Literature Review of Quantitative Microbial Risk Assessments Related to Aerosolization of Livestock Manure and Municipal Biosolids

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This is a presentation of previous quantitative microbial risk assessments (QMRAs) related to practices being considered in Wisconsin by the Manure Irrigation Workgroup. [Presented via web meeting on 4/14/14]

It is a review of studies that have estimated health risks (e.g., of infection or illness) due to aerosolization and downwind transport of pathogenic microorganisms in fecal material. It is not a review of the aerosolization and downwind transport of microorganisms in a more general sense (i.e., in the absence of accompanying risk estimates).

The studies covered by this literature review represent the work of essentially two groups. Four studies (Brooks et al. 2005a, Brooks et al. 2005b, Brooks et al. 2012, and Dowd et al. 2000) come from Charles Gerba, Ian Pepper (both of the University of Arizona Department of Soil, Water, and Environmental Science) and their students. Two more studies (IDEQ 2006 and IDEQ 2010) were completed internally by the Idaho Department of Environmental Quality (IDEQ) for their own regulatory purposes. Finally, Robert Dungan's (USDA-ARS Northwest Irrigation and Soils Research Laboratory) work appears to be influenced by the IDEQ studies, and it is presumably motivated by the same circumstances in Idaho that prompted IDEQ to complete its own QMRAs.

Summary

1. Five reports in scientific literature, one report from Idaho Department of Environmental Quality, and one unpublished data set
2. Three of these seven deal with livestock manure, and only two of those three consider spray irrigation
3. Wide variability in methods

We found seven studies in total that considered scenarios reasonably similar to those being considered by the Workgroup. Five of these studies (Brooks et al. 2005a, Brooks et al. 2005b, Brooks et al. 2012, Dowd et al. 2000, and Dungan 2014) have been published in the peer-reviewed, scientific literature. A sixth study (IDEQ 2006) is outlined by a report assembled by IDEQ, while the seventh study (IDEQ 2010) is unpublished data produced by IDEQ.

Only three of the seven studies deal with livestock manure, and only two of those three consider spray irrigation of livestock manure. This is a very small body of relevant literature (even when considering all seven studies), so it is crucial to practice restraint when attempting to draw broad conclusions from these data.

These studies vary significantly in their methods and assumptions. This variation in approach produces significant variation in the risk estimates, and it is not clear at this time which approaches (if any) might best represent the scenarios under consideration by the Manure Irrigation Workgroup. This is an additional reason to practice restraint when attempting to draw broad conclusions from these data.

Source

Paper	Source Types	Application Method
Brooks et al. 2005a	inoculated groundwater	spray tanker
Brooks et al. 2005b	municipal	mechanical, spray tanker, and irrigation
Brooks et al. 2012	bovine, municipal, poultry, swine, untreated municipal	mechanical
Dowd et al. 2000	municipal post-application	not applicable
Dungan 2014	bovine	center pivot
IDEQ 2006	hypothetical	center pivot
IDEQ 2010	bovine	center pivot

With regard to human health risks posed by pathogenic microorganisms, the sequence of events our research team is considering is 1) the aerosolization of a pathogen source (i.e., livestock manure being land-applied via spray irrigation), 2) the potential downwind transport of pathogens, 3) the ingestion and/or inhalation of those transported pathogens by human receptors, and 4) subsequent infection and/or illness. This slide and the following five slides outline how each study treats some (but not all) important elements of that process.

With regard to aerosolization of a pathogen source, both the source type and application method are potentially important. Only Brooks et al. 2012, Dungan 2014, and IDEQ 2010 consider livestock (and more specifically, bovine) manure. Of those three, Dungan 2014 and IDEQ 2010 consider spray irrigation (i.e., center pivot application). The studies that consider municipal biosolids and/or mechanical application of the source may be informative, but they are probably less relevant to the scenarios being considered by the Manure Irrigation Workgroup. None of these studies appear to have considered traveling gun application of livestock manure.

