Using genomes and evolutionary analyses to screen for host-specificity and arms-race

dynamics in the plant pathogen *Xylella fastidiosa*

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ABSTRACT

Xylella fastidiosa infects several economically important crops in the Americas, and it

also recently emerged in Europe. It is not clear, however, whether *X. fastidiosa* isolates display

specialization to plant hosts and, if so, what genetic determinants underlie the associations. Here,

using a set of *Xylella* genomes reflective of the genus-wide diversity, we performed a pan-

genome analysis based on both core and accessory genes. We first investigated evolutionary

relationships among isolates, recapitulating the three recognized *X. fastidiosa* subspecies based

on information from both core and accessory genes. We used these phylogenies as the basis to

test associations between genetic divergence and host species, yielding significant evidence for

specialization of *X. fastidiosa* to plant host species for core, but not accessory, genes. This

observation places constraint on the hypothesis that host specificity is conferred by shifts in

accessory gene content. We also analyzed the ratio of nonsynonymous to synonymous

substitutions in both core and accessory genes to identify positively selected genes that are

potentially involved in arms-race dynamics. Arms-race genes may contribute to interactions with

the plant hosts or insect vectors, and they are thus candidates to act as virulence or pathogenicity

factors. We uncovered evidence of positive selection across codons of 19.5% (200 of 1,205) core

genes and 7.7% (181 of 2,349) accessory genes. Most of these genes had unknown functions, but

we identified some tractable candidates including *nagZ_2*, which encodes a beta-glucosidase that

is important for biofilm formation *Neisseria gonorrhoeae*, and *cya*, which modulates gene

expression in pathogenic bacteria.

INTRODUCTION

Bacteria exhibit extensive intraspecific variation in genome content. This variation is the raw material for evolutionary adaptation, including the evolution of pathogenicity and virulence (Furuya and Lowy 2006; Yacoubi et al. 2007; Juhas 2015; Chen et al. 2018). One example of genome variation comes from an early study of *Escherichia coli* that compared two pathogenic strains and one non-pathogenic laboratory strain (Welch et al. 2002). Of the entire set of protein coding genes annotated by the three genomes, only 39.2% were shared among the three isolates. Intriguingly, the two pathogenic strains each had 1,300 unique genes, while the laboratory strain had only 585, suggesting that genes that vary across accessions (i.e., accessory genes) contribute to virulence. Similar patterns have been illustrated for plant pathogens (Badet and Croll 2020; Kim et al. 2020). In *Xanthomonas*, for example, horizontal gene transfer (HGT) has shuffled virulent accessory genes from pathogenic strains to previously non-pathogenic strains (Chen et al. 2018), facilitating the infection of common bean (*Phaseolus vulgaris* L.). In short, accessory genes contribute to host-pathogen interactions, making them a critical focus for comparative analyses of genome evolution and function.

Here we investigate variation in the genome content of another plant pathogen. *Xylella fastidiosa* is endemic to the Americas and was first identified as the causal agent of Pierce's Disease (PD), an economically devastating disease in grapevines (*Vitis vinifera* ssp. *vinifera*) (Sicard et al. 2018; Burbank and Roper 2021). *X fastidiosa* causes additional economically and ecologically impactful diseases like citrus variegated chlorosis, coffee leaf scorch, oak leaf scorch and elm leaf scorch among others. Historically, the geographic distribution of *X. fastidiosa* was limited to the Americas, but it has recently been introduced to the European continent by anthropogenic transmission, which has further expanded its host range and led to

emerging diseases like olive quick decline syndrome (OQDS) in Italy (Schuenzel et al. 2005;

Loconsole et al. 2016). Since its detection in Italy, many olive trees have succumbed to OQDS

and *X. fastidiosa* has been detected in various plants species in Europe including France, Spain,

and Portugal (Chatterjee et al. 2008; Rapicavoli et al. 2018). In susceptible hosts, *X. fastidiosa*

can often be lethal, leading to significant crop losses, and it continues to threaten crops globally,

which has been further compounded by its recent spread in Europe (Tumber et al. 2014; Alston

et al. 2015).

For each of these diseases, *X. fastidiosa* is transmitted by xylem-feeding insect vectors to

the plant host, where it then utilizes cell wall degrading enzymes to systemically colonize the

xylem. In the xylem, it forms biofilms that are thought to be integral to virulence (Koo et al.

2017; Castro et al. 2021). Colonization is also governed, in part, by virulence and pathogenicity

factors that influence a wide range of bacterial functions – e.g., biofilm formation, host cell wall

degradation, regulatory systems, stress responses and bacterial membrane composition --

although other abiotic factors (like plant drought stress) likely also contribute to disease

progression (Rapicavoli et al. 2018). Given its economic impact, the effects and mechanisms of

X. fastidiosa infection have been studied widely, especially in grapevine (Roper and Lindow

2016). However, many pathogenicity factors likely remain undiscovered, and crucial questions

remain unanswered about the genetic factors that govern host-pathogen interactions and potential

host specialization (Rapicavoli et al. 2018).

In this context, it is helpful to recognize that *X. fastidiosa* consists of three commonly

recognized subspecies that form distinct phylogenetic clades: ssp. *fastidiosa*, *multiplex*, and

pauca. Each subspecies has unique phenotypic characteristics and DNA markers (Marcelletti and

Scortichini 2016). Two other subspecies, *morus* and *sandyi*, have also been suggested, though

they are not recognized as broadly (Burbank and Roper 2021); indeed, *morus* is believed to be a

product of a recombination event between *fastidiosa* and *multiplex* isolates (Sicard et al. 2018).

The recognition of subspecies is critical, because they loosely correlate with specific plant hosts

(Nunney et al. 2013). For example, cross-inoculation experiments have shown some almond

isolates cannot cause disease in grapes, a mulberry isolate does not cause disease in grapes and

that strains infecting citrus plants do not cause disease in coffee plants (and *vice versa*). These

observations suggest that genetic differences among strains can facilitate host-plant

specialization (Almeida and Purcell 2003; Hernandez-Martinez et al. 2006; Almeida et al. 2008;

Roper and Lindow 2016). However, there is not a clear one-to-one correspondence between

pathogen and host, because some strains can infect more than one host species, as demonstrated

by a strain that causes PD in grapevines and also leaf scorch in almonds (Almeida and Purcell

2003).

