Global Biogeography of the Soil Virosphere

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ABSTRACT

Historically neglected by microbial ecologists, soil viruses are now thought to be critical to global biogeochemical cycles. However, our understanding of their global distribution, activities, and interactions with the soil microbiome remains limited. Here, we present the Global Soil Virus (GSV) Atlas, a comprehensive dataset from 2,953 soil metagenomes that is comprised of 616,935 uncultivated viral genomes (UViGs) and 38,508 unique viral operational taxonomic units (vOTUs). Rarefaction curves from the GSV Atlas indicate that most soil viral diversity remains unexplored, further underscored by high spatial turnover and low rates of shared vOTUs across samples. By examining genes associated with biogeochemical functions, we also demonstrate the viral potential to impact soil carbon and nutrient cycling. This study represents the most extensive characterization of soil viral diversity to date and provides a foundation for developing testable hypotheses regarding the role of the virosphere in the soil microbiome and global biogeochemistry.

Viral contributions to soil ecology are largely unknown due to the extreme diversity of

the soil virosphere. Despite variation in estimates of soil viral abundances (10^7 to 10^{10} viruses per

gram of soil), it is clear that soils are among the largest viral reservoirs on Earth[1–3]. Early

metagenomics investigations have revealed high genetic diversity in soil viruses, with putative

impacts on global biogeochemistry[1,2,4,5]. Still, less than 1% of publicly available viral

metagenomic sequences are from soil[6], reflecting the lack of knowledge about soil viruses and

their ecological roles[4,7].

High soil viral diversity may be due to the structural and/or physico-chemical

heterogeneity of soil compared to other ecosystems[1,8–10], as well as the high diversity of their

microbial hosts. Indeed, soil viral abundance and composition vary with factors such as pH,

temperature, moisture, chemistry, and habitat[10–12]. Much of this viral diversity is contained

within DNA viruses, though RNA viruses also have the potential to influence soil processes[13,14].

While less is known about soil viral activity, a recent study of peatlands reported that close to

60% of soil viral genomes may be involved in active infections[15], consistent with high activity

observed in marine and other systems[4,16–18].

Whether common macroecological patterns apply to the soil virosphere remains an open

question; initial studies of the soil virosphere indicate that the ecology of viruses is at least

partially decoupled from other microorganisms[8,10,19]. A major finding is that soil viral

community turnover may occur over shorter spatial and temporal scales than microbial

communities[8,10,19]. For instance, spatial viral turnover has been shown to be over 5 times higher

than microbial community turnover across an 18m soil transect[8], and only 4% of peatland 'viral

operational taxonomic units' (vOTUs) are shared across continents[20]. Other studies note the

possibility for long-distance soil viral dispersal through atmospheric[21] or aquatic transport[22]

consistent with low turnover. These contrasting results indicate a lack of consensus surrounding

the spatial and temporal patterns of soil viruses and the need for large-scale surveys of the soil

virosphere.

Importantly, soil viruses can influence biogeochemical cycling, antibiotic resistance, and

other critical soil functions by releasing carbon and nutrients during host infection and/or by

altering host metabolism via auxiliary metabolic genes (AMGs)[9,15,18,23–28]. While soil AMG

characterization is nascent[14], marine systems demonstrate the breadth of functions ripe for

discovery in soil[24]. More than 200 viral AMGs encoding functions related to carbon and nutrient

cycling; stress tolerance; toxin resistance; and other processes have been detected in marine

systems[24]. In contrast, only a handful of these functions have been identified as soil viral

AMGs[12,14,15,22,29,30]. AMGs encoding carbohydrate metabolism in particular may be present in

soils, including a few that have been experimentally validated[9,10,15,29–31].

Accordingly, understanding the role of viruses in soil ecosystems is one of the most

pressing current challenges in microbial ecology[32]. Despite the expansion of studies

characterizing soil viruses[4,12,29,30], a comprehensive description of the global soil virosphere has

yet to be performed. Such a description is necessary to begin to address questions regarding the

spatiotemporal dynamics, physicochemical interactions, host organisms, and food web

implications of the soil virosphere. We present a meticulous compilation of the Global Soil Virus

(GSV) Atlas based on previous metagenomic investigations of worldwide soils. This atlas

represents the most extensive collection of soil metagenomes to date, encompassing

contributions from prominent repositories, ecological networks, and individual collaborators.

RESULTS

Global Soil Virus (GSV) Atlas.

For a description of the files contained by the GSV Atlas, please see 'Data Availability'. We amassed 1.25×10^{12} of assembled base pairs (bp) across 2,953 soil samples, including 1,552 samples that were not previously available in the United States Department of Energy's (DOE), Joint Genome Institute's (JGI) IMG/M database (Fig. 1 and 2). These samples were screened for viruses, yielding 616,935 uncultivated virus genomes (UViGs) of which 49,649 were of sufficiently high quality for further investigation (see methods). To quantify the extent of new viral diversity encompassed by the GSV Atlas, we compared sequences from samples not already in IMG/VR to those that were previously deposited. Newly contributed sequences clustered into 3,613 vOTUs of which only 317 clustered with existing viral sequences in IMG/VR. The vast majority associations with IMG/VR were with sequences previously uncovered from soil habitats (Fig. 2b).