Transport

Paper	Wind Speeds (mph)	Fate and Transport Model
Brooks et al. 2005a	"5.1"	empirical
Brooks et al. 2005b	5.1*	empirical
Brooks et al. 2012	5.1*	empirical
Dowd et al. 2000	4.5*, 11.2*, 22.4*, and 44.8*	modified Gaussian dispersion model
Dungan 2014	9.9	Gaussian dispersion model
IDEQ 2006	5.6	Gaussian dispersion model
IDEQ 2010	2.2, 5.6, 11.2, and 22.4	Gaussian dispersion model

The range of wind speeds (a primary driver of transport) and the form of the fate and transport model are both important for predicting the downwind transport of pathogens following aerosolization.

Only two studies consider more than one wind speed. This is a significant shortcoming of the existing body of knowledge, because wind speeds can vary significantly over both short and long time-scales. Furthermore, our analysis of the method presented in Dowd et al. indicates that those authors may have inadvertently excluded wind speed from their analysis by making unconventional modifications to the traditional Gaussian dispersion model. This may mean that only the IDEQ 2010 study considered multiple wind speeds, although we must verify our interpretation of Dowd et al.'s method with the authors of that paper.

Three studies utilize some formulation of the traditional (i.e., unmodified) Gaussian dispersion model. Versions of this model (varying in their levels of sophistication) are used widely by atmospheric scientists and contain input parameters that make them adaptable to a wide variety of meteorological conditions, source geometries, and landscape features. As a result, these are probably the most robust available models for predicting downwind transport of aerosolized pathogens.

Three other studies utilize an empirical fate and transport model. In fact, these three studies all use the same empirical model, which is developed in Brooks et al. 2005a and then applied in the other two Brooks studies. Empirical models can be extremely practical and effective, but their application is limited to circumstances that reflect the conditions for which they were developed. For instance, the empirical model developed in Brooks et al. 2005a represents the fate and transport of coliphage at average wind speeds of 5.1 mph (among a number of other specific meteorological and pathogen source conditions). Thus, its application in Brooks et al. 2005b and Brooks et al. 2012 implies that the wind speed considered in those studies is also 5.1 mph.

Note: Dowd et al. actually worked with two different Gaussian dispersion models: a point-source model and an area-source model. Furthermore, they made two separate modifications to the point-source model. The first modification appears to inadvertently exclude wind speed as a parameter

Field Measurements

Paper	Aerosol Concentrations	Microbial Inactivation
Brooks et al. 2005a	coliphage	none
Brooks et al. 2005b	coliphage and total coliforms	none
Brooks et al. 2012	none	none
Dowd et al. 2000	coliphage and *Salmonella* spp.	none
Dungan 2014	none	none
IDEQ 2006	none	none
IDEQ 2010	none	none

Field measurements are extremely valuable for verifying output and for providing site-specific and case-specific input for fate and transport models.

Aerosol concentrations of pathogens and/or indicator microorganisms can serve as either input or output for fate and transport models. Only three studies measured aerosol concentrations (of indicator microorganisms), and all three of these studies used those concentrations as model input. Brooks et al. 2005a used a series of aerosol concentrations at multiple distances from the source to develop their empirical model, while Brooks et al. 2005b used coliphage and total coliform concentrations at one distance very close to the source to establish initial concentrations for the application of the empirical model from Brooks et al. 2005a. Dowd et al. 2000 also used aerosol concentrations close to the source to determine a source term for their Gaussian dispersion model. None of the three studies that considered livestock manure as a source collected aerosol concentrations, either to provide model input or verify model output.

The microbial inactivation coefficient reflects how quickly microorganisms die while traveling through the air exposed to solar radiation and other hostile environmental conditions. It is an important input parameter for the Gaussian dispersion model, because its value can affect the model output significantly. The four studies that used some form of the Gaussian dispersion model all relied on literature values of microbial inactivation coefficients, covering a limited range of microorganisms and meteorological conditions.

Note: Impact factor is another potentially important measure of microbial death that represents the effects of microbe release from pressurized nozzles (and, possibly, other difficult-to-isolate mechanisms). Impact factor has been considered in several of these studies, but we have not covered their treatment of it in this presentation.

