Specified Project 1
Avian Flu Pandemic Model

One specified project which you can choose if you prefer not to develop your own personal project, is to model the spread of an infectious disease around the world. For example, something like a pandemic of avian flu. I have designed this in such a way that I think it has some synergy with techniques that are also especially applicable to physics, but also should make it clear to you that these techniques are much more widely applicable.
I am not an expert on this stuff, and so there should be no assumption or implication that models being considered are at all reasonable/realistic. When I developed this project there was no confirmed human-human transmission but this was then considered a distinct possibility in the future.

In infectious diseases, there are the concepts embodied in the SEIR model where individual members of the population are considered to either be in the Susceptible, Exposed, Infectious or Recovered states. Immunization is a process through which immunized susceptibles become recovered with a certain efficiency.
Individuals will be assumed to become exposed according to their geometrical closeness to an infected individual. In contrast to much of the literature dealing with deterministic infectious disease modeling using differential equations, we will be using a method which emphasizes the discrete and stochastic nature of such outbreaks.

You should model this using a model of the Earth's population as coordinates on the surface of a unit-sphere. Randomly choose initial day=0 ($\cos\theta$, ϕ) positions for 1,000 individuals on the surface of the unit-sphere.
We will model the system in discrete time steps of days.

We may assign randomly to x% of the population the state Recovered. These individuals are assumed to be immune to the disease, either from natural immunity or through a pre-pandemic immunization program.

On day 1, pick ***randomly*** n susceptible individuals in the world's population of 1,000 to be exposed to the disease. (Note: Only susceptible individuals can be exposed).

Five days after the initial exposure, Exposed individuals become Infectious for 10 days. Infectious individuals can infect any Susceptible person within a certain critical angle, θ_C. The infection probability will be taken to be either :

a) SPATIALLY CERTAIN: 100% or
b) SPATIALLY PROBABLE: $\exp[-0.5\,(\Delta\theta/\sigma_\theta)^2]$ per day, where $\Delta\theta$ is the angular separation of the susceptible and infectious persons, and σ_θ, is like a resolution parameter.

Infection means changing the susceptible person from susceptible to exposed). After 10 days, Infected individuals become Recovered (ie are no longer infectious, and are no longer susceptible).

Each individual is assumed to travel by means of a random walk with an angular speed of ω in mrad/day. The random walk should be implemented as a different random direction each day. For simplicity, it will be sufficient to examine the positions of each individual at the end of each day.

For a number of repetitions of particular "experiments", we will want to measure the distributions of the following observables. Averages and rms's are minimalist requirements. Appropriate graphical representations are encouraged.

i) the "basic reproduction number", R_0, for these models, by counting for n=1 and x=0, the number of secondary cases produced by the initial infected person for a number of independent repetitions.
(Note that for this case you only need to run the simulation until the first

ii) the infection rate (the fraction of susceptible persons who become infected), and

iii) the time in days until there are no more infectious individuals.

A reasonable minimum number of repetitions for each model is probably 25.

<u>Models to Investigate</u>

a) Dependence of outbreak observables on θ_C for the SPATIALLY CERTAIN disease propagation model, with n=1 and x=0, and under static conditions with ZERO mobility (ω = 0). Is there some range of the parameter where the infection rate flips from improbable to highly probable?

b) Dependence of outbreak observables on θ_C for the SPATIALLY CERTAIN disease propagation model, with n=1 and x=0, and under mobile conditions with a mobility (ω = 20 mrad/day). Is there some range of the parameter where the infection rate flips from improbable to highly probable?
(Note: ω=20 mrad/day is a reasonable number for the average spatial separation implicit in N=1000)

c) Dependence of outbreak observables on θ_C for the SPATIALLY PROBABLE disease propagation model, with n=1 and x=0, and under static conditions with ZERO mobility (ω = 0). Take $\sigma_\theta = 0.4\theta_C$. Is there some range of the parameter where the infection rate flips from improbable to highly probable?

(Note that this sort of phase change, from “under-control” to “out-of-control” is a generic feature.)

Possible Additional Variations

0. Dependence on the fraction of initially immune, x.

1. Dependence on the number of initial infections, n.

2. Examine the effectiveness of a quarantine program which succeeds in quarantining individually all infectious individuals 5 days after they become infectious. (only relevant to the MOBILE or SPATIALLY PROBABLE models)

3. Examine the effectiveness of a vaccination program which succeeds in vaccinating 10 people per day after a vaccine has been developed, and is available for administration by day 30. The vaccine should be assumed to be 90% efficient at granting immunity to the immunized susceptibles.

4. Examine the effectiveness of a quarantine program which succeeds in quarantining individually all infectious individuals 5 days after they become infectious, together with all individuals located within 10 mrad.

(Note that study of counter-measure effectiveness makes most sense in the context of a set of parameters which lead to widespread infection).

References

“The Mathematics of Diseases”, Matt Keeling, http://plus.maths.org/issue14/features/diseases/ is a fairly accessible introduction to the basics behind deterministic models, which may be useful background info.
In fact it might be most useful as a counter-point to what you observe with our stochastic model.