission (Re) to heavy drug use (H).
k8	Rate of susceptible population (S) become heavy drug users (H).
k9	Availability of drugs in the system.
	Proportion of drug users caught for in-patient treatment (T <sub>i</sub> ). Therefore, the
b	proportion of drug users caught for out-patient treatment $(T_0)$ is $(1-b)$ .
g1	Rate at which light users (L) quit and become susceptible (S) again.
	Rate at which heavy users (H) become light users (L), which includes
g2	amelioration.
g3	Rate at which in-patient treatment (T <sub>i</sub> ) reverted to heavy drug use (H).
g4	Rate at which in-patient treatment (T <sub>i</sub> ) reverted to light drug use (L).
g5	Rate at which in-patient treatment (T <sub>i</sub> ) enter remission (Re).
g6	Proportion of light drug users (L) entering remission (Re) on their own accord.
g7	Rate at which out-patient treatment (T <sub>o</sub> ) reverted to heavy drug use (H).
g8	Rate at which out-patient treatment (T <sub>o</sub> ) reverted to light drug use (L).

g9	Rate at which out-patient treatment (T <sub>o</sub> ) enter remission (Re).
a1	Effective contact rate between drug barons (D) and susceptible population (S).
a2	Rate at which light users (L) convert from consumer to seller / promoter (D).
a3	Rate at which heavy users (H) convert from consumer to seller / promoter (D).
r1	Per capita mortality rate of population.
r2	Removal rate of heavy users (H) due to events related to drug usage.
r3	Removal rate of rehabilitated users (T) due to events related to drug usage.
r4	Rate at which in-patient treatment (T <sub>i</sub> ) permanently quit (Q).
r5	Removal rate of drug barons (D), which constitutes mainly to law enforcement.
r6	Rate of susceptible (S) maturing into non-susceptible (M)
r7	Rate of light users (L) quitting drug use permanently (Q)
r8	Rate at which out-patient treatment (T <sub>o</sub> ) permanently quit (Q).
c1	Rate of out-patient treatment (T <sub>o</sub> ) entering in-patient treatment (T <sub>i</sub> )
c2	Rate of in-patient treatment (T <sub>i</sub> ) entering out-patient treatment (T <sub>o</sub> )

#### S20. Description of Yang et al.'s Model

Yang et al. [14] model examine susceptible (S) to drug or alcohol usage  $(U_1)$ , and from drug or alcohol usage  $(U_1)$  to treatment  $(U_2)$ .

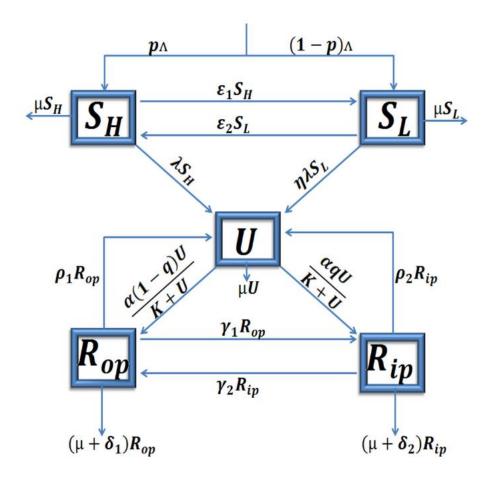


#### S21. Stage 12: Model-6 incorporates Yang et al.'s Model

Susceptible (S), drug usage  $(U_1)$ , and treatment  $(U_2)$  in Yang et al. [14] are addressed in Model-6.

### S22. Description of Mushanyu et al. 2016's Model

Mushanyu et al. [15] extend Mushanyu et al. [13] model by splitting susceptible (S) into high  $(S_H)$  and low  $(S_L)$  susceptibility to drug use (U).

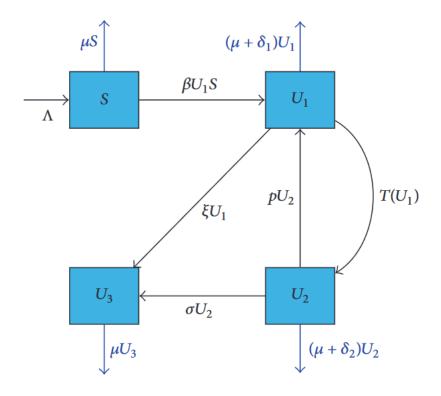


S23. Stage 13: Model-6 partially incorporates Mushanyu et al. 2016's Model

Model-6 addresses in-patient and out-patient treatment, which are deemed to be more visible than low and high susceptibility. In addition, it is generally difficult to accurately categorize a susceptible person as high or low susceptibility as compared to in-patient and out-patient treatment, which are usually documented. Hence, splitting of susceptibility is difficult. Therefore, Model-5 partially incorporates Mushanyu et al. [15] model.

### S24. Description of Wangari and Stone's Model

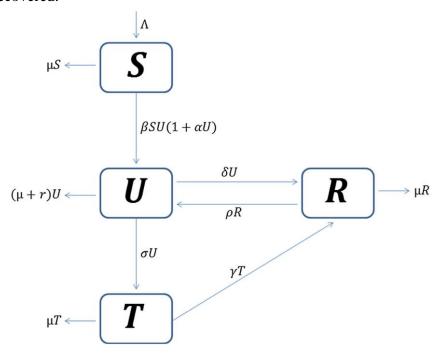
Wangari and Stone's [16] model defines S as susceptible,  $U_1$  as drug users,  $U_2$  as drug users under treatment, and  $U_3$  as individuals successfully treated.



S25. Stage 14: Model-6 incorporates Wangari and Stone's Model Model-6 addresses Wangari and Stone's [16] model as light (L) and heavy drug (H) users are collectively denoted as  $U_1$ , users under treatment (T) corresponds to  $U_2$ , and users in remission (Re) corresponds to  $U_3$ .

#### S26. Description of Mushanyu et al. 2017's Model

Mushanyu et al.'s [17] model defines S as susceptible, U as drug users for both current and relapsed users, T as drug users under treatment, and R as individuals successfully treated or recovered.

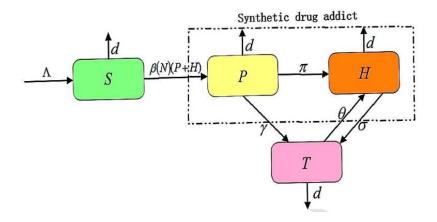


#### S27. Stage 15: Model-6 incorporates Mushanyu et al. 2017's Model

Model-6 addresses Mushanyu et al.'s [17] model as light (L) and heavy drug (H) users are collectively denoted as U, users under treatment (T) has the same definition in both models, and users in remission (Re) corresponds to R (recovered users with potential relapse).