QMRA Data

Paper	Pathogens
Brooks et al. 2005a	coxsackievirus A21 (n = 1)
Brooks et al. 2005b	coxsackievirus A21 and *Salmonella* spp. (n = 2)
Brooks et al. 2012	adenovirus, enteroviruses, norovirus, *C. jejuni*, *E. coli* O157:H7, *L. monocytogenes*, and *Salmonella* spp. (n = 7)
Dowd et al. 2000	coxsackievirus B3 and *S. typhi* (n = 2)
Dungan 2014	*C. jejuni*, *E. coli* O157:H7, enteropathogenic *E. coli* O55 and O111, *L. monocytogenes*, *Salmonella* spp. (n = 5)
IDEQ 2006	*E. coli* (n = 1)
IDEQ 2010	*E. coli* (n = 1)

The identity and number of pathogens included in a QMRA are important for at least two reasons. First, dose-response relationships, which determine the probability of infection or illness for specific pathogens, can vary significantly from one pathogen to another. Second, including more than one pathogen in the QMRA allows for risk estimates to incorporate some of the variability in pathogen types that might be present in source material.

Five studies consider only one or two pathogens. This limits the degree to which broad conclusions can be drawn from their results, although their results are still useful for investigating the relative effects of various source and application conditions.

Two studies consider five or more pathogens; these cover a wider range of variability in the types of pathogens that might be present in source material.

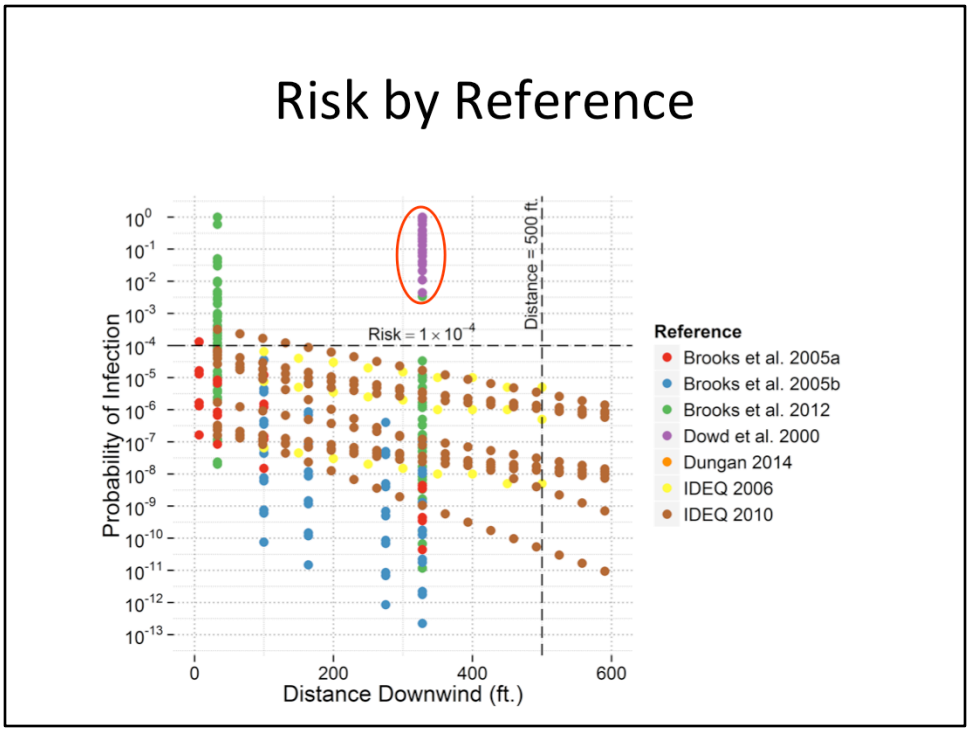
QMRA Data

Paper	Number of Data Points	Variability and Uncertainty*
Brooks et al. 2005a	36	exposure times (n = 2) and source concentrations (n = 3)
Brooks et al. 2005b	72	exposure times (n = 2) and source concentrations (n = 3)
Brooks et al. 2012	129	none*
Dowd et al. 2000	192	exposure times (n = 3)
Dungan 2014	420	aerosolization efficiency (n = 3), dilution (n = 3), meteorology, receptor location (n = 36), and source concentrations (n = 4)
IDEQ 2006	30*	aerosolization efficiency (n = 2) and source concentrations (n = 2)
IDEQ 2010	1,000	aerosolization efficiency (n = 2), flow rate (n = 2), meteorology (n = 3), and use of end gun

Other important factors to consider when assessing the results of a QMRA are the number of data points (number of risk estimates) that have been generated and the mechanism by which variability and uncertainty have been incorporated into the analysis.