We also collected associated environmental parameters describing each sample from the SoilGrids250m database[33]. We assayed a wide variety of soils that ranged from bulk density of 0.24-1.56 (kg/dm³), cation exchange capacity of 6.8-71 (CEC; cmol(c)/kg), nitrogen content of 0.19-22.4 (N; g/kg), pH of 4.3-8.5, soil organic C of 1.9-510.9 (SOC; g/kg), and clay content of 2.7-57.1 (%) (Fig. 1).

The 49,649 UViGs of sufficient quality for downstream analysis clustered into 38,508 vOTUs at the species-like level[34], of which 3,296 were previously unrepresented in IMG/VR (Fig. 2a-b). Only 13.9% of the GSV Atlas' vOTUs appeared in more than one sample, and less than 1% were present in more than 5 samples. At higher taxonomic levels, we found 21,160 and 7,598 clusters at the genus and family level respectively[35]. This equates to an average of 40.01 (range: 1 - 2,124), 35.48 (range: 1 - 1,651), and 24.91 (range: 1 - 896) unique viral clusters per

sample at the species, genus, and family levels. 38,278 out of 38,508 vOTUs (99.4%) had at least

one member assigned to a taxon by geNomad.

We identified 1,432,147 viral genes, of which only 260,258 (~18%) were found in at

least one annotation database (1,022, 3,634, and 145 unique KO, Pfam, and CAZy annotations,

Fig. 2). After filtering to putative AMGs (see methods)[30], we found 5,043 genes that mapped to

83 KEGG pathways (1,941 KO and 3,357 CAZyme, some genes were associated with both KO

and CAZyme). The median per sample putative AMG abundance (gene copies per sample) was

~19 genes (median = 4, reflecting skewing from a few samples with high AMG abundance). The

most abundant KEGG pathways containing putative AMGs were Galactose metabolism,

Glycosaminoglycan degradation, Starch and sucrose metabolism, N-Glycan biosynthesis, and

Folate biosynthesis; while the most abundant gene annotations associated with AMGs were

Glycosyl Transferase Family 4 (GT4), Carbohydrate-Binding Module Family 50 (CMB50), 6-

pyruvoyltetrahydropterin/6-carboxytetrahydropterin synthase (K01737), Glycoside Hydrolase

Family 73 (GH73), and 7-carboxy-7-deazaguanine synthase (K10026) (Fig. 2c-d).

In contrast to the saturation observed in rarefaction curves for microbial taxonomy and

genes annotated by Pfam, rarefaction curves of soil viruses for individual samples (vOTUs and

and viral clusters) and their genes (annotated by Pfams) did not reach an asymptote (Fig. S1).

The number of new and unique vOTUs and viral clusters at the family level (Fig. S1b and S1c)

was linearly related to sequencing depth, while viral Pfams displayed slight curvature. These

linear relationships were observed when considering 2TB of metagenomic sequencing—4-fold

more sequencing depth than any other soil metagenome in this study and 40-fold more than the

Joint Genome Institute (JGI) recommended sequencing depth for soil samples (45 GB). When

considering cumulative unique attributes versus sequencing depth (Fig. S2), relationships in

vOTUs and viral clusters displayed slight curvature, while viral Pfams neared saturation.

Microbial Hosts of Soil Viruses.

We connected 1,450 viruses to putative hosts of 82 different bacterial and archaeal orders

with CRISPR spacers. This equates to 2.78% of QA/QC-ed viral contigs that were associated

with CRISPR spacer hits; roughly 70% more host assignments than in another recent

assessment[4,36]. While we observed a maximum of 73 vOTUs per host (i.e., CRISPR spacer), the

mean overall vOTU per host ratio was 0.42 (median = 0), reflecting the predominance of unique

host associations for individual vOTUs.

Out of 1,223 samples with at least one vOTUs assigned to a host, only 72 samples had an

average of more than one host sequence per vOTU, underscoring the low abundance of detected

hosts across all soils. An average of 0.64 unique host orders were detected per sample, with a

maximum ratio of CRISPR spacer hits to viral sequences of 73. Further, samples with a high

ratio of vOTU:host almost exclusively were matched to host sequences from a single microbial

order, reflecting high phylogenetic conservation of host associations. Of the 10 samples with the

highest CRISPR spacer sequence to viral sequence ratio, only 1 contained a CRISPR spacer

matching more than one microbial order.

The most prevalent host taxa were distributed across distantly-related phyla, including

members of prominent soil orders such as Pseudomonadales, Burkholderiales, Acidobacteriales,

and Bacteroidales (Fig. 3b). The frequency of CRISPR hits associated with Acidobacteriales,

Oscillospirales, Pedosphaerales, and Geobacterales were positively correlated to soil nitrogen,

organic carbon, and CEC; while Enterobacterales, Obscuribacterales, Mycobacteriales,

Pseudomonadales, and Streptomycetales were positively correlated to soil bulk density, and to a

lesser extent, pH and clay.