In this study, we analyze *X. fastidiosa* genome evolution among isolates from different

plant hosts. Our study is not unique in some respects, because numerous comparative genomic

studies of *X. fastidiosa* have been published already. Most of these studies have focused on

clarifying phylogenetic relationships. For example, Marcelletti and Scortichini (2016) studied 21

genomes to resolve taxonomic relationships among subspecies; Giampetruzzi et al. 2017

extended sampling to 27 genomes, in part to place a novel strain (ST53) in the broader *X.*

fastidiosa phylogeny; and Denancé et al. (2019) used kmers from 46 genomes to untangle

species and subspecies relationships. Another recent study compared *X. fastidiosa* populations

from Central/South America (Costa Rica, Brazil), North America (California, Southeastern US),

Europe (Spain, Italy), and Asia (Taiwan) to elucidate the evolutionary origins of the subsp.

fastidiosa and *pauca* (Castillo et al. 2021). Still other studies have focused on populations. For

example, Vanhove et al. (2020) isolated and sequenced *X. fastidiosa* subsp. *fastidiosa* from

symptomatic grapevines from five different California locations (Vanhove et al. 2020). One

common theme of these studies is that they identified the set of genes that were present in all of

their samples (i.e., core genes) and used those genes as the basis to perform phylogenetic

inference. However, most of these studies ignored the evolutionary properties of accessory

genes.

Like previous work, our study begins by identifying the core and accessory genes across

genomes, but it differs from previous work in at least three ways. First, we have sequenced and

assembled 20 new *X. fastidiosa* genomes, which we combined with publicly available data to

build a dataset allows us to investigate patterns of host specificity in a phylogenetic context.

Second, we focus on information from accessory genes to assess their phylogenetic signals,

patterns of their gene gain and loss across the *Xylella* phylogeny, and the potential associations

of genetic divergence with host species. We focus on these features under the hypothesis that

host switching is associated with accelerated turnover of accessory genes. Finally, we perform

extensive analyses of the ratio of nonsynonymous to synonymous (dN/dS or ω) substitutions in

both core and accessory genes. We study ω because genes involved in arms-race (or Red-Queen)

dynamics between pathogens and hosts often have ω values > 1.0, indicating a history of positive

selection (Daugherty and Malik 2012; Aleru and Barber 2020). In other systems, these

approaches have identified molecular functions that contribute to host defense and identified

entirely new genes and pathways involved in pathogen-host interactions (Mitchell et al. 2012; Ng

et al. 2015; Daugherty et al. 2016). Here we apply tests of positive selection to test the

hypothesis that accessory genes are particularly prone to arms race dynamics. By doing so, we

also hope to gain insights into genes that act as virulence or pathogenicity factors.

METHODS

Novel *X. fastidiosa* genomes

Fully extracted DNA from 20 *X. fastidiosa* isolates were provided by the French

Collection of Plant-Associated Bacteria (CIRM-CFBP; http://www6.inra.fr/cirm_eng/CFBP-

Plant-Associated-Bacteria) and from the University of California, Riverside. Genomic DNA was

prepared for Illumina sequencing using the Illumina Nextera DNA Flex Library Prep kit,

following the manufacturer's recommendations and for Pacific Biosciences (PacBio) sequencing

with the SMRTbell Express Template Prep Kit 2.0. SMRTbell libraries had 10kb DNA target

insert size (Pacific BioSciences, Menlo Park, CA) using 360ng of sheared DNA as input. DNA

libraries were sequenced with both Illumina and PacBio technologies at the University of

California, Irvine Genomics High Throughput Facility (https://ghtf.biochem.uci.edu). The

Illumina sequencing reads were quality assessed using FastQC, and reads were trimmed using

Trimmomatic v. 0.32 (Andrews 2010; Bolger et al. 2014) using default options. PacBio

sequencing reads were corrected and trimmed using Canu v. 1.5 (Koren et al. 2017). The long

and short reads were used for genome assembly with Unicycler v. 0.4.8 in hybrid assembly mode

(Wick et al. 2017). Genome assembly statistics were calculated using Quast v. 5.0.2 (Gurevich et

al. 2013). As is common practice (Chase et al. 2018), short contigs (<500 bp) were removed

from the assemblies using Seqkit v. 0.13.2 (Shen et al. 2016).

Genome Assembly of public data and sample set curation

We complemented our set of novel genomes with publicly available data. To do so, we

downloaded all available whole genome assemblies of *X. fastidiosa* and *X. taiwanensis* (as an

outgroup) from the National Center for Biotechnology Information (NCBI) and Sequence Read

Archive (SRA) databases on July 9, 2020. In addition, we downloaded the raw, short-read

sequences for an additional 20 isolates (Castillo et al. 2020; Vanhove et al. 2020). For each

isolate, we gathered information about its geographic origin and its host plant from NCBI and

from the Pathosystems Resource Integration Center (PATRIC) database. To assemble the raw

reads from the 20 unassembled accessions into genomes, we assessed quality and trimmed the

reads and applied SPAdes v. 3.14.0 (Bankevich et al. 2012) with the *--careful* option, following

Vanhove et al. (2020). If long reads were also available, as they were for 5 isolates from the

work of Castillo et al. 2020, then whole genome assembly was performed with Unicycler v. 0.4.8

in hybrid assembly mode (Wick et al. 2017).

In total, we gathered and generated 148 *Xylella* genome assemblies. From this set, we

removed isolates that did not have information about their host isolation source or were lab-

derived recombinant strains. The remaining 129 genomes were re-annotated by the same method

- based on Prokka v. 1.14.6 analysis – that we applied to the new genomes, to ensure

homogeneity. The Prokka analyses were then input into Roary v. 3.13.0 with options *-i 80 -cd*

100 -e -n -z to obtain a core gene alignment for initial comparisons among isolates (Seemann

2014; Page et al. 2015); we defined core genes as those that were detectable in 100% of the

samples. This core set was aligned with MAFFT and polished using gBlocks v. 0.91b

(Castresana 2000; Katoh et al. 2002; Katoh and Standley 2013). The polished alignment was

used as input for RAxML v. 8.2.12 to build a preliminary phylogenetic tree (Stamatakis 2014),

which we used to evaluate and curate the isolates (Supplementary Figure 1).

To curate the dataset, we created a distance matrix from the RAxML phylogenetic tree,

using the Tree and reticulogram REConstruction (T-REX) server (Boc et al. 2012). Many of the

genomes – most of which were gathered for population genomic analyses - were sampled from

the same plant host and were nearly identical genetically. To limit sampling biases for our

species-wide study, we removed clones and near-clones based on the distance matrix. That is, if

two or more isolates had a pairwise distance ≤ 0.0001 and came from the same host, we retained

the isolate with the more contiguous assembly. After applying these filters, our final dataset

consisted of 63 *X. fastidiosa* genomes and one outgroup genome (*X. taiwanensis* PLS229) that

were isolated from 23 distinct plant host species (Supplementary Table 1).