In general, a larger set of data is likely to provide a more robust estimate of risk and to more thoroughly characterize the variability in those risk estimates. With that in mind, the Dungan 2014 and IDEQ 2010 studies stand out in terms of the amount of data they provide for assessing risk. These two studies are two of the three that considered livestock manure as a pathogen source.

Variability and uncertainty can be accounted for by varying parameters in the QMRA (including parameters related to source characteristics, fate and transport, and dose-response modeling). Both the number of varied parameters and the number of variations investigated for any particular parameter influence the quality of the risk estimate. Our own initial formulation of the QMRA model for the scenarios being considered by the Manure Irrigation Workgroup indicate that there are oven a dozen parameters for which the effects of their variation should be included in the analysis. Other than parameters already covered in previous slides, five of the studies listed above investigate the variation of no more than two parameters. Even for the remaining two studies (Dungan 2014 and IDEQ 2010), most varied parameters are

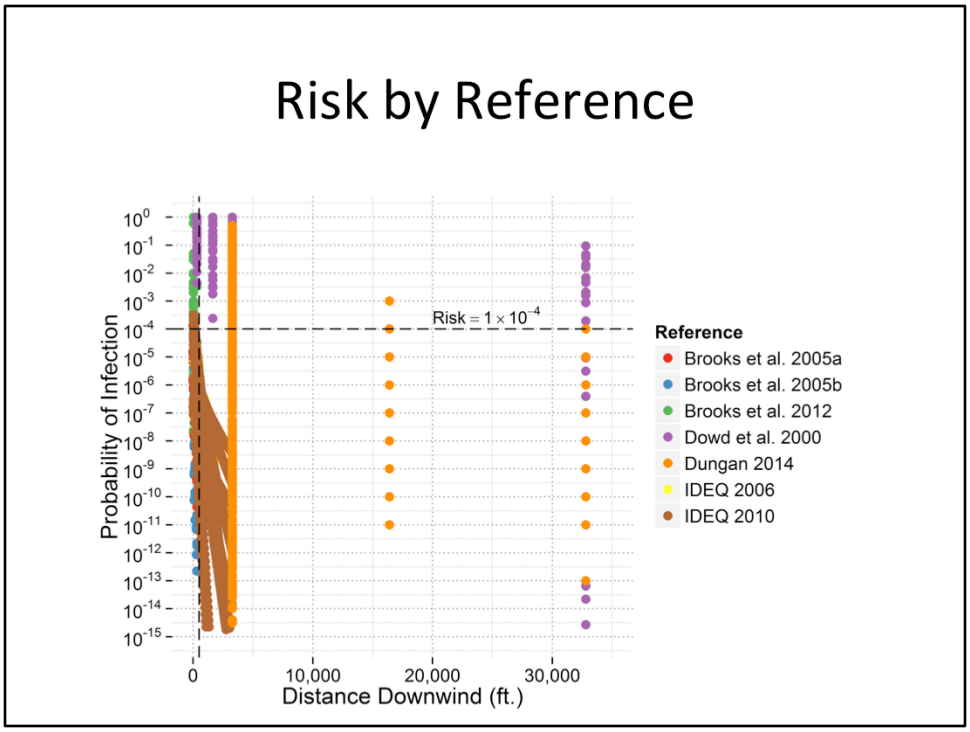


Keeping in mind the variation in methods and assumptions among these seven studies, we can now take a look at their data. You will see several plots that look like this one, with risk estimates (on the *y* axis) plotted against distance (on the *x* axis). Furthermore, each plot will break the data down into groups (different colors represent different groups) based on different factors. This plot separates the data out by study (reference).

