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Emerging human infectious diseases and the links to global food production

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Supplementary Materials:

Materials and Methods

Table S1

External Databases S1-S2

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Materials and Methods:

Fig. 3. To project global human population to 2100, we collected human population data from the World Bank from 1961 to 2016. We then compared the fits (using AICc) of linear, second, and third order models for the relationship between year and population density. We used the best fitting model to project global human population estimates to 2100. See Table S1 for coefficients and statistics for the best fitting model.

To project global nitrogen and phosphorous fertilizer use, pesticide use, cropland area, and irrigated land area to 2100, we collected data from the Food and Agriculture Organization of the United Nations from 1961 to 2016. Our models used annual global human population density from 1961-2016 as the independent variable and annual global nitrogen and phosphorous fertilizer use, pesticide use, cropland area, and irrigated land area as the dependent variables. For each of these five response variables, we compared the fits of four models: 1) no transformations, 2) the dependent variable log transformed, 3) the independent variable log transformed, and 4) both the dependent and independent variables log transformed. The best fitting model was identified using AICc. To project these relationships to 2100, year was substituted for human population density based on the best fitting regression equation for the relationship between year and global human population density. See the provide code and data used to generate Fig. 3. See Table S1 for coefficients and statistics for the best fitting model and R code to generate the figure below.

Fig. 5. We used the Jones et al.¹ database to estimate the contribution of agricultural production to emerging infectious disease (EID) events in humans. This database categorized each of 335 EID events by 13 ‘drivers’. The full list of drivers is listed below. We conservatively only classified “Agricultural industry changes”, “Food industry changes”, and “Land use changes” as agricultural-related drivers to develop Figure 5, even though other drivers, such as “Antimicrobial agent use”, are likely strongly related to agriculture. Each EID event is associated with a date. Thus, we plotted cumulative totals of all and zoonotic EIDs, as well as EIDs in each of the three agricultural groupings, by simply counting up all of the events that occurred at or before a given year.

The full list of the EID drivers from the Jones et al.¹ paper:

- Agricultural industry changes
- Antimicrobial agent use
- Breakdown of public health measures

- Bushmeat
- Climate and weather
- Food industry changes
- Human demographics and behavior
- Human susceptibility to infection
- International travel and commerce
- Land use changes
- Medical industry changes
- Other industries
- Unspecified
- War & famine

R code to generate Fig. 3

```
library(ggplot2)
library(gridExtra)
```

```
#### Code to get data imported to R
```

```
raw <- read.csv("data/Pop-Pest-Crop-Data.csv", na.strings = c("", "NA"))
final <- read.csv("data/Pop-Pest-Crop-Final.csv", na.strings = c("", "NA"))
```

```
detach(raw)
raw<-read.delim("clipboard")
attach(raw)
```

```
detach(final)
final<-read.delim("clipboard")
attach(final)
#### Best fitting models and ggplot code for plotting these models
#### Population
```

```
pop_year <- lm(GlobalPop~poly(Year, degree=3, raw=TRUE), data=raw)
summary(pop_year)
coef(pop_year)
```

```
Population <- ggplot(raw, aes(Year, GlobalPop)) + geom_point() +
  geom_smooth(method = "lm", formula = y ~ poly(x, 3), se=TRUE, fullrange=TRUE) +
  scale_colour_discrete("") + ylab("Global population") + xlim(c(1950, 2100)) +
  annotate("text", x=1950, y=11.5e+09, hjust=-0.2, label="a", size=8)
```

```
#### Nitrogen
```

```
pop_nit <-lm(Nitrogen~LogGlobalPop2, data=raw)
summary(pop_nit)
coef(pop_nit)
```

```
nitro <- data.frame(Year=c(1945,2100), LogGlobalPop2=raw$LogGlobalPop2, Nit=raw$NitrogenMill)
nit_predict <- predict(pop_nit, newdata = nitro, int="confidence")
nit_pred <- as.data.frame(nit_predict)
```

```
Nitrogen <- ggplot(final, aes(Year, NitPred)) + geom_line(color="blue", size=1) +
  geom_point(aes(Year, NitMill)) +
  geom_ribbon(aes(ymin=NitLwrMill, ymax=NitUpMill, x=Year), fill = "steelblue4",
    alpha=0.5) + scale_colour_discrete("") +
  labs(y = expression(paste("Nitrogen " ("metric tons"/10140)))) + xlim(c(1950, 2110)) +
  annotate("text", x=1950, y=150, hjust=-0.2, label="b)", size=8)
```