Metabolic potential encoded by the soil virosphere.

Because viral gene annotations were sparsely distributed across many functions, we

screened all viral genes (regardless of assignment by the AMG pipeline) against KEGG

pathways to understand relationships among genes in the context of known metabolic processes.

Across the entire soil virosphere, we uncovered portions of KEGG pathways that were mostly

complete, including functions involved in amino acid and sugar metabolism and biosynthesis,

antibacterial mechanisms, nucleotide synthesis, and other viral functions (e.g., infection

strategies, Supplemental Material and Fig. 4). Of note, we found nearly complete portions of

energy-generating pathways including the pentose phosphate pathways and F-type ATPase-

mediated portions of photosynthesis. Lipopolysaccharide pathway-related genes (LPS) that may

be important as host receptors for bacteriophage and prevention of superinfection were also

prevelant[37,38].

DISCUSSION

Global Soil Virus (GSV) Atlas.

The GSV Atlas demonstrates the immense, unexplored taxonomic and functional

diversity of the soil virosphere. Viral diversity in the GSV Atlas appeared to be largely distinct

from other global habitats. Nearly 80% of GVS Atlas sequences that clustered with existing

sequences in IMG/VR were attributed to soil or soil-like habitats [i.e. 'other terrestrial' or 'plant-

associated' (rhizosphere)], underscoring the unique composition of the soil virosphere relative to

more well-studied marine and human environments. Additionally, few shared vOTUs and viral

clusters between samples may indicate high spatial turnover (i.e., changes in soil virosphere

composition through space). Recent studies have estimated soil viral diversity is high both

relative to other viral habitats and relative to soil microbial diversity[7,8,10,22]. However, these

estimates have been limited by copious viral and microbial 'dark matter' for which no functional

or taxonomic assignment is known[14,23,32]. Towards this end, the diversity encompassed by the

GSV Atlas can serve as a community resource for characterizing this unknown fraction of the

soil virosphere.

Analysis of the GSV Atlas suggests that extreme spatial heterogeneity may be a key

feature of the soil virosphere at the global scale. While rapid viral spatial turnover was recently

observed across short spatial scales (<10-20m)[8,10], there has been no such demonstration of viral

biogeography across the world. We propose that high rates of spatial turnover could result from

low dispersal rates or distinct temporal dynamics of viral communities relative to other

organisms. For example, while dormant microorganisms and relic DNA can persist for months or

more[39–41], the burst of viral cells associated with active infections may generate short-lived

pulses of distinct viral communities that do not contribute to relic DNA due to their

comparatively small genome sizes versus microorganisms. Additionally, the apparent

discrepancies between microbial and viral dispersal processes could be due to the presence of

free viruses that are not actively involved in microbial infection[14], smaller viral genomes that

could facilitate physical protection, differences in traits that facilitate dispersal between viruses

and microorganisms, variation in bioinformatic pipelines, and/or other ecological differences

between viruses and microorganisms.

Together, these factors make characterizing the soil virosphere an immense challenge for

the coming decade. When examining individual soil samples, the number of new and unique

viral attributes (e.g., vOTUs, clusters, Pfams) was linearly related to sequencing depth,

suggesting that new viral discoveries are likely to continue with increasingly deep sequencing

(Fig. S1). This contrasts with rarefaction curves of the soil microbiome and of microbial hosts of

soil viruses, which both asymptoted well before sequencing depths of typical soil microbial

investigations. Still, when looking at the cumulative number of unique viral attributes detected in

all samples collectively (Fig. S2), many viral attributes began to saturate with sequencing depth.

This suggests that while individual samples do not capture soil viral diversity, we can begin to

constrain the extent of diversity when sequences from thousands of existing samples are

aggregated.

Assembling the GSV Atlas enables us to begin to describe the enormous functional

diversity in the soil virosphere. After filtering viral genes to putative AMGs (see methods), some

KEGG pathways represented by the most putative AMGs were associated with major soil carbon

cycling processes (map00052, Galactose metabolism; map00500, Starch and sucrose

metabolism). Likewise, at the level of gene annotations, the most common putative AMGs

suggested a role for viruses in soil carbon cycles. Glycosyltransferases 4 (GT4) and

glycosylhydrolases 73 (GH73) encode enzymes involved in the metabolism and/or production of

sugars common to soils including sucrose, mannose, glucosamine, and maltose[42,43]; and

Carbohydrate Binding Module 50 (CBM50) has been previously linked to chitin – one of the

most abundant carbon molecules in soil[44].

Collectively, these genes encode the decomposition of chemically complex organic

material for microbial energy generation and growth. Our results are consistent with previous

work from single locations that have hinted at a wide range of possible soil viral AMGs,

including glycoside hydrolases, carbohydrate esterases, and carbohydrate-binding modules[15,23,31].