#### S28. Description of Ma et al.'s Model

Ma et al.'s [18] model defines S as susceptible, P as psychological addicts, H as physiological addicts, and T as users under treatment.

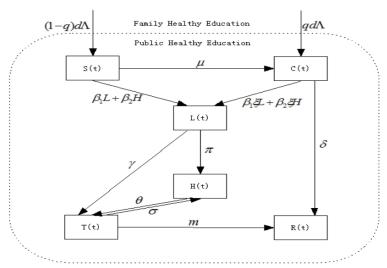


#### S29. Stage 16: Model-6 incorporates Ma et al.'s Model

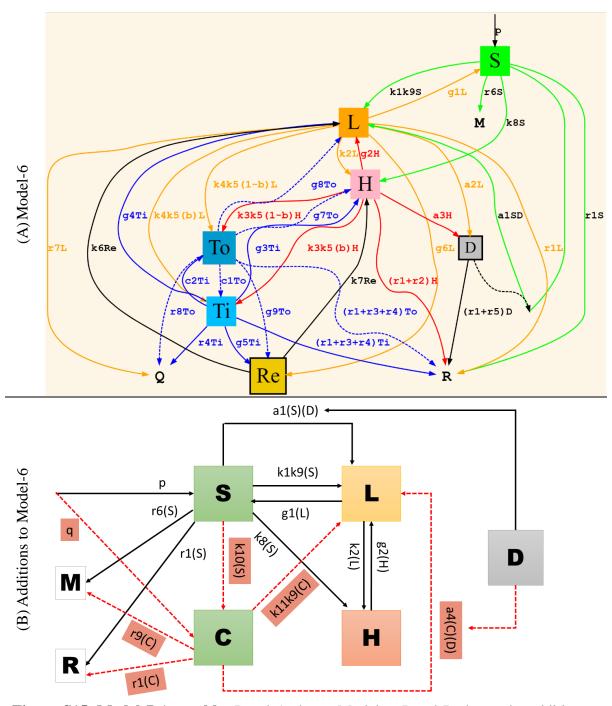
Model-6 addresses Ma et al.'s [18] model as psychological addicts (P) and physiological addicts (H) can correspond to light (L) and heavy (H) users, respectively.

#### S30. Description of Li and Ma's Model

Li and Ma [19] defines susceptibility into 2 classes – those that refused health education (S) and those accepted health education (C). However, both S and C may still end up as light drug users (L) but at different rates. Yet, there may be a small group of C vowed never to do drugs (deemed as removed or R).



S31. Stage 17: Assemble Model-6 and Li and Ma's Model into Model-7 Li and Ma [19] model differentiated susceptible in Model-6 (S) into 2 classes – those that refused health education (S) and those accepted health education (C). Hence, S in Model-6 is split into S and C. This resulted in the addition of the following processes – (1) recruitment from general population to susceptible accepting health education (C), (2) maturing and removal from C, (3) individuals moving from without health education (S) to accepting health education (C), (4) persuasion of C to light drug use (L) by drug sellers (D), and (4) susceptible accepting health education (C) moving into light drug use (L) without drug sellers (D).



**Figure S15. Model-7 Assembly.** Panel A shows Model-6. Panel B shows the addition to Model-6 to form Model-7.

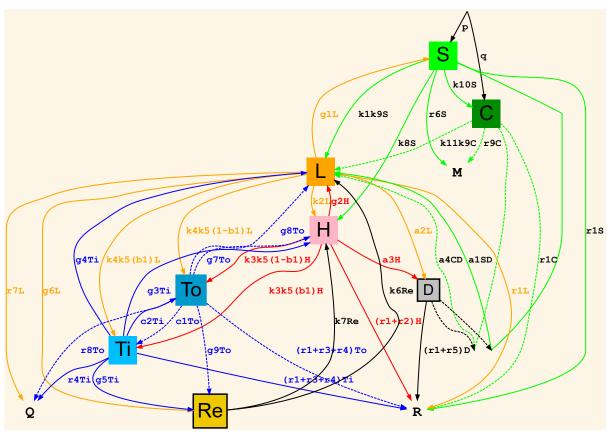


Figure S16. Model-7.

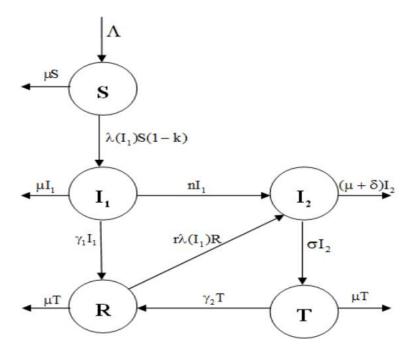
The revised parameters for Model-7 are as follow:

Parameter	Description	
	Recruitment rate from general population into susceptible population without	
р	health education (S).	
	Recruitment rate from general population into susceptible population with	
q	health education (C).	
	Rate at which susceptible population without health education (S) become light	
k1	drug users (L) without the effects of drug barons (D).	
k2	Rate at which light users (L) escalates to heavy drug use (H).	
k3	Proportion of heavy drug users (H) exposed to police search.	
k4	Proportion of light drug users (L) exposed to police search.	
k5	Intensity of policing / police search.	
k6	Rate of relapse from remission (Re) to light drug use (L).	
k7	Rate of relapse from remission (Re) to heavy drug use (H).	
	Rate of susceptible population without health education (S) become heavy drug	
k8	users (H).	
k9	Availability of drugs in the system.	
	Rate at which susceptible population without health education (S) accepts	
k10	health education (C)	
	Rate at which susceptible population with health education (C) become light	
k11	drug users (L) without the effects of drug barons (D).	
	Proportion of drug users caught for in-patient treatment (T <sub>i</sub> ). Therefore, the	
b	proportion of drug users caught for out-patient treatment $(T_0)$ is $(1-b)$ .	