Pan-genome analysis

To perform a pan-genome analysis, we applied Roary to the 64 *Xylella* genomes using *gff*

files from Prokka as input. Roary was applied with the options *-i 80 -cd 100 -e -z*; these options

lower blastp sequence identity to 80% from the default 95% and define a core gene as a gene

present in 100% of the isolates used in the analysis. From the Roary output, we extracted a

representative nucleotide sequence of each core and accessory gene using cdbfasta

(https://github.com/gpertea/cdbfasta) and translated the nucleotide sequence to amino acids using

the transeq command from EMBL-EBI (Madeira et al. 2019). The representative sequences were

the basis for functional categorization -- using the eggNOG-mapper v. 2 (Huerta-Cepas et al.

2017; Huerta-Cepas et al. 2019) -- of both core and accessory genes. Gene Ontology (GO)

enrichment analyses were performed online at (http://geneontology.org) using *Xanthomonas*

campestris as the reference list (Ashburner et al. 2000).

Phylogenetic Tree Construction and Hierarchical Clustering Analysis

We used the core gene alignment from Roary to build a phylogenetic tree. To do so, we

curated the core gene alignment with gBlocks v. 0.91b (Castresana 2000), used the polished

alignment as input for IQtree v. 2.0.3, and selected the best nucleotide model for phylogenetic

tree construction (Nguyen et al. 2015; Kalyaanamoorthy et al. 2017). We ultimately constructed

an unrooted tree using the GTR+F+R8 model with RAxML (Stamatakis 2014), using the 'best

tree' option. Phylogenetic trees were visualized and annotated using the ape package v. 5.5 in R

v. 4.0.2 (Paradis and Schliep 2019; R Core Team 2019). We used the most likely phylogeny to

test associations between phylogenetic relatedness, geography, and host isolation source (plant

taxonomic order information taken from https://www.itis.gov/) with ANOSIM implemented in

the *vegan* package v. 2.5-7 in R (Oksanen et al. 2020).

In addition to a phylogeny based on the core genes, we also built a phylogeny based on

the presence and absence matrix of accessory genes. We applied hierarchical clustering to the

presence-absence matrix using the *pvclust* package v. 2.2 in R with 1000 bootstrap replicates

(Suzuki and Shimodaira 2006). We also utilized the Mantel test (in the *vegan* package) to

measure the correlation between accessory gene content and phylogenetic relatedness. The

Mantel test required two distance matrices, which were generated from the core and accessory

trees by the reticulogram REConstruction (T-REX) server (Boc et al. 2012). We also performed

a DensiTree analysis to assess the overall species tree topology against the topology of individual

gene trees (Bouckaert 2010). Single gene trees were based on alignments from PRANK

(Löytynoja 2014). These core gene alignments were used as input for RAxML to construct gene

trees. DensiTree analyses was performed using the Phangorn package v. 2.5.5 in R (Schliep

2011).

Gain and Loss of Accessory Genes

We utilized GLOOME to investigate gene gain and loss dynamics along the core

phylogenetic tree of *X. fastidiosa* (Cohen et al. 2010). GLOOME uses a mixture-model

approach, coupled with maximum-likelihood inference, to infer rates of gain and loss of genes

along the branches of a phylogeny. It takes as input the phylogenetic topology, in this case the

phylogenetic topology based on core genes, and a presence-absence matrix of accessory genes.

The phyletic pattern of presence and absence was obtained through M1CR0B1AL1Z3R, as

recommended by the GLOOME authors, and then directly input into GLOOME using default

settings (Avram et al. 2019). The default settings included a fixed rate of gene gains and losses

with gamma distributed rates across genes (or sites). Among the output, GLOOME returned two

phylogenetic trees with branch lengths representing either the number of expected gain events or

the number loss events on each branch. As recommended (Cohen et al. 2010), branch lengths

representing relative gain and loss rates were extracted from the phylogenetic trees using FigTree

v. 1.4.4 (http://tree.bio.ed.ac.uk/software/figtree/). To normalize expected gain (or loss) events

with sequence divergence, we calculated the ratio of inferred gain (or loss) against the branch

lengths of the sequence-based core phylogeny. Outlier branches with excess normalized gains or

losses were identified using the interquartile range criterion.

Positive selection analyses

We employed codeml from PAML v. 4.9 to calculate ω, the ratio of nonsynonymous to

synonymous rates (Yang 1997; Yang 2007). We performed *codeml* analysis on nucleotide

alignments of the single-copy core genes and on single-copy accessory genes that were present in

10 or more isolates. For the analysis of individual core genes, *codeml* was performed assuming

the phylogeny inferred from the core gene alignments. For each accessory gene, we generated an

unrooted maximum-likelihood tree based on the DNA alignment of that gene, using RAxML v.

8.2.12.

Given the input phylogenies, we performed *codeml* analyses that relied on calculating

likelihood ratios (LRs) under various models (Yang 2007). Briefly, we used the models to test

the null hypothesis that $\omega = 1.0$ against the alternative of positive selection ($\omega > 1.0$) in two

different ways. The first was a global test across the entirely phylogeny of a gene – i.e., across all

branches and all sites. This test requires the comparison of two models: one (M0) that estimates a

single ω from the data and another that sets $\omega=1.0$ (M1). The two models yielded evidence for

positive selection when the initial ω estimate was >1.0 and when the likelihood of the two

models differed significantly, based on $P < 0.01$ after FDR correction. The second test was

across sites – i.e., testing for specific codons with $\omega > 1.0$ – based on a comparison of models

M1a and M2a from *codeml*.

RESULTS

Core and Accessory Genes in *Xylella*

To investigate genome evolution in *X. fastidiosa*, we sequenced 20 novel *X. fastidiosa*

genomes using hybrid approaches, and we also retrieved publicly available genomes and raw

sequencing data (Supplementary Tables 1 and 2). This led to an initial dataset of 148 assembled

Xylella genomes, which we further reduced to 63 isolates based on two criteria. First, we

removed any genomes that did not include the isolation source (i.e., host species) or geographic

coordinates, leading to 129 remaining genomes. Second, we culled genetic synonyms with a

pairwise genetic distance < 0.0001 when the two isolates came from the same plant host. This

second set removed many genomes that were produced for population genomic studies, leaving a

sample of 63 genomes that were broadly distributed among the subspecies. All our analyses were

performed on this final set of 63 *X. fastidiosa* genomes with the *X. taiwanensis* outgroup.

268   The *X. fastidiosa* genomes in our dataset ranged in size from 2.42 Mb to 2.96 Mb, with

an average length of 2.61 Mb (Figure 1A). Annotation bast on the same method (to help ensure

fair comparisons) resulted in an average of 2,478 predicted genes per genome, with a range from

2,275 to 2,993 genes (Figure 1B). The dataset represents 22 plant hosts representing 12 botanical

orders, including the most (16) from coffee, followed by 7 from almond and grapes (Figure 1C).