Given that a large proportion of soil microorganisms are infected by viruses at any given time[45],

AMGs encoded by soil viruses have the potential to impact global biogeochemical

cycles[15,22,23,31]. The thousands of putative AMGs identified here represent the most extensive

survey to date and further impress the importance of the soil virosphere as a reservoir for

biogeochemical potential.

Microbial Hosts of Soil Viruses.

Unraveling relationships between viruses and their host communities is imperative to

understanding the impact of the virosphere on soil processes. Host presence should be tightly

coupled to viral abundance, and in turn, these linkages are mediated by spatial, temporal, and

environmental factors[15,46,47]. These linkages are also dependent on viral host range (i.e., host

specificity) — higher host specificity should lead to stronger coupling between microbial and

viral abundance and community composition. Viral host specificity is also associated with

ecological factors that impact microbial community composition and may result in tradeoffs

between viral growth and the breadth of the host range[11,48–50]. These dynamics are unresolved in

soils, leading to open questions regarding associations between viral host specificity and

microbial community functions.

Our analysis of the GSV Atlas indicates that limited host infection range may be a

dominant trait across soil viruses. Across the GSV Atlas, there were few hosts per vOTU on

average (mean = 0.42), and of vOTUs associated with multiple host sequences, the vast majority

were linked to multiple hosts of the same phylogenetic clade. While high host specificity has

historically been the prevailing paradigm, our work contrasts recent studies suggesting that some

soil viruses may have broader host ranges than viruses in other habitats[51,52].

As a whole, we identified taxonomically diverse soil microorganisms as viral hosts (Fig.

3). Host sequences spanned nearly every major soil microbial clade, supporting recent studies

that detected soil viral hosts classified as Acidobacteria, Verrucomicrobia, Deltaproteobacteria,

and Gammaproteobacteria[22,23,31]. The ultimate impact of viral predation on soil functions is at

least partially associated with the taxonomic distribution of hosts—viral impacts may be larger

when the hosts contribute to key ecosystem functions. The taxonomic breadth of the microbial

hosts of soil viruses also suggests a role for the soil virosphere in most soil habitats on Earth, as

the microbial hosts found here occupy a wide range of ecological niches. Moreover, some hosts

were susceptible to changes in the environment, underscoring the role that soil heterogeneity

may play both in viral diversity and in shaping viral-host dynamics.

Relationships between environmental factors and host taxa may reflect environmental

filtering on host communities (which in turn, determine the amount and type of viruses present)

or on viruses directly which subsequently impacts host community composition[15,27,53,54]. Viral

infections have been previously linked to soil parameters including moisture[12,30] and carbon and

nitrogen content[9]. In our analysis, bulk density may serve as a proxy for hydrologic connectivity

in the soil matrix. For example, low hydrologic connectivity may create 'spatial refuges' for soil

bacteria from viral infections[8], influence the virus-host encounter rates, and thus structure the

soil virosphere and its hosts. Nutrient amendments are also considered to be drivers of the soil

virosphere, supporting the relationship we observed between carbon, nitrogen, and host taxa.

Metabolic Potential Encoded by the Soil Virosphere.

We detected many hallmarks of viral activity in the soil virosphere, including genes

associated with cell lysis, DNA repair/replication, and other infection signatures. For instance,

across the entire soil virosphere, genes associated with DNA mismatch repair (map03430),

homologous recombination (map03440), and base excision repair (map03410) were prevalent

(Fig. S3). Folate biosynthesis was also common in the soil virosphere. Folate and other B

vitamins are key to bacterial growth (map00670, map00790, Fig. 4)[55] and therefore may be

logical targets for pathogens[56]. Bacterial secretion systems (map03070, Fig. S4), which may be

evolutionarily derived from phages[57], were also found in many soil viruses. Type IV secretion

systems in particular can be used by bacteria to secrete toxins[58] or as a method for DNA transfer

through membranes[59]. Finally, the *Caulobacter* cell cycle (map04112, Fig. S5), which has a

distinct division pattern[60], was rife across soils and may be a promising indicator of viral

infections. The prevalence of viral genes associated with central microbial functions highlights

the potential importance of viral activity in soils and the need for targeted approaches to quantify

the extent and impact of viral gene expression.

The GSV Altas also contains many viral amino acid biosynthesis/degradation pathways

that could be critical in viral life cycles(e.g., map00250, map00260, map00270, map00330,

map00340, Fig. S6). Amino acids are building blocks for cellular material and also support soil

biogeochemical cycles, as they can enhance carbon cycling through priming effects and/or

enhanced nutrient availability[61,62] (e.g., map00500, map00052, map00051, Fig. 4). Collectively,

these pathways demonstrate several possibilities for soil viral impacts on processes that are

central to microbial metabolism and biogeochemical cycling of elements in soil.