	Rate at which light users (L) quit and become susceptible without health
~1	
g1	education (S) again.
- 2	Rate at which heavy users (H) become light users (L), which includes
<u>g2</u>	amelioration.
g3	Rate at which in-patient treatment (T <sub>i</sub> ) reverted to heavy drug use (H).
g4	Rate at which in-patient treatment (T <sub>i</sub> ) reverted to light drug use (L).
g5	Rate at which in-patient treatment (T <sub>i</sub> ) enter remission (Re).
g6	Proportion of light drug users (L) entering remission (Re) on their own accord.
g7	Rate at which out-patient treatment (T <sub>o</sub> ) reverted to heavy drug use (H).
g8	Rate at which out-patient treatment (T <sub>o</sub> ) reverted to light drug use (L).
g9	Rate at which out-patient treatment (T <sub>o</sub> ) enter remission (Re).
	Effective contact rate between drug barons (D) and susceptible population
a1	without health education (S).
a2	Rate at which light users (L) convert from consumer to seller / promoter (D).
a3	Rate at which heavy users (H) convert from consumer to seller / promoter (D).
	Effective contact rate between drug barons (D) and susceptible population with
a4	health education (S).
r1	Per capita mortality rate of population.
r2	Removal rate of heavy users (H) due to events related to drug usage.
r3	Removal rate of rehabilitated users (T) due to events related to drug usage.
r4	Rate at which in-patient treatment (T <sub>i</sub> ) permanently quit (Q).
r5	Removal rate of drug barons (D), which constitutes mainly to law enforcement.
	Rate of susceptible without health education (S) maturing into non-susceptible
r6	(M)
r7	Rate of light users (L) quitting drug use permanently (Q)
r8	Rate at which out-patient treatment (T <sub>o</sub> ) permanently quit (Q).
	Rate of susceptible with health education (C) maturing into non-susceptible
r9	(M)
c1	Rate of out-patient treatment (T <sub>o</sub> ) entering in-patient treatment (T <sub>i</sub> )
c2	Rate of in-patient treatment (T <sub>i</sub> ) entering out-patient treatment (T <sub>o</sub> )
l .	

# S32. Description of Naowarat and Kumat's Model

Naowarat and Kumat [20] define 5 compartments – S as susceptible,  $I_1$  as light drug users,  $I_2$  as heavy drug users, T as drug users in treatment, and R as recovered drug users.

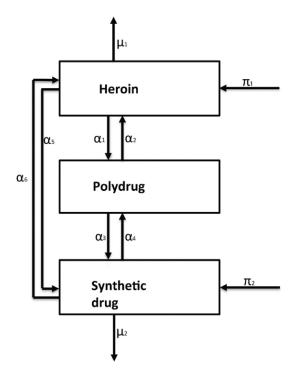


### S33. Stage 18: Model-7 incorporates Naowarat and Kumat's Model

Model-7 addresses the 5 compartments in Naowarat and Kumat's model [20] – S as susceptible (corresponding to S and S), S0, as light drug users (corresponding to S1, S2, as heavy drug users (corresponding to S3, S4, and S5, and S6, as recovered drug users (corresponding to S6, and S7, and S8, as recovered drug users (corresponding to S8, as recovered drug users).

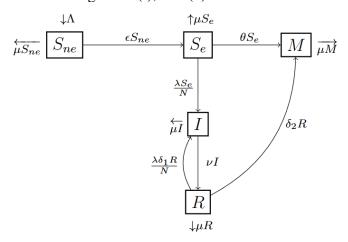
#### S34. Description of Su et al.'s Model

Su et al. [21] examines the shuttling between single drug use (heroin), multidrug use, and synthetic drugs.



#### S35. Description of Memarbashi and Pourhossieni's Model

Memarbashi and Pourhossieni [22] use a 5-compartment model - (i) non-educated susceptible ( $S_{ne}$ ), (ii) educated susceptible ( $S_e$ ), (iii) mature and will not use drugs forever (M), (iv) infected which are drug users (I), and (V) users under treatment or rehabilitation (R).

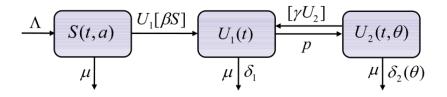


# S36. Stage 19: Model-7 incorporates Memarbashi and Pourhossieni's Model

Model-7 addresses the 5 compartments in Memarbashi and Pourhossieni [22] - (i) non-educated susceptible ( $S_{ne}$ ) can be addressed by susceptible without or refusing health education (S), (ii) educated susceptible ( $S_e$ ) can be addressed by susceptible with or accepted health education (C), (iii) mature and will not use drugs forever (M) can be addressed by removed (R), (iv) infected (I) can be addressed by light (L) and heavy (H) drug users, and (v) users under treatment or rehabilitation (R) can be addressed by in-patient ( $T_e$ ) and out-patient ( $T_e$ ) treatment.

#### S37. Description of Liu and Liu's Model

Liu and Liu [23] model defines S as susceptible,  $U_1$  as drug users not under treatment, and  $U_2$  as drug users under treatment.



### S38. Stage 20: Model-7 incorporates Liu and Liu's Model

Model-7 addresses the 3 compartments in Liu and Liu [23] - (i) susceptible (S) is addressed by susceptible not accepting health education (S) and susceptible accepted health education (C), (ii)  $U_1$  can be addressed by light (L) and heavy (H) drug users, and (v)  $U_2$  can be addressed by in-patient ( $T_i$ ) and out-patient ( $T_0$ ) treatment.

#### S39. Description of Saha and Samanta's Model

Saha and Samanta's [24] model is similar to Ma et al.'s [18] model, which define 4 compartments as (i) susceptible (S), (ii) psychological addicts ( $P_1$ ), (iii) physiological addicts ( $P_2$ ), and (iv) addicts under treatment (T).

#### S40. Stage 21: Model-7 incorporates Saha and Samanta's Model

Model-7 addresses Saha and Samanta's [24] model as psychological addicts  $(P_1)$  and physiological addicts (H) can correspond to light  $(P_2)$  and heavy (H) users, respectively.

#### S41. Description of Duan et al.'s Model

Duan et al. [25] define a 5-compartment model for heroin and HIV co-infection as (a) susceptible (S), (ii) heroin drug users (U), (iii) HIV-infected individuals (V), (iv) heroin/HIV coinfected individuals (I), and (v) individuals with AIDS (A).