Reference lines have been added for risk (probability of infection) equals 1 in 10,000 (1×10^{-4}) and for distance equals 500 feet. The reference risk value of 1 infection in 10,000 people per year is a value that has been discussed in the Manure Irrigation Workgroup as being a potentially acceptable level of risk for human infection by a pathogen. The reference distance is equal to existing setback requirements (from inhabited dwellings) for some systems used for land treatment of industrial liquid wastes, by-product solids, and sludges (Wisconsin Admin Code NR 214).

There are two features of the data that I would like you to see in this plot. The first is the enormous variation in the data. Not accounting for distance, risk estimates vary between about 1 (100% chance of infection) and 1×10^{-13}, which represents a factor of 10,000,000,000,000 (10 trillion). Even when accounting for distance, the data are still highly variable. For instance, at the reference distance of 500 feet, risk estimates vary by a factor of 10,000, between approximately 1×10^{-5} (1 in 100,000 chance of infection) and 1×10^{-10}.

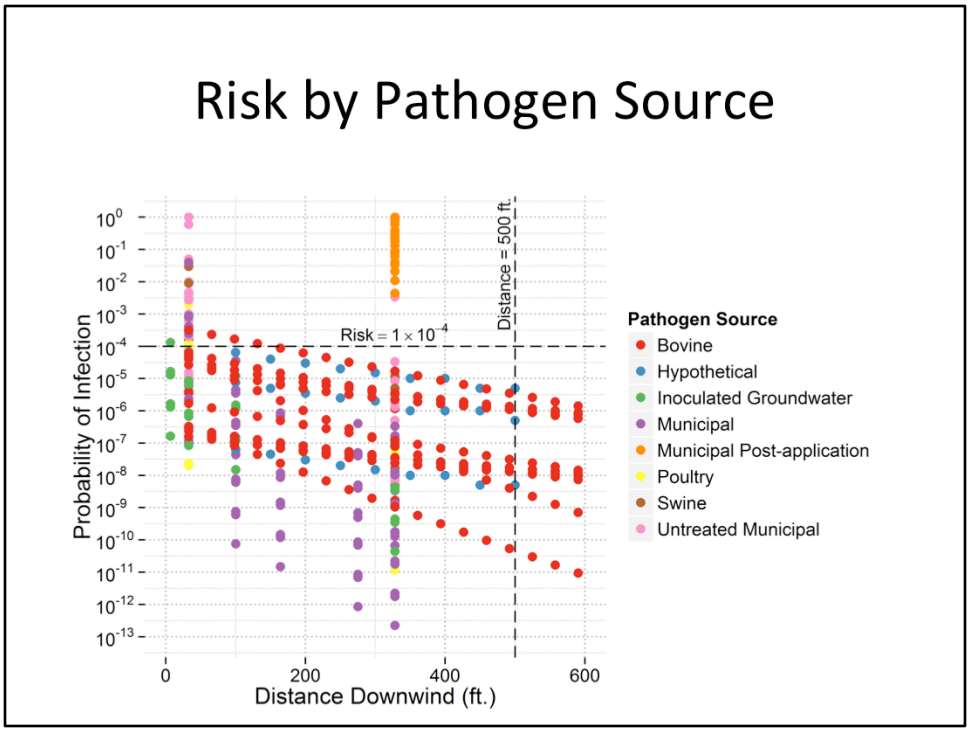
The second feature of the data that is important to see is the location of Dowd et al.'s data (the purple circles highlighted by the red oval). Dowd et al. made some unconventional modifications to the traditional Gaussian dispersion model (see Slide 4). I have excluded the data from the modified point-source model from these plots for now, because they seem likely to be incorrect. However, I have left the data from their area-source model (the purple



The data on the previous plot was not all of the risk data in these seven references, because the *x* axis was limited to 600 feet. The data on the current plot *are* all the data (for risk > "0") that are available in these seven references.