Beyond these pathways, we highlight three KEGG pathways with near-complete portions

represented in the GVS Atlas: F-type ATPase (map00190), pentose phosphate pathway

(map00030), and LPS (map00540). Five of seven subcomponents of the F-type ATPase were

detected in the soil virosphere, while no V- or A-type ATPases were found. Given the

evolutionary similarities between V- and F-type ATPase in particular[63], the lack of any V- or A-

type ATPase components is notable in light of the near complete F-type ATPase. Though there is

some basis for F-type ATPases in viral replication[64], we also note the possible involvement of F-

type ATPase in photosynthetic energy generation[65]. Given the prominence of photosynthetic

marine AMGs[26,66], we highlight the possibility of a viral F-type ATPase as a soil AMG. The

pentose phosphate pathway is also a prevalent and important AMG found in marine ecosystems,

where viral infection diverts carbon towards the pentose phosphate pathway as an 'express route'

of energy generation, at the expense of host carbon metabolism (reviewed in [66]). Finally, we

observed nearly complete LPS pathways in the GSV Atlas. Phages often carry depolymerases

and other enzymes that target LPS or similar outer membrane components to facilitate binding

and entry[37]. However, the representation of the LPS synthesis pathway by putative soil AMGs

indicates that phage may work to change the function of the pathway post-infection, potentially

to prevent superinfection[38]. Collectively, we propose that F-type ATPase, pentose phosphate

pathway, and LPS may be interesting pathways for more targeted investigations into the role of

the virosphere in soil microbiome function.

Future Recommendations.

The field of soil viral ecology is poised for rapid expansion; yet several challenges

remain in fully characterizing soil viral diversity and function. Overcoming these methodological

and ecological hurdles will require broad participation from global researchers. Below, we

present a summary of issues, from our perspective, facing the current generation of soil viral

ecologists and suggestions for surmounting them.

First, we propose methodological investments to improve viral detection and resolve

genomic 'dark matter'. Metagenomic sequencing enables the detection of thousands of viruses

per soil sample, yet the number of viruses detected in soil metagenomes has remained relatively

flat over time[4]. In part, this is because soil metagenomics from shotgun sequencing is highly

fragmented, leading to lower quality UViGs[67,68]. Identifying novel viral sequences and assigning

viruses to microbial hosts are also limited by the extent of our knowledge of viral diversity; thus

expansion of the known virosphere is needed. Technical advances may improve soil virus

identification and host-linkage predictions from shotgun metagenomics, long read sequencing,

and/or targeted sequencing approaches. Promising new methods include experimental

verification of viral activity[29], size fractionation ('viromics')[7,8,15], viral isolation[69], optimized

viral nucleic acid extraction[70], microscopy[29], combined metagenomic assembly[4], and long-read

and/or single-cell sequencing[71,72].

Knowledge about soil viral diversity and function is also limited by gaps in field and

laboratory experiments. The GSV Atlas demonstrates that extensive, spatially-explicit sampling

is needed to capture the high spatial turnover of the soil virosphere. The spatial coverage of most

'global' ecological studies, including this one, often suffers from large data gaps[73]. Concerted

efforts are needed to sample wide spatial domains, including historically undersampled regions,

given the high viral diversity uncovered by the GSV Atlas. Expansion of the known virosphere

in this way will also help to facilitate tool development. Although we did not assess temporal

dynamics, temporally-explicit approaches are likewise needed to characterize temporal dynamics

in soil viral communities. Further, our functional annotation of viral contigs revealed diverse

genes associated with functions relevant to both viral and microbial communities, and it is

impossible to know the true functions of viral genes without targeted functional assays. We

therefore propose that experiments targeting the expression and auxiliary metabolic function of

viral genes are needed to properly assess AMGs in viral communities.

Finally, we still know relatively little about the ecological drivers of soil virus

distribution or how to represent these mechanisms in process-based models. Extreme soil

virosphere diversity renders some common microbial ecology statistical methods unfeasible,

including those often used to test ecological principles (e.g., ordinations, distance-decay,

richness, etc.). This highlights the need for innovative statistical approaches to interpret the soil

virosphere and to develop new theories surrounding their ecological roles. These advances can

help aid development of process-based models, which have made tremendous improvements in

representing soil carbon cycles but are missing dynamics involving the soil virosphere.

Conclusions.

The GSV Atlas is a new public resource that can help generate hypotheses and provide

insight into some of the most pressing challenges in soil viral ecology. We uncovered 616,935

UViGs from global soil samples to show the extreme diversity, spatial turnover, and functional

potential of the soil virosphere. This includes a wide taxonomic array of microbial hosts of soil

viruses, key functions associated with soil carbon cycles, and an assortment of viral metabolisms

that may be critical to deciphering viral ecological principles in the soil ecosystem. We

specifically highlight F-type ATPase, the pentose phosphate pathway, and LPS-related genes, as

well as enzymes involved in carbohydrate metabolism, as fruitful areas for further investigation.

Our work scratches the surface of the soil virosphere and serves as a basis for tool, theory, and

model development to further advance soil ecology, biogeochemistry, ecology, and evolution.