The annotated genomes were the raw material for a pan-genome analysis that categorized each

gene as either core (present in all 64 samples, including *X. taiwanensis*) or accessory genes that

were present in one or more (but not all) genomes (Page et al. 2015). Across all 64 genomes, we

identified 10,428 genes within the pan-genome; of those, 1,025 were core genes and 9,406 were

accessory genes, with nearly 4,000 genes found in only a single isolate (Supplementary Table 3;

Figure 1D). As is common in the literature (Abby and Daubin 2007; Vernikos et al. 2015), we

further delineated accessory genes into 306 soft core genes present in > 95% of isolates (95% <=

isolates < 100%), 2,172 shell genes (15% <= strains < 95%), and 6,974 cloud genes (0% <=

strains < 15%; Supplementary Figure 2). Here, however, we focus on the entire accessory set

without relying on these additional arbitrary categories.

283   We performed functional analyses on both the core and accessory gene sets by grouping

protein coding sequences into clusters of orthologous gene (COG) (Figure 1E-F). Many genes

had unknown functions: 150 core genes and 1,584 accessory genes had unknown functions. We

compared COG category rankings between the core and accessory gene sets, and there were

notable differences between the two gene sets (even though difference was not statistically

significant based on the Wilcoxon non-parametric rank sum test; P = 0.779). After excluding

genes with unknown function, the largest COG categories in the core gene set were 'translation,

ribosomal structure, and biogenesis' (117 genes), 'cell wall/membrane/envelope biogenesis' (99

genes), and 'amino acid transport and metabolism' (82 genes). In contrast, the largest categories

for accessory genes were 'replication, recombination and repair' (538 genes), 'intracellular

trafficking, secretion, and vesicular transport' (365 genes), and 'transcription' (303 genes).

We also investigated the core and accessory gene lists for significant GO-based

enrichment for specific biological processes. GO analysis on the core gene set revealed

enrichment for pyrimidine nucleotide biosynthetic processes, translation, aromatic amino acid

family biosynthetic processes, and RNA methylation (Supplementary Table 4). GO analysis of

the accessory set identified enrichment for glutamine family amino acid biosynthetic processes,

tRNA aminoacylation, ncRNA processing, nucleotide biosynthetic processes, and cellular

component organization or biogenesis (Supplementary Table 5).

Phylogenetic Patterns of Core Genes, Accessory Genes and Hosts

Phylogenetic Relationships We used the core gene alignment to build a maximum

likelihood phylogeny. The topology was highly supported; it had a mean bootstrap support of

93.75% across all nodes, with a median of 100% (Figure 2). The lowest bootstrap supports were

primarily found at nodes separating *X. fastidiosa* strains isolated predominantly from grapevines,

reflecting relatively low evolutionary divergence among these samples. As expected (Denancé et

al. 2019), isolates clustered into three distinct clades representing the three main subspecies

(ssps. *fastidiosa*, *multiplex*, and *pauca*), with 27, 23 and 13 isolates in each clade, respectively.

While the core-gene phylogeny illustrated strong support for three clusters, it is worth noting that

individual core gene tree phylogenies displayed "clouds" around the three clusters, with many

single-gene phylogenies visually discordant (Supplementary Figure 3). Such discordance can

have many potential causes, including limitations in the extent and quality of phylogenetic

information captured within a single gene but also potential HGT events.

To investigate general evolutionary patterns of the accessory gene complement, we

compared the core gene phylogeny against a phylogeny based on accessory gene composition

(Supplementary Figure 4). Both the core gene phylogeny and the accessory gene dendrogram

clustered into three groups, and all members of the groups were consistent between phylogenetic

treatments (Figure 3). This pattern broadly suggests that accessory genes, while defined by their

inconstancy, are not exchanged *en masse* to a sufficient degree to alter phylogenetic signal

among subspecies. Within subspecies, however, relationships at the tips of the phylogeny often

differed between core and accessory trees. As an example, the cluster corresponding to *multiplex*

displayed the most discordance between the core and accessory trees, with all OTUs contributing

to phylogenetic incongruence (Figure 3). Interestingly, our *multiplex* sample also had more plant

host species than our *fastidiosa* and *pauca* samples, suggesting the possibility (but by no means

proving) that host factors may affect or moderate genome content. Nonetheless, we found a

significant correlation between distance matrices based on the core and accessory phylogenies

(Mantel test, R = 0.8411, P < 0.001), which is consistent with the fact that the two trees had the

same three major clades. The overarching impression of these analyses is that accessory gene

composition does not turn-over so rapidly, due to HGT or other mechanisms, to erase

phylogenetic and historical signals of subspecies diversification within *X. fastidiosa*.

We used the phylogenies to test associations between *X. fastidiosa* and their isolation

sources (i.e., geographic location or host plant information) using ANOSIM (see Methods). We

found a weak but significant phylogenetic association (ANOSIM R = 0.08178, P = 0.042)

between the core phylogeny and geographic information, suggesting (not surprisingly) that

strains isolated from similar geographic regions were more genetically similar to one another

than those isolated from different regions. Similarly, comparisons between strains isolated from

different host species revealed a weak significant phylogenetic signal (ANOSIM R = 0.1381, P =

0.047). Since *X. fastidiosa* infects a wide range of plants, we also retrieved the taxonomic order

of each plant host to test for a phylogenetic signal at a deeper taxonomic level. There was a

stronger association between plant order and phylogenetic signal (ANOSIM R = 0.3152, P <

0.0001); in other words, strains isolated from plants within the same taxonomic order were more

phylogenetically similar to one another than isolates taken from unrelated plants.

We hypothesized that accessory genes are crucial in pathogen-host interaction and

therefore repeated ANOSIM analyses with a distance matrix based on the presence and absence

of accessory genes (Figure 3). We found no significant association between accessory gene

content and geographic isolation source (ANOSIM R = 0, P = 0.5307). In contrast, we detected a

weakly significant association between accessory gene content and host species (ANOSIM R =

0.153, P = 0.042), but the association was less pronounced at the level of plant order (ANOSIM

R = 0.08424, P = 0.0784). Overall, associations were less evident based on accessory gene

content vs. the core-gene phylogeny.

Gene Gain and Loss. The sheer number of accessory genes indicate that the genome

content of *X. fastidiosa* is, like other microbes (Bolotin and Hershberg 2015; Iranzo et al. 2019),

shaped by extensive gene gain and loss events that are probably mediated by HGT (Firrao et al.