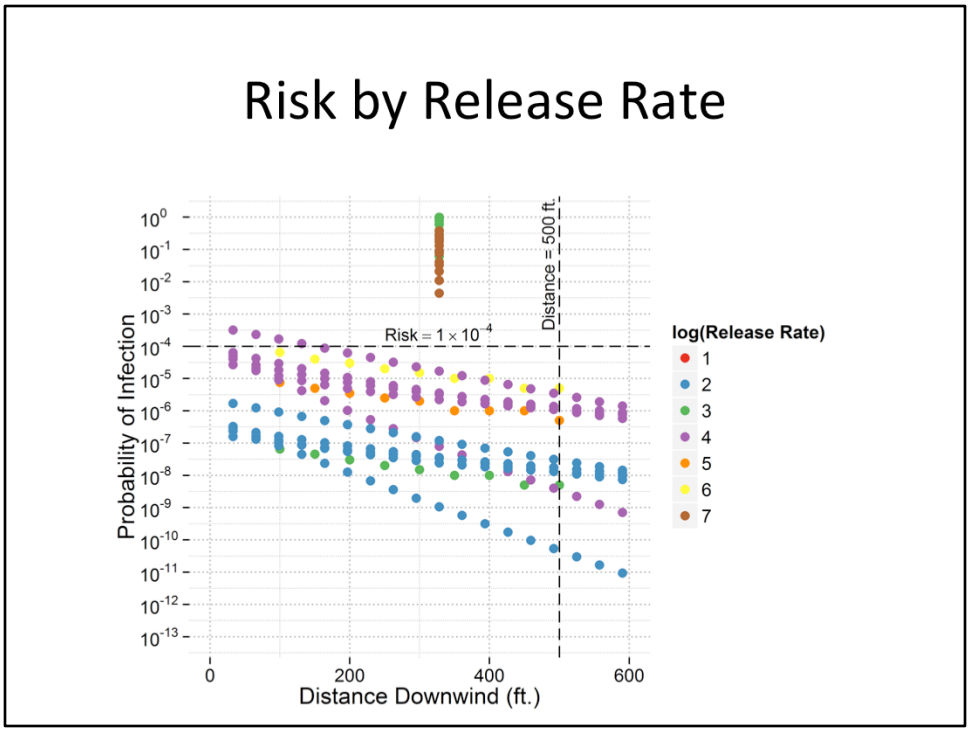
I want you to see all the data, but I am not going to keep showing this plot (where the *x* axis extends beyond 30,000 feet) because it is not practical for looking at the data. I want you to see variations in the data based on different factors related to source characteristics, fate and transport, and dose-response modeling. These trends can be seen when the *x* axis is limited to 600 feet, but when it is extended beyond 30,000 feet, all of those data just turn into a big smear.

Other than seeing all the data, I would also like you to see (again) the tremendous variation in risk estimates in the data set. What appears to be an orange vertical line towards the left side of the plot is the Dungan data for approximately 3,300 feet downwind from the source. It varies from almost 1 to just above 1×10^{-15}, which is a factor of 1,000,000,000,000,000 (1 quadrillion). This variation is a function of the variation in QMRA inputs that Dungan considered. However, drawing broad conclusions from these estimates is not advised because we do not have site-specific and case-specific data (i.e., field measurements) to inform us of which scenarios (very high risk, very low risk, or something in between) might be most applicable to the scenarios being considered by the Manure Irrigation Workgroup.



Now we can move back to looking at the data for downwind distances less than 600 feet. This is the same plot as the very first plot, but now the data are grouped by pathogen source.