#### S42. SubstanceUseModel in Graphviz DOT Language

```
digraph epidemiology {
  bgcolor=oldlace
  start -> S [label="p", penwidth=2, fontsize=20, fontname="Courier-Bold"]
  start -> C [label="q", penwidth=2, fontsize=20, fontname="Courier-Bold"]
  S -> R [label="r1S", penwidth=2, color=green, fontcolor=olive,
fontsize=20, fontname="Courier-Bold"]
  S -> M [label="r6S", penwidth=2, color=green, fontcolor=olive,
fontsize=20, fontname="Courier-Bold"]
S -> C [label="k10S", penwidth=2, color=green, fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  S -> L [label="k1k9S", penwidth=2, color=green, fontcolor=olive,
fontsize=20, fontname="Courier-Bold"]
  S -> H [label="k8k9S", penwidth=2, color=green, fontcolor=olive,
fontsize=20, fontname="Courier-Bold"]
  S -> D 1 [arrowhead = none, penwidth=2, color=green, fontcolor=olive,
fontsize=20, fontname="Courier-Bold"]
  D 1 -> L [label="a1SD", penwidth=2, color=green, fontcolor=olive,
fontsize=20, fontname="Courier-Bold"]
  C -> M [label="r1C", penwidth=2, color=green, style=dashed,
fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  C -> R [label="r9C", penwidth=2, color=green, style=dashed,
fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  C -> L [label="k11k9C", penwidth=2, color=green, style=dashed,
fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  C -> H [label="k12k9C", penwidth=2, color=green, style=dashed,
fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  C -> D_2 [arrowhead = none, penwidth=2, color=green, style=dashed,
fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  D 2 -> L [label="a4CD", penwidth=2, color=green, style=dashed,
fontcolor=olive, fontsize=20, fontname="Courier-Bold"]
  D -> D 1 [penwidth=2, style=dashed]
  D -> D 2 [penwidth=2, style=dashed]
  D -> R [label="(r1+r5)D", penwidth=2, fontsize=20, fontname="Courier-
Bold"]
  L -> S [label="g1L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
```

```
L -> H [label="k2L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
 L -> Ti [label="k4k5(b1)L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
 L \rightarrow To [label="k4k5(1-b1)L", penwidth=2, color=orange,
fontcolor=orange1, fontsize=20, fontname="Courier-Bold"]
 L -> R [label="r1L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
 L -> D [label="a2L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
  L -> Re [label="g6L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
 L -> Q [label="r7L", penwidth=2, color=orange, fontcolor=orange1,
fontsize=20, fontname="Courier-Bold"]
 H -> D [label="a3H", penwidth=2, color=red, fontcolor=red, fontsize=20,
fontname="Courier-Bold"]
 H -> L [label="g2H", penwidth=2, color=red, fontcolor=red, fontsize=20,
fontname="Courier-Bold"]
 H -> R [label="(r1+r2)H", penwidth=2, color=red, fontcolor=red,
fontsize=20, fontname="Courier-Bold"]
 H -> Ti [label="k3k5(b2)H", penwidth=2, color=red, fontcolor=red,
fontsize=20, fontname="Courier-Bold"]
 H -> To [label="k3k5(1-b2)H", penwidth=2, color=red, fontcolor=red,
fontsize=20, fontname="Courier-Bold"]
  Ti -> L [label="g4Ti", penwidth=2, color=blue, fontcolor=blue,
fontsize=20, fontname="Courier-Bold"]
  Ti -> H [label="g3Ti", penwidth=2, color=blue, fontcolor=blue,
fontsize=20, fontname="Courier-Bold"]
 Ti -> To [label="c2Ti", penwidth=2, color=blue, fontcolor=blue,
fontsize=20, fontname="Courier-Bold"]
 Ti -> Re [label="g5Ti", penwidth=2, color=blue, fontcolor=blue,
fontsize=20, fontname="Courier-Bold"]
 Ti -> Q [label="r4Ti", penwidth=2, color=blue, fontcolor=blue,
fontsize=20, fontname="Courier-Bold"]
 Ti -> R [label="(r1+r3+r4)Ti", penwidth=2, color=blue, fontcolor=blue,
fontsize=20, fontname="Courier-Bold"]
  To -> L [label="q8To", penwidth=2, color=blue, style=dashed,
fontcolor=blue, fontsize=20, fontname="Courier-Bold"]
  To -> H [label="g7To", penwidth=2, color=blue, style=dashed,
fontcolor=blue, fontsize=20, fontname="Courier-Bold"]
  To -> Ti [label="c1To", penwidth=2, color=blue, style=dashed,
fontcolor=blue, fontsize=20, fontname="Courier-Bold"]
  To -> Re [label="g9To", penwidth=2, color=blue, style=dashed,
fontcolor=blue, fontsize=20, fontname="Courier-Bold"]
  To -> Q [label="r8To", penwidth=2, color=blue, style=dashed,
fontcolor=blue, fontsize=20, fontname="Courier-Bold"]
  To -> R [label="(r1+r3+r4)To", penwidth=2, color=blue, style=dashed,
fontcolor=blue, fontsize=20, fontname="Courier-Bold"]
  Re -> L [label="k6Re", penwidth=2, fontsize=20, fontname="Courier-Bold"]
  Re -> H [label="k7Re", penwidth=2, fontsize=20, fontname="Courier-Bold"]
 Re -> R [label="r1Re", penwidth=2, fontsize=20, fontname="Courier-Bold"]
  start [shape=point, width=0]
  D 1 [shape=point, width=0]
  D 2 [shape=point, width=0]
  S [shape=square, fillcolor=green1, style=filled, penwidth=0, fontsize=40,
fontname="Arial-Bold"]
```

```
C [shape=square, fillcolor=green4, style=filled, penwidth=0, fontsize=40,
fontname="Arial-Bold"]
  L [shape=square, fillcolor=orange1, style=filled, penwidth=0,
fontsize=40, fontname="Arial-Bold"]
 H [shape=square, fillcolor=pink1, style=filled, penwidth=0, fontsize=40,
fontname="Arial-Bold"]
 Ti [shape=square, fillcolor=deepskyblue1, style=filled, penwidth=0,
fontsize=40, fontname="Arial-Bold"]
  To [shape=square, fillcolor=deepskyblue3, style=filled, penwidth=0,
fontsize=40, fontname="Arial-Bold"]
  Re [shape=square, fillcolor=gold2, style=filled, fontsize=40, penwidth=3,
fontname="Arial-Bold"]
  D [shape=square, fillcolor=grey, style=filled, penwidth=3, fontsize=30,
fontname="Arial-Bold"]
 R [shape=square, penwidth=0, fontsize=30, fontname="Courier-Bold"]
 M [shape=square, penwidth=0, fontsize=30, fontname="Courier-Bold"]
  Q [shape=square, fontsize=30, penwidth=0, fontname="Courier-Bold"]
```