2021). We were interested in assessing the pattern of gene gain and loss across the phylogenetic

tree, hypothesizing that both could be enhanced on branches that lead to host shifts. We used

GLOOME to estimate the number of gain and losses of accessory genes across the *X. fastidiosa*

phylogeny and represented those estimates phylogenetically (Figure 4). Ignoring the branch

leading to the *X. taiwanensis* outgroup (PLS229), the internal branches discriminating the *X.*

fastidiosa subspecies were estimated to average ~550 separate gene gain and gene loss events.

The remainder of the tip and ingroup branches averaged ~100 gene gain and loss events (average

gains/branch = 92.8 genes; average losses/branch = 100.0 genes; Figure 4A&B).

While it is useful to estimate the number of gains and losses on each branch, we thought

it more helpful to normalize the number of estimated gain and loss events by branch lengths,

estimated from the sequence analysis of core genes. This normalization by branch length

converted the number of gene gains and losses to *rates* of gene gain (or loss) relative to sequence

divergence. We then sought to identify branches with aberrantly high rates of gene gain or loss

(Figure 4C&D), which reflect branches with especially notable turnover of accessory genes.

Somewhat surprisingly, we found that most of the phylogenetic lineages with outlier rates were

located at the tips of the phylogenetic tree. For example, of the 21 branches with high rates of

gene gain, 19 were at the tips of the phylogeny (Figure 4A). Similarly, 18 of 21 branches with

high rates of gene loss were external branches. These observations suggest features about the

evolutionary dynamics of genic turnover (see Discussion).

Characterizing selection with ω

We characterized selection on individual genes by estimating the dN/dS ratio (ω); we

especially sought to identify genes that experienced positive selection (i.e., $\omega > 1.0$), because it

is a potential signal of genes that contribute to arms-race dynamics between the pathogen and its

hosts. To do so, we applied a series of nucleotide substitution models to individual genes,

ultimately resulting in tests for positive selection on two levels: globally across a phylogeny and

across codon sites (see Methods). For these tests, we examined the full complement of 1,025

core genes and a subset of 2,349 accessory genes. The accessory subset was defined by presence

at least 10 of the 64 *Xylella* genomes; we chose this subset based on both a practical

consideration (to limit computational burden) and also in recognition that statistical power

decreases with the number of sequences in a dataset.

Testing selection globally for each gene: We first estimated a single ω value for each

gene with the codeml model M0, which assumes that ω is constant across all branches of the

entire gene tree and across all codons in the nucleotide alignment. Applied to the core genes, the

model estimated ω values that ranged from 0.01018 to 0.88905 with an average of 0.15415

(Figure 5A). None of these core genes had a ω estimates ($\hat{\omega}$) higher than 1.0. The range of

$\hat{\omega}$ was substantially broader for accessory genes, from $\hat{\omega} = 0.0001$ to 32.1334, with an average

of 0.51443 (Figure 5B). Despite the wide range of $\hat{\omega}$ values in the accessory set, only 222 genes

(or 9.5%) had a global estimate of $\omega > 1$. The average $\hat{\omega}$ was significantly higher in the

accessory gene set compared to the core genes (unpaired T-test, $P < 0.0001$), reflecting either

lower purifying selection against these genes, more positive selection, or both.

We then tested whether genes have ω significantly different from 1.0. To do so, we

compared the log likelihood from M0 to a model with ω fixed to 1.0. The vast majority (1,021 of

1,025) of core genes had $\hat{\omega}$ significantly < 1.0 ($P < 0.01$, FDR correction; Figure 5A), reflecting

pervasive purifying selection. The trend for accessory genes was not as severe, because 1,040

genes had ω significantly < 1.0 ($P < 0.01$, FDR correction) but 1,282 genes had ω values that

were not significantly different from 1.0 (Figure 5B). Of the 222 genes with ω estimates > 1.0,

only three had statistically significant evidence for positive selection. These three genes are

strong candidates to encode proteins involved in arms-race dynamics, but all three were

annotated as hypothetical genes *(group_1159, group_1160*, and *group_4304*; Supplementary

Table 3).

Positive selection in codon sites: The global test is a conservative criterion to search of

positive selection, perhaps overly so. Accordingly, we turned to an alternative method that tests

for variation in ω among codon sites and identifies whether sites are under positive selection. To

do so, we ran the sites models in *codeml*, which are a group of nested models. For completeness,

we first compared sites model M0, which represents the null hypothesis that there is a single ω

value for all sites, against sites model M3, which permits ω to vary among sites. In the core

genes, the likelihood ratio test was significant for 726 genes ($P < 0.01$, FDR correction),

implying that ω varies among sites. Next, we compared sites model M2a against model M1a to

test for positive selection among sites in the gene. We found that 200 core genes had evidence of

positive selection among sites ($P < 0.01$, FDR correction); of these, 199 were also significant for

the M0-M3 comparison. We also tested for positive selection on codon sets within the 2,349

accessory genes by comparing sites model M2a against M1a. Of those, 181 genes yielded

evidence of positive selection among sites ($P < 0.01$, FDR correction, 7.7% of accessory genes),

of which 173 were also significant for the M0-M3 comparison. To sum: 19.5% (i.e., 200 of

1,024) of core genes had significant evidence for codons under positive selection, while 7.7%

(181/2,349) of accessory genes contained codons with an apparent history of positive selection.

Interestingly, of the 181 accessory genes, 41 of these had estimates of $\omega > 1.0$ across all sites and

phylogenetic branches, even though the global test was not significant for any of these genes. We

nonetheless consider these 41 to be the strong candidates to have experienced positive selection.

DISCUSSION

Host-pathogen interactions can drive rapid evolution of pathogenic bacteria, particularly

for genes involved in arms-race dynamics (Daugherty and Malik 2012; Sironi et al. 2015). Here,

we investigated the genomic evolution of the plant pathogen, *X. fastidiosa*, through comparative

genomic analysis of genomes that represent diversity across the species, based on a sample set of

64 genomes. The sample was isolated from 23 different plant hosts (**Figure 1C**) from throughout

the world, with the majority from the United States (n=21) followed by Costa Rica (n=14) and

Brazil (n=8; Supplementary Figure 1). With these data, we constructed a pangenome that

contained 1,024 core genes and 9,406 accessory genes, reflecting numbers similar to previous

studies that used fewer samples or subspecies-specific sets of *X. fastidiosa* genomes

(Giampetruzzi et al. 2017; Castillo et al. 2020). These values illustrate, however, that less than

half of the ~2,748 coding sequences (per genome average) are likely to be essential, because

most genes vary across isolates. Of the core genes, the majority were involved in essential

cellular processes -- such as translation, cell wall biogenesis, and amino acid metabolism

(**Figure 1E**) -- as expected (Tettelin et al. 2008).