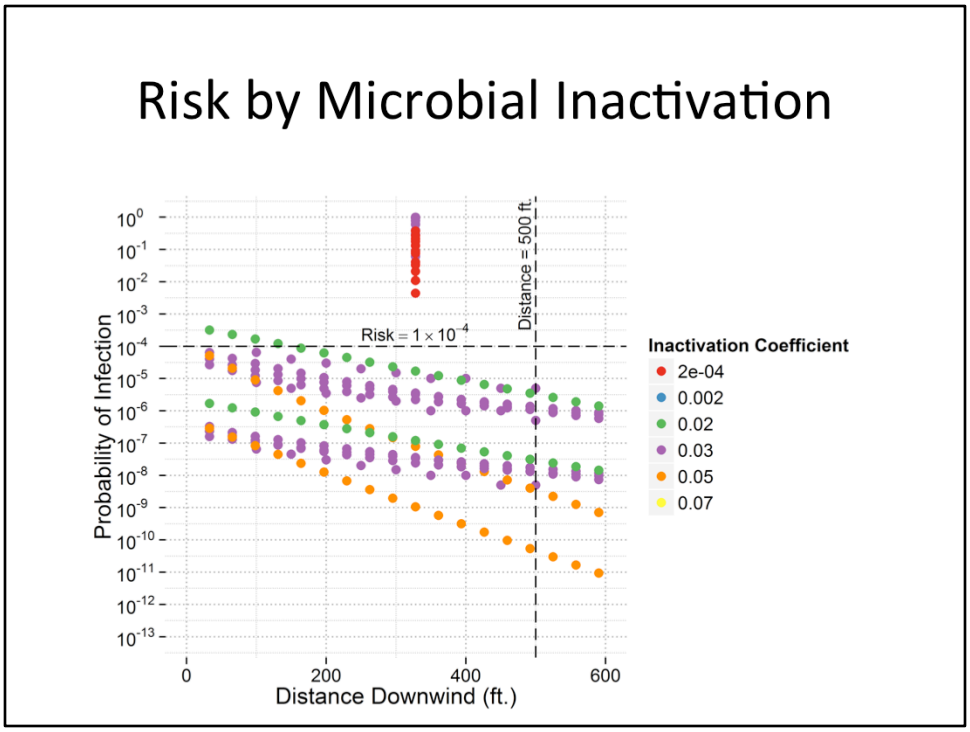
There do not seem to be any particularly obvious trends, but this plot serves as another opportunity to highlight the variation in risk estimates. Estimates of risk for bovine pathogen sources (which are mostly from the IDEQ 2010 study on this plot) are highly variable due to variability in the QMRA input parameters (other than pathogen source). For instance, at 500 feet, the risk estimates span approximately five orders of magnitude (a factor of 10,000).



This is the same plot again, but now the data are grouped according to the $\log_{10}$ of the release rate. As an example, a value of 2 (the blue circles) indicates a release rate of approximately 100 microorganisms per second, while a value of 6 (the yellow circles) indicates a release rate of approximately 1,000,000 microorganisms per second.

For the most part, these data look how you might expect. Lower release rates at the source (e.g., the blue circles) result in lower risk estimates, and higher release rates at the source (e.g., the yellow circles) result in higher risk estimates.

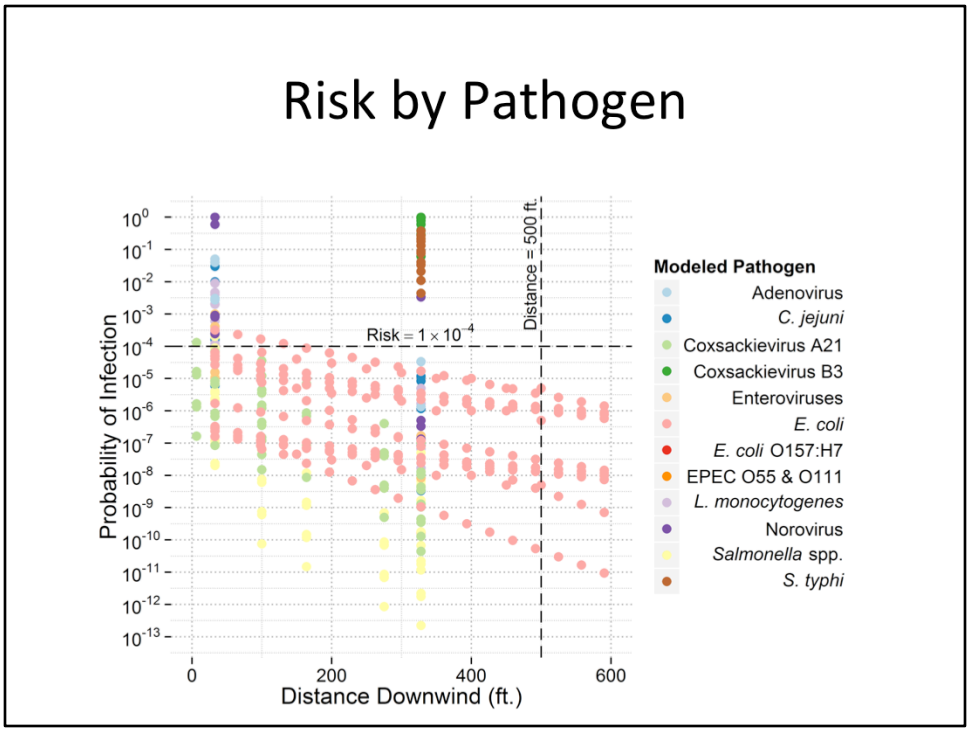
The Dowd et al. data (those data that form a vertical line at the very top of the plot) appear to be an outlier, but not just because of where they are relative to the rest of the data. They also do not follow the trend just described above very well. Even though Dowd et al. investigated release rates of 1,000 microorganisms per second (the green circles) and 10,000,000 microorganisms per second (the brown circles), they estimated some similar values of risk for those two release rates.