# S43. Python Implementation of SubstanceUseModel (SubstanceUseModel.py)

Substance use epidemiological model written in Python

```
Yap et al. (2024) Assembly of Substance Use or Abuse Epidemiological Models.
import argparse
# Step 1: Setup command-line parser
              = argparse.ArgumentParser(prog="python SubstanceUseModel.py",
description="Substance use epidemiological model (written in Python) by Yap
et al. (2024) Assembly of Substance Use Epidemiological Models.")
# Step 1.1: Compartment initial conditions (in percentage)
parser.add argument("-S", type=float, default=99.9957, help="Percentage of
population that
                                                                              without health
                                        is
                                                 susceptible
                                                                                                                      education
Default=49.9939")
parser.add argument("-C", type=float, default=99.9957, help="Percentage of
population that is susceptible with health education (S). Default=50.000")
\verb|parser.add_argument("-L", type=float, default=0.005, help="Percentage of type=float, default=0.005, help=float, default=0.005, help=
population that is light drug user (L). Default=0.005")
parser.add_argument("-H", type=float, default=0.0005, help="Percentage of
population that is heavy drug user (H). Default=0.0005")
parser.add argument("-Ti", type=float, default=0.0002, help="Percentage of
population that is under in-patient treatment (Ti). Default=0.0002")
parser.add argument("-To", type=float, default=0.0003, help="Percentage of
population that is under out-patient treatment (To). Default=0.0003")
parser.add_argument("-D", type=float, default=0.0001, help="Percentage")
population that is drug sellers (D). Default=0.0001")
parser.add_argument("-Re", type=float, default=0.0005, help="Percentage of
population that is in remission (Re). Default=0.0005")
parser.add argument("-R", type=float, default=0.0,
                                                                                                            help="Percentage
population that is dead or removed (R). Default=0.0")
parser.add argument("-Q", type=float, default=0.0, help="Percentage")
                                                                                                                                                   of
population that permanently quitted drug use (Q). Default=0.0")
parser.add argument("-M", type=float, default=0.0, help="Percentage")
population that matured from susceptible (M). Default=0.0")
# Step 1.2: Model parameters
```

```
parser.add_argument("-p", type=float, default=0.05, help="Recruitment rate from general population into susceptible population without health education (S). Default=0.05")
```

parser.add\_argument("-q", type=float, default=0.15, help="Recruitment rate from general population into susceptible population with health education (C). Default=0.15")

parser.add\_argument("-k1", type=float, default=0.2, help="Rate at which susceptible population without health education (S) become light drug users (L) without the effects of drug barons (D). Default=0.2")

parser.add\_argument("-k2", type=float, default=0.5, help="Rate at which light users (L) escalates to heavy drug use (H). Default=0.5")

parser.add\_argument("-k3", type=float, default=0.4, help="Proportion of heavy drug users (H) exposed to police search. Default=0.4")

parser.add\_argument("-k4", type=float, default=0.2, help="Proportion of light drug users (L) exposed to police search. Default=0.2")

parser.add\_argument("-k5", type=float, default=1.00, help="Intensity of policing / police search. Default=1.00")

parser.add\_argument("-k6", type=float, default=0.05, help="Rate of relapse from remission (Re) to light drug use (L). Default=0.05")

parser.add\_argument("-k7", type=float, default=0.01, help="Rate of relapse from remission (Re) to heavy drug use (H). Default=0.01")

parser.add\_argument("-k8", type=float, default=0.01, help="Rate of susceptible population without health education (S) become heavy drug users (H) without the effects of drug barons (D). Default=0.01")

parser.add\_argument("-k9", type=float, default=1.00, help="Availability of drugs in the system. Default=1.00")

parser.add\_argument("-k10", type=float, default=0.3, help="Rate at which susceptible population without health education (S) accepts health education (C). Default=0.3")

parser.add\_argument("-k11", type=float, default=0.1, help="Rate at which susceptible population with health education (C) become light drug users (L) without the effects of drug barons (D). Default=0.1")

parser.add\_argument("-k12", type=float, default=0.001, help="Rate of susceptible population with health education (C) become heavy drug users (H) without the effects of drug barons (D). Default=0.001")

parser.add\_argument("-b1", type=float, default=0.2, help="Proportion of light drug users (L) caught for in-patient treatment (Ti). Therefore, the proportion of light drug users caught for out-patient treatment (To) is (1-b1). Default=0.2")

parser.add\_argument("-b2", type=float, default=0.8, help="Proportion of heavy drug users (H) caught for in-patient treatment (Ti). Therefore, the proportion of heavy drug users caught for out-patient treatment (To) is (1-b2). Default=0.8")

parser.add\_argument("-g1", type=float, default=0.2, help="Rate at which light users (L) quit and become susceptible without health education (S) again. Default=0.2")

parser.add\_argument("-g2", type=float, default=0.4, help="Rate at which heavy users (H) become light users (L), which includes amelioration. Default=0.4")

parser.add\_argument("-g3", type=float, default=0.01, help="Rate at which inpatient treatment (Ti) reverted to heavy drug use (H). Default=0.01")

parser.add\_argument("-g4", type=float, default=0.02, help="Rate at which in-patient treatment (Ti) reverted to light drug use (L). Default=0.02")

parser.add\_argument("-g5", type=float, default=0.2, help="Rate at which in-patient treatment (Ti) enter remission (Re). Default=0.2")

parser.add\_argument("-g6", type=float, default=0.015, help="Proportion of light drug users (L) entering remission (Re) on their own accord. Default=0.015")