We used the set of core genes to infer a maximum likelihood phylogeny. As with

previous systematic treatments of *X. fastidiosa* (Yuan et al. 2010; Marcelletti and Scortichini

2016; Denancé et al. 2019), our phylogeny identified three clades corresponding to the three

main subspecies (*fastidiosa, multiplex*, and *pauca*). The phylogeny suggests that *pauca* is the

oldest among the three, because it diverged prior to the divergence of *multiplex* and *fastidiosa*

(**Figure 2**). Interestingly, based on our sample, it is not clear that *pauca* has greater diversity of

host species despite its greater age. Our sample includes 13 *pauca* strains from 7 plant hosts (a

ratio of 0.54 hosts per strain), while *multiplex* has a similar ratio (23 strains from 12 different

plant hosts = 0.52 hosts/strain). In contrast, *fastidiosa* has a much lower ratio of 0.27

hosts/strains, with 27 strains from 10 plants. These ratios may certainly reflect properties of our

sample more than biological trends – e.g., much of the research on subspecies *fastidosa* have

focused on PD in grapevines and so is biased – but these observations nonetheless suggest that

the older age of *pauca* has not led to obviously greater host diversity than *multiplex*.

The question of plant host specialization

The phenomenon of host specialization of *X. fastidiosa* (and perhaps whether it exists at

all) is somewhat unclear. On the one hand, *X. fastidiosa* is a generalist known to colonize or

infect over 350 plant species (Sicard et al. 2018). Furthermore, some strains are known to cross-

infect hosts, such as the isolate that causes both PD and almond leaf scorch (Chen et al. 2010).

On the other hand, experimental work has shown some evidence of host specificity with respect

to colonization and disease progression (Almeida et al. 2008). For example, *X. fastidiosa*

isolates known to cause citrus variegated chlorosis and coffee leaf scorch were apparently unable

to colonize the alternative host (Almeida et al. 2008). Similarly, Castillo et al. 2020 demonstrated

that the *X. fastidiosa* ssp. *fastidiosa* isolates from coffee or periwinkle did not efficiently infect

grapevines, even though ssp. *fastidiosa* commonly infects grapevines.

In addition to experimental evidence, the question of host specialization has been

addressed previously using phylogenetic approaches based on multilocus sequencing typing

(MLST) data. In this work, Sicard et al. (2018) generated MLST data from 7 housekeeping genes

from 50 *X. fastidiosa* genotypes. After building a phylogeny, they tested coevolutionary

relationships between host species and *X. fastidiosa* MLST types but found no significant

evidence of coevolution, implying a lack of host specialization. We have revisited this issue

using whole genome sequence data and a larger sample of isolates. We found a significant, non-

random association between phylogenetic relationships and both the species and taxonomic order

of plant hosts (P < 0.0001). These results are consistent with some level of specialization of *X.*

fastidiosa to plant hosts. Although it is difficult to compare ANOSIM results across studies, it is

worth noting that the association of *X. fastidiosa* to plant order is similar in magnitude to the

association between a gut colonizing bacterium (bifidobacteria) and the host species from which

it was isolated (Rodriguez and Martiny 2020).

Given some evidence for host specialization, we hypothesized that it is driven in part by

accessory gene content. Under this hypothesis, we predicted an association between genes and

hosts should be as (or more) pronounced for accessory genes than for core genes. Instead, we

found no significant association between accessory gene complement and taxonomic order and

only a weak association with plant species. Our results are unlike, for example, the case of

bifidobacteria, where the association with host species was nearly as strong for accessory genes

as for host genes (Rodriguez and Martiny 2020). We do not know why we did not detect a signal

for host specialization of accessory genes, but we can think of three explanations. One is that our

hypothesis is incorrect – i.e., that host associations, to the extent they exist, are not driven by

accessory genes but rather evolutionary divergence in core genes. Another is statistical power:

because there are many more sequence changes among the core genes than there are changes in

accessory gene content, the distance matrix for core genes likely has a higher signal-to-noise

ratio than accessory gene content. Finally, if accessory genes do mediate host shifts, it is possible

– and even likely - that only a subset of accessory genes drive these shifts. Under this scenario,

there may be significant associations for a small subset of accessory genes, but the signal of this

association is weak across the entire accessory gene set. This conjecture seems reasonable given

that *X. fastidiosa* interacts not only with plants but also insect vectors and microbial

communities. Hence, some subset of accessory genes may contribute to these interactions, rather

than plant host interactions. Untangling our three explanations should be possible, but it will

likely require even larger datasets (to tackle potential issues of statistical power) and also a better

understanding of *X. fastidiosa* diversity within and among insect vectors.

The pattern of gene gain and loss events

Another potential tool to study adaptation to specific hosts is by examining shifts in gene

composition through gene duplication, deletion, or HGT events (Hurles 2004; Arnold et al.

2022). We estimated the number of gene loss and gain events along the core-gene phylogeny,

and then normalized those numbers relative to sequence divergence. Using this approach, we

found that most branches followed a consistent rate of gene gain or loss relative to sequence

divergence. The fact that the accessory gene phylogeny recapitulates the three subspecies (Figure

3) suggests, along with previous evidence, that *X. fastidiosa* evolves predominantly through

vertical inheritance and intraspecific recombination, rather than HGT from other bacterial

species (Nunney et al. 2013; Castillo and Almeida 2021).

We have, however, identified 19 and 18 lineages with enriched gain or loss events,

respectively, and most of these branches were at the tip of the phylogeny. Again, a potential

explanation for these gain and loss dynamics is that they reflect host shifts. There are some

isolated examples that are consistent with this hypothesis. For example, isolates XF6c, Pr8x,

RAAR17, and OLS0478 in *pauca* have branches with enriched gene gains (Figure 4A). Two of

these (OLS0478 and Pr8x) were isolated from oleander and plum, respectively, and are the only

isolates associated with those plant hosts in their clades, suggesting a host shift. More globally,

however, the evidence for this hypothesis is unconvincing. When we, for example, contrast gene

gains between pairs of sister taxa with the same plant host, three of the 16 sister pairs had

enriched rates of gene gain. This proportion of enriched branches was not significantly lower

than the reminder of the tree ($P > 0.05$; Fisher's Exact Test), despite the fact that the sister taxa

did not experience a host shift. All of these inferences are of course dependent on our sample and

ignore the vector component of the *X. fastidiosa* lifecycle, so there are limitations to our

conclusions. At present, however, the evidence for an association between host shifts and

enhanced gene gain and loss events is weak.

This leaves unexplained the pattern of enriched rates of gene gain and loss at the tips of

the tree. We suspect this pattern is analogous to patterns of mutations in populations. New

mutations begin as rare, low frequency variants in single individuals. Eventually most of these

mutations are removed by the processes of genetic drift and natural selection, so that there are

more new mutations in populations than old mutations. In a phylogenetic context, these new

mutations would be evident at the tip of the trees, so it may be reasonable to expect higher

effective rates of gene gain and loss in the 'newest' phylogenetic branches. This explanation only

has credence, however, if the observed gain and loss events are both recent – i.e., newer than the

sequence mutations that define the tip branches – and frequent.