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Acknowledgements. This work was supported by the U.S. Department of Energy (DOE), Office of Biological and Environmental Research (BER) as part of BER's Genomic Sciences Program (GSP) under FWP 70880. A portion of this work was conducted by the U.S. Department of Energy Joint Genome Institute (https://ror.org/04xm1d337), a DOE Office of Science User Facility, is supported by the Office of Science of the U.S. Department of Energy operated under Contract No. DE-AC02-05CH11231. We thank Young Song for his help in data visualization.

Author Contributions. EBG, RW, JKJ, DPE, NCK, and JEM conceived of this project. EBG, RW, APC, RYN, MN, and AC conducted data analysis. EBG, RW, APC, RYB, NCK, JKJ, KSH, and JEM contributed to manuscript drafting and revisions. The Soil Virosphere Consortium contributed metagenomic data and reviewed the manuscript.

Competing interests. The authors declare no competing interests

FIGURES

Fig. 1. Data collection and workflow. a, Global distribution of samples, scaled by assembled

base pairs. In order horizontally, histograms of (**b**) mean soil bulk density (kg/dm³), cation

exchange capacity (cmol(c)/kg), clay content (%), total nitrogen content (g/kg), pH, and soil

organic carbon (g/kg) associated with our samples from the SoilGrids250 database (0-5 cm). **c,**

Sequence processing pipeline.

Fig. 2. Data description. a, shows the count of each category across the full dataset. **b**, shows

the proportion of samples obtained from IMG/VR versus the number of new samples contributed

(upper left). Within new samples, we identified 3,613 vOTUs of which 317 clustered with

sequences already in IMG/VR (middle). Sequences in IMG/VR that clustered with vOTUs

containing new sequences were mostly associated with soil habitats (lower left). **c-d,** relative

abundance of putative AMGs grouped by KEGG pathway **(c)** and by annotation **(d)**.

Fig. 3. Relationships between soil viruses and their hosts. a, Cumulative Distribution

Function plot showing the ratio of CRISPR spacer hits to viral sequences per sample. Inset

shows a zoomed portion of the plot from 0 to 0.08 along the y-axis. **b,** Phylogenetic tree of

bacterial hosts at the order level. Phylum taxonomy is shown in the inner circle and the

abundance of CRISPR spacer hits to each order is shown in the outer circle. Two archaeal orders

(Nitrososphaerales and Halobacteriales) of hosts are not shown. **c**, Correlation between

frequency of CRISPR hits (defined as total CRISPR spacer hits per microbial order) and

environmental parameters from SoilGrids250m. Color denotes Spearman rho. For inclusion in

the heatmap, host order must be present in more than 5 samples.

Fig. 4. Metabolic potential encoded by the soil virosphere. A cellular diagram depicting

portions of the F-type ATPase (map00190), lipopolysaccharide pathway (map00540), pentose

phosphate pathway (map00030), and vitamin B- and amino acid-related KEGG pathways in the

soil virosphere. Genes detected in the soil virosphere are colored according to pathway type.

Undetected genes and associated metabolites (unmeasured) are grayed out. Arrow width deontes

gene abundance.

METHODS

Data Collection and Curation.

We collected a total of 2,953 soil metagenomic samples from soils from major

repositories and ecological networks including the JGI Integrated Microbial Genomes and

Microbiomes (IMG/M) platform, MG-RAST metagenomics analysis server, Global Urban Soil

Ecological Education Network (GLUSEEN), Earth Microbiome Project (EMP), and National

Ecological Observatory Network (NEON) plus submissions from individual collaborators. This

included 1,552 samples not previously included in IMG/M (Fig. 1 and 2).

For samples collected via JGI IMG/M, we retrieved all studies with GOLD[74] ecosystem

type of "Soil" as of August 2020. We manually curated metagenomic sequences to remove

misclassified data as follows. We removed samples from studies with the following: (1) GOLD

ecosystem types: Rock-dwelling, Deep subsurface, Plant litter, Geologic, Oil reservoir, Volcanic,

and Contaminated; (2) GOLD ecosystem subtypes: Wetlands, Aquifer, Tar, Sediment, Fracking

Water, and Soil crust; (4) words in title: wetland, sediment, acid mine, cave wall surface, mine

tailings, rock biofilm, beach sand, Petroleum, Stalagmite, Subsurface hydrocarbon microbial

communities, Vadose zone, mud volcano, Fumarolic, enriched, Composted filter cake, Ice

psychrophilic, oil sands, groundwater, Contaminated, rock biofilm, Deep mine, coal mine fire,

Hydrocarbon resource environments, Marine, enrichment, groundwater, mangrove, saline desert,

Hydroxyproline, Rifle, coastal, compost, biocrust, crust, Creosote, soil warming, Testing DNA

extraction, and/or Agave; (5) GOLD geographic location of wetland; and (6) GOLD project type

of Metagenome - Cell Enrichment. Additionally, sample names that indicated experimental

manipulation (e.g., CO_2 enrichment or nitrogen fertilization) or were located in permafrost layers

were manually excluded. This resulted in 1,480 curated metagenomes from publicly available

data in IMG/M.