parser.add\_argument("-g7", type=float, default=0.015, help="Rate at which
out-patient treatment (To) reverted to heavy drug use (H). Default=0.015")

```
parser.add_argument("-g8", type=float, default=0.025, help="Rate at which
out-patient treatment (To) reverted to light drug use (L). Default=0.025")
parser.add argument("-g9", type=float, default=0.2, help="Rate at which out-
patient treatment (To) enter remission (Re). Default=0.2")
parser.add argument("-a1", type=float, default=0.4, help="Effective contact
rate between drug barons (D) and susceptible population without health
education (S). Default=0.4")
parser.add_argument("-a2", type=float, default=0.04, help="Rate at which
light users (L) convert from consumer to seller / promoter
Default=0.04")
parser.add argument("-a3", type=float, default=0.08, help="Rate at which
heavy users (H)
                  convert from consumer to seller / promoter
Default=0.08")
parser.add argument("-a4", type=float, default=0.2, help="Effective contact
rate between drug barons (D) and susceptible population with health education
(S). Default=0.2")
parser.add argument("-r1", type=float,
                                       default=0.2,
                                                     help="Per
mortality rate of population. Default=0.2")
heavy users (H) due to events related to drug usage. Default=0.001")
parser.add argument("-r3", type=float, default=0.003, help="Removal rate of
rehabilitated users (T) due to events related to drug usage. Default=0.003")
parser.add argument("-r4", type=float, default=0.1, help="Rate at which in-
patient treatment (Ti) permanently quit (Q). Default=0.1")
parser.add argument("-r5", type=float, default=0.02, help="Removal rate of
drug barons (D), which constitutes mainly to law enforcement. Default=0.02")
parser.add argument("-r6", type=float, default=0.005, help="Rate of
susceptible without health education (S) maturing into non-susceptible (M).
Default=0.005")
parser.add argument("-r7", type=float, default=0.01, help="Rate of light
users (L) quitting drug use permanently (Q). Default=0.01")
parser.add argument("-r8", type=float, default=0.1, help="Rate at which out-
patient treatment (To) permanently quit (Q). Default=0.1")
parser.add argument("-r9",
                          type=float, default=0.01, help="Rate
susceptible with health education (C) maturing into non-susceptible (M).
Default=0.01")
parser.add argument("-c1", type=float, default=0.001, help="Rate of out-
patient treatment (To) entering in-patient treatment (Ti). Default=0.001")
parser.add argument("-c2", type=float, default=0.01, help="Rate of in-
patient treatment (Ti) entering out-patient treatment (To). Default=0.01")
# Step 1.3: Simulation parameters
parser.add argument("-step", type=float, default=0.00274, help="Simulation
time step. Default=0.00274")
parser.add_argument("-end", type=float, default=10.0, help="Simulation end
time. Default=10.0")
# Step 1.4: Get command-line options
args = parser.parse args()
# Step 2: Initial conditions in percentage
y = list(range(11))
y[0] = args.S
y[1] = args.C
y[2] = args.L
y[3] = args.H
y[4] = args.Ti
y[5] = args.To
y[6] = args.D
y[7] = args.Re
y[8] = args.R
y[9] = args.Q
y[10] = args.M
```

```
print("--- Compartment Initial Conditions ---")
compartment names = ["S", "C", "L", "H", "Ti", "To", "D", "Re", "R", "Q",
"M"]
for i in range(len(compartment names)):
    print("%s = %f" % (compartment_names[i], y[i]))
# Step 3: Model parameters
print("--- Model Parameters ---")
p = args.p
print("p = %f" % p)
q = args.q
print("q = %f" % q)
k1 = args.k1
print("k1 = %f" % k1)
k2 = args.k2
print("k2 = %f" % k2)
k3 = args.k3
print("k3 = %f" % k3)
k4 = args.k4
print("k4 = %f" % k4)
k5 = args.k5
print("k5 = %f" % k5)
k6 = args.k6
print("k6 = %f" % k6)
k7 = args.k7
print("k7 = %f" % k7)
k8 = args.k8
print("k8 = %f" % k8)
k9 = args.k9
print("k9 = %f" % k9)
k10 = args.k10
print("k10 = %f" % k10)
k11 = args.k11
print("k11 = %f" % k11)
k12 = args.k12
print("k12 = %f" % k12)
b1 = args.b1
print("b1 = %f" % b1)
b2 = args.b2
print("b2 = %f" % b2)
g1 = args.g1
print("g1 = %f" % g1)
q2 = args.q2
print("g2 = %f" % g2)
q3 = args.q3
print("g3 = %f" % g3)
g4 = args.g4
print("g4 = %f" % g4)
g5 = args.g5
print("g5 = %f" % g5)
g6 = args.g6
print("g6 = %f" % g6)
g7 = args.g7
print("g7 = %f" % g7)
g8 = args.g8
print("g8 = %f" % g8)
g9 = args.g9
print("g9 = %f" % g9)
a1 = args.a1
print("a1 = %f" % a1)
a2 = args.a2
```

```
print("a2 = %f" % a2)
a3 = args.a3
print("a3 = %f" % a3)
a4 = args.a4
print("a4 = %f" % a4)
r1 = args.r1
print("r1 = %f" % r1)
r2 = args.r2
print("r2 = %f" % r2)
r3 = args.r3
print("r3 = %f" % r3)
r4 = args.r4
print("r4 = %f" % r4)
r5 = args.r5
print("r5 = %f" % r5)
r6 = args.r6
print("r6 = %f" % r6)
r7 = args.r7
print("r7 = %f" % r7)
r8 = args.r8
print("r8 = %f" % r8)
r9 = args.r9
print("r9 = %f" % r9)
c1 = args.c1
print("c1 = %f" % c1)
c2 = args.c2
print("c2 = %f" % c2)
# Step 4: Set up ODEs
def S(t, y):
         # Susceptible without health education (S), y[0] = args.S
         \# S = [p + g1L] - [r1S + r6S + k1k9S + k8k9S + a1SD + k10S]
         incoming = p + g1*y[2]
        outgoing = r1*y[0] + r6*y[0] + k1*k9*y[0] + k8*k9*y[0] + a1*y[0]*y[6] +
k10*y[0]
        return incoming - outgoing
def C(t, y):
         # Susceptible with health education (C), y[1] = args.C
         \# C = [q + k10S] - [r9C + r1C + k9k11C + k9k12C + a4CD]
         incoming = q + k10*y[0]
         outgoing = r9*y[1] + r1*y[1] + k9*k11*y[1] + k9*k12*y[1] + a4*y[1]*y[6]
        return incoming - outgoing
def L(t, y):
         # Light drug users (L), y[2] = args.L
         \# L = [k1k9S + a1SD + k9k11C + a4CD + q2H + g4Ti + g8To + k6Re] - [g1L]
+ k2L + k4k5(b1)L + k4k5(1-b1)L + r1L + a2L + q6L + r7L
        incoming = k1*k9*y[0] + a1*y[0]*y[6] + k9*k11*y[1] + a4*y[1]*y[6] +
g2*y[3] + g4*y[4] + g8*y[4] + k6*y[7]
         outgoing = g1*y[2] + k2*y[2] + k4*k5*(b1)*y[2] + k4*k5*(1-b1)*y[2] +
r1*y[2] + a2*y[2] + g6*y[2] + r7*y[2]
        return incoming - outgoing
def H(t, y):
         # Heavy drug users (H), y[3] = args.H
         \# H = [k8k9S + k9k12C + k2L + g3Ti + g7To + k7Re] - [a3H + g2H + (r1+r2)H
+ k3k5(b2)H + k3k5(1-b2)H
         incoming = k8*k9*y[0] + k9*k12*y[1] + k2*y[2] + g3*y[4] + g7*y[4] +
k7*y[7]
         outgoing = a3*y[3] + g2*y[3] + (r1+r2)*y[3] + k3*k5*(b2)*y[3] + k3*k5*(1-r2)*y[3] + 
b2)*y[3]
         return incoming - outgoing
def Ti(t, y):
```

```
# In-patient treatment (Ti), y[4] = args.Ti
    \# Ti = [k4k5(b1)L + k3k5(b2)H + c1To] - [g4Ti + g3Ti + c2Ti + g5Ti +
r4Ti + (r1+r2+r3)Ti