The identification of putative arms-race genes

Many previous studies have implicated genes and their protein products in ongoing arms-

races between pathogens and their hosts (Anderson et al. 2010; Schulte et al. 2010). One way to

approach this question is agnostic of function, which is to screen for genes with a history of

positive selection. In our case, a set of positively selected *X. fastidiosa* genes represents potential

candidate virulence factors and also factors that mediate interactions with the environment,

including plant host, insect vectors, or members of the microbial community. Previous research

on *X. fastidiosa* has searched for signatures of selection by comparing levels of polymorphism or

rates of synonymous and nonsynonymous mutations in the core genome using Tajima's D and

the McDonald-Kreitman test (Castillo et al. 2020; Castillo et al. 2021). These population-based

tests generally search for a signal of local adaptation, rather than arms-race dynamics. Another

work has measured ω in core genes but without statistically testing for positive selection

(Castillo and Almeida 2021). Thus, no other work on *X. fastidiosa* has yet taken as thorough an

approach to search for signals of positive selection.

To study positive selection, we estimated ω, or the ratio of nonsynonymous to

synonymous mutations, for each core gene and for each accessory gene found in 10 or more

isolates. In total, this exercise encompassed 3,373 genes: 1,024 core and 2,349 accessory genes.

We began by applying a global test that estimates ω over all sites and phylogenetic lineages.

This approach can be overly conservative, because a significant test of $\omega > 1.0$ requires that

positive selection is very strong, acts across many sites in a gene, is present in most of the

branches of the phylogeny, and/or all of the above. As expected, we found only a few genes

(three accessory genes in total) that were significant for positive selection with this test.

Unfortunately, the annotations of these few genes yielded no insights into their functions. This

test did allow, however, for two broad generalizations about patterns of selection in *X. fastidiosa*.

First, as a group the core genes are under strong purifying selection with most (>99%) having ω

estimates significantly < 1.0. Interestingly, the highest ω value for a core gene set was $\omega =$

0.889, for a hypothetical protein within unknown function but with a possible role in the cell

membrane (EggNOG query OG: ENOG5031E4H). Second, accessory genes generally have

lower levels of purifying selection, as evidenced by a lower proportion (45%) of significant tests

for $\omega < 1.0$ and by much higher average $\hat{\omega}$ values (0.15415 vs. 0.51443; Figure 5A). The

proportion of significant tests must be compared between genic sets with caution, because the

smaller sample sizes (n=10 to 63) for accessory genes likely reduce statistical power relative to

the n=64 samples for all core genes, as do any differences in gene lengths. Nonetheless, the

contrasting pattern of ω is consistent with the ideas that core genes have conserved biological

functions and that accessory genes are more amenable to evolutionary change due to their

nonessential, but still potentially biological relevant, cellular roles (Horesh et al. 2021).

Accessory genes may also experience higher variation in their selection dynamics because

recombination affects them more than core genes (Castillo and Almeida 2021).

Given few signals of positive selection, we turned to codon site models, which identify

evidence of particular codon sites with histories of positive selection. To our surprise, we not

only found evidence of positive selection in core genes, but the proportion of positively selected

genes was higher for core genes (at 19.5%) than for accessory genes (8.1%). These proportions

may again reflect differences in statistical power between the two groups, but the data

nonetheless suggest that a large number of core genes have some history of positive selection.

The salient question is whether these genes give some clue to function. Of the 200 core genes

with evidence for positive selection at the codon level, we found 26% were unannotated. The

remaining genes were enriched for GO categories related to tryptophan, glutathione, and

threonine biosynthetic process along with fatty acid catabolic process, lipid modification, and

nucleoside triphosphate biosynthetic process among others (Supplementary Table 6), none of

which seem especially integral to interactions with plant or insect hosts. We also performed a

functional analysis by grouping the protein coding sequences of these 200 core genes into COG

categories to infer cellular functions. Excluding the category of unknown function (which was

the largest with 29 instances), the two largest categories were 'amino acid transport and

metabolism' and 'cell wall/membrane/envelope biogenesis' followed by 'energy production and

conversion' and 'intracellular trafficking, secretion, and vesicular transport' (Supplementary

Figure 6A).

592   Of the 181 accessory genes with evidence for positive selection at the codon level, 82%

were not annotated for function. To infer function, we performed a similar functional analysis

and found that the largest categories (excluding the category of unknown function) were

'intracellular trafficking, secretion, and vesicular transport,' 'replication, recombination, and

repair,' and 'post-translational modification, protein turnover, and chaperones' (Supplementary

Figure 6B). Intriguingly, of this set of 181 genes, 41 overlapped with the set of 222 genes that

had a gene-wide estimate of $\hat{\omega} > 1$. While these are especially strong candidates for arms-race

genes, a disappointing 95% of them were unannotated for function. Two genes had annotations

which we could explore further: *nagZ_2* with $\hat{\omega} = 3.77387$ and *cya* with $\hat{\omega} = 1.2424$. The gene

nagZ_2 encodes a beta-glucosidase that is important for biofilm formation in *Neisseria*

gonorrhoeae, suggesting it could play a similar role in *X. fastidiosa*. It merits further functional

analysis, since biofilms are important to the infection cycle (Bhoopalan et al. 2016). We also

examined *cya*, which encodes adenylate cyclase and plays essential roles in regulation of cellular

metabolism (Danchin et al. 1984). Interestingly, the protein is involved in the cyclic AMP

system, which is a global regulator in gram-negative bacteria and has been shown to modulate

gene expression in pathogenic bacteria (Smith et al. 2004; Kim et al. 2005).

608   As a final exercise, we cataloged the incidence of positive selection in a set of 35 genes

that have been listed as virulence and pathogenicity factors in *X. fastidiosa* (Rapicavoli et al.

2018). Of the 35, we could identify 29 in our database (Table 1). We expected that this set of 29

genes would be enriched for evidence of positive selection relative to the genomic background,

because these genes are putatively involved in arms-race interactions. The trend for these genes

was in the right direction for enrichment, because 7 of 29 (= 24%) were significant vs. 352 of

3345 (= 10.5%) in the rest of the genome. However, the difference in proportions was only

borderline significant (Fisher Exact Test, $P = 0.078$). Nonetheless, this set of experimental genes

is quite interesting. Of the seven with evidence of positive selection, six encode proteins

associated with the membrane of gram-negative bacteria and are involved in membrane transport

or adhesin. Specifically, the genes *fimF, xadA* and *xatA* encode proteins involved in fimbrial

adhesion, non-fimbrial adhesion, and biofilm formation, respectively, and the genes PD1311,

tonB1, and *xpsE* encode proteins involved in membrane transport (Ma Rodriguez et al. 1993; Sun

et al. 2005; Abbas et al. 2007; Das et al. 2009; Zeiner et al. 2012). The remaining gene *lesA/lipA*

is an extracellular lipase that affect biofilm stability in *X. fastidiosa*, similar to other pathogens

like *Pseudomonas aeruginosa* (Tielen et al. 2013; Nascimento et al. 2016).