After collating samples from JGI IMG/M and the newly collected samples from external

networks and collaborators, the final dataset consisted of 2,953 soils with 2,015,688,128 contigs,

representing 1.2 terabases of assembled DNA sequences.

In parallel, we retrieved mean values for soil parameters from the SoilGrids250m

database from 0-5 cm[33]. SoilGrids250m is a spatial interpolation of global soil parameters using

~150,000 soil samples and 158 remote sensing-based products. Here, we focus on six

parameters often associated with soil microbial communities: bulk density, cation exchange

capacity, nitrogen, pH, soil organic carbon, and clay content. Because our focus on spatial

dynamics and soils were collected at various times, we did not include temporally dynamic

variables such as soil moisture or temperature in our set of environmental parameters, though we

acknowledge they may have profound impacts on the soil virosphere.

Assembly and Annotation of Samples added to IMG/M.

To standardize data analysis across all samples, the 1,552 soil metagenomic samples not

collected from IMG/M were analyzed using the JGI's Metagenome Workflow [75]. In brief,

samples were individually assembled using MetaSpades v. 3.1. 1,476 of the 1,552 assembled soil

samples passed default quality control thresholds[76], yielding 133 gigabases of assembled DNA in

241,465,924 contigs. Additionally, three very large metagenomes (>1TB each) were assembled

separately due to computational limitations in standard workflows[77]. The resulting assemblies

were assigned GOLD identification numbers and imported into IMG/M and processed using

version 5.0.0 of the IMG/M Metagenome Annotation Pipeline to align with data obtained

directly from IMG/M[75].

Virus identification, clustering, and host prediction.

We performed an initial identification of viral contigs using using a modified version of

the IMG/VR v3's virus identification pipeline (code available at

https://github.com/snayfach/MGV/tree/master/viral_detection_pipeline)[35,36]. The pipeline

identifies viruses based on the presence of 23,841 virus protein families, 16,260 protein families

of microbial origin from the Pfam database[78] and VirFinder[79] to identify putative viral genomes

in contigs that were at least 1 kb long. During the course of this study, geNomad (version

1.3.3)[80], a tool for virus identification with improved classification performance was released and

incorporated into our pipeline to improve prediction confidence and perform taxonomic

assignment. We further processed predicted viral sequences using CheckV v1.0.1 (database

version 1.5)[81] to assess the quality of the viral genomes. As this study focused on non-integrated

virus genomes, contigs that were flagged by either geNomad or CheckV as proviral were

discarded. From the remaining contigs, virus genomes were selected using the following rules:

(1) contigs of at least 1kb with high similarity to genomes in the CheckV database (that is, that

had high- or medium-quality completeness estimates) or that contained direct terminal repeats

were automatically selected; (2) contigs longer than 10kb were required to have a geNomad virus

score higher than 0.8 and to either encode one virus hallmark (e.g., terminase, capsid proteins,

portal protein, etc.), as determined by geNomad, or to have a geNomad virus marker of at least

5.0; (3) contigs shorter than 10 kb and longer than 5 kb were required to have a geNomad virus

score higher than 0.9, to encode at least one virus hallmark, and to have a virus marker

enrichment higher than 2.0. This resulted in 49,649 viral contigs that we used for downstream

analysis. All viral contigs are available at: https://doi.org/10.25584/2229733.

Viral genomes were clustered into viral operational taxonomic units (vOTUs) following

MIUViG guidelines (95% average nucleotide identity, ANI; 85% aligned fraction[34]). In brief, we

performed an all-versus-all BLAST (version 2.13.0+, '-task megablast -evalue 1e-5 -

max_target_seqs 20000') search to estimate pairwise ANIs and AFs, as described in Nayfach et

al.[81] and employed pyLeiden (available at: https://github.com/apcamargo/pyleiden) to cluster

genomes, using as input a graph where pairs of genomes that satisfied the MIUViG criteria were

connected by edges. Viruses were also grouped at approximate genus-level (40% AAI —

average amino acid identity; 20% shared genes) and family-level (20% AAI; 10% shared genes)

clusters using DIAMOND[82] for protein alignment and Markov Cluster Process (MCL)[83] for

clustering[35].

Viral sequences were assigned to putative host (bacterial and archaeal) taxa through

matches to a previously described database of CRISPR spacers of 1.6 million bacterial and

archaeal genomes from NCBI GenBank and MAGs (release 242; 15 February 2021)[84–88].

Sequences of viral genomes were queried against the spacer database

(https://portal.nersc.gov/cfs/m342/crisprDB) using blastn (v2.9.0+, parameters: '–

max_target_seqs = 1000 –word_size = 8 –dust = no'). Only alignments

with at least 25 bp, less than 2 mismatches, and that covered ≥95% of

the spacer length were considered. Viral sequences were assigned to

the host taxon at the lowest taxonomic rank that had at least two

spacers matched and that represented >70% of all matches.