    incoming = k4*k5*(b1)*y[2] + k3*k5*(b2)*y[3] + c1*y[5]
    outgoing = g4*y[4] + g3*y[4] + c2*y[4] + g5*y[4] + r4*y[4] +
(r1+r2+r3)*y[4]
    return incoming - outgoing
def To(t, y):
    # Out-patient treatment (To), y[5] = args.To
    \# To = [k4k5(1-b1)L + k3k5(1-b2)H + c2Ti] - [g8To + g7To + c1To + g9To]
+ r8To + (r1+r3+r4)To]
    incoming = k4*k5*(1-b1)*y[2] + k3*k5*(1-b2)*y[3] + c2*y[4]
    outgoing = g8*y[5] + g7*y[5] + c1*y[5] + g9*y[5] + r8*y[5] +
(r1+r3+r4)*y[5]
    return incoming - outgoing
def D(t, y):
    \# Drug sellers (D), y[6] = args.D
    \# D = [a2L + a3H] - [(r1+r5)D]
    incoming = a2*y[2] + a3*y[3]
    outgoing = (r1+r5)*y[6]
    return incoming - outgoing
def Re(t, y):
    \# Remission (Re), y[7] = args.Re
    \# Re = [g6L + g5Ti + g9To] - [k6Re + k7Re + r1Re]
    incoming = g6*y[2] + g5*y[5] + g9*y[5]
    outgoing = k6*y[7] + k7*y[7] + r1*y[7]
    return incoming - outgoing
def R(t, y):
    \# Removed (R), y[8] = args.R
    \# R = r1S + r1C + (r1+r5)D + r1L + (r1+r2)H + (r1+r2+r3)Ti + (r1+r3+r4)To
+ r1Re
    incoming = r1*y[0] + r1*y[1] + (r1+r5)*y[6] + r1*y[2] + (r1+r2)*y[3] +
(r1+r2+r3)*y[4] + (r1+r3+r4)*y[5] + r1*y[7]
    return incoming
def Q(t, y):
    # Quitted (Q), y[9] = args.Q
    \# Q = r7L + r4Ti + r8To
    incoming = r7*y[2] + r4*y[4] + r8*y[5]
    return incoming
def M(t, y):
    # Matured (M), y[10] = args.M
    \# M = [r6S + r9C]
    incoming = r6*y[0] + r9*y[2]
    return incoming
# Step 5: Model setup
f = list(range(11))
f[0] = S
f[1] = C
f[2] = L
f[3] = H
f[4] = Ti
f[5] = To
f[6] = D
f[7] = Re
f[8] = R
f[9] = Q
f[10] = M
# Step 6: ODE solver
def DP5 (funcs, x0, y0, step, xmax,
```

```
overflow=1e100, zerodivision=1e100):
yield [x0] + y0
def solver(funcs, x0, y0, step):
    n = len(funcs)
    f1, f2, f3 = [0]*n, [0]*n, [0]*n
    f4, f5, f6, f7 = [0]*n, [0]*n, [0]*n
    y1 = [0]*n
    for i in range(n):
        try: f1[i] = funcs[i](x0, y0)
        except TypeError: pass
        except ZeroDivisionError: f1[i] = zerodivision
        except OverflowError: f1[i] = overflow
    for j in range(n):
       y1[j] = y0[j] + (0.2*step*f1[j])
    for i in range(n):
        try: f2[i] = funcs[i]((x0+(0.2*step)), y1)
        except TypeError: pass
        except ZeroDivisionError: f2[i] = zerodivision
       except OverflowError: f2[i] = overflow
    for j in range(n):
       y1[j] = y0[j] + (3*step*f1[j]/40.0) + (9*step*f2[j]/40.0)
    for i in range(n):
       try: f3[i] = funcs[i]((x0+(0.3*step)), y1)
        except TypeError: pass
       except ZeroDivisionError: f3[i] = zerodivision
       except OverflowError: f3[i] = overflow
    for j in range(n):
       y1[j] = y0[j] + (44*step*f1[j]/45.0) + (-56*step*f2[j]/15.0) +
                (32*step*f3[j]/9.0)
    for i in range(n):
        try: f4[i] = funcs[i]((x0+(0.8*step)), y1)
        except TypeError: pass
        except ZeroDivisionError: f4[i] = zerodivision
       except OverflowError: f4[i] = overflow
    for j in range(n):
       y1[j] = y0[j] + (19372*step*f1[j]/6561.0) + 
                (-25360*step*f2[j]/2187.0) + 
                (64448*step*f3[j]/6561.0) + \
                (-212*step*f4[j]/729.0)
    for i in range(n):
        try: f5[i] = funcs[i] (x0+(8*step/9.0), y1)
        except TypeError: pass
       except ZeroDivisionError: f5[i] = zerodivision
       except OverflowError: f5[i] = overflow
    for j in range(n):
        y1[j] = y0[j] + (9017*step*f1[j]/3168.0) + 
                (-355*step*f2[j]/33.0) + (46732*step*f3[j]/5247.0) + 
                (49*step*f4[j]/176.0) + (-5103*step*f5[j]/18656.0)
    for i in range(n):
        try: f6[i] = funcs[i](x0+step, y1)
        except TypeError: pass
       except ZeroDivisionError: f6[i] = zerodivision
       except OverflowError: f6[i] = overflow
    for j in range(n):
        y1[j] = y0[j] + (35*step*f1[j]/384.0) + 
                (500*step*f3[j]/1113.0) + (125*step*f4[j]/192.0) + 
                (-2187*step*f5[j]/6784.0) + (11*step*f6[j]/84.0)
    for i in range(n):
        try: f7[i] = funcs[i](x0+step, y1)
        except TypeError: pass
```

```
except ZeroDivisionError: f7[i] = zerodivision
            except OverflowError: f7[i] = overflow
        for i in range(n):
            try: y1[i] = y0[i] + (step * \
                    ((35*f1[i]/384.0) + (500*f3[i]/1113.0) + 
                     (125*f4[i]/192.0) + (-2187*f5[i]/6784.0) + 
                     (11*f6[i]/84.0))
            except TypeError: pass
            except ZeroDivisionError: y1[i] = zerodivision
            except OverflowError: y1[i] = overflow
        return y1
    while x0 < xmax:
        y1 = solver(funcs, x0, y0, step)
        y0 = y1
        x0 = x0 + step
        yield [x0] + y0
# Step 7: Simulation parameters
time step = args.step
end time = args.end
# Step 9: Simulate model
print("--- Simulation Results ---")
print(",".join(["Time", "S", "C", "L", "H", "Ti", "To", "D", "Re", "R", "Q",
"M"]))
for i in [x for x in DP5(f, 0.0, y, time step, end time)]:
  print (",". join ([str(z) for z in i]))
S44. Commandline Usage of SubstanceUseModel.py
usage: python SubstanceUseModel.py [-h] [-S S] [-C C] [-L L] [-H H] [-Ti
      TI] [-To TO] [-D D] [-Re RE] [-R R] [-Q Q] [-M M] [-p P] [-q Q] [-k1
      K1] [-k2 K2] [-k3 K3] [-k4 K4] [-k5 K5] [-k6 K6] [-k7 K7] [-k8 K8]
      [-k9 K9] [-k10 K10] [-k11 K11] [-k12 K12] [-b1 B1] [-b2 B2] [-g1 G1]
      [-g2 G2] [-g3 G3] [-g4 G4] [-g5 G5] [-g6 G6] [-g7 G7] [-g8 G8] [-g9
      G9] [-a1 A1] [-a2 A2] [-a3 A3] [-a4 A4] [-r1 R1] [-r2 R2] [-r3 R3]
      [-r4 R4] [-r5 R5] [-r6 R6] [-r7 R7] [-r8 R8] [-r9 R9] [-c1 C1] [-c2
      C2] [-step STEP] [-end END]
Substance use epidemiological model (written in Python) by Yap et al.
(2024) Assembly of Substance Use Epidemiological
Models.
optional arguments:
  -h, --help show this help message and exit
  -S S
             Percentage of population that is susceptible without health
education (S). Default=49.9939
             Percentage of population that is susceptible with health
education (S). Default=50.000
             Percentage of population that is light drug user (L).
Default=0.005
             Percentage of population that is heavy drug user (H).
Default=0.0005
 -Ti TI
            Percentage of population that is under in-patient treatment
(Ti). Default=0.0002
 -To TO
             Percentage of population that is under out-patient treatment
(To). Default=0.0003
 -D D
              Percentage of population that is drug sellers (D).
Default=0.0001
 -Re RE
            Percentage of population that is in remission (Re).
Default=0.0005
```