CONCLUSIONS

We performed comparative genomic analysis of *X. fastidiosa* genomes to explore the

evolutionary history of the core and accessory genes in this plant pathogen and to explore genetic

determinants that may contribute to host specificity or virulence. Using phylogenetic methods

and association tests, we found that *X. fastidiosa* shows evidence for adaptation to host plants as

reflected in their evolutionary history of core genes. We also inferred that the evolutionary

dynamics of *X. fastidiosa* accessory gene complement tends to retain information about vertical

inheritance and intraspecific recombination rather than horizontal gene transfer between

interspecifics. We also found evidence of positive selection in 200 and 181 core and accessory

genes using sites models, suggesting that *X. fastidiosa*, like other pathogens, is undergoing

adaptive evolution in response to its hosts.

DATA AVAILABILITY STATEMENT

All high-throughput sequence data generated in this study have been submitted to the NCBI

Sequence Read Archive database at https://www.ncbi.nlm.nih.gov/sra and can be accessed with

project number SUB11276742.

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884   **Table 1:** *Codeml* results for experimentally identified virulence and pathogenicity genes, as
885   listed Rapicavoli et al. (2018)
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PD Number	Gene Name	Pan-genome classification	No. Genomes[1]	$\hat{\omega}$ (M0)[2]	M2a vs. M1a p-value[3]
PD0058	*fimF*	Accessory	41	0.31555	**2.93E-08**
PD0062	*fimA*	Accessory	26	0.81255	0.204
PD0233	*rpfB*	Accessory	57	0.16832	1.00
PD0279	*cgsA*	Core	64	0.14876	0.396
PD0406	*rpfC*	Accessory	44	0.34502	1.00
PD0528	*xatA*	Core	64	0.4568	**1.16E-117**
PD0731	*xadA*	Accessory	58	0.39197	**0.003**
PD0732	*xpsE*	Core	64	0.05966	**0.004**
PD0814	*wzy*	Accessory	43	0.17675	1.00
PD0843	*tonB1*	Core	64	0.1126	**4.17E-04**
PD0848	*pilL*	Core	64	0.1808	0.893
PD0986		Core	64	0.10876	1.00
PD1099	*dinJ/relE*	Accessory	25	0.10271	1.00
PD1100		Accessory	15	0.20708	0.648
PD1284	*algU*	Core	64	0.20339	0.979
PD1311		Accessory	33	0.42541	**2.68E-05**
PD1380	*csp1*	Core	64	0.15702	1
PD1391	*gumH*	Accessory	46	0.12964	1
PD1394	*gumD*	Accessory	63	0.12358	0.204
PD1485	*pglA*	Accessory	59	0.27857	0.271
PD1678	*phoQ*	Core	64	0.10503	0.011
PD1679	*phoP*	Core	64	0.02806	1.00
PD1703	*lesA/lipA*	Core	64	0.0676	**0.008**
PD1792	*hxfB*	Core	64	0.10876	1.00
PD1826	*chiA*	Core	64	0.12798	0.695
PD1856	*engXCA1*	Accessory	63	0.25823	0.122
PD1964	*tolC*	Core	64	0.07808	1.00
PD1984	*gacA*	Core	64	0.13444	1.00
PD2118	*hxfA*	Core	64	0.10876	1.00

888   [1] the number of genomes, out of 64, in which the gene was detected.

889   [2] M0 estimates a single ω across the entire phylogeny of sequences.

890   [3] The p-value of tests after FDR correction. Bolded values are significant at p < 0.01. The

891   notation E refers to the power of ten.

Figure 1: Histograms reporting the characteristics of the 64 *Xylella* genomes. A) Genome

lengths, exhibited in base pairs. B) The number of genes within a genome. C) A histogram of the

plant species from which genomes were isolated. D) A histogram of the number of genes found

in *x* number of genomes; this histogram shows, for example, that nearly 4,000 genes are found in

only of the genomes out of the entire sample of 63 genomes and that ~1,000 genes are found in

all 64 genomes; E) the distribution of functional categories for the set of 1,024 core genes and F)

the distribution of functional categories for the set of 9,258 accessory genes. A key to the COG

categories for panels E) and F) is in Figure S5.

Figure 2: The inferred phylogeny of 64 *Xylella* genomes, based on maximum likelihood

inference of core gene alignments. Each isolate is labelled at the tips and is colored according to

the order of the plant isolation source (host). The common name of the host is provided to the

right of order information. The three *X. fastidiosa* subspecies are indicated, as are bootstrap

values at each node. The bootstrap values are pie charts, where black represents the percent of

bootstrap support, and the scale bar reflects the magnitude of sequence divergence per nucleotide

site.

Figure 3: A comparison of the likelihood tree based on the core gene alignments (from Figure 2,

on the left) to a dendrogram based on distances due to gene presence / absence (on the right). As

in Figure 2, the isolates are labelled at the tips of trees, with the colors representing plant order.

Both phylogenies contain three main *X. fastidiosa* clades, representing the three subspecies.

Lines connect the same isolate between the two trees, with angled lines representing topological

discordance between phylogenies. The three *Xylella* subspecies are outlined in a black box and

labelled.

Figure 4: The result of gene gain and loss analyses. A) The phylogeny of the isolates, with

branch lengths proportional to the number of gene gain events. The colored branches are

branches with outlier gene gain rates. B) The phylogeny of the isolates, with branch lengths

proportional to the number of gene loss events. The colored branches are branches with outlier

gene loss rates. C) A plot of the gene gains against sequence divergence; in the plot each dot

represents one of the 125 branches on the phylogeny. Outlier dots are colored red. D) As in C,

with gene losses plotted again sequence divergence.

Figure 5: Estimated values of ω under M0 (the one-ratio model) in the core and accessory genes.

The distribution of $\hat{\omega}$ values is plotted for A) core genes and B) accessory genes. Histogram bars

are shaded to reflect the outcome of the likelihood ratio test (non-significant tests are colored red

and significant tests are colored blue) between a model that estimated $\hat{\omega}$ and a model with ω

fixed to 1.0. The horizontal dashed line denotes $\hat{\omega}$ for each gene set.

Figure 1:

950   **Figure 2:**
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Figure 4:

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