Potential Auxiliary Metabolic Gene (AMG) Prediction.

We leveraged an intermediate output of geNomad (version 1.3.3)[80] ('genes.tsv') to screen

putative AMGs on the detected viral contigs. Proteins of the viral contigs were annotated by

virus and host-specific markers implemented in geNomad. The identified viral hallmark (e.g.,

terminase, major capsid protein) and non-hallmark proteins were labeled as 'VV-1' and 'V*-0'

in geNomad output, respectively. The rest of the viral proteins of the detected viral contigs that

were annotated as non-virus-specific or unclassified were then classified into five categories of

putative AMGs based on the presence of viral hallmark or non-hallmarks up- or down-stream as

mentioned previously[30]. The AMGs with both virus-specific genes ('VV-1' or 'V*-0') were

retained for the following analysis. To improve the functional annotations of the putative AMGs

and highlight the viral potentials of metabolizing carbohydrates and glycoconjugates, the AMG

proteins were also annotated by Carbohydrate-Active enZYmes (CAZY) Database and Kyoto

Encyclopedia of Genes and Genomes (KEGG) database using the default settings in addition to

the functional annotation databases implemented in geNomad. The putative AMG was assigned

to the functional annotation with the highest bitscore (e.g,. duplicate annotations were not

allowed). Following Hurwitz and U'Ren[66] and Hurwitz et al[89], we further screened putative

AMGs to remove genes not found in KEGG pathways. Additionally, in recognition of the

ambiguity in distinguishing genes encoding auxiliary metabolic functions versus core metabolic

processes[66], we discuss the resulting set of genes presented here as 'putative AMGs'.

Statistical Analysis.

All statistical analyses and data visualizations were performed using *R* v 4.1.0[90]. We used

the following packages for data manipulation and visualization: ggplot2[91], reshape2[92],

pheatmap[93], Hmisc[94], ggpubr[95], RColorBrewer[96], maps[97], stats[98] geosphere[99], plyr[100], dplyr[101],

and stringr[102]. Packages pertaining to specific analyses are listed below.

We generated rarefaction curves for individual samples and for cumulative sequencing

depth (Fig. S1 and S2) using the 'phyloseq' package [103] and custom R plots, respectively.

Samples containing less than five vOTUs, viral clusters, or viral Pfams; or less than 100

CRISPR-spacer-based host taxon, microbial Pfams, or microbial taxa were removed for visual

clarity. Removed samples followed the same general trends as presented in Fig. S1. To visualize

saturation across cumulative sequencing depth (Fig. S2), we ordered samples from lowest to

highest total assembled bp and progressively added them along the x-axis. On the y-axis, we plot

the associated cumulative number of unique attributes.

A phylogenetic tree of CRISPR-spaced-based host taxon was generated at the order-level

using phyloT v2[104], an online tree generator based on the Genome Taxonomy Database. Then,

we visualized the tree in R using the packages 'ggtree'[105], 'treeio'[106], and 'ggnewscale'[107]. To

examine relationships between common microbial hosts of soil viruses and soil properties, we

first downloaded data describing bulk density, cation exchange capacity, nitrogen, pH, soil

organic carbon, and clay content from the SoilGrids250m database[33] using the 'soilDB'

package[108]. Mean values of soil properties from 0-5 cm were correlated to the total number of

CRISPR spacer hits per microbial ordered using Spearman correlation.

Finally, we mapped genes detected across the entire soil virosphere (i.e., all samples

combined) to their corresponding KEGG pathways using the 'pathview' package in R[109]. Gene

abundances were converted by log base 10 for visualization.

DATA AVAILABILITY.

The GSV Atlas is available for download at: https://doi.org/10.25584/2229733. It includes all

UViGs regardless of quality (File 1, 616,935 UViGs), a file containing data associated with each

contig that passed QA/QC (File 2, 49,649 contigs), predicted viral protein sequences (File 3,

402,882 predicted protein sequences), a file containing data associated with each gene (File 4,

1,432,147 genes), geographic and physicochemical data of the curated soil samples (File 5, 2,953

samples), and a readme file (File 6).

CODE AVAILABILITY. Code for sequence processing is described in Nayafch et al.[35] and is

available in the materials associated with those publications. All other code is available upon

request.

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a

b

Bulk Density (kg/dm³)

Cation Exchange Capacity (cmol C/kg)

Clay Content (%)

Total N (g/kg)

pH

SOC (g/kg)

3.59 × 10^4
1.22 × 10^10
2.74 × 10^10
6.99 × 10^10
1.48 × 10^11

c

Global Soil Virus Atlas

NEON
EMP
GLUSEEN
JGI-IMG
Individuals
MG-RAST

IMG

viral sequence detection

MGV detection
geNOMAD
checkV

Phage (vOTU) clustering

Functional Annotation
Pfam   CAZY
KEGG   geNOMAD markers

Host Assignment

Putative Auxiliary Metabolic Gene Identification