- -R R  $\,$  Percentage of population that is dead or removed (R). Default=0.0  $\,$
- -Q Q Percentage of population that permanently quitted drug use (Q). Default=0.0
- -M M  $\,\,$  Percentage of population that matured from susceptible (M). Default=0.0  $\,$
- -p P Recruitment rate from general population into susceptible population without health education (S).

Default=0.05

-q Q Recruitment rate from general population into susceptible population with health education (C).

Default=0.15

 $-k1 \ K1$  Rate at which susceptible population without health education (S) become light drug users (L) without

the effects of drug barons (D). Default=0.2

- -k2 K2 Rate at which light users (L) escalates to heavy drug use (H). Default=0.5
- -k3 K3 Proportion of heavy drug users (H) exposed to police search. Default=0.4
- -k4 K4 Proportion of light drug users (L) exposed to police search. Default=0.2
  - -k5 K5 Intensity of policing / police search. Default=1.00
- -k6 K6 Rate of relapse from remission (Re) to light drug use (L). Default=0.05  $\,$
- $-k7\ \mbox{K7}$  Rate of relapse from remission (Re) to heavy drug use (H). Default=0.01
- -k8 K8 Rate of susceptible population without health education (S) become heavy drug users (H) without the

effects of drug barons (D). Default=0.01

- -k9 K9 Availability of drugs in the system. Default=1.00
- $-k10\ \text{K10}$  Rate at which susceptible population without health education (S) accepts health education (C).

Default=0.3

-k11 Kl1 Rate at which susceptible population with health education (C) become light drug users (L) without the

effects of drug barons (D). Default=0.1

-k12 K12 Rate of susceptible population with health education (C) become heavy drug users (H) without the effects

of drug barons (D). Default=0.001

- -b1 B1 Proportion of light drug users (L) caught for in-patient treatment (Ti). Therefore, the proportion of
- light drug users caught for out-patient treatment (To) is (1-b1). Default=0.2
- -b2 B2 Proportion of heavy drug users (H) caught for in-patient treatment (Ti). Therefore, the proportion of
- heavy drug users caught for out-patient treatment (To) is (1-b2). Default=0.8  $\,$
- -gl Gl  $\,$  Rate at which light users (L) quit and become susceptible without health education (S) again.

Default=0.2

- -g2 G2 Rate at which heavy users (H) become light users (L), which includes amelioration. Default=0.4
- -g3 G3 Rate at which in-patient treatment (Ti) reverted to heavy drug use (H). Default=0.01
- -g4~G4 Rate at which in-patient treatment (Ti) reverted to light drug use (L). Default=0.02
- -g5 G5 Rate at which in-patient treatment (Ti) enter remission (Re). Default=0.2
- -g6 G6 Proportion of light drug users (L) entering remission (Re) on their own accord. Default=0.015

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-q7 G7
            Rate at which out-patient treatment (To) reverted to heavy
drug use (H). Default=0.015
  -q8 G8
             Rate at which out-patient treatment (To) reverted to light
drug use (L). Default=0.025
  -g9 G9
             Rate at which out-patient treatment (To) enter remission
(Re). Default=0.2
  -a1 A1
            Effective contact rate between drug barons (D) and
susceptible population without health education (S).
             Default=0.4
             Rate at which light users (L) convert from consumer to seller
/ promoter (D). Default=0.04
  -a3 A3
           Rate at which heavy users (H) convert from consumer to seller
/ promoter (D). Default=0.08
  -a4 A4 Effective contact rate between drug barons (D) and
susceptible population with health education (S).
             Default=0.2
 -r1 R1
             Per capita mortality rate of population. Default=0.2
 -r2 R2
            Removal rate of heavy users (H) due to events related to drug
usage. Default=0.001
 -r3 R3 Removal rate of rehabilitated users (T) due to events related
to drug usage. Default=0.003
 -r4 R4 Rate at which in-patient treatment (Ti) permanently quit (Q).
Default=0.1
 -r5 R5 Removal rate of drug barons (D), which constitutes mainly to
law enforcement. Default=0.02
 -r6 R6 Rate of susceptible without health education (S) maturing
into non-susceptible (M). Default=0.005
 -r7 R7 Rate of light users (L) quitting drug use permanently (Q).
Default=0.01
 -r8 R8
            Rate at which out-patient treatment (To) permanently quit
(Q). Default=0.1
  -r9 R9 Rate of susceptible with health education (C) maturing into
non-susceptible (M). Default=0.01
 -c1 C1 Rate of out-patient treatment (To) entering in-patient
treatment (Ti). Default=0.001
 -c2 C2
            Rate of in-patient treatment (Ti) entering out-patient
treatment (To). Default=0.01
 -step STEP Simulation time step. Default=0.00274
           Simulation end time. Default=10.0
```

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