Phosphorus

```
pop_phos <- lm(Phosphorus~LogGlobalPop2, data=raw)
summary(pop_phos)
coef(pop_phos)
```

```
phos <- data.frame(Year=c(1945,2100), LogGlobalPop2=raw$LogGlobalPop2, Phos=raw$PhosphorusMill)
phos_predict <- predict(pop_phos, newdata = phos, int="confidence")
phos_pred <- as.data.frame(phos_predict)
```

```
Phosphorus <- ggplot(final, aes(Year, PhosPred)) + geom_line(color="blue", size=1) +
  geom_point(aes(Year, PhosMill)) +
  geom_ribbon(aes(ymin=PhosLwrMill, ymax=PhosUpMill, x=Year), fill = "steelblue4", alpha=0.5) +
  scale_colour_discrete("") +
  labs(y = expression(paste("Phosphorus " ("metric tons"/10{6}s)))) + xlim(c(1950, 2110)) +
  annotate("text", x=1950, y=55, hjust=-0.2, label="c)", size=8)
```

Pesticide Import

```
pop_imp <- lm(LogPestImport~LogGlobalPop2, data=raw)
summary(pop_imp)
coef(pop_imp)
```

```
imp <- data.frame(Year=c(1945,2100), LogGlobalPop2=raw$LogGlobalPop2, Imp=raw$LogPestImport)
imp_predict <- predict(pop_imp, newdata = imp, int="confidence")
imp_pred <- as.data.frame(imp_predict)
```

```
Import <- ggplot(final, aes(Year, ImpPred)) + geom_line(color="blue", size=1) +
  geom_point(aes(Year, LogImp)) +
  geom_ribbon(aes(ymin=ImpLwrLog, ymax=ImpUpLog, x=Year), fill = "steelblue4", alpha=0.5) +
  scale_colour_discrete("") +
  labs(y = expression(paste("Pesticide imports " ("log"[10]*" USD x 10"{3})))) +
  xlim(c(1950, 2110)) + annotate("text", x=1950, y=8.7, hjust=-0.2, label="d)", size=8)
```

Permanent Cropland

```
pop_crop <- lm(LogPermCA~GlobalPop2, data=raw)
summary(pop_crop)
coef(pop_crop)
```

```
crop <- data.frame(Year=c(1945,2100), GlobalPop2=raw$GlobalPop2, Crop=raw$LogPermCA)
crop_predict <- predict(pop_crop, newdata = crop, int="confidence")
crop_pred <- as.data.frame(crop_predict)
```

```
Cropland <- ggplot(final, aes(Year, CAPred)) + geom_line(color="blue", size=1) +
  geom_point(aes(Year, LogPermCA)) +
  geom_ribbon(aes(ymin=CALwrLog, ymax=CAUpLog, x=Year), fill = "steelblue4", alpha=0.5) +
  scale_colour_discrete("") +
```

```
labs(y = expression(paste("Arable and permanent cropland " ("log"[10]*" Ha")))) +
xlim(c(1950, 2110)) + annotate("text", x=1950, y=9.26, hjust=-0.2, label="e", size=8)
```

Land Available for Irrigation

```
pop_irr <- lm(LogIrr~LogGlobalPop2, data=raw)
summary(pop_irr)
coef(pop_irr)
```

```
irr <- data.frame(Year=c(1945,2100), LogGlobalPop2=raw$LogGlobalPop2, Irr=raw$LogIrr)
irr_predict <- predict(pop_irr, newdata = irr, int="confidence")
irr_pred <- as.data.frame(irr_predict)
```

```
Irrigation <- ggplot(final, aes(Year, IrrPred)) + geom_line(color="blue", size=1) +
  geom_point(aes(Year, LogIrr)) +
  geom_ribbon(aes(ymin=IrrLwrLog, ymax=IrrUprLog, x=Year), fill = "steelblue4", alpha=0.5) +
  scale_colour_discrete("") +
  labs(y = expression(paste("Irrigated area " ("log"[10]*" Ha")))) +
  xlim(c(1950, 2110)) + annotate("text", x=1950, y=8.7, hjust=-0.2, label="f", size=8)
```

COMBINE FIGURES

```
gridExtra::grid.arrange(Population, Nitrogen, Phosphorus, Import, Cropland, Irrigation, ncol=3)
```

Table S1. Coefficients for best fitting models shown in Fig. 3.

Response	Intercept	Slope parameter			<i>df</i>	<i>F</i>	<i>R</i> ²
		Year	Year ²	Year ³			
Global human population	2.52E+13	3.79E+10	1.90E+07	-3.17E+03	55	1.48E+05	0.9999
		Log ₁₀ global human population					
Nitrogen use	2.18E+09	-	2.31E+08		41	1.12E+03	0.9648
		Log ₁₀ global human population					
Phosphorus use	5.96E+08	-	6.44E+07		41	1.61E+02	0.7969
		Log ₁₀ global human population					
Log ₁₀ pesticide imports	4.53E+01	-	5.36E+00		52	1.75E+03	0.9711
		Global human population					
Log ₁₀ crop area	9.11E+00		1.30E-11		53	7.20E+02	0.9314
		Log ₁₀ global human population					
Log ₁₀ irrigated area	1.19E-03		8.65E-01		52	2.91E+04	0.9982