And again, this is the same plot, but now with the data grouped by the value of the microbial inactivation coefficient that was considered. The microbial inactivation coefficient reflects how quickly microorganisms die while exposed to harsh conditions in the air following aerosolization and during downwind transport. Larger values of the inactivation coefficient indicate faster death, while smaller values of the inactivation coefficient indicate slower death.

These data also look how you might expect. Lower risk estimates are obtained when microorganisms are assumed to die more quickly (e.g., the orange circles representing an inactivation coefficient of 0.05), and higher risk estimates are obtained when microorganisms are assumed to die more slowly (e.g., the green circles representing an inactivation coefficient of 0.02).

Also, the Dowd et al. data appear to be outliers again. Even though they used microbial inactivation coefficients of 0.03 and 0.0002 (2e-04), which vary by a factor of 150, their risk estimates for these two different values of the microbial inactivation coefficient are approximately equal in some cases.



And finally, the same plot, but now with the data grouped by the modeled pathogen.

There do not seem to be any obvious trends here, but (one last time) this plot is a good opportunity to highlight the variation in the data. For the *E. coli* (pink circles) dose-response relationship (used in IDEQ 2006 and IDEQ 2010), estimated risk values vary by a factor of approximately 10,000 at the reference distance of 500 feet. This variation in risk estimates is a function of variation in all of the other input parameters. Again, this means that site-specific and case-specific data (i.e., field measurements) are critical for appropriately defining the degree to which each input parameter needs to be varied in order to obtain an accurate and robust risk estimate.

Data Gaps

1. Field measurements of aerosol concentrations, particularly for livestock manure sources
2. Field measurements of microbial inactivation
3. Systematic consideration of variability and uncertainty in **all** input parameters

Understanding the data gaps in the existing body of knowledge is crucial to producing accurate and robust risk estimates for the scenarios being considered by the Manure Irrigation Workgroup. Hopefully, some of the points on this final slide sound familiar.

First, we need field measurements of downwind aerosol concentrations, particularly for livestock manure sources, that can be used to verify the output of the Gaussian air dispersion model. Aerosol concentrations of indicator microorganisms and/or pathogens have been collected only rarely in the existing body of work, and never for livestock manure sources.

Second, we would prefer to have field measurements of microbial inactivation to use as input for the Gaussian air dispersion model. The existing body of knowledge has relied on existing values from the literature, which may or may not represent the microorganisms and meteorological conditions that are relevant to the scenarios being considered by the Workgroup. Measuring these microbial inactivation coefficients is extremely difficult, which is probably why the current QMRA studies have relied on literature values. However, we feel that we may have several promising techniques for making these measurements, and if one of these approaches is successful, it will allow us to estimate risk more accurately.

Finally, variability and uncertainty in all input parameters (related to source characteristics, fate and transport, and dose-response modeling) should be considered more thoroughly and systematically. In the larger QMRA literature (i.e., not just QMRA of aerosolized pathogens), this is typically accomplished using a Monte Carlo simulation. In a Monte Carlo simulation, each input parameter is specified in terms of a distribution, rather than as a single value, and risk can be computed based on these distributions an arbitrarily large (e.g., 100,000) number of times. Thus, this approach can be used to constrain risk estimates based on distributions of input parameters extracted from site-specific and case-specific conditions, and it enables extremely large-scale variation of each individual input parameter (e.g., 100,000 values can

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